Betting on the Likelihood of a Short Squeeze

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Abstract

Short squeezes often lead to large increases in stock prices. Using a novel measure of the likelihood of short squeezes we show that it explains *lottery* or *skewness-seeking*-investing. As in other instances of securities with right-skewed returns documented in the literature, these investors buy call options instead of the underlying stocks, to maximize the right-skewness of their investment. In particular, they are willing to pay a premium for the upside potential. This type of investment strategy has attracted much attention recently, but we document that it has been used for decades.

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1 Introduction

Short squeezes often lead to stock price surges. A consequence of this is that the conditional distribution of the returns of stocks subject to a substantial probability of a short squeeze is right-skewed. Accordingly, these stocks present a potentially attractive target to *lottery* or *skewness-seeking* investors (see Brunnermeier, Gollier, and Parker (2007) and Mitton and Vorkink (2007) for analysis of lottery-investing in financial markets). In this paper we study and verify that such is the case; that is, as explained in the previous references, some investors are willing to pay a premium for securities that could experience a positive price jump because of a substantial probability of a short squeeze.

A first challenge in our quest is to assess as objectively as possible the likelihood of a short squeeze or, rather, come up with an objective metric that identifies securities that skewness-seeking investors could consider lottery-like securities because of a potential short squeeze. Our starting point is a proprietary measure, the Data Explorers Increasing Price Squeeze indicator (DIPS), that compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) to determine the likelihood of a rapid increase in price (i.e., price squeeze).[1]

Of course, we do not think skewness-seeking investors use the DIPS measure itself as a guide to their portfolio allocation. Yet, they arguably use public information –such as the one DIPS appears to be based on– that allows them to assess the likelihood of a short squeeze.[2] We hypothesize that the estimates of the good forecasters are correlated with DIPS. For the purposes of our study, DIPS provides an objective measure that mitigates possible data mining concerns.

[1] We describe the database later. It is compiled and owned by IHS Markit (Markit, from now). They do not provide the exact formula they use to come up with the probability of a short squeeze, just the foundations reported here.

[2] A number of high-profile cases in which retail investors have colluded to trigger short squeezes have been recently documented in the press. However, in this study we present evidence of lottery-investing in securities subject to possible short squeezes since at least 2006, the starting point of the DIPS database.

Following existing literature, our analysis focuses on call options written on the stocks susceptible to a short squeeze, rather than on the stocks themselves. It has been shown (e.g., Filippou, Garcia-Ares, and Zapatero, 2021) that in the case of optionable stocks, skewness-seeking investors favor call options over the underlying stocks because the implicit leverage of options magnifies the effect of positive jumps. Our results confirm that call options are the security of choice of investors betting on a short squeeze.

For the specific design of our initial empirical test we rely on the following considerations. On the one hand, our study requires us to set up portfolios of options at some point in time in order to compute their returns and check if they display a negative alpha –proof of overpricing, as expected from the investment decisions of skewness-seeking investors (Brunnermeier et al. (2007) and Mitton and Vorkink (2007)). Given the mechanics of options, and following the options literature, we choose the first trading day following expiration to minimize liquidity and other possible problems documented in the literature (Goyal and Saretto (2009)). On the other hand, we need to offset the idiosyncrasy of the DIPS measure on a particular day by smoothing the measure over a period of time, which would gives us a more representative value. With that goal, we take the time series of DIPS over the three months (we also use a month) previous to the portfolio formation date, and compute the average, the maximum (inspired by the work of Bali, Cakici, and Whitelaw (2011) that we discuss later) and the standard deviation. All three are highly correlated and predict lottery-investing, but we find that the best predictor is the standard deviation. Arguably, a security that has experienced several high values of DIPS over the last period is seen as a more likely candidate for a short squeeze with substantial price implications. We call it std(DIPS) and it is the base measure we use throughout our analysis.

Specifically, in our first test we double-sort into quintiles average returns of portfolios of call options that we set up using the past three-month time series of DIPS of the underlying stocks according to average of DIPS, maximum DIPS over the three months, and std(DIPS)

–we take two of them at a time for a double-sort analysis. We find out that the three measures are priced as proxies of the *lotteryness* of the securities, regardless of each other's level. That is, the higher the average DIPS of the portfolio, the lower the average returns (investors pay a premium) regardless of the level of the std(DIPS), and similarly for all other combinations. In all combinations, a high-minus low portfolio pays a negative return that is statistically significant, but in the case of std(DIPS) is substantially more significant, both statistically and economically. Average DIPS, maximum DIPS and std(DIPS) are positively correlated but, arguably, everything else equal, the skewness-seeking investor prefers calls corresponding to high std(DIPS) stocks because sometimes they reach high levels of DIPS. For that reason, throughout the rest of the paper we focus on std(DIPS) as proxy for skewness.

Next we want to verify whether our measure of skewness, std(DIPS), is a good predictor of short squeezes associated with positive price jumps. For this test, at the same time points we use for the formation of portfolios of call options, we collect stocks in ten bins according to their std(DIPS). Then, we compute the average percentage of stocks in each bin that experience a daily price increase of over 15% over the following month. The difference in the percentage of stocks with such price increases between the decile of stocks of the highest std(DIPS) and the decile of the lowest is very significant. This holds for stocks with daily returns over 20%. Also, in an even more direct test, the difference in percentages is significant for stocks with an increase of two standard deviations in price and a reduction of two standard deviations of the short interest (the result of a short squeeze).

In another verification test, instead of raw option returns we use delta-hedged returns, as it has become customary in the options literature, because delta-hedged returns isolate the option specific part of the return from that due to changes in the price of the stock. Predictably, the results concerning *lotteryness* properties of the options whose underlying stock have high std(DIPS) are stronger than in the previous tests with raw returns.

Also in line with the related literature, we perform cross-sectional regressions of the call returns on std(DIPS) and a number of important variables. Key among them are the measures used in the literature to assess lotteryness of the underlying stock –the MAX variable of Bali et al. (2011) that we discuss later– and the lotteryness of options per se, independently of the underlying stock –the BV-SKEW value of Boyer and Vorkink (2014) that we also discuss later. It might be possible that MAX and/or BV-SKEW subsume the predictive ability of std(DIPS) for the cross-section of option returns. Yet, we find that std(DIPS) helps explain option returns over and above the aforementioned lottery measures. In addition, the coefficient of the std(DIPS) is much larger, indicating a large economic value. In our cross-sectional regressions we also include a large number of controls used in the literature –for example, related to liquidity and momentum. The explanatory power of options returns form std(DIPS) stands after we include all these controls.

We need to check that the effect we are capturing is not due to some unobserved specific characteristic of the DIPS measure, maybe unrelated to the likelihood of a short squeeze. To address this concern we compare std(DIPS) with other measures that reflect the depth of short positions on a given stock and, therefore, might anticipate the possibility of a short squeeze and be used by investors. In particular, we select *short float* (number of shorted shares divided by the number of shares available for trade) and *days-to-cover* (number of shorted shares divided by average trade volume). We first establish that std(DIPS) is positively correlated with both of them. Accordingly, portfolios of call options formed based on these measures provide significant negative returns, as it is the case with std(DIPS).

We conjecture that the lottery-investing the likelihood of a short squeeze generates will lead to a high volume of trade in the corresponding call options, at least compared to other call options. We explore this hypothesis through the analysis of option order imbalances. Two results stand out from our tests. First, as it is possible to break up the order imbalance among *small*, *medium* and *large* customers –given the size of the orders–

we find that there is indeed a higher order volume for high std(DIPS) options, but the effect is concentrated in the small investors category, and there is no effect whatsoever for the large investors. Second, using the last few years of the DIPS databae, we find that there is a positive correlation between the time-series average of popularity in Robinhood (the high profile and sometimes controversial trading platform) and std(DIPS). This reinforces that the main driver of lottery-seeking activity using the likelihood of a short squeeze is retail investing –consistent with previous literature, (e.g., Filippou et al., 2021).

We perform a number of additional robustness tests. One result among them we highlight is the relationship between blocks of shares ownership and std(DIPS): the larger the blockholder ownership proportion, the higher std(DIPS). Unsurprisingly, fewer shares available for trade lead to a higher likelihood of a short squeeze.

The rest of the paper is organized as follows: in section 2 we describe the theoretical framework and position this paper in the relevant literature. In section 3 we describe the data and portfolio construction. Section 4 focuses on the empirical results. Section 5 provides a broad range of robustness and other specification tests.

2 Theoretical Framework and Related Literature

Friedman and Savage (1948) point out that standard utility functions cannot explain why households would buy insurance and, simultaneously devote some resources to gambling. They suggest a different type of utility function that is not strictly concave and can explain this seeming contradiction. Their suggested utility function, though, is *ad hoc* in that it is not based on any axiomatics. More recently, the prospect theory of Kahneman and Tversky (1979) and Tversky and Kahneman (1992) proposes a *value function* that is reminiscent of the Friedman-Savage utility. Intuitively, these convex utility functions (or parts of an otherwise concave utility function) denote risk loving attitudes that might justify embracing additional volatility or positive skewness –even if associated with negative expected returns. Aristidou, Giga, Lee, and Zapatero (2021) show that the optimal investment strategy of agents with utility functions within this class (convex or with convex segments) can be to choose skewed securities. They also show that, among other economic reasons, external habit formation –or relative wealth concerns as in Campbell and Cochrane (1999)– lead to utility functions with convex segments.

There is another strand of the literature that takes skewness-seeking as given and studies its implications for securities. Markowitz (1952) and Kraus and Litzenberger (1976) study equilibrium implications of the demand for *systematic skewness*. Harvey and Siddique (2002) show that systematic skewness helps to explain the cross-section of stock returns. Also, Brunnermeier et al. (2007) and Mitton and Vorkink (2007) demonstrate that demand for *idiosyncratic skewness* leads to lower expected returns in skewed securities. Barberis and Huang (2008) reach a similar conclusion from an equilibrium model derived from the postulates of prospect theory.

Grounded on these foundations, a growing body of research studies the demand of stocks and options as lotteries. Kumar (2009) documents that households prone to buy lottery tickets are also more likely to invest in stocks with lottery characteristics. Yet, estimating skewness ex-ante presents many difficulties. Bali et al. (2011) show that investors looking for right-skewed returns rely instead on a proxy, large positive recent returns. In particular, they allocate stocks to portfolios ranked in deciles according to the size of their largest daily return during the previous month –they also study five-day returns with similar results. This is the MAX measure that they show is associated with negative returns, as skewness seeking-investors are willing to pay a premium for these stocks –we will use the same characterization in this study. Boyer and Vorkink (2014) construct an ex ante skewness measure (BVSKEW) for option returns and document a negative relation between option's lottery-like characteristics and returns, as in the case of stocks. Filippou et al. (2021) show that options displace stocks as the target of skewness-seeking investors, arguably because their implicit leverage magnifies the skewness of the underlying. This is one of the reasons why we will focus on options in this paper.

Overall, as short squeezes imply a jump in the price of the stock –and associated call options– we conjecture that proxies for the possibility of a short squeeze will be used by skewness-seeking investors as indicators of potential investment targets.

3 Data and Portfolio Construction

3.1 Stock and Option Data

Stock Data. Our daily and monthly stock returns and monthly trading volume is obtained from the Center for Research in Security Prices (CRSP), including New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ markets as well as common stocks with share codes 10 and 11, financials and non-financials. The data span the period from January 1996 to September 2019. We also use accounting information for these stocks from the Compustat database.

Option Data. We collect options data from the OptionMetrics IvyDB database and for all exchange-listed options on U.S equities. We focus on end-of-day bid and ask quotes, trading volume, open interest, strike prices, deltas and implied volatility. This data span the period from from January 1996 to September 2019.

We eliminate observations that do not satisfy a number of criteria to guard against tradability concerns. First, to avoid illiquidity concerns, we remove options with no trading volume, options for which the ask price is lower than the bid price, the bid price is equal to zero or the average of the bid and ask quote is less than 0.125 dollars. Second, in order to remove the effect of the early exercise premium in American options, we exclude options whose underlying stock pays a dividend during the remaining life of the option. Finally, we exclude all options that violate arbitrage restrictions.

We construct portfolios of options and their underlying stocks based on the information available on the first trading day (usually a Monday) immediately following the expiration Saturday of the month. We only consider options that expire in the next month. Among these options that expire in the next month, we select those options closest to at-the-money (ATM). In our analysis, ATM options exhibit a moneyness close to 1 within the range of

0.80 and 1.20 (i.e. $0.80 < X/S < 1.20$).[3] Thus, for each stock and each option in our sample, we select the option contract that is closest to ATM and expire the next month. We also consider the behavior of out-of-the-money (OTM) options which are defined as those with moneyness in the interval of $[1,1.20]$ that are closer to 1.20. We confine our attention to call options due to the fact that retail investors and, more importantly, *gamblers*, tend to express their preferences with this type of options (e.g., Shefrin and Statman, 2000).

We also use relative open interest, defined as open interest at the end of the month scaled by the number of shares outstanding, as a proxy for option demand.

Raw Option Returns. We define the return of holding a call option to maturity as follows:

$$RX^{c}_{j,t:T} = \frac{\max(0, S_{j,T} - X_j)}{0.5(P^{ask}_{c} + P^{bid}_{c})} - 1, \tag{1}$$

where X_j is the strike price and $S_{j,T}$ is the price of the of the underlying asset j at maturity or the rebalancing date (i.e. time T). P^{ask}_{c} (P^{bid}_{c}) is the ask (bid) price of the call option at time t.

Delta-hedged Option Returns. To study the price effects that are specific to the option and not purely mechanical due to changes in the price of the underlying, we also compute delta-hedged call option returns.

Following Bakshi and Kapadia (2003); Goyal and Saretto (2009); Cao and Han (2013) among others, we construct a zero-cost portfolio consisting of a long position in a call option and a short position in the underlying security to obtain a portfolio that is expected to pay the risk-free rate. Thus, the delta-hedged call gain (DHCG) is defined as follows:

[3]The moneyness is calculated as the strike price (i.e. X) of the option over the price of the underlying security (i.e. S).

$$DHCG_{t,t+1} = (C_{t+1} - C_t) - \Delta_{C,t}(S_{t+1} - S_t) - r_{f,t}(C_t - \Delta S_t), \tag{2}$$

where $C_{i,t+1}$ represents the call option price at time $t+1$, $\Delta_{C,t} = \partial C_t / \partial S_t$ denotes the delta of the call option and $r_{f,t}$ is the risk-free rate. Following Cao and Han (2013); Eisdorfer, Goyal, and Zhdanov (2019); Cao, Han, Tong, and Zhan (2020) among others, we scale the dollar return by the difference between the Δ amount of stock and the call (e.g., $\Delta_t S_t - C_t$). Thus, the delta-hedged call returns (DHCR) take the form:

$$DHCR_{t,t+1} = DHCG_{t,t+1} / (\Delta_t S_t - C_t). \tag{3}$$

Likelihood of a Short Squeeze. The starting point is the Data Explorers Increasing Price Squeeze indicator (DIPS) reported in Markit. A short squeeze occurs when shares experience a large price increase that forces short sellers to close their positions, which leads to further price increases. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze).[4]

Short Demand and Supply. Our measures of short demand and supply are also from Markit. Demand is daily total shares borrowed from lenders in the database, and the supply represents the daily total lendable inventory available from lenders in the database. We express these measures as a percentage of shares outstanding. Another metric we use is *utilization*, the ratio of shares supplied to shares demanded, the percentage of lendable shares that are actually on loan. We obtain the Daily Cost of Borrowing Score (DCBS), which is the relative cost of borrowing for each stock, measured in a scale from 1 to 10,

[4] This is the explanation provided by Markit, but the specific algorithm is proprietary and not disclosed.

corresponding to lowest and highest cost, respectively. Finally, we report the simple average fee (SAF), which measures the buy-side cost to borrow.[5]

Days-to-Cover. In addition to DIPS, we consider two predictors for the likelihood of short squeezes. First, *days-to-cover* (DTC), the short ratio divided by daily share turnover, where the short ratio is the total shares borrowed as a percentage of shares outstanding (e.g. short demand). We choose the one corresponding to the first trading day (usually a Monday) immediately following the expiration Saturday of the month. The average of daily turnover is over the last three months. DTC measures how many days of average share volume fully directed to cover short positions would take to completely eliminate short positions.

Short Float. It is the percentage of shorted shares in relation to floating shares. Floating shares is the difference between total number of shares outstanding and block ownership.

Fails-To-Deliver. We obtain fails-to-deliver (FTD) data from the SEC website from March 2004 to September 2019.[6] It represents the aggregate net balance of shares that failed to be delivered on a particular settlement date. Similarly to relative short interest, we normalize it by the number of shares outstanding (Fotak, Raman, and Yadav, 2014). Prior to September 16, 2008, if the number was lower than 10,000, it was not recorded, therefore, for consistency, we exclude observations of less than 10,000 shares after that date as well. The FTD data from the SEC represent the open interest of failed-to-deliver trades that occurred up to three days prior.

Threshold List. We also obtained daily information about the Regulation SHO Threshold Security List. To appear on the threshold list, the security must be registered with the SEC

[5]For stock loan fees, we interpolate the missing observations of average lending fees following Blocher and Whaley (2016).

[6]https://www.sec.gov/data/foiadocsfailsdatahtm

and have five or more consecutive days of failed settlement. The failed settlements must also be of a total size of 10,000 shares or more, or at least 0.5% of the security's shares outstanding. They are reported found in the NASDAQ and NYSE websites.

Earnings Surprises. We compute quarterly earnings surprise as the absolute difference between actual EPS for a firm-quarter, obtained from the IBES Adjusted files, and earnings four quarters ago.

Abnormal Volume. The difference between the average daily trading volume over the last month and the average daily trading volume over the last year.

Sentiment of 8K filings. We follow Loughran and McDonald (2011) to compute the sentime of 8k filings. They show that negative words included in the Harvard IV-4 Psychosociological Dictionary (e.g., the Harvard-IV-4 TagNeg (H4N) file) might not fully reflect the tone of financial texts. To address this, they propose an alternative dictionary based on 10-K filings that better captures the tone of documents with financial contexts. Thus, we measure the tone of a filing as the difference between the number of positive and negative tonal words over the total number words of the filing.

Institutional Ownership. We collect end-of-quarter institutional stock holdings from the 13F form of the SEC (Thomson Reuters Institutional, included in WRDS).

Option Order Imbalances. We use signed option trading volume from the International Security Exchange (ISE) Open/Close Trade Profile database, which includes daily buy and sell volume trades and prices for each option traded at the ISE. We extract data on the direction of each trade and on whether the trades open new positions or close existing positions. Trades reported in the ISE Open/Close database represents more than 30% of the total trading volume in individual equity options during our sample period. We focus on opening trades as they are generally more informative than closing trades (e.g. Pan and Poteshman (2006); Ge, Lin, and Pearson (2016)). The signed trading volume for each option is classified into categories by investor types, permitting us to calculate the net buying pressure from end-users (i.e., non-market-maker or investor). For that reason, we focus on the customer category. According to the ISE, the universe of customers comprises retail investors as well as investment banks such as Morgan Stanley and Goldman Sachs who enter trades on behalf of large customers or hedge funds. We show results for all customers and, separately, for small trades (less than 100 contracts each), medium trades (between 101-199 contracts each) and large trades (more than 200 contracts each). We follow Chen, Joslin, and Ni (2018) and Ramachandran and Tayal (2021) and calculate Order Imbalances (OIB) as the cumulative difference of signed option volumes across contracts from all expiration dates.

3.2 Lottery Options Portfolios

DIPS Option Portfolios. We form portfolios of call options on the first trading day following the expiration Saturday of the month and only consider options that expire the following month. Specifically, the first trading day after the expiration Saturday of each month, call option returns (i.e. RX) are allocated into deciles based on the last 3-month standard deviation of the DIPS of the underlying security (e.g., std(DIPS)); then, we compute the equally and open interest weighted average return of each portfolio until the expiration of the options the following month. Our option lottery spread (i.e. HML) portfolio buys the highest std(DIPS) portfolio and short-sells the lowest. We also consider other formation periods (e.g. one month) and we form portfolios at the end of each month, with similar results.

4 Empirical Results

4.1 Baseline Results

Summary Statistics. We first present times-series averages of the cross-sectional mean, median, standard deviation and quantiles of DIPS as well as different measures of shorting activity such as the Daily Cost of Borrowing Score (DCBS), shorting supply, shorting demand, utilization (UTIL), days to cover (DTC), and short float. Specifically, we compute the cross-sectional statistics every day and month and then we report their time-series averages. *Panel A* of Table 1 shows results for daily frequencies and *Panel B* for monthly frequencies. The right panel of Table 1 shows the time-series average of the cross-sectional correlations of the measures. We find that DIPS is highly correlated with Daily Cost of Borrowing Score (DCBS), shorting demand and days to cover (DTC).

[Table 1 about here.]

We also show the characteristics of ATM call options sorted into deciles based on the standard deviation over the previous three months of the DIPS measure (e.g., std(DIPS)). *Panel A* of Table 2 presents time-series averages of the median std(DIPS) of decile portfolios of ATM call options sorted based on std(DIPS) every month, as well as the differences in std(DIPS) between the extreme portfolios. The median standard deviation increases from 0.467 to 2.168 in a statistically significant manner.

Panel B of table 2 shows additional characteristics of such portfolios. In particular, we find that the maximum DIPS increases significantly, as do the maximum 10-day stock return (MAX(10)) and idiosyncratic skewness (ISKEW). This demonstrates that stocks with higher std(DIPS) are right-skewed.

In *Panel B* we present characteristics of the underlying stock: time-series average of median trading volume, stock price, size, illiquidity (ILLIQ), idiosyncratic volatility (IVOL), momentum (MOM), stock reversals (REV), book to market ratio (B/M), debt to assets ratio (D/A), turnover, and institutional ownership (IO). We note here that stocks with higher std(DIPS) tend to be smaller stocks, with lower prices, lower trading volume, lower D/A and lower institutional ownership. In addition, stocks with higher std(DIPS) have higher idiosyncratic volatility, higher turnover and are more illiquid.

Panel C reports option characteristics such as skewness (BV-SKEW), volume, call premium, call bid-ask spreads, option to stock volume ratios (O/S) and the difference between implied volatility and historical volatility (IV-HV). Similarly to MAX(10) we find an almost monotonic increase of BV-SKEW across std(DIPS)-sorted portfolios in an economic and statistically significant manner. We also find that options attached to stocks with higher std(DIPS) have lower call premium, higher bid-ask spreads and higher O/S ratios.

[Table 2 about here.]

Lotteryness of DIPS and DIPS Volatility: Double Sorts. We perform a first exploratory analysis of the DIPS measure. In Table 3 we double-sort ATM raw call options returns in buckets, depending on three different metrics related to the DIPS of their underlying stock: average over the last three months (that we denote by avg(DIPS)); inspired by Bali et al. (2011) we compute for each stock the maximum DIPS over the last three months (max(DIPS)); finally, the standard deviation over the last three months (std(DIPS)).[7] We conjecture that all three are positively correlated, and all are related to the probability of future short squeezes. We want to verify if that is the case and, if so, which of them is the better proxy for *lotteryness*.[8] First, we compare avg(DIPS) and std(DIPS). In the top panel we split ATM call options returns into two halves, high and low, according to the avg(DIPS) of the underlying stocks, and within each half we sort them into five quintiles according to

[7]Table A1 of the Internet Appendix shows results for delta-hedged call options.

[8]Arguably, skewness-seeking investors use an array of different measures to estimate the likelihood of a future short squeeze. We are looking for the DIPS-related measure that best predicts the selections of this class of investors.

std(DIPS) of the underlying stocks, and compute the HML return across std(DIPS) quintiles. In the next panel we split them in two according to std(DIPS) of the underlying stocks and then allocate them in quintiles depending on the avg(DIPS) of the underlying stocks, and compute the corresponding HML. In panels C and D we show the results of similar double-sorts but using now max(DIPS) and std(DIPS).

Overall we observe that all three metrics are predictors of lotteryness, as all the HML portfolios offer negative returns statistically significant regardless of the value (high or low) of the other metric in the double-sort. Nevertheless, we record the largest effect for std(DIPS). Based on this, in the rest of the paper we will use std(DIPS) as the proxy for skewness.

[Table 3 about here.]

DIPS Volatility and Short Squeezes. In the previous analysis, we find evidence that some investors ae willing to pay a premium for call options, possibly hoping that the underlying stock will experience a short squeeze. Next, we want to verify whether the overpayment on the part of this class of investors is justified. That is, we analyze if std(DIPS) is correlated with a higher rate of future short squeezes. We show the results in Table 4.

First, we sort option returns into ten portfolios according to the std(DIPS) of their underlying stocks. In *Panel A* we present for each decile the average percentage of firms that experience a daily return greater than 15% during the holding period. For example, for decile P1, that includes stocks with the lowest std(DIPS), we find that only 0.5% of them achieve a daily return larger than 15% within the month. However, in decile 10, that includes the stocks with highest std(DIPS), almost 11% exhibit extreme returns within the month. From decile 1 to decile 10, the percentage of firms with extreme returns increase monotonically in a statistically significant manner. In *Panel B* we document a similar pattern when we increase the threshold to returns bigger than 20% .

Finally, we want to check that the extreme returns correspond to short squeezes. As the short squeeze implies a drop in short interest because the shorts have to cover their positions, we study whether prices increases are associated with drops in short interest across the same deciles as in the previous panels. We report the results in *Panel C* that shows the average percentage for each decile of firms that experience simultaneously a two-standard deviation increase in price and a two-standard deviation decrease of short interest. The percentage across deciles increases from 3.5% to almost 7%, which is statistically significant.

We point out that even though the percentage of firms with extreme returns increases substantially with std(DIPS) the numbers are still small, in line with the idea that the corresponding options are lottery assets.

[Table 4 about here.]

Delta-Hedged Portfolio Returns. In line with the literature –e.g. Cao and Han (2013); Eisdorfer et al. (2019); Cao et al. (2020)– we consider for our analysis delta-hedged returns. As the previous papers, among others, have pointed out, delta-hedged option returns are useful because they dissociate specific characteristics of option prices from the dynamics of the underlying stocks. We form portfolios of ATM call options sorted into ten deciles according to the std(DIPS) of the underlying stocks and compute their delta-hedged returns for the holding period, as previously defined. *Panel A* of table 5 first displays the returns of equally-weighted decile portfolios as well as the spread portfolio long in the highest std(DIPS) portfolio and short in the lowest. We find that the return of the spread portfolio is negative and statistically significant, which corroborates that std(DIPS) is a proxy for lotteryness. We find similar results also in *Panel A* for open interest-weighted portfolios. *Panel B* of Table 5 reports alphas of the risk-adjusted spread portfolios based on different asset pricing models. Specifically, we show results for CAPM, FF3, Carhart and FF5 models. In all cases they are negative and statistically significant.

[Table 5 about here.]

4.2 Cross-Sectional Regressions

In the previous subsection we have studied the cross-sectional predictive ability std(DIPS) ignoring other factors that might explain call returns, including firm-level information, as we have considered portfolios of calls. To further explore the relationship between std(DIPS) and option returns, we perform a cross-sectional regression that projects option returns at time $t+1$ on a number of predictor variables at time t, including std(DIPS). Table 6 reports the average coefficient of such regression and the corresponding average adjusted R-squared. The set of predictor variables (e.g., $Controls$) includes MAX(10), BV-SKEW, log(Size), price, institutional ownership, book to market, debt to assets, turnover, idiosyncratic volatility, reversal and momentum. Specifically, we focus on the model below:

$$RX_{i,t+1} = \alpha + \beta std(DIPS)_{i,t} + \gamma Controls_{i,t} + \varepsilon_{i,t+1} \tag{4}$$

where $RX_{i,t+1}$ represents the ATM call option return at time $t+1$. From Table 6 it is clear that std(DIPS) is an independent proxy for skewness, and its effect is significant both statistically and economically –we use monthly returns in the empirical model.

[Table 6 about here.]

4.3 DIPS and Other Indicators of Short Squeezes

We also consider possible alternative predictors of short squeezes. Specifically, we use short float and days to cover. To calculate short float we divide the number of shorted shares (short interest) by the number of shares available for trade. Our measure of short interest comes from Markit and represents the daily total shares borrowed from lenders in the database. The number of shares available for trade is the difference between total number of shares outstanding and block ownership. We compute days to cover as short interest divided by the average daily trading volume over the last three months.

Panel A of Table 7 shows time-series average of median short float and days to cover of std(DIPS)-sorted portfolios. We find that both increase with std(DIPS). *Panel B* shows average returns of delta-hedged portfolios of call options sorted on short float and days to cover. Consistent with our previous results, we find a negative relationship between these indicators of the likelihood of a short squeeze and delta-hedged options returns.[9]

[Table 7 about here.]

4.4 Option Order Imbalances

We also examine the trading volume for low and high std(DIPS) portfolios. *Panel A* of Table 8 shows time-series averages of total number of trades of call options across different std(DIPS) portfolios. We find that small traders are net buyers of high std(DIPS) portfolios while we do not find significant trading activity for medium and large customers. *Panel B* of Table 8 shows time-series averages of relative open interest which is defined as the open interest over the shares outstanding. We report that the relative open interest increases with std(DIPS) which confirms the higher demand for these options.

[9] Table A4 of the Internet Appendix shows similar results from 1996; there we use short interest from Compustat.

[Table 8 about here.]

5 Robustness and Complemetary Tests

5.1 Robinhood Popularity

In the previous section we have discussed evidence that "betting" on future short squeezes has been a strategy of skewness-seeking investors for several decades. Yet, short squeezes and their potential rewards have been recently in the front page news: The press (financial and otherwise) has written about the coordination of groups of retail investors who buy particular stocks with the goal of triggering a short squeeze. In a parallel development, some new online platforms, especially Robinhood, have become retailers' favorites for security trading. At the intersection of these two trends, we would expect higher popularity in Robinhood of stocks with higher likelihood of a short squeeze. To explore this hypothesis, we examine whether *Robinhood popularity* is related to std(DIPS). Table 9 shows time-series averages of Robinhood popularity for std(DIPS)-sorted portfolios. In particular, we record the number of Robinhood users who hold a stock at the end of the day –the last number of users reported for that day– and compute the average over the month prior to the formation of the std(DIPS) portfolios, and for each portfolio we average across the stocks in the portfolio. The available date goes from January 2018 to September 2019, and the results strongly support our hypothesis. The positive relationship between Robinhood popularity and prior std(DIPS) is both statistically and economically significant.

[Table 9 about here.]

5.2 Short Squeeze Triggers

We study whether the predictive power of std(DIPS) is robust to the existence of factors that usually trigger or are related to short squeezes. In particular, abnormal volume, sentiment, as reflected in 8K filings, and earnings surprises. Specifically, we double-sort call options into portfolios based on std(DIPS) and the three factors we just listed. *Panel A* of Table 10 shows delta-hedged call option returns of std(DIPS) sorted portfolios for low and high abnormal volume. We find that the strategy offers more negative returns for high abnormal volume portfolios but it is significant for both low and high abnormal volume portfolios. We find a similar pattern in *Panel B* for 8K filings sentiment and in *Panel C* for earnings surprises.[10]

[Table 10 about here.]

5.3 Threshold List and Fails to Deliver

The *Threshold List* is the product of a SEC regulation to identify a sign of possible stock manipulation. It consists of stocks that have at least 10,000 failed to deliver shares for five consecutive settlement days or the failed shares are at least 0.5% of the issuer's total shares outstanding. This is an indication of possible naked shorts –the shorting party does not own the stock. Investors usually view these stocks as good candidates for short squeezes. Table 11 shows time-series average of the median percentage of firms that belong to the threshold list within the month, and fails to deliver (fraction of outstanding shares that failed to deliver during the holding period) for each decile portfolio sorted on std(DIPS). *Panel A* of Table 11 shows that the percentage of firms that are in the threshold list increases with std(DIPS) in a statistically significant manner. *Panel B* of Table 11 shows time-series

[10]Table A7 of the Internet Appendix shows that the abnormal volume, the sentiment of 8K filings and earnings surprises increase with the std(DIPS) in a statistically significant manner.

average of median fails to deliver. In sum, this measure that some people interpret as a predictor of short squeezes is also correlated with std(DIPS).

[Table 11 about here.]

5.4 Blockholder Ownership

We extract firm-level blockholding owernship data from 2006 to 2019, using Schedule 13D and 13G filings from the SEC EDGAR database. Any investor or group (also called beneficial owners) acquiring more than 5% of the voting stock of a public firm is required to file a beneficial ownership report (Schedule 13D or 13G) with the SEC. We construct a dataset of the position of every blockholder at the end of each calendar year.

Table 12 shows the time-series average of median block-holder ownership for each of the decile portfolios based on the std(DIPS) measure over the previous month, as well as the corresponding spread portfolio that goes long in the options portfolio (decile) with high std(DIPS) and sells the portfolio (decile) with low std(DIPS) measure. There is a monotonically increasing relationship between block-holder ownership and std(DIPS). This implies that securities with higher likelihood of a short squeeze have a lower number of shares available to purchase. The rationale behind the connection between the two is straightforward: In the case of high blockholder ownership, triggering a short squeeze takes a (relatively) smaller number of shares.

[Table 12 about here.]

5.5 Short Squeeze Uncertainty and Out-of-the-Money Call Options

So far, our analysis has focused on ATM call options. Here, we present results for out-of-the-money (OTM) call options sorted on std(DIPS). We define OTM call options as those in the [1,1.20] moneyness interval that are closer to 1.20. Similarly to our previous analysis we select one OTM call option per stock. Table 13 reports average returns and alphas of delta-hedged OTM call options sorted on std(DIPS). *Panel A* of Table 13 shows equally-weighted and open interest weighted OTM call options of decile std(DIPS) portfolios. In both cases the returns of the spread portfolio are statistically significant, in line with our findings for ATM call options. *Panel B* shows that the strategy offers very negative and statistically significant alphas. Specifically, we show results for CAPM, FF3, Carhart and FF5 models.

[Table 13 about here.]

6 Conclusions

Short squeezes are often associated with a large positive jump in the price of a stock. We conjecture that skewness-seeking investors try to identify securities that could experience a short squeeze in the near future, and are willing to pay a premium for them. For our analysis we use an existing proprietary measure that estimates the likelihood of a short squeeze, the Data Explorers Increasing Price Squeeze indicator (DIPS). This measure is based on market data, therefore it is feasible for a skewness-seeking investor, retail or otherwise, to come up with an equivalent indicator of a possible short squeeze in the near future. We verify that this measure and, even more strongly, the standard deviation of this measure over a previous period of time, is associated with a negative expected return on call options –standard security of choice by skewness-seeking investors– on the corresponding stock. We find similar results using other indicators of the likelihood of a short squeeze.

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Table 1. Summary Statistics

This table displays time-series averages of the cross-sectional mean, median, standard deviation, quantiles and cross-sectional correlations of the the Data Explorers Increasing Price Squeeze indicator (DIPS) and other measures of shorting activity such as Daily Cost of Borrowing Score (DCBS), shorting supply, shorting demand, utilization (UTIL), days to cover (DTC), and short float. Specifically, we compute cross-sectional summary statistics every month and we report their time-series averages. *Panel A* (*Panel B*) shows results for daily (monthly) frequencies. For monthly frequencies we also report results for the average, standard deviation and maximum DIPS. The data is from CRSP, Optionmetrics and Markit and contains monthly series from July 2006 to September 2019.

Panel A: Daily

	N	Mean	Median	Std	10%	25%	75%	90%	DIPS	DCBS	SUPPLY	DEMAND	UTIL	DTC	Short Float
												Correlations			
DIPS	3328.00	26.62	25.90	3.56	23.87	24.86	27.36	29.91	1.00						
DCBS	3328.00	1.36	1.00	1.22	1.00	1.00	1.01	1.88	0.49	1.00					
SUPPLY	3328.00	0.22	0.25	0.12	0.03	0.12	0.32	0.37	0.03	-0.18	1.00				
DEMAND	3328.00	0.06	0.04	0.07	0.00	0.01	0.08	0.15	0.50	0.33	0.35	1.00			
UTIL	3328.00	0.39	0.22	0.65	0.04	0.09	0.47	0.87	0.29	0.36	-0.34	0.34	1.00		
DTC	3328.00	4.69	3.11	5.22	0.54	1.27	6.35	10.69	0.38	0.19	0.19	0.64	0.30	1.00	
Short Float	3328.00	0.14	0.05	0.37	0.01	0.02	0.14	0.30	0.26	0.20	0.14	0.50	0.17	0.32	1.00

Panel B: Monthly

	N	Mean	Median	Std	10%	25%	75%	90%	avg(DIPS)	std(DIPS)	max(DIPS)	DCBS	SUPPLY	DEMAND	UTIL	DTC	Short Float
												Correlations					
avg(DIPS)	157.00	26.56	25.81	2.54	24.82	25.24	26.79	28.97	1.00								
std(DIPS)	157.00	1.99	1.69	1.18	0.92	1.21	2.40	3.42	0.42	1.00							
max(DIPS)	157.00	29.56	28.36	3.65	26.62	27.25	30.39	34.17	0.87	0.78	1.00						
DCBS	157.00	1.37	1.00	1.20	1.00	1.00	1.03	1.89	0.64	0.43	0.62	1.00					
SUPPLY	157.00	0.22	0.25	0.12	0.03	0.12	0.32	0.37	0.04	-0.07	-0.01	-0.19	1.00				
DEMAND	157.00	0.06	0.04	0.07	0.01	0.01	0.08	0.15	0.63	0.35	0.59	0.34	0.35	1.00			
UTIL	157.00	0.39	0.22	0.62	0.04	0.09	0.48	0.87	0.37	0.27	0.37	0.37	-0.35	0.34	1.00		
DTC	157.00	4.71	3.14	5.20	0.59	1.30	6.35	10.65	0.50	0.14	0.40	0.20	0.19	0.64	0.30	1.00	
Short Float	157.00	0.14	0.05	0.36	0.01	0.02	0.14	0.30	0.33	0.21	0.32	0.20	0.14	0.50	0.17	0.32	1.00

Table 2. Characteristics of std(DIPS) Uncertainty Portfolios

This table displays time-series averages of median characteristics of ATM call options sorted into deciles on the first trading day after the expiration Friday of the month based on the standard deviation over the previous three months of the Data Explorers Increasing Price Squeeze indicator (DIPS) of their underlying stocks. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. *Panel A* shows time-series averages of median std(DIPS) of portfolios sorted based on the std(DIPS) measure. We report in *Panel B* the stock price, the maximum DIPS (expressed in percentage points), the 10-day maximum return of the stock (MAX(10)), momentum (MOM), stock reversals (REV), turnover, illiquidity (ILLIQ), stock volume, institutional ownership (IOR), book to market (B/M), Size, Debt to assets (D/A), idiosyncratic skewness (ISKEW) and idiosyncratic volatility (IVOL). *Panel C* reports option characteristics such as BV-SKEW, option volume, call premium, call bid-ask spreads, option to stock volume ratios (O/S) and the difference between implied volatility and historical volatility (IV-HV). We report Newey and West (1987) t-statistics with 6 lags in parenthesis. The data is from CRSP, Compustat, Optionmetrics and Markit and contains monthly series from July 2006 to September 2019.

Panel A: Portfolios sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
std(DIPS)	0.780	1.024	1.209	1.392	1.584	1.795	2.055	2.395	2.933	4.418	3.639	(39.73)

Panel B: Stock Characteristics of Portfolios sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
max(DIPS)	26.603	27.079	27.422	27.756	28.158	28.533	28.948	29.529	30.477	34.642	8.039	(26.19)
MAX(10)	0.011	0.013	0.014	0.016	0.017	0.019	0.021	0.023	0.026	0.030	0.020	(15.97)
Stock Volume	1.749	1.435	1.157	1.051	0.915	0.843	0.818	0.823	0.802	0.879	-0.870	(-10.82)
Stock Price	62.680	54.734	48.329	43.040	38.626	34.365	29.626	25.259	20.957	15.972	-46.708	(-13.80)
Size	16.542	10.359	6.552	4.562	3.548	2.677	1.996	1.576	1.189	0.825	-15.716	(-14.92)
ILLIQ	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001	0.002	0.002	(18.38)
ISKEW	0.070	0.080	0.089	0.106	0.121	0.112	0.119	0.146	0.150	0.239	0.169	(11.12)
IVOL	0.009	0.010	0.012	0.013	0.015	0.016	0.019	0.021	0.025	0.030	0.021	(31.86)
MOM	0.129	0.135	0.125	0.118	0.119	0.110	0.113	0.085	0.096	0.031	-0.098	(-1.93)
REV	0.013	0.012	0.012	0.011	0.013	0.010	0.012	0.008	0.010	0.019	0.005	(0.77)
B/M	0.334	0.360	0.360	0.375	0.376	0.377	0.378	0.369	0.362	0.374	0.039	(0.85)
D/A	0.243	0.206	0.191	0.188	0.183	0.180	0.172	0.151	0.144	0.140	-0.103	(-7.11)
Turnover	1.384	1.703	1.925	2.145	2.379	2.549	2.848	3.112	3.425	4.191	2.807	(39.09)
IOR	0.791	0.836	0.856	0.869	0.876	0.877	0.876	0.860	0.827	0.718	-0.072	(-5.58)

Panel C: Option Characteristics of Portfolios sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
BV-SKEW	1.466	1.602	1.685	1.737	1.742	1.789	1.840	1.897	1.948	2.013	0.547	(13.40)
Option Volume	86.003	65.355	56.206	50.942	47.490	43.939	51.190	54.039	57.539	89.690	3.687	(0.56)
Call Premium	1.421	1.453	1.482	1.423	1.428	1.381	1.321	1.237	1.151	1.070	-0.351	(-6.33)
Call bid-ask Spread	0.142	0.153	0.164	0.169	0.181	0.182	0.181	0.182	0.188	0.180	0.038	(6.92)
O/S	0.109	0.117	0.127	0.133	0.143	0.145	0.153	0.164	0.170	0.185	0.076	(13.37)
IV-HV	0.027	0.028	0.032	0.033	0.031	0.031	0.033	0.030	0.027	0.021	-0.006	(-0.62)

Table 3. Lotteryness proxies: average DIPS, max(DIPS) and std(DIPS)

This table displays average raw returns of ATM call options double-sorted into quintiles on the first trading day after the expiration Friday of the month based on the standard deviation over the last three months of the Data Explorers Increasing Price Squeeze indicator(DIPS) of their underlying stock and the average over the last three months of the DIPS of their underlying stock. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. We show results for EW portfolios that are double sorted based on average DIPS and the standard deviation of DIPS (*Panel A*). *Panel B* displays results for double sorted portfolios based on the standard deviation of DIPS and average DIPS. *Panel C* shows results for portfolios sorted based on the maximum DIPS over the previous three months and the standard deviation of DIPS. *Panel D* shows results for portfolios that are double sorted based on std(DIPS) and the maximum DIPS. We report Newey and West (1987) t-statistics with 6 lags in parenthesis for the spread portfolios. The data is from CRSP, Optionmetrics and Markit and contains monthly series from July 2006 to September 2019.

Panel A: Portfolios of ATM options sorted based on avg(DIPS) and std(DIPS)

	Low std(DIPS)	P2	P3	P4	High std(DIPS)	HML	t-stat
Low avg(DIPS)	0.229	0.153	0.155	0.112	0.097	-0.132	(-2.79)
High avg(DIPS)	0.146	0.125	0.097	0.022	-0.010	-0.156	(-3.76)

Panel B: Portfolios of ATM options sorted based on std(DIPS) and avg(DIPS)

	Low avg(DIPS)	P2	P3	P4	High avg(DIPS)	HML	t-stat
Low std(DIPS)	0.250	0.228	0.165	0.180	0.220	-0.030	(-0.74)
High std(DIPS)	0.112	0.081	0.091	0.090	-0.049	-0.162	(-3.97)

Panel C: Portfolios of ATM options sorted based on 3 months max(DIPS) and std(DIPS)

	Low std(DIPS)	P2	P3	P4	High std(DIPS)	HML	t-stat
Low max(DIPS)	0.257	0.182	0.201	0.231	0.110	-0.147	(-3.08)
High max(DIPS)	0.111	0.097	0.085	0.050	-0.005	-0.116	(-2.98)

Panel D: Portfolios of ATM options sorted based on 3 months std(DIPS) and max(DIPS))

	Low max(DIPS)	P2	P3	P4	High max(DIPS)	HML	t-stat
Low std(DIPS)	0.243	0.222	0.177	0.211	0.191	-0.052	(-1.31)
High std(DIPS)	0.108	0.087	0.087	0.065	-0.023	-0.131	(-3.73)

Table 4. Std(DIPS) and Short Squeezes

This table displays the percentage of firms that experience a short squeeze during the holding period for portfolios of options sorted into deciles on the first trading day after the expiration Friday of the month based on the standard deviation over the last three months of the Data Explorers Increasing Price Squeeze indicator (DIPS) of their underlying stock. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. *Panel A* presents the percentage of firms with daily returns bigger than 15% during the holding period. *Panel B* shows the percentage of firms in each of the decile portfolios with daily returns bigger than 20% during the remaining life of the options. *Panel C* reports the percentage of firms with an increase of two standard deviation of prices and a reduction of two standard deviation of short interest during the same period. The data is from CRSP, Optionmetrics and Markit and contains monthly series from July 2006 to September 2019.

Panel A: %firms with dailyret>15% of Portfolios of ATM options sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
Mean	0.005	0.010	0.012	0.018	0.022	0.031	0.039	0.056	0.073	0.107	0.102	(7.31)

Panel B: %firms with dailyret>20% of Portfolios of ATM options sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
Mean	0.002	0.003	0.004	0.006	0.007	0.013	0.015	0.021	0.030	0.050	0.048	(6.61)

Panel C: %firms with up (down) dev of price (SI) of 2 std of Portfolios of ATM options sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
Mean	0.035	0.037	0.038	0.039	0.039	0.043	0.045	0.052	0.051	0.067	0.032	(9.21)

Table 5. Std(DIPS): Delta-hedged Call Option Returns

This table displays average returns of ATM call options sorted into deciles on the first trading day after the expiration Friday of the month based on the standard deviation over the last three months of the Data Explorers Increasing Price Squeeze indicator (DIPS) of their underlying stock. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. We show results for EW and open-weighted portfolios (*Panel A*). *Panel B* reports risk-adjusted returns of ATM calls based on the Fama and French (1993) model. We also report results for the universe of options that excludes early exercises. We report Newey and West (1987) t-statistics with 6 lags in parenthesis for the spread portfolios. The data is from CRSP, Optionmetrics and Markit and contains monthly series from July 2006 to September 2019.

Panel A: Portfolios of ATM options sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
EW	-0.010	-0.012	-0.014	-0.017	-0.020	-0.021	-0.026	-0.029	-0.035	-0.043	-0.033	(-12.59)
OIW	-0.008	-0.009	-0.011	-0.009	-0.017	-0.020	-0.025	-0.027	-0.036	-0.041	-0.033	(-8.61)

Panel B: Risk-adjusted Returns of ATM options sorted based on std(DIPS)

	CAPM	Three-Factor	Four-Factor	Five-Factor
EW	-0.033	-0.033	-0.033	-0.034
	(-10.25)	(-9.75)	(-9.78)	(-11.06)
OIW	-0.032	-0.031	-0.031	-0.031
	(-6.92)	(-6.64)	(-6.79)	(-6.71)

Table 6. Cross-Sectional Regressions

This table displays cross-sectional regressions of ATM call options returns on the standard deviation over the last three months of the Data Explorers Increasing Price Squeeze indicator (DIPS) of their underlying stock (e.g., std(DIPS)) and a number of controls. Specifically, our cross-sectional regression takes the following form:

$$RX_{i,t+1} = \alpha + \beta std(DIPS)_{i,t} + \gamma Controls_{i,t} + \varepsilon_{i,t+1} \quad (5)$$

where $RX_{i,t+1}$ represents the ATM call option return at time $t+1$ and the set of controls include MAX(1), BV-SKEW, log(Size), price, institutional ownership, book to market, debt to assets, turnover, idiosyncratic volatility, reversals and momentum. We report Newey and West (1987) t-statistics with 6 lags in parenthesis. The data is from CRSP, Compustat, Optionmetrics and Markit and contains monthly series from July 2006 to September 2019..

At-the-money Call Options			
	(1)	(2)	(3)
	Delta-hedged Call Options		
$std(DIPS)$	-0.838	-0.422	-0.190
	(-13.19)	(-6.69)	(-3.87)
$MAX(10)$		-0.659	-0.349
		(-13.42)	(-4.84)
$BV-SKEW$		-0.003	-0.002
		(-4.52)	(-3.61)
$Ln(Size)$			0.003
			(6.61)
$Ln(StockPrice)$			0.004
			(6.89)
IOR			-0.002
			(-1.00)
B/M			0.004
			(3.63)
D/A			0.006
			(3.49)
$Turnover$			0.001
			(4.25)
$IVOL$			-0.218
			(-3.75)
$ILLIQ^{Stocks}$			-0.390
			(-3.45)
REV			-0.005
			(-1.27)
MOM			-0.002
			(-1.07)
Constant	-0.006	0.003	-0.059
	(-3.06)	(1.49)	(-8.79)
R-squared	0.029	0.053	0.114

Table 7. Std(DIPS) and Other Predictors of Short Squeezes

This table displays results for other indicators of short squeezes. In particular, we show results for short float and days to cover. To calculate short float we divide the number of shorted shares by the number of shares available for trade. We define days to cover by taking the number of currently shorted shares and dividing that amount by the average daily trading volume for the last three months. *Panel A* reports the time series average of median short float and days to cover for portfolios of ATM call options sorted into deciles on the first trading day after the expiration Friday of the month based on the standard deviation over the last three months of the Data Explorers Increasing Price Squeeze indicator (DIPS) of their underlying stock. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. *Panel B* displays average returns of ATM call options sorted into deciles on the first trading day after the expiration Friday of the month based on short float and days to cover. The data is from CRSP, Optionmetrics and Markit and contains monthly series from July 2006 to September 2019.

Panel A: Short Float and Days to Cover of Portfolios of ATM options sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
						Short Float of DIPS Portfolios						
Mean	0.016	0.024	0.034	0.045	0.057	0.070	0.083	0.101	0.124	0.175	0.159	(18.93)
						Days to Cover of DIPS Portfolios						
Mean	1.824	2.079	2.471	2.865	3.192	3.625	3.836	4.141	4.341	4.805	2.981	(12.41)

Panel B: Option Returns Short Float and Days to Cover of Portfolios of ATM options sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
						Short Float of DIPS Portfolios						
Mean	-0.013	-0.014	-0.018	-0.020	-0.023	-0.025	-0.026	-0.028	-0.031	-0.027	-0.014	(-6.21)
						Days to Cover of DIPS Portfolios						
Mean	-0.016	-0.016	-0.020	-0.021	-0.022	-0.025	-0.026	-0.026	-0.027	-0.028	-0.012	(-5.95)

Table 8. DIPS and Option Order Imbalances

This table displays time-series averages of options order imbalances of call options for std(DIPS) portfolios. Specifically, we sort ATM call options into deciles on the first trading day after the expiration Friday of the month based on the standard deviation over the last three months of the Data Explorers Increasing Price Squeeze indicator (DIPS) of their underlying stock. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. *Panel A* displays results for small, medium and large customers. *Panel B* shows time-series average of relative short interest. The data is from CRSP, ISE, Optionmetrics and Markit and contains monthly series from July 2006 to September 2019.

Panel A: Option Imbalances of Customers

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	*t*-stat
						Small Customers						
Mean	-20,970	1,810	15,001	12,645	6,540	13,249	13,256	17,733	19,414	23,335	44,156	(5.19)
						Medium Customers						
Mean	-1,830	-1,079	-4,913	-176	-581	1,311	1,409	1,985	1,188	1,741	3,560	(1.95)
						Large Customers						
Mean	9,897	9,787	14,807	5,130	393	6,384	13,692	9,408	6,440	5,390	-4,541	(-0.55)

Panel B: Relative Open Interest

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	*t*-stat
Mean	0.089%	0.134%	0.210%	0.331%	0.465%	0.605%	0.847%	0.981%	1.108%	1.409%	1.320%	(19.32)

Table 9. DIPS and Robinhood Popularity

This table displays time-series average of the mean Robinhood popularity of the underlying firm for ATM call options sorted into deciles on the first trading day after the expiration Friday of the month based on the standard deviation over the last three months of the Data Explorers Increasing Price Squeeze indicator (DIPS) of their underlying stock. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. We show results for EW and open-weighted portfolios. The data is from CRSP, Optionmetrics and Markit and contains monthly series from July 2006 to September 2019.

Robinhood Popularity												
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
Mean	632	490	413	406	474	515	517	609	761	1192	560	(17.60)

Table 10. DIPS and Short Squeeze Triggers

This table displays average returns of ATM call options double-sorted into quintiles on the first trading day after the expiration Friday of the month based on the standard deviation over the last three months of the Data Explorers Increasing Price Squeeze indicator(DIPS) of their underlying stock and abnormal volume, 8K filings sentiment or earning surprises. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. We show results for EW portfolios that are double sorted based on abnormal volume and the standard deviation of DIPS (*Panel A*). *Panel B* displays results for double sorted portfolios based on 8K filings sentiment and the standard deviation of DIPS. *Panel C* shows results for portfolios sorted based on earning surprises and the standard deviation of DIPS. We report Newey and West (1987) t-statistics with 6 lags in parenthesis for the spread portfolios. The data is from CRSP, Optionmetrics and Markit and contains monthly series from July 2006 to September 2019.

Panel A: Portfolios of ATM options sorted based on Abnormal Volume and std(DIPS)

	Low std(DIPS)	P2	P3	P4	High std(DIPS)	HML	t-stat
Low Abnormal Volume	-0.010	-0.012	-0.016	-0.020	-0.032	-0.022	(-8.65)
High Abnormal Volume	-0.012	-0.018	-0.024	-0.031	-0.043	-0.032	(-9.55)

Panel B: Portfolios of ATM options sorted based on 8K filings Sentiment and avg(DIPS)

	Low avg(DIPS)	P2	P3	P4	High avg(DIPS)	HML	t-stat
Low Sentiment	-0.012	-0.014	-0.018	-0.024	-0.032	-0.021	(-7.80)
High Sentiment	-0.015	-0.019	-0.027	-0.036	-0.047	-0.032	(-11.02)

Panel C: Portfolios of ATM options sorted based on earnings surprises and std(DIPS)

	Low std(DIPS)	P2	P3	P4	High std(DIPS)	HML	t-stat
Low Earnings Surprises	-0.014	-0.016	-0.022	-0.028	-0.038	-0.024	(-9.75)
High Earnings Surprises	-0.012	-0.013	-0.021	-0.025	-0.037	-0.025	(-9.42)

Table 11. Threshold List and Fails to Deliver of DIPS Portfolios

This table displays the percentage of each decile of firms sorted according to their std(DIPS) that are in the SEC Threshold list (*Panel A*), as well as the percentage of fails to deliver in the same portfolios (*Panel B*). To be consistent with other tables, the portfolios are created on the first trading day after the Friday of the month in which options expire, and are composed of stocks sorted according to the standard deviation over the last three months of the Data Explorers Increasing Price Squeeze indicator (DIPS). The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. *Panel A* presents the percentage of stocks in the portfolio that are in the threshold list, which consists of stocks that have at least 10,000 failed to deliver shares for five consecutive settlement days or the failed shares are at least 0.5% of the issuer's total shares outstanding. *Panel B* shows the average for each portfolio of fails to deliver, which is defined as the number of outstanding failed positions (reported three days later) scaled over the holding period (e.g., a month), as a fraction of the total number of shares outstanding of the firm during that month. The data is from CRSP, Optionmetrics, Markit and the SEC and contains monthly series from July 2006 to September 2019.

Panel A: Percentage of firms in Threshold List

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
Mean	0.00%	0.00%	0.04%	0.09%	0.10%	0.10%	0.20%	0.20%	0.33%	1.85%	1.85%	(10.25)

Panel B: Fails to Deliver

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
Mean	0.10%	0.22%	0.25%	0.48%	0.20 %	0.29%	0.35%	0.57%	1.06%	2.66%	2.55%	(3.12)

Table 12. Block-holder Ownership of DIPS Uncertainty Portfolios

This table displays time-series average of the median block-holder ownership of the underlying firm of ATM call options sorted into deciles on the first trading day after the expiration Friday of the month based on the standard deviation over the last three months of the Data Explorers Increasing Price Squeeze indicator (DIPS) of their underlying stock. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. We show results for EW and open-weighted portfolios. The data is from CRSP, Optionmetrics and Markit and contains monthly series from July 2006 to September 2019.

Equally-weighted Portfolios												
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	*t*-stat
Median	20.021	22.357	24.534	26.614	28.463	30.254	31.424	32.947	34.403	36.731	16.710	(29.81)
Median Number of Blocks	2.513	2.771	2.997	3.207	3.376	3.529	3.554	3.669	3.650	3.541	1.029	(14.79)

Table 13. DIPS Uncertainty Portfolios: Delta-hedged OTM Call Option Returns

This table displays average returns of OTM call options sorted into deciles on the first trading day after the expiration Friday of the month based on the standard deviation over the last three months of the Data Explorers Increasing Price Squeeze indicator (DIPS) of their underlying stock. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. We show results for EW and open-weighted portfolios (*Panel A*). *Panel B* reports risk-adjusted returns of ATM calls based on the Fama and French (1993) model. We also report results for the universe of options that excludes early exercises. We report Newey and West (1987) t-statistics with 6 lags in parenthesis for the spread portfolios. The data is from CRSP, Optionmetrics and Markit and contains monthly series from July 2006 to September 2019.

Panel A: Portfolios of OTM options sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
EW	-0.012	-0.013	-0.016	-0.010	-0.018	-0.027	-0.030	-0.031	-0.046	-0.048	-0.035	(-5.48)
OIW	-0.013	-0.011	-0.016	-0.006	-0.021	-0.036	-0.035	-0.041	-0.054	-0.056	-0.043	(-4.42)

Panel B: Risk-adjusted Returns of OTM options sorted based on std(DIPS)

	CAPM	Three-Factor	Four-Factor	Five-Factor
EW	-0.035	-0.035	-0.035	-0.036
	(-5.11)	(-5.27)	(-5.28)	(-5.51)
OIW	-0.032	-0.031	-0.031	-0.031
	(-6.92)	(-6.64)	(-6.79)	(-6.71)

Internet Appendix to

“Betting on the Likelihood of a Short Squeeze”

by

Ilias Filippou   Pedro A. Garcia-Ares   Fernando Zapatero

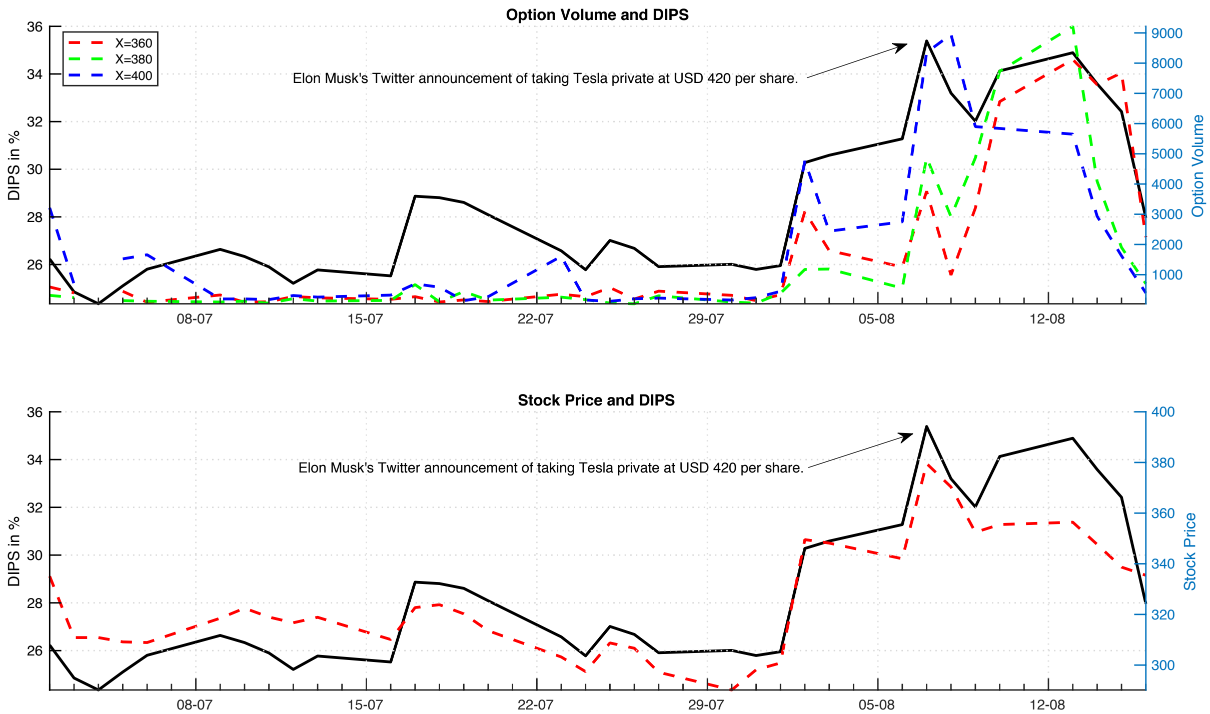
(Not for publication)

Appendix A: Case study: Tesla Inc.

As an approximation to the response of option traders to an increase in short squeeze uncertainty, we describe the activity in the options market resulting from the tweet of Elon Musk in August 2018, which triggered a short squeeze for the shares of Tesla, Inc. Elon Musk announced on the 7th of August 2018 his intention to take Tesla, Inc private at $420 per share. The stock price of Tesla that day was around $379 per share. Figure A1 shows the daily volume of call options with expiration on the third week of August 2018, the daily stock price of Tesla, as well as its daily DIPS value (expressed in percentage points) for the months of July and August of 2018. We present volume values for in-the-money, at-the-money and out-of-the-money call options with strike prices (X in the graph) of 360, 380 and 400, respectively. We find that the DIPS measure reached its highest value on the 7th of August 2018 signaling a higher likelihood of a short squeeze. As result, Tesla's stock price (bottom graph) increased significantly. At the same time, investors responded strongly to the announcement in the options market, as it is indicated by the increase in option trading volume. The standard deviation of DIPS for Tesla, Inc was higher in August than in any other month of 2018. In our sample, Tesla appears in the high std(DIPS) portfolios.

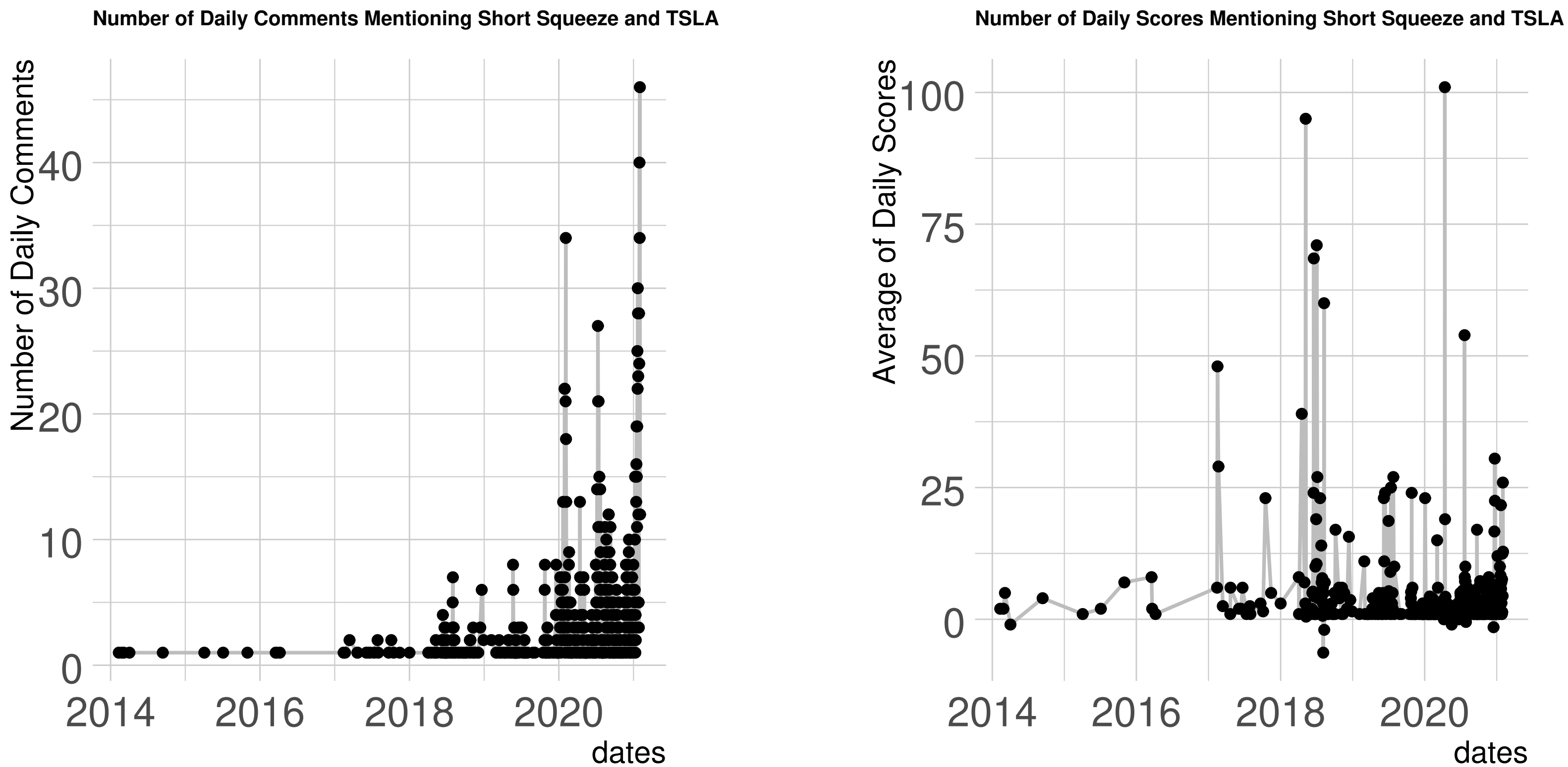
Figure A2 of the Internet Appendix shows the total number of comments and submissions that mention short squeeze and TSLA or Tesla in the same comment in the WallStreetBeats subreddit. The right Panel shows the average number of the score of each comment or submission. The score indicates the importance of the comments in a particular day. We see that the number of comments increase significantly from 2018 until 2021 and the importance comments are around August 2018 (Elon Musk's tweet) and during the Covid crisis. This finding indicates that retail investors might trade the possibility of a short squeeze for Tesla. On the other hand, Figure A3 shows the total number of comments and submissions that mention short squeeze.

Figure A1. ***Elon Musk's Tweet and Option Trading***



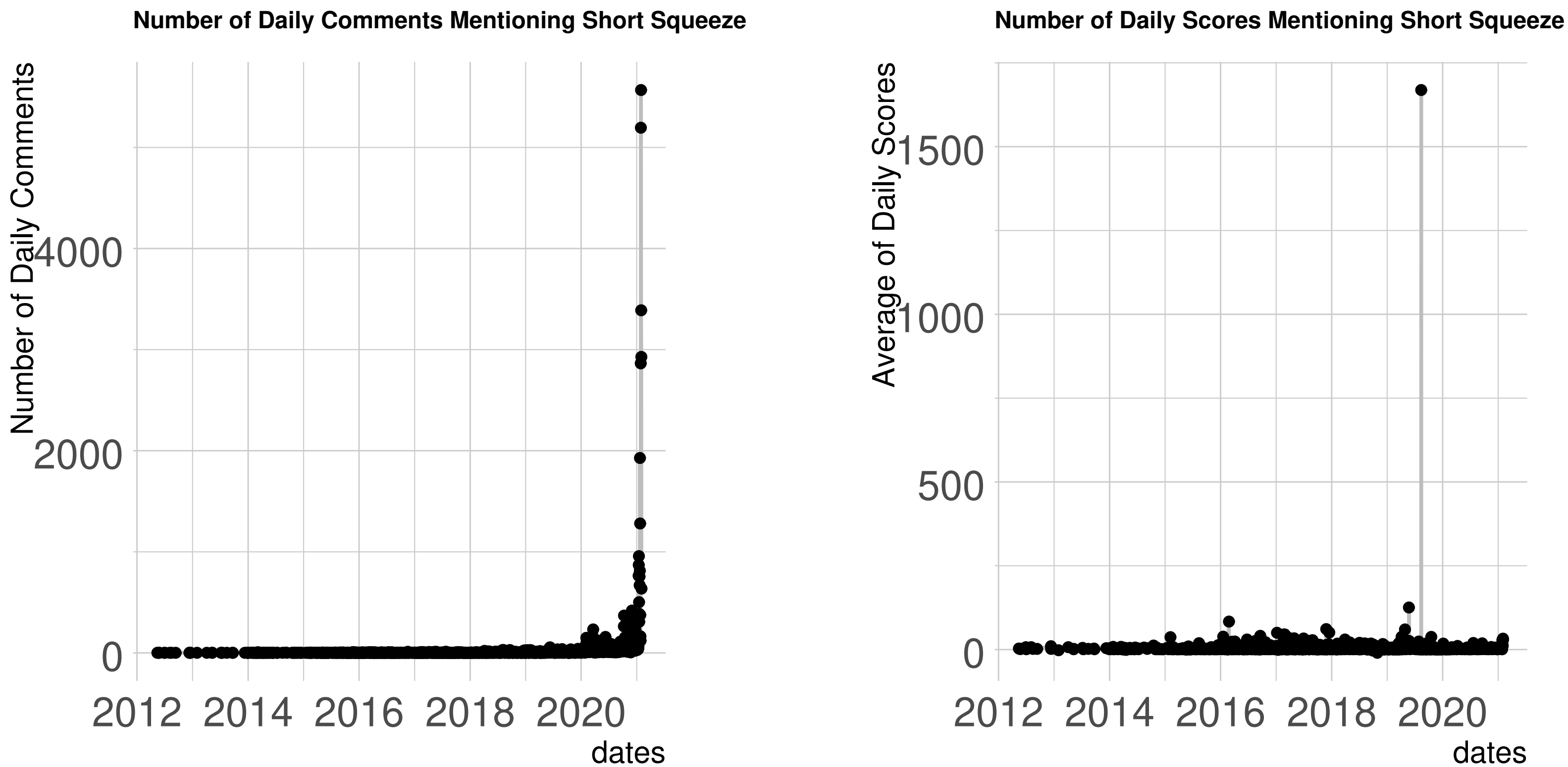
The figure displays option volume (top graph) for call options with strike prices (X) of 360, 380 and 400 and Tesla's stock price (bottom graph). We also show the DIPS of Tesla that is expressed in percentage points. The option data are collected from Datastream and contain daily series from July 2018 to August 2018.

Figure A2. ***Reddit Comments of Short Squeeze and Tesla***



The figure displays the total number of daily Reddit comments and submissions that mention short squeeze and tesla or TSLA in the same comment. The right Panel shows the average daily scores. The option contain daily series from July 2014 to January 2021.

Figure A3. *Reddit Comments of Short Squeeze*



The figure displays the total number of daily Reddit comments and submissions that mention short squeeze in the same comment. The right Panel shows the average score of the comments. The option contain daily series from May 2012 to January 2021.

Table A1. Lotteryness proxies: Average DIPS, Max(DIPS) and std(DIPS)

This table displays average delta-hedged returns of ATM call options double-sorted into quintiles on the first trading day after the expiration Friday of the month based on the last 3-month standard deviation of the Data Explorers Increasing Price Squeeze indicator(DIPS) of their underlying stock and the last 3-month average DIPS of their underlying stock. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. We show results for EW portfolios that are double sorted based on average DIPS and the standard deviation of DIPS (*Panel A*). *Panel B* displays results for double sorted portfolios based on the standard deviation of DIPS and average DIPS. *Panel C* shows results for portfolios sorted based on the maximum DIPS over the previous 3 months and the standard deviation of DIPS. *Panel D* shows results for portfolios that are double sorted based on std(DIPS) and the maximum DIPS. We report Newey and West (1987) t-statistics with 6 lags in parenthesis for the spread portfolios. The data are collected from CRSP, Optionmetrics and Markit and contain monthly series from July 2006 to September 2019.

Panel A: Portfolios of ATM options sorted based on avg(DIPS) and std(DIPS)

	Low std(DIPS)	P2	P3	P4	High std(DIPS)	HML	t-stat
Low avg(DIPS)	-0.010	-0.014	-0.019	-0.026	-0.035	-0.025	(-10.76)
High avg(DIPS)	-0.020	-0.026	-0.028	-0.040	-0.043	-0.023	(-7.53)

Panel B: Portfolios of ATM options sorted based on std(DIPS) and avg(DIPS)

	Low avg(DIPS)	P2	P3	P4	High avg(DIPS)	HML	t-stat
Low std(DIPS)	-0.009	-0.009	-0.011	-0.013	-0.014	-0.004	(-2.76)
High std(DIPS)	-0.036	-0.039	-0.035	-0.037	-0.042	-0.006	(-2.57)

Panel C: Portfolios of ATM options sorted based on 3 months max(DIPS) and std(DIPS)

	Low std(DIPS)	P2	P3	P4	High std(DIPS)	HML	t-stat
Low max(DIPS)	-0.009	-0.010	-0.011	-0.012	-0.018	-0.009	(-4.92)
High max(DIPS)	-0.026	-0.030	-0.037	-0.040	-0.045	-0.019	(-6.42)

Panel D: Portfolios of ATM options sorted based on 3 months std(DIPS) and max(DIPS))

	Low max(DIPS)	P2	P3	P4	High max(DIPS)	HML	t-stat
Low std(DIPS)	-0.009	-0.010	-0.012	-0.012	-0.014	-0.005	(-3.46)
High std(DIPS)	-0.034	-0.035	-0.037	-0.036	-0.046	-0.012	(-4.45)

Table A2. Alternative Measures of DIPS Uncertainty and Portfolio Returns

This table displays average returns of ATM call options sorted into deciles on a monthly basis based on their one-month standard deviation (*Panel A*) Data Explorers Increasing Price Squeeze indicator (DIPS). The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. *Panel B* reports risk-adjusted returns of ATM calls based on the Fama and French (1993) model. We also report results for the universe of options that excludes early exercises. We report Newey and West (1987) t-statistics with 6 lags in parenthesis for the spread portfolios. The data are collected from CRSP and contain monthly series from July 2006 to September 2019.

Panel A: Portfolios of ATM options sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
	Call Option Returns											
EW	0.226	0.198	0.190	0.178	0.122	0.155	0.137	0.099	0.094	0.022	-0.204	(-4.06)
OIW	0.175	0.154	0.128	0.109	0.069	0.064	0.068	0.028	-0.024	-0.036	-0.211	(-3.69)

Panel B: Risk-adjusted Returns of ATM options sorted based on std(DIPS)

	CAPM	Three-Factor	Four-Factor	Five-Factor
	Call Option Alphas			
EW	-0.203	-0.199	-0.198	-0.177
	(-4.00)	(-4.02)	(-4.03)	(-3.75)
OIW	-0.211	-0.207	-0.205	-0.171
	(-3.64)	(-3.51)	(-3.57)	(-2.89)

Table A3. DIPS Uncertainty Portfolios: Delta-hedged Call Option Returns

This table displays average returns of ATM call options sorted into deciles on a monthly basis based on their standard deviation (*Panel A*) Data Explorers Increasing Price Squeeze indicator (DIPS). The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. *Panel B* reports risk-adjusted returns of ATM calls based on the Fama and French (1993) model. We also report results for the universe of options that excludes early exercises. We report Newey and West (1987) t-statistics with 6 lags in parenthesis for the spread portfolios. The data are collected from CRSP and contain monthly series from July 2006 to September 2019.

Panel A: Portfolios of ATM options sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
					1 month std(DIPS)							
EW	-0.010	-0.012	-0.014	-0.017	-0.020	-0.021	-0.026	-0.029	-0.035	-0.043	-0.033	(-12.59)
VW	-0.007	-0.007	-0.011	-0.011	-0.013	-0.014	-0.020	-0.021	-0.025	-0.024	-0.017	(-4.45)
OIW	-0.008	-0.009	-0.011	-0.009	-0.017	-0.020	-0.025	-0.027	-0.036	-0.041	-0.033	(-8.61)

Panel B: Risk-adjusted Returns of ATM options sorted based on std(DIPS)

	CAPM	Three-Factor	Four-Factor	Five-Factor
		1 month std(DIPS)		
EW	-0.033	-0.033	-0.033	-0.034
	(-10.25)	(-9.75)	(-9.78)	(-11.06)
VW	-0.015	-0.015	-0.015	-0.015
	(-3.12)	(-2.78)	(-2.82)	(-3.19)
OIW	-0.032	-0.031	-0.031	-0.031
	(-6.92)	(-6.64)	(-6.79)	(-6.71)

Table A4. Maximum DIPS Portfolios: Delta-hedged Call Option Returns

This table displays average returns of ATM call options sorted into deciles on the first trading day after the expiration Friday of the month based on the last 3-month maximum of the Data Explorers Increasing Price Squeeze indicator (DIPS) of their underlying stock. The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. We show results for EW portfolios using 3 months of DIPS and the maximum 1 or 10 of DIPS (*Panel A*). *Panel B* shows the corresponding results for 1 month maximum DIPS portfolios. We report Newey and West (1987) t-statistics with 6 lags in parenthesis for the spread portfolios. The data are collected from CRSP, Optionmetrics and Markit and contain monthly series from July 2006 to September 2019.

Panel A: Portfolios of ATM options sorted based on 3 months max(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
max(DIPS(1))	-0.011	-0.013	-0.016	-0.017	-0.019	-0.022	-0.025	-0.028	-0.031	-0.039	-0.028	(-14.79)
max(DIPS(10))	-0.011	-0.013	-0.016	-0.017	-0.021	-0.021	-0.025	-0.029	-0.032	-0.039	-0.028	(-14.94)

Panel B: Portfolios of ATM options sorted based on 1 month max(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
max(DIPS(1))	-0.016	-0.014	-0.015	-0.018	-0.018	-0.021	-0.024	-0.027	-0.031	-0.038	-0.022	(-11.14)
max(DIPS(10))	-0.021	-0.015	-0.016	-0.016	-0.019	-0.021	-0.023	-0.025	-0.031	-0.038	-0.017	(-11.11)

Table A5. DIPS Uncertainty and Fails to Deliver

This table displays average returns of ATM call options sorted into deciles on a monthly basis based on their standard deviation (*Panel A*) Data Explorers Increasing Price Squeeze indicator (DIPS). The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. *Panel B* reports risk-adjusted returns of ATM calls based on the Fama and French (1993) model. We also report results for the universe of options that excludes early exercises. We report Newey and West (1987) t-statistics with 6 lags in parenthesis for the spread portfolios. The data are collected from CRSP and contain monthly series from July 2006 to September 2019.

Fails to Deliver of Portfolios of ATM options sorted based on std(DIPS)												
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
Mean	0.001	0.002	0.003	0.003	0.002	0.003	0.004	0.006	0.011	0.025	0.024	(2.96)

Table A6. DIPS Uncertainty and Other Indicators of Short Squeezes

This table displays average returns of ATM call options sorted into deciles on a monthly basis based on their standard deviation (*Panel A*) Data Explorers Increasing Price Squeeze indicator (DIPS). The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. *Panel B* reports risk-adjusted returns of ATM calls based on the Fama and French (1993) model. We also report results for the universe of options that excludes early exercises. We report Newey and West (1987) t-statistics with 6 lags in parenthesis for the spread portfolios. The data are collected from CRSP and contain monthly series from April 1996 to September 2019.

Option Returns Short Float and Days to Cover of Portfolios of ATM options sorted based on std(DIPS)

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
						Short Float of DIPS Portfolios						
Mean	-0.015	-0.016	-0.021	-0.022	-0.024	-0.026	-0.027	-0.031	-0.031	-0.032	-0.017	(-10.40)
						Days to Cover of DIPS Portfolios						
Mean	-0.023	-0.020	-0.021	-0.022	-0.024	-0.025	-0.025	-0.026	-0.027	-0.033	-0.011	(-5.14)

Table A7. DIPS and Short Squeeze Triggers

This table displays time-series average of median abnormal volume, 8K filings sentiment and earning surprises. To be consistent with other tables, the portfolios are created on the first trading day after the Friday of the month in which options expire, and are composed of stocks sorted according to the last 3-month standard deviation of the Data Explorers Increasing Price Squeeze indicator (DIPS). The measure compares securities lending data (change in beneficial owner inventory quantity and loans) to cash market data (average trade volume and close price) in order to determine the risk of a rapid increase in price (i.e., price squeeze). The indicator is based on a scale of 0% to 100%. We show time-series averages of abnormal volume for EW portfolios that are sorted based on the standard deviation of DIPS (*Panel A*). *Panel B* displays results for the sentiment of 8K filings. *Panel C* shows results for earnings surprises. The data are collected from CRSP, Optionmetrics, Markit and the SEC and contain monthly series from July 2006 to September 2019.

Panel A: Abnormal Volume

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
Mean	-155450	-141177	-102811	-58229	-12263	-26405	-66777	143241	263409	528193	683643	(4.99)

Panel B: 8K Filings

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
Mean	0.973	0.984	0.989	1.0125	1.019	1.044	1.075	1.120	1.208	1.341	0.369	(12.45)

Panel C: Earnings Announcements

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
Mean	0.211	0.224	0.230	0.234	0.251	0.264	0.283	0.284	0.349	0.478	0.267	(4.20)