THE OVERNIGHT RETURN, ONE MORE ANOMALY

Abstract

Since the formal development of the efficient market hypothesis, studies of actual market performance have revealed a number of apparent inconsistencies (anomalies). Herein we report on our discovery of evidence anomaly which relates to the behavior of the overnight and subsequent intraday returns.

According to the weak form of the efficient market hypothesis, a time series of returns is supposed to contain no useable degree of auto correlation. Numerous studies have provided strong support for this viewpoint. We may, however, have found evidence which is inconsistent with this hypothesis.

The present study grew out of another study which focuses on the behavior of closed end fund returns. In that study we explored the daily return performance of such funds in conjunction with the daily performance of the funds' NAVs. We bifurcated the daily closed end return into an overnight return which reflect that part of the return that takes place between the close and the next day's open and the intraday return which encompasses that part of the return that occurs from the open to the close.
The two pieces of the daily return exhibited a very strong negative autocorrelation. Naturally we wanted to explore whether a similar phenomenon was occurring for stocks in general. That is the question that this study seeks to answer.

The short answer is yes, we have found the same type of negative auto correlation for stocks in general as we found for the shares of closed end funds. We have found this result for stocks listed on the NYSE, AMEX and NASDAQ. We have found it for both the 2000 to 2005 and 1994 to 1999 periods. When we divide the data into size categories, we find significant relationships for each sub sample. The correlations do, however, tend to be almost monotonically stronger as market capitalization decreases. Not only do we find a powerful negative correlation between the overnight and intraday returns but we also find a relationship between overnight and the prior intraday and the prior overnight returns. The signs of the correlations alternate with adjacent periods having negative correlations and one step back being positively related. We find that the relations hold up as anticipated in a multivariate context. When we add the S&P return to take account of the market return's impact, we find that the regressions' R squares rise but the coefficients on the other dependent variables are largely unaffected. All of our results are highly significant statistically. Most of the R squares are in the low to mid single digits.

THE OVERNIGHT RETURN, ONE MORE ANOMALY

Introduction

Since the formal development of the efficient market hypothesis (8), studies of actual market performance have revealed a number of apparent inconsistencies. So for example the January Effect (5, 16), Day Of The Week Effect (9, 10), Other Seasonal Effects (2, 7, 11, 14, 18), Size Effect (13), Value Line Enigma (15), Low PE effect (3, 4, 13), and a variety of other unusual security market behaviors such as value verses growth stock performance (12) have been documented and classified as anomalies (1). Since the finance profession has not developed a definitive model for how an efficient market is supposed to generate risk adjusted behavior, these apparent inconsistencies (anomalies) are not to be classified as ineffiencies per se. Perhaps they are reflecting various "risks" which have not fully captured by the currently used model (CAPM, APT, Fama French). Or perhaps they are evidence of real ineffiencies. We shall not go there. But we do wish to report on our discovery of what appears to us to be evidence of an anomaly which appears to have a substantial magnitude. This anomaly relates to the behavior of the overnight and subsequent intraday returns.

According to the weak form of the efficient market hypothesis, past returns are not supposed to be useful in formulating predictions of future returns. A time series of returns is supposed to contain no meaningful degree of auto correlation. Or at least if any is present, the magnitude is supposed to be of such a minor level that it can not be used to achieve an enhancement of appropriately risk adjusted returns once transactions costs are taken into account. Numerous studies have provided strong support for this viewpoint. We may, however, have found evidence which is inconsistent with this hypothesis.

The present study has grown out of a different study of ours which focuses on the behavior of closed end fund returns. In that study we explored the daily return performance of such funds in conjunction with the daily performance of the funds' NAVs. In this work we had occasion to bifurcate the daily return into an overnight return which reflect that part of the return that takes place between the close and the next day's open and the intraday return which encompasses that part of the return that occurs from the open to the close. We found that the two pieces of the daily return tended to exhibit a very strong negative autocorrelation. No matter how we subdivided our sample we found that at least for closed end funds, the intraday return tended to be in the opposite direction from the immediately preceding overnight return. This is not supposed to happen in a market that is weak form efficient. Knowing the immediate past overnight return should not help one anticipate what is going to happen over the course of the current day. But that is exactly what our results showed, at least for closed end funds. Naturally we wanted to know if a similar phenomenon was occurring for stocks in general. That is the question that this study seeks to answer.

The short answer is Yes, we have found the same type of negative auto correlation for stocks in general as we found for the shares of closed end funds. We have found this result for stocks listed on the NYSE, AMEX and NASDAQ. We have found it for both the 2000 to 2005 and 1994 to 1999 periods. When we divide the data into size categories, we find significant relationships for each sub sample. The correlations do, however, tend to be almost monotonically stronger as market capitalization decreases. Not only do we find a powerful negative correlation between the overnight and intraday returns but we also find a relationship between overnight and the prior intraday and the prior overnight returns. The signs of the correlations alternate with adjacent periods having negative correlations and one step back being positively related. In other words the adjacent intraday returns tend to move together as do the adjacent overnights but the intraday returns tend to move in the opposite direction from the overnight returns on either side. When we construct regressions with the intraday return as the independent variable and the prior period overnight and intraday returns as dependent variables, we find that the relations hold up as anticipated in a multivariate context. When we add the S&P return to take account of the market return's impact, we find that the regressions' R squares rise but the coefficients on the other dependent variables are largely unaffected. All of our results are highly significant statistically. Most of the R squares are in the low to mid single digits.

While we can't be sure what accounts for this high degree of negative autocorrelation between overnight and intraday returns, we think we understand the cause. We believe that this high level of negative autocorrelation relates to the microstructure of specialists' (or in the case of NASDAQ, the market makers') behavior. To understand the negative autocorrelations described above, we need to focus on how the market makers (and most particularly specialists) are likely to open their assigned stocks. Our discussion uses the term market maker to refer to both the exchange specialist and the OTC market maker since our data set includes both markets. We realize that the rules for the two types of market makers differ. Our description is most appropriate for the specialist but is also generally descriptive of the OTC market makers as well.

The last trade of the day will establish the close. The overnight return is based on the difference between that close and the opening of the following day. That close will typically be at the closing bid or ask level or at a point in between. Rarely will the close be outside the closing bid ask range. The closing price will contain some noise but should not be biased by unusual trades to be either above or below the stock's underling intrinsic value. If the bid-ask spread is relatively narrow, as it usually is for an actively traded security, the close should be a rather reliable index of the market's view of the security's end of the day worth (except in the relatively rare event of a close early in the day).

Once the market closes, some of the unfilled limit orders will expire (day orders). Only those good till cancelled limit orders which remain unfilled will show up as available. Moreover, if the market maker was using his or her own position to supply the bid or ask on one or both sides of the quote, that part of the quote will also disappear at day's end. The market maker is under no obligation to reenter, at the opening, his or her quotes at those end of day levels. As a result of the disappearance of much of the previous day's unfilled orders, the width between the bid prices (highest unfilled buy offer from the prior day) and ask price (lowest unfilled sell offer from the prior day) appearing on the market maker’s books is very likely to be much wider at the opening than it was at the end of the previous day. The market maker will, at a minimum, have considerable flexibility to set the opening somewhere between the highest unfilled bid and the lowest unfilled offer. And if the size of these orders to buy or to sell is small relative to the size of the overnight order flow, the market maker would be able to set the opening outside of this range.

For an actively traded security, orders both to buy and sell the security are likely to have come into the market prior to the opening. The market maker will arrive at the exchange (or in the case of a NASDAQ market maker, at his or her terminal) and see the unfilled and un canceled limit orders from the prior day plus the new orders which have come in overnight. Like the vast majority orders generally, most of the orders which have come in overnight will be market orders (as opposed to limit, short or stop orders). All such market orders must be executed at the opening. The overnight pile may also contain a few limit orders. These newly entered limit orders will, however, only need to be filled as part of the opening transaction if the opening price is at a level which requires their filling. For example a limit order must be part of the opening trade if it is to sell at a level below the opening or to buy at above the opening price. That is, the market maker can not trade through an open limit order and leave it unfilled. Typically, as the trading day is about to begin, the market maker will face an imbalance of orders. That is, the incoming market orders to buy will be for a greater number of shares than the corresponding sell orders or the new sell at market orders will be for a greater number of shares than the corresponding buy orders. But recall that all the market orders must part of the opening trade at the opening price. What is the market maker likely to do?

The market maker could simply open the security at the previous close and make up whatever the imbalance is out of inventory. So if the market orders to buy outnumber those to sell, the market maker would sell the difference out of his or her own inventory and if the sells exceed the buys, the market maker would purchase the excess and add it to inventory. That approach would amount to “leaning against the wind.” Such a strategy might be stabilizing but probably would not be profitable for the market maker. The strategy would have the market maker selling into a market with buying pressure and buying into a market evidencing selling pressure. To the extent that knowledge (as opposed to noise) traders were contributing to the pressure, the market maker would be trading at a disadvantage.

Accordingly, an alternative strategy for the market maker would be to move the opening price away from the previous close in the direction of the order imbalance. Thus if the imbalance was in the direction of an excess of sell (buy) orders, the specialist would tend to open the security below (above) the previous close. That way the market maker might be able to trigger enough limit orders below (above) the prior close to offset the imbalance. And if the market maker had to fill some of the orders by buying into (selling out of) inventory, the purchases (sales) would at least be at a price below (above) the prior close. This approach has at least two advantages for the market maker. First, the market maker receives a fee for exercising limit orders. The more limit orders that are exercised, the greater the fees thereby earned. This strategy would tend to trigger more limit order execution than a strategy of filling the imbalance gap out of inventory. Second, by using limit orders to cover the shortfall, the market maker avoids changes in his or her own inventory. Assuming that the market maker already has his or her inventory position at the preferred level, not having to change it at the opening is advantageous. Market makers are likely to have a target inventory level for each security that they manage. For example they may want to hold in inventory an amount equal to X% of the average daily trading volume of the securities that they handle. The level of X for each security is likely to vary with its volatility as well as the market makers' views of the relevant future. They probably try to end each day close to that target level inventory so that when they go home at night, their risk is constrained to what they think of as an acceptable level. Of course sometimes the market maker may end the prior day away from the target inventory level and therefore wish to adjust his or her inventory at the day's beginning. On such occasions, the market maker may take advantage of the imbalance to make the adjustment, but only if the imbalance is in the desired direction.

A third possible advantage of moving the price away from its prior level is that additional trading in the market makers' assigned securities is thereby encouraged. That is, if the opening is lower than the prior close, buyers may be induced to come into the market and trade. Similarly by opening at above the prior close, sellers are encouraged to enter. Thus those would be traders who wait until after the market has opened to enter their orders, may be more stimulated to trade if the opening is away from the prior close than if it is at the prior close. After all, they probably could have traded yesterday at the prior close level. A greater level of trading activity allows the market maker to earn both a spread and a limit order execution fee on a percentage of the trades. The more trading activity that takes place, the more opportunity the market maker will have to make money on the trades.

Thus we see that the market maker has an incentive to set the opening at a level that is either above or below the prior close rather than at the prior close. If by so doing, the market maker overshoots the equilibrium intrinsic value level, the market price will tend to revert as the day wears on, thereby producing the observed negative autocorrelation.

Two bits of real world evidence tend to bolster our interpretation of how the market microstructure can impact pricing. First, we cite the SEC action in recently obtaining convictions of a couple of specialists. Specifically, two Van der Moolen specialists were convicted of fraud in the first of a number of similar cases that the SEC has brought. The two had been charged with "front running" and "inter positioning". Front running involves trading ahead of a large order in an attempt to take advantage of the old price structure before that large order causes that price structure to change. Inter positioning refers to the practice of almost simultaneously buying from one public trader and selling to another at a higher price, thereby taking a profit out of the trade when the two traders could have been matched up directly with each other for a better price for both public parties to the transaction (6).

The second case involves another SEC action. In this matter a trader named Thomas E. Edgar was charge with a manipulative trading practice known as "marking-the-close". Quoting from the SEC release:

"The Commission's Complaint alleges that one way Edgar carried out his scheme was to mark-the-close in an attempt to increase his profit from the sale of closed-end funds that he owned. Specifically, when Edgar owned a large number of shares of a closed-end fund, typically 2,000 shares, he often placed an additional market order to buy approximately 100 or 200 shares of the same closed-end fund within a few minutes of the close of the market. The execution of these additional market buy orders resulted in an increase to the closing price of the fund. The Commission's Complaint alleges that Edgar's purpose in placing the additional market buy orders at the end of one trading day was to cause an increase to the price of the fund and then to profit from the higher sale price at the beginning of the next trading day (18)."

Neither of these cases is exactly on point with our findings. The first, however, illustrates how specialists may misuse their positions to mange the market to their advantage and in the process manage their assigned securities to the disadvantage of the trading public. The second illustrates how the market for closed end shares may be manipulated by an outside "knowledge" trader at the end of one day in an attempt to impact the opening price on the following day.

Let's now turn to our data and results.

Data

Most work on daily prices and returns utilizes what we call close to close returns. Such returns are calculated by collecting closing prices for each day and computing returns from those values. The close to close return can, however, be viewed as divided into two parts: the overnight return which we define as the opening price for period t minus the t-1 closing price divided by the t-1 closing price and the intra day return which we define as the day t close minus the day t open divided by the day t open. Thus the close to close return reflects the impact of both the overnight return and the intraday return. All of these return calculations need to be adjusted for the impact of dividends.

We obtained from the Center for Research in Security Prices (CRSP) data base various bits of data for their entire list of companies covering first the 2000 to 2005 period. Included in our raw data set are daily open and close prices adjusted for dividends and splits as well as the S&P daily returns. We also collected daily market capitalizations for each company in our sample. After eliminating observations with missing values and windsorizing our data, we divided the data set into three basic groups based on exchange of listing (NYSE, AMEX, and NASDAQ). We further divided each exchange's data into five groups based on market capitalization. With our raw data we computed overnight and intraday returns for each observation. We then created a lagged set of variables for both the intraday and overnight returns. We also created a corresponding dataset for the 1994 to 1999 period.

Univariate Results

The first part of our analysis involved computing correlations among the variables of our various samples and sub samples. We focused on the correlations between the overnight and intraday returns but we also looked at the correlations with lagged values as well. Our correlation results are contained in Exhibit 1A and 1B. These correlations exhibit an extremely consistent picture. For the combined sample the correlation between overnight and intraday returns are a very high -0.22. Moreover, the correlation of the overnight returns with the preceding intraday returns is -0.12 and with the previous overnight returns 0.06, both of which are highly significant statistically. So we see a strong negative autocorrelation between overnight and intraday returns. The overnight returns tend to move in the opposite direction from both the previous intraday and the subsequent intraday returns but in the same direction as the previous overnight returns. All of the correlations are statistically significant at very high levels of confidence.

When we rerun the correlations on each of the separate exchanges the pattern is essentially the same as was found for the combined sample. The correlation levels for the overnight returns are lowest (but still highly significant) on the NYSE (-.07, .06 and -.03 for intraday, lagged intraday and lagged overnight returns respectively) and on balance higher on the AMEX (-.22, .05 and -.09) and NASDAQ (-.25, .06, -.15). When we stratify each of these samples by market capitalization, we find a very nearly uniformly monotonic relationship between the size of the correlation and market capitalization for two of the three sets of correlations. The smaller the market capitalization, the higher is the correlations between the overnight returns and the intraday returns and the lagged overnight returns, the two most closely adjacent return numbers. For the lagged overnight return, however, the correlations tend to be lower and less consistent. While all of the correlations are positive, they exhibit little or no consistent pattern. For the NYSE subgroups the correlations are highest for the small capitalizations and tend to rise with market capitalization For the other two exchanges, however, the correlations are lower for the smaller capitalizations.

Our 1994 to 1999 data set was used to construct a second set of correlations as a check on these findings (Exhibit 1B). We find the same pattern as we found for the more recent time period. In general the correlations between the overnight and the two sets of intraday returns tend to be higher and with the lagged overnight returns tend to be smaller in the earlier time period. So for example the combined sample has correlations between the overnight return and the intraday, lagged overnight and lagged intraday returns of -.29, .01 and -.20 respectively. Once again the subgroup pattern is strong for the two adjacent return correlations but mixed for the correlations between the overnight return and the lagged overnight returns. So we seem to have found a powerful negative first order auto correlation but a much weaker second order relationship.

Multivariate Results

While very interesting in and of themselves, the univariate results lead us in the direction of a multivariate analysis. Specifically, we would like to explore whether these relationships are additive or if one of the relations is dominate. Of even greater interest may be whether the relations can be used ex anti to anticipate future returns? To address these matters, we have run regressions with the intraday return as the dependent variable. The independent variables consist of the overnight, lagged intraday and lagged overnight returns. All of our independent variables represent knowable information which precedes the dependent variable. If the individual variables show up as significant, that would imply that the relations are at least somewhat independent of each other and that their explanatory power is additive. If the R square of the regression is sufficiently high, that would suggest that the relationships tend to explain a meaningful portion of the variability of the dependent variable. That is, our model can be used to test whether or not one could forecast the forthcoming intra day return using only knowable past returns as variables in the model.

Regressions are run for the same sets and subsets as were used for the correlations. The first set of results is contained in Exhibit 2a and 2b. We see that for the combined sample in a multivariate context, the coefficients for each of the variables has the expected sign and is quite significant. The intraday day return varies inversely with the prior overnight and lagged overnight returns and directly with the lagged intraday returns. The R squares are, however, of modest magnitude. The R square for the combined sample is .05. The subgroup results are largely consistent with the combined sample but with some noteworthy differences. Not surprisingly the R square for the NYSE is lowest (.006). Thus our model explains less than one percent of the variability of NYSE intraday returns. The R square is significantly higher for the AMEX (.052) and NASDAQ (.064). Still in the aggregate our model leaves about 94% or 95% of the intraday returns unexplained. The R squares, however, tend to rise as market capitalization declines. As we move down in the size dimension, the R squares range from .002 to .021 for the NYSE while the ranges for the AMEX and NASDAQ are from .011 to .079 and from .012 to .074 respectively. Thus for the small capitalization stocks on the AMEX and NASDAQ, our model explains around 7% or 8% of the intraday return.

Focusing on the coefficients we find a rather consistent pattern for the relationship between the intraday return and the overnight and lagged overnight returns. As with the correlation analysis, the two overnight return variables are very significantly negatively associated with the forthcoming intraday returns. The coefficients tend to rise in magnitude as market capitalization falls for all three exchange subgroups. The coefficients on the lagged intraday return variables, in contrast are not consistent. While many of these coefficients are statistically significant, their signs are at least as frequently negative as they are the positive sign that we expected to find.

Next we want to retest our models in the context of what is happening in the market. One would not know what the market return would be for the forthcoming day. Still we would like to explore whether our results change when the market return is added to the regression model. In fact when we add the S&P return, the R squares rise but the coefficients on the other independent variable are largely unaffected. So for example the regression for the combined sample has and R square of .050 without the S&P variable and .092 with but the coefficients on the overnight variable is -.363 without and -.388 with the S&P variable in the regression. In general the same patterns are observed for the coefficients of the regressions which include the market return variable as those which do not. The differences in the R squares are similar for the sub group regressions. The addition of the market return raises the R squares but has very little impact on the coefficients. When we run the same sets of regressions on the 1994-1999 data sets, the results are very similar.

In an attempt to capture the impact of market capitalization in a more parsimonious model, we created a set of interaction variables. First we constructed the logarithm of the market capitalization of each firm in our sample. We did so because on a priori grounds we expect that the impact of size on the relationships that we are exploring is nonlinear. That is, we believe that as we move up in the size dimension the association between prior returns and subsequent returns tends to decline at a decreasing rate. To capture this impact we formed an interaction variable as the product of our log market capitalization variable with each of the return variables. The results of regressions both with and without the S&P returns are contained in Exhibit 4 and 5 respectively. We see that the overnight return variable continues to be very powerful in explaining the intra day return but that the addition of the market capitalization slope adjuster provides additional explanatory power. The regressions for the various samples have R squares of from .01 (NYSE) to .07 (NASDAQ) for the more recent time period and from .02 (NYSE) to .12 (NASDAQ) for the earlier time period.

The signs on the coefficients have the same or similar patterns as before. The overnight return coefficients are all negative and extremely highly significant (t ratios of over 50). The slope adjuster interaction return variables all have positive and highly significant coefficients indicating that the smaller the market capitalization, the greater the association between the overnight return and the intraday return. The coefficients on the lagged overnight return variables are all negative and highly significant. The sign on the associated interaction terms are generally positive indicating again that the impact is greatest for the smaller capitalization stocks. For the NYSE, however, the interaction term coefficients are negative but very small and not highly significant. The coefficient on the lagged intraday returns and its associated interaction terms presents a mixed picture. The signs on all of the interaction terms are positive and highly statistically significant. This finding suggests that the relationship between adjacent intraday returns is positive and tends to be strongest for the large capitalization firms. The coefficients on the lagged intraday variable itself are, however, anything but consistent. For the more recent time period, the signs are positive overall and for the NYSE but insignificant for the overall variable. And the signs are negative for the AMEX and NASDAQ but insignificant for the latter exchange. For the earlier sample the coefficients are negative and highly significant for the overall group and the AMEX and NASDAQ but positive and significant for the NYSE.

When we rerun these sets of regressions with the market return variable added, we get similar results with higher R squares.

Are These Relationships Exploitable?

Market traders would no doubt like to know if these relationships between intraday and overnight returns can be exploited. That is, can trading rules be formulated to take advantage of the tendency for prices to move in the opposite direction during the day from its direction of movement overnight? If the price direction does indeed tend to reverse from overnight to intraday, perhaps one can use this insight to trade effectively.

One would, for example like to be able to trade on the opening and reverse the position later in the day or at the close. A market maker can (and in many situations probably does) make such trades. So in all probability specialists do exploit this relationship. But could a non market maker trader do so? If a stock is down at the opening, our results suggest that the odds are well above 50% that it will rise over the day and if it is up at the opening, the odds are well above 50% that it will decline over the course of the day. So one strategy would be to trade on the opening and reverse at day's end. But such a strategy has a very serious problem. Unless you are the market maker, you would not know which way to trade at the opening. Knowing that would require knowing the direction of the imbalance of overnight market orders. The market maker knows that information but the public trader will not. Moreover, entering an order to be executed at the opening could itself impact the relationship. So for example if a market order to buy was entered for execution at the opening on the expectation that the stock would open down and rise over the course of the day, the very act of entering that order might cause the stock to open up. So trying to trade effectively at the opening is likely to be difficult.

These considerations suggest a strategy of trading shortly after the opening. At that point in time one would know whether the stock has opened up or down. If a stock opens down substantially, one could enter a buy order while it is (hopefully) still down and reverse when it (hopefully) closes higher. For this strategy to work, the sock's price would have to stay near the opening level for some period of time after the opening. We do not know if that is what generally happens. To examine that question, one would need information on the market's condition in the period immediately after the opening. In particular, one would like to know the bid and ask price levels immediately after the opening. Stocks that open at a low level, may well tend to open at the bid with a wide spread. Similarly a stock that opens way up may often be opening at the ask with a wide spread. If so, much of the price reversal that we observe may reflect a tendency for stocks that open down to do so largely at the bid to tend to close at the ask and vice versa. That kind of behavior would indeed create negative auto correlation in the observed data. But that auto correlation would be difficult for anyone but the market maker to exploit. Further work will be needed to see if a trading rule can be formulated to exploit these tendencies.

On the other hand, one can say with a good deal of confidence that certain behaviors around the time of the market's opening tend to be ill advised. Specifically placing a market order to be executed at the open is like asking for a disadvantageous price. One may sometime get lucky and be on the weak side of the opening order imbalance. But more often than not, one who enters a market order to be executed at the opening is likely to be taken advantage of by the market maker. More shares will be on the strong side of the order imbalance by definition. A limit order should always be used at the opening. And one who wants to trade anyway may find that placing a limit order slightly away from the prior close in the advantageous direction will sometimes snag an attractive price. So for example if you want to buy a couple of hundred shares of a stock which closed at 23.70, you might put in a buy order with a limit of 23.65. If the market maker has an order imbalance such that the stock is opened at 23.10, you will buy it there.

Conclusion

We have explored how overnight and intra day returns are related. Using a large sample over two extensive time periods, we have found a very substantial degree of negative auto correlation. When we divide the sample into exchanges and then further into size categories, the relationships remain for all of the separate groups. The relationships are similar for both the 2000-2005 and 1994-1999 time periods. Both univariate and multivariate analysis support our findings. We also consider whether anyone other than a market maker can exploit these relationships. We conclude that further work is needed to answer this final question. None the less, our results do seem to point to the existence of an anomaly which appears to be inconsistent with what would be expected by the weak form of the efficient market hypothesis.

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Exhibit 1A: Correlations with Overnight Return
2000 - 2005

		Intraday Return	Lagged Intraday Return	Lagged Overnight Return
All Stocks		-0.2207	-0.1229	0.0588
NYSE	All	-0.0722	-0.0336	0.0622
NYSE	Small Cap	-0.1403	-0.0789	0.0770
NYSE	Cap2	-0.0620	-0.0190	0.0824
NYSE	Cap3	-0.0361	-0.0217	0.0651
NYSE	Cap4	-0.0337	-0.0099	0.0413
NYSE	Big Cap	-0.0367	-0.0077	0.0271
AMEX	All	-0.2205	-0.0931	0.0535
AMEX	Small Cap	-0.2610	-0.1668	0.0321
AMEX	Cap2	-0.2404	-0.1085	0.0520
AMEX	Cap3	-0.2047	-0.0585	0.0768
AMEX	Cap4	-0.1710	-0.0088	0.0961
AMEX	Big Cap	-0.0979	0.0534	0.0707
NASDAQ	All	-0.2495	-0.1454	0.0588
NASDAQ	Small Cap	-0.2884	-0.2158	0.0363
NASDAQ	Cap2	-0.3083	-0.1780	0.0736
NASDAQ	Cap3	-0.2668	-0.1281	0.0886
NASDAQ	Cap4	-0.1973	-0.0904	0.0773
NASDAQ	Big Cap	-0.1073	-0.0358	0.0291

Exhibit 1B: Correlations with Overnight Return
1994 - 1999

		Intraday Return	Lagged Intraday Return	Lagged Overnight Return
All Stocks		-0.2852	-0.1992	0.0142
NYSE	All	-0.1335	-0.0925	0.0532
NYSE	Small Cap	-0.2392	-0.1934	0.0484
NYSE	Cap2	-0.1046	-0.0662	0.0671
NYSE	Cap3	-0.0541	-0.0259	0.0630
NYSE	Cap4	-0.0426	-0.0217	0.0466
NYSE	Big Cap	-0.0447	0.0095	0.0476
AMEX	All	-0.2043	-0.1352	0.0141
AMEX	Small Cap	-0.2455	-0.1938	-0.0214
AMEX	Cap2	-0.2290	-0.1643	0.0259
AMEX	Cap3	-0.1902	-0.1042	0.0389
AMEX	Cap4	-0.1581	-0.0768	0.0648
AMEX	Big Cap	-0.0828	0.0051	0.0744
NASDAQ	All	-0.3124	-0.2199	0.0096
NASDAQ	Small Cap	-0.3428	-0.2749	-0.0180
NASDAQ	Cap2	-0.3572	-0.2689	0.0118
NASDAQ	Cap3	-0.3215	-0.2169	0.0272
NASDAQ	Cap4	-0.2664	-0.1499	0.0406
NASDAQ	Big Cap	-0.1730	-0.0572	0.0539

Exhibit 2A: Regression Results (2000 - 2005)

$$Ret\_ID = \beta0 + \beta1*Ret\_ON + \beta2*lagRet\_ID + \beta3*lagRet\_ON$$

		Intercept	Ret_ON	lagRet_ID	lagRet_ON	R^2
All Stocks		0.0238 (22.87)	-0.3632 (-684.08)	0.0024 (7.33)	-0.0505 (-94.17)	0.0496
NYSE	All	0.0422 (37.92)	-0.1325 (-136.16)	0.0076 (14.86)	-0.0426 (-43.94)	0.0057
NYSE	Small Cap	-0.0013 (-0.46)	-0.2169 (-118.69)	0.0148 (12.57)	-0.0314 (-17.21)	0.0209
NYSE	Cap2	0.0367 (14.62)	-0.1293 (-52.53)	0.0063 (5.49)	-0.0459 (-18.68)	0.0044
NYSE	Cap3	0.0604 (24.32)	-0.0758 (-30.10)	-0.0072 (-6.27)	-0.0644 (-25.67)	0.0022
NYSE	Cap4	0.0566 (24.18)	-0.0668 (-28.64)	0.0048 (4.22)	-0.0522 (-22.43)	0.0018
NYSE	Big Cap	0.0510 (22.97)	-0.0675 (-32.02)	0.0155 (13.63)	-0.0282 (-13.39)	0.0019
AMEX	All	0.0275 (8.77)	-0.3426 (-222.72)	-0.0150 (-14.62)	-0.0576 (-36.88)	0.0516
AMEX	Small Cap	-0.0733 (-6.27)	-0.3643 (-109.02)	-0.0608 (-22.69)	-0.0682 (-20.03)	0.0792
AMEX	Cap2	0.0173 (2.28)	-0.3700 (-108.62)	-0.0256 (-10.98)	-0.0613 (-17.65)	0.063
AMEX	Cap3	0.0357 (5.58)	-0.3482 (-93.04)	0.0093 (4.12)	-0.0537 (-14.15)	0.0449
AMEX	Cap4	0.0576 (9.77)	-0.3156 (-78.26)	0.0245 (11.30)	-0.0591 (-14.57)	0.0315
AMEX	Big Cap	0.0496 (10.47)	-0.2009 (-45.07)	0.0127 (5.98)	-0.0646 (-14.55)	0.0107
NASDAQ	All	0.0071 (4.00)	-0.4078 (-554.77)	0.0001 (0.15)	-0.0525 (-70.46)	0.0641
NASDAQ	Small Cap	-0.1395 (-25.40)	-0.4154 (-273.49)	-0.0619 (-51.90)	-0.0705 (-45.69)	0.0938
NASDAQ	Cap2	-0.0022 (-0.53)	-0.4691 (-308.27)	-0.0126 (-11.84)	-0.0634 (-40.51)	0.0993
NASDAQ	Cap3	0.0191 (5.26)	-0.4564 (-269.50)	0.0256 (25.46)	-0.0469 (-27.13)	0.0735
NASDAQ	Cap4	0.0473 (13.57)	-0.3947 (-200.30)	0.028 (28.56)	-0.0501 (-25.32)	0.0408
NASDAQ	Big Cap	0.0427 (12.52)	-0.2219 (-107.12)	0.0262 (26.89)	-0.0282 (-13.69)	0.0121

Note: Coefficients with t-statistics in parentheses.

Exhibit 2B: Regression Results (1994 - 1999)

Ret_ID =β0 + β1*Ret_ON + β2*lagRet_ID + β3*lagRet_ON

		Intercept	Ret_ON	lagRet_ID	lagRet_ON	R^2
All Stocks		0.0470 (47.24)	-0.3946 (-977.26)	-0.0332 (-106.42)	-0.0517 (-125.79)	0.0838
NYSE	All	0.0391 (36.97)	-0.2209 (-256.93)	0.0192 (37.94)	-0.0233 (-27.15)	0.0180
NYSE	Small Cap	0.0013 (0.43)	-0.3345 (-213.29)	-0.0241 (-20.47)	-0.0371 (-23.53)	0.0589
NYSE	Cap2	0.0297 (13.15)	-0.1903 (-91.40)	0.0354 (31.41)	-0.0147 (-7.09)	0.0125
NYSE	Cap3	0.0424 (18.96)	-0.1083 (-46.51)	0.0481 (42.87)	-0.0160 (-6.88)	0.0053
NYSE	Cap4	0.0493 (22.79)	-0.0866 (-36.62)	0.0361 (32.25)	-0.0344 (-14.60)	0.0034
NYSE	Big Cap	0.0614 (29.86)	-0.0812 (-37.80)	0.0021 (1.90)	-0.0284 (-13.23)	0.0021
AMEX	All	0.0724 (21.63)	-0.2932 (-198.52)	-0.0308 (-28.29)	-0.0490 (-32.89)	0.0456
AMEX	Small Cap	-0.0184 (-1.52)	-0.3052 (-98.03)	-0.0711 (-24.85)	-0.0606 (-19.26)	0.0726
AMEX	Cap2	0.0743 (8.79)	-0.3315 (-99.73)	-0.0515 (-20.64)	-0.0491 (-14.63)	0.0588
AMEX	Cap3	0.0808 (12.08)	-0.3032 (-84.00)	-0.0204 (-8.62)	-0.0511 (-14.11)	0.0394
AMEX	Cap4	0.0990 (16.34)	-0.2706 (-69.96)	-0.0067 (-2.89)	-0.0467 (-12.01)	0.0270
AMEX	Big Cap	0.0877 (15.91)	-0.1607 (-35.97)	0.0318 (14.07)	-0.0538 (-12.07)	0.0089
NASDAQ	All	0.0521 (32.95)	-0.4237 (-811.95)	-0.0468 (-111.04)	-0.0600 (-112.34)	0.1022
NASDAQ	Small Cap	-0.1464 (-27.18)	-0.4277 (-372.64)	-0.1169 (-104.80)	-0.0888 (-75.43)	0.1380
NASDAQ	Cap2	0.0464 (11.95)	-0.4670 (-426.34)	-0.0918 (-94.82)	-0.0802 (-71.17)	0.1385
NASDAQ	Cap3	0.0627 (19.17)	-0.4479 (-381.01)	-0.0397 (-43.30)	-0.0559 (-46.31)	0.1072
NASDAQ	Cap4	0.0841 (28.53)	-0.4123 (-309.00)	0.0139 (15.72)	-0.0346 (-25.40)	0.0720
NASDAQ	Big Cap	0.1204 (43.53)	-0.3258 (-198.05)	0.0374 (43.49)	-0.0271 (-16.43)	0.0311

Note: Coefficients with t-statistics in parentheses.

Exhibit 3A: Regression Results (2000 - 2005)

Ret_ID =β0 + β1*SPret + β2*Ret_ON + β3*lagRet_ID + β4*lagRet_ON

		Intercept	SPret	Ret_ON	lagRet_ID	lagRet_ON	R^2
All Stocks		0.0245 (24.13)	0.5690 (661.77)	-0.3886 (-746.59)	0.0010 (3.04)	-0.0475 (-90.57)	0.0917
NYSE	All	0.0425 (39.78)	0.5072 (558.81)	-0.1873 (-199.25)	0.0067 (13.63)	-0.0337 (-36.17)	0.0817
NYSE	Small Cap	-0.0006 (-0.22)	0.2607 (115.08)	-0.2294 (-126.44)	0.0149 (12.74)	-0.0290 (-16.02)	0.0386
NYSE	Cap2	0.0382 (15.65)	0.4220 (209.19)	-0.1684 (-70.15)	0.0068 (6.11)	-0.0391 (-16.33)	0.0585
NYSE	Cap3	0.0614 (26.02)	0.5837 (289.34)	-0.1490 (-61.98)	-0.0084 (-7.77)	-0.0542 (-22.74)	0.1007
NYSE	Cap4	0.0564 (25.71)	0.6367 (327.90)	-0.1648 (-74.71)	0.0020 (1.86)	-0.0384 (-17.62)	0.1247
NYSE	Big Cap	0.0513 (25.02)	0.6728 (367.06)	-0.1961 (-99.26)	0.0142 (13.47)	-0.0096 (-4.95)	0.1511
AMEX	All	0.0258 (8.29)	0.3401 (124.20)	-0.3529 (-230.97)	-0.0155 (-15.30)	-0.0563 (-36.36)	0.0668
AMEX	Small Cap	-0.0717 (-6.15)	0.2322 (24.87)	-0.3674 (-110.11)	-0.0613 (-22.92)	-0.0677 (-19.93)	0.0832
AMEX	Cap2	0.0159 (2.10)	0.2501 (38.54)	-0.3764 (-110.81)	-0.0260 (-11.17)	-0.0605 (-17.48)	0.0706
AMEX	Cap3	0.0344 (5.40)	0.2580 (45.64)	-0.3572 (-95.81)	0.0089 (3.99)	-0.0532 (-14.08)	0.0549
AMEX	Cap4	0.0564 (9.69)	0.3662 (70.33)	-0.3359 (-84.05)	0.0243 (11.36)	-0.0551 (-13.72)	0.0537
AMEX	Big Cap	0.0450 (9.86)	0.5755 (132.83)	-0.2687 (-62.21)	0.0157 (7.68)	-0.0554 (-12.96)	0.0842
NASDAQ	All	0.0093 (5.38)	0.6488 (447.27)	-0.4307 (-596.66)	-0.0014 (-3.13)	-0.0502 (-68.79)	0.1020
NASDAQ	Small Cap	-0.1358 (-24.81)	0.2946 (69.69)	-0.4190 (-276.58)	-0.0626 (-52.64)	-0.0704 (-45.80)	0.0997
NASDAQ	Cap2	0.0003 (0.07)	0.3786 (114.74)	-0.4773 (-315.51)	-0.0134 (-12.70)	-0.0622 (-40.02)	0.1121
NASDAQ	Cap3	0.0216 (6.05)	0.5733 (190.36)	-0.4784 (-286.92)	0.0247 (25.05)	-0.0439 (-25.80)	0.1060
NASDAQ	Cap4	0.0504 (15.07)	0.8710 (296.61)	-0.4529 (-238.07)	0.0264 (28.03)	-0.0435 (-22.90)	0.1154
NASDAQ	Big Cap	0.0450 (14.13)	1.1106 (389.42)	-0.3440 (-175.39)	0.0268 (29.34)	-0.0167 (-8.65)	0.1369

Note: Coefficients with t-statistics in parentheses.

Exhibit 3B: Regression Results (1994 - 1999)

$$Ret\_ID = \beta 0 + \beta 1 * SPret + \beta 2 * Ret\_ON + \beta 3 * lagRet\_ID + \beta 4 * lagRet\_ON$$

		Intercept	SPret	Ret_ON	lagRet_ID	lagRet_ON	R^2
All Stocks		0.0132 (13.35)	0.4271 (415.46)	-0.4031 (-1,005.05)	-0.0349 (-112.76)	-0.0517 (-126.75)	0.0984
NYSE	All	0.0038 (3.66)	0.4338 (402.53)	-0.2488 (-294.22)	0.0170 (34.32)	-0.0222 (-26.33)	0.0570
NYSE	Small Cap	-0.0234 (-7.70)	0.3033 (94.78)	-0.3414 (-218.75)	-0.0253 (-21.68)	-0.0373 (-23.80)	0.0701
NYSE	Cap2	0.0044 (1.95)	0.3155 (133.96)	-0.2090 (-101.27)	0.0342 (30.75)	-0.0135 (-6.56)	0.0346
NYSE	Cap3	0.0112 (5.07)	0.3850 (170.05)	-0.1391 (-60.59)	0.0468 (42.52)	-0.0140 (-6.14)	0.0403
NYSE	Cap4	0.0110 (5.22)	0.4784 (220.18)	-0.1397 (-60.54)	0.0343 (31.51)	-0.0302 (-13.19)	0.0607
NYSE	Big Cap	0.0107 (5.50)	0.6376 (319.65)	-0.1942 (-94.61)	0.0017 (1.63)	-0.0231 (-11.45)	0.1157
AMEX	All	0.0494 (14.77)	0.3000 (84.75)	-0.2978 (-202.36)	-0.0313 (-28.86)	-0.0488 (-32.90)	0.0536
AMEX	Small Cap	-0.0339 (-2.80)	0.1988 (15.30)	-0.3063 (-98.44)	-0.0714 (-24.96)	-0.0606 (-19.28)	0.0743
AMEX	Cap2	0.0548 (6.48)	0.2641 (29.36)	-0.3350 (-100.98)	-0.0518 (-20.81)	-0.0488 (-14.58)	0.0637
AMEX	Cap3	0.0611 (9.14)	0.2639 (36.84)	-0.3089 (-85.81)	-0.0211 (-8.93)	-0.0510 (-14.12)	0.0467
AMEX	Cap4	0.0759 (12.56)	0.2935 (46.06)	-0.2791 (-72.48)	-0.0066 (-2.87)	-0.0452 (-11.68)	0.0380
AMEX	Big Cap	0.0547 (10.02)	0.4188 (73.87)	-0.1838 (-41.60)	0.0314 (14.08)	-0.0520 (-11.84)	0.0359
NASDAQ	All	0.0182 (11.55)	0.4321 (263.97)	-0.4304 (-828.66)	-0.0483 (-115.39)	-0.0600 (-112.92)	0.1126
NASDAQ	Small Cap	-0.1599 (-29.62)	0.1744 (31.00)	-0.4284 (-373.38)	-0.1172 (-105.05)	-0.0889 (-75.52)	0.1389
NASDAQ	Cap2	0.0239 (6.16)	0.2930 (71.69)	-0.4696 (-429.39)	-0.0925 (-95.70)	-0.0801 (-71.26)	0.1423
NASDAQ	Cap3	0.0342 (10.48)	0.3705 (109.30)	-0.4539 (-387.59)	-0.0407 (-44.56)	-0.0556 (-46.30)	0.1157
NASDAQ	Cap4	0.0469 (16.00)	0.4832 (157.49)	-0.4272 (-322.42)	0.0117 (13.39)	-0.0336 (-24.91)	0.0893
NASDAQ	Big Cap	0.0667 (24.62)	0.6997 (253.43)	-0.3780 (-233.30)	0.0340 (40.50)	-0.0207 (-12.79)	0.0751

Note: Coefficients with t-statistics in parentheses.

Exhibit 4: Regression Results

$$Ret\_ID = \beta0 + \beta1*ON + \beta2*(ONxlogCap) + \beta3*lagID + \beta4*lag(IDxlogCap) + \beta5*lagON + \beta6*lag(ONxlogCap)$$

Panel A: 2000 - 2005

	Intercept	ON	ONxlogCap	lagID	lag (IDxlogCap)	lagON	lag (ONxlogCap)	R2
All Stocks	0.0254 (24.41)	-0.8197 (-252.25)	0.0400 (140.38)	0.0006 (1.69)	0.0014 (51.53)	-0.0498 (-90.29)	0.0002 (4.00)	0.0529
NYSE	0.0417 (37.48)	-0.4926 (-84.47)	0.0278 (62.56)	0.0064 (12.44)	0.0006 (15.12)	-0.0416 (-42.46)	-0.0003 (-3.57)	0.0068
AMEX	0.0307 (9.76)	-0.7063 (-58.67)	0.0339 (28.75)	-0.0209 (-19.82)	0.0034 (35.10)	-0.0583 (-35.59)	0.0009 (5.41)	0.0592
NASDAQ	0.0122 (6.84)	-0.7073 (-142.13)	0.0262 (59.09)	-0.0006 (-1.19)	0.0015 (37.83)	-0.0513 (-66.40)	0.0003 (4.75)	0.0668

Panel B: 1994 - 1995

	Intercept	ON	ONxlogCap	lagID	lag (IDxlogCap)	lagON	lag (ONxlogCap)	R2
All Stocks	0.0476 (48.24)	-0.7731 (-266.24)	0.0340 (125.26)	-0.0459 (-144.39)	0.0065 (239.70)	-0.0567 (-131.71)	0.0034 (84.92)	0.0956
NYSE	0.0374 (35.44)	-0.8879 (-174.05)	0.0549 (131.70)	0.0100 (19.62)	0.0027 (68.14)	-0.0211 (-23.73)	-0.0001 (-1.71)	0.0241
AMEX	0.0732 (21.78)	-0.6667 (-53.98)	0.0340 (27.90)	-0.0519 (-45.69)	0.0071 (67.49)	-0.0583 (-36.25)	0.0032 (20.54)	0.0601
NASDAQ	0.0559 (35.32)	-0.6176 (-148.76)	0.0165 (42.05)	-0.0600 (-139.12)	0.0076 (202.68)	-0.0654 (-116.64)	0.0043 (81.43)	0.1160

Note: Coefficients with t-statistics in parentheses.

Exhibit 5: Regression Results

$$Ret\_ID = \beta0 + \beta1*SP + \beta2*ON + \beta3*(ONxlogCap) + \beta4*lagID + \beta5*lag(IDxlogCap) + \beta6*lagON + \beta7*lag(ONxlogCap)$$

Panel A: 2000 - 2005

	Intercept	SP	ON	ONxCap	lagID	lag (IDxlogCap)	lagON	lag (ONxlogCap)	R2
All Stocks	0.0270 (26.63)	0.5690 (659.50)	-0.7080 (-222.68)	0.0277 (99.31)	-0.0002 (-0.52)	0.0014 (51.28)	-0.0463 (-85.86)	0.0002 (3.66)	0.0958
NYSE	0.0425 (39.74)	0.5067 (557.01)	-0.3867 (-68.97)	0.0154 (35.86)	0.0058 (11.79)	0.0006 (15.29)	-0.0331 (-35.12)	-0.0003 (-3.96)	0.0828
AMEX	0.0293 (9.40)	0.3422 (124.11)	-0.6490 (-54.33)	0.0272 (23.21)	-0.0210 (-20.14)	0.0034 (35.31)	-0.0565 (-34.84)	0.0008 (5.26)	0.0750
NASDAQ	0.0156 (8.93)	0.6565 (445.39)	-0.6001 (-123.06)	0.0144 (33.04)	-0.0015 (-3.20)	0.0014 (37.23)	-0.0485 (-64.12)	0.0003 (4.59)	0.1061

Panel B: 1994 - 1995

All Stocks	0.0144 (14.65)	0.4252 (416.08)	-0.7059 (-244.74)	0.0268 (99.41)	-0.0471 (-149.45)	0.0065 (240.60)	-0.0562 (-131.62)	0.0034 (85.50)	0.1105
NYSE	0.0030 (2.87)	0.4266 (396.17)	-0.7831 (-156.35)	0.0439 (107.18)	0.0089 (17.68)	0.0026 (68.12)	-0.0196 (-22.51)	-0.0001 (-1.83)	0.0620
AMEX	0.0500 (14.89)	0.2996 (84.18)	-0.6372 (-51.81)	0.0306 (25.22)	-0.0522 (-46.17)	0.0071 (67.60)	-0.0580 (-36.16)	0.0033 (20.70)	0.0683
NASDAQ	0.0222 (14.10)	0.4361 (266.07)	-0.5655 (-136.92)	0.0109 (27.82)	-0.0613 (-142.96)	0.0076 (203.29)	-0.0650 (-116.68)	0.0043 (81.84)	0.1269

Note: Coefficients with t-statistics in parentheses.