DEMAND FOR OPTION ORDER DELTA (DOOD)

Garrett DeSimone, Ph.D.
head of quantitative research, OptionMetrics

"The Dude abides." - The Dude (The Big Lebowski, 1998)

The explosive growth of the equity options market in the wake of the pandemic has sparked massive interest from media and investors in derivatives phenomena. Meme stock manias have been attributed to the gamma effect. The Nasdaq "whale" was labeled the primary suspect in the melt-up of summer 2020.

While it is evident options order flow influences underlying stock behavior, its less apparent exactly which hedging indicators or greek exposures have predictive power for underlying stock returns. In this paper, we introduce a straightforward measure dubbed Demand for Option Order Delta (DOOD). This metric is calculated as the aggregate sum of delta multiplied by net signed option trades scaled by daily stock volume. In other words, it is a measure of excess demand imbalance for delta by end-users of options.

The strength of DOOD above other measures is the incorporation of signed tick data. OptionMetrics implements the Lee and Ready (1991) tick algorithm, inferring direction by identifying where trades occurred in relation to the spread. Trades are classified such that those closer to the current ask price are treated as buy orders by end-users, and those closer to the current bid as sell orders. This algorithm allows us to generate a daily estimate of net delta positioning by end-users, simply by subtracting buy from sell orders.

Our research establishes that DOOD is a meaningful cross-sectional predictor of stock returns. We utilize a portfolio sorting approach based on this measure, which captures the difference in returns between high and low DOOD stocks. Over a weekly horizon, the spread outperformance of high over low DOOD stocks is 32 bp (17 % annualized). From a risk adjusted perspective, the long/short portfolio also displays a superior Sharpe of 1.08 versus 0.81 against the S&P 500 benchmark and carries a significant 3-Factor alpha of 0.0026 (14% annualized.)

This research is unique, owing it is the first (to our knowledge) to document the variation of portfolio returns based on delta demand. The linkage between equity-options behavior has typically focused on an anecdotal time-series of returns to a single stock or index (For example, large purchases in OTM (out of the money) puts last week are attributed to this week's selloff).

We provide two primary explanations for the observed return patterns. The first is based on the informed trading channel. The options market is the preferred venue for investors with private information due to the ability to attain higher leverage and the ability to conceal trades. Investors with informed bullish sentiment will purchase calls, leading to a positive delta imbalance (high DOOD) and higher stock returns. On the other hand, investors that are pessimistic will purchase puts, leading to a negative delta imbalance (low DOOD).

The second explanation centers on dealer hedging and rebalancing. Stocks with high DOOD are supported by either customer long call pressure or short put pressure. In both cases, dealers who serve a liquidity function must maintain a delta neutral inventory supported by short stock. High DOOD stocks are subject to upward momentum because market makers must increase stock purchases as underlying prices rise.

In the remainder of this paper, we discuss methodology and data, decile portfolio results, strategy performance, and extensions to volatility scaling.

Methodology and Data

This research extends a long line of literature documenting the informational content of options. This paper is closely related to Hu (2014). The author utilizes a similar measure and finds predictive power of order imbalance for future returns in the time-series. The DOOD metric differs by replacing daily stock volume in the denominator. This research also focuses on the cross-sectional predictability of returns, by employing a large universe of single name stocks.

Our sample data on delta covers U.S. optionable securities is retrieved from IvyDB US. Volume data containing directional trades is calculated from IvyDB Signed Volume. The databases are merged at the option symbol level. Next, we compute the daily DOOD measure per security as follows:

$$DOOD_t = \frac{\sum^{n} \Delta_{i,t} * \left(AskVolume_{i,t} - BidVolume_{i,t}\right)}{StockVolume_t}$$

For every option symbol *i*, the option delta is multiplied by the net volume (Total Ask Volume – Total Bid Volume) on that symbol. Next, these values are summed across all n symbols in the entire option chain. Finally, this value is scaled by the underlying stock volume to get a relative measure comparable across securities.

An important assumption of this metric is the assignment of ask volume as demand for options by end-users (E.g., pension funds, individual investors, institutional hedgers). These participants are not serving a market making liquidity function. Therefore, we utilize the assumption that trades designated closer to the ask quote are probable buy orders, since customers absorb the transaction cost of the spread.

Sample and Universe

The sample extends greater than 5 years, starting in Jan 2016 to March 2022. The goal of this research is to document the underlying portfolio return patterns of securities classified by their DOOD value. The focus is on a five-day rebalancing horizon, which strikes a balance between the short-term nature of the signal and costs imposed by high turnover.

Prior to portfolio formation, a series of filters is imposed to remove noise from illiquid securities. These filters include the following:

1. ETFs and indices are excluded.
2. The stock must be optionable.
3. Stocks must be the upper 90% of market capitalization upon portfolio formation.
4. Stock price must be greater than $5 upon portfolio formation.

5. Stocks must have less than 300% implied volatility at time of portfolio formation.
6. Stocks must have at least option ask volume of 1000 at time of portfolio formation.

Next, we utilize the decile sorting approach based on DOOD. Every week stocks are partitioned into deciles based on the level of DOOD. Stocks are equal weighted within each decile portfolio.

Table 1 below documents the descriptive statistics for the top decile and bottom decile portfolios weekly returns. We do not include intermediate portfolios for the sake of brevity since there was no discernable return pattern. The high DOOD decile posts average weekly returns of 0.54% (27% annualized). This is a stark contrast to the low DOOD decile returns of 0.21% (11% annualized). The volatility of each strategy is comparable, although the high DOOD decile is slightly higher at 0.0384. Interestingly, the high DOOD decile displays slight positive skewness compared to the mild negative skewness of low DOOD stocks. This implies low DOOD stocks have a larger left tail and are subject to more extreme losses than high DOOD.

The difference in spreads between portfolios naturally lends itself to a hedged long/short strategy. A strategy that buys high DOOD and sells low DOOD earns a weekly return of 0.32% (17% annualized). The performance of hedged strategy provides economic significance to our findings since it demonstrates meaningfully larger weekly returns into investing in high DOOD over low DOOD stocks.

Table 1 : Average Weekly Decile Portfolio Returns

HIGH DOOD (TOP DECILE)		*LOW DOOD (BOTTOM DECILE)*	
Mean	0.0054	Mean	0.0021
Median	0.0046	Median	0.0007
Std Dev	0.0384	Std Dev	0.0351
Kurtosis	8.8160	Kurtosis	4.9303
Skewness	0.0098	Skewness	−0.1694
Minimum	−0.2093	Minimum	−0.1806
Maximum	0.2133	Maximum	0.1771
N	308.0000	N	308.0000

Portfolios rebalanced weekly based on DOOD(Demand for Options Order Delta)

Table: Garrett DeSimone • Source: OptionMetrics • Created with Datawrapper

Table 2 presents the annualized calculations. We benchmark our portfolios against the S&P 500 (SPX). The long/short portfolio obtains a better Sharpe ratio of 1.03 compared to SPX. The high DOOD portfolio also performs closely to the long/short (L/S), suggesting that the return behavior of the portfolio is primarily driven by the long leg.

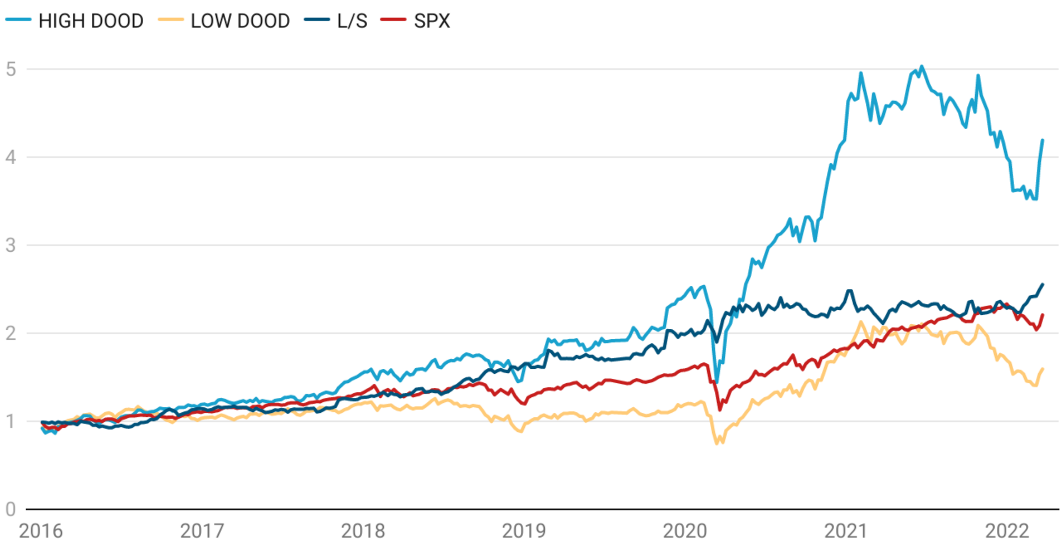
Table 2: Annualized Returns and Volatility of Portfolios

Statistic	*Mean Annualized Return*	*Annualized Volatility*	*Sharpe Ratio*
Long/Short	0.1672	0.1528	1.0300
SPX	0.1352	0.1670	0.8100
High DOOD	0.2680	0.2764	0.9700
Low DOOD	0.1100	0.2500	0.4400

Table: Garrett DeSimone, PhD • Source: OptionMetrics • Created with Datawrapper

Graph 1 displays the cumulative return to each strategy. Both the high DOOD and L/S portfolio beat out SPX, posting a growth in wealth to $4.20 and $2.55, respectively. SPX provided a growth to $2.20. While the L/S return is not nearly as impressive, the short hedge is able to reduce the annual volatility by almost half.

Graph 1: Cumulative Returns of $1 Invested in Strategies



Cumulative returns to portfolios rebalanced weekly on DOOD (Demand for Options Order Delta) metric

Chart: Garrett DeSimone, PhD • Source: OptionMetrics • Created with Datawrapper

In the last piece of this section, we look to assess the L/S performance compared to market returns and other risk factors. The L/S returns are regressed on a Fama-French 3 factor model. Table 3 displays regression results. These results indicate that the L/S strategy provides a strong source of uncorrelated returns without significant exposure to traditional market (MKT-RF), size (SMB) and value (HML) factors. The coefficients are small and are not statistically significant at a 10% level.

The L/S strategy displays a positive excess return, with a weekly alpha of 0.0026 (significant at a 5% level). On an annualized basis, this represents an excess return of 14%. In summation, the L/S performance provides a meaningful value add from a diversification standpoint.

Table 3: Fama-French 3-Factor Regression Results

Dependent Variable : L/S weekly portfolio returns on DOOD
R-squared : 0.089
Df : 300

Variable	Coefficients	Standard Error	t Stat	P-value
Intercept	**0.0026**	**0.0012**	**2.1414**	**0.0331**
MKT-RF	0.0772	0.0502	1.5376	0.1252
SMB	−0.0168	0.0918	−0.1825	0.8553
HML	0.0163	0.0601	0.2707	0.7868

Factor data provided by Kenneth French's website.

Table: Garrett DeSimone, PhD • Source: OptionMetrics.com • Created with Datawrapper

We focus on two explanations for the return patterns documented in this paper. The simplest explanation contends that the DOOD measure proxies for informed directional trading. Traders with private bullish information are likely to take positions in long calls. Stocks with high DOOD have a greater positive delta imbalance relative to other stocks. Logically, these stocks will realize higher average returns if the stock market has an informational lag.

A more complex explanation is attributed to dealer gamma hedging flows. Gamma is the derivative of delta, and measures how delta changes with underlying prices moves. Market makers in equity options are typically short gamma. This requires buying when underlying prices are rising, and selling when they are falling to keep dealer inventory delta neutral. Baltussen et. al (2021) and Beckmeyer and Moerke (2021) document this phenomenon extensively across multiple securities within the time-series and cross-sectionally. The authors find that the last 30-minute return is positively predicted by the return from the rest of the day.

In comparison, our return predictor signaled by delta imbalance is persistent across a horizon spanning several days. Stocks in the highest DOOD decile experience momentum since market makers buy the underlying stock in response to rising prices. Stocks in the lowest DOOD decile experience lower returns since market makers must sell in response to falling prices. In separate findings, we document that the DOOD measure itself is positively autocorrelated in the time series, which would result in continued day-over-day buying by dealers.

Extensions to Volatility Scaling

A feature of the L/S strategy is the clustering of volatility throughout the sample. Since periods of high volatility are associated with negative returns, running this strategy with constant leverage induces an allocation that may not be efficient. A natural solution is to pursue a volatility targeting approach. If volatility is persistent and quasi-predictable, then it is a viable option to increase leverage when volatility is low and decrease leverage when it is high. Therefore, volatility can be "targeted" or set at a constant level of risk exposure.

Our approach is comparable to Harvey et. al (2017). A conditional volatility estimate of the L/S strategy is formed by utilizing the previous 3-months of weekly excess returns to generate the one-week ahead variance forecast. The forecast is computed using the formula as follows:

$$\widehat{\sigma_{t+1}} = \sum^{11} ret^2 / 12$$

This formula focuses on equal weighting of historical returns, due to simplicity and similar estimates of conditional variance compared to exponentially decaying structures documented in Harvey et. al (2017).

In Graph 3, we sort strategy returns into quartiles based on the historical volatility and calculate mean returns and standard deviation. The goal of this graph is to gain an understanding of the risk-return trade-off during different volatility environments. The bottom panel demonstrates the persistence in volatility in the following week. However, the top panel does not show a monotonic increase in returns with increasing quartiles. There is a lack of additional return compensation for investing during higher risk environments. In this case, it would make sense to scale exposure during these periods.

Targeting volatility involves selecting a fixed level of volatility ex-post, and scaling the leverage based on the forecast to achieve that level over the sample. This requires increasing leverage when forecasted vol is below the target and decreasing leverage when above.

Graph 3: Quartile Analysis of Excess Returns

Mean of excess returns are binned by 1-week ahead forward variance forecast

Variance Forecast is obtained from conditional volatility estimate from previous quarter

Chart: Garrett DeSimone, PhD • Source: OptionMetrics • Created with Datawrapper

Graph 3: Quartile Analysis of Excess Returns

Standard deviation of excess returns are binned by 1-week ahead forward variance forecast

Variance Forecast is obtained from conditional volatility estimate from previous quarter

Chart: Garrett DeSimone, PhD • Source: OptionMetrics • Created with Datawrapper

Graph 4 plots the cumulative returns of the L/S strategy at various fixed levels of vol. In all cases, the L/S vol target outperforms SPX. The Sharpe also improves from 1.03 in untargeted to 1.15 for targeted vol. Therefore, systemically increasing leverage during low volatility environments, and increasing during high volatility environments materially improves the risk-return profile of this strategy.

Graph 4: Cumulative Returns to Vol Targeted Strategies

L/S strategy scaled to run constant volatility leading to superior Sharpe

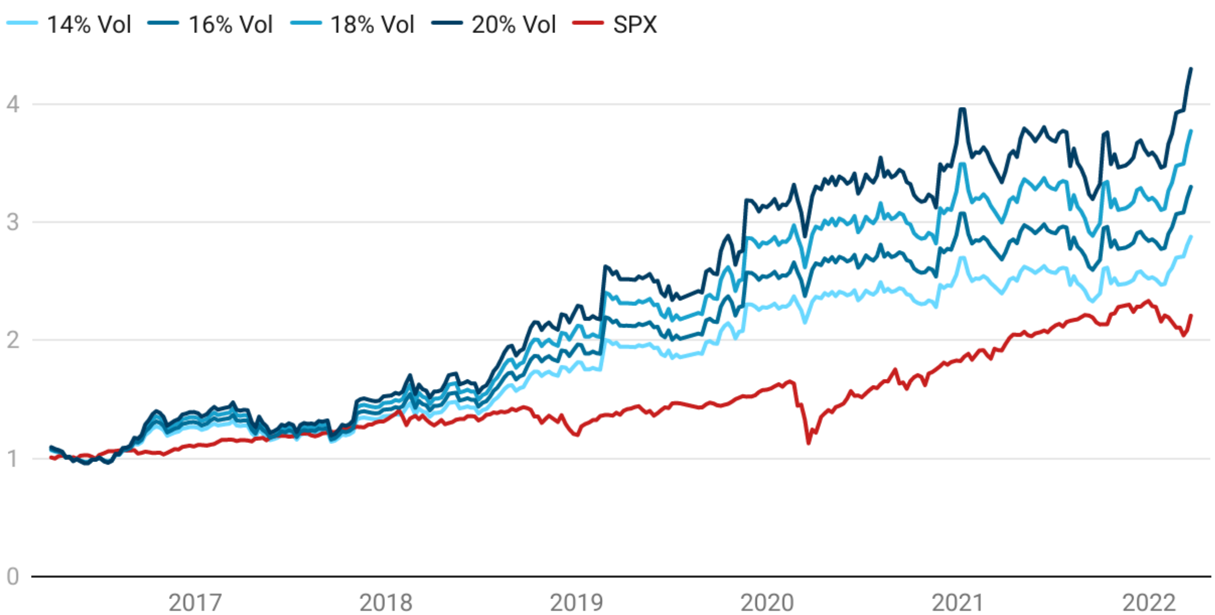


Chart: Garrett DeSimone, PhD • Source: OptionMetrics • Created with Datawrapper

Conclusion

In this research, we introduce a new measure of delta imbalance, namely Demand for Option Order Delta or "DOOD." The novelty of DOOD is derived from the Lee and Ready (1991) signed tick algorithm, which incorporates demand for delta by end-users. Applying a decile sorting approach at a weekly horizon, we demonstrate the spread performance of high DOOD stocks over low DOOD is 32 bp (17% annualized). The L/S strategy produces a meaningfully higher Sharpe relative to the SPX benchmark and a significant 3-Factor weekly alpha of 0.0026.

Our explanations for these results focus on the informed trading channel and gamma hedging relationship. High DOOD stocks have a larger positive delta imbalance, signaling informed bullish sentiment from investors, which is, ultimately, realized in higher future returns. High DOOD stocks are also subject to positive momentum, since rising prices force dealers to purchase underlying shares when their order book is net negative delta.

This research opens several avenues for further exploration. The DOOD metric has a natural application to predicting returns across earnings and monthly expirations. DOOD also allows for additional levels of portfolio dissection across long versus short call or put imbalance.

"Hey, well that's just like...Your opinion, man." - The Dude

References

Baltussen, Guido, et al. "Hedging demand and market intraday momentum." *Journal of Financial Economics* 142.1 (2021): 377-403.

Beckmeyer, Heiner, and Mathis Moerke. "End-of-Day Momentum in the Cross-Section and Option Hedging." *Working Paper*

Harvey, Campbell R., et al. "The impact of volatility targeting." *The Journal of Portfolio Management* 45.1 (2018): 14-33.

Hu, Jianfeng. "Does option trading convey stock price information?." *Journal of Financial Economics* 111, no. 3 (2014): 625-645.

Lee, Charles MC, and Mark J. Ready. "Inferring trade direction from intraday data." *The Journal of Finance* 46.2 (1991): 733-746.