An Empirical Investigation of the Predictive Power of Price Gaps in Futures Markets

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Abstract

We investigate an old principle proposed by market technicians which holds that price gaps (consecutive intraday price ranges that do not overlap) contain information about the distributions of subsequent price movements, and, in particular, that prices will move into the gap within days of its appearance. Since practitioners rarely base their predictions on gaps-information alone we also investigate the extent to which this information is conditioned on the size of the gaps, any accompanying technical chart patterns, and trading volume. We find substantial evidence to support the hypothesis that price gaps contain information about future returns. We also find that the size of the gap, and the volume of trade when the gap appears, contain additional information. We do not find that chart patterns add to the price-gap information in any systematic way.

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1 Introduction

Technical analysts argue that some patterns found in past movements of asset prices contain information about future price movements; economists argue that they do not. Both sides can appeal to theoretical foundations, with technical analysis supported by psychological and behavioural arguments , and economic analysis supported by the efficient markets hypothesis. The empirical evidence is mixed but the broad conclusion to date is that technical analysis 'works' in foreign exchange markets, but not in equity markets. The term 'works' is usually taken to mean that pattern-based predictions can be used to generate excess profits, which is where the conflict with the efficient markets hypothesis arises. A looser interpretation is that patterns have some predictive power for the distribution of returns even if they cannot generate profitable trades. Lo, Mamasky and Wang (2000) find evidence that this is in fact the case for a range of standard technical patterns. In this paper we extend this research to investigate the predictive power of 'price gaps' i.e. the gap between the maximum (minimum) price in one period, and the minimum (maximum) price in the next.

Price gaps have interested technical analysts for many years (see Edwards and Magee (1966)) and have resulted in the stylized rule that there is a tendency for prices to move into a gap in subsequent trading i.e. that past gaps act as an attractor for future prices.[1] While the gaps rule is typically used to predict price levels, it has obvious potential as a predictor of their conditional variance, which makes the Lo, Mamasky and Wang tests appropriate, and raises the possibility that gaps data could contribute to asset price models based on ARCH processes. The aim of this paper is to test the hypothesis that gaps contain information about the futures prices of currencies, fixed income securities, stock indices and commodities. We ask the following questions, (i) Do price gaps contain information about the distribution of future price movements? (ii) Do price gaps act as a magnet for future price movements? (iii) Do price gaps signal profitable trading opportunities? (iv) Do price gaps augment information derived from standard chart patterns and trading volumes?

We address these questions by categorizing price gaps into five standard types, known widely as congestion, breakout, runaway, exhaustion, and island gaps. We then develop simple algorithms to detect and sort the gaps

[1] In some circumstances gaps are treated as repellers; see Section 2 below.

before comparing conditional returns after the appearance of a gap with unconditional returns measured over each asset-price sample as a whole, following Lo, Mamasky and Wang (2000).

The rest of this paper is as follows: Section 2 describes the various types of price gap, their algorithmic identification, and the use of conditioning variables; Section 4 describes our futures data; Section 5 presents the empirical results, and Section 6 concludes.

2 Price gaps: definitions and identification.

2.1 Causes and Types of Price Gap.

Previous research has suggested several possible causes of prices gaps, such as the arrival of new information (Fleming and Remonola (1999a and 1999b) and Fleming (2003)), or a clustering of buy/sell orders driven by prices hitting certain technical levels.[2] (Osler (2003) and Kavajecz and Odders-White (2004)[3]) Technical analysts have grouped price gaps into different types, each of which offers a different prediction about subsequent price behaviour. The main types, introduced below, are discussed further in Edwards and Magee (1966), Schwager (1996), Bulkowski (2005) and Kaufman (2005).[4]

2.1.1 Congestion gaps.

Congestion gaps are commonly seen where prices appear to be constrained between unchanged resistance and support levels before and after the gap emerges i.e. the constraint is believed to persist after the gap has appeared.[5] Since technical analysts interpret these levels as *ex ante* upper and lower bounds on the range of prices subsequent to the gap's appearance, congestion gaps are generally predicted to be filled rapidly. Consequently, Edwards and Magee (1966, p.211) for example, suggest that these gaps have little or no value to traders.

[2]We do not investigate the causes of price gaps. The question of whether price gaps can themselves be predicted is an interesting issue, but outside the scope of our study.

[3]In particular, Kavajecz and Odders-White (2004) find evidence that some technical indicators can capture changes in the state of the limit book orders, indicators such as moving average.

[4]Ex-dividend gaps are not included in the present study since their cause is clear.

[5]The interval bounded by the resistance and support is known as the congestion area.

2.1.2 Breakout gaps.

Breakout gaps occur where the emergence of the gap takes the price outside an established resistance and support range. Breakout gaps typically appear to be accompanied by increased trading volume, and by new highs (lows) for an upward (downward) breakout gap. Edwards and Magee (1966) claim that the probability that a price will continue its direction of movement is increased if it has recently broken out of a range i.e. in this case the gap acts as a repeller.

2.1.3 Runaway gaps.

Runaway gaps occur during a strong price advance or decline.[6] Technical analysis predicts that prices will continue to move in the direction of the gap, and will not reverse to cover the gap in the short-term.

2.1.4 Exhaustion gaps.

Exhaustion gaps are usually described as 'the last gasp' after a strong price trend. The high or low price recorded during the exhaustion gap must be a new high or new low. These gaps are typically accompanied by higher than average volume, and are frequently preceded by other gaps. The 'rule' here is that the gap will be filled quickly, usually within 2 to 5 days.

It is difficult to distinguish, *ex ante*, between runaway and exhaustion gaps, because it is never clear whether the trend is continuing (implying a runaway) or terminating (implying an exhaustion). Conventional wisdom is that the probability that a gap represents an exhaustion increases with the number of runaway gaps preceding it.

> An Exhaustion Gap is seldom the first gap in a runaway move; it is usually preceded by at least one Continuation (Runaway) Gap. Thus, you may ordinarily assume (unless the contrary appears from other and more weighty indications) that the first gap in a rapid advance or decline is a continuation Gap. But each succeeding gap must be regarded with more and more suspicion, especially if it is wider than its predecessor. Edwards and Magee (1966, p.216)

[6] To quantify as a strong price movement, the prices before and on the day the runaway gap occur should be new highs (lows) for an upward (downward) movement.

The obvious problem for our identification algorithm is deciding how many runaway gaps must occur before a gap can be categorized as an exhaustion. For simplicity, we fix the number at 1.

2.1.5 Island gaps.

An Island gap is an island of prices bordered before and after by two gaps. Island gaps are not claimed to be a strong indicator of reversal. Rather, they belong to minor tops in a larger chart formation, such as the head, in the Head-and-Shoulders formation (Edwards and Magee (1966)). Given this interpretation, island gaps are also said to predict some sort of reversion to earlier price levels. For example, if an island top appears, the hypothesis is that near-term[7] prices will decline, and vice versa.

2.2 Identification of Price Gaps

After a price gap has been detected we allocate it to one, and only one, of the first four price gaps. If the island gap condition is satisfied, it will be allocated to this group also.
The formal definitions are as follows, where O_t, H_t, L_t and C_t denote the open, high, low and closing price for day t:

Congestion Gaps

CG indicates a congestion gap; U and D indicate up and down movements, and both conditions (1 and 2) must be satisfied.

UCG1 $L_t > H_{t-1}$

UCG2 C_t and $O_t < \text{Max}(H_{t-1}, ..., H_{t-10})$

and

DCG1 $H_t < L_{t-1}$

DCG2 C_t and $O_t < \text{Min}(L_{t-1}, ..., L_{t-10})$

Breakout Gaps

[7]We define 'near-term' to be 7 trading days.

UBG1 $L_t > H_{t-1}$

UBG2 Either C_t or O_t or $L_t > \text{Max}(H_{t-1}, ..., H_{t-10})$

UBG3 $H_t > \sup(H_t, ..., H_{t-10})$

and

DBG1 $H_t > L_{t-1}$

DBG2 Either C_t or O_t or $L_t < \text{Min}(L_{t-1}, ..., L_{t-10})$

DBG3 $L_t < \inf(L_t, ..., L_{t-10})$

Runaway Gaps

URG1 $L_t > H_{t-1}$

URG2a $H_{t-2} > \text{Max}(H_t : t = -2, ..., -2-k)$ where $k = 15$

URG2b $H_{t-1} > \text{Max}(H_t : t = -1, ..., -1-k)$ where $k = 15$

URG3 $H_t > \sup(H_t, ..., H_{t-15})$

and

URG1 $H_t < L_{t-1}$

URG2a $L_{t-2} < \text{Min}(L_t : t = -2, ..., -2-k)$ where $k = 15$

URG2b $L_{t-1} < \text{Min}(L_t : t = -1, ..., -1-k)$ where $k = 15$

URG3 $L_t < \inf(L_t, ..., L_{t-15})$

Exhaustion Gaps

UEG1 $L_t > H_{t-1}$

UEG2 One or more upward Runaway gaps must occur in the previous 7 days.

UEG3 $H_t > \sup(H_t, ..., H_{t-22})$

and

DEG1 $H_t < L_{t-1}$

DEG2 One or more downward Runaway gaps must occur in the last 7 days.

DEG3 $L_t < \inf(L_t, ..., L_{t-22})$

Island Reversal Gaps

UIG1 $L_{t-1} > H_{t-2}$

UIG2 $L_{t-1} > H_t$

UIG3 $H_{t-1} > \sup(H_t, ..., H_{t-25})$

and

DIG1 $L_{t-2} > H_{t-1}$

DIG2 $L_t > H_{t-1}$

DIG3 $L_{t-1} < \inf(L_t, ..., L_{t-25})$

2.3 Does the size of the gap matter?

We also investigate the hypothesis that the wider the gap, the more informative it is. We categorize the widths into three sizes, all of which relate to the price range prior to the appearance of the gap.

We measure the sizes of upward and downward gaps by $\text{gapdiff}_t = L_t - H_{t-1}$ and $\text{gapdiff}_t = H_t - L_{t-1}$ respectively, and classify 3 sizes as,

1. (small) $\text{gapdiff}_{t,1} \leq |O_{t-1} - C_{t-1}|$
2. (medium) $\text{gapdiff}_{t,2} \leq |H_{t-1} - L_{t-1}|$
3. (large) $\text{gapdiff}_{t,3} > |H_{t-1} - L_{t-1}|$

where O_t, H_t, C_t are the open price, high price and close price at time t respectively.

2.4 Conditioning variables

If gaps are found to contain information about future prices it is reasonable to suspect that this information might also be contained in other, coincident, data. If this is the case, it may be that combining the gaps data with these other sources could provide more reliable information than the gaps alone. We investigate two additional pieces of information: chart patterns and trading volume. Our investigation of chart patterns follows that of

Lo, Mamaysky and Wang (2000) who provide empirical evidence that such patterns alter the empirical distribution of subsequent stock returns in U.S. equity markets. Blume, Easley and O'Hara (1994) show that trading volume around the time of the appearance of a gap may contain information about subsequent price movements.

2.4.1 Chart patterns.

Before searching for patterns in the price series we smooth the data using a local polynomial regression. This allows our identification algorithm to pick out 'large' patterns while ignoring the smaller ones that investors probably treat as noise. Lo, Mamaysky and Wang (2000) also smooth the prices but do so with Nadaraya-Watson kernel estimators. Local polynomial regressions offer two advantages over these kernel estimators: the orders of the bias at the boundaries and in the interior of a price series are similar, which reduces the need to use specific boundary kernels, and we can estimate the regression parameters using least squares. (Fan and Gijbels (1996, Chapter 3), and Hastie, Tibshirani and Friedman (2001, Chapter 5)). [8]

Given a set of extrema $(e_1, e_2, ..., e_m)$ in a window of 30 days we identify the following chart patterns: Head-and-Shoulders, Triangle, Rectangle, Broadening and Double. We then classify each of the identified price gaps according to which, if any, of the chart patterns accompanies it. The results of this classification are presented in Panel A of Table 7.

The five 'canonical' patterns are defined as follows (See Bulkowski (2005), Edwards and Magee (1966) and Kaufmann (2005) for extensive descriptions of chart patterns.), where the points $(e_{m-4}, e_{m-3}, e_{m-2}, e_{m-1}, e_m)$ are the five extrema immediately preceding a price gap i.e. the gap itself occurs from e_m to e_{m+1}.

Most of the patterns are used to predict the direction of movement when prices break out of the pattern. Our investigation does not allow us to test the accuracy of these predictions since we focus only on those breakouts that constitute a gap and we ignore the rest. Our aim is simply to test the hypothesis that a gap that is accompanied by a recent pattern is more informative than a gap that appears on its own.

Head-and-Shoulders

[8] The details of the smoothing method are included in an appendix available on request from the authors.

HSTOP1 e_m is a maximum.

HSTOP2 $e_{m-2} > e_{m-4}$ and $e_{m-2} > e_m$

HSTOP3 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-4, m)$ and $\bar{e} = \frac{e_{m-4}+e_m}{2}$

HSTOP4 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-3, m-1)$ and $\bar{e} = \frac{e_{m-3}+e_{m-1}}{2}$

and

HSBOT1 e_m is a minimum.

HSBOT2 $e_{m-2} < e_{m-4}$ and $e_{m-2} < e_m$

HSBOT3 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-4, m)$ and $\bar{e} = \frac{e_{m-4}+e_m}{2}$

HSBOT4 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-3, m-1)$ and $\bar{e} = \frac{e_{m-3}+e_{m-1}}{2}$

Triangle

TTOP1 e_m is a maximum.

TTOP2 $e_{m-4} > e_{m-2} > e_m$ and $e_{m-3} < e_{m-1}$

and

TBOT1 e_m is a minimum.

TBOT2 $e_{m-4} < e_{m-2} < e_m$ and $e_{m-3} > e_{m-1}$

Rectangle

RTOP1 e_m is a maximum.

RTOP2 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-4, m-2, m)$ and $\bar{e} = \frac{e_{m-4}+e_{m-2}+e_m}{3}$

RTOP3 $\max |e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-3, m-1)$ and $\bar{e} = \frac{e_{m-3}+e_{m-1}}{2}$

RTOP4 $\min(e_{m-4}, e_{m-2}, e_m) > \max(e_{m-3}, e_{m-1})$

and

RBOT1 e_m is a minimum.

RBOT2 $\max|e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-4, m-2, m)$ and $\bar{e} = \frac{e_{m-4}+e_{m-2}+e_m}{3}$

RBOT3 $\max|e_i - \bar{e}| \leq 0.005 \times \bar{e}$, where $i = (m-3, m-1)$ and $\bar{e} = \frac{e_{m-3}+e_{m-1}}{2}$

RBOT4 $\max(e_{m-4}, e_{m-2}, e_m) < \min(e_{m-3}, e_{m-1})$

Broadening

BTOP1 e_m is a maximum.

BTOP2 $e_{m-4} < e_{m-2} < e_m$ and $e_{m-3} < e_{m-1}$

and

BBOT1 e_m is a minimum.

BBOT2 $e_{m-4} > e_{m-2} > e_m$ and $e_{m-3} > e_{m-1}$

Double

DTOP1 e_m is a maximum.

DTOP2 $\max|e_i - \bar{e}| \leq 0.0025 \times \bar{e}$, where $i = (e_{top1}, e_{top2})$ and $\bar{e} = \frac{e_{top1}+e_{top2}}{2}$

DTOP3 $\max|e_{top1,t} - e_{top2,t}| \geq 15$ days

and

DBOT1 e_m is a minimum.

DBOT2 $\max|e_i - \bar{e}| \leq 0.0025 \times \bar{e}$, where $i = (e_{bot1}, e_{bot2})$ and $\bar{e} = \frac{e_{bot1}+e_{bot2}}{2}$

DBOT3 $\max|e_{bot1,t} - e_{bot2,t}| \geq 15$ days

2.4.2 Trading volumes.

The hypothesis we seek to test is that the information content of a price gap is reinforced if it is accompanied by a level of trading that is higher than the recent average, which we measure arbitrarily over the previous 22 days. If the gap-day volume is higher than this average, we have an increasing volume (IV) price gap, the converse being a decreasing volume (DV) price gap.

3 Empirical methods.

3.1 Sampling Conditional and Unconditional Returns

We apply the above algorithms to identify the gaps, and record the continuously compounded returns over the following day, and over the period of 4 days beyond that. This provides 20 sets of conditional returns. In contrast to standard chart patterns such as Head-and-Shoulders, detecting price gaps is immediate since there is less controversy about their formation. In particular there is no need to wait for several days before measuring the conditional returns, as is unavoidable in the tests of Lo, Mamaysky and Wang (2000).

For each price series, we compare the unconditional to the conditional returns after standardising as follows

$$Z_{i,t} \quad = \quad \frac{r_{i,t} - \text{Mean}(r_{i,t})}{\text{S.D.}(r_{i,t})} \tag{1}$$

where the mean and standard deviation are computed for each individual price series.

3.2 Information and Statistical Tests

The specific comparisons that we make are based on a goodness-of-fit test and the Kolmogorov-Smirnov test as proposed by Lo, Mamaysky and Wang (2000).

For the goodness-of-fit test, the procedure is to compare the quantiles of the conditional returns with their unconditional counterparts. The first step is to compute the deciles of unconditional returns and tabulate the relative frequency ($\hat{\delta}_j$) of the conditional returns that fall into the jth decile of the unconditional returns:

$$\hat{\delta}_j \quad = \quad \frac{\text{Number of conditional returns in decile} \quad j}{\text{Total number of conditional returns}} \tag{2}$$

The null hypothesis is that returns are independently and identically distributed and, therefore, that the conditional and unconditional return distributions are identical. The corresponding goodness-of-fit test statistic Q is given by:

$$Q \quad = \quad \sum_{j=1}^{10} \frac{(T_j - 0.10T)^2}{0.10T} \sim \chi_9^2 \tag{3}$$

$$\sqrt{T}(\hat{\delta}_j - 0.10) \sim N(0, 0.10(1 - 0.10)) \tag{4}$$

where T_j is the number of observations in decile j and T is the total number of observations. Asymptotic Z-values for each bin are given by (4).

The Kolmogorov-Smirnov test is derived from the cumulative distribution functions $F_1(z)$ and $F_2(z)$ with the null hypothesis that $F_1 = F_2$. Denote the empirical cumulative distribution functions as $\hat{F}_j(z)$:

$$\hat{F}_j(z) \quad = \quad \frac{1}{T_i} \sum_{k=1}^{T_i} I(Z_{ik} \leq z), \quad i = 1, 2 \tag{5}$$

where $I(\cdot)$ is the indicator function and $(Z_{1t})_{t=1}^{T_1}$ and $(Z_{2t})_{t=1}^{T_2}$ are the two samples. The Kolmogorov-Smirnov statistic is given by the expression:

$$\gamma \quad = \quad \left(\frac{T_1 T_2}{T_1 + T_2} \right)^{1/2} \sup |\hat{F}_1(z) - \hat{F}_2(z)| \tag{6}$$

and the p-values by:

$$\text{Prob}(\gamma \leq x) = \sum_{k=-\infty}^{\infty} (-1)^k \exp(-2k^2 x^2), \quad x > 0 \tag{7}$$

Under the null hypothesis, the statistic γ should be small. An approximate α-level test of the null hypothesis can be performed by computing the statistic and rejecting the null if it exceeds the upper 100αth percentile for the null distribution. (See Press et al. (2002, Section 14.3) and DeGroot (1986))

Finally, a simple t-statistic allows us to test whether the unconditional mean returns are statistically significantly different from zero. The test-statistic is:

$$t = \frac{\bar{z}}{\sigma / \sqrt{T_z}} \tag{8}$$

where $\bar{z}$ is the mean of the normalized conditional returns, σ is their standard deviation, and T_z is the number of observations of the conditional returns $\bar{z}$ in a particular price gap. The null hypothesis is $\bar{z} = 0$. We apply equation (8) to all mean returns.

3.3 Nonparametric Bootstrapping

We construct empirical distributions of the number of price gaps using the simple nonparametric bootstrap discussed in Levich and Thomas (1993). 'Nonparametric' here refers to the fact that we are not imposing any form of statistical distribution on the time series.[9] We then use the empirical distributions to test whether there is anything unusual about our samples in terms of the number of gaps that appear.

The sampling procedure is as follows:

1. Given n returns, we scramble these returns to form a new n-dimensional array, and rebase each one to an initial price of 100. We sample without replacement, so that the unconditional distributions of each bootstrap is identical to those of the associated actual return, and the initial and final prices are the same as the original sample data.

2. We apply the price gap identification algorithm to the scrambled prices to form an empirical distribution for the number of gaps detected, and the distribution of normalized conditional returns up to five days after a price gap is detected. The procedure is repeated 1000 times.

3. We compare the actual number of price gaps with this distribution.

If there is nothing unusual about the numbers of gaps in our samples they should not be significantly different from the numbers of gaps obtained for the shuffled series. We set the rejection criterion at 10%.

4 Data

We use at least 10 years of daily futures prices for each of 28 contracts based on currencies, fixed income, stock index and commodities, giving a total of 164,288 observations. We chose futures rather than underlying assets because they are influenced less by difficulties of short selling. The consecutive price series (which end at the expiration of their contracts) are spliced together to create continuous price series.[10] Details of the contracts in our sample are listed in Table 1.

[9] Alternatively, Brock, Lakonishok and LeBaron (1992) impose and fit random walk, $AR(1)$, GARCH-in-Mean and Exponential-GARCH models to stock index data.

[10] The continuous series are constructed by rebasing successive contract prices following a procedure similar to that in Levich and Thomas (1993), Kho (1996) and Sullivan, Tim-

5 Empirical Results.

5.1 The Price Gap-Fill Hypothesis.

Table 2 presents the results of applying the gap identification algorithm described in Section 2. The first three rows in Panel A record the numbers upward and downward price gaps, sorted according to the 10 gap patterns, and conditioned on increasing (IV) or decreasing volume (DV). Following this is the result for each individual futures contract, for which the first row is the number of gaps detected and the second is the median number of gaps from the 1000 nonparametric bootstraps.

The gaps that appears most frequently are the congestions, followed by breakouts, runaways, exhaustions and islands. The ranking is similar for both upward and downward gaps, and for many of the individual contracts. The numbers of upward and downward gaps are roughly equal across the samples.

For all of the fixed-income and stock index futures, however, the number of upward price gaps exceeds that of the downward gaps. This is due to a general upward trend in futures prices as declining interest rates have led to increases in bond prices over recent decades.

Price gaps appear to be more closely associated with increasing, rather than decreasing trade volumes. For example, the total number of upward price gaps associated with increased volume is 6,578 (57%) compared to 4,966 (43%) with decreased volume.

The number of congestion gaps (UCG and DCG) accompanied by decreasing volume is higher than that for increasing volume, which may suggest that congestion gaps are more prone to subsequent price reversals, since these gaps appear not to be accompanied by heavy trading. For breakout, runaway and exhaustion gaps the numbers with increasing volume are almost twice those with decreasing volume. For example, the numbers for UBG are 3,002 and 1,404, and for UEG 292 and 151, respectively.

The S&P 500 index futures displays the fewest gaps of the all of the contracts; it has nearly forty percent fewer than the US Treasury 10-year future for example. A reason for this could be that S&P is less sensitive to news than are bond futures, possibly due to the relative illiquidity of some of

mermann and White (1999, Section V). The details are included in an appendix available on request from the authors. All data are from Datastream.

the components of the underlying index. Or maybe there was just less news of relevance to stock prices in our sample period.

We cannot reject the hypothesis that the price gaps count from the actual prices equals that of the bootstrap series, which implies that the numbers of price gaps shown by the actual futures prices are not unusually high or low.

Panel B of Table 2 presents the percentages of gaps filled in specific time intervals. The percentage filled within a short period of time is high, varying from 20.70% to 33.80% for 1-day, and from 26.50% to 31.90% for the subsequent 4 days. That is, for our sample, the probability of a gap being filled within 5 days of its emergence was about 0.6. Additional results (not shown in the tables) show that 70% of gaps across all categories are covered within 20 days and 80 percent are filled within 50 days. These simple results provides informal support for the Gap-Fill hypothesis.

Breakout gaps (UBG and DBG) have the lowest percentages filled in 1-day, which may indicate that these gaps capture prices that are breaking out of some important resistance or support levels and are, therefore, less likely to be reversed.

We now ask whether this apparent tendency for gaps to be filled offers traders the opportunity to generate excess returns. Table 3 displays the summary statistics for normalized conditional returns for days 1 to 5 after the price gap is identified.[11] The first column is the unconditional return normalized to zero mean and unit standard deviation. Conditional mean returns with an asterisk are significantly different from the unconditional means based on at 10% t-test. At the bottom of each row is the conditional mean return for gaps accompanied by increasing (IV) and decreasing (DV) volumes.

Four of the five mean returns for upward gaps are negative on day 1. Thereafter however, they display no obvious bias in either direction. For brakeout gaps, the results in row 1 of Table 3 support the earlier result that these gaps have the lowest fill percentage at 1-day, since their conditional 1-day returns are positive and negative respectively. Moreover, the mean returns on day 1 are both statistically significant and are the largest absolute returns for any of the five days post-gap days.

The upward runaway gap (URG) shows some persistence in the mean return, which is positive from day 2 to day 5, while DRG exhibits negative

[11]The results are for returns on the specified days, ie. they are not the cumulative returns from day 1 onward.

mean returns from day 3 to day 5. The average standard deviation of the conditional returns for both URG and DRG are slightly higher than for the congestion and breakout gaps. The standard deviations of the exhaustion gaps (UEG and DEG), exceed those of the other gaps. The one-day Island gaps misbehave in that they are contrary to the hypothesis that UIG should have negative mean returns while DIG should have positive returns. In fact, it is more common to see negative returns for both UIG and DIG.

Increasing volume appears to magnify the mean returns for all price gaps over the first day. This is partially consistent with the results presented by Cooper (1999), who finds that increasing-volume stocks exhibit weaker reversals than decreasing volume stocks in US equity markets. Thereafter there is no consistent pattern, which suggests that the information in trading volumes is useful for only 1 day.

5.2 The Information Content of Price Gaps

5.2.1 Goodness of Fit Tests.

Table 4 presents the goodness-of-fit tests, aggregated across all contracts, and sorted vertically according to gap type, from day 1 to day 5. The results along the rows are the ten deciles of the normalized conditional returns in percentage form. Under the null hypothesis, each bin should contain 10% of the total. The numbers in parenthesies below each percentage are the asymptotic z-values given in equation (4). The last column is the goodness-of-fit Q-statistic computed using equation (3), and the number in parentheses below the Q-statistic is its probability value.

The large Q-statistics for all price gaps on day 1 (except DIG) imply that we can reject the hypothesis that the distributions of unconditional and conditional normalized returns are identical. As we move from day 2 to day 5, however, there is a slight increase in the p-values, especially for UCG and UIG, implying that some of the conditional return distributions become indistinguishable from the unconditional distributions after one day. The highest Q-statistics are shown by the exhaustion gaps (UEG and DEG), and lowest by the downward island gap (DIG).

One clear feature of Table 4 is the variation in the distribution of the normalized returns displayed by the different gaps. For congestion and breakout gaps, the distributions seldom venture more than 1.5 percentage points from the null of 10.00 percent for each decile. The deviation from the null is considerably greater for runaway gaps (URG and DRG), sometimes exceeding three percentage points. For exhaustion gaps (UEG and DEG), the percentage deciles range from 4.93 to 20.90: the weight of the distributions being pushed to both tails of the distribution, suggesting that the typical finding of excess kurtosis in returns may be conditioned by the appearance of specific price gaps.

5.2.2 Kolmogorov-Smirnov Tests.

Table 5 presents the Kolmogorov-Smirnov two-sample distribution tests aggregated across all contracts, sorted horizontally by the gap type, from day 1 to day 5. The parameter γ is the Kolmogorov-Smirnov statistic given in equation (6) and the numbers in parentheses are the probability values.

In general the results are consistent with the goodness-of-fit test though not quite as emphatic. For the first day, 6 of the 10 gaps appear to contain information. For congestion gaps (UCG and DCG) the p-values suggest that any gap effects for dissipate after one day. For breakout gaps however, we find the opposite: On day 1, both UBG and DBG produce insignificant p-values at 0.400 and 0.111 respectively but are below 10% for days 2 to 5. This suggests that prices continue to behave abnormally for a few more days after the penetration of key support or resistant levels. For the effects of runaway gaps (URG and DRG) appear to dissipate by days 3 and 1 respectively. The results for exhaustion price gaps (UEG and DEG) are fairly strong, with p-values that are statistically significant (ranging from 0.000 to 0.064) for all days. Both the goodness-of-fit and the Kolmogorov-Smirnov tests suggest the presence of useful information in the exhaustion gaps.

As with the goodness-of-fit tests, the only price gaps that do not appear to contain any information at all are the islands. This also confirms Edwards and Magee's observation, described earlier, that island gaps are very difficult to identify in real time.

While the results in Table 5 (rows 3 and 5) support the hypothesis that increasing or decreasing volumes add to the information in the price gaps, there is no clear pattern to this. For example, the significant result for the upward runaway appears to arise in the context of increasing, but not decreasing, volume. For the downward runaway it is less clear cut with both volume-based measures being significant at 10%. Nevertheless, of the 21 cases in which the test indicates the presence of information, 12 appear to be related to increasing volume, 4 are related to decreasing volume, and 5 appear to be independent of volume changes.[12]

5.3 Does the Size of the Price Gap Matter?

Table 6 presents the results categorized by size. The first three lines show the price-gap counts for each size: For each type, the small gaps are the most common, followed by medium and large.

For exhaustion gaps (UEG and DEG) the proportion of large gaps exceeds 25%, and is greater than for the others. For the breakaway gap, for example, the percentage for large over the total sample is $\frac{765}{4406} \approx 17.36$ percent and $\frac{732}{4264} \approx 17.17$ percent for upward and downward gap respectively.

The remainder of Table 6 presents summary statistics and information test results for each size. Asterisks by the p-value and $t-$-statistics indicates significance at 10%.

We noted previously that the mean returns on UCG, UBG, URG and UEG are statistically significantly negative on day 1, which results from price reversals that cover the gaps. When we split the gaps by size, some interesting results emerge:

1. The congestion gap (UCG) mean returns are negative for all sizes, and the mean return for small gaps is larger than for the other sizes. This suggests that a contrarian strategy might be profitable here.

2. All upward breakout gaps have positive mean returns and all downward breakout gaps have negative mean returns, suggesting that a trend-following strategy is appropriate following all breakout gaps.

3. For both upward runaway and exhaustion gaps, the mean returns for small and medium gaps are negative, but those for large gaps are positive. Moreover, the mean return for the large gaps is the largest of the three. This pattern is reversed for the downward runaway and exhaustion gaps. This suggests that if the size of the price gap is large enough, then a strong momentum effect tends to follow. The large standard deviations for large runaway and exhaustion gaps also implies that these momentum effects are accompanied by increased volatility i.e. even though traders can earn higher expected returns by trading the URG, UEG, DRG and DEG price gaps, these higher returns are accompanied

[12] This observation is based on the set of test results that are significant at 10%.

by higher risk (as measured by standard deviation). Furthermore, a casual look at the pattern count for large gaps of these types shows that it is not a large number. It is undoubtedly fairly difficult to trade all these gaps over twenty-eight futures contract over a span of 25 years.

4. All large downward gaps (DCG, DBG, DRG and DEG) show negative mean returns i.e. downward momentum effects are strong when the size of the downward gap is large.

For the Exhaustion gaps (UEG and DEG), all the Q and γ statistics are significant at 10% for all sizes at day 1. After day 1, however, only the large gaps show significant Q and γ statistics consistently for five days. The returns for large gaps show the most consistent direction, which is negative for DEG and positive for UEG (except day 5). Lastly, Island gaps (UIG and DIG) have very unreliable results for all days, which is consistent with our earlier findings.

In summary, the results here support the hypothesis that the size of the price gap contains information about the price movement on day 1 but that this generally dissipates by day 2. The effects exhibited by exhaustion gaps appear to be consistent with the momentum effects found by Jegadeesh and Titman (1993, 2001) in US equity markets, and Moskowitz and Grinblatt (1999) for specific industries.

5.4 Conditioning on Chart Patterns

Table 7 presents the results for price gaps conditioned on chart patterns. Panel A presents the count for each of the gap-pattern pairs. Panel B presents the mean and standard deviation for returns conditioned on each pair, followed by the goodness of fit test (Q) and Kolmogorov-Smirnov test (γ) results.

For upward Congestion gaps (UCG), the most frequent pattern is the rectangle (RBOT, RTOP), followed by Head-and-Shoulders and Doubles. The difference in the pattern count between RBOT (432) and RTOP (405) is low. For upward breakout gaps (UBG), the largest count is RBOT (631), followed by HSBOT (469) and TBOT (219). Similarly, for downward breakout gaps (DBG), RTOP (492) has the largest count, followed by HSTOP (394) and TTOP (235).

For upward congestion gaps, the total number of bottom patterns (HSBOT, RBOT, TBOT, BBOT, DBOT) is 1,102 and the total number of top patterns (HSTOP, RTOP, TTOP, BTOP, DTOP) is 997, a difference of only 105. Conversely, for upward breakout gaps, the total number of bottom chart patterns is 1,586, but the total number of top patterns is only 315, a difference of 1,271. This implies that upward breakout gaps (and to a large extent, runaway and exhaustion gaps) experience some form of 'bottoming-out' before an upward price gap occurs. The opposite is the case for downward breakaway gaps, where prices experience some form of 'topping' before a downward gap appears.

Panel B displays summary statistics and information test results for each pattern where the test is based on a comparison of the conditional distribution for each gap-pattern pair, with the unconditional distribution for the sample as a whole (i.e. not with the conditional distribution for a specific gap). As in the previous section an asterisk indicates statistical significance at 10%. Statistically significant results appear to be randomly distributed among the gaps, and across all ten chart patterns. This suggests that no chart pattern is capable of producing reliable results in terms of statistically significant p-values for Q and γ statistics required to reject the hypothesis that conditional returns are similar to unconditional returns. For example, on day 1, the Q statistic for RBOT is significant for UCG, UBG and DBG, but not for the rest of gaps. On day 4, the same pattern is now significant for UIG and DEG. Furthermore, it is difficult to discover any patterns that exhibit significant statistics for the goodness-of-fit, Kolmogorov-Smirnov and t-tests together, even for exhaustion gaps.

The evidence suggests that chart patterns do not add to the information available from price gaps. While the earlier results suggest that price gaps do contain information, this appears to be spread randomly across the patterns. This is not to say that the patterns contain no information, since they may be informative at times when there are no price gaps, and they may contain the same information as the gaps when they do appear. Nevertheless, conditional on the occurrence of a gap, chart patterns appear to provide no incremental information.

6 Conclusion

This paper investigates an old principle proposed by market technicians: the Gap-Fill hypothesis, which holds that when a price gap occurs, it will be *filled* in the near future, and that price gaps contain important information regarding the distributions of subsequent price movements. To test the Gap-Fill hypothesis, we use time series of futures prices and categorize each observed price gap into one of five types commonly used by chartists, i.e. Congestion, Breakout, Runaway, Exhaustion and (one-day) Island. We then categorize further according to a number of conditioning variables to reflect the fact that practioners rarely base their predictions on gaps-information alone. These conditioning variables are gap-size, chart patterns and trading volume.

Several of our results contribute to the literature on technical analysis:

1. The Gap-Fill hypothesis is supported by the data: 30% of gaps are filled on the day after they appear, another 30% are filled during the 4 days after that, and 75% of are filled within 20 days of the gap's appearance.

2. Price gaps contain information regarding the distribution of prices in the days after the gaps appear, and this information appears to deteriorate slowly after the first day. This information appears to be related to trading volumes but this does not appear to be related is any useful way to specific types of gap.

3. In many cases the information derived from price gaps generates statistically significant returns on day 1, but not on subsequent days.

4. Trading volume provides useful additional information regarding sign of the returns, but only for the first day after the gap appears.

5. The size of exhaustion gaps provides additional information that persists for (at least) five days. Other types of gap show less reliable results however.

6. Chart patterns do not add information to that already available from price gaps.

In conclusion, we find evidence that gaps provide information about the distribution of prices on the day after a gap occurs. This information is not generated by all types of gaps however and where it does arise it generally dissipates by the second day after the gap. It would be interesting to apply these tests to intra-day data since day-traders probably rely more than any others on technical indicators in their trading decisions.

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Table 1: Futures Contracts

Futures Contracts	Sample Period	Contracts Months	Observations
	Currencies		
US-Yen	Jan. 78-Jun. 06	3,6,9,12	7184
US-CHF	Jan. 78-Jun. 06	3,6,9,12	7186
US-GBP	Jan. 78-Jun. 06	3,6,9,12	7184
US-AUS	Jun. 88-Jun. 06	3,6,9,12	4555
US-CAN	Sep. 87-Jun. 06	3,6,9,12	4744
	Fixed Income		
US 2Y T-Bond	Jun. 90-Jun. 06	3,6,9,12	4014
US 5Y T-Bond	May. 88-Jun. 06	3,6,9,12	4539
US 10Y T-Note	May. 82-Jun. 06	3,6,9,12	6074
US 30Y T-Bond	Jan. 78-Jun. 06	3,6,9,12	7167
EuroDollar	Dec. 81-Jun. 06	3,6,9,12	6182
UK Long Gilts	Dec. 82-Jun. 06	3,6,9,12	5954
JAP. JGB	Dec. 86-Jun. 06	3,6,9,12	4704
AUS. 3Y T-Note	May. 88-Jun. 06	3,6,9,12	4579
AUS. 10Y T-Bond	Dec. 84-Jun. 06	3,6,9,12	5456
CAN. 10Y Bond	Sep. 89-Jun. 06	3,6,9,12	4211
	Stock Indices		
S&P 500	Apr. 82-Jun. 06	3,6,9,12	6095
FTSE 100	May. 84-Jun. 06	3,6,9,12	5593
Nikkei 225	Sep. 88-Jun. 06	3,6,9,12	4378
Dax	Nov. 90-Jun. 06	3,6,9,12	3938
	Commodities		
Gold	Jan. 79-Jun. 06	2,4,6,8,10,12	6894
Silver	Jan. 79-Jun. 06	3,5,7,9,12	6908
Cotton	Jan. 79-Jun. 06	3,5,7,10,12	6894
Crude Oil	Apr. 83-Jun. 06	1-12	5782
Heating Oil	Jul. 80-Jun. 06	1-12	6507
Cocoa	Jan. 79-Jun. 06	3,5,7,9,12	6886
Coffee	Jan. 79-Jun. 06	3,5,7,9,12	6880
Wheat	Jan. 79-Jun. 06	3,5,7,9,12	6928
Sugar	Jan. 79-Jun. 06	3,5,7,10	6882
	Total Observations		164,288

Source:*Datastream*

Table 2: The Gap-Fill Hypothesis

Futures	Total Up Gaps	Total Down Gaps	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
Panel A: Price Gap Count												
Total	11547	10922	5812	4406	648	446	235	5579	4264	515	322	242
IV	6578	6304	2713	3002	431	292	140	2640	3013	354	183	114
DV	4966	4618	3099	1404	217	151	95	2939	1251	161	139	128
Currencies												
USYen	811	905	400	284	46	46	35	412	351	52	55	35
(Median)	837	932	445	293	42	30	27	484	314	56	46	32
USCHF	605	658	304	208	42	33	18	296	255	47	41	19
(Median)	595	656	308	218	36	20	13	333	231	47	29	16
USGBP	685	616	320	259	48	41	17	301	246	31	21	17
(Median)	703	664	353	257	46	29	18	350	239	37	22	16
USAUS	596	579	312	216	30	23	15	314	202	20	19	24
(Median)	643	580	336	210	38	35	24	320	195	26	20	19
USCAN	317	293	158	122	21	12	4	159	116	13	2	3
(Median)	316	284	162	118	22	9	5	153	108	14	5	4
Fixed Income												
US2Y	284	193	150	110	14	6	4	120	64	7	2	0
(Median)	303	228	150	112	24	12	5	137	73	11	4	3
US5Y	216	157	119	87	6	1	3	96	53	6	1	1
(Median)	242	181	118	92	21	8	3	101	64	11	3	2
US10Y	287	236	138	126	14	7	2	136	92	6	0	2
(Median)	318	236	144	132	28	10	4	126	90	15	3	2

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Futures	Total Up Gaps	Total Down Gaps	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
US30Y	323	302	152	142	17	8	4	145	129	16	9	3
(Median)	326	287	152	134	28	9	3	140	118	21	6	2
ED	277	259	136	114	16	8	3	143	91	13	10	2
(Median)	89	326	189	174	16	6	4	189	121	10	3	3
UKLG	288	238	134	119	23	11	1	128	99	7	2	2
(Median)	304	257	147	122	23	8	4	132	103	16	4	2
JGB	473	374	215	181	39	32	6	205	130	18	13	8
(Median)	478	352	217	182	41	29	9	190	131	17	8	6
AUS3Y	562	437	307	202	26	13	14	267	141	9	5	15
(Median)	586	471	307	201	33	27	18	287	143	18	10	13
AUS10Y	714	633	406	247	21	14	26	388	194	20	10	21
(Median)	721	613	396	229	41	33	22	369	185	25	16	18
CAN10Y	324	292	173	120	14	12	5	169	93	17	8	5
(Median)	320	268	156	120	25	13	6	150	94	14	6	4
Stock Indices												
S&P500	176	153	94	70	12	0	0	87	60	5	0	1
(Median)	205	153	89	89	21	5	1	76	64	10	2	1
FTSE100	405	309	211	148	24	16	6	166	112	12	5	14
(Median)	402	314	200	150	31	15	5	169	118	17	6	4
N225	399	344	220	141	23	11	4	172	135	17	10	10
(Median)	383	360	198	138	25	15	7	172	140	26	14	8
DAX	276	213	148	98	20	6	4	119	76	12	3	3
(Median)	283	204	139	107	23	11	3	108	79	11	4	2

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Futures	Total Up Gaps	Total Down Gaps	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
Commodities												
Gold	507	529	260	185	29	22	11	272	204	26	15	12
(Median)	534	541	280	204	27	13	10	280	211	27	13	10
Silver	401	426	189	140	27	35	10	197	170	25	27	7
(Median)	431	438	221	162	28	12	8	216	175	27	11	8
Cotton	408	433	200	167	19	17	5	191	215	16	7	4
(Median)	426	410	215	162	31	13	5	203	157	32	13	5
Crude	348	338	172	140	17	11	8	161	139	23	9	6
(Median)	321	274	157	126	25	9	4	146	104	16	5	3
Heat	417	421	201	155	29	23	9	202	164	27	19	9
(Median)	402	369	200	152	31	13	6	198	133	24	9	5
Cocoa	428	520	218	176	21	7	6	246	237	17	12	8
(Median)	432	506	224	159	30	13	6	242	194	42	21	7
Coffee	360	384	153	169	16	15	7	175	184	18	3	4
(Median)	347	370	177	136	23	8	3	180	149	27	10	4
Wheat	282	297	138	125	14	3	2	150	130	14	3	0
(Median)	276	283	136	113	20	5	2	129	117	27	8	2
Sugar	378	383	184	155	20	13	6	162	182	21	11	7
(Median)	407	378	203	158	30	12	4	185	150	29	10	4
Panel B: Price Gap Being Filled (Percentage of Total)												
1-Day			33.80	20.70	32.90	30.30	24.30	33.80	22.10	30.60	27.60	32.20
2-5 Day			28.90	30.20	27.00	26.50	31.90	30.10	29.20	28.10	29.40	26.90
6-10 Day			9.39	11.00	8.49	13.70	11.10	9.42	11.70	10.50	12.10	9.09
11-20 Day			7.78	9.33	7.72	7.17	7.23	7.25	9.08	6.59	6.50	7.44

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Futures	Total Up Gaps	Total Down Gaps	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
21-50 Day			6.07	8.56	6.17	6.95	7.66	6.88	9.41	6.01	7.12	8.26
51-75 Day			2.15	3.20	2.62	4.48	2.98	2.08	2.55	2.71	1.55	3.72
76-100 Day			1.14	1.86	2.16	1.79	1.70	1.36	1.97	1.36	0.93	1.24
101-200 Day			2.51	3.68	4.78	4.93	3.40	2.24	3.44	3.88	3.41	2.07
>200 Day			3.92	5.81	3.55	1.57	5.53	4.08	7.16	6.01	7.12	6.61
No Fill			4.37	5.70	4.63	2.69	4.26	2.76	3.37	4.26	4.33	2.48

Table 2 presents the results of applying the gap identification algorithm described in Section 2. The first three rows in Panel A record the numbers upward and downward price gaps, sorted according to the 10 gap patterns, and conditioned on increasing (IV) or decreasing volume (DV). Following this is the result for each individual futures contract, for which the first row is the number of gaps detected and the second is the median number of gaps from the 1000 nonparametric bootstraps.

Table 3: Summary Statistics of Unconditional and Conditional Normalized Returns

Statistics	Unconditional	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
					Day 1						
Mean	-0.0000	-0.0318*	0.0453*	-0.0719*	-0.0400	-0.0822	0.0010	-0.0315*	0.1206*	0.0929	-0.0133
S.D.	1.0000	1.0282	1.0788	1.1298	1.3820	1.1788	1.0369	1.0520	1.2709	1.4456	1.1430
Skew.	-0.2344	0.3711	0.6315	0.6084	-0.5856	-0.6478	-0.3016	-0.4919	0.0632	0.3690	0.7113
Kurt.	10.6242	6.9602	9.3443	5.9317	5.2325	3.2534	4.1404	3.7185	7.1327	2.6084	5.7712
IV Mean	-	-0.0723*	0.0522*	-0.1390*	-0.1300*	-0.0331	0.0167	-0.0498*	0.1850*	0.0952	-0.0301
DV Mean	-	0.0037	0.0306	0.0611	0.1300*	-0.1550*	-0.0131	0.0125	-0.0219	0.0898	0.0017
					Day 2						
Mean	-0.0000	0.0010	-0.0164	0.1298*	0.1065*	-0.0103	-0.0276	0.0266*	0.1168*	-0.0426	-0.0058
S.D.	1.0000	1.0346	1.0255	1.1307	1.3194	1.1763	1.0330	1.1062	1.4541	1.3191	1.0862
Skew.	-0.2344	0.2831	0.7056	0.1394	-0.1640	0.6341	-0.2651	-0.8739	2.8380	0.1470	0.3561
Kurt.	10.6242	5.7559	8.5284	2.3264	2.5668	6.5731	3.9813	11.3040	23.5890	1.1235	1.2055
IV Mean	-	-0.0002	0.0231	0.0943	0.0851*	0.0256	-0.0555*	0.0304*	0.1290*	-0.0026	-0.0710
DV Mean	-	0.0020	-0.1010	0.2010	0.1470*	-0.0632	-0.0026	0.0173	0.0901	-0.0952	0.0523
					Day 3						
Mean	-0.0000	-0.0047	-0.0073	0.0259	0.1149*	-0.0890	0.0022	-0.0021	-0.0579	-0.1413*	-0.0326
S.D.	1.0000	1.0382	1.1001	1.2186	1.3801	1.1951	1.0307	1.0882	1.1866	1.4197	1.0885
Skew	-0.2344	0.2225	1.9764	-0.2092	-0.6943	-0.0230	-0.1636	-0.3828	-0.3985	-0.0896	0.4653
Kurt.	10.6242	6.2587	35.7200	3.2971	5.7672	2.8202	3.8251	6.6020	3.5091	1.3153	1.2454
IV Mean	-	-0.0048	-0.0002	0.0103	0.0637	-0.0843	-0.0334*	-0.0131	-0.0661	-0.0935	-0.1520*
DV Mean	-	-0.0046	-0.0224	0.0567	0.2120*	-0.0960	0.0342*	0.0244	-0.0399	-0.2040*	0.0738
					Day 4						
Mean	-0.0000	-0.0207	0.0305*	0.0172	0.0361	0.0783	-0.0038	-0.0141	-0.0100	-0.1371*	-0.1350*

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Statistics	Unconditional	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
S.D.	1.0000	1.0014	1.0323	1.1368	1.4166	1.2659	1.0484	1.0835	1.2240	1.2860	1.0673
Skew	-0.2344	-0.2766	0.1337	-0.8971	-0.6516	1.4280	0.0394	0.4846	-0.1579	-0.0692	-0.7017
Kurt.	10.6242	3.3699	4.3381	4.6530	2.0531	14.6780	4.3037	6.7417	2.7071	0.5615	2.9010
IV Mean	-	-0.0022	0.0314*	0.0338	0.0084	0.1190*	-0.0033	-0.0082	0.0265	-0.2110*	0.0389
DV Mean	-	-0.0368*	0.0285*	-0.0158	0.0886*	0.0182	-0.0043	-0.0284	-0.0900	-0.0401	-0.2900*
					Day 5						
Mean	-0.0000	-0.0047	-0.0346*	0.0455	-0.0073	0.1826*	0.0254*	-0.0177	-0.0285	-0.1499*	0.1407*
S.D.	1.0000	1.0402	1.0629	1.1350	1.4190	1.1147	1.0567	1.1020	1.2477	1.3062	0.9887
Skew	-0.2344	0.3308	0.2158	-0.3628	-0.6638	1.6552	0.2906	-0.1463	-0.2711	0.1004	0.7280
Kurt.	10.6242	7.9087	4.9763	2.1136	2.9466	13.9570	7.6124	3.5132	4.7005	1.4448	1.2514
IV Mean	-	0.0073	-0.0321	0.0368	0.0206	0.1950	0.0515	-0.0058	-0.0006	-0.0683	0.0474
DV Mean	-	-0.0153	-0.0400	0.0627	-0.0601	0.1640	0.0020	-0.0463	-0.0901	-0.2570	0.2240

Table 3 displays the summary statistics for normalized conditional returns for days 1 to 5 after the price gap is identified.[13] The first column is the unconditional return normalized to zero mean and unit standard deviation. Conditional mean returns with an asterisk are significantly different from the unconditional means based on at 10% t-test. At the bottom of each row is the conditional mean return for gaps accompanied by increasing (IV) and decreasing (DV) volumes.

[13]The results are for returns on the specified days, ie. they are not the cumulative returns from day 1 onward.

Table 4: Goodness-of-Fit Information Tests

	Decile										
Gaps	1	2	3	4	5	6	7	8	9	10	Q-Statistic
					Day 1						
UCG	10.50	10.50	11.30	10.70	9.93	9.41	10.00	8.69	9.05	9.93	32.60
	(1.26)	(1.26)	(3.31)	(1.70)	(-0.18)	(-1.50)	(0.08)	(-3.33)	(-2.41)	(-0.18)	(0.000)
UBG	8.65	10.10	10.70	11.60	11.00	9.12	9.44	8.87	8.85	11.70	55.000
	(-2.99)	(0.12)	(1.48)	(3.54)	(2.28)	(-1.94)	(-1.24)	(-2.49)	(-2.54)	(3.79)	(0.000)
URG	11.30	13.10	11.30	11.30	12.00	9.26	7.25	7.87	5.71	11.00	32.800
	(1.07)	(2.65)	(1.07)	(1.07)	(1.73)	(-0.63)	(-2.33)	(-1.81)	(-3.64)	(0.81)	(0.000)
UEG	16.40	11.20	8.30	8.30	6.50	5.83	9.87	9.64	7.62	16.40	55.20
	(4.48)	(0.85)	(-1.20)	(-1.20)	(-2.46)	(-2.94)	(-0.09)	(-0.25)	(-1.67)	(4.48)	(0.000)
UIG	14.00	10.20	13.60	8.94	6.81	4.68	7.23	9.79	12.80	11.90	20.70
	(2.07)	(0.11)	(1.85)	(-0.54)	(-1.63)	(-2.72)	(-1.41)	(-0.11)	(1.41)	(0.98)	(0.014)
DCG	11.40	9.43	9.27	9.55	8.46	9.70	10.40	10.40	10.80	10.60	37.80
	(3.49)	(-1.42)	(-1.83)	(-1.11)	(-3.83)	(-0.75)	(0.99)	(1.12)	(1.92)	(1.43)	(0.000)
DBG	12.00	9.22	9.12	8.75	9.76	9.85	10.60	10.60	10.30	9.87	33.10
	(4.32)	(-1.70)	(-1.91)	(-2.73)	(-0.53)	(-0.33)	(1.20)	(1.36)	(0.59)	(-0.28)	(0.000)
DRG	13.60	7.96	6.21	6.41	7.96	8.93	12.80	10.90	10.50	14.80	41.80
	(2.72)	(-1.54)	(-2.86)	(-2.72)	(-1.54)	(-0.81)	(2.13)	(0.66)	(0.37)	(3.60)	(0.000)
DEG	15.80	8.70	7.76	6.52	7.45	6.21	7.76	10.60	11.50	17.70	45.30
	(3.49)	(-0.78)	(-1.34)	(-2.08)	(-1.52)	(-2.27)	(-1.34)	(0.33)	(0.89)	(4.61)	(0.000)
DIG	14.90	7.02	8.68	10.30	9.09	9.09	11.60	8.26	11.60	9.50	10.70
	(2.53)	(-1.54)	(-0.69)	(0.17)	(-0.47)	(-0.47)	(0.81)	(-0.90)	(0.81)	(-0.26)	(0.295)
					Day 2						
UCG	10.70	10.50	10.50	9.43	8.88	9.31	9.76	9.86	10.30	10.70	22.00

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	Decile										
Gaps	1	2	3	4	5	6	7	8	9	10	Q-Statistic
	(1.78)	(1.39)	(1.26)	(-1.45)	(-2.85)	(-1.76)	(-0.62)	(-0.36)	(0.82)	(1.78)	(0.009)
UBG	9.94	10.30	11.10	11.30	10.20	9.53	9.71	9.83	8.35	9.78	26.40
	(-0.13)	(0.72)	(2.33)	(2.83)	(0.42)	(-1.03)	(-0.63)	(-0.38)	(-3.65)	(-0.48)	(0.002)
URG	9.72	8.80	12.00	8.18	7.56	8.95	9.26	8.64	11.40	15.40	32.400
	(-0.24)	(-1.02)	(1.73)	(-1.55)	(-2.07)	(-0.89)	(-0.63)	(-1.15)	(1.20)	(4.61)	(0.000)
UEG	13.70	8.52	8.97	10.10	5.83	6.73	7.85	6.95	12.80	18.60	62.70
	(2.59)	(-1.04)	(-0.73)	(0.06)	(-2.94)	(-2.30)	(-1.52)	(-2.15)	(1.96)	(6.06)	(0.000)
UIG	13.60	11.50	8.09	9.36	7.23	8.94	9.79	7.23	13.20	11.10	11.10
	(1.85)	(0.76)	(-0.98)	(-0.33)	(-1.41)	(-0.54)	(-0.11)	(-1.41)	(1.63)	(0.54)	(0.270)
DCG	11.60	9.64	9.79	9.32	9.55	9.16	10.10	10.60	10.10	10.10	25.40
	(4.02)	(-0.89)	(-0.53)	(-1.69)	(-1.11)	(-2.09)	(0.36)	(1.52)	(0.27)	(0.14)	(0.003)
DBG	11.20	9.47	8.54	9.62	8.75	8.54	10.50	10.60	10.80	12.10	55.70
	(2.53)	(-1.14)	(-3.19)	(-0.84)	(-2.73)	(-3.19)	(1.10)	(1.20)	(1.77)	(4.47)	(0.000)
DRG	14.80	7.57	6.41	8.16	8.93	8.93	9.90	10.30	11.50	13.60	32.00
	(3.60)	(-1.84)	(-2.72)	(-1.40)	(-0.81)	(-0.81)	(-0.07)	(0.22)	(1.10)	(2.72)	(0.000)
DEG	18.00	8.39	9.01	6.52	8.39	7.76	7.76	9.01	12.10	13.00	33.40
	(4.79)	(-0.97)	(-0.59)	(-2.08)	(-0.97)	(-1.34)	(-1.34)	(-0.59)	(1.26)	(1.82)	(0.000)
DIG	12.00	13.60	10.30	8.68	8.68	9.09	8.68	7.44	8.26	13.20	10.50
	(1.03)	(1.89)	(0.17)	(-0.69)	(-0.69)	(-0.47)	(-0.69)	(-1.33)	(-0.90)	(1.67)	(0.313)
	Day 3										
UCG	10.80	10.60	9.67	10.40	9.17	9.27	9.76	9.76	9.77	10.70	19.00
	(2.09)	(1.52)	(-0.84)	(1.13)	(-2.11)	(-1.85)	(-0.62)	(-0.62)	(-0.58)	(1.87)	(0.025)
UBG	10.50	11.00	10.10	10.20	9.17	8.81	9.69	10.20	9.37	10.90	21.60
	(1.12)	(2.28)	(0.17)	(0.52)	(-1.84)	(-2.64)	(-0.68)	(0.37)	(-1.39)	(2.08)	(0.010)
URG	11.70	9.26	11.40	8.95	6.48	8.80	8.64	9.26	12.50	13.00	24.60

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	Decile										
Gaps	1	2	3	4	5	6	7	8	9	10	Q-Statistic
	(1.47)	(-0.63)	(1.20)	(-0.89)	(-2.99)	(-1.02)	(-1.15)	(-0.63)	(2.12)	(2.51)	(0.003)
UEG	12.80	9.87	8.07	8.30	6.05	8.30	9.87	8.52	7.40	20.90	71.20
	(1.96)	(-0.09)	(-1.36)	(-1.20)	(-2.78)	(-1.20)	(-0.09)	(-1.04)	(-1.83)	(7.64)	(0.000)
UIG	14.50	11.10	8.09	10.60	7.23	11.50	7.66	13.20	6.38	9.79	15.00
	(2.28)	(0.54)	(-0.98)	(0.33)	(-1.41)	(0.76)	(-1.20)	(1.63)	(-1.85)	(-0.11)	(0.091)
DCG	10.90	10.20	10.10	9.16	8.64	10.10	9.48	10.40	10.20	10.90	26.00
	(2.15)	(0.41)	(0.36)	(-2.09)	(-3.39)	(0.14)	(-1.29)	(0.94)	(0.45)	(2.33)	(0.002)
DBG	10.90	10.70	10.10	9.36	8.77	9.90	9.64	9.10	10.20	11.30	25.10
	(1.97)	(1.61)	(0.23)	(-1.40)	(-2.67)	(-0.22)	(-0.79)	(-1.96)	(0.49)	(2.74)	(0.003)
DRG	13.20	11.80	9.51	10.70	8.74	8.54	7.57	7.57	9.71	12.60	19.000
	(2.42)	(1.40)	(-0.37)	(0.51)	(-0.95)	(-1.10)	(-1.84)	(-1.84)	(-0.22)	(1.98)	(0.026)
DEG	20.20	8.70	9.01	6.21	11.20	6.21	8.07	7.45	8.39	14.60	54.90
	(6.09)	(-0.78)	(-0.59)	(-2.27)	(0.71)	(-2.27)	(-1.15)	(-1.52)	(-0.97)	(2.75)	(0.000)
DIG	14.00	10.30	12.40	10.30	7.85	8.26	7.85	7.02	9.92	12.00	11.50
	(2.10)	(0.17)	(1.24)	(0.17)	(-1.11)	(-0.90)	(-1.11)	(-1.54)	(-0.04)	(1.03)	(0.245)
	Day 4										
UCG	10.20	10.50	10.10	10.20	9.33	9.53	10.50	9.79	9.67	10.10	8.43
	(0.52)	(1.35)	(0.30)	(0.60)	(-1.71)	(-1.19)	(1.17)	(-0.53)	(-0.84)	(0.34)	(0.495)
UBG	10.40	9.42	9.85	9.74	9.19	9.15	10.10	10.30	10.80	10.90	16.10
	(0.92)	(-1.29)	(-0.33)	(-0.58)	(-1.79)	(-1.89)	(0.32)	(0.77)	(1.88)	(1.98)	(0.065)
URG	10.60	10.30	8.33	8.64	10.20	9.57	9.41	9.57	9.10	14.20	15.80
	(0.55)	(0.29)	(-1.41)	(-1.15)	(0.16)	(-0.37)	(-0.50)	(-0.37)	(-0.76)	(3.56)	(0.072)
UEG	17.50	7.62	6.73	5.83	7.40	5.61	7.85	11.90	10.50	19.10	92.10
	(5.27)	(-1.67)	(-2.30)	(-2.94)	(-1.83)	(-3.09)	(-1.52)	(1.33)	(0.38)	(6.38)	(0.000)
UIG	11.10	10.20	8.94	8.51	8.09	11.10	7.23	11.10	10.60	13.20	6.74

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	Decile										
Gaps	1	2	3	4	5	6	7	8	9	10	Q-Statistic
	(0.54)	(0.11)	(-0.54)	(-0.76)	(-0.98)	(0.54)	(-1.41)	(0.54)	(0.33)	(1.63)	(0.336)
DCG	11.20	10.50	10.00	9.52	8.94	8.96	9.84	9.68	9.86	11.40	35.60
	(3.04)	(1.25)	(0.09)	(-1.20)	(-2.63)	(-2.58)	(-0.40)	(-0.80)	(-0.35)	(3.57)	(0.000)
DBG	12.10	11.00	9.87	9.38	8.02	8.91	9.31	10.00	10.70	10.70	52.40
	(4.57)	(2.07)	(-0.28)	(-1.35)	(-4.31)	(-2.37)	(-1.50)	(0.08)	(1.56)	(1.51)	(0.000)
DRG	12.20	11.70	11.30	7.38	8.16	7.77	9.90	8.35	9.71	13.60	20.70
	(1.69)	(1.25)	(0.95)	(-1.98)	(-1.40)	(-1.69)	(-0.07)	(-1.25)	(-0.22)	(2.72)	(0.014)
DEG	19.30	10.60	7.45	7.45	7.76	11.80	5.90	7.76	8.39	13.70	46.70
	(5.54)	(0.33)	(-1.52)	(-1.52)	(-1.34)	(1.08)	(-2.45)	(-1.34)	(-0.97)	(2.19)	(0.000)
DIG	11.20	15.30	11.60	8.68	5.79	9.50	11.20	12.00	4.96	9.92	19.90
	(0.60)	(2.74)	(0.81)	(-0.69)	(-2.19)	(-0.26)	(0.60)	(1.03)	(-2.61)	(-0.04)	(0.019)
	Day 5										
UCG	10.80	10.30	10.00	9.84	9.14	9.79	9.84	10.10	9.76	10.30	10.60
	(2.09)	(0.87)	(0.03)	(-0.40)	(-2.19)	(-0.53)	(-0.40)	(0.30)	(-0.62)	(0.87)	(0.300)
UBG	11.80	10.70	11.50	9.42	8.40	9.06	8.40	9.28	10.80	10.60	61.50
	(4.04)	(1.63)	(3.28)	(-1.29)	(-3.55)	(-2.09)	(-3.55)	(-1.59)	(1.83)	(1.28)	(0.000)
URG	10.80	10.20	10.00	8.64	8.49	6.79	10.50	10.20	10.20	14.20	21.40
	(0.68)	(0.16)	(0.03)	(-1.15)	(-1.28)	(-2.72)	(0.42)	(0.16)	(0.16)	(3.56)	(0.011)
UEG	17.90	10.50	8.30	6.28	4.93	6.95	6.05	6.95	12.80	19.30	104.00
	(5.59)	(0.38)	(-1.20)	(-2.62)	(-3.57)	(-2.15)	(-2.78)	(-2.15)	(1.96)	(6.53)	(0.000)
UIG	8.09	9.36	11.90	4.68	8.09	6.81	11.90	8.51	16.60	14.00	27.20
	(-0.98)	(-0.33)	(0.98)	(-2.72)	(-0.98)	(-1.63)	(0.98)	(-0.76)	(3.37)	(2.07)	(0.001)
DCG	10.50	10.30	10.20	9.73	8.21	9.91	9.28	9.66	10.60	11.60	40.90
	(1.16)	(0.72)	(0.41)	(-0.66)	(-4.46)	(-0.22)	(-1.78)	(-0.84)	(1.61)	(4.07)	(0.000)
DBG	11.80	10.30	10.50	8.91	7.67	9.43	9.47	10.60	10.10	11.10	53.80

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	Decile										
Gaps	1	2	3	4	5	6	7	8	9	10	Q-Statistic
	(4.01)	(0.69)	(1.15)	(-2.37)	(-5.07)	(-1.25)	(-1.14)	(1.31)	(0.23)	(2.43)	(0.000)
DRG	14.20	10.10	9.51	8.93	7.96	7.96	7.57	10.50	10.30	13.00	21.80
	(3.16)	(0.07)	(-0.37)	(-0.81)	(-1.54)	(-1.54)	(-1.84)	(0.37)	(0.22)	(2.28)	(0.009)
DEG	18.00	12.10	7.14	8.39	7.45	9.63	8.70	8.39	8.07	12.10	31.70
	(4.79)	(1.26)	(-1.71)	(-0.97)	(-1.52)	(-0.22)	(-0.78)	(-0.97)	(-1.15)	(1.26)	(0.000)
DIG	9.09	10.70	9.50	9.09	9.09	9.92	7.02	9.50	11.60	14.50	8.41
	(-0.47)	(0.39)	(-0.26)	(-0.47)	(-0.47)	(-0.04)	(-1.54)	(-0.26)	(0.81)	(2.31)	(0.493)

Table 4 presents the goodness-of-fit tests, aggregated across all contracts, and sorted vertically according to gap type, from day 1 to day 5. The results along the rows are the ten deciles of the normalized conditional returns in percentage form. Under the null hypothesis, each bin should contain 10% of the total. The numbers in parenthesies below each percentage are the asymptotic z-values given in equation (4). The last column is the goodness-of-fit Q-statistic computed using equation (3), and the number in parentheses below the Q-statistic is its probability value.

Table 5: Kolmogorov-Smirnov Distribution Tests

Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
					Day 1					
γ	2.46	0.89	1.42	1.31	0.77	1.51	1.20	1.45	1.64	0.51
p-value	(0.000)	(0.400)	(0.036)	(0.064)	(0.598)	(0.021)	(0.111)	(0.031)	(0.009)	(0.955)
IV γ	1.66	1.34	1.58	1.37	0.78	1.32	1.29	1.41	0.96	0.73
p-value	(0.008)	(0.056)	(0.014)	(0.048)	(0.572)	(0.060)	(0.071)	(0.039)	(0.316)	(0.658)
DVγ	1.04	0.31	0.69	1.60	1.20	0.68	0.36	1.27	1.06	0.42
p-value	(0.226)	(1.000)	(0.734)	(0.012)	(0.110)	(0.737)	(1.000)	(0.079)	(0.208)	(0.995)
					Day 2					
γ	0.91	1.48	1.48	2.26	0.85	1.19	2.15	1.12	1.47	0.76
p-value	(0.376)	(0.024)	(0.025)	(0.000)	(0.463)	(0.120)	(0.000)	(0.166)	(0.027)	(0.614)
IV γ	0.83	0.85	1.12	1.77	0.49	1.23	1.97	0.96	1.11	1.01
p-value	(0.492)	(0.460)	(0.166)	(0.004)	(0.967)	(0.099)	(0.001)	(0.320)	(0.166)	(0.263)
DVγ	0.25	1.54	1.17	1.50	0.48	0.32	0.82	0.64	0.99	0.43
p-value	(1.000)	(0.017)	(0.127)	(0.023)	(0.973)	(1.000)	(0.515)	(0.801)	(0.282)	(0.992)
					Day 3					
γ	0.95	1.27	1.36	2.12	0.91	1.09	1.01	1.20	2.03	1.01
p-value	(0.325)	(0.080)	(0.050)	(0.000)	(0.383)	(0.185)	(0.263)	(0.111)	(0.001)	(0.257)
IV γ	0.44	0.94	0.63	1.54	0.80	1.74	0.74	1.14	1.23	1.12
p-value	(0.990)	(0.341)	(0.825)	(0.018)	(0.544)	(0.005)	(0.645)	(0.148)	(0.098)	(0.161)
DVγ	1.09	0.75	1.33	1.39	0.52	1.03	1.14	0.92	1.38	0.35
p-value	(0.189)	(0.624)	(0.057)	(0.043)	(0.946)	(0.236)	(0.151)	(0.361)	(0.044)	(1.000)
					Day 4					
γ	0.80	1.56	0.79	1.95	0.55	1.18	2.03	0.98	1.73	0.62
p-value	(0.538)	(0.015)	(0.564)	(0.001)	(0.927)	(0.122)	(0.001)	(0.290)	(0.001)	(0.840)

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Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
IV γ	0.17	1.41	0.96	1.43	0.41	1.21	1.59	0.94	1.44	0.69
p-value	(0.000)	(0.037)	(0.311)	(0.034)	(0.995)	(0.105)	(0.012)	(0.337)	(0.032)	(0.735)
DVγ	0.75	0.52	0.52	1.62	0.30	0.62	1.08	0.92	1.17	1.08
p-value	(0.635)	(0.952)	(0.952)	(0.011)	(1.000)	(0.843)	(0.192)	(0.362)	(0.127)	(0.193)
					Day 5					
γ	1.00	2.54	0.82	2.43	1.55	1.42	1.41	1.04	1.83	0.96
p-value	(0.268)	(0.000)	(0.506)	(0.000)	(0.016)	(0.035)	(0.037)	(0.231)	(0.003)	(0.311)
IV γ	0.35	1.72	1.09	1.84	1.59	1.50	0.66	1.14	1.15	0.22
p-value	(0.000)	(0.005)	(0.187)	(0.002)	(0.012)	(0.022)	(0.777)	(0.146)	(0.145)	(1.000)
DVγ	1.14	1.09	0.88	1.75	0.37	0.74	1.24	1.05	1.67	1.19
p-value	(0.151)	(0.185)	(0.423)	(0.004)	(0.999)	(0.643)	(0.093)	(0.221)	(0.007)	(0.119)

Table 5 presents the Kolmogorov-Smirnov two-sample distribution tests aggregated across all contracts, sorted horizontally by the gap type, from day 1 to day 5. The parameter γ is the Kolmogorov-Smirnov statistic given in equation (6) and the numbers in parentheses are the probability values.

Table 6: Price Gap Size Evaluation

Gap Size	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
small	Count	3397	2563	435	216	235	3153	2440	303	146	242
medium	Count	1739	1078	142	115	0	1731	1092	148	78	0
large	Count	676	765	71	115	0	695	732	64	98	0
Day 1											
small	Mean	-0.0469*	0.0382*	-0.1139*	-0.1173*	-0.0822	0.0203	-0.0053	0.0941	0.2224*	-0.0133
	S.D	1.0285	1.0088	1.0834	1.2124	1.1788	1.0422	1.0592	1.1216	1.2450	1.1430
	Q	31.600*	36.300*	15.600*	19.100*	20.700*	30.600*	16.700*	16.600*	24.000*	10.700
	γ	2.257*	0.856	1.343*	0.980	0.768	1.565*	0.728	1.294*	1.390*	0.512
medium	Mean	-0.0095	0.0332	-0.2665*	-0.2856*	-	0.0124	-0.0438	0.2717*	0.2158*	-
	S.D.	1.0050	1.0590	0.9254	1.4610	-	0.9924	0.9841	1.3025	1.3621	-
	Q	11.000	14.800*	18.400*	11.200	-	8.170	12.100	22.100*	22.300*	-
	γ	0.793	0.670	1.553*	0.947	-	0.735	0.551	1.348*	1.244*	-
large	Mean	-0.0129	0.0862*	0.5752*	0.3508*	-	-0.1151*	-0.1006*	-0.1035	-0.1980*	-
	S.D.	1.0846	1.3094	1.5110	1.5240	-	1.1122	1.1217	1.7555	1.7328	-
	Q	4.800	22.000*	52.000*	91.300*	-	20.200*	27.400*	26.600*	25.500*	-
	γ	0.176	1.004	1.429*	2.237*	-	1.131	0.952	1.106	1.546*	-
Day 2											
small	Mean	-0.0028	-0.0629*	0.1372*	0.0005	-0.0103	-0.0275	0.0162	0.1058*	0.0457	-0.0058
	S.D	1.0544	0.9698	1.0798	1.2260	1.1763	1.0688	1.1197	1.4227	1.1915	1.0862
	Q	25.500*	31.600*	17.000*	18.200*	11.100	26.200*	41.500*	16.200*	6.470	10.500
	γ	0.759	2.207*	1.079	0.849	0.851	1.001	1.486	0.861	0.360	0.758
medium	Mean	-0.0082	0.0105	0.0992	0.0978	-	-0.0254	0.0410	0.1824*	-0.1067	-
	S.D.	0.9989	0.9818	1.0912	1.2401	-	0.9583	1.0219	1.4978	1.2616	-

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Gap Size	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	Q	9.480	7.400	11.800	21.400*	-	2.860*	12.100	16.600*	17.400*	-
	γ	0.168	0.550	0.773	0.828	-	0.372	0.792	0.814	1.293*	-
large	Mean	0.0433	0.1014*	0.1461	0.3140*	-	-0.0332	0.0397	0.0173	-0.1231	-
	S.D.	1.0245	1.2364	1.4787	1.5357	-	1.0488	1.1808	1.5141	1.5333	-
	Q	12.500	15.500*	31.100*	50.000*	-	8.550	18.200*	7.880	45.100*	-
	γ	0.758	0.946	1.059	1.840*	-	0.471	0.669	0.713	1.703*	-
					Day 3						
small	Mean	0.0026	0.0174	-0.0142	0.0058	-0.0890	0.0083	-0.0232	-0.0877	-0.0391*	-0.0326
	S.D	1.0354	1.0159	1.2537	1.2234	1.1951	1.0338	1.1017	1.1083	1.4153	1.0885
	Q	11.100	6.810	12.800	21.800*	15.000*	22.200*	19.100*	17.500*	29.500*	11.500
	γ	0.776	0.461	0.774	0.649	0.907	1.038	1.346	1.070	0.922	1.012
medium	Mean	-0.0251	0.0029	0.1150	0.0120	-	0.0112	0.0200	-0.0656	0.0012	-
	S.D.	1.0474	1.0120	1.1132	1.5463	-	0.9856	0.9905	1.1860	1.2701	-
	Q	15.000*	14.700*	11.800	11.500	-	14.200	6.610	18.600*	9.950	-
	γ	0.972	0.355	0.979	0.821	-	0.831	0.506	0.563	0.513	-
large	Mean	0.0113	-0.1045*	0.0929	0.4225*	-	-0.0476	0.0350	0.1007	-0.4070*	-
	S.D.	1.0288	1.4359	1.2059	1.4465	-	1.1221	1.1781	1.5121	1.5140	-
	Q	12.400	30.200*	12.500	68.400*	-	11.500	9.040	13.200	40.800*	-
	γ	0.427	1.971*	0.799	1.784*	-	0.498	0.785	0.798	2.043*	-
					Day 4						
small	Mean	-0.0099	0.0323*	0.0217	-0.0519	0.0783	0.0000	-0.0353*	0.0447	0.0275	-0.1350*
	S.D	1.0044	0.9689	1.1179	1.3474	1.2659	1.0852	1.0826	1.1389	1.1358	1.0673
	Q	4.800	8.020	11.400	29.900*	6.740	42.500*	43.900*	14.700	12.400	19.900*
	γ	0.282	0.714	0.668	1.089	0.546	1.200	2.005*	0.765	0.547	0.617
medium	Mean	-0.0455*	0.0082	0.0930	-0.0075	-	-0.0294	0.0534*	-0.0601	-0.2151*	-

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Gap Size	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	S.D.	0.9801	1.0946	1.0792	1.4375	-	0.9688	1.1067	1.3178	1.2458	-
	Q	12.200	13.400	11.800	16.400*	-	11.400	17.300*	23.800*	17.600*	-
	γ	1.106	0.659	0.811	0.626	-	0.266	0.587	0.985	1.237*	-
large	Mean	-0.0109	0.0559	-0.1623	0.2449*	-	0.0427	-0.0444	-0.1528	-0.3204*	-
	S.D.	1.0403	1.1426	1.3441	1.5107	-	1.0686	1.0482	1.3833	1.4944	-
	Q	7.990	19.900*	4.920	79.200*	-	17.600*	8.870	8.500	47.100*	-
	γ	0.430	0.818	0.628	2.088*	-	0.679	0.886	0.627	1.894*	-
Day 5											
small	Mean	0.0104	-0.0152	0.0325	0.0525	0.1826*	0.0209	-0.0204	-0.0372	-0.0522	0.1407*
	S.D	1.0107	1.0490	1.0897	1.5127	1.1147	1.0361	1.1271	1.2744	1.2862	0.9887
	Q	9.660	40.700*	14.300	68.900*	27.200*	34.400*	44.100*	8.520	7.700	8.410
	γ	0.753	0.987	1.026	2.061*	1.554*	1.040	1.198	0.616	0.953	0.964
medium	Mean	-0.0392	-0.0765*	0.0145	-0.0049	-	0.0418*	0.0122	-0.0264	0.0051	-
	S.D.	1.0786	1.0337	1.0649	1.2150	-	1.0704	1.0396	1.1139	1.2015	-
	Q	9.920	16.300*	8.990	13.300	-	7.060	7.690	8.620	3.790*	-
	γ	1.007	1.236	0.434	0.676	-	0.525	0.518	0.452	0.454	-
large	Mean	0.0080	-0.0406	0.1868	-0.1218	-	0.0051	-0.0529	0.0076	-0.4186*	-
	S.D.	1.0842	1.1463	1.4960	1.4310	-	1.1146	1.1079	1.4209	1.3860	-
	Q	18.300*	19.400*	24.900*	53.300*	-	12.700	22.000*	21.900*	39.100*	-
	γ	0.863	0.958	1.509*	1.358*	-	0.360	0.736	0.854	1.788*	-

Table 7: Price Gaps and Technical Chart Patterns

Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
Panel A: Pattern Count											
HSBOT	Count	190	469	76	28	26	260	38	0	0	0
RBOT	Count	432	631	79	22	35	400	116	2	2	0
TBOT	Count	82	219	31	23	15	105	20	0	0	0
BBOT	Count	152	71	7	3	4	84	40	1	6	0
DBOT	Count	246	196	11	4	9	141	77	3	4	0
HSTOP	Count	282	46	0	0	0	155	394	59	23	31
RTOP	Count	405	143	2	2	0	436	492	75	23	37
TTOP	Count	80	19	0	0	0	77	235	34	9	13
BTOP	Count	88	43	5	4	0	158	81	12	1	3
DTOP	Count	142	64	2	4	0	214	138	11	4	5
Panel B: Summary Statistics and Information Tests											
Day 1											
HSBOT	Mean	-0.0063	-0.0204	-0.0377	-0.1646	-0.0266	-0.0930	-0.2407	-	-	-
	S.D.	0.8382	0.9239	0.9209	1.0705	0.9993	0.8729	0.8590	-	-	-
	Q	15.700*	11.800	9.530	11.300	10.200	10.800	7.790	-	-	-
	γ	0.401	0.845	0.507	0.826	0.629	0.969	0.729	-	-	-
RBOT	Mean	-0.0361	0.0435	-0.0901	-0.4781*	-0.2650	-0.0146	-0.1772*	0.0895	0.3622	-
	S.D.	0.7749	0.9001	1.2453	0.8647	0.9151	0.8698	0.7423	0.7824	0.5811	-
	Q	47.500*	25.100*	9.480	12.500	7.000	11.500	16.200*	8.000	8.000	-
	γ	0.988	0.918	0.799	1.415*	0.937	0.423	1.293*	0.376	0.046	-
TBOT	Mean	0.2076*	0.1008	-0.1606	-0.1786	-0.0027	-0.0510	-0.2748	-	-	-
	S.D.	0.8033	0.9847	1.3275	1.1908	1.0877	1.0282	0.8268	-	-	-

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	Q	8.240	17.300*	6.740	7.870	8.330	5.950	10.000	-	-	-
	γ	0.720	0.566	0.718	0.410	0.493	0.171	1.021	-	-	-
BBOT	Mean	0.0215	0.0617	-0.4887	-1.1006*	-0.8925*	-0.1432	0.3737	0.2897	0.7870	-
	S.D.	0.8552	1.0166	1.5814	0.5567	0.6904	1.0813	1.2060	-	1.3488	-
	Q	6.290	13.100	5.860	13.700	6.000	1.950*	8.500	9.000	7.330	-
	γ	0.315	0.214	0.761	1.406*	0.697	0.300	0.867	0.424	0.477	-
DBOT	Mean	-0.0231	-0.0027	0.2316	0.6437	0.0138	0.0026	-0.0772	-0.4676	0.6874	-
	S.D.	0.7863	0.7737	0.6997	0.5156	0.9553	0.9891	1.0666	0.2008	0.7737	-
	Q	8.720	18.300*	6.270	11.000	5.440	11.000	2.610*	7.000	11.000	-
	γ	0.528	0.572	0.232	0.835	0.352	0.214	0.294	0.263	0.691	-
HSTOP	Mean	-0.0919	0.0003	-	-	-	-0.0583	-0.0091	0.0513	0.0985	-0.1562
	S.D.	0.9496	1.0170	-	-	-	0.8735	0.9615	0.8114	1.0108	0.8093
	Q	11.600	4.430	-	-	-	11.500	6.710	4.900	9.610	5.450
	γ	0.875	0.175	-	-	-	0.637	0.252	0.499	0.360	0.640
RTOP	Mean	0.0838*	0.0820	0.1016	-0.4632	-	-0.0699	-0.0588	0.0913	0.2006	-0.0811
	S.D.	0.8189	1.0491	0.6311	0.0430	-	0.8616	0.9160	0.9596	0.6448	0.8487
	Q	14.800*	38.900*	8.000	18.000*	-	15.400*	9.220	11.500	8.740	14.100
	γ	0.996	1.051	0.297	0.394	-	0.853	0.726	0.745	0.382	0.705
TTOP	Mean	-0.1162	-0.3052*	-	-	-	-0.1157	-0.0188	0.4143	-0.0315	-0.3441
	S.D.	1.1211	2.0072	-	-	-	1.1566	1.0416	0.9476	0.7471	1.1284
	Q	14.500	8.890	-	-	-	14.000	8.700	16.000*	7.670	12.400
	γ	0.969	0.649	-	-	-	0.366	0.277	0.828	0.329	0.763
BTOP	Mean	-0.1316	-0.1633	-0.1293	0.0161	-	0.1046	-0.1192	0.4228	0.1350	-0.5573
	S.D.	0.9961	0.9739	0.5850	0.5414	-	0.9785	1.1432	1.1586	-	0.2346
	Q	5.410	15.800	9.000	6.000	-	3.270	11.500	19.700*	9.000	7.000

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	γ	0.679	0.619	0.290	0.174	-	0.469	0.564	1.012	0.521	0.296
DTOP	Mean	0.1171	0.1053	0.5564	0.0509	-	-0.0712	-0.0913	0.4629	0.9307*	0.2201
	S.D.	0.8321	0.8730	0.0121	0.5941	-	0.9862	0.9847	0.7657	1.9268	1.3771
	Q	12.500	7.250	18.000*	16.000*	-	6.000	9.970	8.090	11.000	5.000
	γ	0.454	0.409	0.420	0.022	-	0.450	0.590	0.808	0.527	0.353
Day 2											
HSBOT	Mean	-0.0329	-0.0722	0.0915	-0.0855	-0.0632	0.0159	-0.2005	-	-	-
	S.D.	0.9071	0.8909	0.9236	1.1636	0.8155	0.9679	1.0888	-	-	-
	Q	11.300	12.200	1.370*	7.710	2.460*	7.380	6.740	-	-	-
	γ	0.430	1.095	0.248	0.533	0.237	0.546	0.610	-	-	-
RBOT	Mean	0.0464	-0.0471	0.0151	0.0190	-0.3707	-0.0713	-0.2119*	-0.4538	0.1807	-
	S.D.	0.9037	0.8923	0.8931	0.9305	0.9750	0.8743	1.1366	0.7309	1.1582	-
	Q	3.420*	35.800*	4.160*	6.180	19.000*	9.050	21.200*	8.000	8.000	-
	γ	0.247	1.451*	0.139	0.579	1.157	0.818	1.492*	0.748	0.475	-
TBOT	Mean	0.1910*	0.0390	0.0443	0.4264*	-0.0223	-0.1034	-0.1663	-	-	-
	S.D.	1.1011	1.0949	0.9837	1.2024	0.8282	0.8732	0.7656	-	-	-
	Q	7.020	5.430	8.680	9.610	3.000*	7.100	6.000	-	-	-
	γ	0.491	0.178	0.354	1.018	0.203	0.436	0.471	-	-	-
BBOT	Mean	-0.0441	0.1623	-0.4127	-0.1356	0.1419	-0.1143	-0.0712	-0.0143	0.1800	-
	S.D.	1.0022	1.0134	1.1663	0.7944	1.4622	1.1437	1.2299	-	0.6613	-
	Q	18.000*	2.940*	8.710	7.000	6.000	6.950	17.000*	9.000	7.330	-
	γ	1.257*	0.253	0.697	0.425	0.456	0.707	0.393	0.622	0.289	-
DBOT	Mean	0.0488	-0.0067	0.0323	0.0920	-0.1165	-0.1326	0.1383	0.1002	1.2587*	-
	S.D.	0.8642	0.7766	0.9865	0.5037	0.7579	0.8151	1.0273	0.1841	1.0659	-
	Q	14.200	10.100	6.270	6.000	9.890	19.500*	4.170*	7.000	11.000	-

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	γ	0.232	0.745	0.373	0.290	0.864	0.942	0.261	0.236	1.021	-
HSTOP	Mean	0.0444	-0.0824	-	-	-	0.0191	-0.0305	-0.0590	-0.1134	0.0817
	S.D.	1.0210	1.1605	-	-	-	1.0342	0.9826	0.8902	0.6479	1.3569
	Q	15.000*	7.910	-	-	-	8.940	14.100	11.300	20.900*	10.600
	γ	0.209	0.846	-	-	-	0.486	0.547	0.705	0.694	0.383
RTOP	Mean	0.0098	-0.1200	0.2730	0.1475	-	-0.0148	-0.0951	-0.0470	0.1283	0.1872
	S.D.	0.9063	0.9695	0.9210	1.0848	-	1.0085	0.9992	0.8717	0.5925	1.0504
	Q	14.400	18.900*	8.000	8.000	-	20.700*	12.100	8.330	22.700*	6.510
	γ	0.671	1.491*	0.321	0.465	-	0.401	0.600	0.648	0.771	0.242
TTOP	Mean	0.1139	-0.0459	-	-	-	-0.0375	-0.0270	-0.0286	0.3834	-0.2938
	S.D.	0.9956	1.0309	-	-	-	0.9306	1.0305	1.3467	1.0267	0.7554
	Q	2.000*	8.890	-	-	-	14.600	6.400	6.590	7.670	6.230
	γ	0.415	0.490	-	-	-	0.299	0.338	0.683	0.510	0.622
BTOP	Mean	0.1030	-0.1710	0.4200	-0.2969	-	-0.0480	0.0764	0.2494	0.5384	0.3128
	S.D.	0.9456	0.9841	1.2098	0.5652	-	0.9436	1.1174	1.0593	-	0.3955
	Q	8.140	15.800*	9.000	6.000	-	7.950	4.310	9.670	9.000	7.000
	γ	0.623	0.467	0.158	0.391	-	0.496	0.292	0.405	0.299	0.230
DTOP	Mean	0.0430	0.1095	-0.4073	0.2671	-	-0.0384	-0.0893	-0.1021	-0.6232	-0.1124
	S.D.	0.8461	1.1510	0.0411	0.7437	-	1.0060	0.9047	0.7732	0.5246	2.5386
	Q	8.850	10.100	8.000	11.000	-	8.150	7.650	4.450	21.000*	13.000
	γ	0.469	0.418	0.361	0.157	-	0.102	0.782	0.238	0.948	0.955
					Day 3						
HSBOT	Mean	0.0962	-0.0486	0.0232	-0.5324*	0.0394	0.0716	-0.1542	-	-	-
	S.D.	0.9866	0.9568	1.1625	1.1411	1.2364	0.8815	0.6622	-	-	-
	Q	14.200	18.900*	8.470	20.600*	10.200	5.770	7.260	-	-	-

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	γ	1.132	0.549	0.812	1.168	0.726	0.367	1.014	-	-	-
RBOT	Mean	-0.0045	-0.0200	-0.0200	0.3249*	0.0034	-0.0069	0.0448	-0.6476	-2.4453*	-
	S.D.	0.8948	0.9024	1.0441	0.8259	1.1977	0.8663	0.9969	0.9476	1.7203	-
	Q	11.500	10.500	12.300	13.500	2.430*	14.400	12.600	8.000	18.000*	-
	γ	0.400	1.199	0.534	0.665	0.360	0.340	0.580	0.881	1.398*	-
TBOT	Mean	0.0031	0.0274	0.0729	0.4032*	-0.0786	-0.0608	-0.2756	-	-	-
	S.D.	0.9850	1.1167	1.8144	1.7284	0.9208	0.9233	0.7958	-	-	-
	Q	9.710	6.620	13.800	7.000	7.000	16.600*	8.000	-	-	-
	γ	0.305	0.484	0.624	0.395	0.341	0.188	0.694	-	-	-
BBOT	Mean	0.0109	0.1987	0.4597	-0.2879	1.0576*	-0.0251	0.0795	0.2573	0.4989	-
	S.D.	0.9727	1.0633	1.1785	1.1949	1.0284	1.1737	0.8796	-	0.5185	-
	Q	18.100*	10.800	8.710	7.000	11.000	7.670	4.500	9.000	7.330	-
	γ	0.280	0.504	0.311	0.583	0.986	0.644	0.180	0.444	0.445	-
DBOT	Mean	-0.0148	0.0737	0.6057	1.1572*	-0.3069	0.0334	0.2071*	0.4746	-2.1442*	-
	S.D.	0.7814	0.8547	0.9694	1.8441	1.2837	0.9679	0.8788	0.4869	1.4412	-
	Q	7.660	15.300*	11.700	11.000	9.890	4.040*	7.290	7.000	21.000*	-
	γ	0.417	1.030	0.684	0.536	0.730	0.465	0.905	0.349	1.704*	-
HSTOP	Mean	-0.0267	-0.2490	-	-	-	-0.0921	-0.0279	-0.2428	0.3094	-0.0414
	S.D.	0.9631	1.0100	-	-	-	1.0345	1.0032	0.8678	0.9383	0.9833
	Q	6.940	11.000	-	-	-	9.450	4.020*	9.980	28.700*	3.520*
	γ	0.420	0.526	-	-	-	0.493	0.492	1.060	0.747	0.710
RTOP	Mean	0.0373	-0.1698*	0.1998	-0.0583	-	-0.0490	-0.0114	0.1169	0.2074	-0.0947
	S.D.	0.8444	0.9996	0.0012	0.3636	-	1.0546	0.9887	0.8855	0.7479	0.9700
	Q	6.780	18.300*	18.000*	8.000	-	6.200	10.400	11.800	18.300*	8.140
	γ	0.398	0.973	0.176	0.277	-	0.309	0.631	0.388	0.720	0.802

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
TTOP	Mean	-0.0778	-0.3134	-	-	-	0.1781	0.0019	0.0714	0.7084*	-0.1110
	S.D.	0.9890	0.6642	-	-	-	1.2394	0.9969	1.1515	1.0567	1.0899
	Q	7.750	19.400*	-	-	-	19.000*	11.200	4.240	12.100	10.800
	γ	0.610	0.617	-	-	-	0.530	0.195	0.211	0.793	0.652
BTOP	Mean	0.0425	-0.2226	0.4605	-0.2611	-	-0.1630	-0.0407	-0.1996	0.0941	0.2215
	S.D.	0.9333	0.9000	0.7229	0.5612	-	0.9161	0.9478	0.9011	-	0.5809
	Q	10.400	9.330	9.000	6.000	-	12.800	0.358*	8.000	9.000	7.000
	γ	0.393	0.779	0.270	0.454	-	1.104	0.227	0.610	0.546	0.222
DTOP	Mean	0.0219	-0.1478	-0.1630	-0.4131	-	-0.0801	-0.0034	-0.3251	0.3064	0.4758
	S.D.	0.7580	0.8105	0.5142	0.5114	-	0.9260	1.1099	1.5677	0.4102	0.9599
	Q	8.420	16.600*	8.000	6.000	-	6.650	9.830	2.640*	6.000	5.000
	γ	0.701	0.918	0.414	0.886	-	0.925	0.410	0.583	0.329	0.317
Day 4											
HSBOT	Mean	0.0136	0.1082*	-0.0964	0.1240	-0.2092	-0.1505*	0.1575	-	-	-
	S.D.	0.9721	0.9191	1.1355	0.9449	1.1672	1.0061	1.2532	-	-	-
	Q	16.000*	9.780	7.950	22.700*	6.310	16.200*	13.100	-	-	-
	γ	0.300	0.631	0.386	0.643	0.420	1.212	0.495	-	-	-
RBOT	Mean	0.0413	0.0509	0.1074	0.1921	0.0909	0.0290	-0.0260	-0.3751	-0.1666	-
	S.D.	0.9449	0.8673	0.9219	1.1332	0.9581	0.9534	0.9249	0.2984	1.1699	-
	Q	7.770	10.900	5.430	8.000	3.570*	8.050	9.690	8.000	8.000	-
	γ	0.334	0.723	0.371	0.233	0.234	0.450	0.695	0.447	0.611	-
TBOT	Mean	-0.1287	0.0461	0.1860	-0.3755*	0.2110	-0.0398	-0.4816	-	-	-
	S.D.	0.8213	0.9571	0.8327	1.2520	0.6725	1.1202	1.2808	-	-	-
	Q	4.100*	13.600	6.740	12.200	4.330	3.480*	13.000	-	-	-
	γ	0.458	0.627	0.276	1.019	0.494	0.305	0.797	-	-	-

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
BBOT	Mean	0.0364	0.0021	-0.1076	-0.9722*	0.3224	0.0738	0.3097	0.6190	-0.1737	-
	S.D.	1.0996	1.1589	0.5863	1.6920	2.0336	1.0587	0.9788	-	0.3696	-
	Q	7.740	15.600*	5.860	7.000	6.000	13.100	4.500	9.000	14.000	-
	γ	0.239	0.249	0.244	1.027	0.567	0.441	0.518	0.265	0.049	-
DBOT	Mean	0.0456	0.0608	0.1118	-0.3279	0.0264	0.0012	-0.1174	-0.0456	0.5689	-
	S.D.	0.8524	0.9237	0.7187	1.0365	1.6009	0.9888	0.9966	0.5577	0.4895	-
	Q	11.200	8.390	9.910	6.000	9.890	6.020	8.840	7.000	6.000	-
	γ	0.513	0.545	0.437	0.530	0.697	0.299	0.428	0.436	0.654	-
HSTOP	Mean	-0.0307	0.3304*	-	-	-	0.0062	-0.1230	-0.1213	0.1287	0.1063
	S.D.	0.9345	1.2498	-	-	-	1.0333	0.9644	0.8813	1.0516	0.9644
	Q	6.370	10.500	-	-	-	12.500	14.800*	4.900	14.800*	15.800*
	γ	0.368	0.610	-	-	-	0.239	0.596	0.741	0.391	0.384
RTOP	Mean	-0.0438	0.0152	-0.0787	-0.2886	-	-0.0401	-0.1185	0.0071	-0.2852	-0.1114
	S.D.	0.8352	0.9999	0.0676	0.8668	-	0.9842	1.0132	0.7908	0.7467	0.8245
	Q	16.400*	4.200	18.000*	8.000	-	12.000	16.300*	13.700	22.700*	11.400
	γ	0.738	0.320	0.123	0.582	-	0.533	0.686	0.282	0.960	0.885
TTOP	Mean	-0.1196	0.2525	-	-	-	-0.1205	-0.0696	0.1747	-0.2231	-0.2735
	S.D.	1.0099	0.9903	-	-	-	1.2142	1.0806	1.2992	1.1476	0.7657
	Q	8.500	6.790	-	-	-	4.950	6.660	20.100*	9.890	13.900
	γ	0.762	0.553	-	-	-	0.644	1.100	0.661	0.475	0.739
BTOP	Mean	-0.0125	0.0552	-1.1684	0.1530	-	-0.0270	-0.1262	-0.3066	-0.7464	0.1304
	S.D.	0.9553	0.9682	2.2502	0.4804	-	1.0379	1.0024	1.6020	-	0.2938
	Q	8.360	7.930	17.000*	11.000	-	8.080	18.400*	13.000	9.000	7.000
	γ	0.575	0.299	0.733	0.400	-	0.342	1.004	0.587	1.015	0.143
DTOP	Mean	-0.1191	0.1258	0.5893	0.0554	-	0.0141	-0.0848	0.1563	0.1085	-0.0743

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	S.D.	0.8099	0.7685	0.8772	0.6400	-	0.8811	0.8638	0.7161	1.2354	0.6661
	Q	11.100	17.300*	8.000	11.000	-	7.310	6.640	13.500	6.000	5.000
	γ	1.021	0.447	0.047	0.242	-	0.328	0.545	0.212	0.345	0.443
Day 5											
HSBOT	Mean	-0.0331	-0.0064	-0.1126	-0.1594	0.3666*	0.0366	-0.0233	-	-	-
	S.D.	0.8760	1.0217	1.0664	1.4323	0.8719	0.8968	0.6576	-	-	-
	Q	5.580	5.180	8.210	19.100*	17.800*	14.200	16.200*	-	-	-
	γ	0.483	0.492	0.471	0.913	0.462	0.447	0.523	-	-	-
RBOT	Mean	-0.0316	-0.1393*	0.2936*	0.0556	-0.0104	-0.0458	-0.0942	-0.3994	0.1876	-
	S.D.	0.8516	0.9799	1.1107	1.0382	0.7853	0.8483	0.8139	0.4960	0.6684	-
	Q	13.200	14.600	10.500	5.270	8.710	7.550	9.340	8.000	8.000	-
	γ	0.772	1.365	0.711	0.407	0.359	0.646	0.723	0.525	0.254	-
TBOT	Mean	0.0373	-0.1038	0.3689	-0.1775	-0.2388	0.0002	0.1049	-	-	-
	S.D.	0.9106	1.0260	1.1859	1.2595	1.0879	1.0844	1.1164	-	-	-
	Q	14.800	8.810	7.390	12.200	12.300	16.600*	4.000*	-	-	-
	γ	0.126	0.513	0.497	1.068	0.767	0.472	0.429	-	-	-
BBOT	Mean	-0.0249	-0.0203	-0.3147	0.5525	-0.1855	0.1305	-0.1695	-0.1900	-0.7844	-
	S.D.	0.9542	1.0390	1.2435	0.5550	0.9206	0.9274	1.1192	-	0.3536	-
	Q	21.000*	13.600	8.710	7.000	11.000	5.760	12.000	9.000	14.000	-
	γ	0.383	0.297	0.739	0.287	0.508	0.778	0.858	0.751	0.195	-
DBOT	Mean	0.0185	-0.1314*	0.2976	-0.7402	0.0682	0.0342	-0.0103	-1.0475*	0.0245	-
	S.D.	0.8405	0.8293	0.6929	1.4001	0.9539	0.9816	0.8256	1.0858	0.6035	-
	Q	10.200	10.300	19.000*	11.000	9.890	2.330*	15.100*	7.000	6.000	-
	γ	0.290	1.186	0.744	1.056	0.515	0.286	0.578	1.110	0.173	-
HSTOP	Mean	-0.0045	0.1562	-	-	-	0.0475	-0.0657	0.1047	0.1813	0.0463

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Chart Patterns	Statistics	UCG	UBG	URG	UEG	UIG	DCG	DBG	DRG	DEG	DIG
	S.D.	1.1871	0.6927	-	-	-	0.9139	0.9668	0.8644	1.2168	0.7075
	Q	5.870	12.300	-	-	-	6.740	11.500	5.580	10.500	9.320
	γ	0.711	0.494	-	-	-	0.370	0.496	0.275	0.323	0.447
RTOP	Mean	0.1387*	0.0862	-0.4442	-0.0761	-	0.0082	-0.0611	0.0338	-0.0647	0.2263
	S.D.	0.7868	0.8524	0.3980	0.3243	-	0.8446	0.9922	1.0442	0.8763	0.9746
	Q	24.900*	11.100	8.000	8.000	-	9.140	8.200	2.730*	10.500	10.300
	γ	1.374*	0.588	0.515	0.269	-	0.713	0.760	0.135	0.197	0.922
TTOP	Mean	0.3009*	-0.2379	-	-	-	0.1031	0.0134	0.4369	-0.1972	0.4588
	S.D.	1.0732	1.4879	-	-	-	1.2506	1.1880	1.3664	1.0400	0.8525
	Q	8.500	13.100	-	-	-	11.700	14.100	16.000*	9.890	15.500*
	γ	0.839	0.492	-	-	-	0.575	0.400	1.086	0.412	0.842
BTOP	Mean	0.0299	-0.1221	-0.1517	-0.7588	-	0.1730	-0.0081	-0.4705	-1.3468*	-0.0539
	S.D.	0.9827	1.1464	0.4752	0.2938	-	0.8258	1.0188	0.8612	-	1.0491
	Q	12.000	6.530	9.000	16.000*	-	10.900	11.200	9.670	9.000	7.000
	γ	0.494	0.807	0.618	0.290	-	1.365*	0.664	0.877	1.143	0.440
DTOP	Mean	0.0733	0.0778	-0.4325	0.4766	-	-0.0983	0.0901	0.3295	0.3579	0.9470*
	S.D.	0.9527	1.0862	0.4146	0.9119	-	0.9027	0.9414	0.8956	0.1809	1.5035
	Q	6.590	6.940	8.000	6.000	-	15.000*	10.800	8.090	16.000*	5.000
	γ	0.492	0.360	0.515	0.181	-	1.315*	0.755	0.510	0.768	0.290

Table 7 presents the results for price gaps conditioned on chart patterns. Panel A presents the count for each of the gap-pattern pairs. Panel B presents the mean and standard deviation for returns conditioned on each pair, followed by the goodness of fit test (Q) and Kolmogorov-Smirnov test (γ) results.