Night Trading: Lower Risk but Higher Returns?

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Abstract

This paper demonstrates that overnight returns are subject to highly persistent biases and examines the profitability of overnight-only investments in that context. Overnight returns tend to exceed their intraday counterparts, and the paper first reconciles these patterns by introducing a model that factors in recurring biases. This model identifies one fifth of stocks as having positive and statistically significant overnight biases. Investing overnight in these stocks in the next year yields twice the market's return for a third of the market beta. Results have also implications for daytime investors as these stocks average negative returns intraday. Implementation costs and issues are discussed.

Keywords: Overnight returns, short-term return anomalies, transaction costs, portfolio strategies

JEL codes: G11, G12, N20

Marie-Eve Lachance
Associate Professor, Department of Finance
San Diego State University
5500 Campanile Drive, San Diego, CA 92182-8236
Tel: 616-315-3121
Fax: 619-594-3272
E-mail: marie.lachance@sdsu.edu

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1. Introduction

Most investors are unaware that overnight returns exceed intraday returns in the United States, although this phenomenon is documented in several recent works (Cliff et al. (2008); Kelly and Clark (2011); Berkman et al. (2012)). This observation is surprising given that it is well-known that volatility is lower during the nighttime period. This paper contributes to the literature in four ways by providing new evidence that the overnight return anomaly is pervasive, persistent, predictable, and can be profitable after costs. The paper broadens the scope of the effect by showing that overnight returns beat intraday ones in each of the 23 countries of MSCI's World Index. Moreover, in each country, sorting stocks by past overnight returns remarkably and consistently predicts future overnight returns: A strategy as simple as buying stocks from the previous year's top quartile averages an annual overnight return of 43.7% the next year. This anomaly deserves more attention as it is not limited to a period or country and its superior performance persists several years after portfolios are formed.

More specifically, the paper examines two research questions related to overnight returns. First, is there long-term persistency in overnight returns? In regression analysis, the paper finds that the past year's overnight return is actually the most important predictor of future overnight returns, followed by volatility, turnover, and momentum.[1] Second, can these patterns be

[1] Related works that examine the determinants of overnight and intraday returns include Cliff et al. (2008) (size, liquidity, volatility, volume, previous day's returns), Berkman et al. (2012) (retail attention, institutional ownership), and Lou et al. (2015) (momentum and other trading strategies).

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exploited profitably and reliably with overnight-only investment strategies, even after risk and costs are taken into account? The cost of overnight strategies is generally not quantified in current works, which limits their explicit recommendations for the timing of existing trades—i.e., delaying purchases to the close and sales to the open. Thus, analyzing costs fills a gap in this literature and expands applications to stand-alone alpha-generating investment strategies, which entail larger profit opportunities.

Overnight strategies would be cost-prohibitive with round-trip transaction costs such as those reported in Barber and Odean (2001): 1% for the bid-ask spread and 1.4% in commissions. However, transaction costs have declined sharply over the last decade, and the paper calibrates commission rates realistically by surveying broker fee structures for 2014 in the United States and finding the lowest costs. From a cost standpoint, overnight strategies offer an interesting case because they can be implemented with the exchanges' single-price opening and closing call auctions, saving on the bid-ask spread. The paper finds that the resulting average daily round-trip costs are between 1.5 and 3.1 basis points, depending on the size of the trades.

Hence, abnormal overnight returns must be at least 4%-8% annually to offset transaction costs. Overnight investment strategies should aim to identify stocks that are likely to exceed that threshold by a comfortable margin. The paper's finding that stocks exhibit persistency in their overnight returns facilitates this identification. This is demonstrated formally with Fama-MacBeth (1973) cross-sectional regressions and two datasets. The first sample is based on data from the Center for Research in Security Prices (CRSP) covering the period 1995-2014 for the United States. The second sample uses the constituents of major indexes representing 22 developed countries over the period 2002-2014. With both samples, the regressions show that overnight monthly returns are strongly positively related with each of their lagged values, with lags ranging from one to 60 months. By contrast, the relationship of overnight returns with current and past monthly intraday returns is negative.

These results are not only highly statistically significant, but also economically significant. To make a parallel with Jegadeesh and Titman's (1993) momentum strategy, an "overnight momentum" strategy of picking stocks in the top decile of overnight returns in the United States for the past year and holding them overnight-only for the next year yields an annual return of 40.43%. By contrast, stocks in the bottom decile of past overnight returns underperform overnight with a -17.08% return. Sorting stocks by quartiles of past overnight returns, the same patterns are observed in each of the countries of the international sample. Unlike traditional momentum portfolios, overnight profits do not reverse in the next five years after the decile portfolios are formed.

From a statistical perspective, the continuation of "overnight momentum" profits over several years can be attributed in part to cross-sectional variations in the means of the overnight return processes. In other words, stocks with higher expected overnight returns are more likely to be in the top overnight decile portfolio and more likely to have superior overnight performance in the next period. As Conrad and Kaul (1998) point out, this explanation can generate momentum-type profits even with a random walk model. While cross-sectional variations in expected returns are usually linked with characteristics priced by the market, such as risk, overnight and intraday returns present an unusual situation since they have opposite relationships with factors such as risk. The strong negative relationship between the means of the overnight and intraday return processes suggests that they are distorted by offsetting biases.

This idea is formalized by introducing a new model that incorporates an Overnight Bias Parameter (OBP) in the mean of the overnight return process. This parameter is subtracted from the mean of the intraday return process, leaving total returns unaffected. The OBP can be measured empirically as the intercept in a regression of overnight returns on total returns. The model's ability to predict the out-of-sample partition of returns in the United States is demonstrated by graphing the average overnight and intraday returns for each percentile of the total return distribution, both for predicted and actual values. Despite the model's simplicity, the predicted values fit actual ones extremely well, with R^2s above 0.98. In particular, incorporating biases makes it possible to reconcile the striking empirical observation that average overnight returns are always positive in the period considered, even in the worst percentiles of the total return distribution.

The OBP estimates can be used to determine the cutoff point for inclusion in an overnight portfolio. This portfolio has substantial risk-adjusted returns, even after transaction costs are taken into account. Specifically, the t-statistic of the OBP provides a convenient way to identify stocks with statistically significant overnight biases. Stocks with OBPs that are positive and significant at the 5% level in the previous year are assigned to the Overnight Bias Group (OBG) and represent a meaningful portion of the CRSP sample, averaging 524 stocks a year or 20% of the sample. In the year following this classification, a strategy of investing overnight-only in OBG stocks yields an annual return of 25.87% and a risk-adjusted return of 20.13%. This is a relatively low-risk strategy with a market beta of 0.31 and a standard deviation of 11.46%.

The robustness of the risk-adjusted returns is verified with various sub-samples and alternative methodologies. Most impressively, the risk-adjusted returns for the OBG overnight portfolio are positive in each of the 20 years of the sample. The results also have implications for daytime investors, as OBG stocks have negative intraday returns for 18 of the 20 years. The OBG overnight strategy is viable on an after-cost basis with alphas ranging from 10.45% to

15.69%. By contrast, investing overnight in stocks outside the OBG category is generally a losing proposition when costs are considered. The main limitation of the overnight strategy is that there is an implementation risk if participation in the call auctions is insufficient or if large trades have a price impact. While the paper uses the broadest set of stocks possible for statistical purposes, in practice, liquidity and share price should be considered when selecting stocks to include in an overnight strategy. Excluding stocks that are illiquid or that have low share prices does not affect the strategy's performance.

The paper concludes with an examination of intraday volume and return patterns for OBG stocks with a sub-sample of Trades and Quotes (TAQ) data for 2010-2012. The volume data provide new evidence that, compared to other stocks, OBG stocks have unusually high trading volume around the open. For their part, the return patterns show that excess overnight returns for OBG stocks are actually fully realized minutes *before* the market officially opens at 9:30. Abnormal overnight returns decrease after the open but do not disappear immediately. One can avoid intraday losses for OBG stocks by waiting 30-45 minutes after the open to purchase them.

The paper is organized as follows. Section 2 describes the data. Section 3 demonstrates the persistency of overnight returns over time, evaluates the performance of overnight decile portfolios, and discusses international stocks. Section 4 introduces the overnight bias model, evaluates its fit, and analyzes the determinants of the OBP. Section 5 evaluates the performance of overnight-only investment strategies. Section 6 discusses the implementation of the strategy using the opening and closing call auctions and details intraday patterns. Section 7 concludes.

2. Data

This paper's analysis is founded on a decomposition of daily log returns r_t into their overnight (close-to-open) and intraday (open-to-close) components, which are denoted, respectively, by r_t^O and r_t^I and computed with the following equations:

$$r_t^O = ln\left(\frac{P_t^O + Dividend_t}{P_{t-1}^C}\right), \qquad r_t^I = ln\left(\frac{P_t^C + Dividend_t}{P_t^O + Dividend_t}\right), \tag{1}$$

where P_t^O and P_t^C are the opening and closing prices, and $Dividend_t$ is the dividend paid in dollars on day t. Price and dividend data are taken from CRSP, and prices are adjusted for splits by a factor (1+*facpr*), where *facpr* is CRSP's "factor to adjust prices." For a period T with n trading days, the cumulative log returns for the period are computed with:

$$R_T^O = \sum_{t=1}^{n} r_t^O, \qquad R_T^I = \sum_{t=1}^{n} r_t^I. \tag{2}$$

The notation T in this paper can represent a period of one month or one year. While log returns are generally used in regressions, tables and figures report annualized returns of the standard form $\exp(R_T) - 1$.

The main dataset used for this paper's analysis is CRSP. The sample selection process starts by considering all CRSP securities listed on the NYSE, NYSE MKT (formerly Amex), NASDAQ, and ARCA for the period 1995-2014. The sample is extended to include 1994 data when lagged values are used in computations. All securities are included, with the exception of exchange-traded funds (ETFs), American Deposit Receipts (ADRs), and closed-end funds. On average, there are 5,932 stocks per year, taking into account fractional years. From this initial universe, stocks that have at least 240 trading days for the current and previous years are retained. As low-priced stocks are more prone to errors, the sample eliminates stocks with average prices of less than $5 in any month. A few stocks with annual overnight or intraday returns above 250% are screened out of the sample. Only dates for which both overnight and intraday returns can be computed are kept, representing 99.9% of the sample's observations.[2]

CRSP's permanent identification numbers (*permnos*) are used to track stocks over time. In the sample, one *permno* represents one stock. CRSP is also used to gather information about shares outstanding, daily trading volume, listing exchange, and North American Industry Classification System (NAICS) codes starting in 2004. A subsample of NYSE's Trades and Quotes (TAQ) data for 2010-2012 is used to refine the analysis. The TAQ data are more detailed than CRSP in that they provide a time-stamped record of all trades reported to the Consolidated Tape (including after-hours), along with size, exchange, and condition code information. Other data sources used in this paper include Wharton Research Data Services (for Fama and French's three-factor model variables); FactSet[3] (for institutional ownership); Bloomberg (for earnings announcements, international stocks, and institutional ownership); and I/B/E/S (for earnings announcements).

Table 1 presents the sample's characteristics and contrasts them with those of excluded stocks. The sample retains, on average, 2,554 stocks per year, or 43.1% of the stocks in CRSP's universe. This count proportion understates the economic importance of these stocks: overall, the

[2] For excluded stocks, the proportion of days with missing data is higher, at 13.5%. For included stocks, potential outliers are further screened out of the sample by eliminating some of the observations with absolute daily returns in excess of 20% (0.03% of the sample's observations).

[3] FactSet's data on institutional ownership are available starting in 1999 and only for stocks that currently trade. Bloomberg data are available starting in 2010 and are used to augment FactSet's data for 2010-2014.

sample's stocks account for 91.2% of CRSP's total market capitalization. On average, they have a market capitalization of $5.31 billion and a daily trading volume of $36.73 million. Excluded stocks are much smaller than sample stocks in terms of trading volume and market capitalization. They are more likely to be listed on NASDAQ and are more volatile. Their beta is slightly lower, as they are less correlated with the market than the sample stocks are. Their average share price is much lower, at $11.28, versus $32.98 for the sample (excluding BRKA).

[Table 1 here]

The sample counts 12,847,083 daily observations with average overnight and intraday returns of 0.024% and 0.046%, respectively. Value-weighted returns can provide a better representation of the partition of returns, as smaller stocks are associated with higher intraday and total returns in the data. The sample's value-weighted annualized overnight return is 6.84% and higher than the intraday return of 3.72%. The sample is conservative in the sense that excluded stocks have much higher overnight returns than intraday returns, indicating that this paper's results underestimate the number of stocks affected by positive overnight biases.[4] The sample's total returns are similar to those of excluded stocks and are in line with CRSP's figures for that period. Daily volatility is markedly lower overnight than in the daytime—1.45% versus 2.60%. Overnight returns are less volatile than intraday returns for 98% of stocks.

3. Persistency of Overnight Returns

[4] For excluded stocks, the top and bottom 0.05% of returns are winsorized for Table 1's statistics. Returns for this category should be viewed with caution since they include stocks with share prices below $5, which are more prone to errors. Removing these stocks from the calculations does not affect the conclusion that value-weighted overnight returns are higher than intraday returns.

This paper's thesis is that some stocks have a tendency to perform better overnight and that this trait persists from one period to the next. A sufficient number of stocks with positive overnight biases can explain the presence of excess overnight returns at the market level.

3.1 FAMA-MACBETH REGRESSIONS

A Fama-MacBeth (1973) regression framework is used to test whether past monthly overnight returns predict future ones. Specifically, for every month T in our sample and lag k, a cross-sectional regression of current monthly log overnight returns $R_{i,T}^{O}$ on their lagged values $R_{i,T-k}^{O}$ is performed with the following equation:

$$R_{i,T}^{O} = \alpha_{k,T} + \beta_{k,T} \cdot R_{i,T-k}^{O} + \varepsilon_{i,T}. \tag{3}$$

By repeating the cross-sectional regression for each month in the sample, a time-series of coefficients $\hat{\beta}_{k,T}$ is obtained and can be used to test for statistical significance. This process is repeated for lags k ranging from one to 60 months. The exercise uses only lagged values within the 1995-2014 period and the number of months ranges from 180 for $k = 60$ to 239 for $k = 1$.

In a second set of regressions, monthly overnight returns are regressed on their average cumulative returns up to lag k with:

$$R_{i,T}^{O} = \alpha_{k,T} + \beta_{k,T} \cdot \bar{R}_{i,T-k}^{O} + \varepsilon_{i,t}, \quad \text{where} \quad \bar{R}_{i,T-k}^{O} = \frac{1}{k}\sum_{j=1}^{k} R_{i,T-j}^{O}. \tag{4}$$

Figure 1 summarizes the t-statistics of the $\hat{\beta}_k$ coefficients for each lag k. The bars in the figure represent the results for Equation (3) and the line those for Equation (4). For both regressions, the relationship between monthly overnight returns and their lagged values is positive for each of the 60 lags considered. The results are all statistically significant at the 1% level, with t-statistics ranging from 2.70 to 43.67. Supplemental regressions are used to verify that the results are robust when adding control variables for market capitalization, volume, and standard deviation. On an individual basis, more-recent lags contain more information than older ones. However, more statistical significance can be gained by considering cumulative returns over a few months, with a peak at six months.

[Figure 1 here]

The same equations can be used to test the relationship between current monthly overnight returns and past monthly *intraday* returns. The results illustrated in the bottom portion of Figure 1 reveal quite a striking mirror pattern in which overnight returns are negatively related to past intraday returns for all lags but the last one. Most results are statistically significant at the 1% level. These patterns suggest an inverse relationship between average overnight and intraday returns. This can be confirmed by performing Equation (3) with current monthly overnight and intraday returns, which yields an average coefficient of -0.19 and a t-statistic of -35.97. As longer periods are considered, the effect of noise fades and the relationship strengthens. For instance, using annual returns instead of monthly returns increases the average R^2 of the regressions from 0.10 to 0.30.

3.2 PERFORMANCE OF DECILE PORTFOLIOS

The persistence documented in the previous section suggests that a momentum-like strategy based on past overnight returns could be profitable. This can be illustrated with a decile approach similar to the one proposed by Jegadeesh and Titman (1993) in their seminal paper on momentum strategies. The decile portfolios are rebalanced monthly and based on the past year's overnight returns. The sample used for this exercise is the one described in Table 1 for the 1995-2014 period. On average, each decile counts 255 stocks a year. The stocks in each decile portfolio are weighted daily by market capitalization to produce total returns that are more in line with the market's returns. Table 2 gives the annual returns for an overnight-only strategy for each decile portfolio. The last two columns present the corresponding intraday and full day returns for each portfolio. To account for risk, Table 2 also includes the "alpha" or risk-adjusted return of the overnight strategy measured with the single-index model:

$$r_t^O - r_f = \alpha + \beta\left(r_t^m - r_f\right) + \varepsilon_t, \tag{5}$$

where r_t^O is the overnight return of a decile portfolio; r_f is the risk-free rate; and r_t^m is the market's close-to-close return on day t. Fama-French's three-factor model is considered as an alternative to the single-index model and yields essentially the same results. Note that, in this case, the returns are not in log form. The values for r_f and r_t^m are taken from Fama and French's data.

[Table 2 here]

Table 2 shows that the decile portfolios do not have major differences in terms of total returns; however, there is a clear relationship between the deciles and the partition of overnight and intraday returns. For the top-decile portfolio, overnight returns are 40.43% and intraday returns are -22.07%. Results for the bottom-decile portfolio are the opposite: a -17.08% return overnight and a 33.08% return intraday. The risk-adjusted results indicate similar trends, with annualized alphas of 33.93% and -20.73% for the top- and bottom-decile portfolios, respectively. Portfolios in the intermediate deciles display a smooth progression between these two extremes.

These figures are larger than the 0.68% monthly return that Jegadeesh and Titman (1993) report for the difference between the top- and bottom-decile momentum portfolios. While the traditional concept of momentum is often linked with deviations from fundamental values associated with waves of optimism or pessimism, the last column of Table 2 shows that the continuation of superior *overnight* returns is not accompanied by a continuation in superior *total* returns and that the phenomena are different in nature.

What is the source of the “overnight momentum” strategy’s profits? Turning to the momentum literature and Lo and Mackinlay’s (1990) decomposition, three statistical factors are often cited as potential sources of profits for momentum strategies: positive autocovariances for individual securities; negative autocovariance for the equal-weighted market index; and cross-sectional variance of the mean returns. This paper emphasizes the role of the third component and a simple way to understand why these cross-sectional variations generate profits is that the top decile portfolio is likely to pick stocks with high overnight return means. As Lewellen (2002) puts it, “On average, stocks with the highest unconditional expected returns also have the highest realized returns.” Conrad and Kaul (1998) show that these variations can generate profits even if prices follow a random walk.

Jegadeesh and Titman (2001) suggest that the presence of mean effects can be tested by evaluating the performance of the decile portfolios several years after the portfolios’ formation: if momentum performance is due to higher means, it should persist over time. They find that momentum profits are positive for the first 12 months following the formation period, but then turn negative after 13 to 60 months. This exercise is repeated at the bottom of Table 2 with overnight returns. The performance of the decile portfolios is evaluated in each of the five years following the portfolios’ formation and the results provide evidence that long-term means play a role in our results: performance attenuates over time, but it does not reverse or disappear. Overnight returns for the top-decile portfolio are 24.01% (after one year), 20.30% (after two years), 21.11% (after three years), 17.33% (after four years), and 11.92% (after five years).

If the profitability of an overnight strategy is based on picking stocks with higher expected overnight returns, then the profits of an overnight momentum strategy might simply be a normal reward for selecting stocks with characteristics priced by the market. For instance, stocks in the top decile are riskier, and observing higher returns can be consistent with higher risk. However, this argument does not explain why these riskier stocks simultaneously have the lowest intraday returns and, in particular, why these returns are negative. While recognizing that characteristics priced by the market can explain part of the performance of the overnight momentum strategy, this paper argues that there is more behind the cross-sectional variations in overnight return means than traditional relationships with stock characteristics. Specifically, the means of the overnight and intraday return processes appear to be distorted by offsetting biases. The presence of reversing biases is suggested most notably by the fact that there is more dispersion in the means of overnight and intraday returns than in the means of total daily returns.[5] This idea is also consistent with the earlier finding that the means of overnight and intraday returns are negatively related in the cross-section and would explain why they have opposite relationships with characteristics such as risk. Section 4 will incorporate these biases in a model of overnight and intraday returns.

[5] To take into account that stocks with fewer observations can have more-dispersed means, stocks are first grouped by their number of observations. Standard deviations are computed for each group and then averaged across the groups. The resulting dispersion in means averages 1.48% for overnight returns, 1.72% for intraday returns, and 1.13% for total returns.

3.3 INTERNATIONAL STOCKS

Before presenting the model, the paper evaluates whether persistency in overnight returns is confined to the United States. For this purpose, an additional dataset is constructed with the constituents of major indexes representing the 23 developed markets in MSCI's World Index for the period 2002-2014. The lines "WA" in Table 3 present the weighted-average overnight and intraday returns for each country. The indexes' constituents, weights, dividends, opening prices, and closing prices are taken from Bloomberg.[6] Remarkably, overnight returns dominate intraday returns in all 23 cases, although just barely for New Zealand. Overnight returns average 18.8% versus -9.3% intraday. These results can be contrasted with those of Qiu and Cai (2009), who report higher overnight returns for 14 out of 19 developed countries based on index prices. Index prices can understate overnight returns, as some suffer from stale-quote problems. For instance, the S&P 500 index uses the previous day's closing price for stocks that have not started trading when the market opens. To illustrate this, Table 3 also gives the returns computed with the indexes' opening and closing prices in the lines "Index." Five countries have lower overnight returns on this basis, but they are likely affected by stale prices since they have a high proportion of near-zero (less than 0.01%) overnight returns and much less overnight volatility than their corresponding ETF. Hence, positive overnight spreads are common, which suggests that the phenomenon is not simply spurious.

[Table 3 here]

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[6] The weights are not directly available from Bloomberg for half of the indexes. For these indexes, the weights are approximated with market capitalization proportions, subject to the index's caps. Weighted returns correlate highly with index returns; small differences can arise because of missing observations and methodological differences—e.g., because market capitalization is used instead of float for the weights.

The constituents of the indexes listed in Table 3, with the exception of the United States, are combined into a dataset to test for persistency in overnight monthly returns at the international level. For this exercise, the Fama-MacBeth regressions in Equations (3) and (4) are modified to include country dummy variables. The regression results confirm that the relationship between current and past monthly overnight returns outside the United States is positive for all lags up to 60 months and generally statistically significant. The relationship with intraday returns is negative. Table 3 illustrates persistency at the country level with Table 2's decile methodology applied to the constituents of the indexes. Using index constituents has the advantage of eliminating smaller stocks, but it also creates the caveat that each index's cross-section counts fewer stocks—69 per year, on average. Given the lower number of stocks, Table 3 reports overnight returns based on the past year's quartiles rather than deciles of overnight returns.[7] In each country, current overnight returns increase unambiguously with the quartiles of lagged overnight returns. The overnight return difference between the top and bottom quartiles is high at 40%.

Analyzing each country in detail is beyond the scope of this paper; thus, the remainder of the analysis will focus on American stocks. In particular, transaction costs vary, and are typically higher outside the United States. Hence, the profitability of overnight strategies after costs would need to be evaluated with each exchange's pricing structure, including taxes and regulatory fees. While international exchanges tend to be handicapped by higher costs, Table 3 shows that they offer higher overnight returns, on average. This suggests that overnight strategies could take a

[7] Individual country quartile results should be interpreted with caution, as some of the quartiles have as few as five stocks.

different form at the international level and potentially target indexes rather than individual stocks.

4. Overnight Bias Model

Following Section 3.2's discussion, this section introduces an Overnight Bias Model with offsetting biases in the means of the overnight and intraday return processes. To start with, note that the literature is not entirely clear as to how returns should be modeled during non-trading (overnight) periods. For instance, in his work on the weekend effect, French (1980) contrasts a calendar time hypothesis by which returns accrue continuously and a trading time hypothesis by which returns are generated only during active trading; he finds that returns are inconsistent with both models. One point that is generally agreed upon is that there is less activity overnight: French and Roll (1986) find that more private information is incorporated during the day; George and Hwang (2001) study the rate of information flow during trading and non-trading periods and estimate that the median daytime rate is about seven times higher than the overnight rate; Barclay and Hendershott (2003) examine after-hours trading and attribute 85% of the weighted price contribution to the daytime period.

4.1 MODEL

Using log returns, a stock's total return can be written as $r = r^O + r^I$. In the absence of abnormal returns, the model assumes that, on average, a component $\theta \cdot r$ of returns is earned overnight and the balance $(1 - \theta) \cdot r$ accrues intraday. Absent any bias in the distribution of positive/negative news, the parameter θ should capture differences in information flow and be higher for firms with more overnight activity. Following George and Hwang's (2001) finding that more information is incorporated in prices during the daytime, the model assumes that $\theta < 1/2$. Up to this point, the model predicts that daytime returns should be higher than overnight returns in absolute terms. Overnight returns in excess of $\theta \cdot r$ represent an "overnight bias," which is denoted by a parameter OBP. Each stock can have a different OBP. Since the overnight bias does not affect the stock's total return prospects, intraday returns must be adjusted by a corresponding negative mirror effect $-OBP$. Therefore, the model can be expressed with the following conditional expected returns:

$$\mu_r^O = E[r^O|r] = \theta \cdot r + OBP, \tag{6}$$

$$\mu_r^I = E[r^I|r] = (1-\theta) \cdot r - OBP. \tag{7}$$

This model implies that the means of the overnight and intraday return processes are inversely related through the parameter OBP. Note that this is different from assuming that daily intraday and overnight returns are negatively correlated in the time-series, which should not affect the means of the processes.[8]

To estimate a stock i's parameters θ_i and OBP_i, this paper proposes a simple linear regression model in which daily log overnight returns are regressed on daily log total returns as follows:

[8] Cliff et al. (2008) and Branch and Ma (2012) report a negative cross-sectional relationship between daily intraday and overnight returns but do not discuss time-series properties. In this paper's sample, the average time-series autocorrelations are small and negative, but they are not connected with higher overnight returns.

$$r_{i,t}^{O} = OBP_i + \theta_i \cdot r_{i,t} + \varepsilon_{i,t}. \tag{8}$$

When overnight and intraday returns are uncorrelated, the estimate of the parameter θ has a simple interpretation as the ratio of overnight return variance to total return variance. This parameter can be viewed as a control for the relative quantity of news that arrives overnight. Throughout the paper, the estimates for OBP are presented in annualized form using $(1 + OBP)^{252} - 1$.

This model is estimated for each stock and year included in Table 1's sample, which results in a total of 51,089 pairs of estimates for the parameters OBP and θ. To avoid undue influence from extreme observations, the top and bottom return observations are winsorized in these calculations. The average θ estimate is 17.86% and, confirming the model's earlier assumption, over 99% of the observations have θ estimates of less than one half. The exceptions are usually stocks that are also listed in Europe (such as Unilever and Deutsche Bank), where predictions related to information arrival can be inverted. OBP estimates average 8.38%, and Section 4.3 will analyze further the distribution and determinants of these estimates.

4.2 MODEL FIT AND PREDICTIONS

Figure 2 illustrates the model's ability to fit the data out-of-sample. This figure graphs the average annual overnight and intraday returns as a function of total returns. The averages are computed for each percentile of the total return distribution. The dots represent the actual returns and the lines the values predicted by the model. Specifically, for each stock and month in our sample, the monthly overnight and intraday returns are projected using Equations (6) and (7), the current month's total return, and the parameters OBP and θ estimated with Equation (8) and data from the previous year.[9] The monthly values are compounded to obtain annual values. The model fits the data extremely well, with an R^2 of 0.98 for overnight returns. This is an improvement over an alternative in which overnight returns would be projected simply as a fraction of total returns, which would yield an R^2 of 0.79. Of course, it should be pointed out that the fit here concerns average values; individual overnight returns in any given year can be noisy, and the model only attempts to predict their expected values.

Besides showing that the model fits the data well, Figure 2 provides a surprising new empirical result: average overnight returns are always positive, even when total returns are in the bottom percentiles of their distribution. Again, it should be kept in mind that these are long-term averages and that overnight returns can be negative in any particular year. The model predicts and reconciles Figure 2's puzzling empirical observation. A combination of two factors explains why overnight returns are so resilient when stocks perform poorly. The first one is not related to biases but, rather, to the $\theta \cdot r$ portion of the model: because overnight returns are less sensitive to total returns, they will be less affected than intraday returns in a downturn. Based on the average estimate for θ of 18%, a loss of -10% in total returns translates into a loss of only -1.8% in overnight returns. The second factor is the "bonus" overnight return provided by the parameter OBP, which helps offset losses. This bonus is actually larger for stocks that perform more poorly. For instance, the average OBP is 20.88% for stocks in the bottom decile of total returns, which is sufficient to hedge most losses and even move returns into positive territory.[10]

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[9] The top and bottom 0.5% of the distribution of OBP estimates is winsorized before projecting the values.

[10] Both the best and worst performing stocks have higher OBPs because they tend to be the more volatile stocks. The next section will show that riskier stocks have higher OBPs.

Finally, Figure 2 provides some insights into overnight spreads—i.e., the difference between overnight and intraday returns. The literature has largely equated positive overnight spreads with abnormal overnight returns, but Figure 2 and the Overnight Bias Model show that this measure has limitations, as it is systematically related to performance: overnight spreads are positive in poor performance scenarios and negative in good ones. Thus, observing positive overnight spreads in market downturns does not imply that overnight returns are positively biased; this result should be expected. By the same token, observing negative overnight spreads when the market outperforms does not contradict the existence of overnight biases. More precisely, the model predicts that overnight-only returns dominate full day returns to the extent that the latter do not exceed a threshold $OBP/(1-\theta)$. Accordingly, an important caveat of overnight-only strategies is that they are indicated more in bearish/flat scenarios than bullish ones. The exception is for stocks with high OBPs for which the threshold will be met in all but extremely good scenarios.

[Figure 2 here]

4.3 OVERNIGHT BIAS PARAMETER ESTIMATES AND DETERMINANTS

Table 4 presents the distribution of the OBP estimates and details their relationship with stock characteristics in two ways. The first column gives the results of a Fama-MacBeth regression analysis of determinants. The next four columns present the average characteristics of the sample by level of OBP for the current year. The four categories used are: 1) OBP positive and significant, 2) OBP positive and not significant, 3) OBP negative and not significant, and 4) OBP negative and significant. The positive and significant category is labeled Overnight Bias

Group (OBG)—this group will be the primary focus of the analysis in the next sections. The negative and significant category is labeled Intraday Bias Group (IBG). Statistical significance is at the 5% level in a one-sided test. One advantage of this classification over the deciles used in Table 2 is that it is less biased towards volatile stocks, as the t-statistic controls for volatility. On average, stocks tend to perform better overnight than their relative volatility suggests; the average and median OBPs are 8.38% and 2.56%, respectively. OBG stocks are fairly common, with, on average, 524 stocks per year—this is one out of five stocks in the sample or a third of the sample's trading volume. Stocks with positive, but not significant, OBPs represent another 34% of the sample. The number of stocks in the OBG classification can vary considerably over the years and increases when overnight returns at the market level are higher.

[Table 4 here]

In terms of characteristics, OBG stocks are more volatile, have higher betas, are much more highly traded, are larger in terms of market capitalization, are less likely to be listed on NASDAQ, and have higher returns in the previous year. Momentum stocks fit in this last category. They also have less institutional ownership and are more likely to be value stocks, but these differences are not extreme or systematic across the four groups. In Table 4, the value indicator is the HML coefficient in Fama-French's three-factor model. Although not reported in the table, an examination of the association with NAICS codes indicates that industry distributions are similar for OBG and other stocks; the exception is mining which represents 9.4% of OBG stocks and 5.3% of all stocks.

In line with this paper's thesis that overnight biases have recurring patterns over time, stocks that are in the Overnight Bias Group in the current year have high OBPs in the previous year, with an average of 25.4%. The relationship between OBP_T and OBP_{T-1} can be tested more formally with a Fama-MacBeth regression framework that controls for the effect of other variables. Specifically, for each of the 20 years T in the sample, the following cross-sectional regression is applied:

$$
\begin{aligned}
OBP_{i,T} &= \alpha + \beta_1 \cdot OBP_{i,T-1} + \beta_2 \cdot \sigma_{i,T} + \beta_3 \cdot Turnover_{i,T} + \beta_4 \cdot Mkt\ Cap_{i,T} \\
&+ \beta_5 \cdot NASDAQ_{i,T} + \beta_6 \cdot Return_{i,T-1} + \beta_7 \cdot Value_{i,T} + \beta_8 \cdot Inst\ Own_{i,T-1} + \varepsilon_{i,T}.
\end{aligned}
\tag{9}
$$

The first column of Table 4 presents the average coefficients for this regression along with their t-statistics based on the standard errors $\sigma(\hat{\beta})/\sqrt{20}$. In separate tests, the regression is performed with each individual variable to detect potential multicollinearity problems.

Table 4 indicates that the lagged value OBP_{T-1} is highly statistically significant and is actually the most important determinant of the current OBP_T in terms of t-statistic. Among the other variables, volatility and turnover also play positive and important roles, consistent with Cliff et al.'s (2008) results for daily overnight returns and spreads. Beta is not included in Equation (9), as it is highly correlated with the standard deviation. In a second regression exercise, beta is substituted for σ, resulting in a positive and significant effect. Table 4 indicates a positive relationship with the previous year's return, which is in line with Lou et al.'s (2015) finding that momentum stocks tend to accrue their returns overnight. The negative relationship with institutional ownership is consistent with a similar result in Berkman et al. (2012) for daily overnight returns.[11] The negative relationship with NASDAQ-listing is less clear and might be

[11] The institutional ownership variable is the percentage of a stock's float owned by institutions, where percentages above 100% are winsorized. Quarterly figures are averaged over the year. This variable is used only for 2000-2014, and missing observations (24% of the sample) are replaced by the average institutional ownership for the year.

driven by smaller stocks. While fewer NASDAQ stocks fall into the OBG category, those that do have larger market capitalizations and, on a value-weighted basis, perform better overnight than NYSE stocks. Value and size variables do not appear to play a key role in shaping OBP. The value indicator is not significant, and the market capitalization variable has a low R^2 on an individual basis.

The paper also uncovers a new relationship between overnight returns and recently-issued stocks. The regression in Equation (9) is not a practical framework in which to evaluate these stocks because it requires a minimum of two years of data. To analyze these stocks, Table 1's sample is extended to include partial years of observation. For this exercise, the date of issuance is defined as the date of the first record available in CRSP, which is commonly the date of an IPO. The analysis includes 4,369 firms with issuance dates between January 1, 1995 and December 31, 2014. Figure 3 tracks their monthly overnight and intraday returns in the five years after issuance. Overnight returns are clearly elevated in the months following issuance, with a monthly average of 3.5% in the first three months. They gradually decline over time and reach the sample average after five years. Monthly OBPs follow similar patterns. By contrast, intraday returns start low, at 0.3%, and increase over time. Thus, newer stocks are more subject to overnight biases than those that are more mature. To summarize this section, there are many characteristics associated with higher overnight returns, most of them related more to short-term trading than to long-term investments.

[Figure 3 here]

5. Risk-Adjusted Returns

This section evaluates the performance of overnight-only investment strategies over the period 1995-2014. The preferred strategy is not to invest in all stocks, but to focus on those that had significant overnight biases in the past. The OBP estimates allow us to identify these stocks, using the same four group classification as in Table 4 and the *previous* year's estimates. In other words, Table 5 illustrates the out-of-sample performance of the OBP classification. It presents the results for portfolios representing: 1) each of the four OBP groups; 2) a long position in OBG stocks and a short position in IBG stocks; and 3) all stocks. For each portfolio, returns are computed daily and value-weighted by the previous day's market capitalization. The table also includes the alphas (risk-adjusted returns) and betas computed with Equation (5). Again, alphas are annualized using $(1 + \hat{\alpha})^{252} - 1$.

[Table 5 here]

A strategy of investing in all stocks overnight-only yields a positive risk-adjusted return of 2.07% but lacks statistical significance. The situation is much different when stocks are sorted into the four OBP groups and all alphas are significant. Over the 20-year period covered by the sample, an overnight portfolio invested in OBG stocks yields a 25.87% annual return, or 20.13% on a risk-adjusted basis. This superior performance is not linked with unusually high levels of risk: the portfolio's beta is 0.31 and its standard deviation is 11.46%. While OBG stocks are more volatile than other stocks, this is balanced by the fact that overnight returns are less risky than full-day returns. The combined result is that the overnight OBG portfolio is less volatile than a full-day investment in the market portfolio, which has an annualized return of 10.00% and a standard deviation of 19.34%. In other words, the OBG overnight portfolio easily dominates the market portfolio.

Turning to the other groups, performance is more modest for stocks with positive but insignificant OBPs, with a risk-adjusted return of 3.94%. However, stocks with negative OBPs in the past systematically underperform overnight, and IBG stocks exhibit a negative alpha of -15.60%. This result can be exploited with a short position in IBG stocks. The long OBG-short IBG strategy performs particularly well, with an alpha of 42.30%. Given that it hedges a large portion of market risk, this strategy reduces volatility to only 6.60%. More generally, the long-short strategy is a useful tool for analyzing overnight biases because it cancels out the impact of large market events occurring at a given point in time.

5.1 ROBUSTNESS TESTS

Table 6 presents several robustness test for Table 5's risk-adjusted returns. First, Fama and French's (1993) three-factor regression model is considered as an alternative to the single-index model. This model adds to Equation (5) a factor HML (high-minus-low) for the book-to-market ratio and a factor SMB (small-minus-big) for market capitalization. The change shows virtually no impact on the results. The choice of using value-weighted returns is on the conservative side, as using equally-weighted returns instead increases alpha to 23.86% for OBG stocks. Another concern with overnight returns is that they bear the blunt of earnings announcements. As Jiang, Likitapiwat, and McInish (2012) document, companies now primarily make these announcements after-hours, which impacts overnight returns. Table 6 shows that excluding days with earnings announcements does not affect alpha.[12]

[12] The dates and times of earnings announcements are taken from I/B/E/S. When the data are not available in that database, the information is taken from Bloomberg.

[Table 6 here]

Table 6 subsequently provides the most convincing robustness test for the results by showing that risk-adjusted returns for OBG stocks are positive in each of the 20 years in the sample. While not reported in the table, the intraday returns for OBG stocks are negative in 18 of the 20 years—something that should be a concern for daytime investors. The ordering among the performances of the four OBP groups is constant across all years, and, in particular, IBG stocks have negative alphas every year. Given that one year is a short period, the alphas for OBG stocks are not always statistically significant. The long-short strategy, however, removes most of the impact of market fluctuations and displays positive and significant results at the 1% level in every year.

Examining the individual years in Table 6, two periods are noteworthy. The dot-com bubble was an extreme period in terms of overnight returns, with alpha reaching 19.71% in 1999 at the aggregate market level (53.43% for OBG stocks). The worst year was 2001, due in part to the period of market closure triggered by the September 11, 2001 events. To evaluate how the OBP groups perform in up and down markets, the sample is next sorted by quartile of monthly market performance. The results indicate that the risk-adjusted returns of OBG stocks in the worst-performing months are robust, and even slightly higher. Another way to test the impact of adverse market conditions is to use the periods of market contraction as defined by the National Bureau of Economic Research (NBER). In the sample, these are from March 2001 to November 2001 and from December 2007 to December 2009. Given the short time period, this test excludes September 17, 2001 to avoid confounding effects from the World Trade Center events. Again, the risk-adjusted performance of OBG stocks holds up.

Table 6 provides some additional robustness tests by considering various subsets of stocks. The results are presented for the top and bottom quintiles of the variables listed in Table 4 and for NYSE and NASDAQ stocks. For these calculations, stocks are sorted monthly, based on their characteristics for the previous year. Risk-adjusted returns for OBG stocks remain high for every sub-group; they are at their highest (36.68%) for the most volatile stocks and at their lowest (11.51%) for the least volatile ones. Three variables have alphas above 10% for their top quintile group: standard deviation (18.24%), turnover (17.88%), and previous-year return (12.60%). These could be alternative criteria to select portfolios for an overnight strategy. Whichever characteristic is used, Table 6 shows that it is always beneficial to additionally consider the OBP classification. For instance, within any of the top quintile groups, it is not profitable to invest overnight in stocks that had negative OBPs in the previous year. Furthermore, restricting stocks to those that satisfy the OBG test boosts a category's performance by 18.45%, on average. While this paper focuses on overnight strategies that invest in OBG stocks, the OBP measure is an all-purpose tool with potential applications to a variety of trading strategies that exploit overnight returns.

5.2 TRANSACTION COSTS

The final robustness test presented in Table 5 considers the impact of commissions, which are paramount to the profitability of strategies involving daily trades. Commissions have declined significantly recently, providing the impetus for considering high-turnover strategies that would have been dismissed in the past as being cost-prohibitive. The results presented here are calibrated with fee structures that applied in 2014. Three factors can affect commissions: the broker's commission structure; the stock's price; and the size of the investment. The most common commission structure among online discount brokers is a flat fee per trade, which normally ranges from \$7 to \$10. However, this is not necessarily the most cost-effective way to implement a high-turnover strategy. The alternative is a per-share fee structure on the order of \$0.005 to \$0.01, which is typically cheaper for trades involving a limited number of shares. The illustrations in this section are based on the lowest fees available—i.e., the minimum between a \$7 flat fee and \$0.005 per share (subject to a dollar minimum per trade).[13] In addition to the commission, the costs recognize the regulatory fee paid under Section 31 of the Securities and Exchange Act, which is 0.00221% of sales as of September 30, 2014. More precisely, for a share price of P and an investment of I, the daily percentage round-trip cost is:

$$\% \text{ round-trip cost} = 2 \cdot \min\left[\$7, \max\left[\$0.005 \cdot \frac{I}{P}, \$1\right]\right] / I + 0.00221\%. \qquad (10)$$

For stocks with share prices P above \$50 and investments I of at least \$10,000, annual costs with the per-share fee structure are, at most, 5.60% based on 252 trading days per year. Stocks with share prices lower than \$50 can be more problematic with this structure: the annual percentage costs are 51% for a \$5 stock, 26% for a \$10 stock, and 7% for a \$40 stock. While low-priced stocks have to be viewed carefully with high-turnover strategies, they can be considered in the context of a flat-fee structure and larger investments. For example, for a

[13] For example, Scottrade offers the \$7 flat-fee commission structure and Interactive Brokers the \$0.005 per-share structure. Note that these do not represent the absolute minimum commissions available in the market. Lower prices exist, in particular with high volumes or with an unbundled fee structure.

$100,000 investment and a $7 flat fee, the annual cost would be 4.08%, regardless of the price of the stock.

Since costs can vary with the size of the investment, this section gives the costs for two trade sizes: $10,000 per stock and $100,000 per stock. Specifically, daily percentage costs are computed with Equation (10) and the actual share prices for each day and stock in the sample. These costs are value-weighted and subtracted daily from the portfolio's performance. The average daily costs in the $10,000 and $100,000 cases are 3.1 bps and 1.5 bps, respectively. The impact of these costs on annualized alphas increases with the level of alpha. For OBG stocks, the resulting after-cost alphas are 10.45% and 15.69%, confirming that the overnight strategy can be profitable even after realistic transaction costs are taken into account. The other columns in Table 5 show that long overnight strategies are worthwhile primarily for OBG stocks once costs are recognized. Stocks with positive but not significant OBPs are not profitable after-cost; neither is the overall market. Stocks with negative OBPs obviously perform even worse. In their case, short strategies can be considered. For IBG stocks, the after-cost alpha of the short strategy is significant at 9.19% in the $10,000 case (not in table). The long-short strategy is also very lucrative, with after-cost alphas of 20.60% and 31.80%, but it is more impacted by costs because they have to be paid for each leg of the strategy.

Of course, this is a forward-looking exercise and these results do not imply that the strategy would have been successful 20 years ago with the commission rates that applied at that time. While all securities were included in this computation, *ceteris paribus*, overnight strategies in practice should use stocks with the lowest transaction costs. For instance, the performance in the $10,000 scenario can be improved by restricting stocks to those with share prices above $50.

Excluding stocks with low share prices does not affect the before-cost performance of the OBG portfolio and increases its after-cost alpha to 14.10%.

6. Implementation with the Opening and Closing Call Auctions

An analysis of transaction costs would often also include an allowance for bid-ask spreads. These are omitted here because the overnight strategy presents a singular opportunity to avoid these costs by participating in the exchanges' single-price call auctions at the open and the close. NASDAQ started the Opening and Closing Crosses in 2004 to facilitate price discovery. Market-on-open (MOO) and limit-on-open (LOO) orders can be entered until 9:28, and they execute specifically at the opening price at 9:30. Market-on-close (MOC) and limit-on-close (LOC) orders can be entered until 15:50 and they execute at the closing price at 16:00. The clearing prices in the crosses are determined by an algorithm to maximize the number of contracts executed. The NYSE offers similar MOC/LOC orders that must be entered by 15:45 and MOO/LOO orders that can be entered until the open. The NYSE differs from NASDAQ in that the Designated Market Maker can delay the open.[14]

The auction facilities make it straightforward to implement an overnight investment strategy by entering MOO and MOC orders ahead of time. The 2010-2012 subsample of TAQ data provides information about the call auctions. TAQ identifies opening auction trades by a condition code "O" or "@O" and closing auction trades by "6" or "@6". These trades can be

[14] For more information on the auctions, see Bacidore et al. (2013), Pagano, Peng, and Schwartz (2013), and NASDAQ OMX (2012). The relevant NYSE rules (13, 115D, 123C, and 123D) are available online at http://nyserules.nyse.com/NYSE/Rules/.

located for 97% of the sample's daily observations, and a majority of stocks have identifiable prices for the opening and closing call auctions on over 99% of days. The data indicate fairly prompt opening and closing times, with NASDAQ stocks opening (closing), on average, at 9:30:00 (16:00:03) and NYSE stocks at 9:30:38 (16:02:28). The TAQ call auction prices can be compared with the opening and closing prices reported in CRSP.[15] Most often, these are the same, but discrepancies can arise because of market fragmentation. This typically happens with NYSE-listed stocks since these stocks can trade on other exchanges in the few seconds it takes the NYSE to open them. Specifically, CRSP prices exactly match TAQ's opening and closing auction prices 76% and 98% of the time, respectively. The difference between the average prices in the two datasets is too small (less than one tenth of a penny) to affect earlier conclusions.

The TAQ data can be used to test the sensitivity of returns to timing trades exactly at the open and the close. Minute-by-minute returns are constructed by dividing the last trade price for that minute by the previous day's closing price.[16] The calculations include after-hours trading, which starts at 4:00 and ends at 20:00. If a stock does not trade in a given minute, the last trade price available is used. Note that stocks trade more infrequently before the open, and returns can be stale. Prices are adjusted for dividends and splits and the day of the "flash crash," May 6, 2010, is excluded from the calculations. Figure 4 presents the results separately for the four OBP classifications used in Tables 5 and 6. Specifically, the portfolios are sorted by the previous year's OBPs; the classification is rebalanced monthly, and returns are market-weighted using the

[15] CRSP's documentation describes its opening price as "the first trade of the day" and its closing price as "the last trade price for that day on the exchange on which the security last traded."

[16] For these calculations, only records with correction codes 0 and 1 are used, and those with condition codes 4, L, M, P, Q, U, W, Y, and Z are filtered out. Price jumps that reverse immediately are discarded as outliers.

previous day's market capitalization. The period counts on average 2,390 stocks, 342 of which are in the OBG category.

[Figure 4 here]

Figure 4 reveals that, leading to the open, there is an unmistakable gap between OBG and IBG stocks. The 9:30 daily average return for OBG stocks is 0.083% versus -0.035% for IBG stocks; annualized, this represents a 34.5% difference.[17] Excess overnight returns for OBG stocks are actually fully realized a few minutes before the market officially opens at 9:30. Barclay and Hendershott (2003) study extended-hours trading and describe this environment as being dominated by professional and quasi-professional traders. This observation suggests that more-sophisticated traders can be behind abnormal overnight returns, although it does not rule out that other investors play an indirect role through their anticipated demand.

Excess overnight returns for OBG stocks disappear quickly after the open, but not instantaneously. They decline by 0.02% if sales are postponed by a few minutes after the open and disappear after 45 minutes. All four groups have the same returns after that period and essentially move in tandem for the rest of the day, reflecting market-wide effects. Stocks with positive overnight biases appear to be more subject to selling pressure in the mid-afternoon, but these differences are not statistically significant. For daytime investors, the flip side of excess overnight returns is that OBG stocks tend to experience intraday losses. The graph indicates that, on average, these losses can be avoided by waiting 30-45 minutes after the open to purchase these stocks.

[17] These returns represent an arithmetic average based on the last trade price available at 9:30:00 and can differ from the overnight returns reported earlier, which are computed as a geometric average with opening prices.

One of the limitations of the strategy suggested in this section is that it might be difficult to implement large trades in stocks with limited liquidity at the open. While price impact is a concern for larger trades, it should be pointed out that the auction mechanisms attempt to mitigate this issue by periodically broadcasting order imbalances to attract liquidity to the auctions. The average daily volume of OBG stocks' opening and closing auction trades are, respectively, $1.1 million and $2.4 million, representing 3.8% of the day's trading volume. Figure 4 illustrates the minute-by-minute return volume pattern for OBG stocks, which display the typical U-shape, with heavier trading in the first and last hours of the day.

OBG stocks actually trade much more than other stocks earlier in the day, which is easier to visualize by graphing their volume as a fraction of total market volume. The resulting pattern in Figure 4 is highly skewed towards the open and declines throughout the day. OBG stocks account for 40% of trading volume in the pre-open session and 29% right after the open. This is high when considering that these stocks' share of market capitalization is 15% during the period examined. By the time the market closes, OBG stocks' share of market volume drops to 17%. Traders may be averse to initiating new overnight positions in these stocks due to risks, costs, and constraints.[18]

Whether liquidity is ultimately an issue for an overnight strategy depends on the type of stock involved. Mega-cap stocks such as Apple with $100 million per auction, should have no problem accommodating trades of a reasonable size. At the other extreme, some stocks have limited volume and are less desirable candidates for an overnight strategy. For example, 10%

[18] Pattern day traders' buying power is four times equity during the day but must be restricted to only two times equity by the close. On the cost side, interest on margin accounts is calculated using end-of-day balances, effectively making leveraged investments interest-free during the day and costly overnight.

(25%) of OBG stocks in terms of market capitalization have a cumulative volume of less than \$1 million (\$5 million) in the first 15 minutes of trading. This is not a critical issue as these stocks can be identified in advance and excluding them does not reduce overnight returns for OBG stocks. Between the two extreme cases lies a scenario in which trades get only partially executed in the opening auction and have to be completed in the subsequent continuous auction. To estimate overnight returns that take into account post-opening prices, volume-weighted average prices (VWAPs) are computed using two alternative stopping points: 1) a fixed period of 15 minutes after the open; and 2) a volume-based clock of \$5 million within that 15 minutes.[19] Daily overnight returns decline to 0.056% with the fixed-period VWAPs, but hold steady at 0.084% with the volume clock. Although the OBG overnight strategy still yields excess returns with these liquidity considerations taken into account, investors should be mindful that executing trades farther from the open can reduce returns.

7. Conclusion

The paper's title asks the question: "Night trading: Lower risk but higher returns?" The answer is yes, but only for stocks with positive overnight biases in the past. When transaction costs are taken into account, the affirmative answer is limited to stocks with *significant* and positive overnight biases in the past. The paper makes several contributions to the overnight return literature, most notably by demonstrating that overnight biases are prevalent across the

[19] The opening call auction is included in both calculations. See Easley et al. (2012) for an explanation of volume clocks. VWAPs in this case are computed over the period it takes for cumulative volume to reach \$5 million, but only for stocks that attain that threshold within the first 15 minutes of trading (75% of OBG stocks).

world; they are persistent over time; they can be modeled; and they can be used as the basis for the development of profitable investment strategies even after taking transaction costs into account. These results should be of interest to investors concerned with the optimal timing of trades, to portfolio managers looking for alpha-generating strategies, to market makers holding overnight inventories, and to researchers working with opening prices.

To conclude, an open question for future research is: What causes overnight biases? The existing literature points to different directions in that regard: Kelly and Clark (2011) attribute the effect to semiprofessional traders who sell their positions at the end of the day and re-establish them in the morning; Berkman et al. (2012) emphasizes the role of retail investors and hypothesize that their herding behavior in high-attention stocks pushes opening prices up; Lou et al. (2015) highlight the negative intraday pressure that institutional investors put on momentum stocks. In line with some of these explanations, this paper's volume data show that OBG stocks have a much higher trading volume than other stocks around the open. Order imbalances can result in temporarily higher prices if too many buyers converge in the same stocks at the same time. Whether or not investors attempt to exploit the overnight bias directly, they should, at the very least, be aware of statistical headwinds that may affect their strategies.

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TABLE 1
Sample - Descriptive Statistics

The initial universe of stocks considered is all securities in the CRSP database with the exception of ETFs, ADRs, and closed-end funds. On average, this universe consists of 5,932 stocks per year, and the sample retains 2,554 stocks with at least 240 valid trading days for the current and past years. Stocks with monthly average prices of less than $5 are excluded from the sample. The sample's market capitalization represents 91.2% of CRSP's total market capitalization. Years with annual overnight or intraday returns above 250% as well as days with missing opening or closing prices are screened out. Beta is the market return regression coefficient computed with Equation (5). For excluded stocks, standard deviations and betas are computed only for stocks that trade for an entire year. The sample counts 12,847,083 daily observations, and the table gives an arithmetic average of all daily returns. Daily standard deviations are computed for each stock and averaged across stocks. Value-weighted returns are computed daily for each category and individual returns are weighted by the previous day's market capitalization; the results are compounded and annualized. The period covered is from January 1, 1995 to December 31, 2014.
Source: CRSP

	Sample			Excluded		
Average Annual Values						
Number of Stocks		2,554			3,378	
Market Capitalization ($B)		5.31			0.44	
Daily Trading Volume ($M)		36.73			5.12	
NASDAQ-Listed (%)		41.60			72.43	
Share Price ($)		32.98			11.28	
Standard Deviation (%)		39.78			73.14	
Beta		0.96			0.92	
	Overnight	Intraday	Full Day	Overnight	Intraday	Full Day
Daily (%)						
Average Returns	0.024	0.046	0.067	0.118	0.009	0.082
Standard Deviation	1.45	2.60	2.85	3.09	4.41	4.80
Annualized (%)						
Value-Weighted Returns	6.84	3.72	10.81	26.06	-12.19	10.69

TABLE 2

Overnight-Only Strategy:
Performance of Decile Portfolios Sorted by Lagged Overnight Returns

The table presents the annual returns and standard deviations associated with a strategy of investing overnight-only in decile portfolios, sorted by the past year's overnight returns. Each decile counts, on average, 255 stocks per year. The last two columns give the corresponding intraday and full-day returns for the decile portfolios. Portfolio returns are computed by weighting returns daily by the previous day's market capitalization. The deciles are determined and rebalanced at the beginning of each month. The bottom portion of the table shows the overnight returns of these portfolios from one to five years after the decile portfolios' formation. The table also reports alphas and betas computed according to Equation (5). Annualized alphas are computed with $(1+\hat{\alpha})^{252}-1$, where 252 is the average number of trading days per year. The period covered is from January 1, 1995 to December 31, 2014. All figures are in percent. Significance at the 1% and 5% levels is denoted by ** and *, respectively. *Source*: CRSP

Decile	Overnight-Only Strategy				Intraday	Full
(Previous Year	Overnight	Standard	Single-Index Model			day
Overnight Returns)	Return	Deviation	$\hat{\alpha}$	$\hat{\beta}$	Return	return
1 (Low)	-17.08	10.80	-20.73**	27.84**	33.08	10.35
2	-9.13	9.54	-13.06**	25.49**	20.34	9.35
3	-4.32	9.24	-8.41**	24.65**	17.73	12.64
4	-1.82	9.41	-6.04**	25.19**	12.99	10.94
5	0.86	9.32	-3.47*	25.07**	8.62	9.56
6	4.60	9.31	0.12	24.95**	6.65	11.56
7	9.24	9.55	4.55*	25.40**	-0.06	9.18
8	14.96	10.41	9.85**	28.29**	-3.37	11.10
9	19.82	11.40	14.36**	30.84**	-8.03	10.19
10 (High)	40.43	14.50	33.93**	36.42**	-22.07	9.43

	Overnight Returns in Years After Portfolio Formation					
Decile	Initial	1 year	2 years	3 years	4 years	5 years
1 (Low)	-17.08	-7.09	-1.67	-0.77	-0.65	-0.26
2	-9.13	-2.64	0.70	-1.00	2.33	1.98
3	-4.32	-0.63	1.65	1.74	1.68	1.37
4	-1.82	1.94	3.06	3.38	2.58	1.77
5	0.86	4.67	5.88	3.87	1.78	2.72
6	4.60	7.01	6.08	4.28	2.63	2.80
7	9.24	7.26	4.92	5.61	5.36	5.23
8	14.96	9.59	8.69	7.36	8.01	4.37
9	19.82	14.36	11.67	12.34	10.14	8.45
10 (High)	40.43	24.01	20.30	21.11	17.33	11.92
N	2,554	2,223	1,963	1,788	1,660	1,574

TABLE 3

Developed Markets Indexes:

Overnight and Intraday Returns by Lagged Overnight Returns Quartiles

The tables below present overnight and intraday returns for indexes representing the countries included in MSCI's World Index. The "Index" line is based on published opening prices for the indexes and can suffer from a stale-quote problem, as some indexes use the previous day's closing price for stocks that have not traded yet when the market opens. Results in italics indicate indexes with a large proportion of near-zero overnight returns, which are more likely to be affected by the issue. The line "WA" alleviates the staleness problem by computing a weighted-average of the individual returns of the index's constituents. The bottom portion of each table presents the returns of portfolios sorted by quartiles of overnight returns for the previous year. The calculations use the same methodology as in Table 2 and use the index's constituents as a sample. The number of stocks per index is given in the tables; a few stocks are eliminated because they do not trade over an entire month or over the previous year. The period covered is from January 1, 2002 to December 31, 2014, with the exception of Italy, Israel, Singapore (2009-2014) and New Zealand (2004-2014) for weighted returns. Returns are in local currency, include dividends, and are in percent. *Source*: Bloomberg

Canada / S&P TSX 60		
N=59	Overnight	Intraday
Index	11.8	-4.3
WA	13.8	-5.3
Q1 (L)	-4.5	16.7
Q2	7.1	1.6
Q3	17.7	-10.5
Q4 (H)	39.6	-22.4

United States / S&P 500		
N=496	Overnight	Intraday
Index	*1.5*	*5.0*
WA	5.8	0.9
Q1 (L)	-5.0	13.0
Q2	0.8	6.8
Q3	8.6	-1.1
Q4 (H)	21.5	-12.6

Austria / ATX		
N=20	Overnight	Intraday
Index	*2.2*	*5.1*
WA	18.9	-9.3
Q1 (L)	-5.8	12.6
Q2	16.0	-12.1
Q3	29.3	-12.2
Q4 (H)	53.7	-29.4

Belgium / BEL 20		
N=20	Overnight	Intraday
Index	16.5	-11.5
WA	20.0	-12.1
Q1 (L)	-2.2	9.3
Q2	13.5	-10.7
Q3	33.5	-19.2
Q4 (H)	55.1	-35.6

Denmark / OMX Copen. 20		
N=19	Overnight	Intraday
Index	*10.8*	*-1.2*
WA	36.0	-18.6
Q1 (L)	17.4	-1.8
Q2	30.6	-17.1
Q3	36.9	-23.6
Q4 (H)	56.6	-27.0

Finland / OMX Helsinki 25		
N=24	Overnight	Intraday
Index	*13.0*	*-3.6*
WA	39.8	-21.0
Q1 (L)	16.8	-7.2
Q2	36.4	-14.2
Q3	57.2	-31.3
Q4 (H)	77.0	-39.8

France / CAC 40		
N=39	Overnight	Intraday
Index	13.4	-10.7
WA	14.3	-10.3
Q1 (L)	2.3	2.4
Q2	12.6	-10.0
Q3	20.8	-16.9
Q4 (H)	32.0	-20.8

Germany / DAX		
N=30	Overnight	Intraday
Index	5.9	-0.9
WA	13.7	-7.3
Q1 (L)	6.8	-2.2
Q2	9.9	-10.5
Q3	16.6	-8.0
Q4 (H)	29.3	-21.8

Ireland / ISEQ		
N=48	Overnight	Intraday
Index	*0.2*	*1.4*
WA	26.6	-19.6
Q1 (L)	-8.2	15.9
Q2	8.4	-5.2
Q3	30.2	-13.4
Q4 (H)	89.6	-50.3

TABLE 3 (Continued)

Israel / TA-25		
N=25	Overnight	Intraday
Index	14.4	-5.5
WA	15.0	-0.3
Q1 (L)	0.0	10.3
Q2	7.6	7.0
Q3	26.1	-7.7
Q4 (H)	32.7	-12.6

Italy / MSCI Italy		
N=28	Overnight	Intraday
Index	13.7	-13.3
WA	24.3	-16.7
Q1 (L)	14.6	-6.3
Q2	16.1	-14.9
Q3	35.7	-23.6
Q4 (H)	49.9	-28.1

Netherlands / AEX		
N=24	Overnight	Intraday
Index	12.5	-10.3
WA	14.2	-10.1
Q1 (L)	6.2	2.4
Q2	8.6	-5.1
Q3	20.6	-16.7
Q4 (H)	38.6	-36.1

Norway / OBX		
N=24	Overnight	Intraday
Index	*2.1*	*8.0*
WA	35.0	-17.7
Q1 (L)	23.3	-12.3
Q2	34.7	-13.7
Q3	39.9	-21.1
Q4 (H)	86.2	-46.4

Portugal / PSI 20		
N=19	Overnight	Intraday
Index	13.7	-13.7
WA	14.9	-12.0
Q1 (L)	-10.6	20.8
Q2	11.5	-1.7
Q3	24.1	-24.3
Q4 (H)	40.0	-29.6

Spain / IBEX 35		
N=34	Overnight	Intraday
Index	12.1	-5.9
WA	12.8	-5.8
Q1 (L)	4.1	2.6
Q2	9.8	-5.3
Q3	26.1	-13.1
Q4 (H)	37.6	-18.5

Sweden / OMX Stockholm 30		
N=29	Overnight	Intraday
Index	5.8	1.4
WA	17.4	-7.6
Q1 (L)	9.7	-1.9
Q2	14.5	-6.8
Q3	18.8	-7.4
Q4 (H)	30.6	-15.1

Switzerland / SMI		
N=23	Overnight	Intraday
Index	9.1	-4.3
WA	12.5	-6.4
Q1 (L)	4.5	-0.5
Q2	12.4	-6.6
Q3	17.4	-7.8
Q4 (H)	32.9	-22.2

United Kingdom / FTSE 100		
N=99	Overnight	Intraday
Index	*4.0*	*1.8*
WA	19.2	-11.2
Q1 (L)	9.1	-3.4
Q2	13.9	-4.6
Q3	22.4	-11.7
Q4 (H)	37.5	-23.7

Australia / S&P ASX 200		
N=190	Overnight	Intraday
Index	*7.7*	*1.4*
WA	19.4	-8.0
Q1 (L)	-3.5	9.5
Q2	17.3	-4.8
Q3	27.1	-13.5
Q4 (H)	41.1	-21.8

Hong Kong / Hang Seng		
N=40	Overnight	Intraday
Index	16.5	-7.5
WA	21.0	-9.3
Q1 (L)	5.2	3.1
Q2	17.2	-8.2
Q3	29.2	-16.1
Q4 (H)	47.3	-20.3

Japan / Nikkei 225		
N=222	Overnight	Intraday
Index	13.1	-7.7
WA	16.9	-9.7
Q1 (L)	9.1	-0.3
Q2	15.1	-7.7
Q3	20.0	-13.9
Q4 (H)	26.6	-17.9

New Zealand / NZX 50 Portfolio		
N=46	Overnight	Intraday
Index	*-0.4*	*9.4*
WA	5.7	4.5
Q1 (L)	-14.7	26.8
Q2	5.4	4.8
Q3	11.4	7.0
Q4 (H)	27.8	-14.8

Singapore / FTSE Straits Times		
N=30	Overnight	Intraday
Index	10.5	-3.3
WA	16.0	-0.8
Q1 (L)	9.5	3.9
Q2	12.6	1.4
Q3	20.1	-2.3
Q4 (H)	21.9	-3.2

Average - All Countries		
N=69	Overnight	Intraday
Index	9.1	-3.0
WA	18.8	-9.3
Q1 (L)	3.7	4.9
Q2	14.4	-6.0
Q3	25.6	-13.4
Q4 (H)	43.7	-24.8

TABLE 4

The Overnight Bias Parameter (OBP): Determinants and Distribution

The first column gives the results of a Fama-MacBeth regression analysis, for which the dependent variable is the annualized estimate of OBP_T. Cross-sectional regressions are performed for each of the 20 years T in the sample, and the table reports the average of the time-series coefficients $\hat{\beta}$; their t-statistics are presented in parentheses. Turnover is equal to average daily volume divided by market capitalization. The value indicator is the HML coefficient in Fama-French's three-factor model. Institutional ownership is for 2000-2014 only. The sample's average values for each characteristic are given in the last column. The middle columns give the breakdown of the characteristics as a function of the current year's OBP. The sample is divided into positive and negative estimates, and, within each category, by statistical significance (5% level in a one-sided test). Stocks in the positive and significant category are labeled Overnight Bias Group (OBG) and those with significant and negative estimates Intraday Bias Group (IBG). The period covered is from January 1, 1995 to December 31, 2014. Significance at the 1% and 5% levels is denoted by ** and *, respectively. *Source*: CRSP, Bloomberg, FactSet

	Determinants	Characteristics as a Function of OBP Estimate				
		OBP Positive		OBP Negative		
	OBP_T Regression	Signif. (OBG)	Not Signif.	Not Signif.	Signif. (IBG)	All
OBP_{T-1} (%)	0.2079** (19.44)	25.37	10.65	2.83	-6.01	8.83
Standard Dev. (%)	0.3882** (7.14)	41.14	40.09	39.83	37.05	39.78
Beta	0.0892**[a] (5.98)	1.05	1.02	0.93	0.74	0.96
Turnover (%)	0.1070** (6.19)	92.32	82.03	70.88	47.92	75.72
Market Cap. ($B)	0.0006** (3.21)	5.74	5.92	4.93	4.07	5.31
NASDAQ-listed (%)	-0.0679** (-6.28)	38.56	39.84	43.88	45.17	41.60
Previous Year Total Return (%)	0.0727** (5.96)	30.84	22.06	15.00	8.76	19.75
Value Indicator (%)	0.0041 (0.48)	27.09	20.91	21.68	30.34	23.80
Inst. Own. (%)	-0.1793** (-5.14)	67.64	74.07	73.64	64.81	71.43
Average N	2,554	524	876	778	376	2,554
Average R^2	0.2275					
Average OBP_T (%)		57.65	13.31	-10.74	-32.14	8.38

[a] Coefficient is from a separate regression where beta in substituted to the standard deviation in Equation (9).

TABLE 5

Overnight Performance of Portfolios Sorted by the Overnight Bias Parameter (OBP)

This table presents the annualized returns and standard deviations of overnight-only portfolios, as well as their risk-adjusted returns and betas computed with Equation (5). The first four columns give the results for portfolios sorted according to the sign and significance of the Overnight Bias Parameter (OBP), measured with Equation (8) and returns from the *previous* year. Significance for that classification is at the 5% level in a one-sided test and is based on the OBP's t-statistic. The fifth column gives the results for a long position in the stocks of the first column (Overnight Bias Group) combined with a short position in the stocks of the fourth column (Intraday Bias Group). The sixth column represents a portfolio of all stocks. The portfolios are rebalanced monthly, and daily returns are weighted by the previous day's market capitalization. Daily alphas are annualized with $(1+\hat{\alpha})^{252}-1$, where 252 is the average number of trading days per year. The after-cost results are computed with Equation (10) and illustrated for trade sizes of $10,000 and $100,000 per stock. Costs have more impact on annualized values when returns are higher. The long-short strategy incurs costs on each position. The period covered is from January 1, 1995 to December 31, 2014. Significance at the 1% and 5% levels is denoted by ** and *, respectively. All figures are in percent. *Source*: CRSP

	Portfolios Sorted by Previous Year's OBP					
	OBP Positive		OBP Negative			
	Signif. (OBG)	Not Signif.	Not Signif.	Signif. (IBG)	Long OBG-Short IBG	All Stocks
Avg. Number of Stocks	529	864	778	383	912	2,554
Annualized Returns						
Before-Cost	25.87	8.87	-0.76	-11.98	43.09	6.84
After-Cost						
$10,000 per stock	15.74	0.66	-8.28	-18.87	21.28	-1.27
$100,000 per stock	21.22	4.73	-4.54	-15.35	32.53	2.79
Standard Deviation	11.46	10.38	9.29	8.46	6.60	9.76
Annualized Risk-Adjusted Return $\hat{\alpha}$						
Before-Cost	20.13**	3.94*	-5.06**	-15.60**	42.30**[a]	2.07
After-Cost						
$10,000 per stock	10.45**	-3.90*	-12.26**	-22.22**	20.60**	-5.68**
$100,000 per stock	15.69**	-0.01	-8.68**	-18.84**	31.80**	-1.79
Market Sensitivity $\hat{\beta}$	30.96**	29.12**	25.52**	21.94**	9.03**	27.59**

[a] The alpha for the long-short strategy is $\hat{\alpha}^{OBG}-\hat{\alpha}^{IBG}$ at the daily level, but increases relative to these values when annualized.

TABLE 6

Robustness Tests for Table 5's Risk-Adjusted Returns

This table presents robustness tests for the risk-adjusted returns ($\hat{\alpha}$) reported in Table 5 under alternative methodologies, various periods of time, and sub-groups of stocks. The "By Sub-Groups" results are presented for the top and bottom quintiles for each of the characteristics listed in Table 4; each quintile counts 511 stocks, on average. The period covered is from January 1, 1995 to December 31, 2014. Significance at the 1% and 5% levels is denoted by ** and *, respectively. All figures are in percent. *Sources*: CRSP, Bloomberg, FactSet

	Portfolios Sorted by Previous Year's OBP					
	OBP Positive		OBP Negative			
	Signif. (OBG)	Not Signif.	Not Signif.	Signif. (IBG)	Long OBG-Short IBG	All Stocks
Base Case (Table 5)	20.13**	3.94*	-5.06**	-15.60**	42.30**	2.07
Fama-French 3-Factor	20.06**	3.63	-5.34**	-15.89**	42.71**	1.84
Equally-Weighted	23.86**	5.17**	-5.41**	-17.66**	50.38**	1.04
Excluding Earnings Announcements	20.25**	3.59	-5.41**	-15.88**	42.92**	1.84
By Year						
1995	6.48	-2.67	-9.54**	-17.18**	28.55**	-4.98
1996	15.66	2.83	-6.23	-18.79**	42.38**	-2.93
1997	18.70	10.19	-5.80	-16.86**	42.74**	5.25
1998	31.57*	5.45	-7.46	-21.45**	67.41**	4.82
1999	53.43**	17.13*	0.14	-18.77**	88.78**	19.71*
2000	30.43*	-6.61	-15.60**	-33.02**	94.52**	4.20
2001	2.41	-8.59	-18.79*	-25.91**	38.18**	-15.12
2002	12.49	5.26	-6.55	-19.94**	40.46**	-5.57
2003	17.82**	11.54	5.60	-8.58	28.85**	6.95
2004	14.29**	1.59	-1.03	-11.48**	29.10**	3.65
2005	30.86**	11.26*	1.72	-9.71**	44.90**	11.23**
2006	13.68**	-1.76	-7.06	-19.23**	40.70**	1.08
2007	22.76**	8.35	1.20	-4.16	28.08**	7.98
2008	16.34	-1.42	-14.54	-20.04	45.45**	-6.91
2009	40.86**	10.41	-4.66	-19.85*	75.65**	-1.29
2010	18.98*	2.44	-2.40	-12.23	35.54**	3.17
2011	24.77	7.30	-0.46	-6.60	33.57**	5.08
2012	17.47	0.15	-5.11	-12.36*	34.03**	-0.91
2013	9.93	3.04	-1.09	-3.80	14.27**	2.48
2014	16.13*	7.78	-0.91	-6.92	24.75**	7.85

TABLE 6 (continued)

	Portfolios Sorted by Previous Year's OBP					
	OBP Positive		OBP Negative			
	Signif. (OBG)	Not Signif.	Not Signif.	Signif. (IBG)	Long OBG-Short IBG	All Stocks
By Quartile of Market Performance						
1 (Worst months)	24.42**	5.88	-7.04	-17.06**	49.97**	2.04
2	21.26**	6.47	-1.65	-12.50**	38.55**	4.83
3	14.49**	1.00	-4.96*	-14.29**	33.55**	0.41
4 (Best months)	20.20**	1.69	-6.66	-19.14**	48.61**	0.50
Contraction Periods[a]	22.03	2.91	-14.18	-22.51**	57.41**	-7.22
By Sub-Groups Based on Characteristics						
Standard Deviation						
Top Quintile	36.68**	15.83**	-0.18	-14.88**	60.52**	18.24**
Bottom Quintile	11.51**	0.65	-4.67**	-14.48**	30.36**	-2.72*
Turnover						
Top Quintile	35.17**	12.75**	-0.31	-7.54**	46.18**	17.88**
Bottom Quintile	13.72**	0.23	-5.12**	-17.96**	38.59**	-2.15
Market Capitalization						
Top Quintile	19.68**	3.82	-5.07**	-15.18**	41.07**	2.28
Bottom Quintile	24.32**	4.94**	-7.91**	-20.23**	55.78**	-1.19
NASDAQ (N=1,063)	28.42**	9.29**	-5.83*	-16.63**	53.99**	7.23**
NYSE (N=1,423)	17.76**	3.05	-4.85**	-15.61**	39.51**	1.12
Value Indicator						
Top Quintile	24.03**	7.61**	-3.65**	-14.03**	44.24**	5.45*
Bottom Quintile	22.95**	5.48*	-6.59**	-17.56**	49.09**	4.06
Previous Year Return						
Top Quintile	36.19**	13.07**	0.95	-11.41**	53.70**	12.60**
Bottom Quintile	20.67**	1.70	-7.02**	-18.20**	47.46**	1.48
Institutional Own.[b]						
Top Quintile	17.30**	4.32	-5.03*	-11.36**	32.32**	1.93
Bottom Quintile	21.72**	4.44	-5.59**	-14.55**	42.41**	1.28

[a] Contraction periods as defined by NBER: from March to November 2001 and from December 2007 to June 2009. September 17, 2001 is excluded from this calculation.

[b] For institutional ownership, the period is 2000-2014 and the average number of stocks by quintile is 380.

FIGURE 1

Regressions of Monthly Overnight Returns on Lagged Values: t-statistics

The top portion of the figure presents the results of Fama-MacBeth cross-sectional regressions of monthly overnight returns on 1) lagged monthly overnight returns (bars), and 2) cumulative average monthly overnight returns (line). The results correspond to Equations (3) and (4) and are presented for lags k ranging from one to 60 months. For each regression and lag, a time-series of coefficients $\hat{\beta}_k$ is obtained (the number of months ranges from 180 to 239, depending on k). The figure reports the t-statistics for the tests that the coefficients $\hat{\beta}_k$ are equal to zero. Stocks included are those in Table 1's sample that have monthly returns available from month T to $T-k$ during the period covered. The average number of stocks per regression ranges from 2,528 (for $k=1$) to 1,447 (for $k=60$). The bottom portion of the figure presents the results of similar regressions for which intraday returns are substituted for the independent variables. All returns are log returns. The period covered is from January 1, 1995 to December 31, 2014. *Source*: CRSP

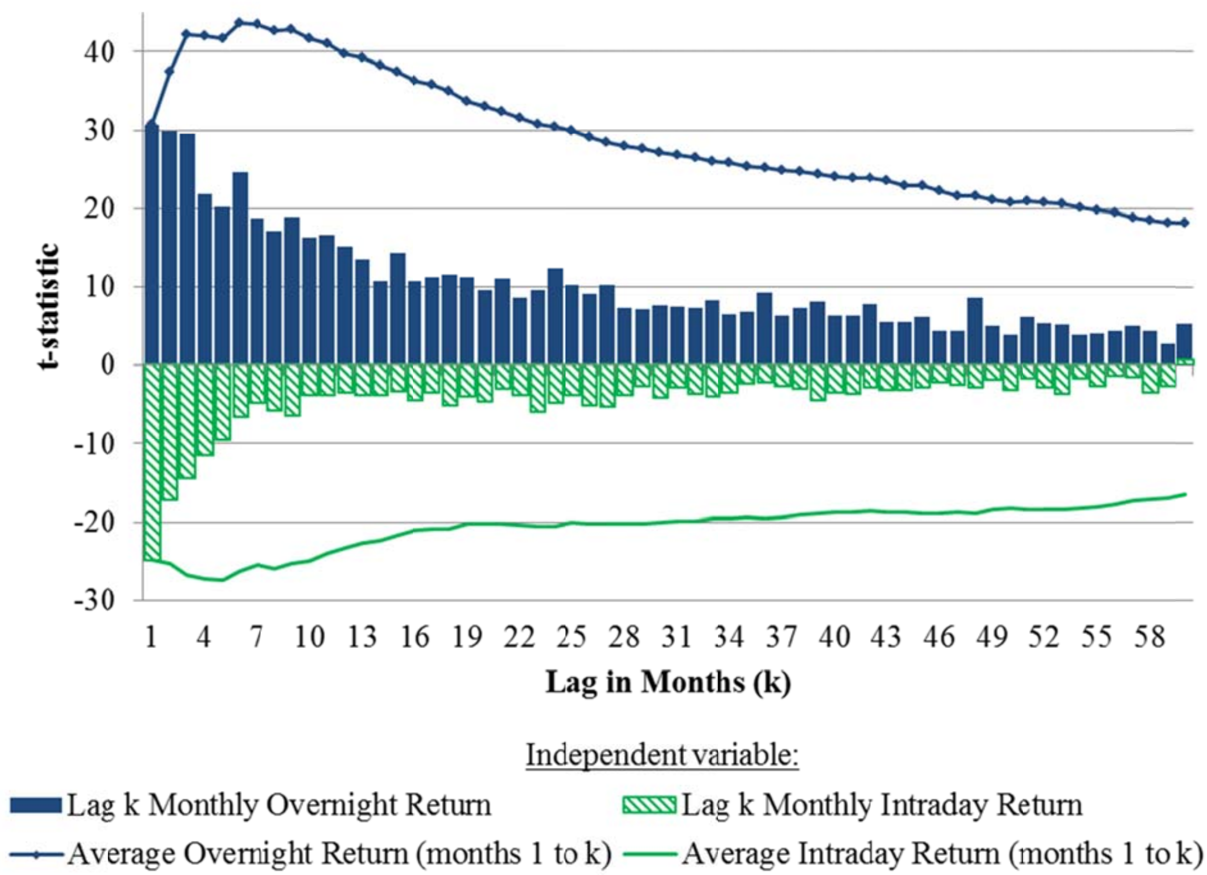

FIGURE 2

Overnight and Intraday Returns as a Function of Total Returns

Total annual returns are computed for each year and stock in Table 1's sample, for a total of 51,089 observations. Annual observations are sorted by percentile of the total return distribution, and the figure presents the average overnight and intraday returns for each percentile. The dots represent actual values and the lines projected values according to Equations (6) and (7). For this projection, the parameters θ and OBP are estimated each month with the previous year's returns; monthly projections are compounded to obtain annual values. Regressing the figure's projected values against actual values yields an R^2 of 0.98 for overnight returns and 0.99 for intraday returns. The period covered is from January 1, 1995 to December 31, 2014. *Source*: CRSP

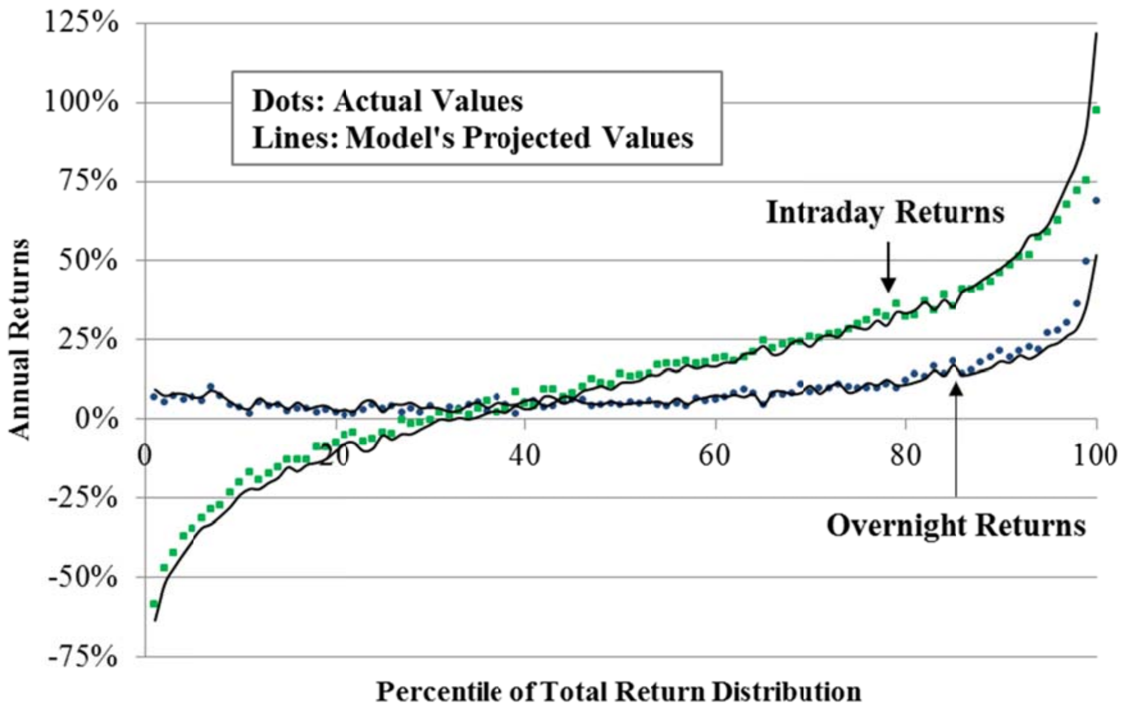

FIGURE 3

Overnight and Intraday Returns as a Function of Time since Issuance

Figure presents the average monthly overnight and intraday returns as a function of the number of months since issuance, where issuance is defined as the first date a stock appears in the CRSP database. The period covered is from January 1, 1995 to December 31, 2014. The sample includes 4,369 issuances that occur during this period. Not all stocks can be tracked for the entire five-year period, including those that are issued after January 1, 2010, those that do not satisfy the sample's inclusion criteria, and those that are delisted. *Source*: CRSP

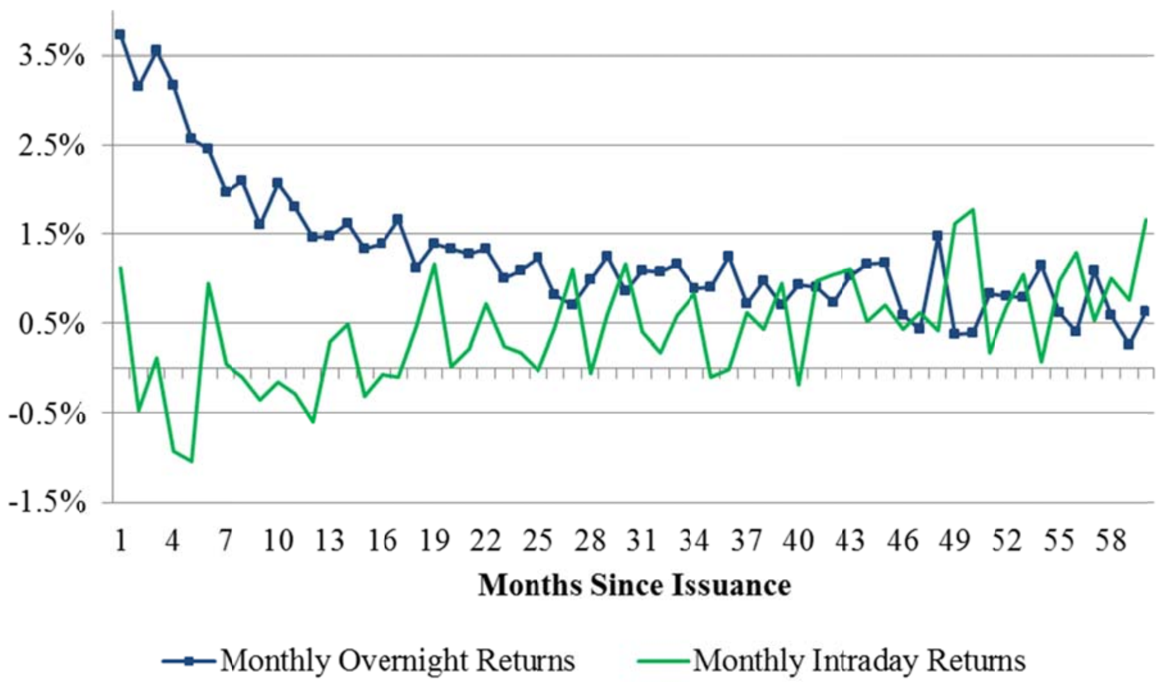

FIGURE 4
Intraday Patterns: Returns and Volume

Figure presents average minute-by-minute daily returns and volumes for portfolios sorted by the previous year's Overnight Bias Parameter (OBP) (same four categories as in Tables 5-6) and rebalanced monthly. For each minute, returns are computed by dividing the last trade price in that minute by the previous day's closing price. For each group, returns are computed as a weighted average based on the previous day's market capitalization. Solid bars represent the average volume per OBG stock and dots give their fraction of total market volume as a group. The period covered is from January 1, 2010 to December 31, 2012. *Source*: TAQ