Return Differences between Trading and Non-trading Hours: Like Night and Day

Michael Cliff

Michael J Cooper

Huseyin Gulen

September 26, 2008

Cliff is with the Pamplin College of Business, Virginia Tech. Cooper is with the David Eccles School of Business, The University of Utah. Gulen is with the Krannert Graduate School of Management, Purdue University. Cooper is the corresponding author at The David Eccles School of Business, The University of Utah, Department of Finance, 1645 E. Campus Center Drive, Salt Lake City, UT 84112, 801-585-6258, mike.cooper@utah.edu. We thank Hank Bessembinder, Sugato Bhattacharyya, Christine Botosan, Markus Brunnermeier, Tarun Chordia, Shane Corwin, Robert Dubil, Mara Faccio, Terry Hendershott, Craig Holden, Mike Lemmon, Uri Lowenstein, Matt Magilke, Stewart Mayhew, Marios Panayides, Jim Schallheim, Steve Slezak, Kumar Venkataraman, and seminar participants at the U. C. Davis/Financial Management Conference on Financial Markets Research, Indiana University Finance Symposium, University of Michigan, and Virginia Tech for helpful comments. We thank Al Carrion and Yung-Yu Ma for excellent research assistant help.

Return Differences between Trading and Non-trading Hours: Like Night and Day

Abstract

We use transaction-level data and decompose the US equity premium into day (open to close) and night (close to open) returns. We document the striking result that the US equity premium over the last decade is solely due to overnight returns; the returns during the night are strongly positive, and returns during the day are close to zero and sometimes negative. This day and night effect holds for individual stocks, equity indexes, and futures contracts on equity indexes and is robust across the NYSE and Nasdaq exchanges. Night returns are consistently higher than day returns across days of the week, days of the month, and months of the year. The effect is driven in part by high opening prices which subsequently decline in the first hour of trading.

JEL classification codes: G1, G12, G14

1. Introduction

In an informationally efficient market, price changes are closely linked to the rate of information flow. Information arrives around the clock but stock price changes are not continuous due to periodic market closures.[1] These sudden daily shifts in trading regime (as markets open and close) have important implications for short term stock price dynamics. With the availability of high frequency data, empirical researchers have provided important evidence on the impact of periodic market closures on trading volume, stock price volatility, and price discovery.[2] Accordingly, a growing body of theory papers has attempted to model the implications of periodic market closures for equilibrium prices (Slezak (1994), Admati and Pfleiderer (1989), Foster and Viswanathan (1990), Hong and Wang (2000) and others). Even though the impact of periodic market closures on trading volume and volatility is well documented, its impact on the first moment of stock returns is still not fully understood. In a broad sense, many of the models developed in the aforementioned theory papers predict lower returns over nontrading periods than trading periods, a prediction consistent with evidence documented in earlier studies on the weekend effect in stock returns. Alternatively, other theory papers predict higher returns during nontrading periods to compensate liquidity providers for bearing extra risk. For example, the model developed in Longstaff (1995) predicts higher returns over periods of market closure arising from a liquidity related non-marketability effect.

In this paper, we provide new evidence on returns over periods when markets are closed and when markets are open. Using transaction-level (trades and quotes (TAQ)) data and decomposing returns into day (open to close) and night (close to open) returns, we find that the US equity premium (as measured by the S&P 500) over the last decade is solely due to overnight returns. The equity premium in the adjacent open to close (daytime) period is zero or even negative, a puzzling finding that implies no reward for bearing risk in daytime volatility. Specifically, for the individual stocks in the S&P 500 index from 1993 to 2006, we find that the average night returns (depending on how we estimate average returns: trade prices versus mid-quote methods, cross-sectional versus pooled averaging) range from 2.82 basis points (t-statistic = 3.86) to 4.76 basis points (t-statistic = 17.83); day returns range from -2.85 basis points (t-statistic = -6.02) to 0.22 basis points (t-statistic = 0.16); and the difference in returns between night and day (i.e., the night minus day return spread) ranges from 2.61 basis points (t-statistic =

[1] For example, daytime rate of information flow is estimated to be seven times that of the overnight rate (George and Hwang (2001).

[2] See, for example, French and Roll (1986), Jones, Kaul and Lipson (1994), George and Hwang (2001), and Ronen (1997).

1.74) to 7.61 basis points (t-statistic = 11.86). This day and night effect is robust to the day of the week; for the stocks in the S&P 500 index we document positive nighttime returns every day of the week, and negative daytime returns 3 out of 5 days of the week, and returns that are close to zero for the other two days of the week. Our result of negative day returns present a serious challenge to traditional asset pricing models from the standpoint that these models do not predict negative average returns.

Our findings are robust across securities and markets. Our initial sample is the individual stocks in the S&P 500 index. Since much of our sample period over the last decade includes the Internet run-up of the late 1990s, we extend our sample to include all of the individual stocks from the AMEX Inter@ctive Week Internet index (IIX). Within this group of 44 stocks, the day and night effect is also strong; the night returns range from 16.84 to 18.44 basis points (all highly statistically significant) and the day returns range from -14.21 to -16.97 basis points (also highly significant). Given that most of these Internet stocks were listed on the Nasdaq market, these results suggest that the day and night results are not an artifact of the NYSE specialist market format. We also extend our sample to include ETFs. Examining ETFs has the advantage that stale-price biases that might be present in index spot prices are minimized. We analyze the day and night returns of fourteen of the largest ETFs over our sample period, including the S&P 500 Spider (SPY), the Nasdaq index triple Q (QQQ) and the Dow Jones Industrial Average Diamond (DIA). Across each of the fourteen ETFs, we find that night returns are greater than day returns. We also examine the S&P 500 E-mini futures contract. Hasbrouck (2003) shows that for the S&P 500 index, most price discovery occurs on the E-mini contract. As with the previous results, the E-mini contract also experiences a day and night effect; the spread between night and day returns is positive and significant. Thus, the day and night effect holds for individual stocks, equity indexes, and futures contracts on equity indexes and is robust across the NYSE, AMEX, Nasdaq, and Chicago Mercantile Exchange, suggesting that our results are not attributable to any particular market structure.

We perform a number of other robustness tests including removing the Internet run-up years from our sample, examining the day and night effect year-by-year, month-by-month, and around the turn-of-the-month; across all of these the tests, we find consistent results that night returns are positive and day returns are close to zero or negative.

Having established that the day and night effect occurs, we investigate a number of potential causes. We ask whether the effect can be explained by risk, the timing and degree of earnings surprises, the advent of ECNs and decimalization, intra-day return movements, return autocorrelations, transaction costs and other measures of liquidity from the market microstructure literature. We find that the day and night effect is not due to portfolio risk as traditionally measured; the standard deviation of returns during the night is always less than the standard deviation of returns during the day. And of course, under the best of circumstances (unless one assumes a negative price of risk), a difference in volatilities cannot explain negative day returns. Further, sorting day and night returns by degree of earnings announcement surprises and whether the earnings information is released during the day or the night, we show that the day and night effect is not determined by earnings announcement information.

We split our data into pre- and post-1998 periods to examine the robustness of our results to the growth of ECNs. Barclay and Hendershott (2003) find that pre-open trading, made possible by ECNs, has contributed to the efficiency of opening prices. The SEC first allowed ECNs in 1995, and by 1998, ECNs had grabbed a significant amount of Nasdaq market volume (and a growing, but still relatively small amount of NYSE volume). For the individual stocks in the S&P 500, we find no real differences across pre- and post-1998. For the group of 14 ETFs, we find strong day and night effects after 1998, but this seems to be due more to a strong day and night effect during the "Internet bubble" years than to a permanent shift in the effect due to ECN activity. Also, splitting our sample pre- and post-decimalization using 2001 as the cutoff does not explain the day and night effect.

The TAQ data allows us to further decompose the day returns into various return intervals throughout the trading day. We find that much of the negative day return is driven by the return over the first hour after market open. Thus, it appears that the positive night returns, measured from close to open, are to some degree related to high opening prices. For example, the return over the first hour for the individual stocks in the S&P 500 index ranges from -1.16 to -3.59 basis points (t-statistics of -1.80 and -13.36, respectively). We also observe similar open hour negative returns for the Internet stocks, 13 out of 14 of the ETFs, and the S&P 500 E-mini futures. We note however that the negative first hour return does not completely explain the positive night return.

To further explore the link among night, day and intraday periods of trade, we regress the night minus day return spread (and other intraday returns) of the S&P 500 stocks on a host of variables from the microstructure literature that might help us better understand the effect. Explanatory variables include the Amihud (2002) illiquidity measure, relative spreads, market capitalization, dollar volume, trade size, a Nasdaq dummy, standard deviation of returns, and lagged returns from the previous day and night. In multiple regressions, we find that the night minus day return spread is greater for smaller capitalized S&P 500 stocks, less illiquid, more volatile, and larger dollar volume stocks. For stocks in the S&P 500 index, we find a stronger effect for NYSE stocks relative to Nasdaq stocks. We also find evidence of important autocorrelations between the night minus day spread and prior returns; the spread is strongly positively correlated with the previous night's return, and negatively correlated with the previous day's return during the first hour and the mid-day segment of trade.

Finally, our results have implications for the weekend effect literature. This effect found evidence in earlier data that Friday close to Monday close returns are significantly negative and returns for the other days of the week are positive.[3] In contrast, we find that the average weekend return over the last decade is significantly *positive,* consistent with our previous findings of positive returns over periods of market closure.

The remainder of the paper is organized as follows. Section 2 describes the data and testing methodology used in our analysis of day and night returns. Section 3 presents results which document the day and night effect along with several robustness tests. Section 4 explores the sources of the day and night effect. Section 5 concludes.

2. Data Sources and Methodology

2.1. Day, Night, and Intraday Return Construction

Our primary data source for stocks and ETFs is the TAQ database from 1993 to 2006. We collect intraday data for three samples of firms; stocks in the S&P 500 index, 14 actively traded exchange-traded funds (ETFs), and the 44 firms in the AMEX Inter@ctive Week Internet Index (IIX). Our S&P 500 sample consists of all firms in the index at a given point in time. For new additions to the index, we add the stock to our sample two weeks after the effective inclusion date to avoid potential listing effects. For deletions from the index, we remove the stock from our sample on the effective deletion date. The list of index membership comes from the msp500list SAS dataset at WRDS. The IIX sample is determined based on the composition of the index as of February 2007. Each firm in the IIX is included for its full duration in the TAQ database. This favors surviving firms but it is not clear that a survivorship bias is important for our results. We are not aware of a source for the historical index composition.

For each firm in our sample, we pull trade and quote data from TAQ for our desired dates. Following the microstructure literature we employ a variety of filters to avoid data errors

[3] See French (1980), Keim and Stambaugh (1984), Gibbons and Hess (1981), Flannery and Protopapadakis (1988), Jaffe and Westerfield (1985), Rogalski (1984), Harris (1986), Smirlock and Starks (1986), and Jain and Joh (1988). Also see Lakonishok and Levi (1982), Gibbons and Hess (1981), Keim and Stambaugh (1984), Chen and Singal (2003), Abraham and Ikenberry (1994), Miller (1988), Lakonishok and Maberly (1990), Chan, Leung, and Wang (2004), Kamara (1997), Sias and Starks (1995), Patell and Wolfson (1982), Penman (1987), and Damodaran (1989) for attempts to explain the day-of-the-week effect.

(i.e., Chordia, Sarkar, and Subrahmanyam (2005) and Bessembinder (2001)). Specifically, we exclude quotes with *mode* of {4, 7, 9, 11, 13, 14, 15, 19, 20, 27, 28} since these modes tend to indicate less-than reliable quotes (e.g., quotes around trading suspensions, quotes not binding for trading, etc.). We only use quotes originating from the security's primary exchange (to avoid the small depth typically associated with auto-quotes from non-primary exchanges). We discard any quotes with non-positive bids, offers, or quote depth.[4] Lastly, we discard quotes with spreads above $5, less than or equal to $0, or above 40% of the mid-quote.

We also screen trade prices. Trades are required to have correction code {0, 1} and condition code (*cond*) not in{'A' 'C' 'D' 'N' 'O' 'R' 'Z'}. Trades originating from any exchange are kept. Multiple trades (or quotes) in a given second are collapsed into a single record by calculating the median. No trades or quotes recorded before 9:30 AM or after 4:00 PM are used. Finally, to minimize microstructure effects, we also screen out months when a stock is trading below $5 as of the close of the prior month.[5]

After applying these filters, we then extract four trade prices per security per day; the first available after 9:30 AM ("opening price"), the last available before 10:30 AM, the last available before 3:00 PM, and the last available before 4:00 PM ("closing price").[6] We then match the prevailing quote to each trade price, using a 2-second adjustment to account for the delayed reporting of trades (Several papers have shown that the standard Lee-Ready five second adjustment is inappropriate in more recent sample periods. See, for example, Vergote (2005)).[7] Nonetheless, our results are robust to alternative delays. To control for stock splits, we use the CRSP *facpr* to adjust the reported TAQ quotes and trade prices.

We then screen the combined trade and quote data for large reversals that are potentially data errors.[8] We identify 995 large reversals (out of 6.9 million observations) in the sample of S&P 500 stocks. If the price reverses but the mid-quote does not, we replace the price with the

[4] Except for Nasdaq stocks from 1/1/1993 through 4/6/1993 when the depth data in TAQ are invalid [TAQ User Manual, p. 25].

[5] The price screen is done to reduce microstructure related errors on very low priced stocks. Examples of papers that use a price screen include Amihud (2002), Chordia, Sarkar, and Subrahmanyam (2005) among others.

[6] Most opening trades (particularly on the NYSE) come before the first quote. To avoid having a missing quote (or missing first trades), opening quotes have their time stamp restated to precede 9:30.

[7] To reduce the data processing burden, we pull quotes from a 10 minute window around the desired trade. This occasionally results in missing quote data. In that case, we calculate quotes as Price*(1 +/- RelSpread) where RelSpread is the average percent bid-ask spread for that time (9:30AM, 10:30AM, 3:00PM, or 4:00PM). In addition, trade/quote timestamps during the IGS data feed regime are adjusted by 3 seconds [TAQ User Manual, p. 17, 25].

[8] We classify the return from *t-1* to *t* (either price- or quote-based) as reversing if it is a) larger in magnitude than three times the standard deviation of daily close-to-close returns and b) larger in magnitude than four times the two-period return from *t-1* to *t+1*.

mid-quote. If the mid-quote reverses but the price does not, we replace the quotes with the price*(1+/-average relspread). We manually review many of the reversals (especially when prices and quotes both reverse). We ultimately correct 711 observations that appear to be data errors and leave 284 reversals that appear to be correct. The ETF and IIX samples are much smaller so we manually check all reversals (46 for ETFs and 66 for IIX). In all of these samples the reversals are less than 0.04% of the sample.

The resulting dataset is further screened for extended non-trading periods. If the asset does not trade for more than four days and the cause is not the Fourth of July, Thanksgiving, Christmas, or September 11, 2001, then we set the return over that period to missing. For shorter horizon trading closures, such as those which occur at the open, (Chakrabarty, Corwin, and Panayides, 2007), we use the first available quote and trade price after the end of the closure to estimate the return over the period of closure. Similarly, when trading closes early (e.g., July 3) we re-use the last available data for the remainder of the day.

High frequency S&P 500 E-mini futures data is obtained from TICK Data. The S&P 500 E-mini futures started trading on September 9, 1997. Our data consists of tick-by-tick data on all S&P 500 E-mini contracts from September 1997 to September 2004. We use TICKWrite software to extract E-mini futures prices in 15 minute intervals.

2.2. Testing Methodology

We calculate returns for the stocks and ETFs over four time intervals; *Night* (close-to-open), *AM* (open to 10:30), *Mid* (10:30 to 3:00), and *PM* (3:00-close).[9] The *Night* return includes split-adjusted dividends as reported on CRSP.[10] As is common in analysis of high-frequency financial data, we work with log returns so we can decompose the close-to-close return into the sum of the night and day returns. Specifically, we write the continuously compounded close-to-close return on day t for asset i as $r^C_{i,t} = r^N_{i,t-1} + r^D_{i,t}$, where the day (open-to-close) return is the sum of the *AM*, *Mid*, and *PM* returns, $r^D_{i,t} = r^A_{i,t} + r^M_{i,t} + r^P_{i,t}$. The time series average returns we report are geometric average returns, therefore their sign indicates whether the asset gained or lost value during that intraday interval over the course of the sample period.

We calculate returns two ways; one, using prices associated with actual trades, and two, using spread mid-quotes. For each of our four subsamples of assets we measure the average

[9] For the E-mini futures, which trade nearly 24 hours per day, the trading volume before 8:30am, when the open-outcry full size S&P 500 futures starts trading, is relatively low especially in the earlier part of the sample. Therefore, we use 8:30am as the opening time for E-minis and 4:00pm as the close. Thus, for E-minis, AM refers to 8:30-9:30, Mid refers to 9:30 to 3:00, and PM refers to 3:00 to 4:00.

[10] Our results are qualitatively similar when we exclude dividends from the night returns.

returns earned in the various time windows by regressing the return series on a set of dummy variables. This enables us to construct standard errors that are robust to correlation across both firms and time arising from the panel structure of our data. More specifically, we stack the four intra-day returns for firm i on date t into a vector $\mathbf{r}_{i,t}$, stack the daily returns for a firm into a T_i-vector $\mathbf{r}_i$, and stack these for all firms into $\mathbf{r}$. To simplify the discussion below, we let t index the time dimension (as opposed to calendar date) so that $t = 1,...,T_i$. The panel is unbalanced in that each of the N firms may have a different length of time series. The overall number of observations is $T^* = \Sigma^N_{i=1} T_i$ and T represents the number of unique time periods. With 13 years of data we have over 3000 trading days and $T > 12{,}000$ time periods.

We define a $T^* \times 4$ matrix of dummy variables $\mathbf{X}$ that identifies the time window of each row of $\mathbf{r}$. The averages of $[r^N \; r^A \; r^M \; r^P]$ are given by the coefficients from the regression $\mathbf{r} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$. To assess statistical significance we account for the fact that the residuals in the panel data structure are likely to be correlated both across firms for a given time (e.g., $e_{i,t}$ and $e_{j,t}$) and across time for a given firm (e.g., $e_{i,t}$ and $e_{i,t-1}$). We do so by clustering on both firm and time when estimating $\mathbf{V}$, the covariance of $\mathbf{b}$. Our procedure generally follows Thompson (2006) and Petersen (2007) with a few modifications.

Our estimator $\mathbf{V} = \mathbf{V}_\mathrm{t} + \mathbf{V}_\mathrm{f} - \mathbf{V}_\mathrm{w}$, where the three matrices are time-clustered, firm-clustered, and White (no clustering) covariances matrices, respectively. Each of these is a "sandwich" HAC estimator that takes the form $(\mathbf{X'X})^{-1}\mathbf{S}(\mathbf{X'X})^{-1}$ where they differ in construction of $\mathbf{S}$, the spectral density matrix of $\mathbf{u}_{i,t} = \mathrm{e}_{i,t}\mathbf{x}_{i,t}$.

The time-clustered term assumes that a common shock at a point in time affects multiple stocks so accounts for cross-asset correlation. This is achieved by using $\mathbf{S}_t = \Sigma^T_{t=1}\boldsymbol{\Omega}_t$ where $\boldsymbol{\Omega}_t = \boldsymbol{\Gamma}_0 + \Sigma^{N-1}_{n=1} \boldsymbol{\Gamma}_n + \boldsymbol{\Gamma}_n'$. The matrix $\boldsymbol{\Gamma}_n = \Sigma^{N-n}_{i=1} \mathbf{u}'_{i,t}\mathbf{u}_{i+n,t}$ measures the correlation between firms that are n apart in the ordering. Because there is no natural ordering of firms, $\boldsymbol{\Omega}_t$ captures all possible interactions of firm i with firm j at time t and $\mathbf{S}_t$ collects all possible time periods.

The firm-clustered term has a similar structure. In general, $\mathbf{S}_f = \Sigma^N_{i=1}\boldsymbol{\Omega}_i$ where $\boldsymbol{\Omega}_i = \boldsymbol{\Gamma}_0 + \Sigma^{T-1}_{\tau=1} \boldsymbol{\Gamma}_\tau + \boldsymbol{\Gamma}_\tau'$. Here the matrix $\Gamma_\tau = \Sigma^{T-\tau}_{t=1} \mathbf{u}'_{i,t}\mathbf{u}_{i,t+\tau}$ measures the correlation between residuals at time t and $t+\tau$ for a given firm i. Thus, $\boldsymbol{\Omega}_i$ amounts to a HAC estimator for a single firm. The general version as written suggests that all possible lags from 0 to $T-1$ should be included. It is well-known that such estimators have poor finite sample properties when an excessive number of lags are included. Standard implementations such as Hansen-Hodrick and Newey-West modify the calculation of $\boldsymbol{\Omega}_i$ by truncating the summation at a much lower lag length k. [The Newey-West procedure also weights $\boldsymbol{\Gamma}_\tau$ by $w_\tau = 1 - \tau/(k+1)$ to ensure the resulting matrix is positive definite.] We follow this intuition and set $k=4$ to correspond to the four holding periods in each day. Including all T-1 lags would entail estimating nonsensical correlations such as between the return during today's open and the closing hour a decade earlier.[11]

Finally, $\mathbf{V}_w = \Sigma^{N}_{i=1} \Sigma^{Ti}_{t=1} \mathbf{u}'_{i,t}\mathbf{u}_{i,t}$ is the conventional White estimator, ignoring any clustering. It needs to be subtracted off to avoid the double-counting of the common-firm, common-time terms (Γ_0) included in both $\mathbf{V}_f$ and $\mathbf{V}_t$. All three $\mathbf{V}$'s are multiplied by a finite sample adjustment of $(T\text{-}1)/(T\text{-}p)$ where p is the dimension of $\boldsymbol{\beta}$. $\mathbf{V}_f$ and $\mathbf{V}_t$ are also multiplied by $N/(N\text{-}1)$ and $T/(T\text{-}1)$ respectively to adjust for the number of clusters.

With the estimates of $\boldsymbol{\beta}$ and $\mathbf{V}$, we can then calculate the average day return and the difference in night and day returns as simple Wald tests. For example, the average day return is **Cb** where **C** = [0 1 1 1]. The corresponding standard error is the square root of **CVC**'.

In the tables, these results are shown as "Pooled Average." Table 1 also reports a "CS Average" which is the cross-sectional average of firm-level time series means, $1/\text{N}\Sigma^{N}_{i=1} 1/T_i\Sigma^{Ti}_{t=1} r_{i,t}$. Inferences here are based on the (reverse) logic of Fama-MacBeth. The standard error is estimated as the *cross-sectional* standard deviation (of time series means), divided by the square root of N. While these cross-sectional averages have an intuitive appeal, and serve as a robustness test for the pooled averages, they have two characteristics that may warrant caution in interpreting these averages. First, they weight all firms equally, meaning firms with short histories have their information weighted disproportionately high. Second, they likely underestimate the standard errors since they ignore the clustering noted above. Lastly, when we perform robustness tests such as examining the day/night returns for various calendar events such as year, or month, we use the pooled procedure from above. All that differs is the definition of the dummy variable matrix **X**.

3. Results

3.1. Day and Night Returns

We start our analysis of by providing a visual perspective of the differences between day and night returns. In Figure 1 we plot the growth of a \$1 investment in trade-price based night returns and the growth of a \$1 investment in trade-price based day returns from February 1993 to December 2006 in the S&P 500 Spider (SPY) exchange traded fund. We do not include

[11] Relative to standard errors from OLS estimations, the clustered standard errors we use are on average, for many of our tests, much larger (about a factor of 7 for the S&P500 stock sample), suggesting that our results are quite conservative relative to OLS standard errors.

transaction costs. The figure suggests that night returns are greater than day returns. The $1 investment grows to $6.54 for night returns and decreases to $0.61 for day returns over 14 years.

Next, we formally test the statistical significance of day and night returns. In Table 1 we examine the individual stocks in the S&P 500 index in Panel A; individual stocks in the AMEX Inter@ctive Week Internet Index in Panel B; exchange traded funds in Panel C; and the S&P 500 E-mini Futures Panel D. In each panel we report returns estimated using trade prices and mid-quotes. Across all of the asset groups, Table 1 documents what we view as the rather striking result that night returns are indeed larger, and in fact most often statistically significantly greater, than day returns. Consider the day and night returns in Panels A.1 and A.2 for the stocks in the S&P 500 index: across returns based on prices, returns based on mid-quotes, and across pooled and cross-sectional averages, the return spread (reported on the table under the "Diff" column header) between night and day returns is always positive; the average night returns range from 2.82 basis points (t-statistic = 3.86) to 4.76 basis points (t-statistic = 17.83), the average day returns range from -2.85 basis points (t-statistic = -6.02) to 0.22 basis points (t-statistic = 0.16) and the night minus day return spread ranges from 2.61 basis points (t-statistic = 1.74) to 7.61 basis points (t-statistic = 11.86).[12]

We find that night returns are greater than day returns in other asset classes as well. In Panels B.1 and B.2 we report results for the 44 individual stocks that make up the AMEX Inter@ctive Week Internet Index. Within this group of stocks, the day and night effect is also strong; night returns range from 16.84 to 18.44 basis points and the day returns range from -14.21 to -16.97 (all highly statistically significant), resulting in night minus day spreads ranging from 31.06 to 35.40 basis points.

In Panels C.1 through C.3, the night returns of the 14 exchange traded funds are also higher than the day returns. Using pooled averages and trade prices, in Panel C.1, the night return averages 5.43 basis points (t-statistic = 4.44) and the day return averages -3.04 basis points (t-statistic = -1.61), for a night minus day spread of 8.47 basis points (t-statistic = 3.77). Again, these results are robust for mid-quote returns and cross-sectional averaging methods. In Panel C.3, we break down the results by specific ETF and report results based on pooled averages of price-based returns. Night return point estimates are greater than day return estimates for each of the 14 ETFs, and the night minus day return spread is statistically significant in 8 out of the 14 ETFs. Finally, in Panel D we examine the returns of the S&P 500 E-mini futures contract. As with the previous results, the E-mini contract also experiences a day and night effect; the night

[12] The night minus day return spread for day t is measured as the difference in the night return from close day $t-1$ to open day t minus the day return from open day t to close day t.

average return is 4.79 basis points (t-statistic = 3.57), the day average return is -4.53 basis points (t-statistic = -1.60), and the spread is a 9.32 basis points (t-statistic = 2.98). Thus, the differences in returns across day and night periods hold for individual stocks, traded equity baskets (i.e., ETFs), and futures contracts on equity indexes, are robust to different methods of return estimation (and hence, robust to bid-ask bounce), and are robust across the NYSE, Nasdaq, and Chicago Mercantile Exchange.[13]

Our results do not appear to be driven by increased risk at night relative to the day. The standard deviation of night returns is lower than the standard deviation of day returns. In Table 1, Panel A, the standard deviation of the night returns (estimated from the pooled returns) for the stocks in the S&P 500 index is 124 basis points and the standard deviation of the day returns is 203 basis points. We observe the same patterns for the other asset categories. In Panel B, the 44 stocks in the AMEX Inter@ctive Week Internet Index, the standard deviation of the night returns is 240 basis points and the standard deviation of the day returns is 422 basis points; In Panel C, the ETFs, the standard deviation of the night returns is 88 basis points and the standard deviation of the day returns is 134 basis points; and In Panel D, the S&P 500 E-mini futures contract, the standard deviation of the night returns is 54 basis points and the standard deviation of the day returns is 116 basis points. Thus, the day and night effect is not due to total portfolio risk as traditionally measured; the standard deviation of returns during the night is always less than the standard deviation of returns during the day.

Our result of negative day returns present a challenge to traditional asset pricing models from the standpoint that these models do not predict negative average returns for broad portfolios. Early papers documenting a negative return weekend effect considered alternative hypotheses for the sources of the effect, including a “calendar time” hypothesis (returns are generated continuously) and a “trading time” hypothesis (returns are generated only when the markets are open). Our results are most consistent with a continually operating return generation process, although to explain our results, the calendar time theory would need to be modified to include a prediction that on average the positive returns to firms occur when the market is closed, perhaps due to a systematic bias where firms release “good” information at night and “bad” information during the day. Later in the paper we explore a timing-of-information-release explanation as well as other hypotheses to explain the day and night effect.

[13] We also estimate the percentage of negative returns for the day and night periods. We pool returns for each period (day or night) across stocks and across time. For the S&P 500 stocks, 50.5% of day returns are negative and 39.5% of night returns are negative; for the AMEX Inter@ctive Week Internet Index stocks, 52.1% of day returns are negative and 43% of night returns are negative; and for the ETF sample, 50% of day returns are negative and 43% of night returns are negative. For all asset groups, the differences in the percentage of negative returns across day and night periods are highly statistically significant.

3.2. Daytime Return Decomposition

To begin to explore the sources of the day and night return differential, in Table 1, in the three most right-hand side columns, we decompose daytime returns in three components; "AM" (9:30 to 10:30), "Mid" (10:30 to 3:00) and "PM" (3:00 to 4:00). Many papers have reported interesting intraday U-shaped patterns in volatility, spreads, volume, and the number of trades (Chan, Christie, and Schultz (1995), Barclay and Hendershott (2003) and others). If the night minus day spread and/or the daytime returns are driven by intra-day return patterns, perhaps due to the mechanics of the opening or closing process, we would expect to see systematic differences in returns between the AM, Mid, and PM periods. In addition, if the effects are driven by specialist versus market maker differences, we might expect to see differences in returns across the S&P 500 stocks (of which the vast majority are listed on the NYSE) and Internet stocks (of which the vast majority are listed on the Nasdaq).

In Panel A of Table 1, for the individual stocks in the S&P 500 index, we find that the first hour returns (AM) are on average negative and significant, with returns ranging from -1.16 basis points (t-statistic = -1.80) to -3.59 basis points (t-statistic = -13.36). During the mid-day hours (Mid) the returns are on average close to zero, or slightly negative, and in the last hour of trade (PM), returns are on average positive, with returns ranging from 0.87 basis points (t-statistic = 6.36) to 1.61 basis points (t-statistic = 11.71). For the Internet Index stocks in Panel B, the first hour returns are negative, the mid-day returns are negative, and the PM returns have positive point estimates but in general are not statistically significant. Across the ETFs in Panel C.1 and C.2, the first hour returns are also negative and significant, the mid-day returns are also close to zero or slightly positive, but the PM returns, unlike the PM returns of the S&P 500 stocks, exhibit negative point estimates that are statistically not different from zero. Finally, in Panel D, the S&P 500 E-mini futures also experience statistically significant negative first hour returns, negative but insignificant mid-day returns, and positive but insignificant PM returns. Thus, across the asset categories, no common pattern in mid-day or PM returns is evident. However, all of the assets categories exhibit a strong negative first hour return pattern. In fact, it appears that a majority of the low daytime returns we document come from the first hour of trading. Given that the AM returns are consistently low across assets on the NYSE, AMEX, Nasdaq, and the Chicago Mercantile Exchange, it suggests that the documented return patterns are not solely due to differences in opening procedures across the different exchanges and/or other institutional features (i.e., specialist versus market makers) of the exchanges.

3.3. The Weekend Effect

A direct fall-out of our results that night returns are greater than day returns is a reversal of the much documented weekend effect in returns. French (1980) and many others find that weekend returns are negative (e.g., French found that Friday close to Monday close returns averaged -16 basis points from 1953 to 1977 for the S&P 500 Composite Index; later studies found that much of the weekend effect was generated from Friday close to Monday open). We find in our more recent data that the average weekend return is in the opposite direction of the previously documented effect.

In Table 2, Panel A, we report average day-of-the week returns for the S&P 500 stocks; Panel B, individual stocks in the AMEX Inter@ctive Week Internet Index; Panel C, the S&P 500 Spider (SPY) exchange traded fund; Panel D, the 13 ETFs other than the SPY; and Panel E, the S&P 500 E-mini Futures.[14] The average weekend return, which is listed on the first row and under the first column of each panel, estimated from Friday close to Monday open, is 4.16 basis points (t-statistic = 2.43) for the S&P 500 stocks, 20.42 basis point (t-statistic = 3.71) for the Internet stocks, 8.91 basis points (t-statistic = 3.62) for the SPY ETF, 6.01 basis points (t-statistic = 1.89) for the other 13 ETFs, and 6.20 basis points (t-statistic = 1.79) for the E-mini Futures. Thus, in contrast to the previous weekend effect literatures' finding of a negative weekend return, our results document a positive weekend return which is robust across different asset groups.

3.4. Robustness Tests

Previous papers in the weekend effect literature report important day-of-the-week effects (Harris (1986) and others) in addition to the weekend effect. Other papers find important month-of-the-year effects (Roll (1983), Bouman and Jacobsen (2002) and others). Still other papers report turn-of-the-month effects (Lakonishok and Smidt (1988), Xu and McConnell (2008)). We examine whether our results are driven in-part by these and other calendar effects.

First, consider days of the week. The results in Table 2 show the average night, day, and night minus day returns for each day of the week. From Monday through Friday, average night return point estimates are always positive and average day returns are close to zero or negative for all of the asset categories. The only exception appears to be on Wednesdays; in some of the asset categories we observe a negative night return (the futures) or a Wednesday day return that is larger than the night return (the S&P 500 stocks and the 13 ETFs), but in general the differences

[14] In Table 2 and the remaining tables, we report results using pooled averages and trade prices to estimate returns. We have also estimated Table 2 and the remaining tables using mid-quotes to estimate returns. The results are qualitatively similar to the results using trade prices, and are available from the authors.

are not statistically significant. In addition, our previous finding of negative first hour returns is robust to the day of the week; for the stocks in the S&P 500 and the for the SPY, we observe negative AM returns in 4 out of 5 days, and for the Internet index stocks and the other ETFs, AM returns are negative across all days of the week. Interestingly, Harris (1986) found similar AM period results for his sample on Mondays (prices fall in the first 45 minutes), but found positive returns during the AM period for the other four days of the week. Overall, the day and night effect is robust to the day of the week.

Second, consider the day of the month. Xu and McConnell (2008) report that all of the US equity premium over 1897 to 2005 occurs in the four day interval from the last day of the month until the close of the third day of the next month. They find that in the other 16 trading days of the month, the equity premium is close to zero. Thus, if the turn-of-the-month effect drives our results, we would expect that the night minus day spread would occur primarily around the turn of the month. In Table 3 we report the night and day returns relative to the turn of the month. We report the average night, day and night minus day returns from day -5 to day +5 (where day -1 is the last day of the month) and also report the average returns across all other days of the month. In Panel A we report the results for the SPY ETF. Across all days of the month, the average night minus day return spread (reported in the last row of the table) for SPY is 6.77 basis points (t-statistic = 3.74). During the other days of the month outside of the 10 days around the turn-of-the-month, the average night minus day spread is 7.08 basis points (t-statistic = 2.78). In Panel B, which reports results for the other 13 ETFs, we find similar spreads; the night minus day spread for all days of the month is 8.70 basis points and the spread for the days of the month outside the 10 day window around the turn-of-the-month is a statistically significant 8.95 basis points. On particular days around the turn of the month there are some large night minus day spreads relative to the average monthly spread (for example, on day -1 the SPY spread is 18.73 basis points and the other 13 ETFs average spread is 14.71 basis points), but there are also negative spread point estimates on day -2, so the these variation in daily spreads are consistent with noise. Overall, our results appear to be quite strong outside of the turn-of-the-month period.

Third, consider the month of the year. Many papers have reported strong seasonalities in stock returns, especially a January effect, in which equities earn higher returns in the month of January than in other months. In addition, other papers have reported that equity returns are higher in the November-April period than they are in the May-October period (Bouman and Jacobsen (2002)). If our results are due to these monthly seasonalities, we would expect less of a night minus day return spread in the months outside of November-April and a particularly strong effect in January. In Table 4, we report results for the SPY ETF (Panel A) and the other 13 ETFs (Panel B). For SPY, across all months, the night minus day return spread obtains a positive point estimate in 11 out of 12 months (September is the only month with a negative spread). For the other ETFs, there are also 11 months with positive spreads (October is the only month with a negative spread). For SPY, January is the fourth strongest month in terms of the night minus day return spread. For the other ETFs, January is the third strongest month. For both the SPY and the other ETFs, the day and night effects appear to be strong in the November to April period, although the SPY and the other ETFs also exhibit strong effects in the summer months.

Fourth, we examine the consistency of our results on a year-by-year basis and across longer subperiods. In Table 5, we report the day and night effect over each year from 1993 to 2006. In Panel A we report result for the SPY ETF, and in Panel B, we report results for the other 13 ETFs. Our results appear to be relatively robust across the years; the spread between night minus day returns is positive in 12 out of 14 years for SPY, and the spread between night minus day returns is positive in 11 out of 12 years for the other ETFs. The effect does seem to be stronger during the Internet years of 1997 to 2000, but it is still evident in the years prior to and post the Internet boom years. For example, in Panel A, for SPY, the average night minus day return spread is 8.51 basis points (t-statistic = 2.00) over 1997 to 2000, and it is 3.93 basis points (t-statistic = 3.19) in the other years, and the difference in returns between 1997 to 2000 and the other years is not statistically significant.

We also split our data into pre- and post-1998 periods to examine the robustness of our results to the growth of ECNs. Barclay and Hendershott (2003) find that pre-open trading, made possible by ECNs, has contributed to the efficiency of opening prices. The SEC first allowed ECNs in 1995, and by 1998, ECNs had grabbed a significant amount of Nasdaq market volume (and a growing, but still relatively small amount of NYSE volume). For the SPY we find no real differences across pre- and post-1998. For example, the night minus day spread is 3.88 basis points (t-statistic = 2.14) prior to 1998, and is 6.03 basis points (t-statistic = 2.83) in 1998 and later, and the difference in returns between pre- and post-1998 is not statistically significant. The results are similar with the 13 other ETFs; the night minus day spread is 6.49 basis points (t-statistic = 2.15) prior to 1998, and is 8.64 basis points (t-statistic = 3.55) in 1998 and later. Thus, the night minus day return spread does not appear to be driven away by the advent of ECNs. In addition, our previous finding of negative first hour returns is also robust to the advent of ECNs; for SPY, the AM returns average -1.89 basis points (t-statistic = -2.58) prior to 1998 and -3.44

basis points (t-statistic = -3.66) in 1998 and later. We observe similar AM returns for the other 13 ETFs.[15]

We also examine the effects of decimalization on our results. We split the sample into pre- and post-2001 periods. There is a decrease in the effect post-2001 for the SPY, but the difference in returns is not statistically significant (the night minus day spread is 6.47 basis points in the years prior to and including 2000, and it is 3.59 basis points in years 2001 and later).

Finally, we examine the robustness of our results using CRSP data instead of TAQ data. CRSP reports both opening and closing prices since 1992, so we can estimate day and night returns using their data. In our analysis with the CRSP data, we find many cases where the CRSP and TAQ open and close prices do not agree. We find that part of the discrepancy arises from errors in opening prices reported by CRSP. In addition, in many cases, closing prices from CRSP are generally measured after 4 PM. Nonetheless, after carefully filtering obvious reporting errors in opening prices and measuring log returns using CRSP bid-ask midpoints, we confirm our main findings in the paper with CRSP data: night returns are significantly positive and daytime returns are zero or negative.[16]

4. Sources of the Day and Night Effect

Our results show that the day and night effect is not explained by previously documented seasonalities, ECN activity, or decimalization. It is also not explained by exchange structure differences, asset types, or differences in risk between day and night returns. In this section, we examine an information release timing explanation, we test whether our results are driven by liquidity effects, and we perform Fama and MacBeth (1973) cross-sectional regressions of night and day returns on variables from the microstructure literature in an attempt to better understand our results.

4.1. Does the Timing of Information Releases Matter?

Early papers on the timing of earnings announcements found that firms had a tendency to release bad news after the market closed. For example, Patell and Wolfson (1982) find that good news is more likely to be released while the markets are open but bad news is more likely to appear after the market closes. Bagnoli, Clement, and Watts (2005) find that announcements

[15] We also examine differences in returns before and after Nasdaq's new opening cross procedure was implemented in April 2004 (See Pagano and Schwartz (2005)). We find that the night minus day spread for Nasdaq stocks does decline following the new opening procedures, however we observe a nearly identical change for NYSE stocks so the observed differences in returns are most likely not attributable to the new procedures.

[16] Detailed results of our analysis using CRSP data are available upon request.

made on Fridays (both during trading periods and after the market closes) are more negative relative to other days of the week. However, Damodaran (1989) shows that even though earnings and dividend announcements on Fridays are indeed more likely to contain bad news and result in subsequent negative abnormal returns over the weekend, these bad-news announcements can explain only a small portion of the weekend effect. In more recent work, Doyle and Magilke (2008) reexamine the conventional wisdom that managers are more likely to delay the release of bad earnings information until after the market closes. They find no evidence that managers strategically choose to report bad news after the market closes or on Fridays. They also find no evidence that managers strategically choose to report good news before the market opens or on Monday-Thursday.

The results from the earlier earnings release literature, which suggest lower night returns relative to day returns, do not appear to have the potential to explain our results. However, later papers, such as Doyle and Magilke (2008), who find that managers are no longer systematically releasing negative unexpected information when markets are closed, but in fact are now (and in the last decade) releasing on balance positive unexpected information after close, could potentially explain our results. In Table 6, we test for this positive information release explanation. We use a sample of earnings announcement surprises from Doyle and Magilke (2008).[17] The sample allows us to identify the timing of the earnings announcement as to whether the news release was made during market open or after the market closed. Announcements are segregated based on whether the actual earnings beat (Positive Surprise), met (Neutral Surprise), or fell short (Negative Surprise) of the consensus forecast. All results in the table are limited to 2000-2005 for which the timing of the earnings announcements is available. We report the average night returns, day returns, and the night minus day spread for all days, days excluding earnings announcements, and also break-out the results by the timing and type of earnings announcement. Panel A contains the results for firms in the S&P 500 index while Panel B is for firms in the AMEX Inter@ctive Week Internet Index.

We examine the announcements by the time of occurrence and the type of surprise. We note that over this period, for the S&P 500 firms, many more earnings announcements do in fact occur after the market has closed (9,481 announcements) versus when the market is open (364 announcements). For the announcements which occur at night (i.e., after market close and before market open the next day), approximately 60% are positive surprises, 19% are neutral, and 21%

[17] We thank Matt Magilke for providing us with the data used in Doyle and Magilke (2008). See page 10 of Doyle and Magilke (2008) for details of their sample construction. They collect the timing of the earnings announcement from the Wall Street Journal website from 2000 (the first complete year data is available) through 2005.

are negative. For the IIX stocks in Panel B, an even greater percentage (relative to the S&P 500 stocks) of announcements occur at night (706) versus when the markets are open (12). At night, 71% of the earnings announcements are positive, 19% are neutral, and 11% are negative. As one might expect, positive (negative) night announcements result in high (low) night time returns relative to day returns. Specifically, for positive surprises, depending on when the night announcement occurs (Panel A.1, after the close of the prior day to midnight; Panel A.2, after midnight to the open of the current day) the night minus day spread (estimated using the day and night returns over the period immediately following the earnings announcement) is 109 and 64.5 basis points, respectively, for the S&P 500 stocks. For the IIX stocks, the spread is 161 and 98 basis points, respectively. For night time negative surprises, the night minus day spread is -273 and -127 basis points for the S&P 500 stocks and -753 and 8.92 basis points for the IIX stocks, for the close to midnight and midnight to open periods, respectively.

The critical question however is if the night time positive earnings announcements are creating our results of a positive night minus day return spread. We address this question by excluding all earnings announcements from our sample and then estimating the night minus day return spread. Panel A.4 of Table 6 shows that excluding firms' earnings announcement days (regardless of the timing of the announcement and the type of announcement) does not change our results. Specifically, the night minus day return spread across all days (including earnings announcements) for the S&P 500 firms is 4.40 basis points over 2000-2005. When we exclude all firm observations on the announcement date, the results are essentially unchanged; the night minus day return spread is now 4.44 basis points. Further, we exclude all observations within a window of -1 day to +1 day around the earnings announcements and find that the results are about the same; the night minus day return spread is 4.28 basis points. We find similar results for the stocks in the Internet Index in Panel B; the night minus day return spread across all days is 24.61 basis points. When we exclude all firm observations on the announcement date (within a window of -1 day to +1 day around the earnings announcements) the night minus day return spread is 25.09 (23.91) basis points. Overall, these results show that while there is a tendency in recent years for managers to release positive earnings information after the market closes, it does not explain the day and night effect.

4.2. Liquidity Effects

Next, we examine if the night minus day spread is driven by liquidity effects. Papers have documented a negative relationship between various measures of liquidity and future stock returns (see Amihud (2002), Pastor and Stambaugh (2003), and others). If our results are driven by increased risk or transaction costs of low liquidity stocks, we would expect to find less (more) of a night minus day return spread for the high (low) liquidity stocks. We use various measures to proxy for liquidity.

We use the square root of the Amihud (2002) illiquidity measure ($\sqrt{I}$).[18] This measure is constructed as $1/D \sum_{t=-1}^{t=D} \sqrt{|R_{it}|/VOL_{it}}$ where D is the number of trading days in the past calendar quarter, R_{it} is the close to close return of stock i on day t, and VOL_{it} is the daily volume of stock i on day t. For each firm, we winsorize the volume data at the 1% and 99% points of the individual firm volume distribution over the entire sample. In addition, we winsorize any $\sqrt{I}$ values that are three standard deviations above the mean. We also use the natural log of firm market value (Ln(MV)), measured at the end of the proceeding month, the dollar volume (DVOL) of firm i (winsorized for each firm at 1% and 99%), the average number of shares per trade (AvgTr) (winsorized for each firm at 1% and 99%), and the relative spread (RelSpr), estimated for each firm as the average of four values (estimated at 9:30, 10:30, 3, and 4) of the dollar quoted spread divided by the mid-quote.[19] Numerous studies show that capitalization is related to liquidity since smaller size stocks have larger price impact for a given order flow and a larger bid ask spread (see Amihud and Mendelson (1986) and others). Brennan, Chordia, and Subrahmanyam (1998) find that dollar volume is negatively related to the cross-section of stock returns and Keim and Madhavan (1997) show that institutional trading costs are typically greater for larger trade sizes. Amihud and Mendelson (1986) show that returns are an increasing and concave function of the relative spread. Finally, we examine a measure of firm specific volatility as a proxy for liquidity. Longstaff (1995) develops a model which shows that changes to firm value over a period of non-marketability (e.g., over a period of market closure such as close-to-open) are an approximately linear function of firm standard deviation (see Figure 2 on page 1773 of Longstaff). Thus, higher standard deviation (SD) firms should earn higher returns at night. This relation arises in Longstaff's model because the more volatile is a security's return, the higher is the opportunity costs of not being able to trade for an investor with perfect market timing skills. To construct the SD measure, we use the standard deviation of close-to-close returns over the prior calendar quarter.

In Table 7, we report the results of univariate sorts for the S&P 500 stocks (Panel A) and the IIX stocks (Panel B). We report the night minus day return spread (and night, day, and intraday returns) to low and high portfolios formed from sorting on each of these liquidity

[18] Hasbrouck (2005) uses this measure in his tests of liquidity and returns.
[19] For the liquidity measures which use volume (i.e., $\sqrt{I}$, DVOL, AvgTr) we divide reported volume by 2 for Nasdaq stocks.

variables. For the stocks in the S&P 500 index, the low and high portfolios are the first and fifth quintile. For the stocks in the IIX index, the low and high portfolios are the bottom and top half of the sample. Stocks are value-weighted within each portfolio. All of the sorting variables are lagged one day prior to the returns we seek to explain. Across the measures of liquidity, the general result for the S&P 500 stocks is that the night minus day return spread is not subsumed by liquidity effects. In fact, we find that the spread is actually greater for higher liquidity stocks in two out of the six measures. For example, with the Amihud illiquidity measure, the average night minus day spread is 6.94 basis points for the low illiquidity quintile, and 4.65 basis points for the high illiquidity quintile, resulting in a marginally statistically significant difference of 2.30 basis points (t-statistic = 1.90) across the portfolios.[20] We find similar results using the daily dollar volume measure; the night minus day spread is a statistically significant 7.76 basis points greater for the high dollar volume portfolio relative to the low dollar volume portfolio. We do not find a significant difference in the night minus day spread sorting on firm market value, and sorting on average trade size results in a greater spread for the low trade size portfolio relative to the high trade size portfolio (but the high trade size portfolio is still statistically significant), consistent with a reduction in the spread following periods of (presumably) greater institutional trading.[21] For the relative spread sort, there is a stronger night minus day effect for the high relative spread firms, but the low relative spread firms also exhibit a significant night minus day returns. For the standard deviation sorts, consistent with Longstaff (1995), we find that high SD stocks earn greater night returns than low SD stocks. However, the positive night returns are not subsumed by SD, as both the low and high SD stock portfolios earn statistically significant positive night returns. We also find that the night minus day spread is positively related to SD; the top quintile of SD stocks experience the largest spreads, the middle three quintiles of the SD sorts all have positive but decreasing spread point estimates (and the spreads for the third and fourth highest

[20] We have also performed one-way sorts using the Pastor and Stambaugh (2003) monthly liquidity measure estimated on a daily basis. We find that the night minus day spread is greater for the high liquidity portfolio relative to the low liquidity portfolio. In addition, we have performed sorts splitting the sample into high and low institutional holdings (using the quarterly 13F filings in the CDA Spectrum database). Spiegel and Subrahmanyam (1995) present a model which suggests that large institutional traders who can vary their buying and selling activity across the day will either trade at the open or during periods of unusual demand, suggesting potential interactions between institutional trading and our day and night effect. However, we do not find consistent return differences during the day/night/intraday periods across stocks with high and low institutional holdings for either the S&P500 sample in Panel A of Table 8 or the IIX sample in Panel B of Table 8.

[21] To further investigate whether our results are robust to firm size, we perform the market value sort using deciles. The night minus day return spread is 8.26 (t-statistic = 4.53) basis points for the smallest capitalization decile and is 5.77 basis points (t-statistic = 3.43) for the largest capitalization decile. We also perform quintile and decile sorts on firm price-per-share and find that the day minus night spread is positive and statistically significant for small and large-price firms within the S&P 500.

quintiles are statistically significant), but the lowest quintile SD portfolio's spread is close to zero and statistically insignificant.

In Panel B, the IIX stocks, we also find that the night minus day spread is not predominantly concentrated in low liquidity stocks. Across the six liquidity measures, there is only one case in which we find statistically significantly return differences across high and low liquidity portfolios, and that is for the SD sorts. As with the S&P 500 stocks, we find that higher SD stocks within the IIX stocks experience higher night returns and higher night minus day spreads than do the low SD stocks. However, the low SD stocks still experience statistically significant night returns and night minus day spreads.

The results of the SD sorts are consistent with the Longstaff (1995) model's prediction that stocks should earn a higher return over periods of non-marketability. We note that some caution is in order in interpreting the SD results as being solely due to a non-marketability story since SD may pick up other effects such as increased information releases at night or other risk/mispricing effects. Also, there is an important potential inconsistency between our results and implications from the Longstaff model concerning the source of the day minus night spread. In Longstaff's model, it appears that the price prior to the period of closure would logically be the point at which a non-marketability discount would be impounded into a firm's value, suggesting that the opening price the next morning after closure would not be the point at which the discount would be impounded into firm value, or else the investor who provided liquidity at the close would not be compensated. Thus, Longstaff's model predicts that prices should decline just before close (perhaps very quickly prior to close) but re-open at a "fair" price. However, our results document exactly the opposite: we find (as shown in Table 1) that returns prior to close are positive, and returns in the period after open are negative.

Overall, the tests from this section show that our results are not confined to low liquidity stocks, suggesting that the night minus day return effect is not due to liquidity related risk as traditionally measured, nor is the effect restricted to high transaction cost stocks.[22]

4.3. Fama and MacBeth Cross-Sectional Regressions

Finally, we perform Fama and MacBeth (1973) cross-sectional regressions in an attempt to better understand the multivariate effects of the liquidity and other variables on the night minus

---

[22] The profits to some common anomalies appear to be reduced after controlling for liquidity related trading costs. For example, Chordia, Goyal, Sadka, Sadka, and Shivakumar (2007) find that high returns to post-earnings-announcement drift portfolios occur mainly in highly illiquid stocks. They find that transaction costs may account for anywhere from 66% to 100% of the profits from long-short earnings momentum strategies. See also Lesmond, Schill, and Zhou (2002) and Korajczyk and Sadka (2004) who question if momentum profits are realizable given trading costs.

day spread. For our independent variables, we include the variables from the univariate sorts of Table 7, and we also include a dummy equal to one if a stock is listed on the Nasdaq, since our previous results showed a larger economic effect for the Inter@ctive Week Internet Index (IIX) stocks relative to the S&P 500 stocks. We also include lagged returns from previous night and intra-day periods, in an attempt to better understand possible price pressure effects (e.g., negative autocorrelations could potentially indicate temporary price pressures). Bessembinder and Hertzel (1993) document evidence of important positive stock return autocorrelations around weekends and other non-trading periods and Stoll and Whaley (1990) examine autocorrelation patterns between day and night returns in an attempt to understand opening period volatility. Our regressions are performed daily across all firms in either the S&P 500 or the IIX, and we summarize the results with the time series averages of the daily regression coefficient estimates. We estimate separate models for night, day, night minus day, and the three components of the day return (AM, Mid, and PM).

In Table 8, Panel A, we report the results for the S&P 500 stocks. As with the univariate sorts, the multiple regressions suggest on balance that low liquidity is not driving our results. In the first row, we find that the night minus day spread is stronger for more liquid stocks (lower Amihud illiquidity measure) and for larger dollar volume stocks. We do find that the spread is larger for smaller capitalized stocks within the S&P 500 universe. However, given that the stocks in this group are obviously all quite large on an absolute basis, this result does not seem to be overly concerning. Controlling for all of the variables in the multiple regression, the effect is weaker for Nasdaq stocks within the S&P 500 index relative to NYSE stocks. Consistent with the univariate sorts, we find that the night minus day spread is larger for higher SD stocks. We find a strong link between the previous night's return and next period's night minus day spread; the coefficient on the lagged night return is positive and significant.[23] Also, there is evidence of negative autocorrelation between the components of the day return and the night minus day spread; we find negative and significant coefficients for the AM and Mid day returns, suggestive of an intraday price pressure effect which results in a return reversal in the following night period.

Our previous results in Table 1 showed that much of the low day time return came from the first hour of trade (AM period). In row 4 of Table 8 we examine the determinants of the AM return. The AM return is strongly negatively related to returns over the previous night (the t-statistic on lagged night returns -54.6) and returns in the previous days' PM period (t-statistic = -

[23] The night return on right hand side of the regression equation is measured the day before the night component of the dependent variable, so there is no mechanical link.

16.41). Overall, these results show that as the previous night's return goes up, the next period's night minus day spread goes up, and the next day's AM return goes down. We find qualitatively similar results for the IIX stocks in Panel B but much less evidence from a statistical standpoint that the night minus day spread is related to liquidity; none of the liquidity variables are statistically significant. We find that the night minus day spread is stronger for higher standard deviation stocks and is positively correlated with previous night returns and negatively correlated with returns during the proceeding day (although the AM period is positively correlated, while the Mid and PM periods are negatively correlated).

In rows two and three of Panel A, Table 8, we report regressions for the night and day returns, respectively, of the S&P 500 stocks. These specifications help us understand the components of the night minus day spread. We find that night returns (reported in row 2) are greater for smaller capitalized stocks, NYSE stocks, lower illiquidity stocks, higher dollar volume, higher SD, and higher relative spread stocks. We also find strong positive autocorrelation between night returns and the previous night's return. In addition, as the return in the Mid and PM portions of the day decreases, the night time return increases. For the day returns (reported in row 3), we find that, consistent with much of the liquidity literature, returns tend to increase for more illiquid stocks – we find a positive and significant coefficient on the Amihud illiquidity measure and a negative and significant coefficient on dollar volume. There is also strong negative autocorrelation between day returns and previous night returns. For the IIX stocks in Panel B, the determinants of the night and day returns are not as strongly related to liquidity measures; many of the liquidity measures are not statistically significant. However, for both the night and day return regression, there are autocorrelation effects with the previous night's return and previous days PM return. Finally, although we do not pursue this point, many of the regression results from Table 8 are suggestive of potentially economically significant conditional intraday trading strategies.

Overall, these regressions show that despite relatively large t-statistics on many of the explanatory variables, the models can explain at best approximately 8 to 10 percent of the variation in day and night returns (the last column of both panels A and B reports the average adjusted r-squared from the regressions) for the S&P 500 stocks and between 12 to 16 percent of the variation for the IIX stocks.

5. Conclusion

In this paper, we document a surprising new pattern in returns; night returns, measured from close to open, are greater than day returns, measured from open to close. This pattern in returns produces the unexpected finding that the US equity premium (as measured by the S&P 500) over the last decade is solely due to overnight returns. To a certain extent, some degree of positive overnight returns can be expected due to an illiquidity premium as suggested in the model developed by Longstaff (1995). However, our evidence on day time returns is puzzling because it suggests a zero or negative risk premium during trading hours when the rate of information flow and volatility are much higher compared to overnight periods. Our results are extremely robust; they hold across multiple asset types, different market structures, and are stable across subperiods. We examine a number of potential causes for our results. We find that risk, the timing and degree of earnings surprises, the advent of ECNs and decimalization, return autocorrelations, and liquidity can explain only a small portion of the difference in night and day returns.

We believe our results carry important implications for the efficiency of market opening and closing mechanisms, intraday returns associated with event studies, and for theoretical studies that attempt to explain returns around market closures (Slezak (1994), Longstaff (1995), Admati and Pfleiderer (1989), Foster and Viswanathan (1990), Hong and Wang (2000) and others). Our results may also carry implications for portfolio managers. It may be possible to develop profitable conditional strategies for managers with low marginal trading costs using our results pertaining to which securities experience greater day and night effects. At the very least, our results may provide guidance to investment managers concerning the timing of their buy and sell orders.

Hopefully, future extensions of our results will help explain further the sources of the day and night effect. Potential explanations may come from an examination of the effects of the growing and widespread practice of algorithmic trading (Domowitz and Yegerman (2005a, 2005b) and Yang and Borkovec (2005)) by hedge funds and other financial institutions; perhaps price pressure effects from algorithm generated trading may account for some of the observed price patterns we document.[24]

[24] Domowitz and Yegerman (2005b) document that 61% of U.S. buy-side firms employ model-based execution vehicles of some sort. Also, they show that a survey of European investment managers suggests that 58% process up to 50% of their trading volumes using algorithmic trading programs.

References

Abraham, A. and D. Ikenberry, 1994, The Individual Investor and the Weekend Effect, *Journal of Financial and Quantitative Analysis* 29, 263-277.

Admati, A. and P. Pfleiderer, 1988, A Theory of Intraday Patterns: Volume and Price Variability, *Review of Financial Studies* 1, 3-40.

Admati, A. and P. Pfleiderer, 1989, Divide and Conquer: A Theory of Intraday and Day-of-the-Week Mean Effects, *Review of Financial Studies* 2, 189-223.

Amihud, Y. and Mendelson, H., 1986, Asset Pricing and the Bid Ask Spread. *Journal of Financial Economics* 17, 223-249.

Amihud, Y., 2002, Illiquidity and Stock Returns: Cross-section and Time-series Effects, *Journal of Financial Markets* 5, 31-56.

Bagnoli, M., M. Clement, and S. Watts, 2005, Around-the-Clock Media Coverage and Timing of Earnings Announcements, working paper.

Barclay, M. and T. Hendershott, 2003, Price Discovery and Trading After Hours, *Review of Financial Studies* 16, 1041-1073.

Bessembinder, H. and M. Hertzel, 1993, Return Autocorrelations Around Nontrading Days, *Review of Financial Studies* 6, 155-189.

Bessembinder, H., 2001, Price-Time Priority, Order Routing, and Trade Execution Costs in NYSE-Listed Stocks, working paper.

Bouman, S., and B. Jacobsen, 2002, The Halloween Indicator, Sell in May and Go Away: Another Puzzle, *American Economic Review* 92, 1618-1635.

Brennan, M., T. Chordia, and A. Subrahmanyam, 1998, Alternative Factor Specifications, Security Characteristics, and the Cross-Section of Expected Stock Returns. *Journal of Financial Economics* 49, 345-373.

Chakrabarty, B., S. Corwin, and M. Panayides, 2007, The Informativeness of Off-NYSE Trading During NYSE Market Closures, working paper.

Chan, K.C., W. G. Christie, and P. H. Schultz, 1995, Market Structure and the Intraday Pattern Of Bid-Ask Spreads for NASDAQ Securities, *The Journal of Business*, 68, 35-60.

Chan, S., W. Leung, and K. Wang, 2004, The Impact of Institutional Investors on the Monday Seasonal, *Journal of Business* 77, 967-986.

Chen, H. and V. Singal, 2003, Role of Speculative Short Sales in Price Formation: The Case of the Weekend Effect, *Journal of Finance*, 685-705.

Chordia, T., A. Sarkar, and A. Subrahmanyam, 2005, An Empirical Analysis of Stock and Bond Market Liquidity, *Review of Financial Studies* 18, 85-130.

Chordia, T., A. Goyal, G. Sadka, R. Sadka, and L. Shivakumar, 2007, Liquidity and the Post-Earnings-Announcement Drift, working paper.

Damodaran, A., 1989. The Weekend Effect in Information Releases: A Study of Earnings and Dividend Announcements, *Review of Financial Studies* 2, 607-623.

Domowitz, I. and H. Yegerman, 2005a, Measuring and Interpreting the Performance of Broker Algorithms, ITG Inc. research report.

Domowitz, I. and H. Yegerman, 2005b, The Cost of Algorithmic Trading: A First Look at Comparative Performance, Brian Bruce, ed., Algorithmic Trading: Precision, Control, Execution, New York: Institutional Investor.

Doyle, J. and M. Magilke, 2008, The Timing of Earnings Announcements: An Examination of the Strategic-Disclosure Hypothesis, working paper.

Fama, E., and J. MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81, 607-636.

Flannery, M. and A. Protopapadakis, 1988, From T-Bills to Common Stocks: Investigating the Generality of Intra-Week Return Seasonality, *Journal of Finance* 43, 431-450.

Foster, F. Douglas, and S. Viswanathan, 1990, A Theory of Interday Variations in Volume, Variance, and Trading Costs in Securities Markets, *Review of Financial Studies* 4, 593-624.

French, K., 1980, Stock Returns and the Weekend Effect, *Journal of Financial Economics* 8, 55-69.

French, K., and R. Roll, 1986, Stock Return Variances: The Arrival of Information and the Reaction of Traders, *Journal of Financial Economics* 17, 5-26.

George, T.J., and Chuan-Yang Hwang, 2001, Information Flow and Pricing Errors: A Unified Approach to Esimation and Testing, *Review of Financial Studies* 14, 979-1020.

Gibbons, M. R. and P. Hess, 1981, Day of the Week Effects and Asset Returns, *Journal of Business* 54, 579-596.

Harris, L., 1986, A Transaction Day Study of Weekly and Intradaily Patterns in Stock Returns, *Journal of Financial Economics* 16, 99-117

Hasbrouck, J., 2003. Intraday Price Formation in the Market for U.S. Equity Indexes, *Journal of Finance* 58, 2375-2400.

Hasbrouck, J., 2005, Trading Costs and Returns for US Equities: The Evidence from Daily Data, working paper, New York University.

Hong, Harrison and Jiang Wang, 2000, Trading and Returns under Periodic Market Closures, *Journal of Finance* 55, 297-354.

Jain, P. and G. Joh, 1988, The Dependence between Hourly Prices and Trading Volume, *Journal of Financial and Quantitative Analysis* 23, 269-283.

Jaffe, J. and R. Westerfield, 1985, The Weekend Effect In Common Stock Returns: The International Evidence, *Journal of Finance* 40, 433-454.

Jones, C. M., G. Kaul, and M. Lipson, 1994, Information, Trading, and Volatility, *Journal of Financial Economics 36*, 127-154.

Kamara, A., 1997, New evidence on the Monday seasonal in stock returns, *Journal of Business* 70, 63-84.

Keim, D. and A. Madhavan, 1997, Transaction Costs and Investment Style: An Inter-Exchange Analysis of Institutional Equity Trades, *Journal of Financial Economics 46*, 265-292.

Keim, D. and R. Stambaugh, 1984, A Further Investigation of the Weekend Effect in Stock Returns, *Journal of Finance 39*, 819-835.

Korajczyk, R. and R. Sadka, 2004, Are Momentum Profits Robust to Trading Costs?, *Journal of Finance* 59, 1039-1082.

Lakonishok, J. and M. Levi, 1982, Weekend Effects on Stock Returns: A Note, *Journal of Finance* 37, 883-889.

Lakonishok, J. and S. Smidt, 1988, Are Seasonal Anomalies Real? A Ninety-Year Perspective, *Review of Financial Studies* 1, 403-425.

Lakonishok, J. and E. Maberly, 1990, The Weekend Effect: Trading Patterns of Individual and Institutional Investors, *Journal of Finance* 45, 231-243.

Lee, C. and M. Ready, 1991, Inferring Trade Direction from Intraday Data, *Journal of Finance* 46, 733-747.

Lesmond, D., M. Schill, and C. Zhou, 2004, The Illusory Nature of Momentum Profits, *Journal of Financial Economics* 71, 349-380.

Longstaff, F., 1995, How Much Can Marketability Affect Security Values?, *Journal of Finance*, 50, 1767-1774.

Miller, E., 1988, Why a Weekend Effect?, *Journal of Portfolio Management* Summer, 43 48.

Pagano, M. and R. Schwartz, 2005, Nasdaq's Closing Cross, *The Journal of Portfolio Management*, 31, 100-111.

Pastor, L. and R. Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy* 111, 642-685

Patell, J. and M. Wolfson, 1982, Good News, bad news, and the Intraday Timing of Corporate Disclosures, *The Accounting Review* 47, 509-527

Penman, S., 1987, The Distribution of Earnings News Over Time and Seasonalities in Aggregate Stock Returns, *Journal of Financial Economics* 18, 199-228.

Petersen, M., 2007, Estimating Standard Errors in Finance Panel Dat Sets: Comparing Approaches, forthcoming, *Review of Financial Studies*

Rogalski, R., 1984, New Findings Regarding Day-of-the-Week Returns Over Trading and Non-Trading Periods: A Note, *Journal of Finance* 39, 1603-1614.

Roll, R., 1983, Vas ist das? The Turn-Of-the-Year Effect and the Return Premium of Small Firms, *Journal of Portfolio Management* 9, 18-28.

Ronen, T., 1997, Tests and Properties of Variance Ratios in Microstructure Studies, *Journal of Financial and Quantitative Analysis* 32, 183-204.

Sias, R. and L. Starks, 1995, The day-of-the-week anomaly: The role of institutional investors, *Financial Analysts Journal* 51, 58-67.

Slezak, S., 1994, A Theory of the Dynamics of Security Returns Around Market Closures, *Journal of Finance* 49, 1163-1212.

Smirlock M., and L. Starks, 1986, Day-of-the Week and Intraday Effects in Stock Returns, *Journal of Financial Economics* 17, 197-210

Spiegel, M., and A. Subrahmanyam, 1995, On Intraday Risk Premia, *The Journal of Finance*, 50, 319-339.

Stoll, H. and R. Whaley, 1990, Stock Market Structure and Volatility, *Review of Financial Studies* 3, 37-71.

Thompson, S. B., 2006, Simple Formulas for Standard Errors that Cluster by Both Firm and Time, working paper.

Vergote, O., 2005, How to Match Trades and Quotes for NYSE Stocks, working paper.

Xu, W. and J. McConnell, 2008, Equity Returns at the Turn of the Month, *Financial Analyst Journal* 64, 69-64.

Yang, J. and M. Borkovec, 2005, Algorithmic Trading: Opportunities and Challenges, *Financial Engineering News* 46, 14-15.

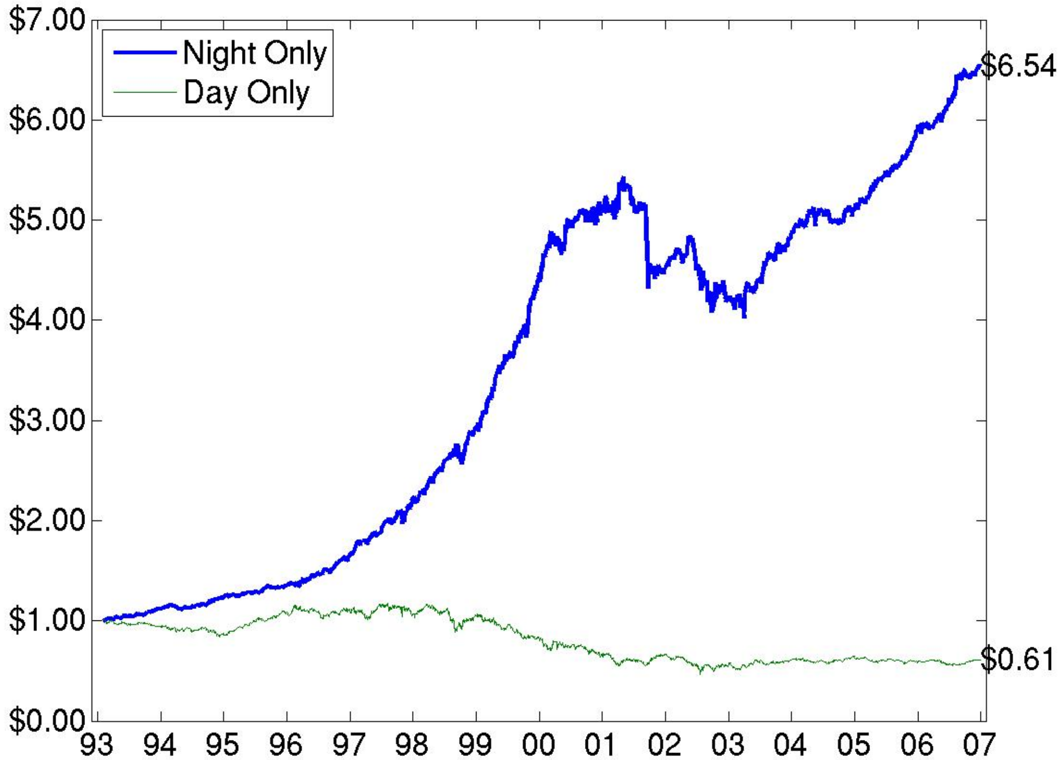

Figure 1
Growth of a $1 investment in night returns (close to open, heavy blue line) and day returns (open to close, thin green line) from 1993 to 2006 in the S&P 500 Spider (SPY) exchange traded fund.

Table 1: Summary of Results

This table summarizes the average return (in basis points) earned during the various intraday periods. Returns in the top sub-panels are calculated from trade prices while those in the bottom sub-panels are based on the mid-point of the prevailing quotes at the time of the trades. Within each sub-panel, two types of averages are reported. "Pooled Average" regresses the panel of returns (stacked for all firms, dates, and daily subperiods) on dummy variables for the Night (4 PM-9:30 AM), AM (9:30-10:30), Mid-day (10:30-3:00), and PM (3:00-4:00) time periods. Standard errors are clustered on firm and time as described in the text. The night minus day return spread (Diff) for day t is measured as the difference in the night return from close day $t-1$ to open day t minus the day return from open day t to close day t. The results for Day and Diff are obtained as linear combinations of the regression parameters. The "CS Average" results are cross-sectional averages of time series means. SD is the cross-sectional standard deviation of time series means and the t-stat is calculated by using SD/$\sqrt{N}$ as the standard error. Panels A through D correspond to different samples of assets. Panel A includes firms that are in the S&P 500 index. The sample period is from 1993 to 2006 and has 843 firms, 3526 dates, and 1,721,025 total firm-day observations. Panel B consists of stocks in the AMEX Inter@ctive Week Internet Index (IIX) as of February 2007. The stocks are assumed to be in the index beginning January 1995. The sample has 44 firms, 3021 dates, and 90,703 total firm-day observations. Panel C is high-volume exchange traded funds (ETFs) with relatively long histories. There are 14 ETFs, 3506 dates, and 29,229 total firm-day observations. Results for individual ETFs are shown in Panel C.3. Superscripts a, b, and c denote values that are statistically different from zero at the 1, 5, and 10% levels, respectively. Panel D is the E-mini futures on the S&P 500 index. For Panel D only, the time intervals are adjusted to reflect the earlier opening of the futures market: Night (4 PM to 8:30 AM), AM (8:30 to 9:30), Mid (9:30 to 10:30), and PM (3:00 to 4:00). The futures sample covers September 1997 to September 2004.

Panel A: S&P 500 Stocks

				Intra-Day		
	Night	Day	Diff	AM	Mid	PM
Panel A.1: Based on Trade Prices						
Pooled Average	4.14	−1.11	5.25	−2.88	0.34	1.43
se	0.71	1.33	1.51	0.66	1.00	0.58
t-stat	5.81	−0.83	3.48	−4.39	0.34	2.48
Pooled SD	124.33	203.47	242.39	119.58	145.31	77.57
CS Average	4.76	−2.85	7.61	−3.59	−0.86	1.61
SD	7.75	13.72	18.62	7.81	8.35	4.00
t-stat	17.83	−6.02	11.86	−13.36	−3.01	11.71
Panel A.2: Based on Mid-Quote						
Pooled Average	2.82	0.22	2.61	−1.16	0.45	0.92
se	0.73	1.31	1.50	0.64	0.98	0.57
t-stat	3.86	0.16	1.74	−1.80	0.46	1.61
Pooled SD	126.82	200.03	240.00	115.31	142.24	77.88
CS Average	3.61	−1.69	5.30	−1.87	−0.68	0.87
SD	7.54	13.84	18.62	7.53	8.11	3.98
t-stat	13.90	−3.54	8.26	−7.23	−2.45	6.36

(Table 1 Cont'd) Panel B: IIX Stocks

	Night	Day	Diff	Intra-Day AM	Mid	PM
Panel B.1: Based on Trade Prices						
Pooled Average	16.95	−14.31	31.26	−11.50	−4.94	2.14
se	2.48	4.11	4.81	2.34	2.90	1.69
t-stat	6.82	−3.48	6.49	−4.91	−1.70	1.27
Pooled SD	240.85	422.06	495.92	245.11	280.60	169.25
CS Average	18.25	−16.77	35.02	−12.52	−6.12	1.87
SD	11.35	17.07	26.88	9.51	9.68	4.70
t-stat	10.67	−6.52	8.64	−8.73	−4.20	2.64
Panel B.2: Based on Mid-Quote						
Pooled Average	16.84	−14.21	31.06	−10.42	−5.13	1.34
se	2.44	4.06	4.75	2.32	2.86	1.67
t-stat	6.90	−3.50	6.54	−4.49	−1.79	0.80
Pooled SD	241.86	416.79	489.79	241.51	274.85	170.37
CS Average	18.44	−16.97	35.40	−11.56	−6.25	0.84
SD	11.20	17.50	27.31	9.47	9.21	5.04
t-stat	10.92	−6.43	8.60	−8.09	−4.50	1.11

Panel C: ETFs

	Night	Day	Diff	Intra-Day AM	Mid	PM
Panel C.1: Based on Trade Prices						
Pooled Average	5.43	−3.04	8.47	−3.49	0.72	−0.27
se	1.22	1.88	2.25	0.91	1.41	0.83
t-stat	4.44	−1.61	3.77	−3.84	0.51	−0.32
Pooled SD	88.48	134.00	164.30	72.66	94.09	53.68
CS Average	5.24	−3.02	8.26	−3.52	0.84	−0.34
SD	2.74	3.62	5.67	2.16	3.45	1.03
t-stat	7.17	−3.12	5.46	−6.09	0.91	−1.25
Panel C.2: Based on Mid-Quote						
Pooled Average	5.68	−3.28	8.96	−3.43	0.44	−0.29
se	1.22	1.84	2.21	0.87	1.38	0.82
t-stat	4.65	−1.79	4.06	−3.94	0.32	−0.35
Pooled SD	87.38	130.39	158.56	67.42	91.86	52.86
CS Average	5.64	−3.42	9.07	−3.58	0.57	−0.41
SD	2.59	4.49	6.68	1.85	3.28	1.49
t-stat	8.14	−2.85	5.07	−7.24	0.65	−1.04

(Table 1 Cont'd)

Panel C.3: Summary of Each ETF

	Sample Period					Intra-Day		
Ticker	Begin	End	Night	Day	Diff	AM	Mid	PM
XLU	1998.12	2006.12	11.06 [a]	−8.65 [a]	19.70 [a]	−8.80 [a]	0.86	−0.70
QQQ	1999.03	2006.12	8.26 [a]	−9.42 [b]	17.68 [a]	−3.16	−4.44	−1.82
SMH	2000.05	2006.12	3.65	−9.55	13.20 [c]	−0.11	−6.60	−2.84
MDY	1995.05	2006.12	9.09 [a]	−3.77 [c]	12.86 [a]	−4.11 [a]	−0.19	0.52
XLE	1998.12	2006.12	7.22 [a]	−1.99	9.20 [a]	−2.42	0.65	−0.22
IWM	2000.05	2006.12	6.12 [a]	−2.45	8.57 [b]	−5.02 [a]	2.15	0.42
SPY	1993.02	2006.12	5.36 [a]	−1.42	6.77 [a]	−1.89 [a]	0.68	−0.22
DIA	1998.01	2006.12	4.41 [a]	−1.65	6.06 [b]	−2.17 [b]	0.26	0.26
EWJ	1996.03	2006.12	2.37	−2.36	4.73	−5.16 [a]	2.03	0.77
XLF	1998.12	2006.12	3.86 [b]	−0.86	4.72	−2.08	0.50	0.72
XLB	1998.12	2006.12	4.03 [b]	−0.52	4.55	−4.03 [b]	4.68 [b]	−1.17
IVV	2000.05	2006.12	2.51 [c]	−1.84	4.36	−1.32	0.12	−0.64
OIH	2001.02	2006.12	2.81	0.07	2.74	−3.76	3.58	0.25
EFA	2001.08	2006.12	2.65	2.12	0.53	−5.24 [a]	7.52 [a]	−0.15

Panel D: S&P 500 E-Mini Futures

				Intra-Day		
	Night	Day	Diff	AM	Mid	PM
Average	4.79	−4.53	9.32	−2.84	−2.87	1.18
SD	54.78	115.85	127.56	30.47	94.86	52.59
t-stat	3.57	−1.60	2.98	−3.81	−1.24	0.92

Table 2: Average Returns by Day

This table examines the average return (in basis points) earned during the various intraday periods by day of the week. Returns are calculated from trade prices. The average returns are coefficients from a regression of the panel of returns (stacked for all firms, dates, and daily subperiods) on dummy variables for the Night (4 PM-9:30 AM), AM (9:30-10:30), Mid-day (10:30-3:00), and PM (3:00-4:00) time periods for each of the days of the week. Standard errors are clustered on firm and time as described in the text. The results for Day and Diff are obtained as linear combinations of the regression parameters. Superscripts a, b, and c denote values that are statistically different from zero at the 1, 5, and 10% levels, respectively. t-statistics are shown in parentheses. The Night column is the return ending at the open on the indicated day, so the entry on the Monday row is the weekend return. Panel A includes firms that are in the S&P 500 index. The sample period is from 1993 to 2006 and has 843 firms, 3526 dates, and 1,721,025 total firm-day observations. Panel B consists of stocks in the AMEX Inter@ctive Week Internet Index (IIX) as of February 2007. The stocks are assumed to be in the index beginning January 1995. The sample has 44 firms, 3021 dates, and 90,703 total firm-day observations. Panel C is for the S&P 500 Depository Receipt (SPY), an ETF. Panel D is for the sample of 13 other ETFs for the period May 1995 through December 2006. Panel E is the E-mini futures on the S&P 500 index. For Panel E only, the time intervals are adjusted to reflect the earlier opening of the futures market: Night (4 PM to 8:30 AM), AM (8:30 to 9:30), Mid (9:30 to 10:30), and PM (3:00 to 4:00). The futures sample covers September 1997 to September 2004.

Panel A: S&P 500 Stocks

				Intra-Day		
Day	Night	Day	Diff	AM	Mid	PM
Monday	4.16 [b]	−0.86	5.02	1.11	−1.38	−0.58
	(2.43)	(−0.28)	(1.43)	(0.68)	(−0.63)	(−0.42)
Tuesday	6.35 [a]	−4.66	11.01 [a]	−4.17 [a]	−1.41	0.92
	(4.43)	(−1.57)	(3.34)	(−2.92)	(−0.64)	(0.68)
Wednesday	1.73	2.84	−1.11	−2.10	2.60	2.34 [c]
	(1.20)	(0.93)	(−0.33)	(−1.56)	(1.10)	(1.69)
Thursday	3.08 [b]	0.23	2.85	−2.96 [b]	1.10	2.09
	(2.02)	(0.08)	(0.86)	(−2.13)	(0.49)	(1.63)
Friday	5.40 [a]	−3.09	8.49 [b]	−6.03 [a]	0.67	2.27 [b]
	(2.94)	(−1.11)	(2.54)	(−3.88)	(0.32)	(2.23)
All	4.14 [a]	−1.11	5.25 [a]	−2.88 [a]	0.34	1.43 [b]
	(5.81)	(−0.83)	(3.48)	(−4.39)	(0.34)	(2.48)

(Table 2 Cont'd) Panel B: IIX Stocks

				Intra-Day		
Day	Night	Day	Diff	AM	Mid	PM
Monday	20.42 [a]	−20.89 [b]	41.31 [a]	−14.95 [b]	−7.69	1.74
	(3.71)	(−2.16)	(3.71)	(−2.56)	(−1.18)	(0.43)
Tuesday	26.18 [a]	−30.67 [a]	56.84 [a]	−13.04 [b]	−12.28 [c]	−5.35
	(5.60)	(−3.24)	(5.38)	(−2.47)	(−1.85)	(−1.30)
Wednesday	8.34	−8.21	16.55	−10.19 [b]	1.76	0.21
	(1.40)	(−0.84)	(1.44)	(−1.96)	(0.24)	(0.05)
Thursday	15.45 [a]	3.10	12.35	−4.36	0.15	7.31 [c]
	(2.67)	(0.35)	(1.16)	(−0.88)	(0.02)	(1.95)
Friday	14.60 [b]	−15.10 [c]	29.70 [a]	−15.19 [a]	−6.85	6.93 [b]
	(2.55)	(−1.91)	(3.04)	(−3.08)	(−1.25)	(2.46)
All	16.95 [a]	−14.31 [a]	31.26 [a]	−11.50 [a]	−4.94 [c]	2.14
	(6.82)	(−3.48)	(6.49)	(−4.91)	(−1.70)	(1.27)

Panel C: SPY

				Intra-Day		
Day	Night	Day	Diff	AM	Mid	PM
Monday	8.91 [a]	1.38	7.54	2.06	0.60	−1.28
	(3.62)	(0.37)	(1.61)	(1.21)	(0.25)	(−0.73)
Tuesday	7.99 [a]	−3.04	11.03 [a]	−2.52	0.01	−0.53
	(4.36)	(−0.84)	(2.67)	(−1.64)	(0.00)	(−0.31)
Wednesday	3.41 [c]	1.94	1.47	−1.38	3.28	0.04
	(1.85)	(0.56)	(0.36)	(−0.92)	(1.29)	(0.02)
Thursday	3.59 [c]	−1.83	5.42	−1.91	−0.05	0.13
	(1.81)	(−0.56)	(1.41)	(−1.28)	(−0.02)	(0.08)
Friday	3.08	−5.40	8.48 [b]	−5.44 [a]	−0.46	0.50
	(1.35)	(−1.64)	(2.05)	(−3.20)	(−0.20)	(0.38)
All	5.36 [a]	−1.42	6.77 [a]	−1.89 [a]	0.68	−0.22
	(5.84)	(−0.92)	(3.74)	(−2.64)	(0.64)	(−0.30)

(Table 2 Cont'd) Panel D: ETFs Other than SPY

				Intra-Day		
Day	Night	Day	Diff	AM	Mid	PM
Monday	6.01 [c]	−5.52	11.52 [b]	−2.99	−1.50	−1.02
	(1.89)	(−1.26)	(2.12)	(−1.37)	(−0.47)	(−0.51)
Tuesday	8.98 [a]	−11.33 [a]	20.32 [a]	−4.05 [c]	−3.27	−4.00 [c]
	(3.62)	(−2.58)	(4.03)	(−1.88)	(−1.03)	(−1.92)
Wednesday	1.97	4.00	−2.03	−1.86	5.71	0.15
	(0.66)	(0.83)	(−0.36)	(−0.87)	(1.53)	(0.07)
Thursday	5.53 [b]	1.69	3.84	−3.09	2.09	2.69
	(1.98)	(0.38)	(0.73)	(−1.51)	(0.61)	(1.41)
Friday	4.76	−5.30	10.06 [b]	−6.53 [a]	0.40	0.82
	(1.57)	(−1.32)	(1.99)	(−2.96)	(0.13)	(0.56)
All	5.44 [a]	−3.26 [c]	8.70 [a]	−3.71 [a]	0.72	−0.27
	(4.22)	(−1.65)	(3.67)	(−3.86)	(0.49)	(−0.32)

Panel E: S&P 500 E-Mini Futures

				Intra-Day		
Day	Night	Day	Diff	AM	Mid	PM
Monday	6.20 [c]	−2.27	8.47	−3.62 [a]	1.94	−0.59
	(1.79)	(−0.33)	(1.08)	(−3.39)	(0.35)	(−0.19)
Tuesday	9.36 [a]	−9.54	18.90 [a]	−0.95	−7.10	−1.49
	(3.43)	(−1.56)	(2.95)	(−0.74)	(−1.46)	(−0.49)
Wednesday	−0.42	−0.77	0.34	−2.18 [c]	1.25	0.16
	(−0.15)	(−0.12)	(0.05)	(−1.76)	(0.24)	(0.03)
Thursday	1.65	1.56	0.09	−3.58 [b]	0.56	4.58
	(0.53)	(0.25)	(0.01)	(−2.00)	(0.11)	(1.63)
Friday	7.18 [b]	−11.19 [c]	18.37 [b]	−4.09	−10.55 [b]	3.45
	(2.54)	(−1.73)	(2.57)	(−1.62)	(−1.98)	(1.52)
All	4.79 [a]	−4.53	9.32 [a]	−2.84 [a]	−2.87	1.18
	(3.57)	(−1.60)	(2.98)	(−3.81)	(−1.24)	(0.92)

Table 3: Average Returns by Days from Turn-of-Month

This table examines the average return (in basis points) earned during the various intraday periods by days relative to the turn of the month. Returns are calculated from trade prices. The average returns are coefficients from a regression of the panel of returns (stacked for all firms, dates, and daily subperiods) on dummy variables for the Night (4 PM-9:30 AM), AM (9:30-10:30), Mid-day (10:30-3:00), and PM (3:00-4:00) time periods for each of the calendar years. Standard errors are clustered on firm and time as described in the text. The results for Day and Diff are obtained as linear combinations of the regression parameters. Panel A is for the S&P 500 Depository Receipt (SPY), an ETF. Panel B is for the sample of 13 other ETFs. Superscripts a, b, and c denote values that are statistically different from zero at the 1, 5, and 10% levels, respectively. t-statistics are shown in parentheses.

Panel A: SPY

				Intra-Day		
Relative Date	Night	Day	Diff	AM	Mid	PM
–5	9.46 ^{a}	−1.43	10.89	−0.43	−5.27	4.27
	(2.64)	(−0.20)	(1.34)	(−0.15)	(−0.91)	(1.30)
–4	5.52	−0.62	6.14	2.16	0.41	−3.19
	(1.40)	(−0.07)	(0.60)	(0.56)	(0.08)	(−0.93)
–3	6.54 ^{c}	−3.44	9.99	−0.90	−4.51	1.97
	(1.75)	(−0.51)	(1.32)	(−0.28)	(−0.92)	(0.63)
–2	4.55	4.59	−0.05	3.35	0.35	0.89
	(1.21)	(0.67)	(−0.01)	(1.07)	(0.07)	(0.30)
–1	5.87 ^{c}	−12.87 ^{c}	18.73 ^{b}	−0.89	7.55	−19.53 ^{a}
	(1.71)	(−1.75)	(2.25)	(−0.24)	(1.52)	(−5.00)
+1	10.45 ^{a}	18.36 ^{b}	−7.91	−4.56	11.00 ^{b}	11.92 ^{a}
	(2.65)	(2.40)	(−0.93)	(−1.15)	(1.97)	(3.62)
+2	6.83 ^{c}	0.57	6.27	−2.74	5.74	−2.43
	(1.72)	(0.08)	(0.74)	(−0.92)	(1.05)	(−0.66)
+3	4.54	4.41	0.13	1.49	3.17	−0.26
	(1.13)	(0.68)	(0.02)	(0.54)	(0.67)	(−0.07)
+4	12.06 ^{a}	−3.19	15.26 ^{c}	−1.76	−2.85	1.41
	(2.87)	(−0.46)	(1.84)	(−0.52)	(−0.63)	(0.44)
+5	3.44	−1.42	4.86	−0.67	−4.41	3.66
	(0.67)	(−0.21)	(0.54)	(−0.20)	(−0.92)	(1.14)
Other	3.94 ^{a}	−3.14	7.08 ^{a}	−3.14 ^{a}	0.29	−0.29
	(2.96)	(−1.48)	(2.78)	(−3.28)	(0.20)	(−0.30)
All	5.36 ^{a}	−1.42	6.77 ^{a}	−1.89 ^{a}	0.68	−0.22
	(5.84)	(−0.92)	(3.74)	(−2.64)	(0.64)	(−0.30)

(Table 3 Cont'd) Panel B: ETFs Other than SPY

				Intra-Day		
Relative Date	Night	Day	Diff	AM	Mid	PM
–5	7.74	−0.03	7.77	1.13	−5.95	4.79
	(1.47)	(−0.00)	(0.73)	(0.26)	(−0.80)	(1.43)
–4	10.68 [b]	1.51	9.17	−0.89	3.32	−0.92
	(2.44)	(0.17)	(0.90)	(−0.18)	(0.52)	(−0.22)
–3	6.09	−5.79	11.88	−3.43	−4.18	1.82
	(1.10)	(−0.68)	(1.17)	(−0.76)	(−0.67)	(0.54)
–2	6.41	8.46	−2.05	2.36	2.27	3.83
	(1.21)	(1.01)	(−0.21)	(0.59)	(0.34)	(1.22)
–1	10.90 [b]	−3.82	14.71	2.79	10.41 [c]	−17.02 [a]
	(2.43)	(−0.46)	(1.56)	(0.60)	(1.79)	(−4.46)
+1	20.37 [a]	12.64	7.74	−12.88 [b]	15.88 [b]	9.64 [b]
	(3.93)	(1.22)	(0.67)	(−2.39)	(2.04)	(2.37)
+2	5.37	1.85	3.52	−3.03	9.62	−4.74
	(0.95)	(0.20)	(0.33)	(−0.77)	(1.36)	(−1.22)
+3	−0.11	−2.13	2.02	−1.27	1.87	−2.74
	(−0.02)	(−0.24)	(0.19)	(−0.32)	(0.26)	(−0.78)
+4	13.40 [b]	2.10	11.30	−2.95	2.30	2.75
	(2.19)	(0.24)	(1.06)	(−0.61)	(0.37)	(0.70)
+5	1.62	−16.56 [c]	18.18 [c]	−7.10	−9.21	−0.25
	(0.25)	(−1.87)	(1.65)	(−1.50)	(−1.43)	(−0.07)
Other	2.93	−6.02 [b]	8.95 [a]	−4.78 [a]	−0.99	−0.26
	(1.55)	(−2.19)	(2.68)	(−3.72)	(−0.48)	(−0.21)
All	5.44 [a]	−3.26 [c]	8.70 [a]	−3.71 [a]	0.72	−0.27
	(4.22)	(−1.65)	(3.67)	(−3.86)	(0.49)	(−0.32)

Table 4: Average Returns by Month

This table examines the average return (in basis points) earned during the various intraday periods by month. Returns are calculated from trade prices. The average returns are coefficients from a regression of the panel of returns (stacked for all firms, dates, and daily subperiods) on dummy variables for the Night (4 PM-9:30 AM), AM (9:30-10:30), Mid-day (10:30-3:00), and PM (3:00-4:00) time periods for each of the calendar years. Standard errors are clustered on firm and time as described in the text. The results for Day and Diff are obtained as linear combinations of the regression parameters. Panel A is for the S&P 500 Depository Receipt (SPY), an ETF. Panel B is for the sample of 13 other ETFs. Superscripts a, b, and c denote values that are statistically different from zero at the 1, 5, and 10% levels, respectively. t-statistics are shown in parentheses.

Panel A: SPY

				Intra-Day		
Month	Night	Day	Diff	AM	Mid	PM
January	8.52^{a}	-1.83	10.35	-2.55	-2.73	3.45
	(2.73)	(-0.31)	(1.48)	(-0.94)	(-0.66)	(1.37)
February	6.41^{a}	-8.30	14.71^{b}	-7.07^{a}	-1.68	0.46
	(2.87)	(-1.59)	(2.56)	(-2.75)	(-0.46)	(0.17)
March	2.62	1.17	1.46	-0.37	2.80	-1.27
	(0.82)	(0.22)	(0.23)	(-0.15)	(0.79)	(-0.51)
April	9.71^{a}	-3.88	13.59^{b}	-2.71	-2.53	1.37
	(2.85)	(-0.67)	(2.02)	(-1.16)	(-0.60)	(0.55)
May	5.23^{b}	0.69	4.54	-3.10	2.51	1.29
	(2.04)	(0.14)	(0.80)	(-1.31)	(0.73)	(0.54)
June	3.74	-0.76	4.50	1.78	1.27	-3.81^{c}
	(1.37)	(-0.17)	(0.85)	(0.88)	(0.39)	(-1.79)
July	4.50	-5.47	9.97	-6.55^{a}	-1.38	2.46
	(1.64)	(-0.92)	(1.55)	(-2.71)	(-0.34)	(0.89)
August	4.18	-6.69	10.86^{c}	-5.23^{b}	0.82	-2.27
	(1.61)	(-1.22)	(1.73)	(-2.02)	(0.23)	(-0.85)
September	-3.19	0.28	-3.46	-1.33	3.77	-2.16
	(-0.62)	(0.05)	(-0.45)	(-0.47)	(0.99)	(-0.81)
October	6.14	5.65	0.49	0.74	1.38	3.53
	(1.63)	(0.87)	(0.07)	(0.25)	(0.30)	(1.29)
November	9.62^{a}	2.28	7.33	-0.65	5.00^{c}	-2.07
	(3.40)	(0.55)	(1.48)	(-0.32)	(1.65)	(-0.93)
December	7.24^{a}	-0.91	8.15	3.82^{c}	-1.54	-3.18
	(2.70)	(-0.21)	(1.60)	(1.84)	(-0.55)	(-1.46)
All	5.36^{a}	-1.42	6.77^{a}	-1.89^{a}	0.68	-0.22
	(5.84)	(-0.92)	(3.74)	(-2.64)	(0.64)	(-0.30)

(Table 4 Cont'd) Panel B: ETFs Other than SPY

				Intra-Day		
Month	Night	Day	Diff	AM	Mid	PM
January	8.23 [b]	−7.83	16.06 [c]	−6.68 [c]	−2.09	0.94
	(2.01)	(−1.07)	(1.90)	(−1.95)	(−0.36)	(0.33)
February	8.87 [a]	−12.76 [c]	21.63 [a]	−9.38 [a]	−1.50	−1.88
	(2.93)	(−1.96)	(3.00)	(−3.08)	(−0.30)	(−0.63)
March	4.71	0.79	3.93	1.14	1.79	−2.15
	(0.98)	(0.12)	(0.48)	(0.38)	(0.39)	(−0.63)
April	15.01 [a]	−6.15	21.16 [b]	−1.80	−3.91	−0.45
	(3.31)	(−0.85)	(2.47)	(−0.49)	(−0.68)	(−0.17)
May	2.88	−0.00	2.88	−5.96 [c]	4.85	1.10
	(0.77)	(−0.00)	(0.39)	(−1.79)	(1.06)	(0.37)
June	7.67 [c]	−8.25	15.92 [b]	−3.33	−3.22	−1.70
	(1.90)	(−1.32)	(2.14)	(−1.07)	(−0.69)	(−0.63)
July	3.55	−11.85	15.39	−8.28 [b]	−5.29	1.72
	(0.79)	(−1.45)	(1.64)	(−2.31)	(−0.86)	(0.45)
August	4.02	−2.71	6.72	−6.21 [c]	3.39	0.10
	(1.09)	(−0.41)	(0.88)	(−1.82)	(0.69)	(0.04)
September	−6.46	−8.21	1.75	−3.82	−0.40	−3.99
	(−1.00)	(−1.14)	(0.18)	(−1.03)	(−0.07)	(−1.27)
October	4.04	8.95	−4.91	−1.82	7.43	3.35
	(0.75)	(1.13)	(−0.51)	(−0.49)	(1.22)	(1.03)
November	6.42	6.19	0.23	−2.31	7.35 [c]	1.15
	(1.59)	(1.06)	(0.03)	(−0.82)	(1.70)	(0.43)
December	7.26 [c]	−0.07	7.33	2.86	−1.01	−1.91
	(1.91)	(−0.01)	(1.12)	(1.09)	(−0.26)	(−0.77)
All	5.44 [a]	−3.26 [c]	8.70 [a]	−3.71 [a]	0.72	−0.27
	(4.22)	(−1.65)	(3.67)	(−3.86)	(0.49)	(−0.32)

Table 5: Average Returns by Year

This table examines the average return (in basis points) earned during the various intraday periods by calendar year. Returns are calculated from trade prices. The average returns are coefficients from a regression of the panel of returns (stacked for all firms, dates, and daily subperiods) on dummy variables for the Night (4 PM-9:30 AM), AM (9:30-10:30), Mid-day (10:30-3:00), and PM (3:00-4:00) time periods for each of the calendar years. Standard errors are clustered on firm and time as described in the text. The results for Day and Diff are obtained as linear combinations of the regression parameters. Panel A is for the S&P 500 Depository Receipt (SPY), an ETF. Panel B is for the sample of 13 other ETFs. Superscripts a, b, and c denote values that are statistically different from zero at the 1, 5, and 10% levels, respectively. t-statistics are shown in parentheses.

Panel A: SPY

				Intra-Day		
Year	Night	Day	Diff	AM	Mid	PM
1993	4.82 ^{a}	−2.60	7.42 ^{b}	−4.81 ^{a}	0.47	1.74
	(2.67)	(−0.81)	(2.04)	(−3.35)	(0.19)	(1.10)
1994	4.04 ^{c}	−3.84	7.87 ^{c}	−3.22 ^{b}	1.33	−1.95
	(1.77)	(−1.03)	(1.75)	(−1.99)	(0.50)	(−1.04)
1995	3.68 ^{b}	9.11 ^{a}	−5.44	0.78	5.34 ^{b}	3.00 ^{b}
	(2.05)	(3.02)	(−1.52)	(0.57)	(2.34)	(2.02)
1996	7.72 ^{b}	0.40	7.32	−1.49	4.35	−2.46
	(2.39)	(0.09)	(1.29)	(−0.70)	(1.46)	(−1.11)
1997	11.75 ^{a}	−0.52	12.27	0.43	3.88	−4.83
	(2.97)	(−0.08)	(1.54)	(0.14)	(0.90)	(−1.36)
1998	10.83 ^{b}	−0.93	11.76	−2.00	−3.08	4.14
	(2.45)	(−0.14)	(1.44)	(−0.67)	(−0.65)	(1.13)
1999	16.56 ^{a}	−9.05	25.61 ^{a}	−8.49 ^{a}	−1.27	0.71
	(4.32)	(−1.52)	(3.57)	(−2.97)	(−0.30)	(0.22)
2000	5.62	−9.37	14.99 ^{c}	0.89	−4.97	−5.29
	(1.41)	(−1.22)	(1.77)	(0.26)	(−0.90)	(−1.57)
2001	−5.04	−0.12	−4.93	−2.57	−0.91	3.37
	(−0.88)	(−0.02)	(−0.49)	(−0.65)	(−0.17)	(1.02)
2002	−2.72	−7.14	4.41	−2.16	−1.85	−3.13
	(−0.58)	(−0.80)	(0.44)	(−0.56)	(−0.31)	(−0.76)
2003	5.53 ^{c}	4.30	1.23	−5.44	5.52	4.22 ^{c}
	(1.72)	(0.72)	(0.18)	(−1.63)	(1.32)	(1.86)
2004	2.13	1.99	0.14	0.92	1.41	−0.34
	(1.02)	(0.51)	(0.03)	(0.55)	(0.47)	(−0.20)
2005	5.66 ^{a}	−3.83	9.49 ^{b}	−0.26	−0.88	−2.69 ^{c}
	(3.59)	(−1.05)	(2.28)	(−0.18)	(−0.33)	(−1.72)
2006	4.15 ^{b}	1.66	2.49	0.78	0.14	0.73
	(2.53)	(0.46)	(0.62)	(0.48)	(0.06)	(0.53)
All	5.36 ^{a}	−1.42	6.77 ^{a}	−1.89 ^{a}	0.68	−0.22
	(5.84)	(−0.92)	(3.74)	(−2.64)	(0.64)	(−0.30)

(Table 5 Cont'd) Panel B: ETFs Other than SPY

				Intra-Day		
Year	Night	Day	Diff	AM	Mid	PM
1995	11.06 [b]	−1.29	12.34 [c]	−2.87	1.23	0.35
	(2.56)	(−0.24)	(1.94)	(−1.64)	(0.29)	(0.14)
1996	3.11	−2.66	5.76	−2.21	0.57	−1.01
	(0.81)	(−0.75)	(1.05)	(−1.12)	(0.21)	(−0.55)
1997	3.38	−3.44	6.82	−2.22	−1.11	−0.11
	(0.54)	(−0.61)	(0.76)	(−0.66)	(−0.27)	(−0.04)
1998	13.11 [c]	−7.39	20.50 [b]	−6.28 [b]	−4.69	3.58
	(1.93)	(−1.22)	(2.24)	(−2.05)	(−1.15)	(1.03)
1999	17.10 [a]	−7.92 [c]	25.01 [a]	−7.13 [a]	0.54	−1.33
	(4.73)	(−1.65)	(4.12)	(−3.20)	(0.15)	(−0.52)
2000	9.26 [b]	−12.72 [c]	21.98 [a]	−2.06	−6.45	−4.20
	(1.96)	(−1.89)	(2.68)	(−0.66)	(−1.28)	(−1.40)
2001	−7.75	1.26	−9.02	−2.49	0.82	2.94
	(−1.40)	(0.16)	(−0.94)	(−0.68)	(0.14)	(0.83)
2002	−0.91	−8.11	7.19	−4.82	−0.10	−3.19
	(−0.17)	(−0.98)	(0.73)	(−1.26)	(−0.02)	(−0.84)
2003	9.79 [a]	2.45	7.34	−8.49 [a]	8.25 [b]	2.69
	(3.04)	(0.46)	(1.17)	(−2.78)	(2.14)	(1.34)
2004	6.12 [b]	−1.11	7.23	−1.85	1.43	−0.69
	(2.35)	(−0.26)	(1.45)	(−0.90)	(0.44)	(−0.40)
2005	8.23 [a]	−3.05	11.28 [b]	−2.14	0.61	−1.52
	(4.65)	(−0.76)	(2.55)	(−1.08)	(0.20)	(−0.93)
2006	4.89 [b]	0.15	4.74	−1.39	0.42	1.13
	(2.11)	(0.03)	(0.93)	(−0.62)	(0.12)	(0.67)
All	5.44 [a]	−3.26 [c]	8.70 [a]	−3.71 [a]	0.72	−0.27
	(4.22)	(−1.65)	(3.67)	(−3.86)	(0.49)	(−0.32)

Table 6: Earnings Announcements

This table examines the average return (in basis points) earned during the various intraday periods. Subpanels 1 through 3 condition on the time of the earnings announcement and Surprise Category. Surprise Category is one of: Negative (actual earnings less than consensus), Neutral (met consensus), Positive (beat consensus). Subpanel 4 reports the average returns for all days, all days except the announcement days ("Excl EA"), and all days except the three-day window around the announcements. The N column shows the number of announcements for a given surprise category and earnings announcement time. The "% of Category" column shows each N as a percentage of the total number of announcements for that Surprise Category. The sample of announcements is from Doyle and Magilke (2007). Returns are calculated from trade prices. Since many cells contain relatively few observations, statistical significance is not reported. Panel A contains the results for the sample of firms in the S&P 500 index while Panel B is firms in the AMEX Inter@ctive Week Internet Index (IIX). All results in the table are limited to the 2000-2005 sample period for which the earnings announcements are available.

Panel A: S&P 500 Stocks

Surprise		% of				Intra-Day		
Category	N	Category	Night	Day	Diff	AM	Mid	PM
Panel A.1: Announcements Between Close of Prior Day and Midnight (2652 firm-days)								
Negative	507	24.2	−258.37	15.25	−273.62	16.51	−11.71	10.45
Neutral	527	28.3	−160.28	22.76	−183.05	1.03	18.40	3.33
Positive	1618	27.5	127.04	18.04	109.00	−4.78	21.68	1.14
Panel A.2: Announcements Between Midnight and Open of Current Day (6829 firm-days)								
Negative	1489	71.0	−138.10	−10.64	−127.47	−21.82	3.45	7.73
Neutral	1258	67.7	−22.86	−27.59	4.73	−17.18	−11.17	0.76
Positive	4082	69.3	76.48	11.98	64.50	−2.64	10.28	4.34
Panel A.3: Announcements During Trading Hours (364 firm-days)								
Negative	100	4.8	−52.36	−27.75	−24.60	1.03	−24.58	−4.20
Neutral	74	4.0	−0.26	10.36	−10.62	33.51	−33.23	10.07
Positive	190	3.2	24.67	68.51	−43.83	19.47	40.87	8.17
Panel A.4: Full Sample (731,773 firm-days)								
All Days			2.54	−1.86	4.40	−4.19	1.64	0.70
Excl EA			2.48	−1.96	4.44	−4.17	1.55	0.66
Excl EA−1:+1			2.32	−1.97	4.28	−4.01	1.49	0.55

(Table 6 Cont'd) Panel B: IIX Stocks

Surprise Category	N	% of Category	Night	Day	Diff	Intra-Day AM	Mid	PM
Panel B.1: Announcements Between Close of Prior Day and Midnight (552 firm-days)								
Negative	50	65.8	−741.52	11.48	−753.00	−11.45	67.37	−44.44
Neutral	107	80.5	−368.16	−28.83	−339.33	34.40	−33.15	−30.08
Positive	395	77.6	175.22	13.98	161.25	5.39	9.66	−1.08
Panel B.2: Announcements Between Midnight and Open of Current Day (154 firm-days)								
Negative	25	32.9	−153.09	−162.01	8.92	−188.75	34.38	−7.65
Neutral	24	18.0	−357.41	70.67	−428.08	−122.55	131.08	62.13
Positive	105	20.6	86.44	−11.86	98.29	−13.03	10.95	−9.78
Panel B.3: Announcements During Trading Hours (12 firm-days)								
Negative	1	1.3	55.70	167.11	−111.41	55.70	55.70	55.70
Neutral	2	1.5	336.54	109.19	227.35	−203.11	184.70	127.60
Positive	9	1.8	28.20	−1.98	30.18	20.46	63.79	−86.23
Panel B.4: Full Sample (57,147 firm-days)								
All Days			7.87	−16.74	24.61	−7.63	−10.53	1.41
Excl EA			8.14	−16.95	25.09	−7.65	−10.84	1.54
Excl EA–1:+1			7.58	−16.33	23.91	−6.83	−10.84	1.33

Table 7: Intraday Returns by Univariate Sorts

This table shows the average return for each intraday period for groups formed based on various firm characteristics: the natural log of Market Capitalization as of the prior month (ln(MV)); the square root of the Amihud illiquidity measure ($\sqrt{I}$); dollar volume (DVOL, in \$billions); average trade size (AvgTr, in thousands of shares); the relative bid-ask spread (RelSpr, in percentage); and the daily volatility of close-to-close returns (SD, in percentage). Panel A contains the results for the sample of 843 firms that were in the S&P 500 between 1993 and 2006 while Panel B is 44 firms from 1995 through 2006 that are in the AMEX Inter@ctive Week Internet Index (IIX) as of February 2007. The Low and High portfolios in Panel A are the first and fifth quintiles. The Low and High portfolios in Panel B are the bottom and top half of the sample. Portfolios are value-weighted. Superscripts *a*, *b*, and *c* denote values that are statistically different from zero at the 1, 5, and 10% levels, respectively. *t*-statistics are shown in parentheses.

Panel A: S&P 500 Stocks

				Intra-Day		
	Night	Day	Diff	AM	Mid	PM
			Panel A.1: ln(MV)			
Low	4.96 [a]	−2.23	7.19 [a]	−3.55 [a]	−0.60	1.92 [a]
	(7.58)	(−1.29)	(4.22)	(−4.42)	(−0.50)	(3.42)
High	4.52 [a]	−1.56	6.08 [a]	−2.17 [a]	0.14	0.47
	(5.31)	(−1.10)	(3.81)	(−3.13)	(0.14)	(0.72)
Low–High	0.44	−0.67	1.11	−1.37 [b]	−0.74	1.45 [a]
	(0.88)	(−0.59)	(0.88)	(−2.26)	(−0.95)	(4.32)
			Panel A.2: $\sqrt{I}$			
Low	4.99 [a]	−1.96	6.94 [a]	−2.07 [a]	−0.01	0.12
	(5.94)	(−1.38)	(4.37)	(−3.00)	(−0.01)	(0.18)
High	3.40 [a]	−1.24	4.65 [a]	−3.25 [a]	−0.46	2.47 [a]
	(5.20)	(−0.74)	(2.79)	(−4.02)	(−0.40)	(4.34)
Low–High	1.58 [a]	−0.72	2.30 [c]	1.18 [c]	0.46	−2.35 [a]
	(3.15)	(−0.67)	(1.90)	(1.91)	(0.61)	(−7.14)
			Panel A.3: DVOL			
Low	2.09 [a]	−1.17	3.26 [b]	−2.79 [a]	−0.73	2.35 [a]
	(3.57)	(−0.77)	(2.15)	(−3.76)	(−0.68)	(4.41)
High	6.77 [a]	−4.26 [a]	11.02 [a]	−3.73 [a]	−0.55	0.03
	(7.05)	(−2.63)	(6.12)	(−4.64)	(−0.48)	(0.04)
Low–High	−4.68 [a]	3.09 [a]	−7.76 [a]	0.95	−0.18	2.32 [a]
	(−7.02)	(2.73)	(−5.75)	(1.34)	(−0.22)	(6.02)
			Panel A.4: AvgTr			
Low	3.57 [a]	−3.72 [b]	7.29 [a]	−3.39 [a]	−1.58	1.25 [c]
	(4.21)	(−2.06)	(3.87)	(−3.73)	(−1.25)	(1.68)
High	4.56 [a]	0.29	4.27 [a]	−2.73 [a]	1.31	1.71 [a]
	(5.66)	(0.20)	(2.69)	(−3.90)	(1.30)	(3.10)
Low–High	−0.99 [c]	−4.02 [a]	3.02 [a]	−0.66	−2.89 [a]	−0.46
	(−1.93)	(−4.05)	(2.73)	(−1.11)	(−4.34)	(−1.22)
			Panel A.5: RelSpr			
Low	3.47 [a]	−1.10	4.57 [a]	−2.19 [a]	0.64	0.45
	(4.62)	(−0.74)	(2.91)	(−3.17)	(0.62)	(0.70)
High	5.29 [a]	−2.44	7.73 [a]	−3.94 [a]	−0.83	2.34 [a]
	(6.73)	(−1.40)	(4.32)	(−4.75)	(−0.71)	(3.94)
Low–High	−1.82 [a]	1.34	−3.16 [a]	1.74 [a]	1.48 [b]	−1.88 [a]
	(−3.79)	(1.22)	(−2.75)	(2.98)	(2.03)	(−5.80)
			Panel A.6: SD			
Low	1.54 [a]	2.26 [b]	−0.71	−0.48	1.45 [c]	1.29 [a]
	(3.31)	(2.04)	(−0.63)	(−0.85)	(1.86)	(2.87)
High	8.57 [a]	−8.82 [a]	17.38 [a]	−6.63 [a]	−3.39 [b]	1.20
	(6.98)	(−3.62)	(6.95)	(−5.56)	(−2.08)	(1.42)
Low–High	−7.03 [a]	11.07 [a]	−18.10 [a]	6.14 [a]	4.84 [a]	0.09
	(−6.96)	(5.21)	(−8.43)	(5.43)	(3.51)	(0.15)

(Table 7 Cont'd) Panel B: IIX Stocks

	Night	Day	Diff	Intra-Day AM	Intra-Day Mid	Intra-Day PM
			Panel B.1: ln(MV)			
Low	21.88 [a]	−11.89 [b]	33.77 [a]	−14.35 [a]	−3.36	5.82 [a]
	(9.02)	(−2.46)	(6.34)	(−5.61)	(−1.11)	(3.92)
High	16.51 [a]	−11.68 [a]	28.19 [a]	−9.08 [a]	−2.15	−0.44
	(7.21)	(−2.74)	(6.08)	(−3.77)	(−0.79)	(−0.29)
Low–High	5.36 [a]	−0.21	5.57	−5.27 [a]	−1.20	6.26 [a]
	(3.33)	(−0.07)	(1.51)	(−2.79)	(−0.62)	(4.75)
			Panel B.2: $\sqrt{I}$			
Low	17.14 [a]	−11.84 [a]	28.98 [a]	−9.24 [a]	−2.06	−0.53
	(7.28)	(−2.78)	(6.29)	(−3.82)	(−0.75)	(−0.35)
High	20.81 [a]	−11.85 [b]	32.66 [a]	−14.36 [a]	−3.67	6.18 [a]
	(8.82)	(−2.45)	(6.13)	(−5.69)	(−1.22)	(4.27)
Low–High	−3.67 [b]	0.01	−3.68	5.12 [a]	1.60	−6.72 [a]
	(−2.22)	(0.00)	(−1.02)	(2.80)	(0.83)	(−5.29)
			Panel B.3: DVOL			
Low	19.05 [a]	−9.83 [b]	28.87 [a]	−13.01 [a]	−3.66	6.85 [a]
	(8.31)	(−2.05)	(5.47)	(−5.32)	(−1.23)	(4.72)
High	19.02 [a]	−14.11 [a]	33.14 [a]	−10.42 [a]	−2.08	−1.61
	(7.78)	(−3.25)	(7.01)	(−4.17)	(−0.75)	(−1.07)
Low–High	0.02	4.29	−4.26	−2.59	−1.58	8.46 [a]
	(0.01)	(1.42)	(−1.14)	(−1.41)	(−0.79)	(6.63)
			Panel B.4: AvgTr			
Low	19.28 [a]	−13.89 [a]	33.17 [a]	−12.58 [a]	−2.66	1.35
	(7.76)	(−2.83)	(6.30)	(−4.62)	(−0.86)	(0.84)
High	18.56 [a]	−9.21 [b]	27.77 [a]	−10.34 [a]	−2.63	3.76 [a]
	(8.36)	(−2.22)	(6.08)	(−4.73)	(−1.00)	(2.82)
Low–High	0.72	−4.68	5.40	−2.24	−0.03	−2.41 [c]
	(0.46)	(−1.56)	(1.60)	(−1.24)	(−0.01)	(−1.93)
			Panel B.5: RelSpr			
Low	16.79 [a]	−11.79 [a]	28.59 [a]	−8.38 [a]	−2.63	−0.78
	(7.25)	(−2.72)	(6.10)	(−3.45)	(−0.95)	(−0.52)
High	21.17 [a]	−12.04 [b]	33.21 [a]	−14.99 [a]	−2.93	5.88 [a]
	(8.81)	(−2.53)	(6.35)	(−6.01)	(−0.98)	(4.13)
Low–High	−4.38 [a]	0.25	−4.62	6.61 [a]	0.30	−6.66 [a]
	(−2.72)	(0.09)	(−1.32)	(3.70)	(0.16)	(−5.59)
			Panel B.6: SD			
Low	11.97 [a]	−3.07	15.04 [a]	−5.36 [b]	−0.59	2.88 [b]
	(5.74)	(−0.81)	(3.56)	(−2.64)	(−0.24)	(2.22)
High	26.46 [a]	−21.62 [a]	48.09 [a]	−18.14 [a]	−5.20	1.72
	(10.03)	(−4.09)	(8.49)	(−6.34)	(−1.57)	(1.05)
Low–High	−14.49 [a]	18.55 [a]	−33.05 [a]	12.79 [a]	4.61 [b]	1.16
	(−8.68)	(6.00)	(−9.19)	(7.12)	(2.25)	(0.94)

Table 8: Fama-MacBeth Regressions

This table shows results of Fama-MacBeth regressions. The explanatory variables are a Nasdaq dummy (omitted for the Internet sample); the natural log of Market Capitalization as of the prior month (ln(MV)); the square root of the Amihud illiquidity measure ($\sqrt{I}$); dollar volume (DVOL, in \$billions); average trade size (AvgTr, in thousands of shares); the relative bid-ask spread (RelSpr, in percentage); the daily volatility of close-to-close returns (SD, in percentage); and the return in each of the four prior return windows. The average number of firms per regression is reported as $\bar{N}$ in the table. Each regression is reported on three rows, comprised of the time series average of the cross-sectional regression coefficients, the standard error calculated as $\sigma(\hat{\beta}_t)/\sqrt{T}$, and the t-statistic. Panel A contains the results for the sample of 843 firms that were in the S&P 500 between 1993 and 2006 while Panel B is 44 firms from 1995 through 2006 that are in the AMEX Inter@ctive Week Internet Index (IIX) as of February 2007.

Panel A: S&P 500 Stocks

									Lagged Return				
Dep Var	Int	Nasdaq	$\ln(MV)$	$\sqrt{I}$	DVol	AvgTr	RelSpr	SD	r^n	r^{AM}	r^{Mid}	r^{PM}	$\bar{R}^2; \bar{N}; T$
$r^n - r^d$	66.36	−7.51	−4.46	−283.09	53.35	−3.13	8.88	7.19	0.056	−0.007	−0.020	−0.021	0.0831
se	8.32	1.45	0.51	39.70	6.53	0.60	2.12	0.65	0.003	0.003	0.003	0.032	488.0
t-stat	7.97	−5.18	−8.81	−7.13	8.17	−5.25	4.19	10.99	17.60	−2.48	−7.76	−0.66	3525
r^n	46.79	−1.42	−2.90	−186.19	33.44	−0.04	5.49	2.16	0.029	0.001	−0.013	−0.079	0.0830
se	4.00	0.65	0.24	19.04	3.46	0.37	1.16	0.32	0.002	0.001	0.001	0.030	488.0
t-stat	11.69	−2.19	−11.82	−9.78	9.68	−0.12	4.72	6.79	15.55	0.80	−10.01	−2.66	3525
r^d	−14.76	5.57	1.25	86.03	−18.55	2.98	−3.58	−5.12	−0.132	0.011	0.006	−0.067	0.1016
se	7.41	1.20	0.46	32.66	5.67	0.49	1.69	0.59	0.004	0.002	0.002	0.006	488.0
t-stat	−1.99	4.65	2.74	2.63	−3.27	6.11	−2.12	−8.76	−36.79	4.45	2.50	−11.59	3525
r^{AM}	−9.13	1.45	0.64	27.40	0.08	0.67	−1.42	−2.12	−0.129	0.027	0.009	−0.068	0.1004
se	4.28	0.71	0.26	22.01	3.07	0.29	1.13	0.31	0.002	0.002	0.001	0.004	488.0
t-stat	−2.13	2.03	2.45	1.24	0.03	2.28	−1.25	−6.88	−54.63	17.08	6.15	−16.41	3524
r^{Mid}	2.12	3.03	0.10	5.99	−7.25	1.89	−2.65	−2.86	−0.002	−0.030	0.003	−0.028	0.0842
se	5.03	0.79	0.31	22.56	3.94	0.33	1.12	0.39	0.002	0.002	0.002	0.003	488.0
t-stat	0.42	3.82	0.33	0.27	−1.84	5.78	−2.36	−7.39	−0.72	−13.73	2.10	−9.24	3525
r^{PM}	−8.82	1.03	0.57	49.17	−12.61	0.54	0.44	−0.47	−0.008	−0.013	−0.027	0.027	0.0851
se	2.55	0.50	0.16	11.02	2.15	0.15	0.56	0.18	0.001	0.001	0.001	0.002	488.0
t-stat	−3.45	2.08	3.54	4.46	−5.86	3.60	0.78	−2.66	−9.03	−14.31	−31.07	16.87	3511

Table 8: (Continued)

Panel B: IIX Stocks

								Lagged Return				
Dep Var	Int	$\ln(MV)$	$\sqrt{I}$	DVol	AvgTr	RelSpr	SD	r^n	r^{AM}	r^{Mid}	r^{PM}	$\bar{R}^2; \bar{N}; T$
$r^n - r^d$	−134.86	6.90	−61.72	−67.16	−5.08	12.78	12.28	0.166	0.029	−0.027	−0.108	0.1340
se	79.44	5.07	106.95	67.56	9.86	11.07	2.43	0.023	0.014	0.012	0.020	33.1
t-stat	−1.70	1.36	−0.58	−0.99	−0.52	1.15	5.06	7.35	1.99	−2.19	−5.26	2643
r^n	−7.50	−0.13	−84.49	4.53	−1.29	9.94	4.39	0.074	0.022	−0.017	−0.127	0.1654
se	28.45	1.75	48.47	20.78	3.55	5.28	1.01	0.009	0.006	0.005	0.010	33.1
t-stat	−0.26	−0.08	−1.74	0.22	−0.36	1.88	4.34	7.95	3.69	−3.27	−12.68	2643
r^d	91.57	−4.65	0.57	53.01	5.03	2.31	−8.47	−0.186	0.001	0.015	−0.056	0.1392
se	58.20	3.64	89.36	47.39	8.18	9.53	1.97	0.017	0.012	0.010	0.017	33.1
t-stat	1.57	−1.28	0.01	1.12	0.61	0.24	−4.30	−10.88	0.08	1.49	−3.36	2643
r^{AM}	15.54	−0.69	56.29	33.85	6.66	−10.11	−4.77	−0.208	0.023	0.017	−0.087	0.1542
se	32.13	2.02	51.32	26.02	4.75	5.78	1.12	0.011	0.007	0.006	0.010	33.1
t-stat	0.48	−0.34	1.10	1.30	1.40	−1.75	−4.25	−19.44	3.35	2.81	−8.51	2642
r^{Mid}	71.84	−4.11	−142.85	−0.07	−2.53	9.69	−3.26	0.020	−0.014	0.015	0.010	0.1200
se	39.82	2.50	59.06	32.41	5.33	6.36	1.43	0.012	0.008	0.007	0.011	33.1
t-stat	1.80	−1.64	−2.42	−0.00	−0.48	1.52	−2.28	1.68	−1.78	2.34	0.91	2643
r^{PM}	−17.98	0.98	78.73	8.32	9.62	2.84	−0.77	−0.007	0.005	−0.004	0.014	0.1399
se	23.49	1.45	37.73	19.76	3.48	3.90	0.86	0.008	0.005	0.004	0.007	33.2
t-stat	−0.77	0.67	2.09	0.42	2.77	0.73	−0.89	−0.86	1.07	−1.02	1.98	2631