Price Discovery in South African Financial Markets: investigating the relationship between South Africa's stock index futures market and the underlying market

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This paper investigates price discovery in the association between the South African stock index market, and the underlying market. Employing an unstructured VAR, on intraday data at the 2, 6, and 10 minute frequency for 1998, and end-of-day data for 1996-98, we find that futures markets lead spot markets. While precluding Fama informational efficiency, this does not preclude zero-arbitrage efficiency.

1 Introduction

Speculative trading, hedging and arbitraging are generally viewed as three of the most important functions of futures markets. However, it is also argued that futures markets play an important role in price discovery. Price discovery implies that the futures market can be used for pricing spot market transactions (Working, 1948, Wise, 1978). In order to determine whether the futures market provides price information, the temporal relationship between futures and spot markets must be examined for any evidence of a lead-lag relationship between futures prices and spot prices.

The presence of the price discovery relationship between spot and futures markets also provides insight into the relative informational efficiency of the two markets. In terms of Fama (1970), in efficient capital markets new information should be reflected simultaneously on both the futures and spot markets and therefore any price changes in the two markets should be perfectly contemporaneously correlated. If price changes in the futures market lead those in the spot market then there is some inefficiency in the market, as information is traded on the futures market before the spot market. However, the literature on the relationship between futures and spot markets recognizes the centrality of the role and function of arbitrageurs who transmit information into both futures and spot markets by taking advantage of risk free profitable opportunities between futures and spot markets. A linkage between spot market and the futures market is maintained by arbitrageurs, such that a no-arbitrage pricing relationship between the futures price and the underlying spot price is determined by the net cost of holding the asset relative to taking a futures position. In attempting to exploit relative misspricing across the spot and futures market, arbitrageurs ensure that this fair value is relatively quickly reestablished - though the presence of transactions costs may allow some divergence of the actual price from its fair price. This understanding of the impact of arbitrage leads to a specific conception of efficient futures and spot markets. An efficient market is defined as one in which there are no risk-free returns above opportunity costs and transaction costs, given investors' information i.e. there are no profitable arbitrage opportunities - see Dwyer and Wallace (1992).[1]

The purpose of this research is to examine the relationship between the Johannesburg Stock Exchange (JSE) All Share Index and its corresponding

[1] And also the work of Levich (1985) and Ross (1987).

futures contract, the South African Stock Exchange (SAFEX) All Share Index futures contracts. The question here is whether price discovery takes place in the index futures or in the index spot market.

Different characteristics of these two markets make it likely that new information will be reflected on the index futures market before it affects the spot market. According to Powers & Vogel (1981), the futures market is more efficient than the spot market because transaction costs are lower, trading volumes are greater, capital requirements are smaller, and market players can sell short without having to borrow to buy the securities. The infrequent trading of stocks within the index can also induce an observed lead-lag relationship. Markets for individual stocks are not perfectly continuous. The index lags behind the true value of the underlying index stocks when any of the constituent stocks have not recently traded since underlying stock values may change between trades (see Fisher, 1966). Alternatively, the futures price represents a single claim on all the shares, and thus does not suffer from the nonsynchronous trading effect of the spot index. Therefore, assuming that the index futures prices instantaneously reflect new information, observed futures returns should be expected to lead observed stock index returns because of infrequent trading, even though there is no economic significance to this behaviour whatsoever (Stoll and Whaley, 1990). For example, consider the reaction to an interest rate cut. The futures market would respond quickly, while the spot index would only reflect this information once the price of each of the component stocks had moved accordingly. This nonsynchronous trading effect is then exacerbated by thin trading (or infrequent trading) of component stocks. According to Harris (1989) the nonsynchronous trading problem is greatest when prices are analysed over short time intervals, such as are examined in studies of intraday data, and when trading is thin. Stoll and Whaley (1990) also considered how delays in computing and recording stock index values could induce a spurious lead from the futures to the spot market.

We note immediately that where futures markets are thin, a symmetrical problem may occur, viz., an absence of trading opportunity may preclude the price of the futures index to move in order to reflect the value of the underlying assets. Where futures trades are not as frequent as spot trades, lack of movement in the futures price may not be an expression of an absence of price discovery, but simply of the thinness of the futures market. It is the absence of trading *opportunity* rather than the absence of price discovery that may serve to explain the absence of price movement in the futures market.

This would serve to render any apparent lead on the part of spot prices against futures prices spurious.

Chan (1992) highlighted a differential response to market-wide information vs firm-specific information. He shows that the feedback from futures to the spot is greatest when there is greater market-wide information. Because of the greater ease of transacting on the futures market, one may expect a quicker and more accurate response to an announcement of macroeconomic information which affects the entire market. It would take the spot market longer to adjust and discount the effect the information would have on each of its component stocks. However, in the case of an announcement affecting an individual stock, the spot market is likely to adjust more quickly. Consequently, the lead-lag pattern was found to vary consistently with the extent of market-wide movement. Where more stocks move together (market-wide information), the futures market leads more strongly. The futures market is then the main source of market-wide information, while the cash market is the main source of firm-specific information. Since firms-specific information is diversifiable and market-wide information is systematic, the discovery of market-wide information is more important, so that the feedback from the futures market into the cash market is larger than the reverse.

2 Prior Findings

Several studies have examined this temporal relationship between index futures and the spot market.

One of the earliest studies was conducted by Zeckhauser and Niederhoffer (1983) using the daily spot and futures prices of the Value Line and S&P 500 over a three-month period. They found that market index futures contracts anticipate market movements. This was based on the evidence that futures prices move more rapidly to equilibrium value than spot prices (i.e. they exhibit a lack of momentum) and that futures prices often lie below the spot prices, despite the time value of money. In analysing the predictive value of the futures market, Zeckhauser and Niederhoffer (1983) used a relatively crude technique. They simply examined the correlation between the daily basis (the difference between the closing futures and spot price) and three different moves in the spot price - to the next day open, to the next day close, and to the close three days later. They found that the larger the basis is - that is, the more the futures price exceeds the spot - the greater is the tendency for the spot to rise. Consequently, the futures index has some ability to anticipate movements in the spot, particularly for the near term.

Using daily data, Ng (1987) finds that futures innovations cause spot price changes, and that futures lead spot prices by one day. In addition, she finds that spot prices do not cause futures prices.

Finnerty and Park (1987) used intraday spot and futures prices of the Chicago Board of Trade's Major Market Index (MMI) and the Maxi Major Market Index (MMMI). For every reported change in the index price (based on at least minute-to-minute data), the closest preceding change in the futures price was identified. They ran 2 regressions for each contract - a basic model testing the relation between the change in the spot index and the change in the closest previous futures price and a modified regression model using a dummy variable to control for the expiration week or month. The results suggest index futures prices lead spot prices, however results for the MMI contract suggest a differential relation over the contract life with a more intense relationship near contract expiration.

Similarly, Kawaller, Koch & Koch (1987) studied the intraday pricing relationship for spot indices and futures contracts using minute-to-minute data, while also testing for a differential response over contract life. However, their study was based on the S&P 500 and used a more rigorous statistical technique. Three-stage least-squares regression is used to estimate lead and lag relationships with estimates for expiration days of the S&P 500 futures compared with estimates for days prior to expiration. This enables an investigation of whether the distributed lags vary systematically throughout the life of each futures contract and whether they differ on expiration days as opposed to nonexpiration days. They found that while index futures and spot index prices move largely in unison, the lead from S&P 500 futures to spot prices extends for between 20 and 45 minutes, while the lead from spot to futures prices rarely extends beyond one minute. In addition, the expiration days do not demonstrate a temporal character substantially different from earlier days. Thus, while arbitrage activity may be presumed to be greatest at expiration, transactions under such arbitrage conditions are not sufficiently strong or pervasive to alter the empirical price relationship for the entire day. Finally, as regards market efficiency, they conclude that since the majority of price movements for the S&P500 are contemporaneous, this casts doubt on the likelihood of the lead-lag structure providing exploitable profit opportunities.

Kawaller et al's findings (1987) were supported by Herbst, McCormack and West* (1987). However, Herbst et al. also considered the influence of nonsynchronous trading by arguing that the more pronounced lag in the Value Line index relative to the S&P 500 index reflects the difference in the underlying indices i.e. the Value Line index contains more securities.

The impact of nonsynchronous trading on the lead-lag structure was then formally addressed by Harris (1989) and Stoll and Whaley (1990) and Chan (1992).

Harris (1989) examined five-minute changes in the S&P 500 index and futures contract over a very short sample period, a ten day interval surrounding the October 1987 stock market crash. By examining cross-correlations, he found that even after the effect of nonsynchronous trading is taken into account, the futures price strongly leads the spot index, while there is little evidence of the spot market leading the futures market.

Stoll & Whaley (1990) investigated the time series properties of five-minute, intraday returns of the S&P 500 and MMI stock index futures contracts and the related spot indices. They first used an ARMA filter to remove the effects of nonsynchronous trading on the S&P 500 and MMI indices. The residuals of this model (i.e. return innovations) are then used as a proxy for true' stock index returns. The temporal relation between the futures and stock returns is then estimated using multiple regression with lead, contemporaneous, and lag futures returns as independent variables and stock return innovations as dependent variables. They found that index futures price changes lead spot index changes by about five to ten minutes, but the feedback from the spot market into the futures market is much shorter than that.

Chan (1992) investigated five-minute intraday returns on the MMI and returns on the MMI and S&P 500 futures. A multiple regression model, similar to that used by Stoll and Whaley (1990), was estimated with lead, contemporaneous, and lag futures returns as independent variables and five-minute MMI spot returns as dependent variables. The MMI was chosen because it comprises frequently traded stocks, minimising the possible spurious lead-lag relationship caused by infrequent trading of a component stock. In addition, it comprises only 20 stocks, allowing the study of the lead-lag relationship between individual stocks and the futures price. By also examining the transaction frequencies of component stocks and futures, Chan investigated the extent to which nonsynchronous trading explains the lead-lag relationship. If this bias is present, MMI futures should lead only infrequently traded stocks. Further, Chan tested whether the relationship changes with (i) bad news versus good news; (ii) relative intensity of trading activities in the two markets; and (iii) the extent of market-wide movements.

Empirical results show strong evidence that the futures market leads the spot market and weak evidence that the spot market leads the futures market. Nonsynchronous trading did not explain the lead-lag relationship well, as the relationship did not vary much with the frequency of trading. Good or bad news was not found to significantly affect the relationship, nor did the relative intensity of trading activities in the two markets. The most significant result was that the feedback from futures to the spot is greatest when there is greater market-wide information (i.e. where more stocks move together). This suggests that the futures market is the main source of market-wide information, while the spot market is the main source of firm-specific information. Since firms-specific information is diversifiable and market-wide information is systematic, the discovery of market-wide information is more important, so that the feedback from the futures market into the spot market is larger than the reverse.

In more recent studies the emphasis has shifted towards more advanced econometric techniques. Ghosh (1993) and Wahab and Lashgari (1993) were the first to introduce cointegration to account for the long run relationship between the spot and futures markets. This approach differs from prior studies which relied on short term dynamics to establish the relationship between the markets. The application of cointegration specifically accounts for the long run equilibrium between economic time series which appear to move together over time. An error correction representation describing each pair of price series is appropriate when series are cointegrated as the models allow valid conclusions to be drawn regarding the lead-lag relationship.

Ghosh (1993) analysed the S&P 500 and Commodity Research Bureau (CRB) indices and futures contracts pairs. Augmented Dickey-Fuller tests were used to test for the stationarity of the data. All time series were found to be I(1). The Engle-Granger method was used to test for cointegration and indicated that the spot series were cointegrated with the contemporaneous futures series for both the S&P 500 and CRB indices. Because they are cointegrated, it was appropriate to represent the spot and futures prices with error correction models (ECMs). ECMs were constructed with equations of the same form. Forecasts from these ECMs were compared to a naive forecasting equation, which simply based the forecast of a future value of a variable on its most recent value. The ECMs improved forecasting of both the S&P 500 and CRB indices. It was established that S&P 500 futures prices caused the S&P 500 index prices in the sense of Granger, while the reverse was true for the CRB.

Wahab and Lashgari (1993) investigated the relationship between the S&P 500 index and futures contracts traded on the Chicago Index and Options Market, and between the Financial Times - Stock Exchange 100 (FTSE 100) index and futures contracts traded on the London International Financial Futures Exchange. The Engle-Granger method was used to test for cointegration. Both the S&P 500 and FTSE 100 index and futures pairs were found to be cointegrated. The resulting ECMs indicated that the spot and futures prices were mostly simultaneously related, with lagged components rather weak in magnitude, and possibly not economically significant or exploitable. However, there was surprisingly stronger evidence of a lead from the spot markets to the futures markets for the S&P 500 and for the FTSE 100 indices than vice versa. The performance of the ECMs in forecasting was significantly better than that of standard vector autoregression models.

Bhar and O'Callagan (1995) used the cointegration technique proposed by Johansen (1988) and Johansen and Juselius (1990) to investigate the relationship between the All Ords Index of the Australian Stock Market and the SPI Futures Index of the Sydney Futures Exchange. When they tested the order of integration of the data, Bhar & O'Callaghan extended the testing beyond the Dickey-Fuller and augmented Dickey-Fuller tests to use the Phillips-Perron test. The two time series were found to be non-stationary and integrated of the same order. Johansen's maximum likelihood approach indicated one cointegrating vector, proving that the All Ords Index and SPI futures prices were cointegrated. The resulting ECMs were found to outperform the naive forecast model. Bhar & O'Callaghan concluded that since cointegration implies causality, the efficient market hypothesis was contradicted in this case.

Cointegration techniques were also employed by Hung and Zhang (1995) and Tse (1995). They found support for the notion that futures prices lead spot prices of the CBT Municipal Bond Index and Nikkei index respectively.

The SA literature on the temporal relationship between the spot and futures market is relatively limited.

In a 1994 study, Betts (1994b) examined the South African index futures market and the JSE. She found that for the All Share Index (ALSI), the index futures tend to lead the spot market with corrections in mispricing occurring in the spot market. However, according to Betts the low liquidity in the spot ALSI market results in the index not reflecting the true level of the market. With respect to the INDI, she also found that the futures tended to lead the spot market. For the GLDI, she found that the futures tended to overreact compared to the spot market.

Johnstone (1996) used cointegration analysis on daily data to examine the causal relationship between the ALSI and the SAFEX March 1997 ALSI futures contract. They were found to be cointegrated, implying the existence of a causal relationship between them. The ECMs performed no better than a naive forecasting model and proved not to be economically exploitable. Johnstone (1996) recognised that a limitation of this study was the sampling period of one day imposed by the availability of data. It is likely that the dynamics of the JSE and SAFEX are shorter than one day. This does not affect cointegration testing, which establishes the existence of a long-term equilibrium relationship between nonstationary variables, but it will affect ECMs, as the short-run dynamic behaviour of the variables will not be accounted for. Future studies would therefore gain significance if intraday data could be collected and analysed. The predictive power of the ECMs would probably improve. Finally, Johnstone's (1996) study is also limited by a failure to consider the effects of nonsynchronous trading.

Also using cointegration techniques, Ferret and Page (1998) examined the temporal pricing relationship between four SA index futures contracts and their underlying spot market indices based on daily closing prices. Their paper provides evidence that the JSE stock index futures contracts are cointegrated with the spot market. Fitted error correction models find that the stock index futures price changes lead those of the underlying spot index by up to three days in reflecting new information. However, Ferret and Page (1998) recognised that their study was not only limited by the use of daily rather than intraday data, but by the use of the mark-to-market prices for futures contracts. The mark-to-market price is an average of the closing bid and ask prices and is therefore not the last traded price of the day. Furthermore, they also ignored the nonsynchronous trading problem.

In general, the SA findings are consistent with the majority of international studies and it appears that trading on the JSE and SAFEX follows a similar pattern to markets elsewhere.

3 Modelling Price Discovery

The question here is whether price discovery takes place in the futures, or in the spot market. Since this question translates into that of whether price changes in the futures market lead those in the spot market, or vice versa, this question can be readily translated into an unrestricted VAR framework. In Kawaller, Koch and Koch (1987), the following model is estimated on intraday data. Given the likely efficiency of futures and spot markets, intraday data will be imperative - and the higher the frequency the better for the proposed line of research. Kawaller, Koch and Koch (1987) employ minute-by-minute data. The proposed model is specified as:

$$i_t = z_1 + \sum_{k=1}^{\infty} a_k i_{t-k} + \sum_{k=0}^{\infty} b_k f_{t-k} + e_{1t} \tag{1}$$

$$f_t = z_2 + \sum_{k=0}^{\infty} c_k i_{t-k} + \sum_{k=1}^{\infty} d_k f_{t-k} + e_{2t} \tag{2}$$

where $i_t = (1 - L) I_t, f_t = (1 - L) F_t$, and I_t, F_t denote the spot and future market indexes. We need to note that the model carries the potential of simultaneity where $c_0, b_0 \neq 0$. Under data at the minute-level frequency, $k = 60$ was the finite lag length chosen. The model allows for the nature of price discovery to be established. Where the $b_k \neq 0, k > 0$, price discovery is in the futures market. Where $c_k \neq 0, k > 0$, price discovery is in the spot market.

Since the question in the present context is into where price discovery takes place in financial markets, the relevant specification is in terms of price data expressed in terms of first differences, rather than levels. Since price discovery implies the exploration of a different price level, price discovery is inherently related to changes in prices rather than price levels. Hence the formulation of the unrestricted VAR in terms of first differences of the variables.

But use of data specified in terms of first differences is justified in terms of the univariate time series characteristics of the data also. Both the price index on the spot and the price index on the futures market are typically $\sim I(1)$, rendering the least squares estimation process underlying VAR estimation inappropriate. Use of the variables in first difference form, would serve to render them stationary, hence making the VAR framework appropriate.

We note that no precendents appear to exist for South Africa, in the sense that no prior studies appear to have been conducted on the question of price discovery, employing the unrestricted VAR methodology in estimation. In this sense the findings of the present study provide new insight into the workings of South African financial markets.

4 The Data

The study employed five data sets which each contained spot and futures prices of the ALSI 40 index (in the spot market it was the level of the ALSI 40 index) at the same time intervals. The data sets are distinguishable in terms of frequency:

- End of day data: the first two data sets employed for the present study employed end-of-day data. The two data sets are distinguished in terms of the time period covered by the data sets, and the specification of the "end-of-day" observation.

  - Data Set A: the sample period covered June 1996 till the end of 1998, and consisted of the *published* closing prices of the JSE and SAFEX. Since the JSE and SAFEX do not share the same official closing time for quoted closing prices, this introduces the possibility of errors in variables into the estimation, since the market with a later quoted closing time would carry the institutionally defined opportunity for price discovery while the closed market was unable to react. This data set provided a total of 751 observations.
  - Data Set B: For this reason we employed a second end-of-day data set, for which close of day data was defined to be the observed price in the spot (ALSI40) and futures (SAFEX) markets at a consistent prespecified time common to both markets. The time point chosen was 4:30pm. End of day data for the whole of 1998 made up this data set. This data set provided a total of 234 observations.

- Intra-day data: a number of additional data sets defined in terms of alternative frequency of observation were employed. All such data sets comprised intra-day data for 1998. Three different frequencies besides end of day were tested:

  - Data Set C: data at ten minute intervals throughout the day, yielding 10094 observations for the 1998 year.

- Data Set D: data at six minute intervals throughout the day yielding 16674 observations for the 1998 year.
- Data Set E: data at two minute intervals throughout the day yielding 49574 observations for the 1998 year.

In each of the intraday data sets, estimation proceeded both on the full data set for the full year, and on estimations for subsamples. The use of subsamples supplemented the use of dummy variables to test for the impact of emerging market crises that occurred during the course of 1998 - particularly May and August 1998. Given the size of the data sets at our disposal, it is feasible to estimate the unrestricted VAR's over subsamples of the full 1998 year, in order to investigate whether our findings for each of the frequencies are affected by the crisis or not.

5 Estimation Results

Price discovery takes place in the futures market in South Africa. This constitutes the central finding that emerges from estimated VAR's.

This finding proves consistent across all data sets employed for the study except that of the highest frequency: Data Set E. Moreover, the finding proves robust to the introduction of a number of alternative tests for the impact of the financial market crises. Nevertheless, there is some evidence to suggest that crisis moths and their aftermath did have some impact on the nature of the price discovery in South African financial markets.

While estimation was in terms of unrestricted VAR's, optimal lag structure within the VAR structure was tested for in terms of an information criterion (two information criteria were employed: Akaike's and the Schwarz-Bayesian). For all data sets employed for the present study, optimal lag structures implied by the information criteria proved parsimonious - proving to be no greater than 8 or 9 even for the highest frequency data employed. Nevertheless, since the primary focus of the present exercise was not an explanatory framework for price changes in spot and futures markets but on price discovery, and since this hinges on the statistical significance of parameters within the VAR, a more generous lag structure than implied by the information criteria was employed throughout the study.

In Tables 1 through 8 we present the two equations of the unrestricted VAR for all data sets but Data Set E (with which we deal separately below), without controlling for the impact of the emerging market crises. We note that in all instances, the evidence shows clearly that the condition for price discovery taking place in futures markets, that in the unrestricted VAR structure we have $b_k \neq 0, k > 0$ and $c_k = 0, k > 0$, is met. Regardless of which data frequency is employed therefore, six or ten minute frequencies for the intra-day data, or the end-of-day data, the implication is therefore that price changes in the futures market lead price changes in the spot market.

Tables 9 and 10 report the two equations of the unrestricted VAR for Data Set E. In contrast to the findings for lower frequency data, the evidence no longer satisfies the condition for price discovery taking place in futures markets, viz. that in the unrestricted VAR structure we have $b_k \neq 0, k > 0$ and $c_k = 0, k > 0$. Instead, we find that $b_k \neq 0, k > 0$ and $c_k \neq 0, k > 0$, such that price discovery may take place in the spot market. However, care should be taken to interpret this finding, since it may reflect an errors in variables problem. Futures trades are not as frequent as spot trades and hence the futures price is often static for periods that exceed two minutes. This creates an errors in variables problem, since the lack of movement in the futures price may not be an expression of an absence of price discovery, but simply of the thinness of the futures market. It is the absence of trading *opportunity* rather than the absence of price discovery that may serve to explain the absence of price movement in the futures market. The statistical consequence of the errors in variables problem would be bias and inconsistency in the Ordinary Least Squares (OLS) estimators which implies that it is not possible to assess the significance of parameters even in large samples - rendering the tests for statistical significance in the high frequency unrestricted VAR's potentially spurious. It is noteworthy that this problem in South African markets mirrors evidence presented for the USA in at least some studies. For symmetrical reasons, US studies have tended to move to 5 minute frequency data in order to avoid potential errors in variables problems. Since for South African markets we find consistent evidence of rice discovery taking place in futures markets at 6 minute frequency data, one potential implication of our findings is that the differential between the efficiency of South African financial markets and those of the US may be smaller than might have been surmised.

Finally, we tested for the sensitivity of our finding that price discovery takes place in futures markets to the impact of emerging markets crises on the South African economy. The impact of the emerging markets crises were tested for in a number of respects:

- Two shocks were controlled for during the course of 1998 (26 May 1998 - the "Asian" crisis and 17 August 1998 - the "Russian" crisis)
- Three different "durations" of the crisis impact was tested for, for each frequency of data: two week, four week and eight week durations.

In each case, the crisis was not found to affect the price discovery findings. Moreover, the crisis variables were found to be significant only in the spot market equation, and not in the futures market equation. The implication of this evidence is thus that the impact of emerging market crises was not such as to affect the source of price discovery in South African financial markets. price discovery continues to take place in the futures rather than the spot market. The only countervailing evidence comes from the high frequency (10-minute and 6-minute) sub-sample data for 1998. For these two data sets, there is some evidence to suggest that in crisis months price discovery is coincident in the futures and spot markets.[2] One interpretation of this evidence is that in crisis periods, market activity moves to the short end - perhaps because market participants while needing to react to the new information, are not certain of its quality, and the duration of the shock. Moreover, given the findings of the presence of arbitrage between the futures and spot markets, and its stabilizing effects noted in the following section, the findings on crisis impacts certainly do not suggest that the futures market exacerbates the magnitude of shock impacts.

6 Evaluation and Discussion of Estimation Results

The main implication of our estimation results is that price discovery takes place in futures rather than spot markets in South Africa. Moreover, this finding appears to be robust to a number of tests for the impact of emerging market crises, and emerges at relative high frequency (6 minute data).

Only two qualifications appear required for this finding. The first concerns the countervailing evidence from the very highest frequency data employed for this study (the two-minute data) - though we noted a possible statistical reason for this aberration. Nevertheless, it should be noted that the statistical errors in variables problem may itself reflect an efficiency problem in the futures market. The fact that the futures market does not trade as frequently

[2] Full results are avaiable from the authors on request.

Ordinary Least Squares Estimation

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Dependent variable is F

720 observations used for estimation from 12 to 731

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Regressor	Coefficient	Standard Error	T-Ratio[Prob]
CONST	-2.6523	3.7590	-.70557[.481]
I(-1)	.10260	.10724	.95680[.339]
I(-2)	-.016214	.10317	-.15715[.875]
I(-3)	.0021373	.10191	.020973[.983]
I(-4)	-.097174	.10090	-.96309[.336]
I(-5)	-.061821	.097453	-.63437[.526]
I(-6)	.085948	.096796	.88793[.375]
I(-7)	.018966	.093947	.20188[.840]
I(-8)	.058318	.093035	.62684[.531]
I(-9)	.0090577	.082252	.11012[.912]
I(-10)	-.035585	.079083	-.44998[.653]
F(-1)	.011991	.091348	.13127[.896]
F(-2)	-.016551	.089196	-.18556[.853]
F(-3)	.0057547	.089520	.064284[.949]
F(-4)	-.046433	.088699	-.52349[.601]
F(-5)	.053208	.086452	.61546[.538]
F(-6)	-.083906	.086206	-.97332[.331]
F(-7)	-.046654	.083976	-.55557[.579]
F(-8)	-.080997	.082886	-.97721[.329]
F(-9)	.041830	.075859	.55142[.582]
F(-10)	.040558	.073323	.55315[.580]

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R-Squared	.034707	R-Bar-Squared	.0070878
S.E. of Regression	100.5348	F-stat. F (20, 699)	1.2566[.201]
Mean of Dependent Variable	-2.5778	S.D. of Dependent Variable	100.8930
Residual Sum of Squares	7064965	Equation Log-likelihood	-4330.5
Akaike Info. Criterion	-4351.5	Schwarz Bayesian Criterion	-4399.6
DW-statistic	1.9984		

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Diagnostic Tests

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Test Statistics	LM Version	F Version
A :Serial Correlation	CHSQ(1)= 1.3321[.248]	F(1, 698)= 1.2938[.256]
B :Functional Form	CHSQ(1)= .9420E-3[.976]	F(1, 698)= .9132E-3[.976]
C :Normality	CHSQ(2)= 4713.0[.000]	Not applicable
D :Heteroscedasticity	CHSQ(1)= 5.4509[.020]	F(1, 718)= 5.4772[.020]

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A:Lagrange multiplier test of residual serial correlation
B:Ramsey's RESET test using the square of the fitted values
C:Based on a test of skewness and kurtosis of residuals
D:Based on the regression of squared residuals on squared fitted values

Figure 1: Inconsistent End-of-Day Results

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                Ordinary Least Squares Estimation
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Dependent variable is I
720 observations used for estimation                    from   12 to  731
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Regressor           Coefficient       Standard Error       T-Ratio[                         Prob]
CONST                  -           2.6865           3.2081              -.83740[.403]
I(-1)                  -.15003            .091520              -1.6393[.102]
I(-2)                  -.23081            .088053              -2.6213[.009]
I(-3)                  -.011985           .086972              -.13780[.890]
I(-4)                  -.12381            .086111              -1.4378[.151]
I(-5)                  -.13351            .083170              -1.6052[.109]
I(-6)                  -.020521           .082610              -.24841[.804]
I(-7)                   .11500            .080178               1.4344[.152]
I(-8)                   .11833            .079400               1.4903[.137]
I(-9)                   .14300            .070197               2.0371[.042]
I(-10)                 -.027969           .067492              -.41441[.679]
F(-1)                   .21257            .077960               2.7266[.007]
F(-2)                   .20468            .076123               2.6888[.007]
F(-3)                   .032528           .076400               .42576[.670]
F(-4)                   .021416           .075699               .28290[.777]
F(-5)                   .11789            .073782              1.5978[.111]
F(-6)                   .0080697          .073571               .10969[.913]
F(-7)                  -.077996           .071668              -1.0883[.277]
F(-8)                  -.10952            .070738              -1.5482[.122]
F(-9)                  -.069314           .064741              -1.0706[.285]
F(-10)                  .022162           .062577               .35415[.723]
*******************************************************************************
R-Squared                            .                  062113       R-Bar-Squared                    .035278
S.E. of     Regression               85.8005       F-                    stat.             F          ( 20, 699)    2.3146[.001]
Mean of Dependent Variable   -                2.9264       S.D. of Dependent Variable       87.3552
Residual Sum of            Squares        5145851        Equation Log-likelihood           -4216.4
Akaike     Info. Criterion              -            4237.4        Schwarz               Bayesian Criterion       -4285.5
DW-    statistic                       1.9640
*******************************************************************************


                     Diagnostic Tests
*******************************************************************************
*    Test Statistics                         *        LM Version                  *          F Version                       *
*******************************************************************************
*                                            *                            *                             *
*   A :Serial Correlation            * CHSQ(    1)=  20.3967[.000]  *  F(    1, 698)=  20.3499[.000]    *
*                                            *                            *                             *
*   B :Functional Form               * CHSQ(    1)=  19.2807[.000]  * F(    1, 698)=  19.2059[.000]     *
*                                            *                            *                             *
*   C :Normality                     *  CHSQ(    2)=    3079.4[.000]  *       Not applicable             *
*                                            *                            *                             *
*   D :Heteroscedasticity            * CHSQ(    1)=  21.6267[.000]  *  F(    1, 718)=  22.2345[.000]    *
*******************************************************************************
   A:Lagrange multiplier test of residual serial correlation
   B:Ramsey's RESET test using the square of the fitted values
   C:Based on a test of              skewness and kurtosis of residuals
   D:Based on the regression of squared residuals on squared fitted values
```

Figure 2: Inconsistent End-of-Day Results

Source	SS	df	MS
Model	418086.254	20	20904.3127
Residual	2130625.96	203	10495.6944
Total	2548712.21	223	11429.2028

Number of obs	224
F(20, 203)	1.99
Prob > F	0.0090
R-squared	0.1640
Adj R-squared	0.0817
Root MSE	102.45

i	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
il1	-.5812747	.1682108	-3.456	0.001	-.912939	-.2496104
il2	-.3763166	.1932975	-1.947	0.053	-.757445	.0048118
il3	-.0580727	.1996446	-0.291	0.771	-.4517158	.3355704
il4	-.1828651	.2006594	-0.911	0.363	-.578509	.2127788
il5	-.3578235	.1998587	-1.790	0.075	-.7518887	.0362418
il6	-.0949178	.1956661	-0.485	0.628	-.4807164	.2908807
il7	-.1143382	.1888268	-0.606	0.546	-.4866515	.2579752
il8	-.0507476	.1816305	-0.279	0.780	-.408872	.3073767
il9	-.0099692	.1728353	-0.058	0.954	-.3507519	.3308135
il10	-.0105856	.1500114	-0.071	0.944	-.306366	.2851947
fl1	.63731	.1386685	4.596	0.000	.3638947	.9107252
fl2	.4203171	.1662464	2.528	0.012	.0925259	.7481083
fl3	.076524	.1745642	0.438	0.662	-.2676675	.4207156
fl4	.1956486	.1765661	1.108	0.269	-.15249	.5437873
fl5	.3117121	.1774368	1.757	0.080	-.0381433	.6615675
fl6	.1412557	.174664	0.809	0.420	-.2031326	.485644
fl7	.1087563	.168432	0.646	0.519	-.2233442	.4408568
fl8	.0831364	.1616593	0.514	0.608	-.2356104	.4018831
fl9	.0744152	.1541192	0.483	0.630	-.2294646	.3782949
fl10	.1672528	.1361076	1.229	0.221	-.101113	.4356186
_cons	-.9508739	6.861953	-0.139	0.890	-14.48072	12.57897

Figure 3: Consistent End-of-Day Results

```
Source |       SS       df       MS              Number of   obs =     224
---------+----------------------------  -            F( 20,   203) =    1.06
   Model |  329304.101    20  16465.2051              Prob > F      =  0.3961
Residual |  3157300.89   203  15553.2064            R-squared     =  0.0944
---------+----------------------------  -             Adj R-squared =  0.0052
   Total |  3486605.00   223    15635.00            Root MSE      =  124.71

------------------------------------------------------------------------------
       f |      Coef.   Std. Err.       t     P>|t|       [95%  Conf. Interval]
---------+--------------------------------------------------------------------
     il1 |  -.0078409   .2047661     -0.038   0.969      -.4115821    .3959004
     il2 |   -.086665   .2353048     -0.368   0.713      -.5506198    .3772898
     il3 |    .266616   .2430312      1.097   0.274      -.2125732    .7458051
     il4 |   .1200816   .2442665      0.492   0.624      -.3615432    .6017064
     il5 |  -.2537559   .2432918     -1.043   0.298      -.7334589    .2259472
     il6 |  -.0557085   .2381881     -0.234   0.815      -.5253484    .4139314
     il7 |  -.1403411   .2298625     -0.611   0.542      -.5935652    .3128831
     il8 |   .0516996   .2211023      0.234   0.815      -.3842519    .4876511
     il9 |  -.0118109   .2103957     -0.056   0.955      -.4266522    .4030303
    il10 |  -.0648156   .1826118     -0.355   0.723      -.4248746    .2952435
     fl1 |    .120681   .1688038      0.715   0.475      -.2121526    .4535146
     fl2 |   .1251068   .2023749      0.618   0.537      -.2739197    .5241332
     fl3 |   -.238066   .2125003     -1.120   0.264      -.6570569    .1809249
     fl4 |  -.0954563   .2149372     -0.444   0.657      -.5192521    .3283394
     fl5 |   .1186974   .2159971      0.550   0.583      -.3071882     .544583
     fl6 |   .0899032   .2126218      0.423   0.673      -.3293272    .5091336
     fl7 |   .0472798   .2050354      0.231   0.818      -.3569924     .451552
     fl8 |  -.0110393    .196791     -0.056   0.955      -.3990557    .3769772
     fl9 |   .0661684   .1876122      0.353   0.725      -.3037502    .4360869
    fl10 |   .2253662   .1656863      1.360   0.175      -.1013206     .552053
   _cons |  -1.957144   8.353186     -0.234   0.815      -18.42728    14.51299
------------------------------------------------------------------------------
```

Figure 4: Consistent End-of-Day Results

```
Source |       SS       df       MS              Number of obs =   10094
---------+------------------------------           F( 20, 10073) =   40.07
   Model |   127441.24    20    6372.062           Prob > F      =  0.0000
Residual |  1601791.44 10073   159.01831           R-squared     =  0.0737
---------+------------------------------           Adj R-squared =  0.0719
   Total |  1729232.68 10093    171.3299           Root MSE      =   12.61

------------------------------------------------------------------------------
       i |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
     il1 |   .2630445   .0100012     26.301   0.000          .24344    .2826489
     il2 |   .0036443    .010339      0.352   0.724       -.0166222    .0239108
     il3 |  -.0107404   .0103389     -1.039   0.299       -.0310066    .0095259
     il4 |   .0005484   .0103393      0.053   0.958       -.0197186    .0208155
     il5 |  -.0033921   .0103391     -0.328   0.743       -.0236587    .0168746
     il6 |   .0107359   .0103377      1.039   0.299       -.0095281    .0309999
     il7 |  -.0103996   .0103373     -1.006   0.314       -.0306628    .0098636
     il8 |  -.0098596   .0103361     -0.954   0.340       -.0301204    .0104012
     il9 |    .010516    .010334      1.018   0.309       -.0097407    .0307726
    il10 |  -.0072279    .009985     -0.724   0.469       -.0268005    .0123447
     fl1 |   .0038667   .0016042      2.410   0.016        .0007222    .0070112
     fl2 |   .0043527   .0016046      2.713   0.007        .0012073     .007498
     fl3 |   .0020984   .0016052      1.307   0.191       -.0010481    .0052449
     fl4 |  -.0027741   .0016052     -1.728   0.084       -.0059207    .0003725
     fl5 |  -.0029198   .0016055     -1.819   0.069        -.006067    .0002273
     fl6 |  -.0011269   .0016058     -0.702   0.483       -.0042745    .0020208
     fl7 |   .0000845   .0016057      0.053   0.958       -.0030629     .003232
     fl8 |  -.0004622   .0016057     -0.288   0.773       -.0036096    .0026853
     fl9 |   .0007684   .0016056      0.479   0.632        -.002379    .0039157
    fl10 |   .0011032   .0016055      0.687   0.492       -.0020439    .0042503
   _cons |  -.0600304   .1255302     -0.478   0.633       -.3060947    .1860339
------------------------------------------------------------------------------
```

Figure 5: Ten Minute Frequency Results

Source	SS	df	MS
Model	36263.6714	20	1813.18357
Residual	62265432.4	10073	6181.41888
Total	62301696.1	10093	6172.76291

Number of obs	10094
F(20, 10073)	0.29
Prob > F	0.9991
R-squared	0.0006
Adj R-squared	-0.0014
Root MSE	78.622

f	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
il1	.0725087	.0623554	1.163	0.245	-.0497204	.1947378
il2	-.0473815	.0644613	-0.735	0.462	-.1737384	.0789755
il3	.0114202	.0644605	0.177	0.859	-.1149353	.1377756
il4	-.0634244	.064463	-0.984	0.325	-.1897848	.062936
il5	.0118124	.0644618	0.183	0.855	-.1145456	.1381704
il6	.0006722	.0644534	0.010	0.992	-.1256694	.1270137
il7	-.0576524	.0644509	-0.895	0.371	-.183989	.0686842
il8	-.0585728	.0644431	-0.909	0.363	-.1848941	.0677484
il9	.0325742	.06443	0.506	0.613	-.0937214	.1588699
il10	.0321962	.0622542	0.517	0.605	-.0898345	.1542268
fl1	-.0013332	.0100016	-0.133	0.894	-.0209385	.018272
fl2	-.0013211	.0100044	-0.132	0.895	-.0209318	.0182895
fl3	.0028332	.0100079	0.283	0.777	-.0167842	.0224507
fl4	.0075012	.0100082	0.750	0.454	-.0121169	.0271193
fl5	-.0011485	.01001	-0.115	0.909	-.0207702	.0184732
fl6	.0003599	.0100117	0.036	0.971	-.019265	.0199848
fl7	.0001838	.010011	0.018	0.985	-.0194398	.0198075
fl8	.0002656	.010011	0.027	0.979	-.019358	.0198891
fl9	.0003263	.0100107	0.033	0.974	-.0192967	.0199492
fl10	-.0003224	.0100098	-0.032	0.974	-.0199437	.0192988
_cons	-.0956756	.7826523	-0.122	0.903	-1.62983	1.438479

Figure 6: Ten Minute Frequency Results

```
Source |       SS       df       MS                  Number of   obs =   16674
---------+------------------------------  -               F( 20, 16653) =   54.93
   Model |  96257.1014    20  4812.85507                  Prob > F      =  0.0000
Residual |  1459088.68 16653   87.617167                 R-squared     =  0.0619
---------+------------------------------  -               Adj R-squared =  0.0608
   Total |  1555345.78 16673  93.2852986                 Root MSE      =  9.3604

------------------------------------------------------------------------------
       i |      Coef.   Std. Err.       t     P>|t|       [95%  Conf. Interval]
---------+--------------------------------------------------------------------
     il1 |    .202587   .0077702     26.072   0.000       .1873566    .2178174
     il2 |   .0900061   .0079271     11.354   0.000       .0744681    .1055442
     il3 |   .0082946   .0079578      1.042   0.297      -.0073034    .0238926
     il4 |  -.0001808   .0079566     -0.023   0.982      -.0157765     .015415
     il5 |  -.0072308   .0079554     -0.909   0.363      -.0228243    .0083627
     il6 |  -.0163874   .0079546     -2.060   0.039      -.0319793   -.0007955
     il7 |   .0098861   .0079555      1.243   0.214      -.0057075    .0254797
     il8 |   .0015694   .0079556      0.197   0.844      -.0140243    .0171632
     il9 |   .0051038   .0079223      0.644   0.519      -.0104248    .0206325
    il10 |   .0009445   .0077602      0.122   0.903      -.0142662    .0161552
     fl1 |   .0031908   .0011898      2.682   0.007       .0008586     .005523
     fl2 |   .0033238   .0011901      2.793   0.005       .0009911    .0056565
     fl3 |   .0009597   .0011903      0.806   0.420      -.0013734    .0032929
     fl4 |   .0019845   .0011903      1.667   0.096      -.0003487    .0043177
     fl5 |   .0024189   .0011904      2.032   0.042       .0000856    .0047523
     fl6 |  -.0013666   .0011906     -1.148   0.251      -.0037003     .000967
     fl7 |  -.0028813   .0011906     -2.420   0.016       -.005215   -.0005476
     fl8 |  -.0003536   .0011908     -0.297   0.766      -.0026877    .0019804
     fl9 |  -.0001135   .0011908     -0.095   0.924      -.0024477    .0022206
    fl10 |  -.0019966   .0011908     -1.677   0.094      -.0043307    .0003374
   _cons |  -.0347533   .0724953     -0.479   0.632      -.1768518    .1073453
------------------------------------------------------------------------------
```

Figure 7: Six Minute Frequency Results

Source	SS	df	MS
Model	23130.786	20	1156.5393
Residual	62233904.9	16653	3737.09871
Total	62257035.7	16673	3734.00322

Number of obs	16674
F(20, 16653)	0.31
Prob > F	0.9986
R-squared	0.0004
Adj R-squared	-0.0008
Root MSE	61.132

f	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
il1	.0733668	.0507463	1.446	0.148	-.0261013	.1728349
il2	.0288565	.0517713	0.557	0.577	-.0726207	.1303337
il3	-.0328367	.0519712	-0.632	0.528	-.1347058	.0690325
il4	-.0067266	.0519636	-0.129	0.897	-.1085807	.0951275
il5	-.0102267	.051956	-0.197	0.844	-.112066	.0916126
il6	-.0392677	.0519508	-0.756	0.450	-.1410969	.0625615
il7	-.0221971	.0519565	-0.427	0.669	-.1240374	.0796431
il8	.0095836	.0519569	0.184	0.854	-.0922574	.1114247
il9	.0276578	.05174	0.535	0.593	-.0737581	.1290737
il10	-.0424763	.0506807	-0.838	0.402	-.1418159	.0568634
fl1	-.0009264	.0077707	-0.119	0.905	-.0161578	.014305
fl2	-.0004484	.0077724	-0.058	0.954	-.015683	.0147863
fl3	-.0004934	.0077739	-0.063	0.949	-.0157311	.0147442
fl4	-.0015904	.007774	-0.205	0.838	-.0168282	.0136474
fl5	-.0007154	.0077745	-0.092	0.927	-.0159542	.0145234
fl6	.0024032	.0077754	0.309	0.757	-.0128375	.0176439
fl7	.0002641	.0077757	0.034	0.973	-.0149772	.0155053
fl8	.0086443	.007777	1.112	0.266	-.0065994	.023888
fl9	-.000454	.0077772	-0.058	0.953	-.0156982	.0147901
fl10	.0004611	.007777	0.059	0.953	-.0147826	.0157048
_cons	-.0558788	.4734594	-0.118	0.906	-.9839095	.8721519

Figure 8: Six Minute Frequency Results

```
Source |       SS       df       MS                  Number of   obs =   49574
---------+-----------------------------  -              F( 20, 49553) =   79.44
   Model |  41697.8231    20  2084.89116                 Prob > F      =  0.0000
Residual |  1300527.05 49553  26.2451727               R-squared     =  0.0311
---------+-----------------------------  -              Adj R-squared =  0.0307
   Total |  1342224.87 49573   27.075724               Root MSE      =   5.123

------------------------------------------------------------------------------
       i |      Coef.   Std. Err.       t     P>|t|       [95%  Conf. Interval]
---------+--------------------------------------------------------------------
     il1 |   .0593704   .0045014     13.189   0.000       .0505476    .0681933
     il2 |   .0982479   .0045092     21.788   0.000       .0894098     .107086
     il3 |     .06915   .0045307     15.263   0.000       .0602697    .0780302
     il4 |    .038386   .0045412      8.453   0.000       .0294853    .0472868
     il5 |   .0395582   .0045435      8.707   0.000       .0306529    .0484634
     il6 |   .0204023    .004543      4.491   0.000        .011498    .0293066
     il7 |   .0088209   .0045405      1.943   0.052      -.0000786    .0177204
     il8 |  -.0032587   .0045297     -0.719   0.472       -.012137    .0056196
     il9 |   .0022664   .0045076      0.503   0.615      -.0065685    .0111013
    il10 |    .001207   .0044996      0.268   0.789      -.0076122    .0100262
     fl1 |   .0007619   .0006507      1.171   0.242      -.0005135    .0020372
     fl2 |   .0015601   .0006507      2.398   0.017       .0002847    .0028355
     fl3 |   .0010226   .0006507      1.571   0.116      -.0002529    .0022981
     fl4 |   .0006293   .0006508      0.967   0.334      -.0006462    .0019048
     fl5 |   .0017295   .0006508      2.658   0.008        .000454     .003005
     fl6 |   .0006445   .0006508      0.990   0.322      -.0006311    .0019201
     fl7 |   .0000176   .0006508      0.027   0.978       -.001258    .0012932
     fl8 |  -.0002921   .0006508     -0.449   0.654      -.0015676    .0009835
     fl9 |   .0013901   .0006508      2.136   0.033       .0001146    .0026657
    fl10 |   .0010015   .0006508      1.539   0.124      -.0002741    .0022771
   _cons |  -.0110885   .0230097     -0.482   0.630      -.0561879    .0340108
------------------------------------------------------------------------------
```

Figure 9: Two Minute Frequency Results

```
Source |       SS       df       MS              Number of   obs =   49574
---------+------------------------------  -            F( 20, 49553) =    0.47
   Model |  11861.4369    20  593.071847               Prob > F      =  0.9772
Residual |  62240560.7 49553  1256.04021             R-squared     =  0.0002
---------+------------------------------  -            Adj R-squared = -0.0002
   Total |  62252422.2 49573  1255.77274             Root MSE      =  35.441

------------------------------------------------------------------------------
       f |      Coef.   Std. Err.       t     P>|t|       [95%  Conf. Interval]
---------+--------------------------------------------------------------------
     il1 |   .0685982   .0311407      2.203   0.028       .0075621    .1296342
     il2 |   .0352992   .0311944      1.132   0.258      -.0258421    .0964406
     il3 |     .01038   .0313432      0.331   0.741      -.0510529     .071813
     il4 |  -.0027134   .0314156     -0.086   0.931      -.0642884    .0588616
     il5 |   .0031831   .0314314      0.101   0.919      -.0584229    .0647891
     il6 |   -.019188   .0314282     -0.611   0.542      -.0807876    .0424116
     il7 |   .0297202   .0314112      0.946   0.344      -.0318461    .0912865
     il8 |  -.0086608   .0313363     -0.276   0.782      -.0700803    .0527588
     il9 |  -.0091719   .0311831     -0.294   0.769      -.0702912    .0519475
    il10 |  -.0315378   .0311277     -1.013   0.311      -.0925485    .0294729
     fl1 |   .0000804   .0045015      0.018   0.986      -.0087426    .0089034
     fl2 |  -.0005395   .0045015     -0.120   0.905      -.0093626    .0082836
     fl3 |  -.0006186   .0045018     -0.137   0.891      -.0094422     .008205
     fl4 |  -.0001127   .0045019     -0.025   0.980      -.0089364    .0087111
     fl5 |  -.0003489   .0045019     -0.078   0.938      -.0091727    .0084748
     fl6 |  -.0000717   .0045022     -0.016   0.987      -.0088961    .0087527
     fl7 |  -.0008805   .0045022     -0.196   0.845      -.0097049    .0079439
     fl8 |   .0001708   .0045021      0.038   0.970      -.0086534    .0089951
     fl9 |  -.0002294   .0045021     -0.051   0.959      -.0090537    .0085948
    fl10 |  -.0006536   .0045023     -0.145   0.885      -.0094782    .0081709
   _cons |  -.0177348   .1591799     -0.111   0.911      -.3297294    .2942598
------------------------------------------------------------------------------
```

Figure 10: Two Minute Frequency Results

as the spot implies that it is thinner than the spot market, and thinner markets are informationally poorer than thick markets. The South African futures market is therefore not as efficient as it might ideally be. On the other hand, since the US market suffers from similar though less severe problems, provides some grounds for reassurance.

There is an additional advantage that attaches to the present model. Some information concerning the role of arbitraging in markets emerges from the evidence. Where arbitrage is present, we would anticipate that the lag lengths in the models are relatively short, such that price information comes to be reflected in market prices rapidly. By contrast, where the arbitrage is relatively weak, we would expect lag lengths to be relatively long. As such the findings that should emerge from the present section should carry at least some implications for our understanding of the impact of arbitrage (perverse, or beneficial) in the South African markets. Given that the maximum lag with which changes in futures prices lead the spot market appears to be of the order of 7 six minute periods (see Tables 7 and 15 by way of example), the implication is that the maximum lag for price discovery is no greater than 40 minutes. One interpretation here is thus that the brevity of this lag effect is such as to give some prior expectation that arbitrage effects will be found to be present between futures and spot markets in South Africa. This question is explored in greater detail in Fedderke and Joao (1999).

Since the futures market in South Africa leads the spot market, we cannot conclude in favour of Fama (1970) informational efficiency. However, the possibility of no-arbitrage efficiency cannot be precluded. And indeed, in Fedderke and Joao (1999) we establish that no-arbitrage efficiency is present in South Africa's futures market.

References

Betts, A., 1994b, *Hedge Ratios: The Optimal Choice*, Simpson McKie Inc Publication, Johannesburg, June.

Bhar, R. and O'Callaghan, D., 1995, Cointegration, Error Correction and Forecasting of the All Ord's Index and SPI Futures Price Index May and June 1993, Paper presented at the Seventh Annual Australian Finance and Banking Conference, Sydney.

Chan, K., 1992, "A Further Analysis of the Lead-lag Relationship Between the Cash Market and Stock Index Futures Market," *Review of Financial Studies*, 5, 123-152.

Fedderke, J.W., and Joao, M., 1999, "Arbitrage, Cointegration and Efficiency in Financial Markets in the Presence of Financial Crisis," University of the Witwatersrand: Mimeo.

Ferret, A. and Page, M.J., 1998, "Cointegration of South African Index Futures Contracts and their Underlying Spot Market Indices," *Journal for Studies in Economics and Econometrics*, 22, 69-90.

Finnerty, J.E. and Park, H.Y. 1987 "Stock Index Futures: Does the Tail Wag the Dog? A Technical Note," *Financial Analysts Journal*, 43, 57-61.

Fisher, L., 1966, "Some New Stock Market Indexes," *Journal of Business*, 39, 191-225.

Ghosh, A., 1993, "Cointegration and Error Correction Models: Intertemporal Causality Between Index and Futures Prices," *Journal of Futures Markets*, 13, 193-198.

Harris, L., 1989, "The October 1987 S&P 500 Stock Futures Basis," *Journal of Finance*, 44, 77-99.

Herbst, A.F., McCormack, J.P., and West, E.N., 1987, "Investigation of a Lead-lag Relationship Between Spot Indices and their Futures Contracts," *Journal of Futures Markets*, 7, 373-381.

Hung, M. and Zhang, H., 1995, "Price Movements and Price Discovery in the Municipal Bond Index and the Index Futures Markets," *Journal of Finance*, 42, 1309-1329.

Johansen, S., 1988, "Statistical Analysis of Cointegration Vectors," *Journal of Economic Dynamics and Control*, 12, 231-254.

Johansen, S, and Juselius, K., 1990 "Maximum Likelihood Estimation and Inference on Cointegration - With Applications to the Demand for Money," *Oxford Bulletin of Economics and Statistics*, 52, 169-210.

Johnstone, K.B., 1996 *The Relationship Between the JSE All Share Index and ALL share Index Futures Contracts*, Unpublished MBA Report, University of the Witwatersrand.

Kawaller, I.G., Koch, P.D. and Koch, T.W., 1987, "The Temporal Price Relationship Between S&P 500 Futures and the S&P 500 Index," *Journal of Finance*, 42, 1309-1329.

Ng, N., 1987, "Detecting Spot Prices Forecasts in Futures Prices Using Causality Tests," *The Review of Futures Markets*, 6, 250-267.

Powers, M., and Vogel, D., 1981, *Inside the Financial Futures Markets*, First Edition, New York: John Wiley and Sons.

Stoll, H.R., and Whaley, R.E., 1990, "The Dynamics of Stock Index and Index Futures Returns," *Journal of Financial and Quantitative Analysis*, 25, 441-468.

Tse, Y.K., 1995, "Lead-lag Relationship Between the Spot Index and Futures Price of the Nikkei Stock Average," *Journal of Forecasting*, 14, 553-563.

Wahab, M., and Lashgari, M., 1993, "Price Dynamics and Error Correction in Stock Index and Stock Index Futures Markets: A Cointegration Approach," *Journal of Futures Markets*, 13, 711-742.

Wiese, V., 1978, "Use of Commodity Exchanges by Local Grain Marketing Organisations," in A. Peck (ed.), *Views from the Trade* (Chicago: Board of Trade of the City of Chicago).

Working, H., 1948, "Theory of the Inverse Carrying Charge in Futures Markets," *Journal of Farm Economics*, 30.

Zeckhauser, R., and Niederhoffer, V., 1983, "The performance of Market Index Futures Contracts," *Financial Analysts Journal*, 39, 59-65.