Overnight Return, the Invisible Hand Behind The Intraday Return?

A Retrospective

Ben Branch
Aixin Ma

Abstract

In an effort to extend our study on the relationship between overnight and intraday returns, we expand the study horizon to include more recent, relatively "calm" market years. We find that the autocorrelation between overnight and intraday returns persisted among smaller stocks, but not for the S&P500. Such a relationship is monotonic in nature – the stronger the overnight return, the further the opposite direction of the intraday return tends to be. We also find evidence that the market has indeed become less volatile in recent years, and the market factor plays a more significant role in stock returns.

The current study was inspired by two previous studies. Branch, Ma and Sawyer (2010) studied how returns of closed-end funds were related to their net asset value's (NAV) performance. Therein the authors bifurcated the daily returns of closed-end funds into overnight returns and intraday returns. They found a strong negative autocorrelation between the two components of the close to close return. A more recent, related study (Branch & Ma, 2012) extends the study to include all stocks listed on the major U.S. exchanges. The authors reported a similar autocorrelation between the stock's overnight and intraday returns.

Studies have shown that return anomalies tend to fade over time and, in some cases, totally disappear once the market learns of them (Jegadeesh & Titman, 1993; Fama, 1998). To test whether market efficiency has caught up with the overnight-intraday return anomaly, we extend the study horizon of Branch and Ma (2012) to the 2011 – 2017 period. Our results indicate that the anomaly persisted. On the other hand, the overnight and intraday returns of the S&P500 are now slightly positively correlated, supporting the market efficiency hypothesis, at least for the large caps. The autocorrelation between overnight and intraday returns is monotonic – the more positive (negative) the overnight return, the more negative (positive) the intraday return. Mean and quartile returns for both overnight and intraday returns are lower than those reported in Branch and Ma (2012), indicating that the market has become less volatile in recent years.

The rest of the paper is organized as follows. In section I, we update the literature review in Branch and Ma (2012). In section II, we discuss the data and methodology. In section III, we present the results of our statistical analyses. In section IV, we attempt to offer explanation why such abnormal relationship exists between overnight and intraday returns. In section V, we conclude.

I. Literature Review

A number of issues related to the relationship between overnight and intraday returns are considered in the market microstructure literature and reported in Branch and Ma (2012). Hong and Wang (2000) reported the U-shaped pattern for intraday return; Stoll and Whaley (1990) reported that "…the overnight return tends to be reversed by the following daytime return" while "…the daytime return is much less likely to be reversed by the return in the following night." Inci, Lu and Syhun (2010) discovered that selling by corporate insiders could help explain the price reversal.

Since the publication of Branch and Ma (2012), a number of notable studies have been added to the literature. Bollerslev, Li and Todorov (2016) reports a significant risk premium associated with "intraday discontinuous and overnight market returns".

Lou, Polk and Skouras (2015) "…document strong overnight and intraday firm-level return continuation along with an offsetting cross-period reversal effect, all of which lasts for years."

Aboody et al. (2018) demonstrate that for harder-to-value firms, investor sentiment tends to drive mispricing and as a result, stocks with higher overnight returns tend to underperform, and vice versa.

Blose, Gondhalekar and Kort (2018) study two products, the COMEX gold front month contract and the SPDR Gold Share ETF, for the 1985 to 2012 period. The authors find that for the former, "…overnight returns…are significantly positive, whereas day returns are significantly negative". The authors also claim that such asymmetry in returns persisted over time.

Lachance (2015) reports that one fifth of the stocks studied exhibit positive and statistically significant abnormal returns. These pricing "biases" could form the basis of a meaningful trading strategy.

Chen and Kawaguchi (2018) observe positive and significant abnormal intraday returns and ensuing significant negative abnormal overnight returns in the Japanese real estate investment trust (J-REIT) market. The authors contribute such reversal to the investor heterogeneity because overseas investors trade against Japanese domestic investors.

Liu and Tse (2017) study US ETFs and international index futures. The authors report a significant reversal effect in the two markets. They also report lower volatility associated with overnight returns vs that of the intraday returns.

Monteiro and Manso (2017) report that for US equity indices for the 20-year period from January 3rd, 1994 to January 3rd, 2014, did not exhibit "…statistically significant pervasive night or daytime effects…".

Semenov (2015) concludes that for small, high-momentum stocks, predictability of price movement increases, with open-to-open returns yielding higher predictability than close-to-close returns.

II. Data and methodology

The current study covers the seven-year period of January 2011 to December 2017. As in our prior study Branch and Ma (2012), we used the Center for Research in Security Prices (CRSP) database for daily stock prices. To account for distortions caused by stock splits and dividends, we used the CRSP cumulative factor to adjust prices (CFACPR) to calculate adjusted close and open prices. We used the exchange traded Standard and Poor's Depositary Receipt (SPDR, with AMEX symbol SPY) as a proxy for the market instead of the S&P 500 for the following reason. The S&P 500 calculates its open price using component stocks' prices at 9:31 am. Many stocks, however, have not opened by that time. As a result, the open price of the S&P 500 is often the stale price of its previous close, producing an S&P 500 0% overnight return for a vast number of the days. The SPDR, on the other hand, almost always opens by 9:31 am with a current price based on the S&P 500 futures.

We follow the same methodology in Branch and Ma (2012), which is modeled after the Fama-MacBeth two-stage method. Our interest focuses on the relationships between returns bifurcated into two distinct time frames, the overnight returns and the intraday returns. Together the two return formulations constitute a third return, the close-to-close return. Figure 1 illustrates these three return formulations.

Insert Figure 1 about here

The three returns are calculated as follows:

$$overnight\ return_t = \left(\frac{open_t - close_{t-1}}{close_{t-1}}\right) * 100\%; \qquad (1)$$

$$intraday\ return_t = \left(\frac{close_t - open_t}{open_t}\right) * 100\%; \qquad (2)$$

$$close - to - close\ return_t = \left(\frac{close_t - close_{t-1}}{close_{t-1}}\right) * 100\%. \qquad (3)$$

We model our analysis after the Fama-MacBeth two-stage method. In Stage One, we compute cross-sectional correlations daily and obtain a time series of daily correlation coefficients. In Stage Two, we calculate the means and perform statistical analyses using the time series result from Stage One.

For correlations involving various S&P 500 returns, we slightly adjust our method to address one issue: on any given day, returns for the S&P 500 are the same for all stocks, and all correlations associated with the S&P 500 returns appear to be zero. Our solution is straightforward. In Stage One, we calculate correlation coefficients using time series returns for each individual stock and the S&P500. In Stage Two, we calculate the means and perform statistical analysis by cross-section using the coefficients we obtained in Stage One.

We analyze the negative autocorrelation using two methods, the nonparametric univariate analysis and regression analysis. The univariate analysis has at least one advantage over parametric analyses – it does not assume normal distribution of stock returns. In univariate analyses, we first calculate the means of intraday returns conditional on whether the associated overnight returns are up or down.

We then tabulate these means of intraday returns based on the quartile of the overnight returns.

In Equation 4, the basic model of our regression analysis, we seek to isolate the autocorrection among overnight returns, intraday returns, and the one-leg lagged overnight and intraday returns.

$$ID = \beta_0 + \beta_1 * ON + \beta_2 * lagID + \beta_3 * lagON + e, \qquad (4)$$

the betas are various coefficients, ID and ON are the intraday and overnight returns of day t, and lagID and lagON are the intraday and overnight returns of day t – 1.

As a robust measure, we then proceed to run three more models adding the S&P 500, size, and various interaction terms as regressors.

Other robustness checks include analyzing the sample as a whole as well as analyzing different subsamples. For example, we analyze both unwinsorized and winsorized data by removing the top and bottom 0.05% of the observations. We also analyze stocks on the NYSE, AMEX, and NASDAQ separately. To account for bid-ask bounce, we also substitute the closing bid-ask midpoint for the close price.

III. Results

Table 1 reports the correlations between pairs of different returns. Several results are clearly different in the current study from Branch and Ma (2012). For one, the correlation between stock overnight return and that of the S&P500 has a much higher magnitude in the current study, while the correlation between stock intraday return and that of the S&P500 is now a bit lower. This indicates that the market factor plays a larger role in the overnight market. Two, probably more importantly, the correlation between the overnight and intraday return of the S&P500 is now positive. The disappearance of the reversal effect between the overnight and intraday returns of the S&P500 is somewhat supportive of the findings in previous studies that the market tends to become more efficient over time and abnormal returns tend to fade (Jegadeesh & Titman, 1993; Fama, 1998).

The correlation between stock intraday and overnight returns is still negative, but with a lower magnitude. This observation also fits the hypothesis that abnormal returns tend to fade over time.

Insert Table 1 about here

Table 2 report univariate analysis of stock intraday and overnight returns. In Branch and Ma (2012), the means for the intraday and overnight returns are both positive. In the current study, however, the two now have different signs. The mean overnight return is positive at 0.044%, whereas the mean intraday return is negative at -0.018%. This is consistent with the findings of Blose, Gondhalekar and Kort (2018). It is also worth noting that stocks returns are much less volatile in the current study horizon, for both stocks and the S&P500 index. This can be seen from the smaller range and less extreme min and max returns for intraday, overnight and S&P500.

Insert Table 2 about here

In Table 3 and Table 4, we analyze the relationship between intraday and overnight returns depending on whether the overnight return is positive or negative. The reversal effect is clearly demonstrated here. When overnight return is down, the ensuing intraday return is positive; and vice versa. Both results are highly statistically significant. We further compare the two return series in Table 4. One can clearly see the monotonic nature in their relationship – the more positive the overnight return, the more negative the ensuing intraday return, and vice versa.

Insert Table 3 about here

Insert Table 4 about here

We report regression result in Table 5. Regardless of the model used, overnight return has significant negative coefficient on the ensuing intraday returns. Even though all results are significant, the magnitude of the overnight return coefficient on intraday return dropped in all models. Based on this evidence, one can claim that the reversal effect faded compared to what Branch and Ma (2012) observed, offering supporting evidence to the market efficiency hypothesis. In Model 4 where we added interactive factors, the ONxCAP factor, the interactive factor between overnight return and market cap, has a positive, statistically significant coefficient of 0.053. This supports our findings in Table 1. For large caps represented by the S&P500, the overnight return now positively contributes to the ensuing intraday return, signaling the disappearance of the reversal effect.

The adjusted R-squared went down dramatically in the current study, almost halved, indicating that the reversal factor and other related factors now play a lessor role in determining the intraday returns, and that other significant factors exist that are not captured in the models used.

IV. What Causes the Negative Autocorrelation?

A. Market-Maker Behavior: How opening and closing prices are determined.

The overnight return is based on the difference between the closing price and the following day's opening price. How market makers (especially specialists) tend to open their assigned stocks can help explain the negative autocorrelations we have found. Similarly, an understanding of the role of institutional investors at the market's close is helpful. A stock will typically close within the range of its bid and ask as of the close. The closing price will reflect the impact of some noise but does represent the market's real-time assment of the stock's intrinsic value. If the bid-ask spread is relatively narrow, as is typical of an actively traded security, the close should be a reliable index of the market's view of the security's end-of-the-day worth. Even if the spread is wide, the close should generally be an unbiased estimate of what the market thinks. The increasing importance of index funds which generally prefer to trade on the close (to minimize tracking error), has resulted in 26% of NYSE trading place on the close in 2017 versus 17% in 2012. This high percentage of the total volume most of which comes from institutional and presumably professional traders, adds to our confidence that the closing price tends to be a reliable estimate of the market's real time estimate of each stock's intrinsic value.

After the market closes, only those unfilled good-till-cancelled (GTC) limit orders will remain on the books. Any part of the quote provided by the market maker will also disappear at day's end. The absence of much of the previous day's unfilled orders will tend to widen the difference between the bid price (highest unfilled buy offer) and ask price (lowest unfilled sell offer) on the market maker's books. The wider the spread, the greater the market maker's latitude is in setting the opening of his or her stocks. The opening level most attractive to the market maker may, however, be disadvantageous to many others. The market maker is likely to set the opening between the highest unfilled bid and the lowest unfilled offer; but if the imbalance between buy and sell orders is large enough, the market maker may set the opening outside of this range. Orders both to buy and sell an actively traded stock are likely to have been entered prior to the market's opening. The orders entered prior to the market's opening, like most of the orders entered during the trading day, are market (as opposed to limit, short, or stop) orders. At the beginning of the trading day, the number of shares of market orders to buy and sell generally differ; but all such market orders (as well as any consistent limit orders) must be executed at the opening. The market maker can choose where to set the opening price but must make sure all orders tradeable at the set level are exicuited at the opening. The market maker might choose to open the security at the previous close and make up the buy-sell imbalance out of inventory. Such a “leaning against the wind” strategy could well be stabilizing. It would, however have the market maker selling (buying) into a market with buying (selling) pressure. This in turn would likely be trading at a disadvantageous price against knowledge traders, who take account of any information becoming public after the market’s prior trading day close. Alternatively, the market maker could move the opening price toward the order imbalance. Thus, if the imbalance involves an excess of sell (buy) orders, the security could be opened below (above) the previous close. The goal would be to trigger enough limit orders below (above) the prior close to offset the imbalance. This approach provides the market maker with several benefits. First, more limit orders are executed. The market maker receives a fee for each such transaction. Second, using limit orders to cover at least part of the shortfall, allows the market maker to limit changes in his or her inventory. Most market makers have a target inventory level. It might be based on some percent of the average daily trading volume for each security they handle. They try to limit their exposure to unexpected overnight developments by ending each day with inventory close to that target level. Sometimes the market maker may end the trading day significantly away from the target. When that happens he or she may wish to adjust. Moving the opening price lower or higher may be more attractive to the market maker with a need to load or unload shares. Third, moving the price away from its prior close encourages trading in the market maker’s assigned securities. That in turn enhances the opportunity for the market maker to earn more trading profits. If no orders come in overnight, the market maker is unlikely to open the stock until new orders surface, sometimes well beyond the opening bell. When such orders do surface, they are likely to be market orders. That will present the market maker with the same basic situation. When faced with an order imbalance, a market maker has incentives to set the opening either above or below the prior close. This will often overshoot the equilibrium market clearing price. As the day wears on, the market price tends to revert to its intrinsic value thereby producing the observed negative autocorrelation. Market-maker behavior could also help explain the observed size effect in our study. Larger companies’ shares tend to be more actively traded, have more orders at the open, and have more investors ready to take advantage of an imbalance at the open. Manipulating larger companies’ stock prices requires more capital commitment and attracts more attention. The smaller price movement commonly associated with these larger companies also provides less incentive for market makers to try to move the price away from a market clearing level. Therefore, we expect large companies’ shares to experience lower price reversals during the day when the price is more in line with the intrinsic value because of lower market-maker manipulation.

B. B. Literature on Specialist Behavior

How the specialist system and individual specialists behave receives a significant amount of attention. Most of that attention has focused on NYSE specialists. Both Smidt (1971) and Barnea (1974) find differences in the ways individual specialist firms perform. They find variations in price volatility and bid-ask spreads across specialist firms even after other factors are taken into account. Corwin’s (1999) conclusions are similar. In an extension 98 Journal of applied finance – no. 2, 2012 work, Coughenour and Deli (2002) explore how the behavior of closely held verses widely owned specialist firms differ. Specifically, they find that those specialists whose owners having their own capital at risk, have a greater incentive to limit adverse selection costs in their market making function but are more capital constrained in providing liquidity. As a result, owner-specialists are less likely to stabilize the market at the opening than are other specialist firms. Thus when faced with an order imbalance, specialists who put their own funds at risk are particularly inclined to manage their assigned stocks so as to open away from the prior close. Bondarenko and Sung (2003) develop a model for specialist behavior in the presence of limit orders. They find that when the limit order book is extensive, specialists have an incentive to trade with the market; when it is thin, they tend to trade against the market. In other words, when orders are imbalanced in a thin market, the specialist has an incentive to take the trade's other side. Presumably that imbalance incentivizes the specialist to move the price at least temporarily in his/her favor. Cao, Choe, and Hatheway (1997) and Huang and Liu (2004), discovers that specialist firms use some of their market-making profits from actively traded securities to subsidize market-making for less actively traded securities.

C. Bid-Ask Bounce

The so called "bid-ask bounce" offers a possible explanation for the negative autocorrelation of intraday and overnight returns. Consider a stock that trades within the same bid and ask range for several days. Suppose that the stock first closed at the bid. On the following day, the stock opens either at the bid or the ask. Opening at the bid results in no price change. Opening at the ask, however, registers a positive overnight move even though the bid-ask quote has not changed. We observe the same phenomenon when the market closes again. So if the bid and the ask remain as before, every price change will happen in the opposite direction from the prior price change. Thus the price will bounce back and forth between the bid and the ask, producing the observed negative autocorrelation even though the underlying price quote has not moved. Furthermore, even when the bid-ask quotes do change, stocks randomly opening and closing at the bid and ask exhibit some degree of negative autocorrelation. Lease, Masulis, and Page (1991) who explore the impact of the bid-ask bounce, find that the midpoint between the bid and ask is a better proxy for the "price" when an order imbalance is present. Johnson, Johnson, and Shanthikuma (2008) explore the role of bid-ask bounce in stock returns. They find that stocks that close just above a round number, e.g., $15.01, are considerably more likely to rise on the following day than are those that close just below a round number, e.g., $14.99. Price "movement" caused by bid-ask bounce can be effectively dealt with using a midpoint quote between the bid price and the ask price, as suggested by Berkman et al. (2011). Bid-ask bounce does not seem to explain much of the observed microstructure anomalies, however. We find replacing the close price with the midpoint of the bid-ask spread has no meaningful impact on our results. In Johnson, Johnson and Shanthikuma (2008), even though removing the impact of bid-ask bounce reduces the magnitude by about 50%, the results remain robust. Additionally, a random bid-ask bounce does not produce overwhelmingly positive overnight returns versus overwhelmingly negative intraday returns, as observed by Berkman et al. (2011).

D. Alternative Explanations

Other researchers provide still other explanations for the causes of the overnight-intraday reversal phenomenon. Berkman et al. (2011, p. 26) sugested that the phenomenon can be attributed to higher open prices and subsequent lower close prices, particularly "for stocks that are difficult to value and costly to arbitrage…," and is " …larger in magnitude during periods of high investor sentiment." Barber and Odean (2008) hypothesize that higher open prices may be caused by retail investors' herding to buy attention-seeking stocks at the open. Whether such a herd mentality also causes the same reversal effects in other securities as observed in Branch, Ma and Sawyer (2010) and Cliff, Cooper and Gulen (2008) has yet to be studied.

E. Practical Implications

Can market participants formulate trading rules to take advantage of the overnight-intraday price reversal movement? One possible strategy would focus on stocks that open away from their prior close. One would buy a stock when it opens down or sell it short when it opens higher and then reverse the trade at the subsequent close. Implementing such a strategy, however, requires knowing which way to trade at the opening. To do so, one would need to know the direction of the overnight order imbalance. The market maker has such knowledge. The public does not. Moreover, adding an order to be executed at the opening could impact the relationship. If, for example, a market order to buy was entered prior to the opening based on the expectation that the stock will open down and rise over the course of the day, the very act of entering that buy order might reverse the selling imbalance and thus cause the stock to open higher. Consequently, trying to trade profitably at the opening is likely to be difficult. An alternative strategy would involve trading shortly after the opening. To be effective, the stock would need to remain available for a trade near the opening level for at least a short time after the opening. This strategy may also be very difficult to implement. Transaction costs coupled with small price movements in the reverse direction before the intended trade could wipe out any profit potential. Many stocks do, however, trade prior to the opening. Perhaps such trading could provide a clue to where a stock is likely to open. Weather pre-market trading does accurately forecast the opening price is, however, an empirical question that needs to be explored.

One can, however, avoid certain disadvantageous trading behaviors around the open. Specifically, using a market order at the open is almost always inadvisable. Sometimes one could land on the weak side of the opening imbalance by luck. However, more often one would be on the side to be exploited.

V. Conclusion

In this study we extend Branch and Ma (2012) to include data from more recent years. We find that the autocorrelation between overnight and intraday returns persisted in our sample, at least for small-cap stocks. For large caps represented by the S&P500, however, the reversal effect disappeared, offering support to the market efficiency hypothesis. The persistent negative correlation between overnight and intraday return is monotonic in nature – the more positive the overnight return, the more negative the ensuing intraday return; and vice versa. Our regression analyses find evidence that the market factor now plays a bigger role in stock returns, and the reversal factor now plays a less significant role. This offers further support to the market efficiency hypothesis. We also find evidence that the market has become less volatile in our sample period.

References

Aboody, D., Even-Tov, O., Lehavy, R., & Trueman, B. (2018). Overnight Returns and Firm-Specific Investor Sentiment. *Journal of Financial and Quantitative Analysis, 53*(2), 485-505.

Barber, B. M., & Odean, T. (2008). All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *The Review of Financial Studies, 21*(2), 785-818.

Barnea, A. (1974). Performance Evaluation of New York Stock Exchange Specialists. *The Journal of Financial and Quantitative Analysis, 21*(2), 511-535.

Berkman, H., Koch, P., Tuttle, L., & Zhang, Y. (2011). Paying Attention: Overnight Returns and the Hidden Cost of Buying at the Open. *Journal of Financial and Quantitative Analysis, 47*(4), 715-741.

Blose, L. E., Gondhalekar, V., & Kort, A. (2018). Overnight Returns and Firm-Specific Investor Sentiment. *Journal of Financial and Quantitative Analysis, 53*(2), 485-505.

Bollerslev, T., Li, S. Z., & Todorov, V. (2016). Roughing up Beta: Continuous vs. Discontinuous Betas, and the Cross-Section of Expected Stock Returns. *Journal of Financial Economics, 120*(3), 464-490.

Bondarenko, O., & Sung, J. (2003). Specialist Participation and Limit Orders. *Journal of Financial Markets, 6*(4), 539-571.

Branch, B., & Ma, A. (2012). Overnight return, the invisible hand behind intraday returns? *Journal of Applied Finance, 22*(2), 90-100.

Branch, B., Ma, A., & Sawyer, J. (2010). Around-the-Clock Performance of Closed-End Funds. *Financial Management, 39*(3), 1177-1196.

Cao, C., Choe, H., & Hatheway, F. (1997). Does the Specialist Matter? Differential Execution Costs and Intersecurity Subsidization on the New York Stock Exchange. *The Journal of Finance, 52*(4), 1615-1640.

Chen, J., & Kawaguchi, Y. (2018). A Revisit of the Cross-Section of Overnight and Intraday Abnormal Returns: Evidence from the Japanese REIT Market. *International Journal of Economics and Finance, 10*(1), 46-63.

Cliff, M., Cooper, M. J., & Gulen, H. (2008, October). *Return Differences between Trading and Nontrading Hours: Like Night and Day.* Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1004081

Corwin, S. A. (1999). Differences in Trading Behavior across NYSE Specialist Firms. *The Journal of Finance, 54*(2), 721-745.

Coughenour, J. F., & Deli, D. N. (2002). Liquidity Provision and the Organizational Form of NYSE Specialist Firms. *The Journal of Finance, 57*(2), 841-869.

Fama, E. (1998). On Market Efficiency. *Journal of Financial Economics, 49*(3), 283-306.

Hong, H., & Wang, J. (2000). Trading and Returns under Periodic Market Closures. *Journal of Finance, 55*(1), 297-354.

Huang, R. D., & Liu, J. W. (2004, January). *Do Individual NYSE Specialists Subsidize Illiquid Stocks.* Retrieved from ResearchGate: https://www.researchgate.net/publication/245966339_Do_individual_NYSE_specialists_subsidize_illiquid_stocks

Inci, A. C., Lu, B., & Syhun, H. N. (2010). Intraday Behavior of Stock Prices and Trades around Insider Trading. *Financial Management, 39*(1), 323-363.

Jegadeesh, N., & Titman, S. (1993). Return to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance, 48*(1), 65-91.

Johnson, E., Johnson, N. B., & Shanthikumar, D. (2008, August 2008). *Round Numbers and Security Returns.* Retrieved from Semantic Scholar: https://pdfs.semanticscholar.org/7731/c305735ecb9cf3f3f48afff5293ecb934e14.pdf

Lachance, M.-E. (2015, July 22). *Night Trading: Lower Risk But Higher Returns?* Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2633476

Lease, R. C., Masulis, R. W., & Page, J. R. (1991). An Investigation of Market Microstructure Impacts on Event Study Returns. *The Journal of Finance, 46*(4), 1523-1536.

Liu, Q., & Tse, Y. (2017, March). Overnight returns of stock indexes: Evidence from ETFs and futures. *International Review of Economics & Finance, 48*, 440-451.

Lou, D., Polk, C., & Skouras, S. (2015, January). *A Tug of War: Overnight Versus Intraday Expected Returns.* Retrieved from Marshall School of Business, University of Southern California: http://fbe.usc.edu/seminars/papers/F_1-30-15_LOU.pdf

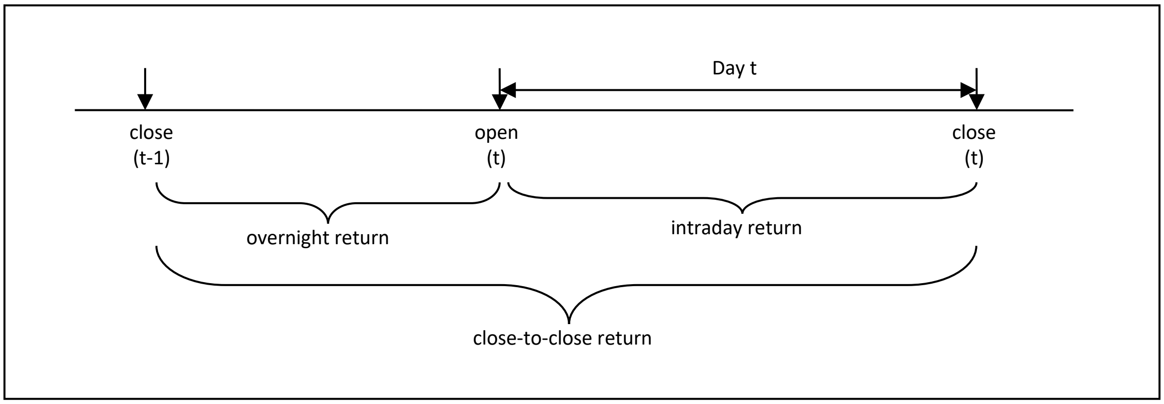
Monteiro, J., & Manso, J. (2017, January). Are There Night and Day Time Effects in US Equity Index Returns? A Robust Econometric Analysis. *International Journal of Economic Perspectives, 11*, 291-313.

Semenov, A. (2015, July). The small-cap effect in the predictability of individual stock returns. *International Review of Economics & Finance, 38*, 178-197.

Smidt, S. (1971). Which Road to an Efficient Stock Market: Free Competition versus Regulated Monopoly. *Financial Analyst Journal, 27*(5), 18-20, 64-69.

Stoll, H. R., & Whaley, R. E. (1990). Stock Market Structure and Volatility. *The Review of Financial Studies, 3*(1), 37-71.

Figure 1: Timeline of Returns



Note: Overnight, intraday and close-to-close returns are calculated as follows:

$$overnight\ return_t = \left(\frac{open_t - close_{t-1}}{close_{t-1}} \right) * 100\%;$$

$$intraday\ return_t = \left(\frac{close_t - open_t}{open_t} \right) * 100\%;$$

$$close - to - close\ return_t = \left(\frac{close_t - close_{t-1}}{close_{t-1}} \right) * 100\%.$$

Table1: Correlation Matrix

Panel A: 2018 results								
	ON	ID	SP_ON	SP_ID	lagON	lagID	lagSP_ON	lagSP_ID
ON	1	-0.191	0.389	0.040	0.046	-0.078	-0.025	0.014
ID		1	0.023	0.303	-0.035	0.010	0.016	-0.012
SP_ON			1	0.037	-0.022	-0.001	-0.053	-0.008
SP_ID				1	0.009	-0.024	0.019	-0.071
lagON					1	-0.191	0.360	0.037
lagID						1	0.023	0.298
lagSP_ON							1	0.036
lagSP_ID								1
Panel B: 2012 results								
ON	1	-0.252	0.193	0.006	0.028	-0.151	-0.015	0.036
ID		1	0.029	0.187	-0.039	0.015	0.000	0.014
SP_ON			1	-0.043	-0.021	0.012	-0.066	0.020
SP_ID				1	-0.006	-0.014	-0.009	-0.065
lagON					1	-0.244	0.185	0.006
lagID						1	0.028	0.184
lagSP_ON							1	-0.043
lagSP_ID								1

Notes:

ON, ID, SP_ON and SP_ID stand for stock overnight return, stock intraday return, SPY overnight return and SPY intraday return, respectively. LagXX stands for the lagged return for its respective stock return, and lagSP_XX stands for the lagged return for its respective SPY return.

All correlation coefficients are significant at 0.01.

Table2: Distribution of Returns

	Stocks		SPY	
	Overnight	Intraday	Overnight	Intraday
Panel A: 2018 results				
#Obs.*	1760	1760	1760	1761
Mean*	0.044% (3.824)	-0.018% (-1.16)	0.020% (1.48)	0.026% (1.66)
Max	2.686%	3.732%	3.102%	3.683%
75%	0.271%	0.348%	0.272%	0.384%
50%	0.060%	0.029%	0.033%	0.058%
25%	-0.145%	-0.345%	-0.205%	-0.277%
Min	-4.142%	-4.136%	-5.131%	-4.175%
Panel B: 2012 results				
#Obs.*	4280	4280	4279	4280
Mean*	0.025% (3.39)	0.038% (2.87)	0.036% (3.57)	-0.004% (-0.26)
Max	5.101%	6.249%	6.068%	9.074%
75%	0.210%	0.444%	0.324%	0.524%
50%	0.034%	0.117%	0.061%	0.034%
25%	-0.141%	-0.332%	-0.227%	-0.513%
Min	-5.446%	-7.149%	-8.322%	-8.991%

Notes:

Student’s t-values are in parentheses. Results are similar based on Sign test or Signed Rank test.

Table3: Distribution of Returns –
When overnight return is down vs. when overnight return is up

	Overnight return is Down	Overnight return is UP	Overnight return is zero
Panel A: 2018 results			
Mean* Overnight Return	-0.874% (-106.37)	0.904% (113.18)	0.000% (n/a)**
Mean* Intraday Return	0.216% (14.21)	-0.242 (-15.85)	-0.035% (-2.30)
Panel B: 2012 results			
Mean* Overnight Return	-1.838% (-160.01)	1.914% (154.04)	0.000% (n/a)**
Mean* Intraday Return	0.658% (46.68)	-0.601 (-40.83)	0.005% (0.45)

Notes:

**Because every overnight return in this group is 0%, Student's t value cannot be calculated.

Student's t-values are in parentheses. Results are similar based on Sign test or Signed Rank test.

Table4: Detailed Distribution of Returns –
When overnight return is down vs. when overnight return is up

Overnight Return		0 – 25th	26 – 50th	51 – 75th	76 – 100th
Overnight return is down					
Mean overnight return*	2018	-2.304% (-124.638)	-0.705% (-77.76)	-0.359% (-57.70)	-0.131% (-45.67)
	2012	-4.765% (-170.97)	-1.539% (-141.41)	-0.749% (-132.51)	-0.299% (-110.93)
Mean intraday return*	2018	0.640% (34.10)	0.141% (8.39)	0.073% (4.75)	0.021% (1.60)
	2012	1.828% (98.65)	0.528% (34.01)	0.226% (16.62)	0.062% (5.07)
Overnight return is up					
Mean overnight return*	2018	0.132% (53.50)	0.358% (66.28)	0.698% (84.58)	2.429% (120.43)
	2012	0.289% (108.01)	0.740% (130.46)	1.545% (137.15)	5.081% (162.94)
Mean intraday return*	2018	-0.001% (-0.10)	-0.069% (-4.57)	-0.164% (-9.58)	-0.734% (-38.41)
	2012	-0.049% (-4.02)	-0.195% (-13.91)	-0.497% (-30.62)	-1.668% (-83.89)
Overnight return is zero**					
Mean overnight return	2018	0.00% (N/A)			
	2012	0.00% (N/A)			
Mean intraday return	2018	-0.027% (-9.93)			
	2012	0.039% (24.50)			

Notes:

**Since every overnight return in this group is 0, all quartiles are the same and student's t values cannot be calculated.

Student's t-values are in parentheses. Results are similar based on Sign test or Signed Rank test.

Table5: Regression Analysis

										Adj. R^2
Model 1										
ID =		β0	+ β1*ON	+ β2*LagID	+ β3*lagON					
	2018	0.001%	-0.319	-0.012	-0.048					0.051
		(0.06)	(-121.94)	(-6.03)	(-19.57)					
	2012	0.045%	-0.368	-0.035	-0.062					0.077
		(3.53)	(-280.19)	(-34.16)	(-62.67)					
Model 2										
ID =		β0	+ β1*ON	+ β2*LagID	+ β3*lagON	+ β4*ONxCAP	+ β5*LagIDxCAP	+ β6*LagONxCAP		
	2018	-0.006%	-0.572	-0.058	-0.086	0.056	0.009	0.008		0.062
		(-0.44)	(-152.22)	(-21.40)	(-26.51)	(66.53)	(16.74)	(10.40)		
	2012	0.052%	-0.890	-0.354	-0.236	0.029	0.018	0.010		0.085
		(71.16)	(-84.04)	(-50.15)	(-29.73)	(47.52)	(44.65)	(20.95)		
Model 3										
ID =		β0	+ β1*SP_ON	+ β2*ON	+ β3*LagID	+ β4*lagON				
	2018	-0.009%	0.33	-0.295	-0.009	-0.031				0.031
		(-13.48)	(256.03)	(-594.22)	(-30.74)	(-65.15)				
	2012	0.041%	0.388	-0.357	-0.027	-0.055				0.063
		(58.21)	(362.04)	(-1381.50)	(-145.22)	(-212.29)				
Model 4										
ID =		β0	+ β1*SP_ON	+ β2*ON	+ β3*LagID	+ β4*lagON	+ β4*ONxCAP	+ β5*LagIDxCAP	+ β6*LagONxCAP	
	2018	-0.010%	0.25	-0.536	-0.048	-0.094	0.053	0.007	0.013	0.036
		(-15.14)	(187.42)	(-476.16)	(-58.86)	(-82.78)	(237.91)	(46.04)	(59.78)	
	2012	0.038%	0.355	-0.771	-0.390	-0.226	0.024	0.020	0.009	0.065
		(54.70)	(325.07)	(-319.16)	(-226.68)	(-94.75)	(169.54)	(211.15)	(68.52)	

Notes:

ID, ON and SP_ID stand for stock intraday return, stock overnight return and SPY overnight return, respectively. LagXX is the lagged return for its respective stock return and lagSP_XX is the lagged return for its respective SPY return. XXxCAP is the cross-term of ON (ID) times the natural log of the market capitalization, and lagXXxCAP is the lagged value of its respective XXxCAP term.