Impact of Embedded Leverage on Trading Activity in Spot, Options, and Futures Markets

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Abstract

Embedded leverage helps investors evade leverage constraints and can potentially impact relative trading activity across markets. Using option/stock, option/future, and future/stock volume ratios as measures of relative trading activity, we empirically find that trading is high in securities offering higher embedded leverage in general and especially during earnings announcements. We further corroborate our results through an examination of the exogenous shock to embedded leverage induced by the COVID-19 pandemic. Additionally, we find that embedded leverage incentivizes information generation that reduces future price uncertainty.

Keywords: embedded leverage, trading volume, spot, options, futures, information generation, earnings announcement, emerging markets

JEL: G12, G13, G14

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1. Introduction

In the last few decades, the trading activity in derivatives securities has increased manyfold. The expansion of trading activity in the derivatives market not only provides investors with alternate avenues to trade, but also helps them evade short selling constraint (Figlewski and Webb, 1993; Danielsen and Sorescu, 2001), benefit from embedded leverage, and take positions with asymmetry payoffs. Derivatives markets are known to attract informed traders due to embedded leverage and also contribute to the price discovery (Easley, O'hara and Srinivas, 1998; Chakravarty, Gulen and Mayhew, 2004; Aggarwal and Thomas, 2019; Patel, Putniņš, Michayluk and Foley, 2020). The derivatives market volume is also known to contain information about future stock returns and improve stock price informativeness.[1] There is, thus, a rich interplay of information trading between derivatives and the stock market that has implications for price discovery, asset prices, and market quality. The relative trading volume across markets can reflect this information (Johnson and So, 2012), hence, there is a limited but expanding literature that examines the determinants of relative trading activity across markets and its implications for asset prices (Roll, Schwartz and Subrahmanyam, 2010; Johnson and So, 2012; Ge et al., 2016). We attempt to further the empirical literature by examining the impact of embedded leverage on relative trading activity across different securities in a unique market setting wherein all three types of instruments – single stock options (SSO), single stock futures (SSF), and spot being traded on the same platform and are very liquid.

Previous studies have found that relative option-to-spot (O/S) volume is explained by options' delta (Δ) and trading costs (measured by spread), along with other intuitive factors like size, and institutional holding. Intriguingly, less is known about the impact of embedded leverage on the relative trading activity across markets (spot, options, and futures). Embedded leverage is an important feature of derivatives securities. It helps investors to gain larger market exposure with the same amount of capital, thereby magnifying the expected returns from the position without the risk of incurring more than

[1]See Pan and Poteshman (2006); Ni, Pan and Poteshman (2008); Cremers and Weinbaum (2010); Xing, Zhang and Zhao (2010); Johnson and So (2012); Hu (2014); Lin and Lu (2015); Ge, Lin and Pearson (2016); Hu (2018); Zhou (2021); Cao, Goyal, Ke and Zhan (2022a).

100% loss and with no need for dynamic rebalancing (Black, 1972; Biais and Hillion, 1994; Frazzini and Pedersen, 2022). Additionally, embedded leverage offered by derivatives can attract non-informed traders who want to bet on their belief (Roll et al., 2010). Thus, embedded leverage offered by different instruments linked to a single asset can be important selection criteria for investors considering taking a position on the underlying security. As our first hypothesis, we empirically test this conjecture by examining the impact of embedded leverage on relative trading activity in spot, options, and futures markets.

Informed traders trade in derivatives to evade leverage constraints and maximize their profit (Easley et al., 1998). Hence, higher embedded leverage can lead to a higher informed trading in derivatives markets. So, during periods of high information flow like earnings announcements (EA), there will be more trading in derivatives securities offering higher embedded leverage. This leads to our second conjecture, wherein we examine the ability of embedded leverage to explain the relative trading of different derivatives instruments during the period of high information flow like EA.

Furthermore, due to embedded leverage derivatives provide incentive to generate private information, and as more information is generated about the fundamentals of the underlying its volatility decreases (Grossman, 1977, 1987; Biais and Hillion, 1994; Cao, 1999). This would reduce volatility in the future period as some of the information that becomes public in the future is already impounded in prices. This leads to our third conjecture that high embedded leverage induced trading leads to lower volatility in the subsequent period.

To conduct our analysis, we use Indian financial market data. The choice of the market is primarily driven by the fact that the Indian financial market is one of the few markets in the world where all three instruments – spot, single stock options (SSO), and single stock futures (SSF) markets are highly liquid. This renders our setting much richer as we have three different securities trading (spot, SSO, and SSF) for a particular firm, with two of them (SSO and SSF) offering embedded leverage. The difference in the embedded leverage of SSO and SSF written on the same underlying allows us to test our conjecture directly. Furthermore, the existence of parallel liquid SSO and SSF along with spot allows us to examine the determinants of O/F, and F/S ratios hitherto not examined in the literature. Our sample is an unbalanced panel that includes 321 unique firms having derivatives trading on the National Stock Exchange (NSE) and spans from January 2011 to August 2021.[2] We consider all the near-month options and futures contracts (expiring on the last Thursday of every month) in the sample because they are the most liquid contracts.

Following Roll et al. (2010), we measure the relative trading activity across three markets using ratios of the trading volume. Specifically, we use O/S, O/F, and F/S ratios to compare the relative trading across the three markets. We measure embedded leverage of options contracts following Frazzini and Pedersen (2022), and define it as $|\frac{\partial O}{\partial S}\frac{S}{O}| = |\Delta\frac{S}{O}|$, where S is the price of the underlyings' security, O is the price of the option contract, and Δ is options delta. [3] Intuitively, the embedded leverage measure captures the one percentage point change in the options price for a one percentage point change in the price of the underlying. We then estimate the underlying-level average embedded leverage by taking the volume-weighted ($Lev-SSO-VW$) and equally-weighted ($Lev-SSO-EW$) averages across all options contracts traded for an underlying. We find substantial cross-sectional and time-series variation in both variables.

We can't apply the same formula to estimate the embedded leverage of futures contracts because they are priced to have an initial market value of zero. When investors take position (either long or short) in the futures market, their investment is in the form of the margin money (usually expressed as a fraction of the underlying stock price) that they are required to deposit with the broker. The futures contracts have embedded leverage because the margin is much less than the stock price. Since the delta of short maturity futures contracts is very close to one, the formula for embedded leverage of

[2]The panel is unbalanced because firms having derivatives keeps on changing, some firms are added and some are dropped based on the criterion defined by the market regulator.

[3]The embedded leverage measure is known as Ω in the derivatives literature, where it is used as a measure of options' elasticity.

future contracts simplifies to the reciprocal of the required margin. The NSE, like many other derivative exchanges, charges risk-based margins where stocks with high volatility (σ) attract proportionately higher margins. While the actual margin setting process is quite complex with numerous adjustments (and could also depend on the overall portfolio of the investor), the most important component of the margin is 3.5 σ. To compute margins, NSE uses the exponentially-weighted moving average volatility ($EWMA\ Vol$) as the estimate of σ. We, therefore, use the reciprocal of ($3.5 \times EWMA\ Vol$) as our proxy for the embedded leverage of the futures contract ($Lev - SSF$).

We employ both panel regression with appropriate fixed effects, and Fama and MacBeth (1973) type cross-sectional regression to examine the impact of embedded leverage on relative trading activity. In both the regression models, we find that the relative trading volume ratios (O/S, O/F, and F/S) are high for underlying having derivatives securities offering higher embedded leverage. These results are robust to alternative regression specifications and controlling for a wide range of variables. In our baseline results, we find that a one unit increase in $Lev - SSO - VW$ leads to a 3.7 and 2.8 percentage point increase in O/S and O/F ratios. Similarly, a one unit increase in $Lev - SSF$ leads to an increase in F/S ratio by 1 percentage point. The impact is statistically and economically significant. Our results are consistent with the arguments that investors face leverage constraint, and therefore trade more in the instruments that provide higher embedded leverage (Black, 1972, 1992; Frazzini and Pedersen, 2014, 2022).

In our above analysis, we have used the average embedded leverage offered by all options contracts as an explanatory variable whenever O/S or O/F is the dependent variable. But there is considerable variation in the embedded leverage offered by different options contracts written on a particular underlying. Next, we exploit this variation and use options contract-level data to examine the impact of embedded leverage on trading volume across contracts. We expect to observe high trading volume in options contracts having high embedded leverage. In our analysis, we first divide the contract-level sample into four parts based on the moneyness– ATM Call, OTM Call, ATM Put, and OTM Put, and then estimate the ratio of the volume in a particular contract with the total volume across contracts in a category (*Vol Ratio*) for an underlying. We regress *Vol Ratio* on the embedded leverage (Ω) of a contract. Consistent with our expectation, we find across all the four categories options contracts having higher embedded leverage attract higher trading volume. The results are robust even after controlling for firm and day fixed effects.

We further explore how COVID-19 induced heterogeneity in the drop of embedded leverage impact the relative trading activity. This analysis serves two purposes. First, it allows us to improve our identification because COVID-19 was an exogenous shock to the embedded leverage of the securities. Second, during the COVID-19 period, the leverage constraint became binding because of the increase in margins (Foley, Kwan, Philip and Ødegaard, 2022). Therefore theoretically, embedded leverage becomes even more important for investors. This analysis allows us to test the conjecture empirically. Our COVID-19 analysis confirms the baseline findings. We find that during the COVID-19 period, the firms where the drop in embedded leverage is higher experience a larger drop in O/S, O/F, and F/S relative to other firms where the drop in embedded leverage is relatively low.

Another obvious corollary of our baseline results is that firms having options or futures securities offering higher embedded leverage will have higher O/S, O/F, and F/S ratios before earnings announcements (EA). For example, if the information content of these ratios before EA is caused by informed trading in the derivatives (options/futures) market, and informed traders prefer to trade in the options/futures market because of implicit leverage offered by derivatives as suggested in the literature (Easley et al., 1998; Roll et al., 2010). Then, we expect to observe higher O/S, O/F, and F/S ratios for firms having options and futures securities offering high embedded leverage as we move close to EA day. Consistent with our expectation, we find that the increase in O/S, O/F, and F/S ratios is more pronounced for firms having derivatives contracts offering higher embedded leverage.

Having shown the impact of embedded leverage on relative trading activity across the three markets, we turn our attention to examining its implications. We examine how the high trading volume in options and futures securities having high embedded leverage affects the underlying price stability. Using idiosyncratic volatility ($IVOL$) as the measure of the price stability, we find that the portion of relative volume ratios that is explained by embedded leverage is negatively associated with the next months' $IVOL$. This result is consistent with the argument in the literature that derivatives provide embedded leverage, which incentivizes investors to generate private information, and as more information is generated about the fundamentals of the underlying its volatility decreases (Grossman, 1977, 1987; Biais and Hillion, 1994; Cao, 1999). It is also consistent with the theoretical prediction that informed investors prefer to trade in securities that offer higher implicit leverage given they are liquid (Easley et al., 1998).

Overall our study contributes to the literature that studies the determinants of relative trading volume across markets and its implication for asset prices and market quality. Roll et al. (2010) uses options delta, and trading costs along with other variables like institutional holding, and size to explain variation in O/S ratio. Their findings also suggest that the variation in O/S may be driven by informed traders. Following Roll et al. (2010), some recent studies empirically show that O/S contain information about future stock returns (Johnson and So, 2012; Ge et al., 2016). In contrast, we use embedded leverage, a factor hitherto not considered in the literature, to explain the relative trading across spot, options, and futures markets. The theoretical motivation for doing so comes from leverage constraint literature that suggests that investors would trade more in securities that provide high embedded leverage to evade leverage constraint (Black, 1972, 1992; Frazzini and Pedersen, 2014, 2022). Importantly, we arrive at our conclusion by using not only the O/S ratio but also O/F, and F/S ratios which is novel to the literature. The use of Indian financial market data allows us to do so.

We also contribute to the literature on financial markets trading activity (volume) around EA. The previous studies document that O/S, O/F, and F/S ratios increase during EA and contain information about the impending EA (Roll et al., 2010; Rai and Tartaroglu, 2015; Jain, Agarwalla, Varma and Pandey, 2019a). The literature interprets this as evidence of informed trading before EA in the derivatives market. Our results show that the heterogeneity in the increase of these ratios before EA is explained by the embedded leverage offered by the derivatives contracts. We provide direct empirical evidence in favor of theoretical predictions that informed investors trade in the derivatives market before EA because it provides embedded leverage that helps them maximize the profit on their position (Augustin and Subrahmanyam, 2020).

Lastly, our finding that the proportion of relative volume ratios explained by embedded leverage is negatively associated with the future volatility complements the findings in the literature that argues derivatives trading reduces informational uncertainty of the underlying securities, thus, improving price stability (Grossman, 1977, 1987; Biais and Hillion, 1994; Cao, 1999). This result is also related to studies that document the bright side of derivatives trading (Roll, Schwartz and Subrahmanyam, 2009; Naiker, Navissi and Truong, 2013; Blanco and Wehrheim, 2017; Bernile, Hu, Li and Michaely, 2021; Cao et al., 2022a; Cao, Hertzel, Xu and Zhan, 2022b).

The rest of the paper is structured as follows. Section 2 explains the institutional setting, data, and variables used in the study along with summary statistics and empirical specifications. Section 3 discusses the baseline results. Section 4 and 5 examine the impact of embedded leverage over volume across options contracts and trading activity across markets during COVID-19 crisis, respectively. Section 6 and 7 examine the role of embedded leverage during EA and the impact of embedded leverage induced derivatives trading on firms' price stability, respectively. Section 8 presents the robustness tests used in the study, and 9 concludes.

2. Data, Empirical Specifications, and Preliminary Evidence

2.1. Institutional Setting

India has a very liquid and well-regulated financial market. Out of the two major exchanges, the National Stock Exchange (NSE) is the largest exchange where stock, and derivatives, which include single stock and index options and futures, trade simultaneously.[4] The existence of liquid stock, and derivatives (both index and single stock options and futures contracts) trading on the same platform makes NSE unique. It has almost 99.99% market share of derivatives trading in India. The derivatives trading started on NSE in the year 2000 with the introduction of index futures based on the popular NIFTY 50 index. By November 2001, it launched index options, single stock options, and futures. NSE now is one of the worlds' largest derivatives trading venues, in 2021 approximately 8.85 trillion futures and options contracts traded on it, which is near twice the volume at CME Group (4.82 trillion) and four times at the Korean Exchange (2.18 trillion) (FIA, 2021). According to WFE Derivatives Report 2021, NSE ranks seventh, and fifth in the world by SSO and SSF volume (WFE, 2022). Recent studies done using NSE derivatives data have empirically established that the Indian equity options market is micro efficient and has low mispricing (Jain, Varma and Agarwalla, 2019b; Agarwalla, Saurav and Varma, 2022). All the options contracts that trade on NSE are European in nature post-January 2011. Single stock derivatives contracts traded on NSE have a maximum of 3-month trading cycle– the near month (expiring in one month), next month (expiring in two months), and far month (expiring in three months).[5]

In India, not all stocks have derivatives trading against them. Only a subset of large market capitalisation stocks belonging to a diverse set of industries acts as an underlying for derivatives (both options and futures). The Indian financial market regulator, Security and Exchange Board of India (SEBI), specifies the eligibility criteria for the induction and removal of stocks from the derivatives segment.[6] Sometimes large IPOs are directly included in the derivatives segment from the listing date itself. Past research has documented strong empirical evidence of the existence of the expiry day effect in the Indian derivatives market (Vipul, 2005; Agarwalla and Pandey, 2013).

[4]The other major exchange is the Bombay Stock Exchange (BSE). Both the exchanges feature in the top ten exchanges out of all the members of the World Federation of Exchanges (WFE) in terms of domestic market capitalization (WFE, 2018).

[5]For more details on the contract specifications traded on NSE please see https://www.nseindia.com/products-services/equity-derivatives-contract-specifications.

[6]SEBI prescribed eligibility criteria include market size, traded values, delivery value, and quarter sigma. For more details please see https://www.nseindia.com/products-services/equity-derivatives-selection-criteria.

2.2. Data and Variable Construction

2.2.1. Data

Our sample consists of all the stocks on the NSE that have derivatives trading on them, and it spans January 2011 to August 2021 (the last available data at the commencement of the project). We did not consider data before 2011 because the volume was low in the SSO market, it only picked up after NSE shifted from American to European options in January 2011 (Jain et al., 2019b).

The data used in the study come from various sources. The spot market data such as stock volume, return, and stock price is taken from CMIE $Prowess_{dx}$.[7] The database is maintained by the Center for Monitoring Indian Economy and is a high-quality source of accounting and stock market-related data of Indian listed and unlisted firms.[8] All the derivatives market-related data is taken from NSE Bhav files.[9] The file provides details of derivatives contracts like closing price, opening price, volume, open interest, etc for both single stocks and index options and futures contracts at a daily frequency. We consider only near-month contracts in the analysis.[10] We apply two filters to our derivatives contract-level data. First, we eliminate SSO and Index options contracts whose price lay outside the Black models' arbitrage bound. Second, we remove expiry week from our sample, i.e all the observations having time to expiry less than eight days are removed from the sample. The second filter was applied to take care of the huge expiry day effect reported in the Indian market (Vipul, 2005; Agarwalla and Pandey, 2013).[11] Information of EA dates is taken from the NSE Website.[12] The daily excess Fama and French (1993) and Carhart (1997) factor returns is taken from the Indian Institute of Management Ahmedabads' (Agarwalla, Jacob and Varma, 2013) online library. [13] The risk-free rate

[7] https://prowessdx.cmie.com

[8] The data source has been used by various previous studies, for eg. Vig (2013); Siegel and Choudhury (2012); Gopalan, Mukherjee and Singh (2016).

[9] https://www1.nseindia.com/products/content/derivatives/equities/archieve_fo.htm

[10] By near-month contract, we mean contracts expiring on the last Thursday of every month. We only consider near-month contracts because next month and far-month contracts are illiquid in India.

[11] In one of the robustness tests we show that our baseline results remain robust even after including expiry week observations.

[12] https://www.nseindia.com/companies-listing/corporate-filings-announcements

[13] https://faculty.iima.ac.in/~iffm/Indian-Fama-French-Momentum/

used in the estimation of implied volatility and delta is taken from the Reserve Bank of India (RBI) website. Lastly, the spread estimation is done using NSE order book snapshot files.

We merge data obtained from different sources using unique firm identification (NSE Firstsymbol and CMIE $Prowess_{dx}$ Company Code), and date. In the merger process, we lost data of eight firms due to data unavailability. It is less than 3% of the number of unique firms (321) in our sample. Our final dataset is an unbalanced panel, because of two reasons. First, the sample of stocks having derivatives trading keeps on changing in the Indian financial market. New stocks are added or stocks having derivatives are removed from the derivatives segment based on conditions mandated by the regulator. Second, there are missing values of some of the independent variables used in the study. Therefore, the number of observations may vary from analysis to analysis. In our primary analysis, we use data at daily frequency, but in the robustness test, we use data at monthly frequency. For that, we convert all the variables available at the daily frequency to monthly frequency by taking their monthly average.

2.2.2. Embedded Leverage Measures

To conduct our analysis, we need to define the embedded leverage of the financial instruments considered in the study i.e options and futures. We follow Frazzini and Pedersen (2022) and estimate the leverage of an options contract using the following formula:

$$Leverage(\Omega_{i,j,t}) = |\frac{\partial O_{i,j,t}}{\partial S_{j,t}} \frac{S_{j,t}}{O_{i,j,t}}| = |\Delta_{i,j,t} \frac{S_{j,t}}{O_{i,j,t}}| \quad (1)$$

where, $\Omega_{i,j,t}$ is embedded leverage of contract i of underlying j on day t. $O_{i,j,t}$ is the price of options contract i of underlying j at day t, and $S_{j,t}$ is the price of the underlying asset. This measure is basically the elasticity of the options contract. It measures the percentage change in the price of the options contract for a one-percentage-point change in the price of the underlying stock. In other words, options contracts' embedded leverage measures its return magnification with respect to the return of the underlying asset.

We use embedded leverage estimated at the contract level to calculate the volume and equally-weighted leverage at the underlying-day level using the following formula:

$$Lev - SSO - VW_{j,t} = \frac{\sum_{i=1}^{n} Vol_{i,j,t} \times \Omega_{i,j,t}}{\sum_{i=1}^{n} Vol_{i,j,t}} \tag{2}$$

$$Lev - SSO - EW_{j,t} = \frac{\sum_{i=1}^{n} \Omega_{i,j,t}}{n} \tag{3}$$

where, $Lev-SSO-VW_{j,t}$ and $Lev-SSO-EW_{j,t}$ are volume and equally weighted embedded leverage of underlying i on day t. $Vol_{i,j,t}$ is volume of options contract i of underlying j on day t. n is the number of contracts of an underlying traded on the day t.

The embedded leverage measure used for options can't be used to measure the leverage of futures contracts. Futures contracts are priced to have an initial market value of zero, so, technically they have infinite embedded leverage as per Eq. (1). However, when investors take position in the futures market, they have to post margin, and due to this they can't get infinite leverage. Therefore, by replacing the security price with the margin required in Eq. (1), we can estimate the embedded leverage of futures contracts (Frazzini and Pedersen, 2022). The new formula is written below:

$$Lev - SSF(\Omega_{j,t}) = \left|\frac{\partial F_{j,t}}{\partial S_{j,t}} \frac{S_{j,t}}{M_{j,t}}\right| = \left|\Delta_{j,t} \frac{S_{j,t}}{M_{j,t}}\right| \tag{4}$$

where, $\Omega_{j,t}$ is embedded leverage of futures contract of underlying j on day t. $M_{j,t}$ is the margin required to be posted for underlying j at day t, and $S_{j,t}$ is the price of the underlying asset.[14]

When investors take position in the futures market, their investment consists of only

[14]We have used only near month contracts in our study, so, we have one futures contract for every underlying. Therefore, we have not used contract level subscript i in the formula. But the formula can be easily generalized in the case of multiple futures contracts for the same underlying.

the margin that they are required to post. The futures have embedded leverage because the margin is much less than the stock price. Since short maturity futures have a delta very close to one, the above formula for embedded leverage of future contracts simplifies to the reciprocal of the required margin (expressed as a fraction of the stock price). The NSE like many other derivative exchanges charges risk based margins where stocks with high volatility (σ) attract proportionately higher margins.[15] While the actual margin setting process is quite complex with numerous adjustments (and could also depend on the overall portfolio of the investor), the most important component of the margin is 3.5 σ. To compute margins, NSE uses the exponentially-weighted moving average volatility ($EWMA\ Vol$) as the estimate of σ. We therefore use the reciprocal of ($3.5 \times EWMA\ Vol$) as our proxy for the embedded leverage of the futures contract ($Lev-SSF$). Our SSF embedded leverage measure is written below.

$$Lev - SSF_{j,t} = \frac{1}{3.5 \times EWMA\ Vol_{j,t}} \tag{5}$$

2.2.3. Volume Measures

To measure the relative trading activity across three markets, we use the ratio of the trading volume in spot, futures, and options markets. Because we have three markets, hence, three relative volume ratios are possible namely– option/stock, option/future, and future/stock. Following, Roll et al. (2010), we estimate the option to stock volume ratio (O/S) by first aggregating total volume across all the listed options of an underlying at a daily frequency, and divide it by the volume in the stock market.[16] Similarly, we estimate the option to future volume (O/F) ratio by dividing the total number of traded contracts

[15]For futures contracts NSE charges three different kinds of margins (VaR margin, Extreme Loss Margin, and mark-to-market margin). The final margin is the total of these margins. For more details please see - https://www.nseindia.com/products-services/equity-market-margins

[16]We consciously choose not to estimate the O/S ratio in INR terms, because the relation between O/S estimated in Indian rupees (INR) term and embedded leverage can be ambiguous. The options contract having higher embedded leverage are cheap, ceteris paribus. Suppose, there are two options contract, L and H, with low and high embedded leverage, respectively. Everything being equal $P_L > P_H$, where P is the price of the option. If N_L and N_H are options traded concurrently for L and H, and we expect $N_L < N_H$. However, the rupee value of options traded would be $P_L N_L$ and $P_H N_H$ for L and H. So even though $N_L < N_H$, we can have a situation when $P_L N_L > P_H N_H$ given $P_L > P_H$, and price difference is large enough.

across strikes of an underlying with the total number of traded futures contracts at a daily frequency. To estimate futures to stock volume (F/S), we divide the total number of traded futures contracts of an underlying with spot volume.

In our options contract level analysis, we use the log of the ratio of volume in a contract with total volume across all contracts ($Vol\ Ratio$) of an underlying in a particular category (ATM-Call, ATM-Put, OTM-Call, OTM-Put) as a measure of trading activity. For every underlying day pair, we first divide all traded options contracts into four categories based on their moneyness (defined as K/S (S/K) for call (put) option contracts). Next, we categorize a call or a put option as OTM if the moneyness of the option is between 1.05 to 1.20. Similarly, a call or a put option is categorized as ATM if the moneyness of the option is between 0.95 to 1.05. The rest of the options are categorized as ITM.[17] Our categorization scheme is similar to Xing et al. (2010). Finally, we estimate $Vol\ Ratio$ for each traded options contract by taking the natural logarithm of the ratio of total volume in that contract with total volume across all the contracts falling in that category.

$$Vol\ Ratio_{i,j,t} = Log\left(\frac{Volume_{i,j,t}}{\sum_{i=1}^{n} Volume_{i,j,t}}\right) \tag{6}$$

2.2.4. Control Variables

We use a set of control variables to make sure that the relationship between embedded leverage and trading activity across the market is not driven by any known factors in the literature (Roll et al., 2010; Ge et al., 2016). *Size* is the natural logarithm of the firms' market capitalization in INR million. *No. of Strikes* is the total number of near-month contracts traded of an underlying. *Institutional Holding* is the percentage of total outstanding shares held by institutional investors. *Volume SSF* is the natural logarithm of total volume in near-month futures contracts. *Delta* is the average daily delta of all the options contracts of an underlying with put options deltas being reversed in sign by multiplying -1. *Time to Expiry* is the time period remaining before expiry

[17] We neglect ITM options for analysis because the volume in these options is very low.

defined as the number of days before expiry divided by 365. $ATM - IV$ is the implied volatility of at-the-money options ($0.95 \leq moneyness(strike\ price/stock\ price) \leq 1.05$) estimated using Black (1976) model. For underlying having multiple options contract in the stipulated moneyness range, we take the volume weighted average of implied volatility. $\%\ Spread - SSO$ is the volume weighted daily average Bid-Ask spread ($\frac{Ask-Bid}{Ask+Bid/2} \times 100$) of all near-month options contracts of an underlying estimated at a daily frequency. $\%\ Spread - SSF$ is the Bid-Ask spread ($\frac{Ask-Bid}{Ask+Bid/2} \times 100$) of near-month future contracts of an underlying. $Spread\ Ratio$ is the ratio of $Spread - SSO$ and $Spread - SSF$ ($\frac{Spread-SSO}{Spread-SSF}$). All the variables are defined along with the source from which they are taken in Table A1 .

2.3. *Summary Statistics and Preliminary Evidence*

Table 1 reports the summary statistics and correlation between all the variables used in the study. From the Panel A of the table, we can see the mean value of $Log(O/S)$, $Log(O/F)$, and $Log(F/S)$ are -0.908, -1.515, and 0.565, respectively. The average number of options contracts for an underlying is 16.70, the average institutional holding is 8.145%, and the average SSO and SSF relative spreads are 16.44% and 0.16%, respectively. The mean values of our main explanatory variables – $Lev - SSF$, $Lev - SSO - VW$, and $Lev - SSO - EW$ are 14.32, 19.627, and 19.456, respectively.

Panel B of Table 1 reports the correlation between the variables used in the study. As expected the correlation of $Log(O/S)$ and $Log(O/F)$ with $Lev-SSO-VW$ and $Lev-SSO-EW$ is positive. Similarly, the correlation between the $Log(F/S)$ and $Lev-SSF$ is positive. The correlation of other independent variables with main dependent variables is along the expected lines. For example, $\%\ Spread - SSO$ is negatively correlated with $Log(O/S)$ and $Log(O/F)$. Similarly, $\%\ Spread - SSF$ is negatively correlated with $Log(F/S)$.

Next, we present univariate relation between relative volume ratios and embedded leverage measures. In Figure 1, we plot the $Log(O/S)$ and $Log(O/F)$ ratio against $Lev - SSO - VW$ for Tata Consultancy Services (TCS) and NIFTY 50 Index along with fitted line.[18] In Panels (a) and (b), we show the relation between $Log(O/S)$ and $Log(O/F)$ of TCS with the embedded leverage, respectively. As can be seen in the figures, the fitted line is upward slopping showing that with the increase in embedded leverage of options contracts the $Log(O/S)$ and $Log(O/F)$ increases. We find similar, pattern in the case of NIFTY 50 index options contracts (Panel (c) and (d) of Figure 1).

It is known that embedded leverage of options contract varies with times to expiry (Karakaya, 2014). To make sure the univariate results that we report above are not driven by simple variation in time to expiry, we first divide every near-month option series of TCS into four weeks (Week 1, 2, 3, and 4), and then estimate average of $Log(O/S)$, $Log(O/F)$, and $Lev - SSO - VW$ for each week separately for each series. Week 4 values are removed because that is the expiry week. In Panel (a) and (b) of Figure A1 , we plot the weekly average of $Log(O/S)$ and $Log(O/F)$ against the weekly average $Lev - SSO - VW$, respectively for weeks 1, 2, and 3 separately. As can be seen, even after controlling for time to expiry the positive univariate relationship between relative volume ratios and embedded leverage holds.

Finally, we show the time series average of main independent ($Lev - SSO - VW$, $Lev - SSO - EW$, and $Lev - SSF$), and dependent variables ($Log(O/S)$, $Log(O/F)$, and $Log(F/S)$) in Figure A2 and A3 . Panel (a) of Figure A2 shows the time series pattern of $Lev - SSO - VW$ and $Lev - SSO - VW$, whereas Panel (b) of the same figure shows the time series pattern of $Lev - SSF$. As can be seen in both the panels, the embedded leverage measure shows a huge drop around the COVID-19 time period (February 2020 to May 2020). The sharp increase in options premium and margin required on futures position may result into this kind of pattern during COVID 19 period (Agarwalla, Varma and Virmani, 2021a; Foley et al., 2022). Figure A3 shows the evolution of volume ratios in the time period considered in the study. Both $Log(O/S)$ and $Log(O/F)$ show a continuously increasing trend which shows that over period of time Indian options market has become more liquid. $Log(F/S)$ does not show an increasing pattern because

[18] TCS is the second largest firm in India in terms of market capitalization, and NIFTY 50 Index is a diversified stock index that includes 50 firms accounting for 13 sectors of Indian economy.

the Indian SSF market is historically very liquid. One pattern that is very evident from the figure is the drop in all the volume ratios around the COVID-19 time period. Interestingly, the drop in embedded leverage coincides with the drop in the volume ratios. We utilize the heterogeneity in the drop of embedded leverage across stocks to study how embedded leverage affects relative trading activity during highly uncertain times i.e COVID-19 period.

2.4. Empirical Specifications

To empirically examine the relationship between embedded leverage and relative trading activity across the three markets, we estimate how the relative volume ratios of firms vary with respect to the embedded leverage offered by their derivatives contracts. To do so, we estimate a panel data regression model mentioned below:

$$Var_{j,t} = \beta \ Embedded\ Leverage_{j,t} + \sum_{i=1}^{n} \beta_i Control_{i,j,t} + \gamma_j + \eta_t + \epsilon_{j,t} \tag{7}$$

where, $Var_{j,t}$ represents a vector of dependent variables for firm j at trading day t. In our baseline analysis, we consider three dependent variables– $Log(O/S)_{j,t}$, $Log(O/F)_{j,t}$, and $Log(F/S)_{j,t}$. The term $Embedded\ Leverage_{j,t}$ represents our main independent variables. In the baseline estimation, we consider three different measures of embedded leverage two from the options market– $Lev - SSO - VW$ and $Lev - SSO - EW$, and one from the futures market– $Lev - SSF$. $Control_{i,j,t}$ includes $Size$, $No.\ of\ Strikes$, $Institutional\ Holding$, $Volume\ SSF$, $Delta$, $ATM-IV$, $ATM-IV \times Time\ to\ Expiry$, $Spread - SSO$, and $Spread - SSF$ (see Table A1 for variables definition). γ_j, and η_t are firm, and date-level fixed effects. The firm and date level fixed effects absorb any time-invariant observed and unobserved firm characteristics, and any systemic shock that affects all the firms on a particular day, respectively. In an alternate specification, we use firm-month-year fixed effects to control for any observed and unobserved factors that vary at the firm-month-year level.

β is our variable of interest. If the high embedded leverage of an instrument leads to higher trading in that instrument relative to other instruments for a firm, then we expect the following. First, options market-related embedded leverage measures, $Lev-SSO-VW$ and $Lev-SSO-EW$, to load positively on $Log(O/S)$ and $Log(O/F)$. Intuitively, it means that for firms having options contracts offering higher embedded leverage investors prefer the options market over futures and spot market leading to higher O/S and O/F values. Second, our futures market embedded leverage measure, $Lev-SSF$, to load positively on $Log(F/S)$. The intuition is similar to before. Therefore, we expect the beta to be positive and statistically significant when $Log(O/S)$, $Log(O/F)$, and $Log(F/S)$ are dependent variables with $Lev-SSO-VW$, $Lev-SSO-EW$ and $Lev-SSF$ as the main independent variables.

Next, we examine the cross-sectional effect of embedded leverage on relative trading activities across– spot, futures, and options markets. For that, we estimate cross-sectional regression (Fama and MacBeth, 1973) at the daily frequency with relative volume ratios as dependent variables and embedded leverage measures as independent variables along with other controls and test the significance of cross-sectional beta of embedded leverage variables. This method alleviates any concern of results being driven by variation in embedded leverage of options contract due to time to expiry because in our sample all options contracts across firms have same time to expiry on a given trading day, the frequency at which we estimate cross-sectional regression. As the residuals of the cross-sectional regression may be serially correlated we use Newey and West (1987) adjusted standard errors with 12 lags. The cross-sectional regression estimated at daily frequency is mentioned below:

$$Var_j = \beta_t \; Embedded \; Leverage_j + \sum_{i=1}^{n} \beta_i Control_{i,j} + \epsilon_j \qquad (8)$$

where Var_j represents a vector of dependent variables for firm j. In our baseline analysis, we consider three dependent variables– $Log(O/S)_j$, $Log(O/F)_j$, and $Log(F/S)_j$. The term $Embedded \; Leverage_j$ represents our main independent variables. In the baseline estimation, we consider three different measures of embedded leverage $Lev-SSO-$

VW and $Lev-SSO-EW$, and $Lev-SSF$. $Control_{i,j}$ includes $Size$, $No.\ of\ Strikes$, $Institutional\ Holding$, $Volume\ SSF$, $Delta$, $ATM-IV$, $ATM-IV \times Time\ to\ Expiry$, $Spread-SSO$, and $Spread-SSF$ (see Table A1 for variables definition).

For each trading day in our sample, we estimate the regression model mentioned above with our three dependent variables separately. This exercise gives us time series of the beta coefficients (β_t) of embedded leverage along with the beta values of the independent variables. Next, we estimate the mean and standard error of all the time series betas separately. The mean value of β_t is our variable of interest here. As before, we expect the mean value of β_t to be positive and statistically significant when $Log(O/S)$ and $Log(O/F)$ are dependent variables with $Lev-SSO-VW$ and $Lev-SSO-EW$ as the main independent variables. Similarly, the mean of β_t would be positive and statistically significant when $Log(F/S)$ is the dependent variable with $Lev-SSF$ as the main independent variable.

3. Result

3.1. Panel Regression Results

Table 2 reports the estimated coefficients of Eq. (7). Columns (1)-(4), (5)-(8), and (9)-(10) report the results when the dependent variable is $Log(O/S)$, $Log(O/F)$, and $Log(F/S)$, respectively. In columns (1-8), we find that both the measures of options leverage ($Lev-SSO-VW$ and $Lev-SSO-EW$) are positively associated with O/S and O/F ratios. The coefficients of embedded leverage measures in all the specifications are both economically and statistically significant. In our baseline specifications for O/S, with both firm and time level fixed effects (Columns (1) & (3)), we find one unit increase in value-weighted leverage (equally-weighted leverage) of a firm leads to a 3.7 (3.3) percentage point increase in the O/S ratio. Similarly, in our baseline specifications for O/S, (Columns (5) & (7)), we find one unit increase in value-weighted leverage (equally-weighted leverage) of a firm leads to a 2.8 (2.0) percentage point increase in the O/F ratio. The results remain robust even when we use firm-month-year level fixed effects.

Columns (9)-(10) of Table 2 report the estimated coefficients of Eq. (7), when the dependent variable is $Log(F/S)$ and main independent variable is embedded leverage offered by futures contracts ($Lev - SSF$). In both the columns, we find that $Lev - SSF$ is positively associated with $Log(F/S)$. The results can be interpreted in light of low $EWMA\ Vol$ leads to lower margin requirement on futures position that increases the embedded leverage ($Lev - SSF$) offered by futures contracts that in turn positively affects the relative volume of futures with respect to spot. The coefficients of $Lev - SSF$ in all the specifications are both economically and statistically significant. Specifically, in our baseline specifications with both firm and time level fixed effects (Columns (9)), we find one unit increase in $Lev - SSF$ of a firm leads to a 1.0 percentage point increase in the F/S ratio. The results remain robust even when we use firm-month-year level fixed effects.

Assuringly, the empirical result is consistent across specifications. Taken together, the above evidence suggests that for firms having options contract that offers on an average high embedded leverage the relative options to spot and future volume is high. Similarly, when embedded leverage offered by futures contracts of a firm is high the relative futures to spot volume is high.

3.2. Cross-sectional Regression Results

In this section, we discuss the results of our cross-sectional regression analysis. Table 3 reports the time series statistics of all the coefficients estimated by using Eq. (8). Columns (1)-(2), (3)-(4), and (5) report the results when the dependent variable is $Log(O/S)$, $Log(O/F)$, and $Log(F/S)$, respectively. As before, we find that both the measures of options leverage ($Lev - SSO - VW$ and $Lev - SSO - EW$) are positively associated with O/S and O/F ratios (see column (1-4) of Table 3). We find one unit increase in the value-weighted leverage (equally-weighted leverage) of a firm leads to a 5.0 (3.9) percentage point increase in the O/S ratio. Similarly, we find one unit increase in the value-weighted leverage (equally weighted leverage) of a firm leads to a 4.2 (1.3) percentage point increase in the O/F ratio. The mean value of the time series coefficients of $Lev - SSO - VW$ and $Lev - SSO - EW$ are both economically and statistically significant across all specifications.

Lastly, in column (5) where $Log(F/S)$ is the dependent variable and the main independent variable is embedded leverage offered by futures contracts ($Lev - SSF$), we find that $Lev - SSF$ is positively associated with $Log(F/S)$. The coefficient of $Lev - SSF$ is both economically and statistically significant. Specifically, we find one standard deviation increase in $Lev - SSF$ of a firm leads to a 30 bps increase in the F/S ratio.

Taken together, the above evidence suggests that in a cross-section firms having options contracts that offer on an average high embedded leverage the relative options to spot and future volume is high. Similarly, when embedded leverage offered by futures contracts of a firm is high the relative futures to spot volume is high in a cross-section.

4. Options Contract Level Analysis

Our analysis thus far provides strong empirical evidence of the higher trading activity in the derivatives instruments with higher embedded leverage. While the previous analysis is done at the firm level by taking the average embedded leverage of all options contracts of a firm on a particular trading day. We now focus our attention on the relation of embedded leverage with the relative trading activity across options contracts. In other words, we use options contract level data to examine the impact of options contracts' embedded leverage over traded volume across contracts. To conduct our examination we estimate the regression model mentioned below:

$$Vol\ Ratio_{i,j,t} = \beta_1 Embedded\ Leverage_{i,j,t} + \beta_2 Spread - SSO_{i,j,t} + \gamma_j + \eta_t + \epsilon_{i,j,t} \quad (9)$$

where, $Vol\ Ratio_{i,j,t}$ represents a vector of dependent variables which is log of the ratio of volume in options contract i of firm j at time t with total options volume across all the options contracts in a category of firm j at time t (see subsubsection 2.2.3 for more details). The term $Embedded\ Leverage_{i,j,t}$ represents our main independent variables which is embedded leverage of contract i of firm j at time t. $Spread - SSO_{i,j,t}$ is relative bid-ask spread of contract i of firm j at time t (see Table A1 for variables definition). It is important to control bid-ask spread because it is a direct measure of trading cost and is known to affect the trading behavior of (informed) traders (Muravyev and Pearson, 2020). γ_j, and η_t are firm, and date-level fixed effects. The firm and date level fixed effects absorb any time-invariant observed and unobserved firm characteristics, and any systemic shock that affects all the firms on a particular day, respectively. We divide the contract level sample into four parts – ATM Call, OTM Call, ATM Put, and OTM Put based on the moneyness of the contracts and estimate the above equation for four subsamples separately.[19]

Table 4 reports the estimated coefficients of Eq. (9). We find that the coefficient of leverage is statistically and economically significant for all categories of options contracts. Specifically, in our full model, having firm and date fixed effects, we find that a unit change in embedded leverage of the options contracts leads to a 6.5, 2.0, 6.0, and 2.6 percentage point increase in the relative volume ($Vol\ Ratio$) of options contracts in case of ATM Call (Column (2) Panel A), OTM Call (Column (4) Panel A), ATM Put (Column (2) Panel B), and OTM Put (Column (4) Panel B), respectively.

Our contract level analysis provides empirical evidence of higher trading volume in options contracts having higher embedded leverage. We tend to interpret these results as higher demand for options contracts having high embedded leverage by investors.

5. Embedded Leverage, Relative Volume, and COVID 19 Crisis

In this section, we examine the role of embedded leverage in explaining the relative trading activity during a period of high uncertainty i.e COVID-19 crisis.[20] We use heterogeneity in the drop of embedded leverage across SSOs/SSFs during the COVID-19

[19] We define the moneyness of call (put) options as strike/stock price (stock/strike price) and categorize a call or a put option as OTM if the moneyness of the option is between 1.05 to 1.20. Similarly, a call or a put option is categorized as ATM if the moneyness of the option is between 0.95 to 1.05. Additionally, we remove deep out/in of the money options because they constitute hardly 1-2% of the total volume traded.

[20] During COVID-19 crisis the liquidity in the financial markets around the world dropped drastically, due to high uncertainty and binding margins (Foley et al., 2022). Indian financial market experienced similar pattern (Agarwalla, Varma and Virmani, 2021b; Agarwalla et al., 2021a; Bansal, Gopalakrishnan, Jacob and Srivastava, 2022).

period to identify the impact of embedded leverage over relative trading volume.[21] Using COVID-19 as a shock that caused exogenous variation in the embedded leverage offered by SSOs/SSFs, we aim to show that firms where drop-in embedded leverage is higher experience a larger drop in $Log(O/S)$, $Log(O/F)$, and $Log(F/S)$ relative to other firms where the drop in embedded leverage is relatively low.

To test our conjecture, we first did a univariate analysis. We divide our sample that spans from February 2020 to May 2020 into quintiles using the distribution of embedded leverage measures ($Lev - SSO - VW$, $Lev - SSO - EW$, and $Lev - SSF$). We then estimate the mean value of $Log(O/S)$, $Log(O/F)$, and $Log(F/S)$ for each quintile, and, then, check if the difference in the mean between quintiles one (lowest leverage) and five (highest leverage) is statistically significant using Newey and West (1987) adjusted standard errors. Table 5 reports the results of our analysis. In Panel A, B, and C, we form quintiles using the values of $Lev - SSO - VW$, $Lev - SSO - EW$, and $Lev - SSF$ respectively. As can be observed in Panel A and B of the table as we move from quintile 1 (lowest options leverage) to quintile 5 (highest options leverage) both the relative volume measures ($Log(O/S)$ and $Log(O/F)$) increase monotonically. Consistent with our other results, we find $Log(F/S)$ increases as embedded leverage offered by futures contracts increases (Panel C). The difference between the relative volume ratios of the lowest embedded leverage quintile and highest embedded leverage quintile is both statistically and economically significant in all the columns.

To further test the robustness of our univariate results, we estimate the following regression model:

[21] One reason why we expect the cross-sectional variation in the fall of embedded leverage across SSOs is because for some firms the options had become more expensive than the others due to differences in the exposure to the pandemic (Agarwalla et al., 2021b). Similarly, the difference in the exposure to the pandemic would result in variation in the increase of $EWMA\ Vol$ across firms generating cross-sectional variation in the margin requirement resulting in cross-sectional variation in the embedded leverage ($Lev - SSF$) across SSFs.

$$
\begin{aligned}
Var_{j,t} = \beta\ Embedded\ Leverage_{j,t} + \delta\ COVID + \alpha\ Embedded\ Leverage_{j,t} \times COVID \\
+ \sum_{i=1}^{n} \beta_i Control_{i,j,t} + \gamma_j + \eta_t + \epsilon_{j,t}
\end{aligned}
\tag{10}
$$

where, $Var_{j,t}$ represents a vector of dependent variables for firm j at time t. In our baseline analysis, we consider three dependent variables– $Log(O/S)_{j,t}$, $Log(O/F)_{j,t}$, and $Log(F/S)_{j,t}$. The term $Embedded\ Leverage_{j,t}$ represents our main independent variables. In the baseline estimation, we consider three different measures of embedded leverage two from the options market– $Lev-SSO-VW$ and $Lev-SSO-VW$, and one from the futures market– $Lev-SSF$. $COVID$ is a dummy variable that takes the value one if the trading days lie between February 2020 to May 2020 and zero otherwise. $Control_{i,j,t}$ includes $Size$, $No.\ of\ Strikes$, $Institutional\ Holding$, $Volume\ SSF$, $Delta$, $ATM-IV$, $ATM-IV \times Time\ to\ Expiry$, $Spread-SSO$, and $Spread-SSF$ (see Table A1 for variables definition). γ_j, and η_t are firm, and date-level fixed effects. In an alternate specification, we use firm-month-year fixed effects to control for any observed and unobserved factors that vary at the firm-month-year level. The coefficient of interest for us is the interaction between $COVID$ and embedded leverage measures i.e α.

Table 6 reports the estimated coefficients of Eq. (10). In Columns (1)-(4), (5)-(8), and (9)-(10) $Log(O/S)$, $Log(O/F)$, and $Log(F/S)$ are dependent variables respectively. Consistent with our expectation, we find the interaction coefficient of $COVID$ and embedded leverage measures in all the regression specifications where $Log(O/S)$ and $Log(O/F)$ are dependent variables are positive, and statistically significant. Specifically, in our full model with $Log(O/S)$ as the dependent variable (columns (1) and (3)), we find that during the COVID-19 period a unit change in $Lev-SSO-VW$ ($Lev-SSO-VW$) leads to a 4.9 (4.7) percentage point increase in O/S, which is substantially more than the impact of $Lev-SSO-VW$ ($Lev-SSO-VW$) during normal times. Similarly in our full model with $Log(O/F)$ as the dependent variable, a unit change in $Lev-SSO-VW$ ($Lev-SSO-VW$) leads to a 4.0 (3.1) percentage point increase in O/F, which is substantially more than the impact of $Lev - SSO - VW$ ($Lev - SSO - VW$) during normal times (see columns (5) and (7)). Lastly in the full model with $Log(F/S)$ as the dependent variable (see column (9)), we find that a standard deviation increase in the $Lev - SSF$ leads to an 1.5 percentage point increase in the F/S.

Taken together the results of this section provide strong empirical evidence that during the COVID-19 period firms with larger drop-in embedded leverage experienced a larger drop in O/S, O/F, and F/S relative to other firms where the drop in embedded leverage is relatively low. We interpret these results as evidence of the significant role that embedded leverage of an instrument plays in explaining trading activity across markets.

6. Role of Embedded Leverage During Earnings Announcements

In this section, we examine the impact of embedded leverage over the relative trading activity across markets before earnings announcements (EA). It is known in the literature that (informed) traders prefer the derivatives market over the spot market while trading before EA leading to increase in derivatives to stock volume around EA (we check the validity of this assertion in our sample and present the result in Table A2).[22] One of the reasons why investors with private information prefer the derivatives market over the spot market to trade before EA is the presence of embedded leverage in the derivatives instrument (Black, 1975; Diavatopoulos et al., 2012).[23] A direct implication of this before EA can be a higher relative volume in a derivatives instrument with respect to spot or other derivatives instruments if it offers higher embedded leverage. Hence, we can expect to observe, before EA the relative options/stock, and options/future volume to be higher for firms having options contracts offering higher embedded leverage. Similarly, for firms having futures contracts that offer higher embedded leverage the future/stock

[22] Due to the prevalence of informed trading in the derivatives market around EA, various options market variables like implied volatility, skewness of the implied volatility curve, options/stock, and futures/stock volume contains information about the impending earnings announcements (Roll et al., 2010; Diavatopoulos, Doran, Fodor and Peterson, 2012; Rai and Tartaroglu, 2015; Lu and Ray, 2016; Jain et al., 2019a). Please see Augustin and Subrahmanyam (2020) for a comprehensive review of literature on informed trading in the options market before scheduled or unscheduled announcements.

[23] Another reason can be the absence of short selling constraint in the derivatives market.

volume would be higher before EA. We empirically test this conjecture using the following regression model:

$$
\begin{aligned}
Var_{j,t} = \beta\ Embedded\ Leverage_{j,t} + \sum_{i=-1}^{-3} \beta_i TD[i] + \sum_{i=-1}^{-3} \alpha_i\ Embedded\ Leverage_{j,t} \times TD[i] \\
+ \delta_1 EA\ Day + \delta_2\ Embedded\ Leverage_{j,t} \times EA\ Day \\
+ \sum_{i=1}^{n} \beta_i Control_{i,j,t} + \gamma_j + \eta_t + \epsilon_{j,t}
\end{aligned}
\tag{11}
$$

where, $Var_{j,t}$ represents a vector of dependent variables for firm j at time t. In our baseline analysis, we consider three dependent variables– $Log(O/S)_{j,t}$, $Log(O/F)_{j,t}$, and $Log(F/S)_{j,t}$. The term $Embedded\ Leverage_{j,t}$ represents our main independent variables. In the baseline estimation, we consider three different measures of embedded leverage – $Lev-SSO-VW$, $Lev-SSO-VW$, and $Lev-SSF$. $TD[i]$ is a dummy variable that takes the value one for i^{th} trading day before the earnings announcement and zero otherwise. $EA\ Day$ is the dummy variable that becomes one for EA day and zero otherwise. $Control_{i,j,t}$ includes $Size$, $No.\ of\ Strikes$, $Institutional\ Holding$, $Volume\ SSF$, $Delta$, $ATM-IV$, $Spread-SSO$, $Spread-SSF$, and $BHAR[-1,+1]$ (see Table A1 for variables definition). γ_j, and η_t are firm, and date-level fixed effects.[24] While estimating the model we consider a subsample that spans from three trading days before EA to EA day. Thus, in the model the third trading day prior to EA is the base for $TD[i]$ and $EA\ Day$ dummy variables.

The coefficients of interest for us are the interaction of $Embedded\ Leverage$ with $TD[i]$ (α_i) and $EA\ Day$ (δ_2). A positive coefficient of interaction can be interpreted as evidence that on that trading day the impact of embedded leverage over relative volume across markets is greater than our base trading day i.e third trading day prior to EA.

Table 7 reports the estimated coefficients of Eq. (11). In columns (1-2), (3-4),

[24]The date level fixed effects capture any shock to all the firms on a given day. Hence, it captures the effects of the announcement of a large firms over all other firms in the same industry.

and (5) $Log(O/S)$, $Log(O/F)$, and $Log(F/S)$ are dependent variables respectively. For $Log(O/S)$ and $Log(O/F)$, we find that the interaction coefficients of both $TD[-1]$ and EA day with embedded leverage measures ($Lev - SSO - VW$ and $Lev - SSO - EW$) are positive and significant. Similarly, for $Log(F/S)$, we find that the interaction coefficients of both $TD[-1]$ and EA day with $Lev - SSF$ are positive and significant only for EA Day. Additionally, we observe in all the columns that as we move close to the EA Day the magnitude of the interaction coefficients increases monotonically. Taken together, we interpret this as evidence that the impact of embedded leverage over the trading activity across different markets becomes, even more, stronger before EA, and the impact increases as we move close to EA day.

This result is significant because it is known that higher options volume before EA mitigates the problem of post-earnings announcement drift ($PEAD$) (Truong and Corrado, 2014; Rai and Tartaroglu, 2015).

7. Effect of Embedded Leverage Induced Derivatives Trading on Spot Price Volatility

Our results thus far provide empirical evidence that firms having derivatives contracts that offer high embedded leverage have higher relative derivatives to spot volume. In this section, we intend to examine how the part of derivatives volume that is explained by embedded leverage impacts future price stability measured by idiosyncratic volatility ($IVOL$) of the underlying. This is important to understand because the theoretical argument about the impact of high derivatives trading volume on the stability of the underlying price is ambiguous. Derivatives provide embedded leverage, and with sufficient liquidity an avenue to do transactions at a lower cost. Thus, providing incentive for private information generation and as more information is generated about the fundamentals of the underlying it volatility will decrease (Grossman, 1977, 1987; Biais and Hillion, 1994; Cao, 1999). Whereas, if the derivatives trading is excessively speculative it can adversely affect the stability of the stock prices (Stein, 1987; Massa, 2002).[25] The em-

[25] By excessively speculative we mean when derivatives traders have less than perfect information.

pirical evidence regarding the relationship between derivatives volume and volatility are equally sparse and tenuous (Edwards, 1988; Harris, 1989; Damodaran, 1990; Damodaran and Lim, 1991). So, if derivatives' embedded leverage incentivizes investors to generate private information and trade using it in the derivatives markets is the primary reason why we observe the higher value of relative volume ratios for underlying having higher embedded leverage. We expect to observe a negative relation between the part of volume ratios explained by embedded leverage and next month $IVOL$.[26] Whereas, the opposite would be true if derivatives' embedded leverage results in excessively speculative trading in the derivatives market.

To conduct our analysis, we first decompose the relative volume ratios into two components, one that is explained by embedded leverage measures, and second that is orthogonal to it. For that we estimate the following regression equation:

$$Var_{j,m} = \beta_0 + \beta_1 Embedded\ Leverage_{j,m} + \epsilon_{j,m} \tag{12}$$

where, $Var_{j,m}$ represents a vector of dependent variables for firm j of month m. In our baseline analysis, we consider three dependent variables– $Log(O/S)_{j,m}$, $Log(O/F)_{j,m}$, and $Log(F/S)_{j,m}$. The term $Embedded\ Leverage_{j,m}$ represents our main independent variables ($Lev - SSO - VW$, $Lev - SSO - EW$, and $Lev - SSF$). All the variables used in the regression are converted to monthly frequency by taking the average at the month-year level.[27] Estimation of Eq. (12) provides us two vectors for each volume ratio; one that is explained by embedded leverage measures and the other that is orthogonal to it (residuals).

In our preliminary analysis, we examine the univariate relationship between volume ratios and next month's $IVOL$. We consider three different volume ratios– actual volume ratios ($Log(O/S)$, $Log(O/F)$, $Log(F/S)$) which include both the components the

[26]Informed traders prefer to trade in derivatives market due to embedded leverage offered by derivatives contracts (Easley et al., 1998; Roll et al., 2010).

[27]We choose to do the analysis at monthly frequency because our variable of interest idiosyncratic volatility is available at monthly frequency.

one explained (predicted) by embedded leverage and the part that is orthogonal to it, the part of the volume ratios that is explained by embedded leverage ($Pre\ Log(O/S)$, $Pre\ Log(O/F)$, $Pre\ Log(F/S)$), and orthogonal component ($Res\ Log(O/S)$, $Res\ Log(O/F)$, $Res\ Log(F/S)$). After sorting the data into quartiles based on the actual, predicted, and residual relative volume ratios, we report the average value of next month's IVOL for each quartile. Table A3 reports the results. In Panel A, B, and C of the table quartiles are formed using actual, predicted, and residual values of $Log(O/S)$, $Log(O/F)$, and $Log(F/S)$. The last row of all the panels reports the difference in the mean of quartiles one and four. In all the panels the mean of next months' $IVOL$ show a monotonic decrease as we move from quartile one to four of predicted volume ratios, the difference in mean of the first and fourth quartile is statistically significant. Whereas, the $IVOL$ does not show any pattern in the cases when quartiles are formed by using actual or orthogonal components of volume ratios. This result provides preliminary evidence that derivatives trading explained by embedded leverage is driven primarily by informed traders.

Next, we check the robustness of our univariate result in the multivariate setting. For that we estimate the following regression equation:

$$IVOL_{j,m+1} = \beta V\hat{ar}_{j,m} + \sum_{i=1}^{n} \beta_i Control_{i,j,m} + \gamma_j + \eta_m + \epsilon_{j,m} \qquad (13)$$

where, $IVOL_{j,m+1}$ represents a vector of dependent variables which is idiosyncratic volatility of month $m+1$ for firm j. $V\hat{ar}_{j,m}$ is the predicted values of volume ratios ($Log(O/S)$, $Log(O/F)$, and $Log(F/S)$) of month m for firm j. $Control_{i,j,m}$ includes $Size$, $Institutional\ Holding$, and $ATM-IV$ (see Table A1 for variables definition). γ_j, and η_m are firm, and month-level fixed effects. The inclusion of firm and month-level fixed effects is crucial, they absorb any time-invariant observed and unobserved firm characteristics, and any systemic shock that affects all the firms in a particular month, respectively. All the variables used in the regression are converted to monthly frequency by taking the average at the month-year level. We estimate the model for each of the predicted volume ratios separately. The coefficient of interest for us is β. As explained earlier, we expect it to be negative and statistically significant.

Table 8 reports the estimated coefficients of Eq. (13). In panel A, B, and C the regression model is estimated with $Pre\ Log(O/S)$, $Pre\ Log(O/F)$, and $Pre\ Log(F/S)$ as main independent variables, respectively. Consistent with our univariate results, we find that in all the regression specifications the coefficients of predicted volume ratios are negative, and economically and statistically significant. Specifically, in our full model with firm and month-year fixed effects (column (4) of all the panels), we find that a percentage point increase in embedded leverage explained O/S, O/F, and F/S results into 40, 110, and 200 bps decrease in the next months' $IVOL$.[28]

The findings of this section provide evidence that the part of derivatives volume that is explained by embedded leverage reduces future $IVOL$ of the underlying. This result is consistent with the argument in the literature that derivatives provide embedded leverage, which incentive investors to generate private information, and as more information is generated about the fundamentals of the underlying, its volatility decreases (Grossman, 1977, 1987; Biais and Hillion, 1994; Cao, 1999; Hu, 2018).

8. Robustness

To check the robustness of our results we conduct several tests. First, to make sure our baseline results are not driven by the expiry week filter, we replicate our baseline results without removing expiry week data. The replicated result of Eq. (7) using sample including expiry week is shown in Table A4. Assuringly, the results are qualitatively similar to that of reported in the Table 2.

Second, in our baseline analysis, we report the contemporaneous relationship between the relative volume measures and embedded leverage. To show that the result remains robust even with the lagged value of embedded leverage measures. We replicate our results using the lagged value of embedded leverage. We estimate Eq. (7), and (8), Fama and MacBeth (1973) type cross-sectional regression, using one day lagged

[28] As an alternative to $IVOL$, we also use total volatility which is standard deviation of stocks' daily return at monthly frequency and find similar results.

value of our embedded leverage measures instead of contemporaneous values. Table A5 and A6 report the coefficients estimated using the former and latter regression models, respectively. The results remain qualitatively similar to our baseline results.

Third, we check the robustness of the relation between options/futures ratio with embedded leverage after controlling for $Lev - SSF$ and embedded leverage of options contracts ($Lev - SSO - VW$ and $Lev - SSO - EW$) along with the liquidity of both markets in the same regression model. We define a *Spread Ratio* with the ratio of $\%\ Spread - SSO/\%\ Spread - SSF$. The variable captures the relative liquidity of the options and futures market of a particular firm. A higher value of the *Spread Ratio* means that the futures market is relatively more liquid than options. We replicate our result reported in columns (5-8) of Table 2, by replacing $\%\ Spread - SSO$ with *Spread Ratio* and adding embedded leverage measures of both options and futures markets as the independent variable. Table A7 reports the results, as expected we find the positive (negative) relation between embedded leverage of options (futures) market and $Log(O/F)$ ratio, the result remains robust even after controlling explicitly for the relative liquidity of both the markets.

Fourth, we check the robustness of our results by doing the analysis at a monthly frequency rather than at a daily frequency. For that, we convert all the variables available at the daily frequency into monthly frequency by taking their monthly average. We replicate our results at monthly frequency using both panel (Eq. (7)), and cross-sectional regression (Eq. (8)). Table A8 and A9 report the coefficients estimated using the former and latter regression models, respectively. The results remain qualitatively similar to our baseline results.

Fifth, we use the volume of ATM options instead of total options volume to estimate the options/stock and options/futures ratio. We aggregate the volume of call and put option contracts having moneyness (strike/stock price for call options and stock/strike price for put options) between 0.95 to 1.05 for every underlying to estimate $Log(ATM - O/S)$ and $Log(ATM - O/F)$. We replicate our baseline model (Eq. (7)) using $Log(ATM -$

O/S) and $Log(ATM - O/F)$ as dependent variables. Table A10 reports the estimated coefficients. In all the columns we find that embedded leverage measures are positively associated with $Log(ATM - O/S)$ and $Log(ATM - O/F)$, which is consistent with our previous findings.

Lastly, we check the robustness of our contract level analysis done in section 4 by replicating our result using NIFTY Index options data.[29] As done in the main analysis, we first divide the NIFTY Index option contracts into four categories ATM Call, OTM Call, ATM Put, and OTM Put based on the moneyness, and estimate Eq. (9) for four subsamples separately. Table A11 reports the estimated coefficients of Eq. (9) for four subsamples separately. The results are similar to what we find using single stock options data. In all the categories, contracts offering higher embedded leverage attract higher options volume.

9. Conclusion

We investigate the impact of embedded leverage on relative trading activity in spot, options, and futures markets. For that, we use 11 years of Indian financial market data that include all the listed NSE firms having derivatives trading on them. We find that the embedded leverage, as measured by average Ω across all contracts, offered by options contracts is positively associated with the option/stock and options/futures volume. Similarly, embedded leverage offered by futures contracts is also positively associated with futures/stock volume. The results are both statistically and economically significant to alternative methods, alternative fixed effects, and a range of additional controls. We, further, corroborate our baseline findings by exploiting COVID-19 as an exogenous shock that induced heterogeneity in the drop of derivatives contracts' embedded leverage across firms. We also establish the importance of embedded leverage in explaining the trading volume across options contracts of a firm. Our results lend support to the findings in

[29]NIFTY 50 Index is a diversified stock index that includes 50 firms accounting for 13 sectors of the Indian economy. The NIFTY Index options contracts are one of the most liquid contracts in the world (FIA, 2021)

the leverage constraint literature that investors are leverage constraints so they prefer trading in securities that offer higher embedded leverage.

Next, we provide empirical evidence that firms having options or futures securities offering higher embedded leverage have higher O/S, O/F, and F/S ratios before earnings announcements (EA). This result is consistent with the prediction in the literature that informed traders prefer to trade in the options/futures market because of implicit leverage offered by derivatives (Easley et al., 1998; Roll et al., 2010). Lastly, we examine how the high trading volume in options and futures securities having high embedded leverage affects the underlying price stability. Using idiosyncratic volatility ($IVOL$) as the measure of the price stability, we find that the portion of relative volume ratios that is explained by embedded leverage is negatively associated with the next months' $IVOL$. This result is consistent with the literature that finds the bright side of derivatives trading (Grossman, 1977, 1987; Biais and Hillion, 1994; Cao, 1999; Pan and Poteshman, 2006). It is also consistent with the theoretical prediction that informed investors prefer to trade in securities that offer higher implicit leverage given they are liquid (Easley et al., 1998).

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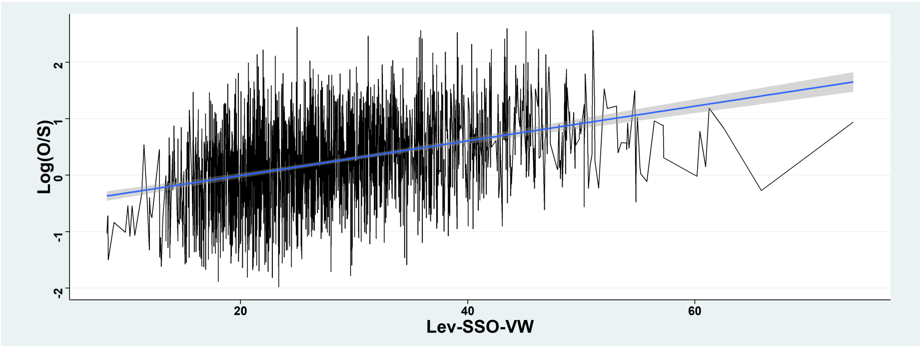
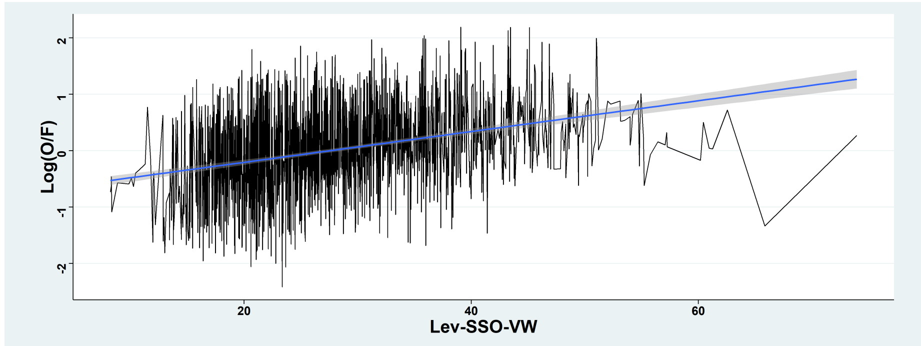
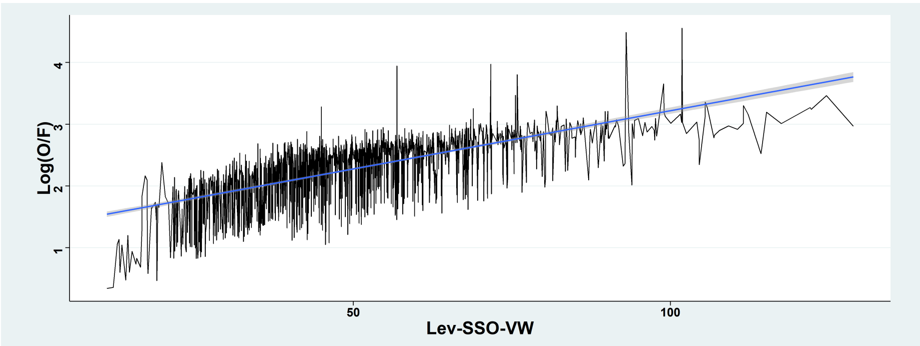
Figure 1: Log(O/S), Log(O/F), and Embedded Leverage



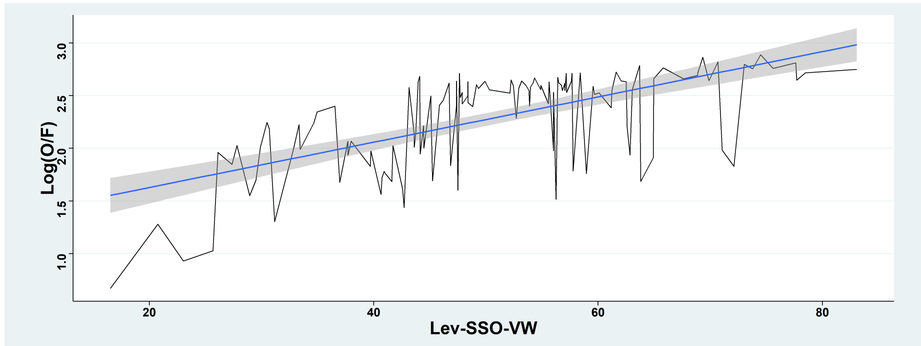
(a) TCS: Log(O/S) Daily Frequency



(b) TCS: Log(O/F) Daily Frequency



(c) NIFTY: Log(O/F) Daily Frequency



(d) NIFTY: Log(O/F) Monthly Frequency

Figures show the univariate relationship of Log(O/S), and Log(O/F) with embedded leverage along with a fitted trend line. Panel (a) and (b) show the trend for Tata Consultancy Services (TCS), and Panel (c) and (d) for the NIFTY 50 index, respectively. Log(O/S) and Log(O/F) are option/stock and option/future log volume ratio. Lev-SSO-VW is the volume-weighted embedded leverage of all the options contracts of an underlying. In Panel (d) graph is plotted by taking the monthly average of Log(O/F) and Lev-SSO-VW. The sample period spans from January 2011 to August 2021.

Table 1: Summary Statistics and Correlation Table

Panel A														
Statistics	Log(O/S)	Log(O/F)	Log(F/S)	Size	No. of Strikes	Ins. Holding	Volume SSF	Delta	ATM-IV	% Spread-SSO	% Spread-SSF	Lev-SSF	Lev-SSO-VW	Lev-SSO-EW
Mean	-0.908	-1.515	0.565	12.211	16.706	8.145	14.751	0.341	0.379	16.448	0.162	14.327	19.627	19.456
Median	-0.566	-1.242	0.590	12.244	15.000	0.000	14.898	0.340	0.358	9.038	0.114	13.746	18.398	18.332
Std. Dev.	1.603	1.486	0.629	1.336	10.805	15.595	1.735	0.059	0.143	20.479	0.155	4.967	7.416	7.204
Min	-9.494	-9.379	-7.365	9.234	1.000	0.000	9.599	0.137	0.134	1.377	0.025	4.782	7.363	7.181
Max	15.491	3.112	16.527	15.381	56.000	62.240	18.390	0.523	1.001	128.181	0.997	29.115	83.254	70.662
Panel B														
Log(O/F)	0.937	1												
Log(F/S)	0.37	0.022	1											
Size	0.339	0.409	-0.117	1										
No. of Strikes	0.678	0.733	-0.01	0.492	1									
Ins. Holding	0.015	0.016	0.001	0.022	0.027	1								
Vol. SSF	0.569	0.525	0.232	0.043	0.502	0.027	1							
Delta	-0.231	-0.236	-0.032	-0.006	-0.06	0.001	-0.126	1						
ATM-IV	0.173	0.229	-0.113	-0.295	0.276	-0.012	0.457	-0.057	1					
% Spread-SSO	-0.706	-0.701	-0.156	-0.376	-0.533	-0.014	-0.426	0.067	-0.184	1				
% Spread-SSF	-0.426	-0.383	-0.203	-0.541	-0.445	-0.029	-0.123	0.014	0.187	0.551	1			
Lev-SSF	0.038	0.011	0.08	0.421	-0.103	0.03	-0.341	0.026	-0.646	-0.029	-0.277	1		
Lev-SSO-VW	0.058	0.03	0.086	0.393	-0.09	0.021	-0.308	-0.148	-0.64	0.052	-0.252	0.628	1	
Lev-SSO-EW	0.037	0.003	0.098	0.392	-0.114	0.021	-0.338	-0.201	-0.658	0.052	-0.263	0.648	0.978	1

The table reports the summary statistics (Panel A) and correlation (Panel B) between the variables used in the study. Log(O/S), Log(O/F), and Log(F/S) are option/stock, option/future, and future/option log volume ratio. Size is a natural log of the firms' market capitalization in million rupees. No. of Strikes is the number of near-month traded contracts of an underlying. Ins. Holding is the proportion of total outstanding shares held by institutional shareholders. Volume SSF is the natural log of the total volume in the near-month futures contract of an underlying. Delta is the average daily delta of all the traded options contracted of an underlying with put options delta being reversed in sign. ATM-IV is the implied volatility of at-the-money options contracts of an underlying. % Spread-SSO is the volume weighted daily average bid-ask spread of all near-month options contracts of an underlying. % Spread-SSF is the bid-ask spread of near-month futures contract of an underlying. Lev-SSF is one by 3.5 time exponentially weighted moving average volatility of the stock. Lev-SSO-VW, and Lev-SSO-EW are the volume and equally weighted embedded leverage of all the options contracts of an underlying. The sample period spans from January 2011 to August 2021.

Table 2: Panel Data Regression: Relative Trading, and Embedded Leverage (Daily Frequency)

Dependent variable:	Log(O/S)				Log(O/F)				Log(F/S)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Size	0.151***	0.879***	0.146***	0.800***	0.082***	0.632***	0.086***	0.582***	−0.016***	0.351***
	(0.004)	(0.023)	(0.004)	(0.023)	(0.004)	(0.019)	(0.004)	(0.019)	(0.002)	(0.014)
No. of Strike	0.032***	0.046***	0.032***	0.047***	0.038***	0.050***	0.038***	0.051***		
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0002)	(0.0003)		
Institutions Holding	−0.0003		−0.0003		−0.0002		−0.0003		−0.0001	
	(0.0002)		(0.0002)		(0.0002)		(0.0002)		(0.0001)	
Volume SSF	0.305***	0.152***	0.299***	0.146***						
	(0.002)	(0.003)	(0.002)	(0.003)						
Delta	−1.954***	−0.830***	−1.697***	−0.508***	−2.147***	−0.969***	−2.061***	−0.779***		
	(0.028)	(0.024)	(0.030)	(0.025)	(0.025)	(0.021)	(0.026)	(0.021)		
ATM-IV	0.414***	0.990***	0.202***	0.981***	1.494***	0.992***	1.146***	0.983***	−0.259***	0.236***
	(0.039)	(0.018)	(0.040)	(0.018)	(0.034)	(0.015)	(0.035)	(0.015)	(0.010)	(0.010)
ATM-IV × Time to Expiry	−6.463***	−7.697***	−4.464***	−7.441***	−5.750***	−8.061***	−2.725***	−8.048***		
	(0.640)	(0.187)	(0.643)	(0.188)	(0.559)	(0.159)	(0.562)	(0.160)		
% Spread-SSO	−0.031***	−0.014***	−0.031***	−0.014***	−0.027***	−0.012***	−0.027***	−0.012***		
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)		
Lev-SSO-VW	0.037***	0.022***			0.028***	0.014***				
	(0.0005)	(0.0003)			(0.0004)	(0.0003)				
Lev-SSO-EW			0.033***	0.025***			0.020***	0.015***		
			(0.001)	(0.0004)			(0.0004)	(0.0003)		
% Spread-SSF									−1.693***	−0.891***
									(0.012)	(0.013)
Lev-SSF									0.010***	0.018***
									(0.0003)	(0.0004)
Firm-Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Date-Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Firm-Month-Year-Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	226,479	226,479	226,479	226,479	226,479	226,479	226,479	226,479	227,906	227,906
Adjusted R^2	0.813	0.903	0.811	0.903	0.834	0.918	0.832	0.918	0.443	0.696

The table reports the estimated coefficients of Eq. 7. Columns (1-4), (5-8), and (9-10) report the results when Log(O/S), Log(O/F), and Log(F/S) are dependent variables, respectively. Log(O/S), Log(O/F), and Log(F/S) are option/stock, option/future, and future/option log volume ratio. All variables are defined in Table A1 . The standard errors are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to August 2021.

Table 3: Cross-Sectional Regression: Relative Trading, and Embedded Leverage (Daily Frequency)

Dependent variable:	Log(O/S)		Log(O/F)		Log(F/S)
	(1)	(2)	(3)	(4)	(5)
Size	−0.163***	−0.150***	−0.009	0.022***	−0.129***
	(0.0055)	(0.0055)	(0.0064)	(0.0038)	(0.0037)
No. of strikes	0.050***	0.050***	0.059***	0.058***	
	(0.0024)	(0.0024)	(0.0021)	(0.0020)	
Institutions Holding	−0.002***	−0.002***	−0.001***	−0.001***	−0.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Volume SSF	0.332***	0.333***			
	(0.0072)	(0.0075)			
Delta	−2.063***	−1.832***	−3.140***	−3.314***	
	(0.0779)	(0.0888)	(0.0862)	(0.0938)	
ATM-IV × Time to Expiry	−9.020***	−18.665***	46.200***	20.448***	
	(2.3133)	(2.1874)	(2.2082)	(1.7400)	
% Spread-SSO	−0.041***	−0.040***	−0.037***	−0.037***	
	(0.0016)	(0.0015)	(0.0010)	(0.0010)	
Lev-SSO-VW	0.050***		0.042***		
	(0.0021)		(0.0022)		
Lev-SSO-EW		0.039***		0.013***	
		(0.0021)		(0.0022)	
ATM-IV					0.331***
					(0.0533)
Spread-SSF					−2.107***
					(0.0939)
Lev-SSF					0.003**
					(0.0013)
Constant	−3.949***	−3.853***	−2.067***	−1.413***	2.455***
	(0.1776)	(0.1819)	(0.1106)	(0.1042)	(0.0738)
Observations	226479	226479	226479	226479	227906
Adjusted R^2	0.74	0.735	0.684	0.676	0.202

The table reports the estimated coefficients of Fama and MacBeth (1973) type cross-sectional regression (Eq. 8), estimated at daily frequency. We first estimate the cross-sectional regression at daily frequency and obtain the coefficients of the respective independent variables. Our first step gives us a time series of coefficients for each independent variable. These coefficients are then averaged, and the corresponding t-statistic is calculated using the Newey and West (1987) standard errors with 12 lags. Columns (1-2), (3-4), and 5 report the results when Log(O/S), Log(O/F), and Log(F/S) are dependent variables, respectively. Log(O/S), Log(O/F), and Log(F/S) are option/stock, option/future, and future/option log volume ratio. All variables are defined in Table A1 . Newey and West (1987) adjusted standard errors with 12 lags are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to August 2021.

Table 4: Options Contracts Volume and Embedded Leverage

Panel A

	ATM Call		OTM Call	
Dependent variable:	Vol Ratio			
	(1)	(2)	(3)	(4)
Leverage	0.032***	0.065***	0.030***	0.020***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Spread-SSO	−1.991***	−2.638***	−2.375***	−2.821***
	(0.008)	(0.008)	(0.005)	(0.004)
Firm-Fixed Effects	Yes	Yes	Yes	Yes
Date-Fixed Effects	No	Yes	No	Yes
Observations	1,099,561	1,099,561	1,140,668	1,140,668
Adjusted R^2	0.172	0.310	0.253	0.371

Panel B

	ATM Put		OTM Put	
Dependent variable:	Vol Ratio			
	(1)	(2)	(3)	(4)
Leverage	0.029***	0.060***	0.027***	0.026***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Spread-SSO	−1.494***	−2.035***	−1.999***	−2.327***
	(0.008)	(0.008)	(0.004)	(0.004)
Firm-Fixed Effects	Yes	Yes	Yes	Yes
Date-Fixed Effects	No	Yes	No	Yes
Observations	1,003,226	1,003,226	863,900	863,900
Adjusted R^2	0.164	0.296	0.270	0.383

The table reports the estimated coefficients of Eq. 9. In Panel A Columns (1-2) and (3-4) report the coefficients when the regression model is estimated using ATM Call and OTM Call subsamples, respectively. Similarly, Panel B Columns (1-2) and (3-4) report the coefficients when the regression model is estimated using ATM Put and OTM Put subsamples, respectively. All variables are defined in Table A1 . Standard errors are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to August 2021.

Table 5: Univariate Analysis: Embedded Leverage, Relative Volume and COVID 19 Crisis

Panel A				
Quintile Lev-SSO-VW	Mean Log(O/S) (1)	t-stat (2)	Mean Log(O/F) (3)	t-stat (4)
1 (Lowest)	−1.552	−17.911	−1.403	−15.694
2	−1.1710	−13.034	−1.243	−15.062
3	−0.910	−11.272	−1.124	−15.124
4	−0.662	−7.713	−1.010	−12.894
5 (Highest)	−0.159	−1.510	−0.654	−6.768
5-1	1.393***	11.553	0.748***	6.360
Panel B:				
Quintile Lev-SSO-EW	Mean Log(O/S) (1)	t-stat (2)	Mean Log(O/F) (3)	t-stat (4)
1 (Lowest)	−1.557	−17.908	−1.4017	−15.673
2	−1.1374	−12.837	−1.2179	−14.979
3	−0.939	−11.404	−1.137	−15.103
4	−0.613	−7.45	−0.968	−12.828
5 (Highest)	−0.209	−1.925	−0.709	−7.143
5-1	1.348***	10.928	0.691***	5.779
Panel C:				
Quintile Lev-SSF	Mean Log(F/S) (1)	t-stat (2)		
1 (Lowest)	−0.142	−4.915		
2	0.062	2.698		
3	0.211	9.617		
4	0.440	17.380		
5 (Highest)	0.554	25.989		
5-1	0.697***	19.935		

The table reports the univariate relationship of Log(O/S), Log(O/F), and Log(F/S) with embedded leverage during COVID 19 period. In Panel A, B, and C we first divide our sample into quintiles using Lev-SSO-VW, Lev-SSO-EW, and Lev-SSF, respectively and then estimate the mean value of Log(O/S), Log(O/F), and Log(F/S) for each quintile. The last row (5-1) of each panel reports the difference in mean between quintiles 1 and 5. All variables are defined in Table A1 . t-stat (reported in columns (2) and (4)) are estimated using Newey and West (1987) adjusted standard errors with 12 lags. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from February 2020 to May 2020.

Table 6: Panel Regression: Embedded Leverage, Relative Volume, and COVID 19 Crisis

Dependent variable:	Log(O/S)				Log(O/F)				Log(F/S)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Size	0.150***	0.817***	0.144***	0.729***	0.080***	0.583***	0.084***	0.526***	−0.017***	0.339***
	(0.004)	(0.023)	(0.004)	(0.023)	(0.004)	(0.019)	(0.004)	(0.020)	(0.002)	(0.014)
No. of Strikes	0.031***	0.045***	0.032***	0.047***	0.038***	0.050***	0.038***	0.051***		
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0002)	(0.0003)		
Institutions Holding	−0.0003		−0.0003		−0.0003		−0.0003		−0.0001	
	(0.0002)		(0.0002)		(0.0002)		(0.0002)		(0.0001)	
Volume SSF	0.305***	0.153***	0.299***	0.147***						
	(0.002)	(0.003)	(0.002)	(0.003)						
Delta	−1.953***	−0.818***	−1.693***	−0.487***	−2.146***	−0.960***	−2.057***	−0.762***		
	(0.028)	(0.024)	(0.030)	(0.025)	(0.025)	(0.020)	(0.026)	(0.021)		
ATM-IV	0.438***	1.039***	0.227***	1.034***	1.518***	1.032***	1.168***	1.026***	−0.257***	0.244***
	(0.040)	(0.018)	(0.040)	(0.018)	(0.035)	(0.015)	(0.035)	(0.015)	(0.010)	(0.010)
ATM-IV × Time to Expiry	−6.663***	−7.271***	−4.687***	−6.945***	−5.958***	−7.721***	−2.912***	−7.656***		
	(0.640)	(0.187)	(0.644)	(0.188)	(0.559)	(0.160)	(0.563)	(0.161)		
% Spread-SSO	−0.031***	−0.014***	−0.031***	−0.014***	−0.027***	−0.012***	−0.027***	−0.012***		
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)		
Lev-SSO-VW	0.037***	0.022***			0.028***	0.014***				
	(0.0005)	(0.0003)			(0.0004)	(0.0003)				
Lev-SSO-EW			0.033***	0.025***			0.020***	0.015***		
			(0.001)	(0.0004)			(0.0004)	(0.0003)		
% Spread-SSF									−1.693***	−0.887***
									(0.012)	(0.013)
Lev-SSF									0.010***	0.017***
									(0.0003)	(0.0005)
Lev-SSO-VW × COVID	0.012***	0.046***			0.012***	0.036***				
	(0.002)	(0.002)			(0.002)	(0.001)				
Lev-SSO-EW × COVID			0.014***	0.052***			0.011***	0.041***		
			(0.002)	(0.002)			(0.002)	(0.001)		
Lev-SSF × COVID									0.005***	0.011***
									(0.001)	(0.002)
Firm-Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Date-Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Firm-Month-Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	226,479	226,479	226,479	226,479	226,479	226,479	226,479	226,479	227,906	227,906
Adjusted R^2	0.813	0.903	0.811	0.904	0.834	0.918	0.832	0.919	0.443	0.696

The table reports the estimated coefficients of Eq. 10. In Columns (1-4), (5-8), and (9-10) Log(O/S), Log(O/F), and Log(F/S) are dependent variable, respectively. COVID is a dummy variable that takes the value one for trading days between February 2020 to May 2020, and 0 otherwise. All variables are defined in Table A1 . Standard errors are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to August 2021.

Table 7: Earnings Announcements, Embedded Leverage, and Relative Volume

Dependent variable:	Log(O/S)		Log(O/F)		Log(F/S)
	(1)	(2)	(3)	(4)	(5)
Lev-SSO-VW	0.026***		0.017***		
	(0.002)		(0.002)		
Lev-SSO-EW		0.023***		0.009***	
		(0.002)		(0.002)	
Lev-SSF					0.012***
					(0.002)
TD[-2]	0.063	0.073*	0.023	0.030	0.020
	(0.042)	(0.042)	(0.036)	(0.036)	(0.029)
TD[-1]	0.125***	0.097**	0.076**	0.068*	0.011
	(0.044)	(0.045)	(0.038)	(0.039)	(0.030)
EA Day	0.048	0.025	0.158***	0.152***	−0.031
	(0.048)	(0.049)	(0.041)	(0.042)	(0.031)
Lev-SSO-VW × TD[-2]	−0.001		0.0002		
	(0.002)		(0.002)		
Lev-SSO-VW × TD[-1]	0.004*		0.004**		
	(0.002)		(0.002)		
Lev-SSO-VW × EA Day	0.015***		0.014***		
	(0.002)		(0.002)		
Lev-SSO-EW × TD[-2]		−0.002		−0.0003	
		(0.002)		(0.002)	
Lev-SSO-EW × TD[-1]		0.005**		0.004**	
		(0.002)		(0.002)	
Lev-SSO-EW × EA Day		0.017***		0.015***	
		(0.003)		(0.002)	
Lev-SSF × TD[-2]					−0.001
					(0.002)
Lev-SSF × TD[-1]					0.003
					(0.002)
Lev-SSF × EA Day					0.009***
					(0.002)
Controls	Yes	Yes	Yes	Yes	Yes
Firm-Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Date-Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Observations	14,854	14,854	14,854	14,854	14,912
Adjusted R^2	0.815	0.814	0.834	0.833	0.447

The table reports the estimated coefficients of Eq. 11. In Columns (1-2), (3-4), and (5) Log(O/S), Log(O/F), and Log(F/S) are dependent variable, respectively. TD[-2], TD[-1], and EA Day are dummy variables that take the value one for two trading days before EA day, one trading day before EA day, and EA announcement day, and zero otherwise. Controls include Size, No. of Strikes, Institutional Holding, Volume SSF, Delta, ATM-IV, % Spread-SSO, % Spread-SSF, and BHAR[-1,+1]. All variables are defined in Table A1 . Standard errors are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. All EAs during the sample period of January 2011 to August 2021 are considered in the analysis.

Table 8: Embedded Leverage, Relative Volume, and IVOL

Panel A				
Dependent variable:	IVOL			
	(1)	(2)	(3)	(4)
Size				−0.002***
				(0.0001)
Institutions Holding				0.00002*
				(0.00001)
ATM-IV				0.018***
				(0.001)
Pre Log(O/S)	−0.051***	−0.035***	−0.030***	−0.004**
	(0.001)	(0.001)	(0.001)	(0.002)
Constant	−0.038***			
	(0.001)			
Firm-Level-Fixed Effects	No	Yes	Yes	Yes
Month-Year-Fixed Effects	No	No	Yes	Yes
Observations	20,643	20,643	20,643	20,478
Adjusted R^2	0.143	0.208	0.315	0.346

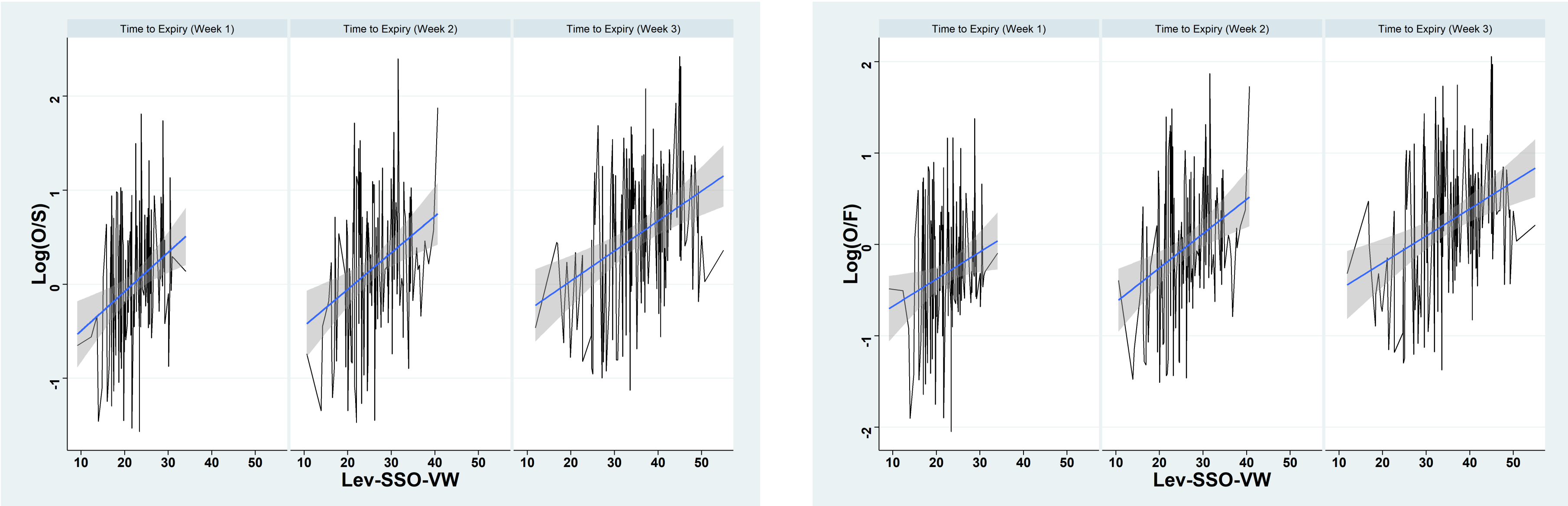
Panel B				
Dependent variable:	IVOL			
	(1)	(2)	(3)	(4)
Size				−0.002***
				(0.0001)
Institutions Holding				0.00002*
				(0.00001)
ATM-IV				0.018***
				(0.001)
Pre Log(O/F)	−0.123***	−0.084***	−0.074***	−0.011**
	(0.002)	(0.003)	(0.003)	(0.004)
Constant	−0.191***			
	(0.004)			
Firm-Level-Fixed Effects	No	Yes	Yes	Yes
Month-Year-Fixed Effects	No	No	Yes	Yes
Observations	20,643	20,643	20,643	20,478
Adjusted R^2	0.143	0.208	0.315	0.346

Panel C				
Dependent variable:	IVOL			
	(1)	(2)	(3)	(4)
Size				−0.002***
				(0.0001)
Institutions Holding				0.00002*
				(0.00001)
ATM-IV				0.017***
				(0.001)
Pre Log(F/S)	−0.104***	−0.068***	−0.059***	−0.020***
	(0.002)	(0.002)	(0.003)	(0.003)
Constant	0.079***			
	(0.001)			
Firm-Level-Fixed Effects	No	Yes	Yes	Yes
Month-Year-Fixed Effects	No	No	Yes	Yes
Observations	20,643	20,643	20,643	20,478
Adjusted R^2	0.144	0.206	0.316	0.348

The table reports the estimated coefficients of Eq. 13. Panel A, B, and C report the results of Eq. 13 using Pre Log(O/S), Pre Log(O/F), and Pre Log(F/S) as independent variables, respectively. Pre Log(O/S), Pre Log(O/F), and Pre Log(F/S) are predicted values of Log(O/S), Log(O/F), and Log(F/S) using regression Eq. (12). All the regressions are estimated at monthly frequency, we convert variable available at daily frequency in monthly frequency by averaging the over month-year. All variables are defined in Table A1 . Standard errors are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to March 2021.

A Appendix - Figures and Tables

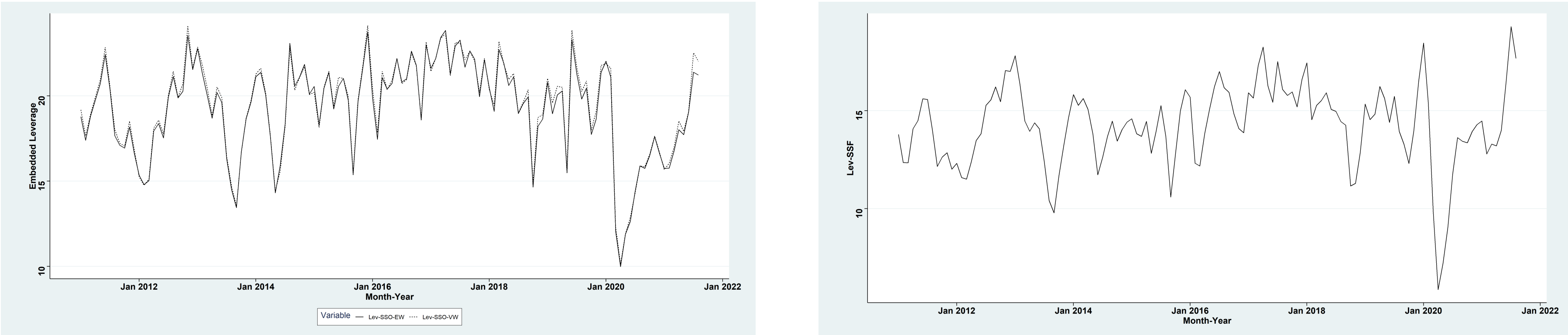
Figure A1 : Log(O/S), Log(O/F), and Embedded Leverage



(a) (b)

Figures show the univariate relationship of Log(O/S), and Log(O/F) with embedded leverage along with a fitted trend line for Tata Consultancy Services (TCS) on a weekly frequency. Every near-month option series of TCS is first divided into four weeks (Week 1, 2, 3, and 4), and then average Log(O/S), Log(O/F), and Lev-SSO-VW are estimated for each week separately for each series. Week 4 values are removed because that is the expiry week. In Panel (a) and (b) we plot the weekly average of Log(O/S) and Log(O/F) against the weekly average Lev-SSO-VW, respectively for weeks 1, 2, and 3 separately. All variables are defined in Table A1 . The sample period spans from January 2011 to August 2021.

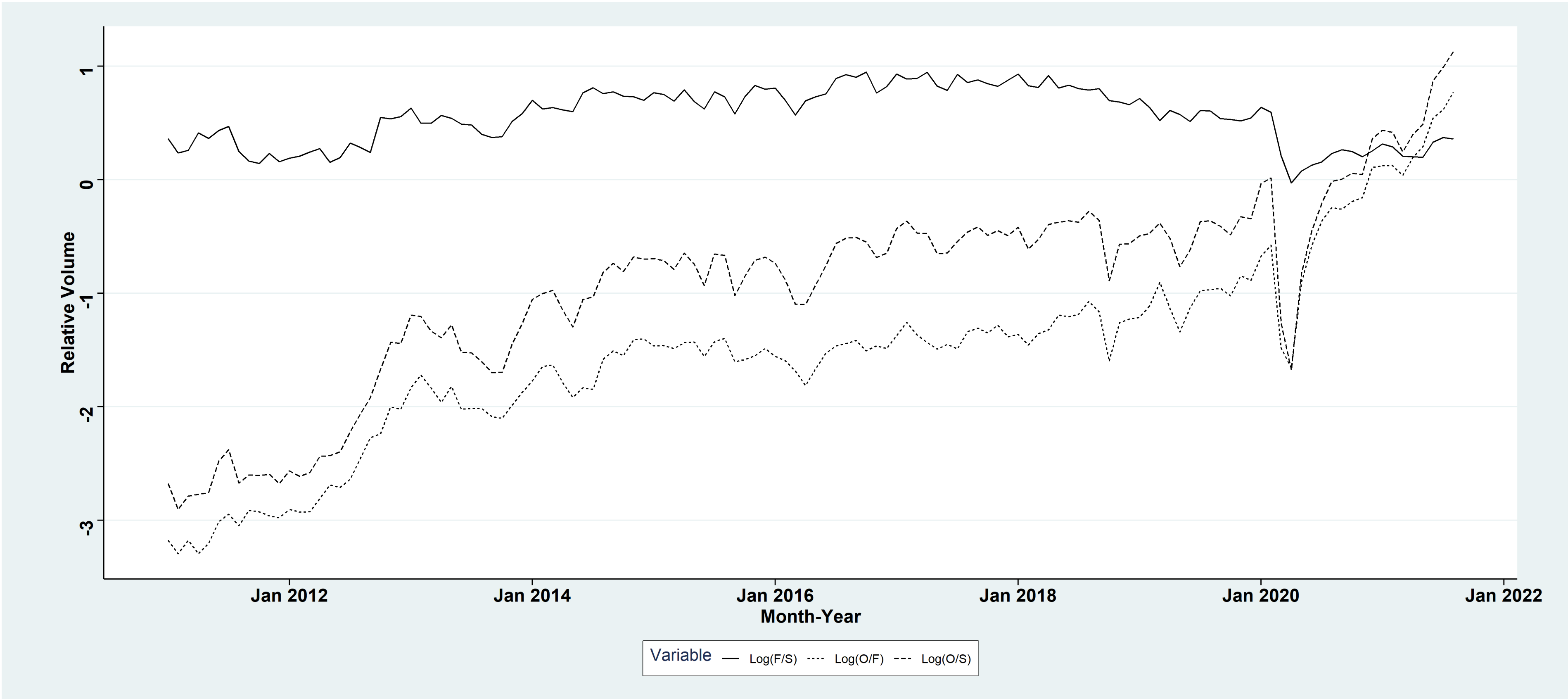
Figure A2 : Embedded Leverage (Time Series)



(a) (b)

Figures show the time series average of embedded leverage measures at a monthly frequency. Panel (a) shows trends of Lev-SSO-VW and Lev-SSO-VW, and Panel (b) shows trends of Lev-SSF. Lev-SSO-VW, Lev-SSO-EW, and Lev-SSF are estimated by taking the average of their daily values at the month-year level. All variables are defined in Table A1 . The sample period spans from January 2011 to August 2021.

Figure A3 : Relative Volume (Time Series)



Figures show the time series average of Log(O/S), Log(O/F), and Log(F/S) at a monthly frequency. Log(O/S), Log(O/F), and Log(F/S) are estimated by taking the average of their daily values at the month-year level. All variables are defined in Table A1 . The sample period spans from January 2011 to August 2021.

Table A1 : Variable Construction Details

Variable Name	Variable Definition	Source
Log(O/S)	Natural logarithm of the ratio of total options volume in near month contracts with total stock volume	NSE Bhav Files & CMIE Prowess
Log(O/F)	Natural logarithm of the ratio of total options volume in near month contracts with total futures volume in near month contracts	NSE Bhav Files
Log(F/S)	Natural logarithm of the ratio of total futures volume in near month contracts with total stock volume	NSE Bhav Files & CMIE Prowess
Log(ATM-O/S)	Natural logarithm of the ratio of total at-the-money options volume in near month contracts with total stock volume	NSE Bhav Files & CMIE Prowess
Log(ATM-O/F)	Natural logarithm of the ratio of total at-the-money options volume in near month contracts with total futures volume in near month contracts	NSE Bhav Files
Vol Ratio	Log of the ratio of volume in a contract with total volume across contracts of an underlying in a particular category (For every underlying we define the category as ATM-Call, OTM-Call, ATM-Put, OTM-Put)	NSE Bhav Files
Size	Natural logarithm of the firms' market capitalization in million rupees	CMIE Prowess
BHAR[-1,+1]	For a trading day buy and hold return from one trading day before to one trading day after	CMIE Prowess
No. of Strikes	Number of traded near month options contracts of an underlying	NSE Bhav Files
Institutional Holding	Percentage of total outstanding shares held by institutional investors	CMIE Prowess
Volume SSF	Natural logarithm of total volume in near month futures contracts	NSE Bhav Files
Delta	Average daily delta of all the traded options contracts of an underlying (with put deltas being reversed in sign)	NSE Bhav Files
Time to Expiry	Time period remaining before expiry day defined as number of days before expiry/365	NSE Bhav Files
ATM-IV	Implied volatility of at-the-money options contracts ($0.95 \leq moneyness(strike\ price/stock\ price) \leq 1.05$) estimated using Black (1976) model. For underlying having multiple options contract in the stipulated moneyness range, we take the volume weighted average of implied volatility.	NSE Bhav Files

Table A1 : Variable Construction Details

Variable Name	Variable Definition	Source
% Spread-SSO	Volume weighted daily average Bid-Ask spread ($\frac{Ask-Bid}{Ask+Bid/2} \times 100$) of all near month options contracts of an underlying	NSE Order Book Snapshot
% Spread-SSF	Bid-Ask spread ($\frac{Ask-Bid}{Ask+Bid/2} \times 100$) of near month future contracts of an underlying	NSE Order Book Snapshot
Spread Ratio	Ratio of % Spread-SSO and % Spread-SSF ($\frac{\%Spread-SSO}{\%Spread-SSF}$)	NSE Order Book Snapshot
Lev-SSF	One divided by 3.5 times exponentially weighted moving average volatility of the underlying estimated by taking lambda = 0.94	CMIE Prowess
Leverage	$\Omega_{i,j,t} = \lvert \frac{\partial O_{i,j,t}}{\partial S_{j,t}} \frac{S_{j,t}}{O_{i,j,t}} \rvert$. Where, $\Omega_{i,j,t}$ is embedded leverage of contract i of underlying j at day t. $O_{i,j,t}$ is the price of options contract i of underlying j at day t, and $S_{j,t}$ is stock price.	NSE Bhav Files & CMIE Prowess
Lev-SSO-VW	Volume weighted daily average leverage ($\frac{\sum_{i=1}^{n} Vol_{i,j,t} \times \Omega_{i,j,t}}{\sum_{i=1}^{n} Vol_{i,j,t}}$) of all near month options contract of an underlying	NSE Bhav Files
Lev-SSO-EW	Equally weighted daily average leverage ($\frac{\sum_{i=1}^{n} \Omega_{i,j,t}}{n}$) of all near month options contract of an underlying	NSE Bhav Files & CMIE Prowess
IVOL	Idiosyncratic volatility estimated by first regressing daily returns of a stock on Fama and French (1993)-Carhart (1997) four factor daily return within a year, and then estimating standard deviation of the residuals every month.	CMIE Prowess
TD[-2]	A dummy variable that takes the value one for trading days that are two days before EA day and zero otherwise	NSE Website
TD[-1]	A dummy variable that takes the value one for trading days that are one day before EA day and zero otherwise	NSE Website
EA Day	A dummy variable that takes the value one for EA day and zero otherwise	NSE Website

Table A2: Earnings Announcements, and Relative Options to Spot and Futures Volume

Dependent variable:	Log(O/S)		Log(O/F)		Log(F/S)
	(1)	(2)	(3)	(4)	(5)
Size	0.203***	0.197***	0.107***	0.111***	0.010
	(0.016)	(0.017)	(0.014)	(0.014)	(0.010)
No. of Strikes	0.024***	0.025***	0.030***	0.030***	
	(0.001)	(0.001)	(0.001)	(0.001)	
Institutions Holding	0.0004	0.0004	−0.0002	−0.0003	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Volume-SSF	0.279***	0.276***			
	(0.009)	(0.009)			
Delta	−1.816***	−1.610***	−2.282***	−2.269***	
	(0.114)	(0.120)	(0.099)	(0.104)	
ATM-IV	0.011	−0.086	1.005***	0.815***	−0.193***
	(0.079)	(0.079)	(0.068)	(0.068)	(0.041)
% Spread-SSO	−0.033***	−0.033***	−0.029***	−0.029***	
	(0.0005)	(0.0005)	(0.0004)	(0.0004)	
% Spread-SSF					−1.688***
					(0.051)
BHAR[-1,+1]	−0.330**	−0.437***	−0.141	−0.206*	0.271***
	(0.134)	(0.135)	(0.116)	(0.116)	(0.081)
Lev-SSO-VW	0.028***		0.020***		
	(0.002)		(0.002)		
Lev-SSO-EW		0.025***		0.011***	
		(0.002)		(0.002)	
Lev-SSF					0.015***
					(0.001)
TD[-2]	0.042**	0.038**	0.028**	0.024*	0.012
	(0.016)	(0.016)	(0.014)	(0.014)	(0.010)
TD[-1]	0.192***	0.187***	0.147***	0.141***	0.053***
	(0.017)	(0.017)	(0.015)	(0.015)	(0.010)
EA Day	0.313***	0.317***	0.411***	0.410***	0.092***
	(0.019)	(0.019)	(0.016)	(0.016)	(0.011)
Firm-Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Date-Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Observations	14,854	14,854	14,854	14,854	14,912
Adjusted R^2	0.814	0.813	0.834	0.832	0.446

The table reports the estimated coefficients of following regression model:

$$Var_{j,t} = \beta\ Embedded\ Leverage_{j,t} + \sum_{i=-1}^{-3} \beta_i TD[i] + \delta_1 EA\ Day + \sum_{i=1}^{n} \beta_i Control_{i,j,t} + \gamma_j + \eta_t + \epsilon_{j,t} \tag{14}$$

In Columns (1-2), (3-4), and (5) Log(O/S), Log(O/F), and Log(F/S) are dependent variable, respectively. TD[-2], TD[-1], and EA Day are dummy variables that take the value one for two trading days before EA day, one trading day before EA day, and EA announcement day, and zero otherwise. All variables are defined in Table A1 . Standard errors are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. All EA during the sample period of January 2011 to August 2021 are considered in the analysis.

Table A3 : Univariate Analysis: Embedded Leverage, Relative Volume, and IVOL

Panel A

Qartile Log(O/S) (1)	IVOL (2)	t-stat (3)	Qartile Pre Log(O/S) (4)	IVOL (5)	t-stat (6)	Qartile Res Log(O/S) (7)	IVOL (8)	t-stat (9)
1	0.0186	83.14	1	0.0237	77.09	1	0.0185	84.34
2	0.0189	76.53	2	0.0191	123.94	2	0.0188	75.66
3	0.0187	77.74	3	0.0168	146.45	3	0.0187	78.75
4	0.0177	85.09	4	0.0144	117.79	4	0.0180	82.64
4-1	−0.0009***	−3.11		−0.0092***	−28.16		−0.0005	−1.66

Panel B

Qartile Log(O/F) (1)	IVOL (2)	t-stat (3)	Qartile Pre Log(O/F) (4)	IVOL (5)	t-stat (6)	Qartile Res Log(O/F) (7)	IVOL (8)	t-stat (9)
1	0.0181	94.95	1	0.0237	77.09	1	0.0181	94.78
2	0.0183	89.05	2	0.0191	123.94	2	0.0183	88.95
3	0.0190	79.51	3	0.0168	146.45	3	0.0189	79.41
4	0.0185	59.60	4	0.0144	117.79	4	0.0186	59.71
4-1	0.0003	0.87		−0.0092***	−28.16		0.0005	1.45

Panel C

Qartile Log(F/S) (1)	IVOL (2)	t-stat (3)	Qartile Pre Log(F/S) (4)	IVOL (5)	t-stat (6)	Qartile Res Log(F/S) (7)	IVOL (8)	t-stat (9)
1	0.0203	59.28	1	0.0236	77.55	1	0.0199	58.03
2	0.0181	88.58	2	0.0189	137.78	2	0.0182	89.01
3	0.0178	104.18	3	0.0170	124.90	3	0.0180	102.34
4	0.0178	102.17	4	0.0144	124.72	4	0.0180	103.26
4-1	−0.0024***	−6.73		−0.0091***	−28.51		−0.0018***	−5.08

The table reports the univariate relationship of actual, predicted, and residual relative volume ratios (Log(O/S), Log(O/F), Log(F/S)) with idiosyncratic vol (IVOL). The predicted volume ratios are estimated using Eq. 12, and residual volume ratios are defined as the difference between actual and predicted volume ratios. Panel A, B, and C report univariate relation between actual, predicted, and residual Log(O/S), Log(O/F), and Log(F/S), and next month's IVOL, respectively. Columns (2), (5), and (8) report the mean value of IVOL for each quartile formed using volume ratios. The last row (4-1) of each panel reports the difference in mean between quartiles 1 and 4. All variables are defined in Table A1 . t-stats are estimated (reported in columns (3), (6), and (9)) using Newey and West (1987) adjusted standard errors with 12 lags. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to March 2021.

Table A4: Panel Regression: Relative Volume and Embedded Leverage (including expiry week)

Dependent variable:	Log(O/S)		Log(O/F)		Log(F/S)
	(1)	(2)	(3)	(4)	(5)
Size	0.167***	0.156***	0.098***	0.099***	−0.037***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
No. of Strikes	0.030***	0.031***	0.037***	0.037***	
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	
Institutions Holding	−0.0002	−0.0002	−0.0002	−0.0002	−0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Volume-SSF	0.289***	0.287***			
	(0.002)	(0.002)			
Delta	−1.834***	−1.604***	−2.144***	−2.102***	
	(0.022)	(0.023)	(0.020)	(0.021)	
ATM-IV	0.457***	0.267***	1.294***	1.027***	−0.362***
	(0.024)	(0.024)	(0.022)	(0.021)	(0.009)
ATM-IV × Time to Expiry	−10.623***	−8.355***	−7.406***	−4.190***	
	(0.435)	(0.429)	(0.385)	(0.381)	
% Spread-SSO	−0.028***	−0.029***	−0.026***	−0.026***	
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Lev-SSO-VW	0.020***		0.012***		
	(0.0003)		(0.0002)		
Lev-SSO-EW		0.020***		0.008***	
		(0.0003)		(0.0003)	
% Spread-SSF					−1.723***
					(0.011)
Lev-SSF					0.014***
					(0.0003)
Firm-Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Date-Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Observations	305,558	305,558	305,558	305,558	307,927
Adjusted R^2	0.812	0.811	0.832	0.831	0.541

The table reports the coefficients of Eq. 7 estimated using sample that includes expiry week data. In Columns (1)-(2), (3)-(4), and (5) Log(O/S), Log(O/F), and Log(F/S) are dependent variables respectively. Lev-SSO-VW and Lev-SSO-EW are the volume and equally weighted embedded leverage of all the options contracts of an underlying. Lev-SSF is one by 3.5 times the exponentially weighted moving average volatility of the stock. All variables are defined in Table A1 . Standard errors are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to August 2021.

Table A5: Panel Regression: Relative Volume and Lagged Embedded Leverage (Daily Frequency)

Dependent variable:	Log(O/S)		Log(O/F)		Log(F/S)
	(1)	(2)	(3)	(4)	(5)
Size	0.140***	0.134***	0.073***	0.073***	−0.016***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)
No. of Strikes	0.030***	0.031***	0.037***	0.037***	
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	
Institutions Holding	−0.0002	−0.0003	−0.0002	−0.0002	−0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Volume-SSF	0.307***	0.306***			
	(0.002)	(0.002)			
Delta	−2.224***	−2.201***	−2.374***	−2.372***	
	(0.028)	(0.029)	(0.025)	(0.025)	
ATM-IV	−0.114***	−0.201***	1.058***	0.905***	−0.277***
	(0.040)	(0.040)	(0.035)	(0.035)	(0.010)
ATM-IV × Time to Expiry	−2.525***	−1.690**	−2.174***	−0.783	
	(0.699)	(0.699)	(0.610)	(0.611)	
% Spread-SSO	−0.033***	−0.033***	−0.029***	−0.029***	
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	
Lag Lev-SSO-VW	0.032***		0.023***		
	(0.0005)		(0.0004)		
Lag Lev-SSO-EW		0.031***		0.019***	
		(0.001)		(0.0004)	
% Spread-SSF					−1.690***
					(0.012)
Lag Lev-SSF					0.009***
					(0.0003)
Firm-Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Date-Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Observations	208,194	208,194	208,194	208,194	227,698
Adjusted R^2	0.807	0.806	0.830	0.829	0.442

The table reports the coefficients of Eq. 7. In Columns (1)-(2), (3)-(4), and (5) Log(O/S), Log(O/F), and Log(F/S) are dependent variables respectively. Lag Lev-SSO-VW and Lag Lev-SSO-EW are the volume and equally weighted embedded leverage of all the options contracts of an underlying lagged by one day. Lag Lev-SSF one by 3.5 time the exponentially weighted moving average volatility of the stock lagged by one day. All variables are defined in Table A1 . Standard errors are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to August 2021.

Table A6: Cross-Sectional Regression: Relative Volume and Lagged Embedded Leverage (Daily Frequency)

Dependent variable:	Log(O/S)		Log(O/F)		Log(F/S)
	(1)	(2)	(3)	(4)	(5)
Size	−0.161***	−0.152***	−0.006	0.013*	−0.129***
	(0.0055)	(0.0054)	(0.0066)	(0.0069)	(0.0038)
No. of Strikes	0.049***	0.048***	0.057***	0.057***	
	(0.0023)	(0.0023)	(0.0019)	(0.0019)	
Institutions Holding	−0.002***	−0.002***	−0.001***	−0.001***	−0.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Volume SSF	0.331***	0.333***			
	(0.0075)	(0.0076)			
Delta	−2.341***	−2.341***	−3.396***	−3.449***	
	(0.0824)	(0.0842)	(0.0903)	(0.0927)	
ATM-IV × Time to Expiry	−18.823***	−24.577***	38.903***	24.805***	
	(2.0457)	(1.9444)	(1.9820)	(1.6295)	
% Spread−SSO	−0.042***	−0.042***	−0.038***	−0.038***	
	(0.0015)	(0.0015)	(0.0010)	(0.0010)	
Lag Lev-SSO-VW	0.043***		0.035***		
	(0.0017)		(0.0016)		
Lag Lev-SSO-EW		0.037***		0.018***	
		(0.0017)		(0.0017)	
ATM-IV					−0.167***
					(0.0630)
% Spread-SSF					−2.104***
					(0.0939)
Lag Lev-SSF					0.02*
					(0.0013)
Constant	−3.521***	−3.454***	−1.675***	−1.356***	2.469***
	(0.1648)	(0.1629)	(0.1052)	(0.0984)	(0.0732)
Observations	208194	208194	208194	208194	227698
Adjusted R^2	0.735	0.732	0.675	0.671	0.202

The table reports the estimated coefficients of Fama and MacBeth (1973) type cross-sectional regression (Eq. 8), estimated at daily frequency. We first estimate the cross-sectional regression at daily frequency and obtain the coefficients of the respective independent variables. Our first step gives us a time series of coefficients for each independent variable. These coefficients are then averaged, and the corresponding t-statistic is calculated using the Newey and West (1987) standard errors with 12 lags. Columns (1-2), (3-4), and (5) report the results when Log(O/S), Log(O/F), and Log(F/S) are dependent variables, respectively. Log(O/S), Log(O/F), and Log(F/S) are option/stock, option/future, and future/option log volume ratio. Lag Lev-SSO-VW and Lag Lev-SSO-EW are the volume and equally weighted embedded leverage of all the options contracts of an underlying lagged by one day. Lag Lev-SSF one by 3.5 time the exponentially weighted moving average volatility of the stock lagged by one day. All variables are defined in Table A1 . Newey and West (1987) adjusted standard errors with 12 lags are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to August 2021.

Table A7: Panel Regression: Log(O/F) and Embedded Leverage of SSO and SSF

Dependent variable:	Log(O/F)					
	(1)	(2)	(3)	(4)	(5)	(6)
Size		0.370***	1.282***		0.375***	1.240***
		(0.004)	(0.021)		(0.004)	(0.021)
Institutions Holding		0.0005**			0.0005**	
		(0.0002)			(0.0002)	
Delta		−2.028***	−0.576***		−1.936***	−0.432***
		(0.026)	(0.022)		(0.028)	(0.023)
ATM-IV		2.213***	1.739***		1.776***	1.736***
		(0.037)	(0.016)		(0.037)	(0.016)
ATM-IV × Time to Expiry		−1.715***	−9.974***		2.450***	−10.627***
		(0.600)	(0.170)		(0.607)	(0.170)
Lev-SSF	−0.012***	−0.017***	−0.006***	−0.012***	−0.013***	−0.006***
	(0.0005)	(0.0005)	(0.001)	(0.0005)	(0.001)	(0.001)
Spread Ratio	−0.006***	−0.005***	−0.002***	−0.006***	−0.005***	−0.002***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Lev-SSO-VW		0.036***	0.014***			
		(0.0005)	(0.0003)			
Lev-SSO-EW					0.024***	0.013***
					(0.001)	(0.0003)
Firm-Fixed Effects	Yes	Yes	No	Yes	Yes	No
Date-Fixed Effects	Yes	Yes	No	Yes	Yes	No
Firm-Month-Year-Fixed Effects	No	No	Yes	No	No	Yes
Observations	231,986	226,460	226,460	231,986	226,460	226,460
Adjusted R^2	0.784	0.809	0.906	0.784	0.806	0.906

The table reports the estimated coefficients of Eq. 7 when the dependent variable is Log(O/F). Lev-SSO-VW and Lev-SSO-EW are the volume and equally weighted embedded leverage of all the options contracts of an underlying. The spread ratio is the ratio of % Spread-SSO with % Spread-SSF. All variables are defined in Table A1 . Standard errors are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to August 2021.

Table A8: Panel Regression: Relative Volume, and Embedded Leverage (Monthly Frequency)

Dependent variable:	Log(O/S)		Log(O/F)			Log(F/S)
	(1)	(2)	(3)	(4)	(5)	(6)
Size	0.091***	0.085***	0.067***	0.067***	0.327***	−0.038***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)	(0.007)
No. of Strikes	0.033***	0.033***	0.038***	0.038***		
	(0.001)	(0.001)	(0.001)	(0.001)		
Institutions Holding	−0.001	−0.001	−0.0001	−0.0001	0.001	−0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)
Volume-SSF	0.354***	0.356***				
	(0.009)	(0.009)				
Delta	−2.714***	−2.631***	−3.173***	−3.222***	−2.988***	
	(0.130)	(0.132)	(0.117)	(0.120)	(0.118)	
ATM-IV	−0.427***	−0.491***	1.343***	1.174***	2.267***	−0.447***
	(0.075)	(0.075)	(0.067)	(0.068)	(0.065)	(0.035)
% Spread-SSO	−0.031***	−0.031***	−0.028***	−0.028***		
	(0.0003)	(0.0003)	(0.0003)	(0.0003)		
Spread Ratio					−0.007***	
					(0.0001)	
Lev-SSO-VW	0.036***		0.029***		0.047***	
	(0.002)		(0.001)		(0.002)	
Lev-SSO-EW		0.035***		0.023***		
		(0.002)		(0.002)		
% Spread-SSF						−1.538***
						(0.032)
Lev-SSF					−0.018***	0.007***
					(0.002)	(0.001)
Firm-Level-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,437	17,437	17,437	17,437	17,436	17,691
Adjusted R^2	0.901	0.901	0.907	0.906	0.906	0.580

The table reports the estimated coefficients of Eq. 7 at monthly frequency. In Columns (1-2), (3-5), and (6) Log(O/S), Log(O/F), and Log(F/S) are dependent variables, respectively. All the variables used in the estimation are converted to monthly frequency by taking the average at the month-year level. All variables are defined in Table A1 . Standard errors are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to August 2021.

Table A9 : Cross-Sectional Regression: Relative Volume, and Embedded Leverage (Monthly Frequency)

Dependent variable:	Log(O/S)		Log(O/F)		Log(F/S)
	(1)	(2)	(3)	(4)	(5)
Size	−0.177***	−0.166***	0.015***	0.039***	−0.139***
	(0.0080)	(0.0078)	(0.0053)	(0.0057)	(0.0048)
No. of Strikes	0.054***	0.053***	0.055***	0.054***	
	(0.0027)	(0.0027)	(0.0019)	(0.0019)	
Institutions Holding	−0.002**	−0.002**	−0.001*	−0.001*	−0.001**
	(0.0010)	(0.0010)	(0.0004)	(0.0003)	(0.0005)
Volume SSF	0.333***	0.334***			
	(0.0094)	(0.0097)			
Delta	−3.601***	−3.795***	−6.167***	−6.736***	
	(0.2166)	(0.2303)	(0.2144)	(0.2195)	
ATM-IV	−1.091***	−1.576***	2.473***	1.173***	−2.18***
	(0.1397)	(0.1449)	(0.1338)	(0.1335)	(0.1039)
% Spread-SSO	−0.040***	−0.040***	−0.037***	−0.038***	
	(0.0015)	(0.0015)	(0.0011)	(0.0012)	
Lev-SSO-VW	0.038***		0.040***		
	(0.0031)		(0.0021)		
Lev-SSO-EW		0.026***		0.008**	
		(0.0034)		(0.0026)	
% Spread-SSF					−2.241***
					(0.0780)
Lev-SSF					0.0003
					(0.0022)
Constant	−2.836***	−2.478***	−1.421***	−0.381**	2.708***
	(0.1891)	(0.2033)	(0.1578)	(0.1581)	(0.1215)
Observations	17437	17437	17437	17437	17691
Adjusted R^2	0.841	0.839	0.789	0.784	0.273

The table reports the estimated coefficients of Fama and MacBeth (1973) regression (Eq. 8) estimated at monthly frequency. Columns (1-2), (3-4), and (5) report the results when Log(O/S), Log(O/F), and Log(F/S) are dependent variables, respectively. All the variables used in the estimation are converted to monthly frequency by taking the average at the month-year level. All variables are defined in Table A1 . Newey and West (1987) adjusted standard errors with 12 lags are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to August 2021.

Table A10 : Panel Data Regression: Log(ATM-O/S) and Embedded Leverage (Daily Frequency)

Dependent variable:	Log(ATM-O/S)				Log(ATM-O/F)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	0.282***	2.092***	0.254***	1.957***	0.227***	1.896***	0.205***	1.790***
	(0.005)	(0.027)	(0.005)	(0.027)	(0.004)	(0.024)	(0.004)	(0.024)
No. of Strikes	0.027***	0.030***	0.029***	0.033***	0.030***	0.038***	0.031***	0.040***
	(0.0003)	(0.0005)	(0.0003)	(0.0005)	(0.0003)	(0.0004)	(0.0003)	(0.0004)
Institutions Holding	−0.0001		−0.0001		−0.0002		−0.0002	
	(0.0002)		(0.0002)		(0.0002)		(0.0002)	
Volume SSF	0.299***	0.172***	0.306***	0.163***	1.010***	0.919***	1.014***	0.912***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Delta	−0.165***	0.266***	0.492***	0.918***	−0.317***	0.133***	0.197***	0.660***
	(0.031)	(0.029)	(0.033)	(0.030)	(0.027)	(0.025)	(0.028)	(0.026)
ATM-IV	−0.049	1.291***	0.351***	1.276***	1.076***	1.335***	1.345***	1.323***
	(0.044)	(0.021)	(0.044)	(0.021)	(0.038)	(0.019)	(0.038)	(0.019)
ATM-IV × Time to Expiry	−10.498***	−12.590***	−13.938***	−8.787***	−10.950***	−12.756***	−13.248***	−9.124***
	(0.712)	(0.223)	(0.708)	(0.222)	(0.618)	(0.197)	(0.615)	(0.197)
% Spread-SSO	−3.484***	−2.145***	−3.449***	−2.136***	−2.995***	−1.970***	−2.968***	−1.973***
	(0.013)	(0.015)	(0.013)	(0.015)	(0.011)	(0.013)	(0.011)	(0.013)
Lev-SSO-VW	0.040***	0.029***			0.033***	0.020***		
	(0.001)	(0.0004)			(0.0005)	(0.0003)		
Lev-SSO-EW			0.054***	0.043***			0.044***	0.033***
			(0.001)	(0.0004)			(0.0005)	(0.0004)
Firm-Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Date-Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Firm-Month-Year-Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	226,415	226,415	226,415	226,415	226,415	226,415	226,415	226,415
Adjusted R^2	0.782	0.871	0.786	0.874	0.930	0.957	0.930	0.958

The table reports the estimated coefficients of Eq. 7. In Columns (1-4), and (5-8) Log(ATM-O/S), and Log(ATM-O/F) are dependent variables, respectively. Lev-SSO-VW and Lev-SSO-EW are the volume and equally weighted embedded leverage of all the options contracts of an underlying. All variables are defined in Table A1 . Standard errors are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to August 2021.

Table A11 : NIFTY: Contract Level Analysis

Panel A				
	CE-ATM		CE-OTM	
Dependent variable:	Vol Ratio			
	(1)	(2)	(3)	(4)
Leverage	0.023***	0.041***	0.030***	0.020***
	(0.0003)	(0.0004)	(0.0005)	(0.001)
Spread-SSO	−16.721***	−18.096***	−5.006***	−5.615***
	(0.181)	(0.173)	(0.033)	(0.037)
Constant	−5.497***		−5.596***	
	(0.021)		(0.037)	
Date Fixed Effects	No	Yes	No	Yes
Observations	36,782	36,782	30,953	30,953
Adjusted R^2	0.238	0.367	0.439	0.507

Panel B				
	PE-ATM		PE-OTM	
Dependent variable:	Vol Ratio			
	(1)	(2)	(3)	(4)
Leverage	0.027***	0.071***	0.030***	0.028***
	(0.0004)	(0.001)	(0.0005)	(0.001)
Spread-SSO	−30.652***	−33.022***	−5.006***	−7.805***
	(0.328)	(0.304)	(0.033)	(0.046)
Constant	−5.261***		−5.596***	−5.037***
	(0.022)		(0.037)	(0.029)
Date Fixed Effects	No	Yes	No	Yes
Observations	34,252	34,252	30,953	35,819
Adjusted R^2	0.273	0.458	0.439	0.451

The table reports the estimated coefficients of Eq. 9 for the NIFTY sample. In Panel A Columns (1-2) and (3-4) report the coefficients when the regression model is estimated using ATM Call and OTM Call subsamples, respectively. Similarly, Panel B Columns (1-2) and (3-4) report the coefficients when the regression model is estimated using ATM Put and OTM Put subsamples, respectively. All variables are defined in Table A1 . Standard errors are reported in the parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. The sample period spans from January 2011 to August 2021.