A HIGH-FREQUENCY, VOLUMETRIC TRADING STRATEGY

by

David Polinsky
Ph.D., Mechanical Engineering, U. C. Berkeley 1989
B.S.C.E., Civil Engineering, Cornell University 1982

Sisi Zhang
B.A., Economics & Finance, Linfield College 2007

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Name:	**David Polinsky**
	Sisi Zhang
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Supervisory Committee:

Andrey Pavlov
Senior Supervisor
Associate Professor

Evan Gatev
Second Reader
Assistant Professor

Date Defended/Approved:

ABSTRACT

We test a candidate high-frequency investment strategy, which utilizes the time series of price, volume and a novel interaction term to forecast intra-day returns over a continuous 101 day period from January 4 to May 28, 2010. The strategy uses minute-level data calculate regression coefficients from one-day for the purposes of trading the following day, thereby avoiding data snooping bias. Finally regressing the daily returns against the Fama-French Four Market Factors reveals significant alphas for more than half of the traded stocks.

Keywords: High Frequency Trading; Volume-Augmented, Momentum Trading, Fama French Four Factor Model

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1 INTRODUCTION

Since the early days of modern financial theory, both academics and real world investors have endeavoured to forecast returns based on an analysis of recent price histories, going back at least as far at Alexander (1961) and Fama (1966). No clear consensus has emerged in the published literature about whether such strategies can produce persistent profits which are superior to a long term buy and hold strategy, particularly after taking into consideration transaction costs and management fees. (Within the academic community, such return-history driven trading is referred to as momentum strategies, while investors describe trend following strategies as being based on technical analysis.) Despite the lack of consensus within the academic setting about whether momentum strategies work, technical analysis remains a widely-used forecasting tool which has been incorporated in financial real-time databases from Google Finance to Bloomberg.

Filters rules have been tested which set different minimum thresholds for the size of forecast returns prior to acting on a buy or sell signal, and are designed to ensure that the gains from trading are greater than transaction costs. Since Alexander (1961) and Fama (1966), a very rich literature has developed on the selection of appropriate filter rules, including Sweeney (1988), Agyei-Ampomah (2006), Corrado (1992) and Cooper (1999).

While price return history is the primary focus of momentum trading literature, less attention has been paid to the use of trading volume time series for forecasting purposes. Generally trading volume information is interpreted in a behavioural context as evidence of market under-reaction or over-reaction to news. Corvig and Ng (2004) have further analyzed serial correlation in trading volumes and the different trading patterns of institutional versus individual investors.

Some recent research has focused on whether trading volume data can be used to augment momentum strategies. (We refer to analytical methods for forecasting price returns based on volume data as being “volumetric”.) Here again no clear consensus has emerged on whether fixed trading rules can be found from volume data. Lee and Swaminathan (2000) have suggested, for example, that high volume stocks which have recently run up are due for short term reversals, whereas low volume winners are more likely to have sustained momentum returns. Other researchers, such as Agyei-Ampomah (2006) found exactly the opposite.

In this paper we are agnostic about whether price & volume data can be used to develop stationary trading rules. Rather we take a strictly empirical approach: we use recent in-sample regression results from the preceding day to develop forecasts for the minute-by-minute trading in the following day.
Our method differs from that of Agyei-Ampomah (2007) in that we are using regressions on 1 minute interval data to develop a high frequency trading signals which algorithmically determine when to open, close or hold positions, whereas Agyei-Ampomah used monthly interval data to create portfolios of pre-determined holding periods between 3 and 12 months.

Our strategy implementation does not include filter rules (i.e., in our approach, any forecast gain greater than zero is interpreted as a buy signal for the long strategy). Hence each security is traded almost 50% of the time, based on the regression forecast buy, sell or hold signal. Note that since transaction costs per trade are fixed, while returns are variable, our focus is on identifying a family of potentially profitable trading strategies. We leave for further research the goal of optimizing this trading strategy such that the number of trades is minimized.

The explanatory power of the Fama Franch Four Factor model has been widely demonstrated both by the authors themselves (for example, Fama (2008)) as well as by a other authors (for example, Her (2003)). Following the methods of these precedent papers, we regress the daily return from our volume-augmented (intraday) momentum strategy against the Fama French Four Factor Model (which includes market risk premium, as well as the cross-sectional risk premiums for relative size, book-to-market and lastly and 200-trading-day momentum premium). Our regressions reveal positive alphas which cannot be explained solely by these 4 factors. We assert that these persistent alphas are the result of market inefficiencies tied to the flow of intraday signals contained in price, trading volume and their interaction.

2 DATA

Our implementation of a volume-augmented momentum trading strategy utilizes the shortest time interval for which both price and volume data is readily available through Bloomberg, namely 1 minute data. Unfortunately Bloomberg only archives historical data for a rolling 120 trading day period. Additionally our analysis is constrained by the approximately 1 month delay for the publication of daily Fama French factors on the Kenneth French website. Therefore our time series record is limited to 102 days worth of data, representing the trading days between January 4 and May 28, 2010. In addition a standard trading day on the New York Exchanges runs from 9:30 AM – 4:00 PM EST, resulting in a daily trading record of 392 minutes.

20 stocks were chosen from the S&P500, by picking random numbers in the range 1-500 corresponding to each of the index constituents. We consider the use of S&P500 components for testing to be very conservative, in the sense that the S&P500 constituents are among the most widely traded of all securities. And hence market inefficiencies are likely to be very quickly traded on to the point that they are no longer profitable.

Dividend-paying stocks were arbitrarily excluded from the list of chosen stocks, as the impact of ex-dividend dates on our chosen trading strategy is outside of the scope of this paper. Therefore a total of 46 random picks were required to come up with 20 dividend-free securities.

Time series records were constructed for each of the 20 securities containing a time and date stamp, minute-average volume and minute-average of the actual transaction prices. The total record length for the 102 days for each security was 39,989 data points. Bid-ask minute-average quotes were ignored, as these are subject to manipulation by market makers as well as institutional investors doing price discovery. Also bid-ask quotes do not contain volume information, as there is no data on linkage with closed transactions resulting from the quotes.

The data was “cleaned” by the removal of minute intervals in which no shares were traded. Despite the fact that all securities studied are large cap S&P500 constituents, when viewed on a 1 minute filter, many are surprisingly illiquid. The periods for which no shares changed hands range from effectively 0 to as high as 8.8 per-cent of the 1 minute periods , with a 20 stock average of 1.6 per-cent.

Additional summary statistics for the 20 securities during the trading/analysis period are presented in Table 1. What is most striking about these statistics is the relatively large volatility of trading volumes when viewed on 1 minute (averaging) intervals. The volume average/volatility ranges from 11% to 90% over the 20 stocks, with a 20 stock average of 55%. Taking one stock, ZMH, as an example, the corresponding price average/volatility is 2900%, a difference of 2 orders of magnitude. This extreme volatility in trading volume as compared to price volatility suggests the need either for more complex volume-related factors or the application of filtering of the volume data.

Fama French Daily Factors were collected for the same 102 day period for the purpose of analyzing the relationship of common market factors to trading strategy excess returns . The four Fama French factors are (1) the market risk premium, (2) size risk premium (formed from a long portfolio of small companies and a short portfolio of large companies), (3) value risk premium (formed from a long portfolio of high (book-to-market) companies and a short portfolio of low (book-to-market) growth companies and (4) a lagged-momentum factor for the preceding 2-12 months (formed from a long portfolio in high growth companies and a short portfolio in slow growth companies). The second, third and fourth factors capture cross-sectional variation in the market, whereas the first factor represents the CAPM market risk premium.

3 METHODOLOGY

To test the ability of volume-related independent variables to improve the forecasting ability of momentum trading strategies, a very simple, but novel regression model was formed as. For each stock, the regression model takes as known the recent price and volume history from the current one minute interval as well as the preceding one minute interval. Independent variables formed with this raw data are then regressed on log price return in the next one minute interval. The resulting regression equation can be thought of as forecasting the forward price in the following one minute period. The test sample for each regression consists of the raw data from the 392 minute intervals in each trading day. The base case regression model used is:

$$\ln\left(\frac{P_{t+1}}{P_t}\right)=\alpha_0+\beta_1\ln\left(\frac{P_t}{P_{t-1}}\right)+\beta_2\left(V_t-V_{t-1}\right)+\beta_3V_t\left(P_t-P_{t-1}\right)$$

The first independent variable is the log of the price return in the current period. If there were no other factors in the model, the regression equation would simply be a measure of serial correlation in price returns. The second independent variable is a measure of the volume change between the current and preceding time period. And the third independent variable is an interaction term between the most recent trading volume and the most recent price change. If the minimum trade execution times were a minute (for example), this term would represent the different short term expectations of buyers and sellers. The value of new long position is: $V_t * P_t$. Whereas the short positions decided to sell a total dollar value of: $V_t * P_{t-1}$.

To investigate whether the regression model suffers from multicollinearity, simple correlations (i.e., with zero lags) were calculated for each of the pairs of factors using a subset of the 20 stocks. Significant correlations were found between the price-return and price-volume interaction factors (on the order of 0.4-0.5), suggesting the presence of a degree of multicollinearity between these 2 factors. Multicollinearity makes interpretation of the regression results more difficult, as the factors are not linearly independent. However since the factors are still far from a perfect linear combination of each other, the regression results are still valid.

The second and third factors are each representative of a potentially large family of similar functional forms which capture the effects of volume, volume changes, price changes and their interaction. Anecdotal parameter in-sample testing was done on 3 additional forms of each of these variables. For the trading volume factor, the alternative forms which were looked at are:

Case 1:	V_t	(turn-over)
Case 2:	$\ln (V_t)$	(log turn-over)
Case 3:	$\ln (V_t/V_{t-1})$	(relative volume change)

For the volume-price interaction factor, alternative forms which were studied include:

Case 4:	$V_t * (P_t - P_{t-1})$	(short term gain for long investors at time t)
Case 5:	$P_t * \ln (V_t/V_{t-1})$	(price * relative volume change)
Case 6:	$\ln (P_t/P_{t-1}) * V_t$	(relative price change * current volume)

Coach Industries (Ticker "COH") was arbitrarily chosen for the purposes of limited testing of alternative functional forms of the variables. R-squared values and T-Stats were very similar for the different cases, and so it was not possible to draw meaningful conclusions on such a limited test basis.

In a real world development of a trading strategy, optimal selection of the function forms of the parameters would be critical and needs to be done over enough different time periods and securities that data snooping bias is entirely avoided. For the purposes of this paper however, the goal is only to show that some persistent anomalous returns can be found which cannot be explained by a traditional market model, such as the Fama French Four Factor model.

We wished to avoid the issues of strong serial correlation (in the residual errors) and strong heteroscedasticity (evidenced by high White Test statistics). And for this reason a GARCH(1,1) method was chosen for all evaluations of the trading strategy.

The trading strategy regressions were run in two stages. The first stage consisted of calculating the four regression coefficients for each day and for each security. Goodness of Fit (R^2) and T-stats were also recorded for each regression. This approach can be thought of as a daily calibration of the regression coefficients.

Then the regression coefficients for each day were used to do out-of-sample forecasting of the minute-by-minute returns in the following day. The trading strategy consists of taking (or holding) a long position in one share for each minute interval in which the model forecasts a price increase and selling (or continuing to not own) a share during each one minute interval for which the regression model forecasts a price decrease. Note that the buy (or sell) decision was not conditioned on whether the current actual price was lower than the purchase price for the currently open trade. Also no attempt was made to impose a filter on the magnitude of the buy (or sell) signal before implementing a trade. Hence shares are being traded in this strategy during approximately 50% of the one minute intervals – clearly an unrealistic strategy, but one which is sufficient for demonstrating the dual purposes of this paper: first showing that signals derived from a knowledge of price and volume history alone can beat a buy and hold strategy and secondly demonstrating that the strategy returns can not be explained solely by the 4 market risk factors from Fama French.

The profit (or loss) for each trade was calculated as sales price minus purchase price. And then the total profits (or loss) for each day were tallied up and normalized by the daily opening price, for the purpose of calculating total daily returns.

Because the stock selection process excluded dividend paying stocks, no adjustments needed to be made for dividend payments.

Average values (over the 101 trading period) for the regression coefficients, R-bar squared and T-Stats for alpha are shown in Table 2. Note the while r-bar squared values are very small (0.06 average), the average of the absolute value of the T-Stats for alpha is also very low, suggesting the regression model may be robust in its explanatory ability. The regression coefficients themselves are not at all stationary from day-to-day, suggesting that the predictive ability of the regression model suffers a time decay.

Also the only coefficient which is largely consistent in its sign is that of the stock price return, which is negative in 17 out of 20 cases. This does not however demonstrate negative serial correlation in price returns, because some of the dependence of the forecast variable is correlated with the price-volume interaction term.

Instead of calibrating the forecast model based on the previous day's results, one could imagine improvements to the model which utilize continuous real time calibration of the coefficients, creating in effect a moving average model. Further study also needs to be done to evaluate the optimal sample size/duration for the calibration periods and the forward prediction period.

4 TRADING STRATEGY RESULTS

The final output of the trading strategy model is a 101 day series of daily returns (called “Strategy Return”) for each stock. These returns series were compared with the actual realized daily returns (called “Actual Return”) for the same securities over the 101 day period. And lastly a hybrid daily return series was constructed (called “Excess Return”) which was long in the trading strategy and short in the actual stock. If the Actual and Strategy Returns are highly correlated, then the Excess Return would be equivalent to a hedged strategy.

Statistical results for all 3 strategies are shown in table 3, 4 and 5. What is initially striking is that 17 out of 20 stocks tested showed higher average daily Strategy Returns than Actual returns. If these one share per stock positions were combined into equally weighted portfolio, the result would be an average daily Strategy Return of 0.40% compared to an Actual average daily Return of only 0.05%. Also 16 out of 20 had lower daily volatility, or a portfolio average Strategy volatility of 1.6% compared to 1.7% for the Actual Return portfolio. On average 61% of the positions for the Strategy resulted in positive daily returns compared to 53% for the Actual Returns. And Sharpe Ratio for the Strategy is an order of magnitude higher than for the Actual Returns

Again looking at the equally weighted portfolio return distributions, Strategy skewness is closer to zero than Actual skewness. And Strategy kurtosis is closer to normal (3) than Actual kurtosis. So in summary when the stock stocks are combined into an equally weighted portfolio, all of the statistical characteristics of the trading strategy are superior to the actual returns, albeit on a limited sample of only 101 trading days.

Running simple correlations between the Actual and Strategy daily returns showed a portfolio average correlation of 0.47, with a lowest stock correlation of 0.19 and a high of 0.68. A better way to visualize this moderate correlation is by looking at the time series of daily returns which are plotted in figures 1-3 for 3 stocks. The time series shows that the trading strategy is a partial hedge for the stock during extensive periods of time.

It is easy to model the effects of transaction costs on the Strategy Return. If we assume a round trip trading cost of 0.1 basis points and an average of 200 transactions per day (which is very close to trading 50% of the time), then transaction costs will reduce the average daily return by 0.1%. In this case, the trading strategy for the price weighted average portfolio will still be profitable. However the average daily return of the portfolio will be reduced from 0.397% to 0.297%.

5 COMPARISON WITH FAMA FRENCH

The question arises as to whether the 101-day strategy return time series is an anomaly or whether these returns can be fully explained by the Fama French four-factor model. The Fama French Four Factor Model includes a factor for the market risk premium, plus cross-sectional factors for the relative performance of small vs. large firms and growth vs. value firms. The fourth factor captures the low frequency price momentum of the highest growth stock vs. the lowest growth rate stocks over the preceding 2 to 12 months. The explanatory ability of the momentum factors we first argued for by Jegadeesh and Titman (1993). Technical analysts typically use a 220 day moving average for prices which is crudely related to the (fourth) momentum factor. And the second factor is commonly related to investment strategies based on company size. And the third factor is common related to the difference between value and growth strategies.

The regression model used in section 3 of this paper, by contrast, captures the high frequency (short duration) momentum in price returns, volume changes and their interaction. So regressing the (aggregate) daily Strategy Return premiums against the Fama French factors should reveal whether the Strategy Returns are capturing unique high frequency factors, or whether they are solely explained by the 4 Fama French market factors. The regression equation is as follows:

$$r_t - r_{ft} = a + b(r_{MKT} - r_{ft}) + sr_{SMBt} + hr_{HMLt} + mr_{Mt}$$

The results of the Fama French regressions on the Actual, Strategy and Excess Returns minus the 30 day Treasure rates are shown in Table 6 - 10. Looking at the Actual Return results, the T-stats for alpha on 20 out of 20 are less than the critical value, confirming that, at least for these stocks and this time period, all of the anomalies of the Actual Returns can be explained by the 4 factors. This is a fortuitous result for the purpose of our analysis, as it suggests there are no significant idiosyncratic factors during our study period for these individual stocks.

Looking at the Fama French regression results for the Strategy Return, 8 out of 20 have T-stats for alpha, which are greater than the critical value at a 95% confidence level, suggesting that there are persistent, abnormal returns which cannot be explained by the (low frequency) market model. Interestingly the Excess Return (Strategy Return – Actual Return) has slightly higher average T-stats, as 10 out of 20 stocks have significant alphas. So in other words high frequency momentum returns (associated with price momentum, volume momentum and their interaction) can not be fully explained by the Fama French Four-Factor model.

Possible alternative explanations for these abnormal high frequency returns are: (1) market responses to firm-specific news, (2) idiosyncratic intraday trading patterns of high frequency traders.

6 CONCLUSION

While the low frequency (2-12 month) persistence of momentum returns is very well documented within finance literature, the ability to forecast returns from high frequency price and volume data is much less accepted. This preliminary study provides evidence of the explanatory power of a volume-augmented, high frequency momentum factor model. The model includes a novel interaction term between the most recent trading volume-level and price changes.

7 REFERENCES

[1] Alexander, Sidney S. (1961). Price Movements in Speculative Markets: Trends and Random Wals. *Industrial Management Review*, II (May, 1961), 7-26.

[2] Agyei-Ampomah, S., 2006. The Post-Cost Profitability of Momentum Trading Strategies: Further Evidence from the UK. *European Financial Management*, 13, 776-802.

[3] Cooper, M., 1999. Filter Rules on Price and Volume in Individual Security Overreaction. *Review of Financial Studies,* 12, 901-933. [4] Sweeney, R.J., 1988. Some New Filter Rule Tests: Methods and Results. *Journal of Financial and Quantitative Analysis*, 23, 285-300.

[4] Corrado, C., Lee, S., 1992. Filter Rule Tests of the Economic Significance of Serial Dependence in Daily Stock Returns. *Journal of Financial Research*, 15, 369-387.

[5] Covrig, V., Lilian, N., 2004. Volume Autocorrelation, Information and Investor Trading. *Journal of Banking & Finance*, 28, 2155-2174.

[6] Fama, E.F., Blume, M.E., 1966. Filter Rules and Stock Market Trading. Security Prices: a Supplement. *Journal of Business*, 39, 226-241.

[7] Fama, E.F., French, K., 2008. Dissecting Anomalies. *Journal of Finance*, 113, 1653-1678.

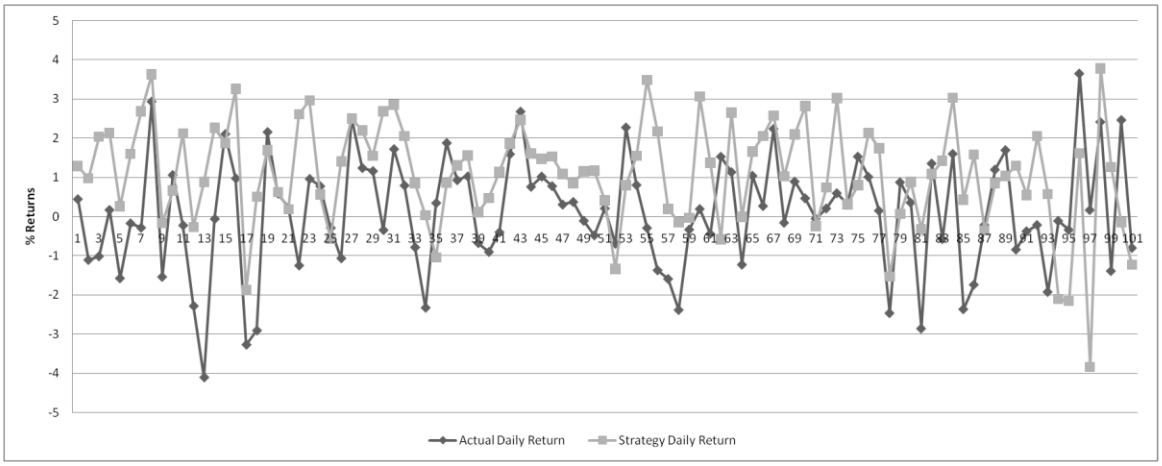
[8] Jegadeesh, N., Titman, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *The Journal of Finance*, 48, 65-91

[9] Lee, C.M.C., Swaminathan, B., 2000. Price Momentum and Trading Volume, *Journal of Finance*, 55, 2017-2069.

[10] L'Her J., Masmoudi, T., Suret, J., 2003. Evidence to Support the Four-Factor Pricing Model from the Canadian Stock Market, un-published report.

8 FIGURES

Figure 1: Actual and Strategy Daily Returns for EMC

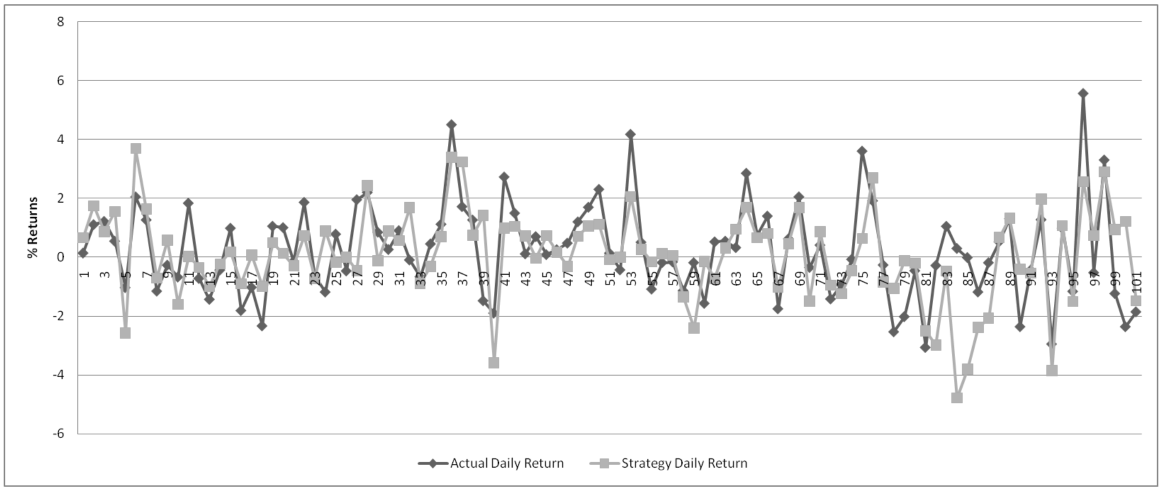


This figure shows a time series plot of the Actual and Strategy Daily Returns vs. Time for the 101 day period for the stock EMC. EMC was chosen for this first plots as it is representative of the best of 20 stocks in terms of highest Strategy average daily return, standard deviation of average daily return and the T-stat for the abnormal return coefficient a in the Fama French regression.

Figure 2: Actual and Strategy Daily Returns for CRM

This figure shows a time series plot of the Actual and Stategy Daily Returns vs. Time for the 101 day period for the stock CRM. CRM was chosen for this plots as it is representative of the middle performance of the 20 stocks, with typical values (relative to the other 19 stocks) for Strategy average daily return, standard deviation of average daily return and the T-stat for the abnormal return coefficient a in the Fama French regression.

Figure 3: Actual and Strategy Daily Returns for BIG



This figure shows a time series plot of the Actual and Stategy Daily Returns vs. Time for the 101 day period for the stock BIG. BIG was chosen for this plots as it is representative of the worst performance of the 20 stocks, with low values (relative to the other 19 stocks) for Strategy average daily return, standard deviation of average daily return and the T-stat for the abnormal return coefficient a in the Fama French regression.

9 TABLES

Table 1: Select Statistics of 20 Randomly Selected Stocks

Volumetric Characteristics of 20 Select Stocks from S&P 500								
	Market Cap. (Billion)	Total Shares (Million)	Volume Average (1,000)	Volume Volatility (1,000)	Volume Avg./Vol. (%)	Max Volume (1,000)	No Trade (%)	Avg. Daily Turnover (%)
SHLD	$7	115	3.3	29.2	11.4	1,612	5.2	1.1
WLP	$22	427	15.8	23.5	67.2	1,064	0.0	1.4
CRM	$12	129	5.1	8.1	63.4	329	0.8	1.6
CAM	$9	244	12.1	21.1	57.2	536	0.2	1.9
PDCO	$3	124	3.2	6.7	47.4	402	5.2	1.0
CSCO	$130	5,710	133.0	194.6	68.4	13,247	0.3	0.9
BIG	$3	81	4.0	6.8	58.9	428	1.8	1.9
DELL	$26	1,960	69.5	106.7	65.1	4,729	0.3	1.4
BTU	$11	269	16.3	17.5	93.5	487	0.0	2.4
DNR	$6	399	21.9	89.0	24.6	16,539	0.1	2.2
CEPH	$5	75	4.5	12.5	36.2	739	1.7	2.4
LXK	$3	78	5.8	10.2	57.4	486	1.4	2.9
VRSN	$5	182	10.1	23.5	43.1	1,158	1.4	2.2
EMC	$42	2,060	61.6	86.3	71.4	4,119	0.0	1.2
STJ	$12	327	8.5	15.3	55.8	749	0.7	1.0
PTV	$4	133	6.7	23.8	28.2	4,220	1.5	2.0
JDSU	$2	220	19.9	30.3	65.8	1,265	0.7	3.5
NBR	$5	285	17.6	19.7	89.5	501	0.1	2.4
ZMH	$11	203	4.6	9.2	50.6	351	1.2	0.9
SRCL	$6	85	1.6	4.2	39.5	266	8.8	0.8
Avg.	$16	655	21.3	36.9	54.7	2,661	1.6	1.8

Summary statistics for 20 randomly selected, non-dividend paying stocks from the SNP500. All values are for the trading period from January 4 till May 28, 2010. Volume data is based on one minute intervals during the trading day from 9:30 AM till 4:15 PM EST. No Trade represents the percentage of one minute intervals during which no shares traded hands.

Table 2: Strategy Average Regression Coefficients and R^2

$$\ln\left(\frac{P_{t+1}}{P_t}\right)=\alpha_0+\beta_1\ln\left(\frac{P_t}{P_{t-1}}\right)+\beta_2\left(V_t-V_{t-1}\right)+\beta_3V_t\left(P_t-P_{t-1}\right)$$

	$\alpha_0 * 10^3$	β_1	β_2	β_3	R^2
SHLD	0.00389	-0.00025	-0.00188	-0.02508	0.034
WLP	-0.00429	-0.00023	0.00024	0.00728	0.056
CRM	0.00411	0.00044	0.00414	-0.05838	0.036
CAM	-0.00338	-0.00050	0.00273	0.02719	0.052
PDCO	0.00110	-0.00057	0.00025	-0.19908	0.069
CSCO	-0.00101	-0.00156	0.00008	0.01798	0.054
BIG	0.00110	-0.00057	0.00025	-0.19908	0.069
DELL	-0.00242	-0.00160	-0.00006	0.01686	0.057
BTU	-0.00527	-0.00008	0.00001	-0.00773	0.042
DNR	-0.00046	-0.00032	0.00051	-0.03554	0.042
CEPH	-0.00107	-0.00038	0.00112	-0.02913	0.058
LXK	0.01268	0.00047	0.00412	-0.21307	0.047
VRSN	0.00388	-0.00103	-0.00133	0.01364	0.046
EMC	0.00283	-0.00185	-0.00002	0.03356	0.042
STJ	0.00019	-0.00085	-0.00006	0.15822	0.082
PTV	0.00538	-0.00062	0.00084	-0.05725	0.040
JDSU	0.00720	-0.00169	0.00037	0.20914	0.041
NBR	-0.00809	0.00002	-0.00018	-0.07014	0.035
ZMH	-0.00451	-0.00038	-0.00158	-0.09125	0.085
SRCL	0.00173	-0.00110	-0.00501	-0.04346	0.090

These are the average of the regression coefficients from 101 consecutive days of in-sample testing, along with the corresponding measure of Goodness of Fit, R^2. α_0 is the 101 day average abnormal return. β_1 is the 101 day average of the regression coefficients for the log price return. β_2 is the 101 day average of the log of the volume change. β_3 is the 101 day average of the regression coefficient for the price-volume interaction term. Note the only term which is primarily of the same sign for most of the stocks is β_1 .

Table 3: Actual Daily Return Statistics

	Average	Std. Dev.	Sharpe Ratio	Skew.	Kurtosis	Min.	Max.	Positive Returns
SHLD	0.063	2.24	0.03	-0.20	1.44	-7.28	6.65	55
WLP	-0.020	1.74	-0.01	-0.33	1.70	-6.96	4.09	49
CRM	0.196	2.10	0.09	0.09	1.19	-5.38	11.11	56
CAM	-0.109	2.54	-0.04	-0.54	2.81	-10.67	8.04	54
PDCO	0.075	1.20	0.06	-0.75	2.58	-5.08	2.74	53
CSCO	-0.045	1.28	-0.04	-0.50	0.33	-3.81	2.96	53
BIG	0.241	1.58	0.15	0.54	0.89	-3.07	5.56	53
DELL	-0.054	1.49	-0.04	-0.26	0.35	-4.09	3.69	51
BTU	-0.193	2.50	-0.08	-0.31	0.20	-7.21	6.32	48
DNR	0.083	2.22	0.04	0.13	0.44	-5.54	6.64	54
CEPH	0.036	1.20	0.03	-0.51	2.20	-4.82	3.34	55
LXK	0.231	2.04	0.11	-0.26	1.14	-5.74	5.38	57
VRSN	0.280	1.50	0.19	2.40	14.41	-3.17	9.65	57
EMC	0.102	1.45	0.07	-0.30	0.21	-4.10	3.65	53
STJ	-0.008	1.02	-0.01	-0.08	0.39	-3.05	2.33	48
PTV	0.084	1.44	0.06	0.38	0.30	-3.53	3.68	50
JDSU	0.167	2.86	0.06	-0.03	1.27	-8.45	9.92	55
NBR	-0.172	2.61	-0.07	0.11	0.00	-6.32	7.78	49
ZMH	-0.055	1.24	-0.04	-0.34	0.19	-3.41	2.43	53
SRCL	0.111	1.00	0.11	-0.09	1.18	-3.10	3.17	56
Avg.	0.051	1.76	0.03	-0.04	1.66	-5.24	5.46	53

Daily Actual Return statistics from the historical price record from January 4 to May 28, 2004. Actual Daily Returns are normalized against daily opening price. All return values and return distribution statistics and are in percentages, except for Sharpe Ratio, Skewness and Kurtosis.

Table 4: Strategy Daily Return Statistics

	Avg.	Std. Dev.	Sharpe Ratio	Skew.	Kurt.	Min.	Max.	Positive Returns	Actual-Strategy Corr.
SHLD	0.529	2.38	0.22	2.32	14.08	-4.96	15.19	65	0.41
WLP	-0.080	1.47	-0.05	0.06	1.48	-4.53	5.18	46	0.60
CRM	0.398	1.79	0.22	-0.23	2.25	-5.18	6.04	62	0.48
CAM	0.052	1.97	0.03	0.91	6.77	-5.83	10.24	51	0.16
PDCO	0.308	0.99	0.31	0.83	2.01	-1.72	3.95	60	0.48
CSCO	0.466	1.19	0.39	-0.79	2.03	-3.86	3.05	70	0.57
BIG	0.071	1.54	0.05	-0.49	1.02	-4.78	3.69	54	0.63
DELL	1.057	1.66	0.64	-0.11	0.22	-3.24	6.11	73	0.26
BTU	0.236	2.05	0.12	-0.09	-0.01	-4.68	5.30	59	0.68
DNR	0.239	2.15	0.11	0.14	0.78	-6.45	6.07	51	0.56
CEPH	-0.022	1.05	-0.02	-1.45	9.98	-5.99	2.88	50	0.66
LXK	0.246	2.02	0.12	-1.65	8.51	-10.83	4.66	56	0.56
VRSN	0.457	1.21	0.38	-0.30	0.92	-2.90	3.80	71	0.19
EMC	1.086	1.36	0.80	-0.67	1.09	-3.84	3.78	81	0.41
STJ	0.250	1.44	0.17	1.71	7.82	-2.58	8.02	53	0.28
PTV	0.398	1.28	0.31	-0.26	1.37	-3.98	3.92	67	0.44
JDSU	1.436	3.33	0.43	0.04	1.24	-8.57	12.21	71	0.59
NBR	0.356	2.14	0.17	0.23	1.34	-5.93	8.06	57	0.64
ZMH	0.036	1.13	0.03	-0.47	1.80	-3.92	2.93	54	0.47
SRCL	0.421	0.83	0.51	-0.12	0.36	-2.21	2.16	72	0.28
Avg.	0.397	1.65	0.25	-0.02	3.25	-4.80	5.86	61	0.47

Strategy Daily Return statistics from the trading strategy for the period January 4 to May 28, 2004. Strategy Daily Returns are normalized against daily opening price. All return values and return distribution statistics and are in percentages, except for Sharpe Ratio, Skewness, Kurtosis and Actual-Strategy Correlation

Table 5: Excess Daily Return Statistics

	Average	Std. Dev.	Sharpe Ratio	Skew.	Kurtosis	Min.	Max.	Positive Returns
SHLD	0.466	2.52	0.18	2.05	7.61	-4.01	13.50	51
WLP	-0.059	1.46	-0.04	0.14	0.67	-3.59	4.71	46
CRM	0.201	1.99	0.10	0.13	1.96	-5.63	6.80	50
CAM	0.161	2.95	0.05	3.51	23.65	-4.79	20.91	52
PDCO	0.233	1.13	0.21	0.60	0.81	-2.44	3.43	57
CSCO	0.511	1.15	0.45	0.59	1.98	-2.58	4.76	67
BIG	-0.170	1.34	-0.13	-0.48	1.78	-5.07	3.57	45
DELL	1.111	1.92	0.58	-0.17	2.01	-5.09	6.56	76
BTU	0.429	1.86	0.23	0.71	2.04	-4.43	6.89	55
DNR	0.157	2.06	0.08	-0.26	0.92	-6.79	5.55	51
CEPH	-0.059	0.94	-0.06	0.27	0.47	-2.36	2.87	47
LXK	0.015	1.89	0.01	0.17	1.26	-5.27	5.76	50
VRSN	0.177	1.74	0.10	-1.84	15.05	-10.59	6.56	53
EMC	0.984	1.53	0.65	-0.36	0.60	-4.01	4.99	74
STJ	0.258	1.51	0.17	2.42	11.69	-2.33	9.10	55
PTV	0.315	1.44	0.22	0.53	2.48	-3.08	6.27	61
JDSU	1.269	2.84	0.45	1.57	6.91	-4.44	16.28	67
NBR	0.527	2.06	0.26	0.04	0.63	-4.92	6.13	58
ZMH	0.092	1.22	0.08	0.17	1.76	-4.09	3.97	47
SRCL	0.310	1.11	0.28	0.61	1.38	-2.16	4.14	59
Avg.	0.346	1.73	0.19	0.52	4.28	-4.38	7.14	56

Excess Daily Return are formed from the difference between Strategy Returns and Actual Returns for the period January 4 to May 28, 2004. Strategy Daily Returns are normalized against daily opening price. All return values and return distribution statistics and are in percentages, except for Sharpe Ratio, Skewness, and Kurtosis.

Table 6: Abnormal Return and T-Stats; Fama French Four Factor Regressions

$$r_t - r_{ft} = a + b(r_{MKT} - r_{ft}) + sr_{SMBt} + hr_{HMLt} + mr_{Mt}$$

	Actual Return *a*	Actual Return t(*a*)	Strategy Return *a*	Strategy Return t(*a*)	Excess Return *a*	Excess Return t(*a*)
SHLD	-0.025	-0.131	0.462	1.891	0.486	2.143
WLP	0.044	0.254	-0.034	-0.245	-0.078	-0.512
CRM	0.112	0.702	0.340	1.950	0.229	1.198
CAM	-0.251	-1.085	0.075	0.372	0.325	1.106
PDCO	0.079	0.853	0.294	2.924	0.215	2.224
CSCO	-0.048	-0.434	0.473	4.099	0.521	4.454
BIG	0.177	1.132	-0.016	-0.104	-0.193	-1.420
DELL	-0.080	-0.578	1.021	5.987	1.101	5.690
BTU	-0.244	-1.130	0.209	1.096	0.450	2.391
DNR	0.041	0.206	0.235	1.098	0.194	0.952
CEPH	0.071	0.698	0.034	0.325	-0.038	-0.426
LXK	0.219	1.226	0.274	1.356	0.054	0.287
VRSN	0.245	1.730	0.423	3.414	0.178	1.031
EMC	0.070	0.576	1.040	7.585	0.970	7.063
STJ	-0.012	-0.127	0.287	1.985	0.299	1.922
PTV	0.046	0.351	0.415	3.167	0.368	2.600
JDSU	0.124	0.520	1.444	4.507	1.320	4.564
NBR	-0.322	-1.458	0.286	1.316	0.607	3.293
ZMH	-0.048	-0.457	0.055	0.494	0.103	0.858
SRCL	0.135	1.447	0.405	4.764	0.270	2.579
Avg.	0.017	0.215	0.386	2.399	0.369	2.100

These are the abnormal returns (*a*) and corresponding t-stats (t(*a*)) when the trading Actual, Strategy and Excess Returns of each stock are regressed against the Four Daily Fama French Factors. The Average T-Stats in the last row are based on the absolute value of the T-Stats for the individual stocks.

Table 7: Market *b* and T-Stats; Fama French Four- Factor Regressions

$$r_t - r_{ft} = a + b(r_{MKT} - r_{ft}) + sr_{SMBt} + hr_{HMLt} + mr_{Mt}$$

	Actual Return *b*	Actual Return t(*b*)	Strategy Return *b*	Strategy Return t(*b*)	Excess Return *b*	Excess Return t(*b*)
SHLD	0.429	1.389	-0.706	-1.764	-1.135	-3.051
WLP	0.787	2.788	0.818	3.565	0.031	0.124
CRM	0.167	0.642	0.134	0.468	-0.033	-0.107
CAM	-0.080	-0.211	0.206	0.625	0.285	0.592
PDCO	0.632	4.171	0.182	1.105	-0.450	-2.834
CSCO	0.507	2.814	0.347	1.835	-0.160	-0.833
BIG	-0.271	-1.052	-0.141	-0.563	0.129	0.578
DELL	0.289	1.271	-0.036	-0.128	-0.325	-1.024
BTU	0.024	0.068	0.082	0.264	0.058	0.187
DNR	-0.485	-1.478	0.012	0.033	0.497	1.484
CEPH	0.895	5.352	0.490	2.887	-0.405	-2.802
LXK	0.144	0.490	0.502	1.517	0.358	1.158
VRSN	-0.013	-0.057	0.103	0.507	0.116	0.411
EMC	-0.263	-0.908	0.159	0.480	0.422	1.264
STJ	-0.012	-0.127	0.287	1.985	0.299	1.922
PTV	0.046	0.351	0.415	3.167	0.368	2.600
JDSU	0.124	0.520	1.444	4.507	1.320	4.564
NBR	-0.322	-1.458	0.286	1.316	0.607	3.293
ZMH	-0.048	-0.457	0.055	0.494	0.103	0.858
SRCL	0.135	1.447	0.405	4.764	0.270	2.579

These are the market risk premium coefficients (*b*) and corresponding t-stats (t(*b*)) when the trading Actual, Strategy and Excess Returns of each stock are regressed against the Four Daily Fama French Factors.

Table 8: Size *s* and T-Stats, Fama French Four- Factor Regressions

$$r_t - r_{ft} = a + b(r_{MKT} - r_{ft}) + sr_{SMBt} + hr_{HMLt} + mr_{Mt}$$

	Actual Return *s*	Actual Return t(*s*)	Strategy Return *s*	Strategy Return t(*s*)	Excess Return *s*	Excess Return t(*s*)
SHLD	0.435	0.950	-0.341	-0.574	-0.776	-1.406
WLP	-0.256	-0.612	0.024	0.069	0.280	0.755
CRM	0.084	0.216	0.392	0.924	0.308	0.665
CAM	0.395	0.703	-0.599	-1.228	-0.993	-1.389
PDCO	-0.008	-0.035	0.209	0.854	0.216	0.920
CSCO	0.032	0.121	-0.080	-0.286	-0.113	-0.396
BIG	0.050	0.132	0.491	1.319	0.441	1.332
DELL	0.118	0.349	0.448	1.081	0.331	0.703
BTU	-0.851	-1.623	-0.582	-1.258	0.270	0.586
DNR	-1.292	-2.656	-0.687	-1.319	0.605	1.219
CEPH	0.255	1.030	-0.312	-1.242	-0.568	-2.651
LXK	-0.569	-1.308	-0.279	-0.568	0.290	0.633
VRSN	0.234	0.678	0.461	1.533	0.228	0.544
EMC	-0.263	-0.908	0.159	0.480	0.422	1.264
STJ	-0.164	-0.708	-0.229	-0.653	-0.065	-0.173
PTV	-0.207	-0.643	-0.478	-1.502	-0.271	-0.787
JDSU	-0.645	-1.113	-1.145	-1.470	-0.500	-0.712
NBR	0.004	0.007	0.142	0.269	0.138	0.308
ZMH	-0.199	-0.782	-0.474	-1.762	-0.275	-0.947
SRCL	0.000	-0.001	0.109	0.528	0.109	0.430

These are the size risk premium coefficients (*s*) and corresponding t-stats (t(*s*)) when the trading Actual, Strategy and Excess Returns of each stock are regressed against the Four Daily Fama French Factors.

Table 9: Value *h* and T-Stats, Fama French Four- Factor Regressions

$$r_t - r_{ft} = a + b(r_{MKT} - r_{ft}) + sr_{SMBt} + hr_{HMLt} + mr_{Mt}$$

	Actual Return *h*	Actual Return t(*h*)	Strategy Return *h*	Strategy Return t(*h*)	Excess Return *h*	Excess Return t(*h*)
SHLD	0.692	1.162	0.691	0.895	-0.001	-0.001
WLP	0.099	0.182	0.387	0.873	0.288	0.596
CRM	0.067	0.133	0.195	0.354	0.129	0.213
CAM	1.839	2.517	0.288	0.453	-1.552	-1.668
PDCO	0.225	0.770	0.471	1.479	0.246	0.803
CSCO	-0.041	-0.118	-0.029	-0.078	0.013	0.034
BIG	0.301	0.607	0.986	2.034	0.685	1.590
DELL	0.066	0.151	-0.373	-0.690	-0.439	-0.717
BTU	0.925	1.354	0.590	0.980	-0.334	-0.558
DNR	1.291	2.039	1.293	1.907	0.002	0.003
CEPH	-0.212	-0.658	-0.528	-1.613	-0.316	-1.134
LXK	-0.515	-0.911	-0.286	-0.449	0.229	0.384
VRSN	-0.755	-1.683	0.276	0.703	1.030	1.890
EMC	-0.482	-1.276	0.760	1.759	1.241	2.853
STJ	0.326	1.081	-0.637	-1.395	-0.963	-1.958
PTV	-0.096	-0.228	-0.060	-0.144	0.036	0.080
JDSU	-0.350	-0.465	0.507	0.500	0.857	0.937
NBR	1.837	2.630	1.311	1.910	-0.526	-0.902
ZMH	-0.446	-1.344	0.048	0.138	0.494	1.306
SRCL	-0.244	-0.828	0.516	1.920	0.760	2.295

These are the book-to-market risk premium coefficients (*h*) and corresponding t-stats (t(*h*)) when the trading Actual, Strategy and Excess Returns of each stock are regressed against the Four Daily Fama French Factors.

Table 10: Momentum *m* and T-Stats, Fama French Four- Factor Regressions

$$r_t - r_{ft} = a + b(r_{MKT} - r_{ft}) + sr_{SMBt} + hr_{HMLt} + mr_{Mt}$$

	Actual Return *m*	Actual Return t(*m*)	Strategy Return *m*	Strategy Return t(*m*)	Excess Return *m*	Excess Return t(*m*)
SHLD	0.490	0.929	0.966	1.413	0.476	0.749
WLP	-0.825	-1.709	-1.171	-2.986	-0.346	-0.811
CRM	1.583	3.556	0.402	0.822	-1.182	-2.210
CAM	0.304	0.469	0.195	0.347	-0.109	-0.132
PDCO	-0.134	-0.518	-0.490	-1.741	-0.356	-1.315
CSCO	0.174	0.564	0.097	0.301	-0.076	-0.233
BIG	0.832	1.895	-0.075	-0.175	-0.907	-2.378
DELL	0.361	0.928	0.428	0.895	0.067	0.123
BTU	1.362	2.253	0.838	1.572	-0.524	-0.988
DNR	1.316	2.348	-0.254	-0.424	-1.571	-2.748
CEPH	-0.642	-2.250	0.021	0.073	0.664	2.690
LXK	1.698	3.389	0.294	0.520	-1.405	-2.658
VRSN	1.156	2.913	-0.280	-0.807	-1.436	-2.977
EMC	1.251	3.743	-0.474	-1.239	-1.724	-4.477
STJ	0.044	0.166	0.382	0.944	0.338	0.775
PTV	1.154	3.114	0.451	1.231	-0.702	-1.770
JDSU	2.310	3.460	1.123	1.251	-1.188	-1.465
NBR	1.040	1.682	-0.218	-0.359	-1.258	-2.436
ZMH	0.726	2.473	0.332	1.070	-0.394	-1.176
SRCL	-0.093	-0.356	-0.391	-1.645	-0.299	-1.018

These are the 2-12 month momentum coefficients (*m*) and corresponding t-stats (t(*m*)) when the trading Actual, Strategy and Excess Returns of each stock are regressed against the Four Daily Fama French Factors.