Predicting Trading Volume Distributions using Social Media Signals

Abstract

Trading volume predictions in the stock market are as important as predicting price movements. There have been numerous attempts to build models predicting trading volume using market data. In this paper, we explore the use of social media signals to predict trading volume. We use two techniques to evaluate the signals. First, we use linear regression testing in a base model, social media model and a social media enhanced model. Next, we look at the correlation analysis to our covariates. The universe of stocks used in our study is the S&P-500 stocks. Our findings indicate that social media signals have significant influence over next day intraday trading volume. We also find these findings are consistent in different scenarios and factor combinations.

Keywords: Social Media Sentiment, Market Sentiment, Trading Volume, Predictive Modelling



1. Introduction

Trading volume predictors are part of a continuous iterative research process at most firms. Trading volume depends on multiple factors such as the market activity, political events, global unrest and human behavior. VWAP estimates and trades depend on using accurate expectations of trading volume. Algorithmic execution uses volume predictions to optimize trade sizes to realize the best price without creating adverse market impact.

In our literature review, we came across some interesting research on trading volume predictors. There are ARMA models that use all available trade volume data as presented by (Satish, Saxena, & Palmer, 2014). There is also a good case to use price action in addition to intraday volume as a covariate in the model as presented by (Ribom & Sjoberg, 2015). All the literature, however, only uses market data in their models. There is no metric used to factor in the behavioral impact on volume. There is enough evidence to support that investors are not rational and are driven by emotion. We use social media signals as a proxy for human behavior and market sentiment. Our aim is not to provide a volume predictor model that can be used as is in a live environment. Our goal is to present evidence to validate the use the of social media signals in models to improve the existing predictors.

2. Factor Description

Our social media metrics are taken from <u>Social Market Analytics</u>. Social Market Analytics (SMA) uses its patented algorithmic system to create actionable intelligence from social media traffic. The process separates the signal from the noise and provides users with a predictive signal that leads market movements. SMA provides a family of quantitative metrics that can be used as additional indicators in trading strategy to create excess returns. Analysis in this paper is based upon a metric derived from SMA's **S-Volume** factor. We focus on three core metrics in our analysis. Additional information on other metrics is available in SMA whitepapers.



The **S-Volume** on any given security is defined as the volume of unique tweets received from approved accounts during an observation window. An account becomes approved by SMA's algorithm, which considers factors such as but not limited to, tweet frequency, tweet volume, forward looking nature etc. Figure 1 below illustrates this through an observation window of 24 hours.

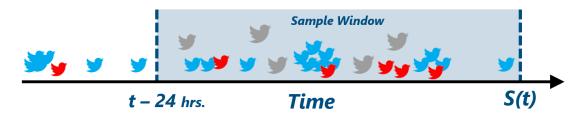


Figure 1: SMA's Process to Extract Signal from Noise

The Twitter birds in Figure 1 represent all the tweets that came in during our sampling window. For our research, we used sampling window of different lengths, ranging from 1 minute to 24 hours.

The **blue** birds represent the population of tweets that come in from a source approved by SMA.

The **red** birds represent the population of tweets that are ignored because they are either duplicates of other tweets or are coming from sources that are not approved.

The grey birds represent the population of tweets from accounts that have been identified but not rated due to lack of activity or age of the account.

S-Volume is the number of "blue" birds that came in during our sample window. This number is interchangeably also referred to as indicative tweet volume. This value is always an integer greater than or equal to 0.





Raw-Volume is the number of tweets that came in during our sample window. This is also interchangeably referred to as total tweet volume. This value is always an integer greater than or equal to 0. Raw-Volume will generally be greater than S-Volume.

Another core metric used in our research is **SV-Score**. SV-Score is the normalized value of indicative tweet volume. The value is normalized by computing the Z-Score of S-Volume with respect to a 20 day mean and 20-day standard deviation as in the equation below.

$$SV_Score_t = \frac{S_Volume_t - MA_{20}(S_Volume_t)}{SD_{20}(S_Volume_t)}$$

where,

 S_{Volume_t} is the volume of tweets at time t

 $MA_{20}(S_{Volume_t})$ is the 20 moving average of S_{Volume} at time t

 $SD_{20}(S_{Volume_t})$ is the 20 standard deviation of S_{Volume} at time t

Equation 1: Calculation of SV-Score

The third metric that we use is called **S-Poster**. This metric refers the number of unique contributors of indicative tweets in the sample window.

3. Universe and Test Interval

We test our predictor on a time series of the S&P 500 names. If a stock was removed from the index, we do not try to make a prediction for it on the following day.

The time interval we used for our study was a 6-month period 2017-02-17 to 2017-10-17.

The interval was chosen due to ease of data handling of raw-tweets (about 6 million during our observation window) and the intraday 1-minute price date for securities.

In our future study, we will extend this to the full out of sample data range from SMA that starts in 2011-12-01.



4. Volume Regression Models

Based on our research, we find that a linear regression models is a good way to evaluate the goodness of a fit in our predictor model.

We perform a linear regression, where our response (dependent) variable is the **Total Volume** in the subsequent trading session today and the covariates are the social media related metrics as below.

Response Variable	Covariates
Trading Volume Today	Raw Volume from 16:00 yesterday to 9:25 today
	SV-Score at 09:25 today (24-hour sample window)
	Poster count at 09:25 (24-hour sample window)
	Trading Volume Yesterday (Optional)

The definition of the covariates and the calculation based on sample window is discussed in the section "Factor Description" above. Trading Volume is defined as the total trading volume between [09:30, 16:00] US Eastern time. We ignore pre-market hours and after-hours trading volume for this study. To avoid any look ahead biases, we sample all our covariates before the market open.

As a **base model**, we chose a model which has no social media variable input. It is only dependent on the previous day value of response variable.

$$y_t = \beta_0 + \beta_1 y_{t-1} + \varepsilon$$

Equation 2: Base Regression Model





We find significant autocorrelation for most of the stocks in our universe. This makes intuitive sense as the events of the previous day have influence on the trading volume on the next day. The plot in Figure 2 below shows the behavior for AT&T during our test interval.

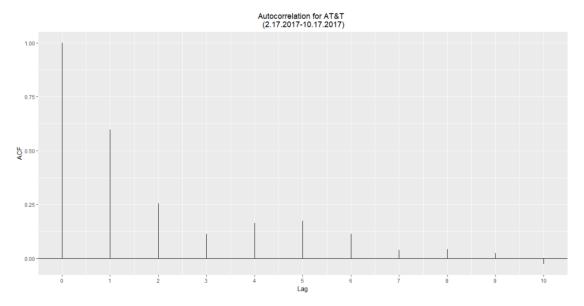


Figure 2: ACF test for Autocorrelation in Trading volume for AT&T

Using the Base Model, the regression results show decent adjusted R-squared values. A sample of values for 20 stocks is shown in the table below. A detailed table of results can be found in the Appendix.

Ticker Symbol	Regression Adj R ²
NVDA	26.7%
NFLX	23.6%
MU	15.0%
GILD	33.6%
HD	8.1%
KR	40.9%
WMT	11.5%
BA	27.4%
AAL	17.4%
TGT	10.6%
DIS	10.6%
INTC	14.1%
AMGN	16.5%
CSCO	25.4%



NKE	15.5%
SBUX	28.7%
GE	10.2%
ВМҮ	29.4%
IBM	11.1%
AAPL	13.4%

Table 1: Regression Results of base model for 20 stocks

Next, we move on to create an **enhanced model** with our sentiment covariates included in the model. For this exercise, to test the validity of our factor, **we remove the previous day trading volume**. The regression model is defined in Equation 3.

$$y_t = \beta_0 + \beta_1 Raw_Volume_{16:00-09:25} + \beta_2 SV_Score_{09:25} + \beta_3 Poster_Count_{09:25} + \varepsilon$$
Equation 3: Regression Model for Enhanced Model

Table 2 below shows the R² values of stocks in Table 1 for the enhanced model in comparison to the base model.

Ticker Symbol	Base Model R ²	Enhanced Model R ²	Improvement
NVDA	26.7%	39.5%	48.0%
NFLX	23.6%	69.7%	195.2%
MU	15.0%	56.1%	274.8%
GILD	33.6%	49.1%	46.2%
HD	8.1%	36.7%	354.3%
KR	40.9%	80.4%	96.6%
WMT	11.5%	32.8%	186.1%
BA	27.4%	56.4%	105.9%
AAL	17.4%	21.7%	25.0%
TGT	10.6%	55.1%	420.7%
DIS	10.6%	61.8%	484.5%
INTC	14.1%	33.3%	136.2%
AMGN	16.5%	52.7%	219.1%
CSCO	25.4%	68.4%	169.7%
NKE	15.5%	55.2%	255.7%
SBUX	28.7%	71.4%	149.0%
GE	10.2%	44.4%	335.0%
ВМҮ	29.4%	34.0%	15.8%
IBM	11.1%	69.5%	523.4%
AAPL	13.4%	23.0%	70.9%

Table 2: Regression Results for Enhanced Model





The results show strong evidence that even in the absence of information about the previous day's volume, the social media signals provide a better model to predict the total trading volume through the day. The 20-stock sample is a good representative of our universe. The detailed results are in the Appendix below.

A histogram of the regression fit for the base model and the improved model is presented in the figure below. The histogram shows a comparison of the Adj. R² values for both the base and the enhanced model. The visual shows that in the base model, most of the stocks are clustered around 0 to 0.2 values. However, in the enhanced model, this cluster diffuses into other higher values. This implies that the enhanced model shows a better fit than the base model.

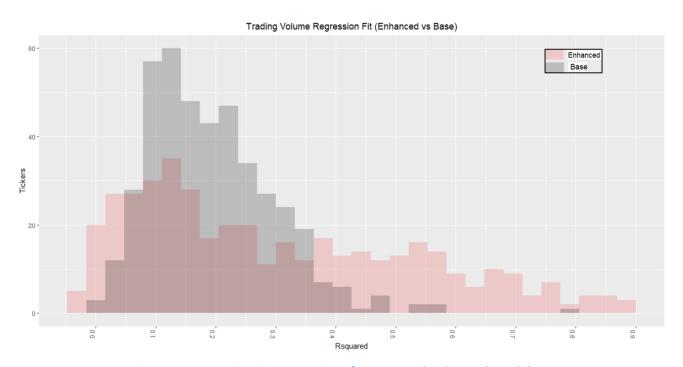


Figure 3: Regression Fit Comparison for Base and Enhanced Model

We also ran another version of the enhanced model where we use the previous day's trading volume as another covariate. The results show improvements from both, the base model and the social media only model. Figure 3 below shows the improvement from the base model



when adding the previous day's trading volume covariate to the social media model.

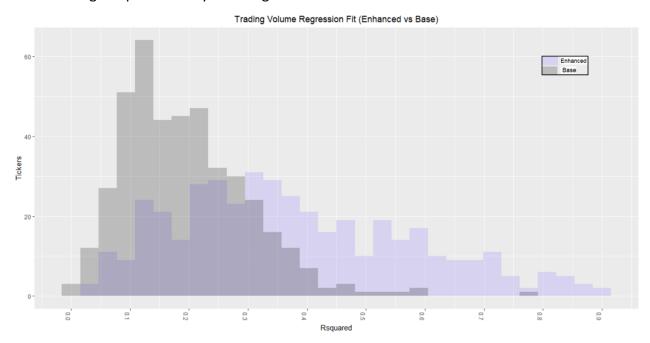


Figure 4: Regression Fit Comparison for Base and Enhanced Model

We see that the diffusion is even higher in this case, and the improvements from the base model are very significant. These results provide evidence that our model with all covariates included has the best fit in predicting intraday volume. The results for 20 stocks sample is tabulated below. We see the improvement is better than a social media only model. Improvement is percentage change in R-Squared between the Base Model and the Enhanced Model.

Ticker Symbol	Base Model R ²	Social Media Model R ²	Enhanced Model R ²	Improvement
NVDA	26.7%	47.4%	47.4%	77.8%
NFLX	23.6%	69.7%	71.1%	200.9%
MU	15.0%	56.1%	57.2%	282.0%
GILD	33.6%	49.1%	57.7%	71.8%
HD	8.1%	36.7%	38.1%	371.5%
KR	40.9%	80.4%	81.2%	98.3%
WMT	11.5%	32.8%	34.8%	203.3%
BA	27.4%	56.4%	56.0%	104.6%
AAL	17.4%	21.7%	27.6%	58.8%
TGT	10.6%	55.1%	55.4%	423.5%
DIS	10.6%	61.8%	62.6%	492.3%
INTC	14.1%	33.3%	35.2%	149.6%





AMGN	16.5%	52.7%	52.9%	220.4%
CSCO	25.4%	68.4%	69.4%	173.5%
NKE	15.5%	55.2%	57.1%	267.9%
SBUX	28.7%	71.4%	76.4%	166.3%
GE	10.2%	44.4%	44.0%	330.7%
BMY	29.4%	34.0%	41.8%	42.2%
IBM	11.1%	69.5%	70.8%	534.8%
AAPL	13.4%	23.0%	25.6%	90.2%

Table 3: Comparison of R² values for Base, Social Media and Enhanced Model

Correlations of Factors

We next analyze the correlation of social media covariates to our response variable (total trading volume of the day). For the 20 stocks that we presented in the tables above, the Spearman correlation coefficients are encouraging.

Ticker Symbol	Raw Volume	SV-Score	Poster Count
NVDA	0.59	0.36	0.53
NFLX	0.53	0.29	0.47
MU	0.49	0.28	0.42
GILD	0.49	0.38	0.51
HD	0.48	0.21	0.25
KR	0.47	0.29	0.57
WMT	0.44	0.34	0.46
BA	0.43	0.15	0.39
AAL	0.42	0.31	0.40
TGT	0.41	0.41	0.47
DIS	0.41	0.25	0.33
INTC	0.40	0.30	0.40
AMGN	0.38	0.28	0.54
CSCO	0.36	0.33	0.41
NKE	0.35	0.39	0.44
SBUX	0.32	0.33	0.40
GE	0.29	0.26	0.43
BMY	0.29	0.29	0.42
IBM	0.28	0.24	0.34
AAPL	0.28	0.17	0.46

Table 4: Correlations of the covariates to the response variable



The correlations show a significant relationship between social media signals and the next session trading volume for a security. We also plot a histogram of the correlation of total trading volume with raw volume and poster count across all securities in the universe.



Figure 5: Histogram of Raw Volume correlation with Trading Volume

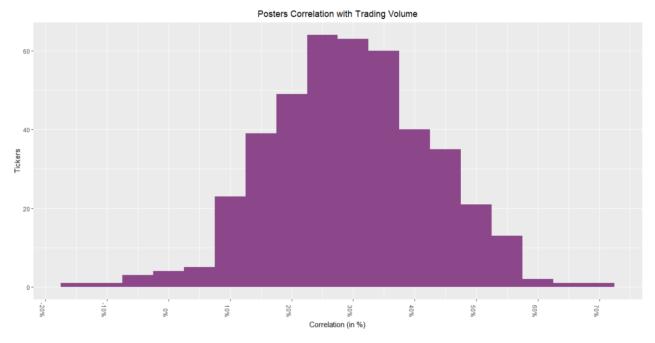


Figure 6: Histogram of Poster Count Correlation with Trading Volume



The histograms show a right skew in both the charts. The mean of the values for enhanced model is right of the median which shows encouraging results. This correlation is slightly stronger in the Poster count than in the raw-volume. Our hypothesis is that Poster count is a better covariate since Poster count is derived from the number of approved Twitter sources and Raw-Volume is the absolute volume of unique content. Both cases provide evidence to support the fact that pre-market message count (Raw-Volume) and professional investors engagement (Poster count) are strong predictors of trading volume.

5. Conclusion and Future Work

The results of this paper demonstrate the utility of social media factors in a canonical volume predictor model. The regression model provides evidence for a strong relationship between social media signals and the next day's trading volume. Our focus was not to create a model but to evaluate the quality of these signals in an environment. Social Market Analytics based volume predictor the signals have passed our evaluation tests.

In our work, we also came across encouraging results in predicting the mean trading volume and intraday trading volume volatility. These predictions are also helpful in predicting the volume distribution of securities. For future work, we plan to test the model over multiple horizons. We also want to study the impact that the sector of a security has on the results. In addition to regression analysis, we want to explore classification models that incorporate market and social media data to predict trading volume changes. Also, the next extension will include using the predicted value at start of the day and modifying it intraday as more information comes in.



6. References

Ribom, H., & Sjoberg, M. (2015). Intraday Analysis and Prediction of Volume Distribution on the Stockholm Stock Exchange.

Satish, V., Saxena, A., & Palmer, M. (2014). Predicting Intraday Trading Volume and Volume Percentages. *Journal of Trade*.





7. Appendix

The table below shows the Adj. R² values of our Base Model, Social Media Model and the Enhanced Model in columns 2-4. It also has the correlation of our covariates to next session trading volume in columns 5-7.

Ticker	Base	Social Media	Enhanced	Raw -	SV-	Poster
Symbol	Model	Model	Model	Volume	Score	Count
NVDA	26.7%	39.5%	47.4%	0.59	0.36	0.53
NFLX	23.6%	69.7%	71.1%	0.53	0.29	0.47
MU	15.0%	56.1%	57.2%	0.49	0.28	0.42
GILD	33.6%	49.1%	57.7%	0.49	0.38	0.51
HD	8.1%	36.7%	38.1%	0.48	0.21	0.25
KR	40.9%	80.4%	81.2%	0.47	0.29	0.57
WMT	11.5%	32.8%	34.8%	0.44	0.34	0.46
ВА	27.4%	56.4%	56.0%	0.43	0.15	0.39
AAL	17.4%	21.7%	27.6%	0.42	0.31	0.40
TGT	10.6%	55.1%	55.4%	0.41	0.41	0.47
DIS	10.6%	61.8%	62.6%	0.41	0.25	0.33
INTC	14.1%	33.3%	35.2%	0.40	0.30	0.40
AMGN	16.5%	52.7%	52.9%	0.38	0.28	0.54
CSCO	25.4%	68.4%	69.4%	0.36	0.33	0.41
NKE	15.5%	55.2%	57.1%	0.35	0.39	0.44
SBUX	28.7%	71.4%	76.4%	0.32	0.33	0.40
GE	10.2%	44.4%	44.0%	0.29	0.26	0.43
BMY	29.4%	34.0%	41.8%	0.29	0.29	0.42
IBM	11.1%	69.5%	70.8%	0.28	0.24	0.34
AAPL	13.4%	23.0%	25.6%	0.28	0.17	0.46
MCD	27.8%	39.0%	43.7%	0.26	0.24	0.34
CELG	25.7%	25.6%	35.2%	0.25	0.22	0.33
ATVI	16.6%	8.9%	17.7%	0.23	0.28	0.33
AMZN	27.2%	14.6%	29.3%	0.22	0.12	0.30
XOM	9.8%	10.0%	16.2%	0.22	0.32	0.42
F	9.4%	7.6%	10.3%	0.20	0.23	0.30
FB	12.6%	43.9%	43.6%	0.19	0.29	0.41
MSFT	23.8%	23.2%	33.5%	0.19	0.19	0.45
С	13.2%	30.3%	31.8%	0.17	0.31	0.44
WFC	16.6%	19.4%	30.3%	0.17	0.20	0.27
Т	40.2%	50.3%	59.1%	0.17	0.24	0.35
ABBV	20.7%	15.6%	25.3%	0.15	0.24	0.35



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CVX	26.4%	7.2%	27.9%	0.14	0.23	0.27
BAC	15.9%	23.0%	23.2%	0.13	0.38	0.54
JPM	15.5%	37.9%	39.5%	0.12	0.43	0.52
GOOG	27.4%	20.8%	35.8%	0.11	0.28	0.25
VZ	26.3%	39.2%	44.6%	0.09	0.15	0.32
GS	15.5%	33.1%	32.6%	0.08	0.43	0.55
CAT	12.2%	14.8%	16.2%	0.08	0.24	0.35
PFE	26.9%	15.1%	29.5%	0.07	0.19	0.35
КО	26.8%	13.8%	28.8%	0.03	0.23	0.40
JNJ	23.2%	24.5%	33.1%	-0.01	0.37	0.45
V	13.0%	16.9%	25.7%	-0.02	0.15	0.20
MRK	17.4%	7.5%	21.2%	-0.03	0.17	0.21
MMM	14.2%	42.4%	42.2%	-0.04	0.18	0.32
GM	10.1%	-1.4%	9.5%	-0.10	0.18	0.29
COST	26.9%	28.8%	36.5%	0.77	0.35	0.69
CMG	25.9%	28.9%	28.6%	0.68	0.24	0.41
AMAT	30.8%	31.7%	45.2%	0.48	0.33	0.34
PYPL	23.7%	43.1%	46.4%	0.36	0.09	0.35
LMT	21.7%	28.7%	35.0%	0.36	0.25	0.31
CRM	21.9%	40.2%	42.1%	0.24	0.23	0.51
CMCSA	13.6%	29.4%	31.4%	0.19	0.21	0.31
PCLN	18.1%	65.9%	65.8%	0.18	0.22	0.28
CVS	3.6%	11.5%	12.2%	0.15	0.32	0.32
MS	15.5%	19.2%	23.1%	-0.01	0.30	0.42
PG	4.9%	2.1%	6.1%	-0.06	0.08	0.24
М	9.2%	31.2%	33.4%	0.40	0.26	0.40
BBY	19.0%	82.4%	82.2%	0.28	0.22	0.37
DAL	21.8%	26.3%	31.5%	0.27	0.38	0.40
QCOM	14.6%	54.9%	54.6%	0.24	0.16	0.41
PEP	18.5%	11.0%	20.0%	0.02	0.25	0.34
UNH	37.1%	11.4%	40.7%	0.02	0.20	0.25
LOW	11.3%	60.9%	61.2%	0.44	0.34	0.43
AVGO	22.1%	56.6%	56.9%	0.41	0.23	0.43
WDC	4.6%	12.4%	14.0%	0.28	0.18	0.23
MO	23.7%	27.9%	31.3%	0.27	0.19	0.28
AGN	29.5%	17.1%	33.9%	0.19	0.03	0.21
СНК	12.3%	30.2%	29.6%	0.17	0.28	0.36
LUV	19.4%	8.1%	23.1%	0.17	0.09	0.09
TWX	10.1%	5.9%	11.1%	0.13	0.16	0.24
BIIB	12.2%	23.5%	25.8%	0.08	0.24	0.32
AXP	17.2%	48.9%	51.3%	0.02	0.27	0.33



MA	16.4%	11.8%	22.5%	-0.09	0.14	0.18
FCX	8.5%	41.6%	41.4%	0.53	0.29	0.42
UA	8.8%	58.3%	58.3%	0.40	0.36	0.35
CSX	23.1%	65.8%	68.6%	0.29	-0.01	0.27
ADBE	27.3%	54.4%	56.5%	0.15	0.18	0.43
DOW	2.2%	5.6%	5.1%	0.10	0.24	0.28
WYNN	11.1%	48.0%	47.8%	0.44	0.32	0.41
WBA	14.9%	42.8%	46.0%	0.41	0.17	0.40
EBAY	15.3%	50.5%	51.8%	0.33	0.24	0.29
ORCL	30.3%	80.0%	80.6%	0.31	0.26	0.49
LLY	13.2%	51.6%	53.0%	0.23	0.27	0.34
REGN	21.0%	34.7%	35.4%	0.19	0.31	0.45
RTN	16.7%	13.5%	23.5%	0.14	0.22	0.18
CL	21.8%	25.5%	28.0%	0.12	0.19	0.33
UAL	17.7%	43.4%	46.3%	0.30	0.30	0.38
FDX	35.4%	42.9%	58.3%	0.20	0.08	0.38
VRTX	4.8%	81.4%	81.7%	0.49	0.33	0.45
SWKS	22.0%	36.7%	39.2%	0.40	0.24	0.48
COP	5.3%	50.6%	50.2%	0.17	0.17	0.24
MDT	30.3%	19.2%	36.1%	0.17	0.25	0.37
EOG	18.4%	19.2%	26.8%	0.17	0.25	0.27
UTX	7.5%	18.4%	19.2%	0.15	0.21	0.33
GLW	20.5%	32.1%	37.0%	0.11	0.20	0.33
UPS	17.5%	22.5%	31.2%	0.09	0.18	0.20
DD	5.5%	1.6%	4.1%	-0.20	0.03	0.10
ULTA	20.4%	76.0%	76.7%	0.59	0.34	0.55
HAL	18.3%	15.9%	25.5%	0.16	0.19	0.31
PM	8.1%	11.3%	16.0%	-0.09	-0.03	0.12
WFM	1.7%	87.5%	88.9%	0.53	0.21	0.53
FOXA	46.6%	32.1%	51.6%	0.33	0.05	0.24
ABT	22.9%	19.6%	31.7%	0.15	0.25	0.27
BLK	27.5%	12.6%	31.5%	0.12	0.15	0.11
AET	22.4%	2.8%	21.7%	-0.04	0.06	0.14
JWN	19.6%	74.7%	74.5%	0.39	0.24	0.50
KMI	11.8%	43.0%	43.7%	0.23	0.32	0.38
CBS	32.8%	15.2%	40.4%	0.22	0.00	0.09
CTL	11.2%	3.5%	11.0%	0.17	0.33	0.31
MRO	12.9%	30.3%	30.1%	0.27	0.30	0.37
VLO	9.1%	12.4%	16.5%	0.22	0.33	0.27
AA	3.3%	8.2%	7.6%	0.20	0.18	0.35
GD	17.5%	30.6%	38.4%	0.14	0.14	0.21



0	14.6%	21.5%	24.3%	-0.13	-0.03	0.26
KSS	13.3%	60.1%	59.9%	0.33	0.41	0.35
GIS	7.5%	10.7%	11.8%	0.28	0.30	0.26
AIG	31.1%	21.0%	35.0%	0.13	0.02	0.36
TJX	34.6%	55.4%	56.9%	0.59	0.42	0.49
LB	12.5%	62.3%	66.1%	0.56	0.50	0.52
MYL	22.2%	66.3%	68.6%	0.49	0.33	0.45
EA	36.0%	39.7%	44.8%	0.16	0.15	0.37
SLB	11.0%	5.8%	12.6%	0.04	-0.02	0.21
CCL	19.9%	27.8%	35.9%	0.35	0.30	0.37
DE	12.3%	72.0%	72.6%	0.33	0.19	0.48
KHC	58.2%	47.3%	60.5%	0.29	0.07	0.21
HPE	22.8%	52.3%	58.1%	0.23	0.15	0.40
MDLZ	25.4%	8.6%	27.0%	0.19	0.24	0.32
USB	16.8%	11.6%	18.2%	-0.11	0.11	0.32
FL	30.2%	84.2%	88.0%	0.69	0.20	0.59
HUM	20.4%	9.8%	24.0%	0.19	0.15	0.34
HON	11.0%	8.5%	12.8%	0.19	-0.01	0.25
ISRG	11.7%	52.5%	53.6%	0.33	0.08	0.09
SO	36.6%	15.6%	40.7%	0.04	0.33	0.27
INCY	21.0%	55.0%	54.6%	0.44	0.15	0.65
LRCX	17.8%	35.6%	41.7%	0.38	0.14	0.39
MON	22.1%	47.0%	49.4%	0.22	0.33	0.56
APA	11.2%	15.5%	21.2%	0.09	0.15	0.13
VIAB	8.9%	67.5%	67.5%	0.44	0.23	0.29
MAR	21.5%	33.8%	40.8%	0.35	0.22	0.49
ALXN	21.9%	41.2%	41.4%	0.31	0.17	0.45
EXPE	8.7%	24.2%	23.6%	0.27	0.14	0.27
TXN	17.8%	9.4%	19.2%	0.10	0.23	0.30
MCHP	22.5%	25.3%	34.2%	0.05	0.16	0.31
CI	12.7%	13.6%	20.2%	0.05	0.09	0.25
RCL	18.0%	37.7%	43.0%	0.36	0.06	0.10
ACN	20.8%	52.3%	52.1%	0.23	0.24	0.47
PHM	18.7%	20.4%	26.8%	0.17	0.32	0.42
TSCO	5.1%	43.7%	43.2%	0.03	0.30	0.35
YUM	33.9%	2.7%	34.1%	0.01	0.15	0.20
ALK	29.7%	-0.8%	30.5%	-0.06	0.05	0.00
AMD	32.2%	57.8%	61.8%	0.62	0.42	0.57
TRIP	19.3%	55.6%	57.6%	0.51	0.27	0.47
NUE	9.0%	20.5%	20.0%	0.33	0.35	0.46
ADI	55.2%	60.6%	72.0%	0.29	0.05	0.38



Г			1	1		1
HRL	9.6%	72.0%	71.8%	0.21	0.30	0.43
OXY	41.2%	21.5%	41.3%	0.14	0.06	0.28
NEM	24.0%	16.8%	26.7%	0.06	0.13	0.22
K	19.4%	10.3%	21.0%	0.05	0.38	0.38
DUK	28.1%	0.1%	26.6%	-0.20	0.00	-0.02
GPS	16.8%	49.6%	53.7%	0.46	0.39	0.41
APC	12.2%	16.8%	21.1%	0.33	0.19	0.34
DLTR	16.8%	42.2%	43.6%	0.30	0.20	0.39
СОН	6.9%	83.9%	84.7%	0.29	0.32	0.28
CHTR	12.9%	45.6%	48.7%	0.22	0.08	0.30
ESRX	24.6%	26.4%	34.1%	0.13	-0.01	0.28
SPG	35.7%	16.9%	38.5%	0.12	-0.14	0.26
AMT	31.8%	12.7%	32.3%	-0.03	0.21	0.26
HPQ	13.5%	48.6%	48.6%	0.37	0.21	0.27
PXD	22.3%	66.0%	66.0%	0.31	0.05	0.15
MAT	28.6%	55.5%	59.9%	0.30	0.08	0.27
COG	9.4%	0.0%	8.7%	0.20	0.15	0.17
D	34.7%	4.6%	36.9%	0.18	0.02	0.05
COF	13.7%	48.0%	48.5%	0.17	0.25	0.29
STZ	15.2%	43.8%	43.8%	0.11	0.16	0.21
AFL	29.9%	3.1%	30.5%	-0.15	0.19	0.20
MNST	24.5%	57.3%	60.0%	0.41	0.16	0.30
HOG	12.4%	82.2%	82.1%	0.38	0.26	0.41
SYMC	20.1%	37.6%	45.1%	0.34	0.16	0.40
ADSK	9.4%	61.7%	62.0%	0.28	0.07	0.42
DG	8.3%	46.6%	46.1%	0.27	0.13	0.38
CTSH	36.0%	8.3%	36.1%	0.09	0.15	0.20
NOV	9.5%	-0.5%	7.5%	0.02	0.08	0.17
EW	23.8%	16.7%	29.2%	-0.01	0.10	0.26
TRV	9.1%	27.4%	30.4%	-0.05	0.03	0.25
NDAQ	21.9%	-1.0%	20.3%	-0.13	0.11	0.12
AAP	9.1%	84.9%	84.8%	0.62	0.23	0.54
ILMN	9.7%	69.8%	69.5%	0.30	0.34	0.30
SYK	8.6%	8.8%	11.5%	0.10	0.24	0.18
MET	20.3%	-0.7%	18.3%	0.01	0.06	0.14
PSX	14.6%	2.3%	15.0%	-0.14	0.01	0.04
AZO	14.5%	70.8%	70.5%	0.56	0.30	0.59
BAX	8.7%	2.0%	9.5%	0.06	0.02	0.07
ANTM	11.5%	10.6%	15.6%	0.02	0.05	0.17
APD	10.1%	22.7%	24.1%	-0.05	0.17	0.21
PRGO	8.5%	52.0%	59.6%	0.36	0.34	0.51



LEN	36.0%	34.4%	46.5%	0.33	0.29	0.48
STX	10.8%	74.3%	74.2%	0.30	0.16	0.29
DVN	10.8%	4.4%	11.0%	0.10	0.23	0.27
BBT	19.8%	14.4%	25.7%	-0.06	0.25	0.31
ROST	16.2%	62.6%	64.5%	0.49	0.47	0.45
ALB	34.6%	57.4%	63.3%	0.38	0.18	0.28
TSN	15.8%	47.8%	48.5%	0.28	0.24	0.37
CF	16.5%	16.2%	22.2%	0.19	0.24	0.27
EMR	29.8%	14.1%	32.8%	0.18	0.07	0.30
NSC	26.3%	4.0%	24.4%	0.13	0.12	0.17
KEY	11.7%	5.9%	13.7%	0.05	0.25	0.25
TIF	13.1%	61.9%	61.8%	0.38	-0.04	0.35
HP	15.3%	24.1%	26.7%	0.17	0.03	0.35
PPG	52.9%	49.9%	57.9%	0.14	0.01	0.16
NEE	7.8%	0.3%	6.7%	-0.03	0.14	0.13
PX	17.2%	6.1%	18.6%	-0.03	0.25	0.35
KORS	12.3%	66.2%	67.7%	0.44	0.12	0.42
HAS	17.6%	68.5%	71.4%	0.32	0.16	0.27
BSX	7.4%	21.0%	20.4%	0.32	0.31	0.36
PPL	5.1%	1.6%	5.0%	0.14	0.25	0.26
PNC	23.3%	12.2%	29.8%	0.11	0.10	0.18
UNP	23.8%	26.3%	35.7%	0.08	0.05	0.19
BK	29.0%	12.1%	30.3%	0.00	0.28	0.12
NOC	34.4%	4.5%	35.4%	-0.04	0.16	0.14
COL	19.2%	58.2%	60.6%	0.49	0.16	0.47
SPLS	28.3%	43.8%	53.7%	0.41	0.25	0.21
PGR	11.0%	13.0%	16.0%	0.22	0.24	0.29
SCHW	15.9%	33.7%	38.0%	0.13	0.43	0.43
PRU	5.5%	9.4%	14.4%	0.10	0.23	0.19
CME	16.6%	-3.1%	14.8%	-0.03	0.02	0.02
RHT	22.8%	70.3%	70.6%	0.33	0.21	0.20
XLNX	8.8%	30.1%	29.5%	0.27	0.19	0.48
FMC	5.0%	61.4%	64.3%	0.26	0.10	0.43
ALL	32.9%	17.8%	36.3%	0.07	0.01	0.25
CXO	16.9%	42.1%	43.2%	0.01	0.11	0.19
SIG	17.1%	56.3%	55.8%	0.55	0.14	0.47
CAH	7.9%	65.2%	66.1%	0.36	0.08	0.40
RRC	17.3%	38.7%	41.7%	0.30	0.18	0.28
KMB	37.3%	13.1%	40.7%	0.10	-0.09	0.12
CERN	29.3%	-1.4%	30.8%	0.04	0.07	-0.05
ICE	30.9%	12.1%	31.8%	-0.12	0.30	0.31



OBLY	0.5%	22.40/	24.20/	0.64	0.04	0.53
ORLY	9.5%	33.4%	34.2%	0.61	-0.04	0.53
OKE	39.1%	29.4%	46.5%	0.53	0.13	0.36
GOOGL	24.4%	23.5%	34.5%	0.52	0.25	0.43
NRG	39.1%	87.0%	87.1%	0.46	0.18	0.37
PVH	34.4%	68.9%	70.6%	0.40	0.38	0.47
MOS	30.3%	27.4%	50.0%	0.37	0.23	0.31
СРВ	43.4%	54.6%	70.4%	0.35	0.14	0.27
HOLX	31.8%	50.8%	62.8%	0.29	0.15	0.13
MCK	7.4%	54.8%	54.8%	0.26	0.36	0.41
HES	19.3%	25.8%	31.6%	0.22	0.23	0.37
MPC	25.1%	9.0%	26.2%	0.05	-0.05	0.13
WMB	31.1%	-0.4%	29.8%	-0.16	0.11	0.20
KMX	40.3%	62.7%	64.8%	0.43	0.35	0.47
NTAP	13.8%	54.1%	54.8%	0.40	0.45	0.49
ES	5.9%	8.9%	13.5%	0.38	-0.05	0.20
CMI	10.9%	59.4%	60.4%	0.32	0.02	0.24
DPS	19.5%	12.3%	27.5%	0.25	0.21	0.34
FITB	13.2%	13.4%	19.4%	0.12	0.27	0.27
XEC	14.1%	7.5%	14.2%	0.24	0.13	0.32
DLR	16.0%	61.3%	61.0%	0.23	0.01	0.15
DFS	28.3%	19.1%	34.1%	0.14	0.08	0.28
HSY	17.6%	16.9%	27.5%	0.09	0.28	0.28
VFC	36.4%	16.7%	39.4%	0.03	0.20	0.30
МСО	29.5%	14.3%	36.7%	0.01	0.02	0.15
STT	8.2%	-0.2%	5.9%	-0.02	0.23	0.18
EL	25.4%	46.0%	47.7%	0.51	0.25	0.45
INTU	34.8%	31.8%	50.5%	0.31	0.32	0.44
IFF	23.7%	22.2%	35.1%	0.15	0.20	0.17
FOX	32.5%	12.3%	35.5%	0.10	0.13	0.27
DISH	22.9%	24.9%	30.8%	0.09	0.25	0.37
RF	14.5%	21.6%	25.9%	0.08	0.37	0.28
EXC	13.5%	3.5%	13.3%	-0.03	-0.01	0.18
ABC	8.6%	46.2%	47.4%	0.38	0.13	0.21
BDX	47.5%	47.9%	62.3%	0.29	-0.14	0.28
DHI	24.7%	13.2%	24.0%	0.19	0.09	0.33
TMO	19.1%	11.4%	28.3%	0.13	0.18	0.29
CBOE	31.0%	10.8%	35.8%	0.03	0.24	0.26
PSA	13.2%	6.4%	13.4%	0.02	0.03	0.11
CLX	36.2%	7.2%	36.8%	-0.07	0.09	0.21
EQIX	20.7%	19.5%	30.0%	-0.10	0.13	0.25
ED	17.6%	2.1%	15.9%	0.05	0.06	0.26



CHD	21.2%	5.5%	23.3%	-0.04	0.35	0.29
VTR	33.8%	11.8%	33.6%	-0.21	-0.11	0.12
DRI	10.9%	75.1%	75.0%	0.39	0.38	0.34
AKAM	11.4%	74.8%	74.5%	0.34	0.01	0.49
SHW	3.6%	51.9%	51.4%	0.18	0.10	0.14
ADS	13.4%	39.1%	40.1%	0.09	0.24	0.31
FAST	18.8%	82.2%	82.2%	0.53	0.17	0.42
CCI	18.6%	16.7%	27.0%	0.38	-0.06	0.19
ADM	11.2%	12.5%	13.3%	0.27	0.19	0.33
JNPR	14.8%	27.2%	32.3%	0.14	0.01	0.27
ETFC	16.8%	44.9%	45.7%	0.12	0.20	0.31
STI	23.7%	5.0%	21.6%	0.04	0.21	0.23
APH	5.7%	8.7%	8.9%	0.04	0.05	0.13
ADP	11.6%	26.7%	30.0%	0.66	0.08	0.49
ITW	12.2%	29.6%	30.0%	0.26	0.13	0.30
AWK	19.2%	7.2%	20.1%	0.20	-0.03	0.16
DLPH	21.5%	7.6%	21.5%	0.14	0.08	0.24
PLD	23.4%	1.1%	21.0%	0.08	0.13	0.18
SJM	31.8%	50.3%	67.6%	0.42	0.11	0.31
RL	58.2%	55.3%	69.8%	0.25	0.17	0.40
FE	22.2%	9.2%	24.0%	0.20	0.01	0.20
KIM	36.5%	9.7%	40.8%	0.10	-0.01	0.28
SWK	20.0%	42.0%	45.4%	-0.01	0.14	0.34
TROW	12.0%	18.5%	22.9%	-0.06	0.32	0.35
HRB	12.3%	65.1%	64.7%	0.42	0.06	0.48
MSI	11.2%	39.0%	46.8%	0.31	0.29	0.49
SYY	4.7%	11.6%	13.2%	0.27	0.02	0.13
FIS	21.4%	7.5%	24.4%	0.14	0.03	0.13
WM	6.5%	10.4%	13.0%	-0.01	-0.02	0.14
GWW	25.1%	69.4%	69.1%	0.38	0.15	0.45
CA	11.6%	52.6%	52.1%	0.34	0.08	0.36
QRVO	27.8%	14.9%	29.0%	0.31	0.15	0.26
HBAN	21.4%	39.9%	43.1%	0.18	0.11	0.35
MAC	9.0%	10.5%	16.5%	0.16	0.17	0.31
GGP	16.6%	34.1%	37.7%	0.40	-0.16	0.18
NBL	26.7%	25.1%	35.4%	0.30	-0.13	0.32
KLAC	18.3%	19.1%	25.1%	0.25	0.12	0.29
NWL	16.5%	49.6%	52.0%	0.18	-0.10	0.06
НВІ	24.8%	31.8%	45.6%	0.16	-0.09	0.23
CNC	35.5%	11.5%	39.9%	0.13	0.20	0.21
DISCA	11.7%	74.3%	74.0%	0.53	-0.03	0.50



JBHT	12.0%	33.3%	38.3%	0.34	0.28	0.32
TDG	30.8%	23.8%	36.1%	0.34	-0.19	0.32
GRMN	11.6%	65.3%	65.3%	0.31	0.23	0.23
URI	10.7%	48.8%	48.9%	0.23	0.23	0.19
NFX	5.7%	21.8%	21.5%	0.23	0.30	0.37
MKC		40.1%				
	11.4%		51.3%	0.54	-0.01	0.36
EQT	25.5%	51.8%	52.3% 10.5%	0.35	0.10	0.53
BEN	7.5%	5.8%		0.17	0.17	0.12
PH	8.4%	0.8%	7.3%	0.17	0.23	0.25
DOV	18.0%	13.4%	20.3%	0.16	0.25	0.35
AME	24.2%	1.9%	26.2%	-0.04	-0.04	-0.09
AEP	0.6%	8.8%	8.0%	-0.12	0.17	0.12
ETN	23.0%	38.3%	40.0%	0.31	0.18	0.22
HCA	36.0%	33.3%	47.4%	0.28	0.11	0.22
XYL	21.6%	11.6%	26.1%	-0.05	0.27	0.08
CAG	29.2%	15.8%	33.9%	0.32	0.13	0.29
RIG	11.8%	4.3%	13.4%	0.19	0.03	0.14
A	24.4%	53.7%	53.0%	0.13	0.17	0.24
НСР	26.9%	1.4%	25.0%	0.07	0.06	0.12
FISV	10.5%	16.5%	16.6%	0.07	-0.01	0.19
XEL	11.2%	1.7%	11.0%	0.04	0.10	0.14
MTB	20.9%	21.5%	26.6%	-0.03	0.12	0.19
SNI	15.4%	86.2%	86.3%	0.61	0.06	0.57
PAYX	22.1%	32.4%	36.4%	0.55	0.22	0.41
DHR	6.5%	60.0%	59.6%	0.37	0.10	0.26
IR	4.0%	19.7%	19.9%	0.31	0.27	0.36
TSO	11.9%	6.7%	13.3%	0.29	0.12	0.36
CMA	8.9%	9.9%	13.1%	0.29	0.12	0.21
EIX	5.6%	4.4%	6.8%	0.09	-0.13	0.10
AMP	10.7%	13.4%	21.7%	0.05	0.14	0.18
VAR	9.5%	9.6%	16.4%	0.03	0.33	0.23
HSIC	48.8%	40.9%	60.3%	0.36	0.27	0.31
ВНІ	10.9%	2.6%	11.6%	0.07	0.04	0.23
ZION	15.2%	3.4%	14.9%	-0.21	0.13	0.13
YHOO	78.7%	37.0%	82.3%	0.40	0.23	0.29
CTXS	33.2%	45.3%	48.5%	0.33	0.10	0.26
WYN	6.5%	40.5%	40.4%	0.23	-0.03	0.27
KSU	22.1%	6.0%	21.9%	0.23	0.31	0.24
DGX	8.4%	53.1%	52.5%	0.21	0.08	0.26
SRCL	22.0%	17.3%	26.1%	0.20	0.27	0.43
LVLT	12.6%	-2.1%	12.7%	-0.03	-0.19	-0.15



CDN	26.00/	15 50/	27.40/	0.00	0.20	0.16
GPN	26.0%	15.5%	37.1%	-0.08	0.26	0.16
ESS	5.6%	6.2%	9.8%	0.20	-0.06	0.06
CNP	3.0%	-0.2%	1.8%	0.15	0.07	0.17
COO	16.9%	37.7%	43.9%	0.11	0.23	0.22
PEG	26.2%	11.8%	29.6%	0.04	0.34	0.36
BLL	41.7%	4.3%	41.0%	-0.12	0.01	0.12
TEL	21.1%	10.8%	25.3%	-0.16	0.22	0.26
LYB	20.5%	7.6%	19.9%	-0.16	-0.11	0.16
HST	27.8%	16.1%	28.9%	0.10	0.08	0.18
XRX	47.6%	5.7%	51.8%	0.06	0.30	0.16
HIG	4.9%	-1.0%	2.4%	-0.02	0.13	0.16
CBG	29.3%	-1.9%	26.7%	0.05	0.10	0.13
WY	4.6%	12.9%	12.5%	-0.21	0.13	0.23
EXR	6.1%	22.3%	24.1%	0.28	0.11	0.29
HCN	20.8%	8.4%	22.8%	0.04	0.15	0.36
BWA	8.1%	2.0%	6.0%	0.02	0.21	0.20
EMN	13.7%	0.7%	11.7%	0.01	0.21	0.19
ZTS	35.4%	11.8%	36.9%	0.22	0.13	0.17
NTRS	31.5%	77.4%	83.0%	0.13	0.15	0.25
LH	25.5%	6.1%	26.9%	-0.14	0.12	0.19
COTY	26.6%	87.7%	89.8%	0.36	0.04	0.44
VMC	21.7%	25.1%	30.4%	0.35	0.35	0.42
IPG	19.8%	58.5%	58.1%	0.24	0.21	0.33
AES	13.8%	35.4%	45.9%	0.23	0.41	0.29
GT	15.2%	65.2%	79.4%	0.22	-0.17	0.28
RAI	23.2%	-2.8%	20.8%	0.13	0.02	0.10
FTI	4.6%	6.7%	9.4%	0.05	0.24	0.12
EQR	32.1%	3.5%	34.7%	-0.01	0.26	0.18
IP	11.2%	4.7%	12.5%	-0.09	-0.01	0.17
GPC	22.1%	38.1%	41.8%	0.57	0.10	0.33
SEE	13.1%	56.7%	57.3%	0.33	0.15	0.34
SRE	18.7%	11.8%	21.3%	0.24	0.41	0.48
JEC	1.0%	20.8%	19.5%	0.23	-0.03	0.21
DTE	8.5%	-0.4%	6.8%	0.15	0.16	-0.02
MMC	10.0%	16.8%	25.3%	0.08	0.28	0.23
PCG	17.3%	4.0%	16.4%	-0.03	-0.05	0.21
EFX	16.1%	3.0%	16.2%	-0.05	-0.13	-0.06
FLR	7.1%	59.4%	58.8%	0.59	0.11	0.27
DVA	13.0%	36.6%	37.1%	0.37	0.01	0.27
UHS	8.9%	57.1%	56.8%	0.32	0.06	0.16
NLSN	30.9%	7.0%	33.4%	0.24	0.19	0.14



IRM	8.4%	32.7%	34.6%	0.17	-0.01	0.25
TAP	27.7%	31.9%	32.3%	0.17	0.06	0.15
PWR	9.9%	12.9%	21.2%	0.12	0.18	0.12
ECL	28.0%	24.7%	36.6%	0.00	0.37	0.38
LNC	18.2%	-1.1%	16.9%	-0.01	0.06	0.17
ZBH	31.6%	25.5%	36.0%	0.31	-0.16	0.34
VNO	21.1%	23.3%	27.4%	0.09	0.09	0.29
MAS	36.1%	-3.9%	34.1%	-0.04	0.04	0.15
RSG	25.2%	1.1%	22.2%	-0.07	-0.12	0.08
SCG	42.5%	41.1%	51.9%	0.42	0.03	0.29
TXT	12.0%	8.3%	16.3%	0.23	0.20	0.32
ROK	17.2%	7.0%	16.3%	0.01	0.23	0.30
FLS	9.0%	72.9%	72.4%	0.47	0.18	0.45
MNK	9.8%	25.7%	35.3%	0.43	0.24	0.27
XRAY	30.5%	38.3%	52.2%	0.39	-0.05	0.25
WHR	5.2%	17.0%	19.2%	0.35	0.44	0.49
OMC	1.8%	25.1%	24.9%	0.33	0.10	0.33
LLL	16.6%	19.6%	22.7%	0.16	-0.06	0.28
PFG	32.7%	5.9%	35.1%	-0.08	-0.15	0.08
AVB	-0.2%	24.4%	23.5%	0.26	-0.16	-0.03
EVHC	17.5%	44.4%	46.6%	0.20	0.27	0.44
WU	18.2%	10.6%	22.6%	0.11	0.01	0.25
IDXX	26.6%	18.8%	42.5%	0.08	0.09	0.14
PBCT	14.4%	18.5%	23.8%	0.06	0.04	0.33