THE INFORMATIONAL CONTENT OF END-OF-THE-DAY INDEX FUTURES RETURNS IN CANADA

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ABSTRACT

The Informational Content of End-of-the-Day Index Futures Returns in Canada

Rosemary Shuttleworth

This study investigates the information which may be contained in index futures returns during the additional fifteen minutes of trading which take place after the stock market has closed A significantly positive relationship was found between end-of-the-day (4:00pm to 4 15pm) futures returns, and the mean overnight spot return, and also with the conditional variance of overnight spot return These results were confirmed using three different models GARCH(1,1), GJR GARCH, and Asymmetric GARCH models. The lagged unexpected EOD futures return was found to be positively related to the overnight spot return only when the Asymmetric GARCH model was used, and when the GARCH(1,1) model was used with unexpected EOD returns being estimated by an ARIMA(4,4) process Some indication of a weekend effect in the overnight spot returns, which is anticipated by the futures market at the end of the day on Friday, was found. The unexpected EOD futures returns were found to be unrelated to the trading period spot returns.

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Introduction

Futures markets have several functions. One is to provide a hedge against positions taken in various spot markets, and another is the transmission of information to the spot market, or the price discovery function. The market for futures contracts on market indexes (index futures) on the Toronto Stock Exchange (TSE) remains open fifteen minutes later than the stock market. This fact gives rise to the question of what type of information may be reflected in this additional trading time. The return for the last fifteen minutes of trading (referred to as the end-of-day, or EOD futures return), may contain information held by informed traders that would not be reflected in the cash index until the next morning when the stock market opens. In addition, this return may contain "noise", or the trading activity of liquidity traders, who are not privately informed. This study tests the relationship between the EOD index futures return and the overnight spot return, and conditional variance of the overnight spot return. If the EOD return reflects the activity of privately informed traders, rather than "noise" traders, as well as information released publicly in this fifteen minutes, we would expect to find a significantly positive relationship in both cases. The results of this study confirm this hypothesis. Previous studies have also found that the EOD return is not totally reflected in the overnight spot return, but is also significantly positively related to the trading period spot return for the following two days. This was not found to be the case in this study

Many empirical studies have also found that the market for index futures leads the cash index market by several minutes. The inference is that the index futures market reflects information more quickly than the cash index market because the transaction costs are lower and there is no short selling constraint The cash index also experiences nonsynchronous trading effects. The index value lags behind the fundamental market value of the underlying composite stocks when some of these stocks are not frequently traded The infrequent trading results in the quoted price being a stale price, which may not reflect all relevant information about the stock It is this stale price that is used in computing the value of the index The index futures however, reflect the expected future value of the underlying stocks themselves, and so do not experience any nonsynchronous trading effect This is another reason why the index futures tend to lead the cash index.

The significant aspects of this research are that it has not been done before on Canadian data, it combines various tests of other studies that have not previously been undertaken together, and adds other models, which have not been used in EOD studies before Some investigation of day-of-the-week (DOW) effects in the futures index and cash index is also done.

Two futures contracts on market indexes have existed in Canada, futures on the TSE 300 Composite Index and futures on the Toronto 35 index. The TSE 300 Composite Index was introduced in 1977, and futures contracts on the index started trading in 1984 The futures contract ceased trading in 1987, due to low volume, and the introduction of the Toronto 35 index, which was accompanied by a futures contract on that index The TSE 300 Composite Index tracks the performance of 300 stocks, divided into 14 major groups and 41 subgroups, which are meant to be representative of the overall performance of the Toronto Stock

Exchange The Toronto 35 Index tracks the TSE 300 very closely, and is made up of 35 of the largest and most liquid stocks listed in Canada, which represent all the major sectors found in the TSE 300 This study focuses on the intraday behaviour of the more recent Toronto 35 futures contract and its corresponding spot index

The organization of this paper is as follows: in the first section the relevant literature on the subject will be reviewed, the hypotheses to be tested in this study will be described in the second section The data and methodology to be used will be outlined in the third section, followed by a discussion of the results, and concluding remarks, in the fourth and fifth sections.

Section I : Literature Review

The two major studies that relate to EOD futures returns are Herbst and Maberly [1993] and Hiraki, Maberly and Takezawa [1993], hereinafter referred to as HMT. The results and implications of these studies are discussed briefly in this section

The informational content of the EOD index futures returns of the Nikkei 225 futures contract in Japan was examined by Hiraki, Maberly and Takezawa [1993], for the period 1988 to 1991 Using a GARCH(1,1) model, they break down the EOD futures return into an expected and unexpected component. The expected component represents all public information, and is estimated by using the most recent price history of futures prices. The unexpected component is due to informed and noise traders, and is assumed to be fully reflected in the overnight spot returns The unexpected component is the variable of interest, since it occurs in the 4.00pm to 4 15pm trading time They find a significant positive relationship between the unexpected component of EOD futures returns and the overnight spot returns, and between the unexpected component and the conditional variance of the overnight spot returns The unexpected EOD futures return is also found to be positively related to the following overnight spot return, meaning that the EOD futures return (day j) has an effect on the immediately following overnight spot return (day j to j+1) as well as the next overnight spot return (day j+1 to day j+2). A two stage GARCH regression was used The unexpected component of EOD futures returns was estimated in the first stage and used in the second stage as an explanatory variable of mean overnight spot returns and of the conditional variance of overnight spot returns. Their model also included dummy variables for days of the week, to test for any weekend or day-of-the-week (DOW) effects The lagged S&P500 index return was included as an explanatory variable of overnight spot returns, to see if there is any spillover effect from New York to Tokyo. This spillover effect was found to be significant, but the only significant DOW effect found was a positive Wednesday overnight spot return In addition, EOD futures returns were found to be significantly positively related to the next two days' trading period spot returns.

A GARCH model was used because of its ability to capture the leptokurtic distribution of financial returns series. These series often exhibit "clustering" of volatilities, meaning periods of high volatility or low volatility may persist The GARCH model can also effectively capture the clustering of volatilities since its' conditional variance equation contains lags of the error term and lags of the conditional volatility. The authors conclude that EOD Nikkei futures price changes are reflective of trading by informed traders, but that noise prevents this information from being instantly and clearly revealed The futures return during the end-of-day period helps spot traders discover information of informed traders, and also provides the market reaction to information released publicly over the EOD trading period. The private information contained in the EOD futures return is not totally reflected in the overnight spot return, but is also reflected in the next two spot trading periods

Herbst and Maberly [1992] investigate the informational content of EOD returns for the S&P500 index futures, from 1982 to 1988. They hypothesize that EOD trading consists of activity by informed and uninformed traders. Informed traders will wish to trade on their information before the close of trading, since during non-trading hours, the information they have will gradually disseminate into the market, and they will lose potential arbitrage opportunities For this reason, the authors feel that the volatility of EOD futures returns reflects activity, and therefore information production, by traders, and especially by informed traders. As a result, it also reflects the incentive for other traders to gather information on the next day's opening spot price. The authors argue that informed traders will prefer to trade during periods of higher liquidity trading volume, when their trading will have little effect on prices According to Admati and Pfleiderer [1988], periods of higher liquidity trading volume often occur at the end of the day. It is hypothesized that the incentive to gather information on the next day's spot price is positively related to the portion of the next morning's spot price which cannot be predicted by the previous day's closing spot price. (If the closing spot price fully predicts what the next morning's spot price will be, for example, then there is no incentive to gather any further information about the next morning's spot price) Specifically, the unpredictable portion of the next morning's spot price is represented by the volatility of the residuals from a regression of the next morning's spot price on the closing spot price the previous day (discussed in more detail in the next section) The main hypothesis they wished to test is that EOD futures returns volatility, representing information production, is positively related to the incentive to gather information on the next day's spot price (so EOD futures volatility should be positively related to the volatility of the regression residuals) Tests for possible DOW effects are also incorporated into their study. They reject the hypothesis that the residuals' volatility is equal across weekdays, meaning that the incentive to gather information varies over different weekdays In other words, the closing spot price has a varying predictability of the next morning's spot price, depending on the day of the week The hypothesis that EOD futures returns volatility are equal across days of the week is also rejected. The volatilities of the residuals and of the EOD futures returns are both highest on Friday and lowest on Wednesday The sample correlation coefficient between EOD futures returns volatility and the residuals' volatility is positive 0.881, meaning that EOD futures returns volatility is positively related to the incentive to gather information on the next day's spot price.

Another hypothesis tested by Herbst and Maberly was whether the magnitude of EOD futures returns is positively related to the flow of information created by the activity of informed traders. A subsample was created for "large" EOD futures returns (returns are defined as "large" if the return is at least one standard deviation larger or smaller than the mean return of the sample). It is assumed that on average, the flow of information is greater at the end of the day for large returns. For the large return subsample, the sample correlation coefficient between the futures return and the corresponding spot return was larger than the corresponding sample correlation coefficient for the entire sample. In addition, the mean EOD futures return for Friday is negative (for both the large return sample and entire sample), while the Monday 11 am spot return is also negative for both samples. The Wednesday EOD futures return for the large return sample is also negative, as is the 11am Thursday spot return for this sample This supports the hypothesis that the magnitude of the EOD futures return is positively related to the flow of information at the end of the day, and shows evidence of a weekend effect in the spot and EOD futures returns. The Friday close to Monday open spot return is negative, which is anticipated by the Friday EOD return. Herbst and Maberly also find that positive (negative) EOD futures returns are associated with positive (negative) 11 am spot returns. They conclude that EOD volatility is associated with the production of information, and that the flow of information is a function of the day of the week, with relatively more unfavourable information being produced on Fridays.

Both HMT's and Herbst and Maberly's hypotheses were based in part on a theoretical model developed by Admati and Pfleiderer [1988]. This study investigated intraday patterns of trading behaviour in the stock market. The authors found that volume and volatility patterns emerge endogenously due to the behaviour of liquidity traders and informed traders[1] At least some liquidity traders are assumed to have discretion in timing their trades to some extent, and it is conjectured that at equilibrium, if these traders can allocate their trades across different periods, their trading is more concentrated in periods that are more advantageous to them. The authors hypothesize that informed traders tend to trade more actively when liquidity trading is concentrated, due in part to lower transactions costs during these periods. The transactions costs are assumed to be supported by the non-discretionary liquidity traders Assuming that information acquisition is *endogenous* (e g is acquired through observing prices, volume and volatility of the market, rather than from outside information), then more traders become privately informed in periods of more concentrated liquidity trading, and prices are more informative in those periods Although their study was not undertaken on the index cash or futures market, the results are important for determining the informational content of the end of day futures returns. At the open and close of trading, there is expected to be a greater number of non-discretionary liquidity traders, due to orders being placed to be executed "at the open", or because of settlement procedures. This will attract discretionary liquidity traders, because their transactions costs should be lower at these times since the market is thicker Informed traders will also time their trades during these periods, and as a result, prices are expected to be more informative at the beginning and end of the trading day

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[1] Informed traders trade on the basis of private information, while liquidity traders trade for some reason outside of the financial market itself. For example, they trade because they need to free up capital, or for portfolio balancing reasons. These were determined to be the two major motives for trade

Brock and Kleidon [1992] dispute Admati and Pfleiderer's model with another theoretical model of trading volume at the open and close of each day They hypothesize that demand for trades will be greater, and relatively less elastic, at the beginning and end of each trading day. This is due to several factors, such as the fact that many orders may be placed to be executed "at the open", or that traders may wish to close or offset their position at the end of the day if they do not want to be exposed to risk during the non-trading hours. For these reasons, demand for trades will be higher at the beginning and end of each trading day, and traders will be less concerned with price. As a result, market makers can increase transactions costs, as measured by the bid-ask spread. Under Brock and Kleidon's model, transactions costs will be higher at the beginning and end of each day, rather than lower, as hypothesized by Admati and Pfleiderer. The implication for this study is that if Brock and Kleidon's theory is correct, we would not expect to find any significant relationship between the EOD futures return and the overnight spot return, since the EOD futures return would be made up only of liquidity trading, or "noise".

Gerety and Mulherin [1992] study trading volume at the open and close of the New York Stock Exchange, and find that volume at the close is positively related to expected overnight volatility. The volume at the market open is found to be positively related to the expected volatility from the previous non-trading period. They conclude that traders respond to the expected overnight volatility based on their ability to bear risk while the market is closed, which agrees with Brock and Kleidon's theory that the non-trading period will cause higher demand at the open and close

Previous studies on weekend effects in futures returns include that by Junkus [1986], who examines the weekend effect in index futures using the S&P500, Value Line, and New York Stock Exchange indices for a roughly two year period 1982-1984 She does not find any significant weekend effects in any of these index futures, or in the cash index, for the sample period. An insignificant negative Friday return is found on the futures contracts, while the index return was positive. She concludes that this lack of weekend pattern may be a temporary effect for the particular time period chosen.

Various explanations for an observed weekend effect in the futures prices have been offered For example, Herbst and Maberly's results using index futures reinforce findings by Harris [1989b] relating to stock prices Harris finds a systematic rise in stock prices at the close of the day and attributes this to most closing prices being at the ask (Investors buy at the ask to make sure their order is accepted before the market closes). He notes that the increase at the end of the day is not immediately reversed the next day. A similar result is found by Herbst and Maberly for index futures prices. Except for Fridays, EOD futures returns tend to be positive Another explanation may be that futures traders often close out long positions at the end of the day, and portfolio managers hedge long stock positions with market indexes since they are aware that mean stock returns are negative over the weekend, which perpetuates the effect It has also been documented by previous studies that unfavourable information is often released on Fridays, and often after the close of trading on Fridays, which would also partially explain the negative Monday effect

Phillips-Patrick and Schneeweis [1988] (referred to as PS) point out that studies of the weekend effect in stock index futures have often used price relatives as measures of return. Because the price of stocks generally declines after the ex-dividend date, and if ex-dividend dates are clustered on Mondays, as has often found to be the case, then part of the negative Monday stock return may be accounted for by the natural decrease in stock prices on the ex-dividend date. Thus, they contend, part of the decrease in the cash index on Monday may be attributable to the underlying stocks going ex-dividend. With regards to the effect of dividend payments on the price of index *futures*, PS refer to the following model

SFP = SCP + r(SCP) - INC

Where	SFP = futures price	r = interest rate applicable in period to delivery
	SCP = spot price	INC = dividend income due prior to delivery

When a dividend is paid, the value of INC decreases, since it represents dividend income remaining before delivery. However, the stock price, SCP, will also decrease by roughly the same amount, so the effect on the futures price should be neutral. Another partial explanation they offer for the weekend effect involves the interest rate component of carry costs, which previous studies had not accounted for. All else being equal, as time passes, the futures price should decrease by the interest cost component that is no longer outstanding. Over the weekend, this amounts to three days worth of interest, whereas on other days the decline would only be equal to one day of interest

Maberly [1989] contends that PS fail to take into account that the futures market trades fifteen minutes later than the cash market, and therefore any dividend and carrying cost information occurring on Monday in the cash market would occur at the EOD Friday in the futures market. He maintains that during the fifteen extra minutes at the end of the day, the futures price is "decoupled" from the spot price, and consequently the equality of PS's equation need not hold. As a result, the 3:00 to 3:15 futures return will take into account factors that will affect the Monday opening stock price, such as dividends, and decreases in carrying costs. Therefore the effect of dividends and carry costs has no effect on the decrease in price of futures contracts over the weekend. He remarks that it has been found that Friday's mean trading period return is negative for futures, consistent with this theory (Dyl and Maberly (1986a)(1986b)).

Schwarz [1991] re-examines PS's and Maberly's arguments, and maintains that dividend information (the presence of ex-dividend stocks) does not affect the futures price. The spot index will be affected at the opening of the ex-dividend day, since the value of the underlying stocks will decline, which changes the value of the index. The index futures price will be unaffected for the reason shown by PS (in their model SCP decreases, but so does INC, offsetting any change in the futures price). He also reasons that the reduced carry cost will not reduce futures prices until time actually passes (the weekend goes by), whereas Maberly seems to be saying that the last fifteen minutes of futures trading on Friday will take into account the carrying cost reduction that will take place over the weekend. Schwarz illustrates this argument with this example: the difference in the prices of a futures contract purchased just before 3:00 and the price of a contract purchased between 3:00 and 3:15 will not be as great as three days worth of interest. This difference will not occur until the time has actually passed.

Schwarz's argument about carrying costs makes intuitive sense. It does not seem logical that the 3 00 to 3:15 futures price should be significantly different from futures prices earlier in the day, all else being equal, given that all futures contracts are settled at the end of trading These two issues - carrying costs and dividends - have not been directly incorporated into the models presented in the next sections, although some measure of the effects may be an appropriate topic for future research

Several previous studies have examined the efficiency of the index futures market and the lead-lag relationship between this market and the cash index market Most of these studies involve separating the trading transactions of both markets for the period under observation into small intervals (e.g five minutes). The correlation with various lags between these intervals in the index futures market and the cash index market is then calculated. The results of these studies help to contribute to our understanding of the information in the end of the day futures returns. The information captured in the EOD futures return may not instantaneously be reflected in the next morning's spot return due to this lead effect, but may be dispersed during later spot trading

Harris [1989a] examines five minute changes in the S&P 500 index and futures contract over a ten day period surrounding the October 1987 stock market crash. A large futures-cash basis[2] was observed for this period, which was partly explained by

[2] Basis simply means the difference between the spot price and the futures price.

nonsynchronous trading, and partly by the disintegration of the two markets during the crash The spot index displays more autocorrelation than the futures, and the futures leads the spot index, even after adjusting for nonsynchronous trading To adjust for non-synchronous trading Harris used the transaction history of all the stocks in the index He attributes much of the remainder of the large basis to the disintegration of the cash and futures markets caused by capacity and/or regulatory disruptions in trading during the crash

The futures market lead over the cash market was found to be on average five minutes, and sometimes longer than ten minutes, by Stoll and Whaley [1990] The S&P 500 and Major Markets indices were used in their study This finding was robust even after accounting for infrequent trading and bid and ask effects They also found that lagged stock index returns have a mild positive correlation with futures returns, which has been confirmed by other studies. An indication of the frequency of trading of stocks was found by looking at the serial correlation of returns with one to twelve lags (of five minute intervals) A less frequently traded stock will have a higher degree of serial correlation Stoll and Whaley found that the index futures returns even tend to lead the returns of very frequently traded stocks such as IBM.

Chan [1992] investigates several possible causes of the lead-lag relationship between the cash and futures markets: the short selling constraint in the cash market, the nonsynchronous trading problem, the level of intensity of trading in both markets, and market-wide information. To find whether the lead-lag relationship is caused solely by the nonsynchronous trading effect in the cash index, using the MM index futures, he calculates the trading frequencies and nontrading probabilities of the 20 underlying stocks. He finds that the lead-lag relationship is not totally explained by the nonsynchronous trading problem Further, he found that the lead lag relationship held during the 1984-85 time period when some stocks were more frequently traded than the index futures contracts. Little evidence was found that the lead-lag relationship is affected by the intensity of trading activity in the cash and futures market, though the lead-lag pattern did vary consistently with the level of market-wide movement. Chan attributes this to differential transaction costs and expected profits in the futures market, which makes it the main source of market-wide information.

Herbst, McCormack and West [1987] examine the Value Line and S&P 500 index, and find that the index futures prices tend to lead those of their cash indices. The spot index can react in less than one minute although there are indications of some lags of up to sixteen minutes for the Value Line Index and eight minutes for the S&P 500. They conclude that knowledge of the lead is unlikely to provide arbitrage opportunities, since it is so small. They attribute the high volatility of the index futures to their observation that the index futures tend to move to the 'leading side' of the spot index in anticipation of its direction. For example, if the futures market anticipates that the cash index will go up, it will go up slightly more.

The volatility of the index futures and the cash index was studied by Kawaller, Koch and Koch [1990]. They calculated variance measures for minute to minute price changes on a daily basis and across thirty minute intervals for the S&P 500 index and index futures. The volatility of the index futures was found to be greater than that of the cash index, and the volatility of both was found to increase in absolute terms from 1984 through 1986 Another finding was that the index futures and cash index volatility increased directly with the volume of futures trading. MacKinlay and Ramaswamy [1988] also find that the volatility of the index future price changes (for the S&P 500 index) exceed the volatility of price changes in the cash index, even after controlling for nonsynchronous prices in the index quotes Harris [1989b] compares the S&P 500 stock return volatilities to the volatilities of a matched set of stocks No significant difference in volatility is observed from 1975 to 1983 before the start of trade in index futures and index options. After this time, S&P 500 stocks have been relatively more volatile, but Harris does not believe the increase to be economically significant, and believes it may be attributable to factors other than the start of derivative trade

Most interesting for the purposes of this paper, Kawaller, Koch and Koch find that the cash index volatility was substantially greater in the first thirty minutes of trading each day than at other times. Using thirty minute dummy variables, a pattern was found in which cash index and futures price volatility increase substantially prior to closing each day and increase further just after opening the next day. No systematic pattern of futures volatility leading index volatility was found, which was investigated due to concerns after the stock market crashes of 1987 and 1989 that index futures caused the underlying stocks to become more volatile They found that the daily trading volume on the NYSE sometimes affects the index volatility, but never affects the futures volatility. Kawaller, Koch and Koch [1993] discover that the relationship between the cash and futures prices becomes stronger as the futures price volatility increases They reason that this is because when there is more volatility, information is being captured at a faster rate, so that the futures and equity markets operate more closely as one market

Chung [1991] tests the efficiency of the index futures market by looking for profitable arbitrage opportunities. He does this by comparing the MM index futures and the underlying stocks, rather than the cash index, as had been done in previous studies He takes into account different costs of carry, transaction costs for different classes of traders, alternative execution lags, and the short sale rule. He found that previous studies which had used the cash index instead of the underlying stocks had significantly overestimated the size and frequency of profitable arbitrage opportunities. Thus, it would appear that the index futures market is fairly efficient when comparing it with the underlying stocks. Information seems to be transmitted quickly to the underlying stocks from the index futures market, making arbitrage difficult. If future research is conducted to study the pattern of disperion of the EOD futures information into the spot market over the following day, as is suggested in the concluding section of this paper, it would be useful to keep in mind that the spot prices duirng the will also be affected by information coming from the futures market with perhaps only a few minutes lag

To summarize, the issues investigated in these previous studies, which are relevant for this study are:

The futures market appears to react more quickly than the cash index for several possible reasons:

- The index experiences some nonsynchronous trading effects, which means the index includes stale prices for stocks that have not traded recently
- It is less costly to invest in the index futures contract than in the underlying stocks
- The futures market appears to lead the cash index by five to ten minutes in the U S , even after accounting for non-synchronous trading
- The EOD futures returns seem to have an effect on the overnight spot return and the variance of the overnight spot return, for the Nikkei Index on the Tokyo Stock Exchange
- The futures market reacts to market-wide information more quickly than the cash index
- There may be a weekend effect in EOD futures Friday returns and Monday opening spot returns, which may be partially explained by the ex-dividend days of the underlying stocks and the carry cost of the futures contract It may also be explained by the expectation of a weekend effect in the cash market.

Section II : The hypotheses to be tested in Canada

Our basic hypothesis is that EOD futures trading is made up of activity of informed traders, as well as liquidity traders. These informed traders wish to trade before the market closes, so as not to lose their advantage as information becomes public overnight We expect their trading to be concentrated during certain periods of the day, including the end of the day, activity by non-discretionary and discretionary traders is expected to be concentrated during these times. For this reason, we would expect the EOD futures return to be reflected in the overnight spot return, as the information disseminates. Alternatively, if the EOD futures return represents only the activity of liquidity traders, as proposed by Brock and Kleidon, then no significant relation between this return and the overnight spot return would be expected

The hypotheses and methodology to be used in the Canadian model are similar to those used by Herbst and Maberly and HMT. The specific relationships to be tested are:

- The EOD futures returns are positively related to the overnight spot returns.
- The unexpected component of EOD futures returns is positively related to the mean overnight spot return and to the conditional variance of the overnight spot returns.
- EOD futures volatility is positively related to the incentive to gather information on the next morning's spot price.
- Herbst and Maberly's main hypothesis was based on Grossman's [1977] observation that "the incentive to invest in information gathering on the overnight spot price is inversely related to the forecasting ability of the current spot price to predict the expected future spot price." Therefore, the standard deviation of the residuals from a regression of the 11am spot price on the closing spot price the previous day, should be positively related to the incentive for information gathering on the 11am spot price, and should in turn be positively related to the EOD futures returns volatility.

- EOD futures returns should be positively related to the two following overnight spot returns.
- EOD futures returns should be positively related to the conditional variance of the immediately following overnight spot return.
- The EOD futures return contains information which may not be fully reflected in the overnight spot return, but may also be reflected in the following two days' trading period spot returns.

Section III : Data and Methodology

Data:

The Toronto 35 index and index futures contract from January 2, 1991 to August 11, 1994 were purchased from the Toronto Stock Exchange to be used in this study The opening, 9:30 am, 4:00pm and closing futures prices were extracted from daily trading data tapes from the Toronto Stock Exchange For the futures prices, the closest contract was used. This price was switched to the next month's contract maturity on the expiry date. Because trading is often very thin in later contracts, it was not possible to switch to the next contract maturity at the beginning of the contract month For this reason a dummy variable representing expiry dates was incorporated into the regressions performed, as explained in the next section, to take into account any expiry day effects The opening and closing spot prices were used to calculate overnight spot index returns Days preceding and following holidays were removed from the sample

Methodology

Part I - Various comparison tests

A. Incentive for information gathering

1) Run a regression. $P_{(j+1,t)} = \alpha + \beta P_{(j,t)} + u_t$ Equation (1)

where $P_{(j+1,t)}$ is the opening spot index price on the subsequent trading day (day j+1), and $P_{(j,t)}$ is the closing index price on the previous day, day j.

This regression represents the ability of the closing spot price to predict the next day open spot price, as hypothesized by Herbst and Maberly, and by Grossman The less predictive power it has, the larger the standard deviation of the residuals ($u[t]$) will be, and the more incentive an investor will have to gather information on the next day's spot price. Conversely, if the closing price is greatly predictive of the next morning's price, there is little need to gather any additional information about that price.

2) Calculate the standard deviation of the residuals, $u[t]$, of the above regression, for each day of the week. As done by Herbst and Maberly, these standard deviations can be calculated for each day of the week, and then tested to see if there is a significant difference across weekdays. These standard deviations should be positively related to the incentive for information gathering on the opening spot price. If the standard deviation is large. the closing spot price on day j is less able to predict the opening spot price on day j+1, and there is more incentive to gather information on the opening day j +1 price.

3) Calculate the standard deviation of end-of-the-day futures returns, for each day of the week, and compare to the standard deviation of the residuals $u[t]$, determined in 2) above If informed traders do trade during periods of higher liquidity, which are characterized by higher volatility, then on weekdays with higher EOD volatility, there should be more informed traders trading, and a greater level of information production These days should correspond to weekdays where the closing spot price is less able to predict the opening spot price, and thus there would be more incentive to gather information on the opening spot price. Thus, the days with higher standard deviations of EOD futures returns should also have higher standard deviations of residuals. This can be tested by calculating the sample correlation coefficient between the standard deviation of the residuals and the standard deviation of the EOD futures returns, and by comparing these standard deviations by weekdays. Days with higher standard deviations of EOD futures returns should also have higher standard deviations of the regression residuals u[t]

B. Mean futures and spot returns by day of the week

1) Calculate the mean EOD futures return and the close-to-open spot return for each day of the week . Calculate the sample correlation coefficient between the futures return and the corresponding close-to-open spot return for each weekday This can be done for the entire sample and for a subsample of large EOD returns, since on average, the flow of information should be greater at the end of the day for large returns Calculate F statistics for difference in mean returns over days of the week.

2) Calculate the close-to-open return when the EOD futures return is positive, and when the EOD futures return is negative, to see if positive (negative) EOD futures returns are associated with positive (negative) close-to-open spot returns

Part II - Two stage GARCH models of overnight spot return as a function of unexpected EOD futures returns - GARCH(1,1), GJR GARCH and AGARCH

A. Two Stage GARCH(1,1) Model

1) Run the regression (first stage GARCH(1,1)):

$$EODFRET_t = \theta_0 + \theta_1 OTFRET_t + u_t \quad \text{where } u_t \approx N(0, H_t)$$

Conditional Variance: $H_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta H_{t-1}$

Where EODFRET is the end-of-day futures return, and OTFRET is the open-to-4:00pm futures return, u_t is the error term and H_t is the conditional variance of the error term. The residuals, u_t, from the regression represent the unexpected component of EOD futures returns. The expected component is the open-to-4:00pm futures return. The inclusion of the lagged conditional variance in the conditional variance equation makes this model equivalent to an infinitely lagged ARCH model, since the conditional variance also depends on the lagged residual. The maximum likelihood approach is used to estimate the parameter coefficients, maximizing the log likelihood function:

$$L_T(u) = \sum_{t=1}^{T} l_t(u) \quad \text{where} \quad l_t(u) = -0.5\log(h_t) - 0.5\varepsilon_t^2 / h_t$$

and μ is the vector of parameters to be estimated and T is the sample size.

2) Run another regression (second stage GARCH(1,1)):

$$ONSRET_t = \pi_0 + \pi_1 u_{t-1} + \pi_2 u_{t-2} + \sum_{i=2}^{5} \delta_i D_i + \Phi E_t + v_t \quad \text{where } v_t \approx N(0, Q_t)$$

Conditional variance: $Q_t = \alpha_0 + \alpha_1 v_t^2 + \beta Q_{t-1} + \varphi u_{t-1}^2$

Where ONSRET is the overnight spot return, D_i are dummy variables for days of the week, E_t is a dummy variable to control for expiry day effects, as mentioned earlier, and v_t is the error term Q_t is the conditional variance of the error term This regression tests whether the unexpected component of EOD futures returns explains any part of overnight spot returns for the following two trading days. By including the dummy variables, we can also test for DOW effects in the overnight spot returns. Note that the dummy variables are for Tuesday to Friday. The Monday effect is captured by the constant term, to avoid the model being over-specified. By incorporating the term u_{t-1}^2 into the conditional variance equation, we can examine the relationship between the unexpected component of EOD futures returns, and the conditional variance of the overnight spot return. The log likelihood function to be maximized is the same as in the first stage above

It may be assumed that since a part of the lead-lag relationship between index futures and cash index return is attributable to nonsynchronous trading effects of the cash index, then part of the explanatory effect of end-of-the-day futures returns on overnight spot returns may be attributable to nonsynchronous trading. Hiraki, Maberly and Takezawa do not control for nonsynchronous trading effects, since the manner in which the Nikkei 225 index is constructed greatly reduces these effects. The Nikkei index is based on current bid and ask prices, rather than the last transaction price. It does not appear that Herbst and Maberly controlled for these effects either The nonsynchronous trading effect for the Toronto 35 index is uncertain. the index calculated using the price of the last trade, rather than on the current bid and ask prices. However, the index is made up of stocks of some of the largest and most frequently traded companies, which may cause it to be less susceptible to this effect.

As an alternative to using the first stage GARCH(1,1) model to estimate the unexpected component of EOD futures returns, an ARIMA(4,4) model was used to estimate the unexpected component. This unexpected component was then used in the second stage of the GARCH(1,1) model as discussed above The ARIMA model estimates the unexpected component of EOD futures returns based on the pattern of traders' behaviour at the end of the day for the four previous days. It is reasonable to assume that traders are exposed to unique pressures at the end of the day, that may cause them to behave somewhat differently than they do during the first part of the day. These pressures include settlement procedures and the ability to bear risk during the overnight non-trading period. Thus, by studying end of the day behaviour for previous days, we can predict this behaviour for the current EOD period.

B. GJR GARCH Model

Another GARCH model, proposed by Glosten, Jagannathan and Runkle [1993 - hereinafter referred to as the GJR GARCH model] was also used as an alternative specification. As well as using the lagged squared residual, and lagged conditional variance in the conditional variance equation, this model includes a dummy variable, in both the first and second stages, which represents the square of the lagged residual when this residual is negative. This model thus captures the effect that a negative price move will have on the conditional variance of the following overnight spot return

First Stage: $EODFRET_t = \pi_0 + \pi_1 OTFRET_t + u_t$ where $u_t \approx N(0, H_t)$

Conditional variance: $H_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 S_{t-1}^- u_{t-1}^2 + \beta H_{t-1}$

where S_{t-1}^- is a dummy variable which takes the value 1 when u_{t-1} is negative, and 0 when u_{t-1} is positive.

Second Stage: $ONSRET_t = \pi_0 + \pi_1 u_{t-1} + \pi_2 u_{t-2} + \sum_{i=2}^{5} \delta_i D_i + \Phi E_t + v_t$

where $v_t \approx N(0, Q_t)$

Conditional variance: $Q_t = \alpha_0 + \alpha_1 v_{t-1}^2 + \alpha_2 S_{t-1} v_{t-1}^2 + \beta Q_{t-1} + \varphi u_{t-1}^2$

Where is a dummy variable which takes the value 1 when v_{t-1} is negative, and 0 when v_{t-1} is positive. The other variables are the same as in the GARCH(1,1) model described in 2) above The same log likelihood function as was maximized in the GARCH(1,1) is to be maximized in this model.

C. Asymmetric GARCH

The Asymmetric GARCH, or AGARCH model , is a similar model, except that the conditional variance equation has a somewhat different specification

First Stage: $EODFRET_t = \theta_0 + \theta_1 OTFRET_t + u_t$ where $u_t \approx N(0, H_t)$

Conditional Variance $H_t = \alpha_0 + \alpha_1 |u_{t-1}|^{\alpha_2} + \alpha_3 u_{t-1} + \beta H_{t-1}$

As in the GARCH(1,1) model, the residuals of the regression equation above represent the unexpected component of EOD futures returns, which are used in the second stage regression, as an explanatory variable of overnight spot return:

Second Stage: $$ONSRET_t = \pi_0 + \pi_1 u_{t-1} + \pi_2 u_{t-2} + \sum_{i=2}^{5} \delta_i D_i + \Phi E_t + v_t$$

where $v_t \approx N(0, Q_t)$

Conditional variance: $Q_t = \alpha_0 + \alpha_1 |v_{t-1}|^{\alpha_2} + \alpha_3 v_{t-1} + \beta Q_{t-1} + \varphi u_{t-1}^2$

The conditional variance equation includes a lag of the conditional variance, as in the GARCH(1,1) specification, but in addition includes the absolute value of the lagged error term, as well as the lagged error term itself. This allows the model to capture the effect of the absolute magnitude, whether positive or negative, of the previous period's error term on this period's conditional variance. The inclusion of the lagged error term, rather than the lagged squared error term, allows its direction, as well as its magnitude, to explain the conditional variance Under the AGARCH model, the conditional variance is centred at a positive v_{t-1}, rather than at the origin, and gives different weights to positive and negative news. The GARCH(1,1) model, by including only the square of the lagged residual in the conditional variance equation, gives equal weight to positive and negative news The impact of past return shocks on the return volatility of a model is described by Engle and Ng [1993] as the model's news impact curve. This is a plot of the conditional variance of a model as a function of the return shocks A GARCH(1,1) model has a symmetric news impact curve because equal weight is given to positive and negative return shocks. The GJR GARCH model is asymmetric, since it gives different weight to positive and negative returns. However it is centred at the origin, while the AGARCH model is asymmetric and centred at a positive v_{t-1}.

The various sign bias tests described by GJR and by Engle and Ng [1993] were used to check the specification of the various models. These tests are as follows

i) The sign bias test. A regression of the square of the standardized residuals (from the second stage regression) on a constant and the dummy variable S^-_{t-1} (as used in the GJR GARCH model above) is run. The sign bias test is the t statistic of the coefficient of the dummy variable. This test examines the effect of a positive or negative error term from the previous day on volatility, which has not been captured by the model

ii) The negative sign bias test is the t statistic of the coefficient $S^-_{t-1}\varepsilon_{t-1}$ in a similar regression of the square of the standardized residuals on a constant and the term $S^-_{t-1}\varepsilon_{t-1}$. This test considers the effects that large and small negative returns have on the volatility, which were not captured by the model.

iii) The positive sign bias test. A regression of the squared standardized residuals on a term $S^+_{t-1}\varepsilon_{t-1}$ is run. The positive sign bias test is the t statistic of the $S^+_{t-1}\varepsilon_{t-1}$ term from this regression, and S^+_{t-1} is a dummy variable which is equal to $1 - S^-_{t-1}$ This test considers the effects that large and small positive returns have on the volatility, which were not predicted by the model.

iv) The joint test A regression of the squared standardized residuals on all three terms discussed in the above paragraphs is run. The test statistic is the R^2 of this regression multiplied by the sample size.

These tests are run on both the first and second stages, and all specifications: the GARCH(1,1), GJR GARCH and AGARCH models.

Part III - Unexpected EOD futures returns' effect on trading period returns

The following model is tested:

$$TPSRET_t = \pi_0 + \pi_1 u_{t-1} + \pi_2 u_{t-2} + \pi_3 u_{t-3} + \sum_{i=2}^{5} \delta_i D_i + \Phi E_t + v_t \quad \text{where } v_t \approx N(0, Q_t)$$

This model is run using GARCH(1,1), GJR GARCH, and AGARCH specifications, as in Part II above. The mean model is the same for each of these specifications, but the conditional variances differ:

GARCH(1,1): $Q_t = \alpha_0 + \alpha_1 v_{t-1}^2 + \beta Q_{t-1} + \varphi u_{t-1}^2$

GJR GARCH: $Q_t = \alpha_0 + \alpha_1 v_{t-1}^2 + \alpha_2 S_{t-1} v_{t-1}^2 + \beta Q_{t-1} + \varphi u_{t-1}^2$

AGARCH: $Q_t = \alpha_0 + \alpha_1 |v_{t-1}|^{\alpha_2} + \alpha_3 v_{t-1} + \beta Q_{t-1} + \varphi u_{t-1}^2$

The purpose of these models is to see whether EOD futures returns are fully reflected in overnight spot returns, or whether they are reflected in the trading period spot return for several days

Section IV - Results

A) General Descriptive Statistics

Table I , Part A contains the results of unit root tests on the natural logs of the spot and futures prices used in this study. Both the Dickey-Fuller and Phillips-Perron test were used, and both yielded similar results. The prices all follow random walks The same tests were run on the first differences of the prices, and these were found to be stationary (Part B of Table I).

General descriptive statistics of the various return series used are found in Table II Skewness and kurtosis are significant for overnight spot returns and EOD futures returns, indicating that a GARCH model would be appropriate This conclusion is supported by the results of Engle ARCH tests shown in Table III Correlations between various combinations of returns are shown in Part B of Table II As expected, the correlation between EOD futures returns and the corresponding overnight spot return is positive and at 0.103, is significant at a 1% level.

Part I - Various comparison tests: Results

A. Incentive for information gathering

Regression (1) was run in subsamples based on days of the week The standard deviation of the residuals of the regression are compared to the standard deviation of the EOD futures return for the previous day's trading, and are ranked highest to lowest, as can be seen in Table IV. The incentive to gather information on the next morning's spot price, as estimated by the standard deviations of the regression (1) residuals, is highest for Thursday close to Friday open spot returns. However, Tuesday's EOD futures return has the highest standard deviation. We would expect Tuesday to Wednesday's regression (1) residuals to have the highest standard deviation, if informed traders are trading on Tuesday at the end of the day in the futures market, as indicated by the high Tuesday EOD futures return standard deviation The correlation coefficient between the residual standard deviations and the EOD futures returns standard deviations calculated by weekday is positive, but not significantly different from zero. However, we can conclude from the Bartlett test results, that standard deviations cannot be considered to be equal across weekdays, for both regression (1) residuals, and EOD futures returns. This indicates that the incentive to gather information on the next day's spot price is different across weekdays, being highest from Thursday to Friday and lowest from Wednesday to Thursday We can also conclude that the flow of information being generated at the end-of-day in the futures market differs across weekdays, being lowest on Mondays and highest on Tuesdays.

B. Mean futures and spot returns by day of the week

Table V-A compares the mean overnight spot return and mean EOD futures return by weekday Friday's mean EOD futures return, and the mean Friday to Monday overnight spot return are both negative The mean EOD futures returns are positive for all other days of the week. Monday to Tuesday and Tuesday to Wednesday overnight spot returns are negative, but much less so than the Friday to Monday overnight spot return.

This is evidence of a weekend effect in the spot market, which is anticipated by the futures market. Table V-B shows the same test results for a subsample consisting of large EOD futures returns[3]. The same weekend effect is still present, but no other DOW effects are apparent. The correlation coefficient between mean EOD futures and mean overnight spot returns is higher in value for this subsample, but is only significant at a 10% level, because of the lower sample size

Table VI compares the mean overnight spot return when EOD futures return is negative, and when EOD futures return is positive The mean overnight spot return is positive when EOD futures return is positive, and negative when the mean EOD futures return is negative; however, neither mean overnight spot return is significantly different from zero. The t test indicates, though, that the mean overnight spot return when EOD futures return is negative cannot be considered to be equal to the mean overnight spot return when EOD futures return is positive

We can reach several conclusions from the results discussed above Overnight spot returns and EOD futures returns are significantly positively correlated The levels of production of information are different across different days of the week, as are the levels of incentive to gather information on the next day's opening spot price However, the production of information at the end of the day in the futures market does not seem to be

[3] Where a "large" EOD futures return is more than one standard deviation away from the mean EOD futures return.

able to predict the incentive to gather information on the next day's spot price, at least on a day-of-the-week basis

Part II - Two stage GARCH models of overnight spot return as a function of unexpected EOD futures returns: Results

A. GARCH(1,1) Model results

Results on Engle ARCH tests run on both the first stage and second stage regressions as OLS regressions indicate that an ARCH or GARCH specification is appropriate, as shown in Table III. The results of the first stage GARCH(1,1) regression are shown in Table VII. This is a regression of EOD futures returns on open-to-4:00pm futures returns for the same day, where the open-to-4.00pm return represents the expected component of EOD futures returns, and the residuals of the GARCH regression represent the unexpected component. All coefficients are positive and significant as expected. The sum of the coefficients of the lagged residual and lagged variance coefficients in the conditional variance equation is less than 1, ($\alpha_1 + \beta < 1$), but at 0.84 indicates some persistence of the effect of previous values of residuals and variance, or "shocks" . A second regression, labeled Model B in Table VII, was run, in which the open-to-4:00pm futures return variable was omitted. The log likelihood function value[4] is significantly higher for the first model, labeled Model A, indicating that the open-to-4:00 futures return

[4] The log likelihood function value is the maximum value of the log likelihood function. Since we want to maximize this value, a model with a higher log likelihood function value is preferable to one with a lower value. The likelihood ratio test, described in the Appendix, provides a means of determining whether the difference between two log likelihood function values is significant.

is a significant explanatory variable of EOD futures returns This model is preferable over the restricted model.

The second stage GARCH(1,1) regression results, using Model A in the first stage, are set out in Table VIII. The unrestricted model is labeled Model A In this model, the π_1 coefficient representing the unexpected component of EOD futures returns is positive and significant, as expected. The π_2 coefficient, representing the lagged unexpected component of EOD futures returns, is significant at a ten percent level in Models A and C. The coefficient φ, representing the square of the unexpected futures return, as an explanatory variable of the conditional variance of overnight spot returns, is also positive and significant. Thus, it appears that these results support two of the main hypotheses of this paper: that EOD futures returns are positively related to the following morning's overnight spot return, and that they are also positively related to the conditional variance of the overnight spot returns. The lagged EOD return is only weakly related to the overnight spot return. The other GARCH coefficients of the conditional variance equation, representing a lag of the regression residuals and a lag of the conditional variance, are also positive and significant The sum of the coefficients α_1 and β is 0.44, indicating that shocks are less persistent than in the first stage The kurtosis of the standardized residuals of the regression is still significant, although it has been reduced from that of the original return series used The overnight spot return series had a kurtosis of 4.36, as shown in Table II, while the GARCH residuals have a kurtosis of 3.60

Skewness of the overnight spot return series was significant, but skewness in the GARCH residuals has been reduced to a statistically insignificant level Three other restricted models were run, labeled Models B, C and D in Table VIII. In Model B, the independent variables representing the unexpected component of EOD futures returns, and a lag of this variable, have been dropped, while in Model B, the variable in the conditional variance equation representing the square of the unexpected component has been dropped, and in Model D, all three variables were dropped. Log likelihood function values indicate that Model A is the most preferable model. No DOW pattern is apparent in Models A, B and C, although a negative Friday close to Monday open overnight spot return is weakly significant, at a 10% level, in Model D.

The results of the various sign tests for the GARCH(1,1) model are shown in Table VIII-B. None of these tests are significant, meaning that the conditional variance equation of the GARCH(1,1) model does not seem to require a further parameter representing the direction of the error term. The Box-Lung Q statistic was significant when the regression was run as a regular OLS regression , but has been reduced to a level which is just significant at a 10% level for the standardized residuals of the GARCH(1,1) regression. Thus, the GARCH(1,1) specification appears to capture the clustering of volatilities to some extent.

The same GARCH(1,1) regression was run using the alternate measure of the unexpected EOD futures return as an independent variable in the second stage. As previously mentioned, the unexpected component was represented by the residuals from an ARIMA model on EOD futures returns The model has four moving average lags and four autoregressive lags, all of which are significant, as shown in Table IX. The second stage regression results yield similar results to the previous specification, and can be found in Table X. The coefficient for the unexpected EOD futures component (coefficient π_1) is a positive 0.354, compared to positive 0.294 for the two-stage GARCH(1,1) model just discussed. Coefficients for the other parameters are also quite similar for the two models, as are the level of skewness and kurtosis of the standardized residuals of the regression for both. The sum of the coefficients α_1 and β is 0 43, about the same level of persistence of shocks as the two stage GARCH(1,1) model has The various sign tests, from Table X-B, are similarly insignificant. However, the Q statistic for the residuals of the ARIMA based GARCH(1,1) model is still significant, although it is lower than when the regression is run as a regular OLS regression, as can be seen in Table X-C The log likelihood function value of the unrestricted Model A for the two stage GARCH(1,1) specification is higher than that of Model A for the ARIMA based GARCH(1,1) Model A (741 06 vs 739 320) The function value of the various restricted models are also higher using the two stage GARCH(1,1) specification than when the ARIMA specification is used We can conclude that the results of the ARIMA based GARCH(1,1) model support the results of the two stage GARCH(1,1) model, but that the two stage GARCH(1,1) specification captures the clustering of volatilities somewhat better, and produces higher values of the likelihood function, which we are seeking to maximize.

B. GJR GARCH Model results

A third GARCH model, the GJR model, was examined This model adds the term $S_{t-1}v_{t-1}^2$ to the conditional variance equation, to capture effects that the a negative error term in the previous period will have on the current period's conditional variance. S_{t-1} is a dummy variable, whose value is one when the error term v is negative, and 0 otherwise. This term is positive and significant, as shown in Table XII. The other terms are similar to the previous model results The coefficient for the unexpected component of EOD futures returns, as an explanatory value of overnight spot returns, is positive and significant, and at 0.28, similar in magnitude to the previous models As an explanatory variable of the conditional variance of overnight spot returns, the unexpected component is again positive and significant. The kurtosis of the standardized residuals of the regression is reduced further, although at 3.17, it is still significant Again, restricted versions of the regression, Models B, C and D, were run, and Model A was found to be most preferable, based on its log likelihood function. The log likelihood function values of all four versions of the GJR model are higher than those of the corresponding versions of the GARCH(1,1) model. The sum of the terms α_1 and β is 0.26, which is similar to results for the GARCH(1,1) and ARIMA GARCH(1,1) specifications. The Q statistic on the standardized regression residuals, from Table XII-B, is still significant at 10% using the GJR GARCH model, but is reduced somewhat from a regular OLS specification This Q statistic is higher than that calculated for the ARIMA specification, but not as high as that of the GARCH(1,1) specification. The results of the sign tests, shown in Table XII-A, are insignificant.

C. Asymmetric GARCH Model Results

A third GARCH specification, the Asymmetric GARCH model, was investigated This model includes the absolute value of the lagged error term, and the error term itself in the conditional variance equation, as well as the lagged conditional variance, and the lagged squared unexpected component of EOD futures returns, as was included in the GARCH(1,1) conditional variance equation.

The results of the first stage AGARCH model are shown in Table XIII The second stage results are shown in Table XIV. Again, the unrestricted model is considered preferable from the likelihood ratio test results The log likelihood function values of the unrestricted model and the three restricted models are higher than those of the corresponding models under the GARCH(1,1) or GJR GARCH specifications The unexpected component of EOD futures returns is positive and significant in both the mean and conditional variance equations, and is similar in magnitude to the estimates under the GARCH(1,1) and GJR GARCH models The kurtosis of the standardized residuals is still significant, but is the lowest of the various specifications The α_1 term, representing the absolute value of lagged error terms is positive and significant, at 0 124, meaning a larger magnitude of return shock, whether positive or negative, will have a greater effect on conditional volatility. The α_3 term is negative and significant This indicates that a negative return shock on the previous day will cause an increase in the conditional volatility, while a positive return shock will cause a decrease in volatility The Q statistic for the standardized residuals, from Table XIV-C, is not significant. This model appears to capture the clustering of volatilities quite well, and performs better than the other models in this respect. The results of all sign tests, as shown in Table XIV-B are insignificant. The dummy variable for Friday close to Monday open spot returns is significant and negative, showing a much stronger indication of a weekend effect than the previous models have shown

Part III - Unexpected EOD futures returns' effect on trading period returns

The results of this section are shown in Tables XV, XVI and XVII for the GARCH(1,1), GJR GARCH and AGARCH specifications respectively These models test whether the unexpected EOD futures return is reflected in the trading period spot return over the next three days. Only a weakly significant positive relationship between the EOD return and the immediately following trading period spot return is found in the GARCH(1,1) and AGARCH models The relationship is not significant in the GJR model. No day-of-the-week effects are found in the trading period spot returns, which corresponds with the findings of previous empirical studies which have determined that the weekend effect takes place to a large extent between Friday's close and Monday's open, which was found to be the case in the previous section. Herbst, Maberly and Takezawa's finding that the EOD futures return is reflected in the next two days' trading period spot return does not hold true for Canada.

Conclusions

In this paper, the relationship between the futures return at the end of the day, and the mean and conditional variance of the overnight spot market index return was studied This relationship can tell us how information from the futures market can be used to anticipate the size and direction of the overnight return in the spot market First, the relationship between the volatility of overnight spot returns, representing the production of information, and the incentive to gather information on the next day's overnight spot return, by weekday, was explored. It was found that weekdays with large standard deviations of EOD future returns did not necessarily coincide with weekdays where there was a larger incentive to gather information on the next day's spot price However, it was concluded that these two factors are not equal across weekdays Next, some general tests involving the means of EOD futures returns vs means of overnight spot returns were examined. It was found that there is a positive and significant correlation between EOD futures overnight spot returns, and that the Friday close to Monday open spot index return is negative and the Friday EOD futures return is also negative

The larger part of this study focused on the modeling of the unexpected component of EOD futures returns as an explanatory variable of the mean overnight spot return and conditional variance of the overnight spot return The EOD futures return was found to be significantly positively related to the mean overnight spot return, and to the conditional variance of the overnight spot return Some indications of a weekend effect in the overnight spot return were found. These results were supported by the results of several different models: i) a two stage GARCH(1,1) model, in which the unexpected component of EOD futures returns was estimated in the first stage, and used in the second stage as an explanatory variable of the overnight spot return and of the conditional variance of the overnight spot return, ii) a similar GARCH(1,1) model, however with the unexpected component of EOD futures returns estimated with an ARIMA model, ii) a two stage GJR GARCH model and iii) a two stage Asymmetric GARCH model. All these models partially captured the leptokurtic distributions of the return series, and the clustering of volatilities of these series, although the two stage AGARCH(1,1) performed best in this respect

The EOD futures returns tend to be positive, except for Fridays This supports Harris' hypothesis that transactions at the end of the day have a tendency to be at the asking price This positive swing at the end of the day is reflected in the overnight spot return. It may also be explained by Admati and Pfleiderer's conclusion that these positive EOD futures returns reflect the trading of informed traders, who have knowledge of information that will be released after the close of the futures market, which in general is favourable, except on the weekend.

This study has compared EOD futures return with the spot return from the previous day's close until the next day's open. The relationship between the EOD futures return and the following day's trading period spot return was found to be very week. A topic for future research might be to study the spot return at different points throughout the next day, rather than only at the open, and only on the trading period as a whole, to discern what pattern of dispersion of information may be present. Such a study would provide a clearer picture of how quickly information in the futures market is transmitted to the spot market Another area of interest is the relationship between the volume of EOD futures trading and the overnight spot return, and between EOD volume and the volume of spot trading for various periods on the following day. Table XVIII shows a summary of trading volume by day of the week for the entire sample of data used. As found by Gerety and Mulherin, the volume for the half hour after the open, and the fifteen minutes before the close is much higher than that of similar time intervals at other times of the day

Results - Tables[1]

Part I - Various comparison tests

Table I - Unit Root Tests[2]

	PP	PPT	DF	DFT
Part A - prices				
spot open price	-1.5741	-2.1898	-1.3785	-1.942
spot close price	-1.6040	-2.2197	-1.3120	-1.856
futures open price	-1.5634	-2.2280	-1.5287	-2.175
futures 9 30 price	-1.5920	-2.2232	-1.5805	-2.197
futures 4pm price	-1.6419	-2.2451	-1.4791	-2.038
futures 4:15 price	-1.6453	-2.2444	-1.5095	-2 069
Critical values 95%	-3.37	-3.80	-3.37	-3.80

Table I
Part B - Unit root tests on first differences of prices

First differences	PP	PPT	DF	DFT
spot open	-119 472**	-119.298**	-132.127**	-131 843**
spot close	-118.067**	-117 897**	-137.655**	-137.360**
futures open	-119.481**	-119.313**	-121.147**	-120 890**
futures 9.30	-119.797**	-119.628**	-120.233**	-119.979**
futures 4:00pm	-117.795**	-117.625**	-127.314**	-127 043**
futures 4:15pm	-117 974**	-117.803**	-125.754**	-125 486**
Critical Values 95%	-3.37	-3.80	-3.37	-3.80

Notes: The logs of the prices were used.

PP Phillips-Perron test statistic for unit root without time trend

PPT: Phillips-Perron test statistic for unit root with time trend

DF: Dickey- Fuller test statistic without time trend

DFT: Dickey-Fuller test statistic with time trend

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1 See Appendix A for descriptions of all statistical tests used

2 Significance levels in all tables are indicated by stars:

*	significant at 10% level
**	significant at 5% level
***	significant at 1% level

Part I results, continued

Table II - Descriptive statistics and correlation coefficients

Part A - Descriptive statistics				
	Mean	S.D.	Skewness	Kurtosis
ONSRET	-0.024294	0.26890	-0 15367*	4.3698*
OCFRET	-0.006516	0 66057	-0 08897	4.55873*
OTFRET	-0.012522	0.63904	-0 16576*	2.15406
EODFRET	0.0065972	0 08427	0.34556*	3 83381*
TDSRET	0.0453507	0.61885	-0.19446**	1.99807

Part B - Correlation Coefficients :	
i) EOD futures (day j) and overnight spot (day j to j+1):	0 10345***

Notes: ONSRET = overnight spot return
OCFRET = open to close futures return
OTFRET = open to 4:00pm futures return
EODFRET = 4.00pm to 4:15pm futures return

Table III - Engle ARCH test

Part I) If run $EODFRET_t = \alpha_0 + \alpha_1 OTFRET + u_t$ as a regular OLS regression:		
ARCH test with various lags of residuals:		
	X^2	significance level
1 lag	3.574091	0.05868754
2	4.408468	0.11033500
4	5.635835	0.22804497
10	14.646465	0.14549251
Part 2) If run $ONSRET_t = \alpha_0 + \alpha_1 u_{t-1} + \sum \delta_i D_i + v_t$ as a regular OLS regression:		
	X^2	significance level.
1 lag	1.567356	0.21059134
2	9.315234	0 00948905
4	9.926250	0.04168849
10	15.741791	0.10726634

Table IV : **Residuals from regression: $P_{(j+1,t)} = \alpha + \beta P_{(j,t)} + u_t$ vs. Standard Deviation of EODFRET by weekday**

	#obs	S.D. u(t)	Rank		S.D. EODFRET	Rank
Mon-Tues	167	0 463216	4	Mon.	0.000742	5
Tues-Wed	184	0.478348	3	Tues.	0.000950	1
Wed-Thurs	184	0.455865	5	Wed.	0.000790	3
Thurs-Fri	179	0.636163	1	Thurs.	0.000779	4
Fri-Mon	163	0.579385	2	Friday	0.000912	2
r=		0.051285				
X^2 (Bartlett)		32.87861***			16.30751***	

Note: regular returns used for regression (1).

Table V - A: Mean ONSRET and EODFRET by weekday

	#obs	Mean ONSRET	Rank		Mean EODFRET	Rank	r
Mon-Tues	167	-0.000217	3	Mon.	0.000143	1	0.17263***
Tues-Wed	184	-0.000362	4	Tues.	0.000140	2	0.15366***
Wed-Thurs	184	0.000139	1	Wed.	0.000124	3	0.20859***
Thurs-Fri	179	0.000044	2	Thurs.	0.000027	4	-0.04251
Fri-Mon	163	-0.000881	5	Friday	-0.000119	5	0.044646
r=		0.10345***					
F=		3.87383***		F=	2.997858**		

Table V-B: Mean ONSRET and EODFRET by weekday - large returns sub-sample

	obs	Mean ONSRET	Rank		Mean EODFRET	Rank	r
Mon-Tues	51	0.000014	3	Mon.	0.000522	1	0.28726***
Tues-Wed	48	-0.000341	4	Tues.	0.000386	3	0.21899***
Wed-Thurs	37	0.000364	2	Wed.	0.000410	2	0.26302***
Thurs-Fri	40	0.000670	1	Thurs.	0.000178	4	-0.21046***
Fri-Mon	37	-0 000805	5	Friday	-0.000464	5	0.034058
r=		0 12111*					
F=		1.818993		F=	2.57549*		

Table VI : Overnight spot when EOD futures returns is positive, and when EOD futures return is negative

	Mean overnight spot	Standard deviation
EOD > 0	0.026481	0.28593
EOD = 0	-0 031998	0.24633
EOD < 0	-0.071516	0.27391
t test	3.91764***	

Part II - A. GARCH(1,1) Results

Table VII : GARCH (1,1) Results - first stage

First Stage: $EODFRET_t = \theta_0 + \theta_1 OTFRET_t + u_t$

Conditional Variance: $H_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta H_{t-1}$

(Standard errors in parentheses)

	Model 1	**Model 2**
θ_0	0.0068945**	0.0065853**
	(0 0028032)	(0 0028161)
θ_1	0.0235528***	-
	(0.0032865)	-
α_0	0.00103055***	0.0013296**
	(0.0003997)	(0 0005453)
α_1	0.0207792**	0.0211268**
	(0.0100032)	(0.0106724)
β	0.8289078***	0.7907342***
	(0.0628078)	(0.0820023)
log likelihood	1746.04935	1731.81267
skewness[3]	0.41049***	0 30503***
kurtosis	4 11148***	3.90532***

[3] Skewness and kurtosis for all GARCH models are for the standardized residuals, $u/(H^{0.5})$ for the first stage, and $v/(Q^{0.5})$ for the second stage

Table VII-A Sign tests - Model 1 of GARCH (1,1) from Table VII above

test	coefficient	S.D.	t statistic	significance level
sign bias test	0.1027161	0.1703015	0.60314	0 54657
negative sign bias test	-1.222304	1.740793	-0.70215	0.48277
positive sign bias test	0.3435210	1.5464022	0.22214	0.82426
joint test	1.072			

Table VII-B Lung-Box Q statistics Model 1 of GARCH (1,1) from Table VII

	Q stat 24 lags	significance level
OLS	21.4122	0.61430432
GARCH	21 0169	0.63772605

Table VIII GARCH(1,1) Second stage:

Model: $$ONSRET_t = \pi_0 + \pi_1 u_{t-1} + \pi_2 u_{t-2} + \sum_{i=2}^{5} \delta_i D_i + \Phi E_t + v_t$$

Conditional variance: $Q_t = \alpha_0 + \alpha_1 v_{t-1}^2 + \beta Q_{t-1} + \varphi u_{t-1}^2$

(standard errors in parentheses)

	Model A	Model B	Model C	Model D
π_0	-0.017838	-0.017653	-0.015344	-0.017843
	(0.024131)	(0.024056)	(0.024754)	(0.024530)
π_1	0.294275***	-	0.214769***	-
	(0.109644)	-	(0.084018)	-
π_2	0.170346*	-	0.186063*	-
	(0.105648)	-	(0.111994)	-
δ_1	-0.022933	-0.021643	-0.024568	-0.020144
	(0.031447)	(0.031669)	(0.032663)	(0.032649)
δ_2	0.019264	0.024427	0.022481	0.029279
	(0.029304)	(0.029532)	(0.030711)	(0.0307[illegible]5)
δ_3	0.034621	0.032967	0.028388	0.030930
	(0.027896)	(0.027987)	(0.029065)	(0.028898)
δ_4	-0.042479	-0.050413	-0.053472	-0.056782*
	(0.034408)	(0.034469)	(0.034046)	(0.033912)
Φ	-0.102795**	-0.093916**	-0.101280**	-0.091499**
	(0.049148)	(0.047537)	(0.046754)	(0.045729)
α_0	0.038661***	0.040836***	0.037498***	0.039143***
	(0.005241)	(0.005746)	(0.007430)	(0.007956)
α_1	0.248584***	0.224877***	0.169853***	0.162201***
	(0.041819)	(0.040188)	(0.035943)	(0.035504)
β	0.193411**	0.187272**	0.313968***	0.300243**
	(0.076882)	(0.085671)	(0.114819)	(0.122850)
φ	0.492325***	0.452118***	-	-
	(0.144912)	(0.148525)	-	-
Log likelihood	741.057330	736.140350	736.284170	732.404682
skewness	-0.08133	-0.09884	-0.19830**	-0.18647**
kurtosis	3.60260***	3.55110***	3.85701***	3.72297***

Table VIII-A Log likelihood statistics

(comparison of each Models B, C and D to Model A)

Unrestricted	Restricted	-2(Lr -Lur)	Critical values		
			95%	90%	D.F.
A	B	9.834	3.84	2.71	1
A	C	9.546	3.84	2.71	1
A	D	17.305	5 99	4.61	2
C	D	7.759	3.84	2.71	1
B	D	7.471	3.84	2 71	1

Table VIII-B Sign tests

test	coefficient	S.D.	t statistic	significance level
sign bias test	0.005539	0.159409	0.03475	0.972288
negative sign bias test	-0.140738	0.489220	-0.28768	0.773661
positive sign bias test	-0.425610	0.498159	-0.85436	0.393137
joint test	1.20925			

Table VIII-C Lung-Box Q statistics Model A

	Qstat 24 lags	significance level
OLS	34.4379	0.07718
GARCH (1,1)	33.0654	0.10270

Table IX - GARCH(1,1) ARIMA Model first stage

(alternate method of estimating unexpected portion of EOD futures returns)

Stage 1: unexpected component of EOD futures return is residual from ARIMA (MA=4, AR=4) model

(standard deviations in parentheses.)

lags	coefficient
AR(1)	-1.833054***
	(0.113795)
AR(2)	-2.071579***
	(0.179737)
AR(3)	-1.534430***
	(0.173203)
AR(4)	-0.521941***
	(0.111293)
MA(1)	1.926552***
	(0.116573)
MA(2)	2.139015***
	(0.186643)
MA(3)	1.583158***
	(0.179308)
MA(4)	0.530676***
	(0.112770)
skewness[4]	0.35775***
kurtosis	3.86687***

[4] Skewness and kurtosis are for the residuals of the Box-Jenkins procedure

Table X Second Stage : GARCH(1,1)

(using residuals from ARIMA procedure in Table IX above as independent variable, representing unexpected component of EOD futures returns)

Model : $$ONSRET_t = \pi_0 + \pi_1 u_{t-1} + \pi_2 u_{t-2} + \sum_{i=2}^{5} \delta_i D_i + \Phi E_t + v_t$$

Conditional variance. $$Q_t = \alpha_0 + \alpha_1 v_{t-1}^2 + \beta Q_{t-1} + \varphi u_{t-1}^2$$

(standard errors in parentheses)

	Model A	**Model B**	**Model C**	**Model D**
π_0	-0.020204	-0.018251	-0.018878	-0.017339
	(0.024281)	(0.024005)	(0.024932)	(0.024607)
π_1	0.353796***	-	0.290452***	-
	(0.108078)	-	(0.086726)	-
π_2	0.205863**	-	0.204985*	-
	(0.104915)	-	(0.107645)	-
δ_1	-0.026295	-0.022897	-0.027417	-0.022739
	(0.031741)	(0.031746)	(0.032592)	(0.032691)
δ_2	0.017384	0.025061	0.020731	0.028676
	(0.029347)	(0.029586)	(0.030431)	(0.030614)
δ_3	0.033970	0.032217	0.029822	0.030803
	(0.028064)	(0.027991)	(0.028888)	(0.028868)
δ_4	-0.039431	-0.047456	-0.046265	-0.053744
	(0.034566)	(0.034553)	(0.034154)	(0.034085)
Φ	-0.105052**	-0.093556**	-0.106334**	-0.095349**
	(0.049988)	(0.046866)	(0.048188)	(0.046099)
α_0	0.039713***	0.041716***	0.041105***	0.041465***
	(0.004990)	(0.005711)	(0.006368)	(0.007300)
α_1	0.256025***	0.214745***	0.202978***	0.174811***
	(0.041907)	(0.038941)	(0.039010)	(0.036978)
β	0.171688**	0.181522**	0.237141**	0.259104**
	0.073322**	(0.086051)	(0.098340)	(0.112598)
φ	0.493103***	0.422093***	-	-
	(0.145602)	(0.143539)	-	-
Log likelihood	739.31982	732.23080	735.71534	729.74342
skewness	-0.08728	-0.11168	-0.20748**	-0.19284**
kurtosis	3.64521***	3.63873***	3.85224***	3.74510***

Table X-A - Compare Log likelihood ratios

Unrestricted	Restricted	-2(Lr -Lur)	Critical values		
			95%	90%	D F
A	B	14.178	3 84	2.71	1
A	C	7.209	3 84	2 71	1
A	D	19.153	5 99	4.61	2
C	D	11.944	3 84	2.71	1
B	D	4 975	3 84	2 71	1

Table X-B - Sign tests for ARIMA Model A GARCH(1,1)

test	coefficient	S.D.	t statistic	significance level
sign bias test	0.001665	0.160339	0 01039	0 99172
negative sign bias test	-0 287420	0.578546	-0.49680	0 61946
positive sign bias test	-0 763633	0.705738	-1.08204	0 27954
joint test	1.5539			

Table X-C - Lung-Box Q statistics for ARIMA Model A GARCH(1,1)

	Qstat 24 lags	significance level
OLS	33.1602	0.00704
GARCH	26.9199	0.04238

Part II - B. GJR GARCH model

Table XI GJR GARCH model, first stage

Model $ONSRET_t = \pi_0 + \pi_1 u_{t-1} + \sum \delta_i D_i + \Phi E_t + v_t$

Conditional variance. $H_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 S_{t-1} u_{t-1}^2 + \beta H_{t-1}$

(standard errors in parentheses)

	Model 1	**Model 2**
π_0	0.006889**	0.006557**
	(0 002853)	(0 002873)
π_1	0 023450***	-
	(0 003398)	-
α_0	0.001153**	0.001508**
	(0 000513)	(0.000739)
α_1	0 012379	0.006232
	(0.010855)	(0 011200)
α_2	0.021114	0.030668
	(0.021217)	(0.022998)
β	0 812339***	0.768970***
	(0 079383)	(0 1094683)
Log likelihood	1746 3475	1732.44729
skewness	0 37561***	0.31226***
kurtosis	4 18610***	3 90707***

Table XI-A Sign tests - Model 1 GJR GARCH (from Table XI above)

test	coefficient	S.D.	t statistic	significance level
sign bias test	0.0832123	0.1682403	0.49460	0.62100
negative sign bias test	-0.838611	1.719807	-0.48762	0.62594
positive sign bias test	0.0219708	1.0064641	0.02183	0 98259
joint test	1.177			

Table XI-B Lung-Box Q statistics for Model 1 GJR GARCH (from Table XI above)

	Qstat 24 lags	significance level
OLS	21 4122	0.61430
GARCH GJR	21.0126	0 63798

Table XII Second stage - GJR GARCH

Model: $$ONSRET_t = \pi_0 + \pi_1 u_{t-1} + \pi_2 u_{t-2} + \sum_{i=2}^{5} \delta_i D_i + \Phi E_t + v_t$$

Conditional variance: $Q_t = \alpha_0 + \alpha_1 v_{t-1}^2 + \alpha_2 S_{t-1} v_{t-1}^2 + \beta Q_{t-1} + \varphi u_{t-1}^2$

(S is the same type of dummy variable as S in stage 1 above)

(standard errors in parentheses)

	Model A	Model B	Model C	Model D
π_0	-0 020450	-0 021113	-0.019236	-0 020970
	(0 023552)	(0 023071)	(0 024389)	(0 023903)
π_1	0.278436**	-	0 200285**	-
	(0.111740)	-	(0 080635)	-
π_2	0.152285	-	0 167101	-
	(0.107698)	-	(0 111370)	-
δ_1	-0.019709	-0.017418	-0 020726	-0 016417
	(0 031085)	(0.030910)	(0 032030)	(0 031760)
δ_2	0 025331	0.029723	0.027390	0 032712
	(0.029898)	(0.029426)	(0.031158)	(0 030679)
δ_3	0.034379	0 034052	0 0327689	0 034884
	(0 027191)	(0 026860)	(0 028397)	(0 027980)
δ_4	-0.044640	-0.051071	-0 051766	-0 056505*
	(0.034088)	(0 033782)	(0.033685)	(0 033375)
Φ	-0.093587*	-0.083319*	-0.095317**	-0 084751*
	(0.048927)	(0.047970)	(0.048239)	(0 047427)
α_0	0.041554***	0.043258***	0.043877***	0 045330***
	(0 005728)	(0 005839)	(0 007056)	(0 007284)
α_1	0.108961**	0 088774*	0 099927*	0 085072*
	(0.054815)	(0.048941)	(0.052549)	(0 047014)
α_2	0.259083***	0 270537***	0 192249***	0 214438***
	(0.078496)	(0 071543)	(0 072387)	(0 068156)
β	0.155567*	0.150126*	0 206455**	0 194214*
	(0.080156)	(0.082460)	(0 105195)	(0 107721)
φ	0.561245***	0 529786***	-	-
	(0.166164)	(0 170719)	-	-
Log likelihood	743 80463	739.61395	737.98582	734 74323
skewness	-0.02958	-0 03608	-0 16799**	-0 14603*
kurtosis	3 17330***	3 09545***	3 48300***	3 30210***

Table XII-A Compare Log likelihood ratios

Unrestricted	Restricted	-2(Lr -Lur)	Critical values		D.F.
			95%	90%	
A	B	8.381	3.84	2.71	1
A	C	11 638	3.84	2.71	1
A	D	18.123	5.99	4.61	2
C	D	6.485	3.84	2.71	1
B	D	9.741	3.84	2 71	1

Table XII-B : Sign tests for Model A GJR GARCH

(from Table XII above)

test	coefficient	S.D.	t statistic	significance
sign bias test	-0.141395	0.153117	-0.92345	0.356031
negative sign bias test	0.292318	0.471115	0.62048	0.535103
positive sign bias test	0.163996	0.289317	0.56684	0.5709692
joint test	0.9695			

Table XII-C Lung-Box Q statistics for Model A GJR GARCH

(from Table XII above)

	Q stat 24 lags	significance level
OLS	34.4358	0.077216
GARCH GJR	33 3848	0.096212

Part II - C. AGARCH Results

Table XIII : Asymmetric GARCH (1,1) Results - First Stage

First Stage: $EODFRET_t = \theta_0 + \theta_1 OTFRET_t + u_t$

Conditional Variance: $H_t = \alpha_0 + \alpha_1 |u_{t-1}|^{\alpha_2} + \alpha_3 u_{t-1} + \beta H_{t-1}$

(Standard errors in parentheses)

	Model 1	**Model 2**
θ_0	0 006608**	0.006497**
	(0.002962)	(0.002909)
θ_1	0 024911***	-
	(0 003362)	-
α_0	0.006416*	0.007016***
	(0.003418)	(0.002087)
α_1	0.230591	0.031459
	(5.071763)	(0.038741)
α_2	5 614593	1.496382**
	(34.526601)	(0.719264)
α_3	0.003307	-0.002775
	(0.003294)	(0.003461)
β	0.060934	-0.072700
	(0.500218)	(0.311505)
log likelihood	1727.37290	1717.78067
skewness	0.43358***	0.27758***
kurtosis	4.28676***	3.83106***

Table XIII-A Sign tests - Model 1 of Asymmetric GARCH (1,1)

from Table VII above

test	Coefficient	S.D.	t stat	significance level
sign bias test	0.1399869	0.1709576	0.81884	0.41310
negative sign bias test	-2.243718	2.070843	-1.08348	0.27890
positive sign bias test	0.3328132	1.5501913	0.21469	0.83006
joint test	1.928			

Table XIII-B Lung-Box Q statistics Model 1 of Asymmetric GARCH (1,1)

(from Table VII above)

	Q stat 24 lags	significance level
OLS	21 3652	0.6171
GARCH	22 0617	0.5756

Table XIV Asymmetric GARCH(1,1) Second stage:

Model: $$ONSRET_t = \pi_0 + \pi_1 u_{t-1} + \pi_2 u_{t-2} + \sum_{i=2}^{5} \delta_i D_i + \Phi E_t + v_t$$

Conditional variance: $$Q_t = \alpha_0 + \alpha_1 |v_{t-1}|^{\alpha_2} + \alpha_3 v_{t-1} + \beta Q_{t-1} + \varphi u_{t-1}^2$$

(standard errors in parentheses)

	Model A	**Model B**	**Model C**	**Model D**
π_0	-0.005183	-0.008895	-0.006035	-0.009510
	(0.009212)	(0.012511)	(0.004340)	(0.012529)
π_1	0.334568***	-	0.285686***	-
	(0.089326)	-	(0.069207)	-
π_2	0.169039**	-	0.170557***	-
	(0.081496)	-	(0.058396)	-
δ_1	-0.031398*	-0.025955	-0.030881*	-0.025696
	(0.018438)	(0.016558)	(0.016001)	(0.019729)
δ_2	-0.020960	-0.016585	-0.010975	-0.001398
	(0.016947)	(0.018737)	(0.008789)	(0.014335)
δ_3	0.021666	0.019325	0.024105**	0.034845*
	(0.015351)	(0.016756)	(0.011567)	(0.018716)
δ_4	-0.068051***	-0.075218***	-0.067490***	-0.079486***
	(0.014161)	(0.018807)	(0.005705)	(0.023340)
Φ	-0.064483	-0.064921*	-0.061271***	-0.065223*
	(0.043247)	(0.039469)	(0.006936)	(0.040537)
α_0	0.011018***	0.012204**	0.013422**	0.013555*
	(0.004212)	(0.005487)	(0.006098)	(0.007275)
α_1	0.124049***	0.112014***	0.109661***	0.091789***
	(0.019166)	(0.017183)	(0.014976)	(0.014968)
α_2	0.630877***	0.577554***	0.515679***	0.518678***
	(0.128817)	(0.133664)	(0.115817)	(0.145070)
α_3	-0.033967**	-0.042611***	-0.025525**	-0.029034**
	(0.014034)	(0.013539)	(0.012396)	(0.011979)
β	0.245340***	0.260115***	0.229353***	0.3276365***
	(0.066266)	(0.079319)	(0.072869)	(0.093938)
φ	0.516611***	0.508524***	-	-
	(0.00017)	(0.156842)	-	-
Log likelihood	751.173853	744.058098	744.902883	739.03924
skewness	-0.04094	-0.05428	-0.17485**	-0.17314**
kurtosis	2.92093***	2.72331***	3.33085***	3.02622***

Table XIV-A - Compare log likelihood values

Unrestricted	Restricted	-2(Lr -Lur)	Critical values		D.F.
			95%	90%	
A	B	14.232	3.84	2.71	1
A	C	12.542	3 84	2.71	1
A	D	24 269	5.99	4.61	2
C	D	11.727	3.84	2.71	1
B	D	10.038	3.84	2.71	1

Table XIV-B Sign tests

test	Coefficient	S.D.	t stat	significance level
sign bias test	-0 118401	0.148983	-0.79473	0.426986
negative sign bias test	0.334446	0 457860	0.73046	0.465308
positive sign bias test	-0.023469	0 462980	-0.05069	0 959583
joint test	1.1978			

Table XIV-C Lung-Box Q statistics Model A

	Qstat 24 lags	significance level
OLS	34.4285	0.077337
AGARCH (1,1)	31.7967	0.132115

Part III - Trading period spot returns

Table XV : Unexpected component of EOD futures return as an explanatory variable of trading period spot return - GARCH(1,1) Model.

Model: $$TPSRET_t = \pi_0 + \pi_1 u_{t-1} + \pi_2 u_{t-2} + \pi_3 u_{t-3} + \sum_{i=2}^{5} \delta_i D_i + \Phi E_t + v_t$$

Conditional variance: $$Q_t = \alpha_0 + \alpha_1 v_{t-1}^2 + \beta Q_{t-1} + \varphi u_{t-1}^2$$

(standard errors in parentheses)

	Model A	Model B	Model C	Model D
π0	0.109629***	0.112577***	0.112919***	0.115355***
	(0.040310)	(0.041724)	(0.041937)	(0.043395)
π1	0.330784	-	0.352047*	-
	(0.272316)	-	(0.211811)	-
π2	0.215973	-	0.087479	-
	(0.302786)	-	(0.276567)	-
π3	-0.055906	-	-0.215500	-
	(0.255939)	-	(0.230656)	-
δ1	-0.047307	-0.051511	-0.047578	-0.051284
	(0.055072)	(0.056335)	(0.057024)	(0.058633)
δ2	-0.057114	-0.056413	-0.067280	-0.062932
	(0.061999)	(0.062734)	(0.061810)	(0.061782)
δ3	-0.071581	-0.088223	-0.070993	-0.089209
	(0.063683)	(0.062104)	(0.065677)	(0.064577)
δ4	-0.075432	-0.076678	-0.097652	-0.098065
	(0.067875)	(0.067852)	(0.067722)	(0.068107)
Φ	-0.1974189**	-0.194062**	-0.162050*	-0.157022*
	(0.088117)	(0.086201)	(0.0863438)	(0.083609)
α0	0.0480750***	0.041026***	0.062644***	0.046612***
	(0.013655)	(0.011895)	(0.018027)	(0.014626)
α1	0.056431***	0.050752***	0.082102***	0.068960***
	(0.019081)	(0.017562)	(0.024078)	(0.019966)
β	0.755590***	0.783117***	0.752474***	0.807912***
	(0.051463)	(0.046702)	(0.064321)	(0.053727)
φ	3.255567***	3.096168***	-	-
	(0.831048)	(0.757293)	-	-
log likelihood	13.97052	14.9988	4.90349	5.87568
skewness	-0.17934**	-0.18970**	-0.24580***	-0.23627***
kurtosis	1.71232***	1.73846***	1.98056***	2.06440***

Table XV-A - Compare log likelihood values

Unrestricted	Restricted	-2(Lr -Lur)	Critical values		D.F.
			95%	90%	
A	B	-2.057	3.84	2.71	1
A	C	18.134	3.84	2.71	1
A	D	16.190	5.99	4.61	2
C	D	-1.944	3.84	2.71	1
B	D	18.246	3.84	2.71	1

Table XV-B Sign tests - Model A

test	Coefficient	S.D.	t stat	significance level
sign bias test	-0.056267	0.130230	-0.43206	0.66580
negative sign bias test	-0.031309	0.171848	-0.18219	0.85547
positive sign bias test	-0.062304	0.180336	-0.34549	0.72981
joint test	1.135			

Table XV-C Lung-Box Q statistics Model A

	Qstat 24 lags	significance level
OLS	40.0127	0.021320
GARCH (1,1)	37.9911	0.034746

Table XVI : Unexpected component of EOD futures return as an explanatory variable of trading period spot return - GJR GARCH Model.

Model: $TPSRET_t = \pi_0 + \pi_1 u_{t-1} + \pi_2 u_{t-2} + \pi_3 u_{t-3} + \sum_{i=2}^{5} \delta_i D_i + \Phi E_t + v_t$

Conditional variance: $Q_t = \alpha_0 + \alpha_1 v_{t-1}^2 + \alpha_2 S_{t-1} v_{t-1}^2 + \beta Q_{t-1} + \varphi u_{t-1}^2$

(standard errors in parentheses)

	Model A	Model B	Model C	Model D
π0	0.109881***	0.113383***	0.112729***	0.114840***
	(0.040831)	(0.042245)	(0 042305)	(0 043611)
π1	0.309484	-	0.336975	-
	(0.272632)	-	(0.213255)	-
π2	0.195847	-	0.069554	-
	(0.302449)	-	(0.276496)	-
π3	-0.060113	-	-0.215768	-
	(0.256982)	-	(0.231164)	-
δ1	-0.050946	-0.056449	-0.051585	-0 055332
	(0.055717)	(0.057136)	(0.057915)	(0 059481)
δ2	-0.055902	-0 055658	-0.065654	-0 061374
	(0.062002)	(0.062760)	(0 061926)	(0 061921)
δ3	-0.072313	-0.089876	-0 071619	-0 089739
	(0.063651)	(0.062158)	(0.065606)	(0 064710)
δ4	-0.072443	-0.073508	-0 095217	-0 095423
	(0.068115)	(0.068220)	(0 067932)	(0 0684710)
Φ	-0.200854**	-0.199990**	-0 167233*	-0 164119**
	(0.087826)	(0.086024)	(0.086096)	(0 083451)
α0	0 047709***	0.041353***	0.063275***	0.048043***
	(0 013743)	(0 012193)	(0 018516)	(0 015245)
α1	0 040331*	0 033495*	0.063080**	0 052561**
	(0.020871)	(0.019336)	(0 025364)	(0 020998)
α2	0 029805	0 032015	0 034546	0 030445
	(0.030631)	(0.028245)	(0 033553)	(0 026995)
β	0 758062***	0.783449***	0 751992***	0 804885***
	(0.051721)	(0.047502)	(0 065548)	(0 055264)
φ	3.215561***	3.075394***	-	-
	(0.816356)	(0 744496)	-	-
log likelihood	14.43112	15.61550	5 403[illegible]4	6 42262
skewness	-0.15738*	-0.16420**	-0 22071***	-0 21194***
kurtosis	1 70537***	1 71892***	1.96890***	2 04372***

Table XVI-A - Compare log likelihood values

Unrestricted	Restricted	-2(Lr -Lur)	Critical values		D.F.
			95%	90%	
A	B	-2.369	3 84	2 71	1
A	C	18.054	3 84	2 71	1
A	D	16.017	5.99	4.61	2
C	D	-2 037	3.84	2.71	1
B	D	18 386	3 84	2.71	1

Table XVI-B Sign tests - Model A

test	Coefficient	S.D.	t stat	significance level
sign bias test	-0.095994	0.130117	-0.73775	0 46086
negative sign bias test	0.030638	0.171709	0.17843	0 85843
positive sign bias test	0.001486	0.180223	0.00824	0 99342
joint test	0.65375			

Table XVI-C Lung-Box Q statistics Model A

	Qstat 24 lags	significance level
OLS	39 9970	0.02140
GJR GARCH	39.4062	0.02474

Table XVII : Unexpected component of EOD futures return as an explanatory variable of trading period spot return - AGARCH Model.

Model: $$TPSRET_t = \pi_0 + \pi_1 u_{t-1} + \pi_2 u_{t-2} + \pi_3 u_{t-3} + \sum_{i=2}^{5} \delta_i D_i + \Phi E_t + v_t$$

Conditional variance: $$Q_t = \alpha_0 + \alpha_1 |v_{t-1}|^{\alpha_2} + \alpha_3 v_{t-1} + \beta Q_{t-1} + \varphi u_{t-1}^2$$

(standard errors in parentheses)

	Model A	**Model B**	**Model C**	**Model D**
π0	0.121487***	0.111225***	0.120928***	0.112080***
	(0.042331)	(0.041928)	(0.043609)	(0.043265)
π1	0.316138	-	0.349980*	-
	(0.272764)	-	(0.215050)	-
π2	0.211961	-	0.065534	-
	(0.301752)	-	(0.274518)	-
π3	-0.054238	-	-0.218440	-
	(0.258201)	-	(0.234069)	-
δ1	-0.065408	-0.054038	-0.063652	-0.053046
	(0.057607)	(0.057617)	(0.059518)	(0.060501)
δ2	-0.068168	-0.053925	-0.077295	-0.060115
	(0.062819)	(0.062639)	(0.062870)	(0.062190)
δ3	-0.081644	-0.084572	-0.074779	-0.083369
	(0.063797)	(0.061658)	(0.065774)	(0.064141)
δ4	-0.079588	-0.068203	-0.100356	-0.090622
	(0.067401)	(0.066901)	(0.069197)	(0.068983)
Φ	-0.203154**	-0.197340**	-0.165920*	-0.162632*
	(0.087784)	(0.085899)	(0.086803)	(0.083709)
α0	0.048691***	0.045262***	0.070268**	0.049627***
	(0.014186)	(0.012925)	(0.021058)	(0.016666)
α1	0.037811*	0.035802*	0.080427***	0.068791***
	(0.023557)	(0.022124)	(0.029359)	(0.023844)
α2	2.874644**	2.840511***	2.167904***	2.061544***
	(1.157984)	(1.104504)	(0.725806)	(0.625994)
α3	-0.020987	-0.021627	-0.028529	-0.021701
	(0.016254)	(0.015350)	(0.018270)	(0.014266)
β	0.7654045***	0.779544***	0.734086***	0.800134***
	(0.049509)	(0.046792)	(0.066560)	(0.056250)
φ	3.438111***	3.291031***	-	-
	(0.841806)	(0.786090)	-	-
log likelihood	15.36446	16.64976	5.246056	6.864940
skewness	-0.14488*	-0.14939*	-0.20972**	-0.20715**
kurtosis	1.67671***	1.67662***	1.93438***	2.02546***

Table XVII-A - Compare log likelihood values

Unrestricted	Restricted	-2(Lr -Lur)	Critical values		D F.
			95%	90%	
A	B	-2 571	3 84	2 71	1
A	C	20.237	3 84	2.71	1
A	D	16 999	5.99	4 61	2
C	D	-3.238	3 84	2 71	1
B	D	19 570	3 84	2.71	1

Table XVII-B Sign tests - Model A

test	Coefficient	S.D.	t stat	significance level
sign bias test	-0.124488	0 129613	-0 96046	0 33709
negative sign bias test	0 070249	0.170565	0 41186	0 68054
positive sign bias test	0.044856	0 179957	0.24926	0 80322
joint test	1.1847			

Table XVII-C Lung-Box Q statistics Model A

	Qstat 24 lags	significance level
OLS	39.9440	0 02168
AGARCH	38 7075	0.02930

Table XVIII · **Toronto 35 index futures contract trading volume by weekday** for total sample, 1991-1994

	Mon	Tues	Wed	Thurs	Fri	All days
9.30-10am	4,750	8,186	8,258	8,315	5,783	35,292
10-11am	8,019	10,122	10,348	10,112	6,818	45,419
11-12pm	5,714	7,090	7,739	8,417	6,027	34,987
12-1pm	2,843	4,191	6,448	6,807	5,147	25,436
1-2pm	3,161	3,792	5,984	8,281	2,666	23,884
2-3pm	4,244	6,419	6,100	7,870	3,809	28,442
3-4pm	6,454	9,029	7,594	11,292	5,529	39,898
4-415pm	1,891	1,911	5,645	3,989	2,015	15,451
Total·	37,076	50,740	58,116	65,083	37,794	248,809

APPENDIX A

Explanation of tests used:

1) t test for significance of correlation coefficient between two series:

$t = r\,(\sqrt{(n-2)} / \sqrt{(1 - r^2)})$

where r is correlation coefficient calculated, and n is the number of observations The critical value for the t statistic are:

2.576	0.10 significance level
1.96	0.05 significance level
1.645	0.10 significance level

when the t statistic exceeds the critical value for the chosen significance level, it can be concluded that the correlation between two series is significantly different from zero

2) Bartlett test for equality of variances

$$B = \frac{1}{C}\left[(df_T)\ln MSE - \sum_{i=1}^{r}(df_i)\ln s_i^2\right]$$

where

$$C = 1 + \frac{1}{3(r-1)}\left[\left(\sum_{i=1}^{r}\frac{1}{df_i}\right) - \frac{1}{df_T}\right]$$

$$MSE = \frac{1}{df_T}\sum_{i=1}^{r} df_i s_i^2$$

$$df_T = \sum_{i=1}^{r} df_i$$

where : r is the number of populations being sampled, from 1 to i

s_i^2 is the variance of each sample, and df_i are the degrees of freedom associated with each sample variance.

X^2 critical (4*df*) at 0 10 level = 7 78, at 0 05 level = 9 49, at 0 01 level 13 28

3) F test for equality of means

$$F = \frac{MSTR}{MSE}$$

$$MSTR = \frac{SSTR}{r-1}$$ where $$SSTR = \sum_i \frac{Y_i^2}{n_i} - \frac{Y^2}{n_T}$$, and

$$MSE = \frac{SSE}{n_T - r}$$ where $$SSE = \sum_i \sum_j Y_{ij}^2 - \sum_i \frac{Y_i^2}{n_i}$$

n_T = total observations n_i = observations in each sample r is the number of samples

F upper tail test with ($r - 1$, $n_I - r$) degrees of freedom

4) Engle ARCH test

This test is used to find out whether the square of the residuals of a regression are autocorrelated A significant test statistic indicates that an ARCH or GARCH model may be appropriate.

Run the regression as a regular OLS regression, i e..

$$ONSRET_t = \pi_0 + \pi_1 u_{(t-1)} + \sum \delta_i D_i + \Phi E + v$$

then using the residuals, v_t, run the regression.

$$v_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_i v_{(t-i)}^2 + \varepsilon_t$$

using the R^2 from this equation, calculate test statistic: $T*R^2$

The critical value is the X^2 value with q degrees of freedom.

5) Box Ljung Q test

The purpose of this test is to check whether all the autocorrelation coefficients of a series are zero

$$Q = T\sum_{k=1}^{K}(T+2)/(T-k)\rho_k^2$$

where $\hat{\rho}_k$ is the kth sample autocorrelation function, and T is the number of observations in the sample.

Q is distributed as a X^2 distribution, with k degrees of freedom. This test measures the clustering of volatilities.

6) Likelihood ratio statistic

This statistic compares the explanatory power of two models, an unrestricted model, and a model which is restricted in one or more parameters.

$$L = -2(\ln(L_R) - \ln(L_{UR}))$$

where L_{UR} is the maximum value of the log likelihood function from the unrestricted model, and L_R is the maximum value of the log likelihood function from the restricted model. The statistic follows a X^2 distribution with degrees of freedom equal to the number of restrictions in the restricted model

References

Admati, Anat, and Paul Pfleiderer, "A Theory of Intraday Patterns: Volume and Price Variability," *The Review of Financial Studies*, Vol 1 No 1, Spring 1988 P 3- 40.

Baillie, Richard T , and Tim Bollerslev. "Intra-Day and Inter-Market Volatility in Foreign Exchange Rates," *The Review of Economic Studies*, Vol. 58, 1991 P565 - 585.

Brock, William A , and Allan W. Kleidon, "Periodic Market Closure and Trading Volume - A Model of Intraday Bids and Asks," *The Journal of Economic Dynamics and Control*, Vol 16, 1992 P451-489

Chan, Kalok, "A Further Analysis of the Lead-Lag Relationship Between the Cash Market and Stock Index Futures Market," *The Review of Financial Studies*, Vol 5 No. 1, 1992. P123 - 152

Chung, Y Peter, "A Transactions data Test of Stock Index Futures Market Efficiency and Index Arbitrage Profit," *The Journal of Finance*, Vol. 46 No 5, December 1991. P 1791 - 1809

Engle, Robert F , and Victor Ng, "Measuring and Testing the Impact of News on Volatility," *The Journal of Finance*, Vol. 48, No. 5, December 1993. P 1749 - 1778.

Engle, Robert F , and Joseph Mezrich, "Grappling with GARCH," *Risk*, Vol. 8, No 9, September 1995

Gerety, Mason S , and J Harold Mulherin, "Trading Halts and Market Activity: An Analysis of Volume at the Open and the Close," *The Journal of Finance*, Vol 47, December 1992. P1765 - 1784.

Glosten, Lawrence, R , Ravi Ragannathan, and David E. Runkle, "On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," *The Journal of Finance*, Vol. 48, No. 5, December 1993. P 1779 - 1801.

Hamao, Yasushi, Ronald Masulis, and Victor Ng, " Correlations in Price Changes Across International Stock Markets", *The Review of Financial Studies*, Vol 3 No. 2, 1990. P 281 - 307

Harris, Lawrence, "S&P 500 Cash Stock Price Volatilities," *The Journal of Finance*, Vol. 44, No 5, December 1989. P 1155 - 1175.

-------, "The October 1987 S&P 500 Stock-Futures Basis," *The Journal of Finance*, Vol. 44, No 5, December 1989. P 77 -99.

Heynen, Ronald C., and Harry M. Kat, "Volatility Prediction A Comparison of the GARCH(1,1), EGARCH(1,1) and Stochastic Volatility Model," working paper, Erasmus University of Rotterdam, October 1993.

Herbst, Anthony, Joseph McCormack, and Elizabeth West, "Investigation of a Lead-Lag Relationship Between Spot Stock Indices and their Futures Contracts", *The Journal of Futures Markets*, Vol. 7 No. 4, 1987. P 373 - 381.

Herbst, Anthony, and Edwin Maberly, "The Informational Role of End-of-the-Day Returns in Stock Index Futures," *The Journal of Futures Markets*, Vol 12, No 5, 1992 P 595 - 601.

Hiraki, Takato, Edwin Maberly, and Nobuya Takezawa, "The Information Content of End-of-the-Day Index Futures Returns: International Evidence from the Osaka Nikkei 225 Futures Contract," *Journal of Banking and Finance*, Vol 19 1995 P 921-936

Johnston, J., Econometric Methods, 2nd Edition, McGraw-Hill Book Company, New York, 1963

Junkus, Joan, "Weekend and Day of the Week Effects in Returns on Stock Index Futures", *The Journal of Futures Markets*, Vol 6, No 3, 1986 P 397 - 407

Kawaller, Ira, Paul Koch and Timothy Koch, "Intraday relationships Between Volatility in S&P 500 Futures Prices and Volatility in the S&P 500 Index", *Journal of Banking and Finance*, Vol. 14, 1990. P 373 - 397.

------------, "Intraday Market Behaviour and the Extent of Feedback Between S&P 500 Futures Prices and the S&P 500 Index," *The Journal of Financial Research*, Vol 16, No 2, Summer 1993. P 107 - 121.

Koch, Paul, "Re-examining Intraday Simultaneity in Stock Index Futures Markets," *Journal of Banking and Finance*, V 17, 1993 P 1191 - 1205

Maberly, Edwin, " The Relationship Between Stock Indices and Stock Index Futures from 3:00 to 3:15 : A Note," *The Journal of Futures Markets*, V. 9, N. 3, 1989 P 271 - 272

MacKinlay, A. Craig, and Krishna Ramaswamy, " Index-Futures Arbitrage and the Behaviour of Stock Index futures Prices," *The Review of Financial Studies*, V 1, N 2, Summer 1988. P 137 - 158

Phillips-Patrick, Frederick, and Thomas Schneeweis, " The "Weekend Effect" for Stock Indexes and Stock Index Futures Dividend and Interest rate Effects," *The Journal of Futures Markets*, V 8, N 1, 1988. P 115 - 121

Pindyck, Robert S., and Daniel L. Rubinfeld, Econometric Models & Economic Forecasts, 3rd Edition, McGraw-Hill Inc., New York, 1991.

Schwarz, Thomas, " The Relationship Between Stock Indices and Stock Index Futures from 3:00 to 3:15 A Clarification," *The Journal of Futures Markets*, V 11, N. 5, 1991. P 647 - 649

Stoll, Hans, and Robert Whaley, "The Dynamics of Stock Index and Stock Index Futures Returns," *Journal of Financial and Quantitative Analysis*, V. 25, N. 4, December 1990. P 441 - 468.

Data purchased directly from the Toronto Stock Exchange.