

# Rational repricing of risk during COVID-19: Evidence from Indian single stock options market

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## Abstract

Could the COVID-19 related market crash and subsequent rebound be explained as a rational response to evolving conditions? Our results using multiple forward-looking measures of uncertainty implied from stock option prices suggest so. First, we find a gradual build-up of volatility during the month preceding the spike at the start of the pandemic. Second, while tail risk declined after government interventions, the level of uncertainty remained elevated for stocks across industries. Third, the dynamics of decline in tail risk in stocks was industry-dependent, suggesting that the market performed a fine-grained analysis of each stock's uncertainty through the pandemic.

## KEYWORDS

COVID-19, options pricing, risk-neutral density, volatility smile

## JEL CLASSIFICATION

G01, G13

## 1 | INTRODUCTION

An extensive literature has documented that stock markets crashed in March 2020 as the COVID-19 pandemic spread globally and then recovered most of the ground in the following months. While the facts are undisputed, they do lend themselves to (at least) two alternative interpretations. First, what was observed might simply be a behavioral finance phenomenon of the initial over-reaction, followed by a more sober reassessment when the mammalian (System 2) brain took over from the reptilian (System 1) brain (Camerer et al., 2005; Loewenstein, 2000; Morewedge & Kahneman, 2010). On the other hand, the second interpretation would be that the observed pattern was an efficient market response to an unprecedented negative shock, followed by an equally rational response to the massive monetary and fiscal rescue packages unleashed by governments worldwide. We argue in this paper that we must turn to options prices to identify whether the market was efficient in rationally pricing the future uncertainty amidst the changing scenario. First, options prices contain forward-looking estimates about future uncertainty. Second, while stock prices per se convey views only on directional bets (e.g., will stock prices go up or go down), options prices embed views on asymmetric and nonlinear bets. Options prices capture the market view on whether stock prices are more likely to make large moves or small moves (in either direction), whether large down moves are more likely than large up moves, and so on. Options are traded for various strikes, and each strike adds additional information about the implied market view. Therefore, we must extract the information from all the strikes: the entire volatility smile as it is known in the options pricing literature. This smile also allows us to extract the market-implied probability distribution of *future* stock price movements.

We quantify the uncertainty through the onset of the COVID-19 pandemic and ensuing government-imposed lockdowns by computing volatility smiles and market-implied probability distributions from India's single stock options (SSO) market, one

of the world's largest SSO options market by contract volume (World Federation of Exchanges, 2019). In 2019, it ranked sixth and second globally by SSO and SSF volumes, respectively and the number of SSO and SSF contracts traded in 2019 was 201.9 million and 255.1 million, respectively, with corresponding year-on-year growth rates of 19% and 27%. India has also consistently ranked among world's largest index options markets by contract volume (World Federation of Exchanges, 2019). Another reason for choosing the Indian markets among other emerging markets is that it has liquid markets in *both* single stock futures and options simultaneously. The use of futures prices instead of stock prices means that our volatility estimates are not contaminated by the possible misspecification of dividend yields and cost of carry.

This paper contributes to the stream of post-COVID-19 research on its impact on financial markets using SSO data. There is a sizeable evolving literature in empirical options pricing which documents measuring uncertainty and tail risk using attributes of volatility smile (Hui et al., 2020; Husted et al., 2018; Ornelas & Mauad, 2019). In particular, we use forward-looking measures of “at-the-money” (ATM), “risk reversal” (RR) and “butterfly” (BF) to describe the evolution of uncertainty through the imposition and lifting of government lockdowns as COVID-19 took a foothold in India. A cross-sectional analysis between different attributes using Kendall's  $\tau$  (*tau*) indicates that the different smile attributes measure aspects of uncertainty not captured by the other components.

While other post-COVID-19 studies have used index options data and volatility index (VIX) data to capture disaster risk and market expectations (Hanke et al., 2020; Jackwerth, 2020; Pagano et al., 2020), this is probably the first study that compares the estimates of market implied uncertainty to identify the change in skewness and fat-tailed-ness over time at the stock level. The daily risk-neutral probability density functions extracted from the fitted smile indicate that it is not just the second moments but (mainly) the third and the fourth moments (skewness and fat-tailedness) of the stock prices that varied across the industries and over time. We, therefore, supplement our results with analysis of variance (ANOVA) and carefully conducted regression that separates the control period from other critical periods to disentangle the industry and time effects. We find that tail uncertainty rose sharply in the “peak period” and fell during the “recovery period.” The industry-wise differentiation is found to be entirely in the peak period.

Our results are consistent with a market that responded in a calibrated manner to the unfolding of information about the pandemic, supporting the efficient market view. The statistical significance of the period and industry effect indicates that the market was performing a fine-grained analysis of each stock's uncertainty at each point in time, even on the days with extreme movements. The market estimate of future volatility builds up gradually through February and early March before spiking in mid-March. More importantly, we find that the market response to the aggressive health and the credit/liquidity interventions of late March is extremely nuanced. While the market expectation of tail risks in general and asymmetric negative tail risks reverted to precrisis levels, its expectation of overall uncertainty remained elevated. Rather than a blind risk-on/risk-off gestalt switch, by studying the evolution of measures of uncertainty implied from the options markets, we are led to conclude that the market response was more nuanced—the *level* of risks continued to be high in stocks across industries through the spread of the pandemic, but the extreme tail risks were abated after government response to COVID-19, with a different response across industries. This is consistent because sovereigns have a much lower ability to control a pandemic than a financial crisis like that of 2008/2009. Methodologically, our study contributes to two strands of the literature on using options prices for measuring uncertainty, namely, extracting risk-neutral density from options prices following (Breedon & Litzenberger, 1978) and approximating volatility smile using lower-order polynomials and splines reviewed in Malz (2014).

The rest of the paper is structured as follows. Section 2 describes our research questions and briefly summarizes the existing literature. Section 3 describes the SSO market data and Indian policymakers' response to COVID-19 on key dates, which forms the rationale for our classification of different subperiods. Sections 4 and 5 present our estimation methodology and the main findings. Section 6 concludes.

## 2 | LITERATURE REVIEW AND RESEARCH QUESTIONS

Our study draws on multiple streams of finance literature to formulate our research questions. First is the long-standing debate about whether large market-wide price swings are irrational or rational. Shiller used his Nobel lecture (Shiller, 2014) to present evidence that aggregate stock market price changes reflect animal spirits rather than effective use of all information. During the same award ceremony, Fama used his Nobel lecture (Fama, 2014) to argue equally persuasively that there is no reliable evidence for “bubbles” and that price swings are rational. We do not harbor any delusion of providing conclusive evidence on this question as in Fama's words, “No available empirical evidence convinces both sides.” Therefore, our first research question is much more limited: it asks whether the rapid crash and

recovery in the stock market index during the first few months of the COVID-19 pandemic were consistent with a rational response to uncertainty.

In Kenneth Rogoff's words, COVID-19 is best characterized as an "uncertainty pandemic" (Rogoff, 2020). In the spirit of Rogoff, the second stream of literature our study contributes to relates to tail risk and skewness. Over 70 years ago, Friedman and Savage (1948) demonstrated that choices under uncertainty cannot be explained only by mean and variance but must also consider the skewness of returns. This insight continues to strongly influence on the asset pricing literature (Bali et al., 2011; Leduc & Liu, 2016). The issue of tail risk (skewness and kurtosis) has assumed greater importance after the Global Financial Crisis of 2008/2009 (Acharya et al., 2012, 2017). The COVID-19 pandemic is the kind of event expected to have a strong impact on skewness and kurtosis rather than just on the mean and variance, and options markets allow us to measure this impact. Therefore, our second research question is whether the market response to the pandemic reflected shifts in mean, variance, skewness, and kurtosis or only in a subset of these four moments. We also ask whether there is any evidence of a nuanced appreciation of the differential impact on the four moments as against an indiscriminate panic response. While this has been studied in the context of "normal" crash risk in foreign currency and futures markets (Bartsch, 2019; Engle & Mistry, 2014; Hou & Li, 2020; Wong, 2019), to the best of our knowledge, ours is probably the first study that provides a industry-wise fine-grained response using SSO data.

COVID-19 has affected all industries of the economy (Choi, 2020), with differential impact on certain industries (Gu et al., 2020; He et al., 2020), and this heterogeneity is also apparent from the performance of stocks returns (Albuquerque et al., 2020; Hassan et al., 2020; Ramelli & Wagner, 2020). Some industries, particularly information technology, are witnessing a surge in demand from the segments that have shifted to a work-from-home model. Industries like consumer goods faced supply and demand disruption during the extreme phases of the lockdown but are normalizing as the lockdown is relaxed, although the disease is still spreading. Other industries like financials face uncertainty about future loan losses that could last for several months or years even after the disease is fully brought under control. Given the forward-looking nature of the financial markets, this industry responded most quickly globally (Akhtaruzzaman et al., 2020). For the Indian, US, and Chinese markets, Bansal et al. (2020), Sharif et al. (2020), and Xiong et al. (2020), respectively, have documented significant industry-wise variations in stock market returns. We expect a similar variation in the uncertainty as well, and therefore, our next and final research question is to measure the variation of uncertainty across various industries.

Finally, this paper contributes to the stream of post-COVID-19 research on the pandemic's impact on the stock markets in emerging economies. Topcu and Gulal (2020) document the decline in several emerging stock markets due to COVID-19. However, most of the current literature are focused on the stock market (Akhtaruzzaman et al., 2020; Shehzad et al., 2020; Zhang et al., 2020) rather than the options markets and, therefore, does not (and cannot) study the higher moments of the distribution. The two papers closest to ours are Jackwerth (2020) and Hanke et al. (2020) which study option-implied risk-neutral densities. However, neither of them includes emerging markets. Moreover, they do not use statistical structural break models and are more descriptive in nature.

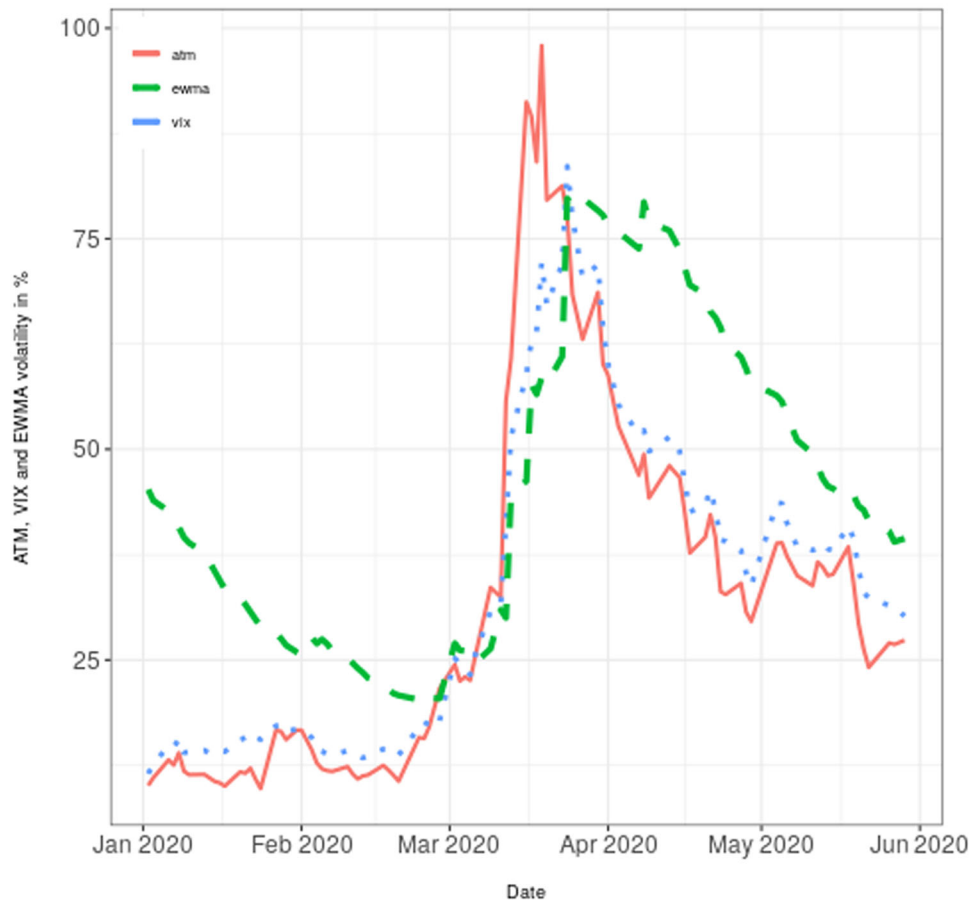
There is a literature gap on how the pandemic impacted volatility, skewness, and kurtosis in emerging market stock indices. We use information from SSO traded on India's National Stock Exchange (NSE), a market unique among other emerging markets in having both liquid futures and options contracts on the same underlying (Jain et al., 2019). Through the onset of the pandemic and ensuing government-imposed lockdowns, our study uses measures of uncertainty that go beyond capturing changes in the market-wide level of implied volatility (captured by measures like VIX), and include variables that quantify the relative difference in left and right tail risks and the convexity of volatility at the stock level.

An important reason for using the options market to measure uncertainty is that these markets are forward-looking. To anticipate the discussion of Figure 1 (whose variables are described in more detail in Section 4.1), implied volatility reacts faster to changing uncertainty than measures based on historical data. The options price reflects the uncertainty over the option's remaining life and not the uncertainty observed in the past. It is well established in the literature that globally implied volatility from the options market leads the realized volatility (Christensen & Prabhala, 1998, Poon & Granger, 2003), and this has been verified in India as well (Jain et al., 2019).

### 3 | DATA: INDIAN SSO MARKET AND CLASSIFICATION OF PERIODS

#### 3.1 | Indian SSO market

India has a very liquid and well-regulated capital market, with the NSE being India's leading stock exchange. As per the Securities Exchange Board of India (2020) annual report, the total market capitalization of all NSE-listed



**FIGURE 1** Comparison of ATM, India VIX and EWMA ( $\lambda = 0.94$ ) for NIFTY for 2020. The figure shows the ATM, India VIX and EWMA time series for the Nifty index from January 1 to May 31, 2020. ATM volatility represents the level of implied volatility and is computed as the estimated volatility smile at  $\Delta = 0.5$  (see Section 4.1.2). India VIX is a volatility index published by the NSE based on the Nifty index options prices. India VIX uses the computation methodology of CBOE with suitable amendments. EWMA is a “moving average” measure of volatility based on historical data computed using the methodology described in Section 4.1. ATM, at-the-money; CBOE, Chicago Board of Exchange; EWMA, exponentially weighted moving average; VIX, volatility index [Color figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

securities on December 31, 2019, was USD 2.16 trillion. The market capitalization-to-GDP ratio for NSE securities was 55.2% on March 31, 2020 (decreased from 78.7% on March 31, 2019, after the market crashed following the onset of COVID-19), and the equity market turnover-to-GDP ratios for 2019–2020 were 47.4% and 1690.1% for the cash and derivatives segment, respectively. There is substantial participation by institutional investors and foreign portfolio investors (FPIs) in the Indian equity market. In 2019–2020, FPIs contributed to 15.1% of the annual cash market turnover and 19.3% of the derivatives market turnover. The market value of assets held by FPIs in the Indian equity market as of March 31, 2020, was 27.6%, with INR 24.9 trillion (Securities Exchange Board of India, 2020). Past studies have found the Indian market to be well integrated with the global markets (Dicle et al., 2010) but have found mixed pieces of evidence regarding the weak-form efficiency of the Indian market (Dicle et al., 2010; Majumder, 2013; Mall et al., 2011; Sharma & Mahendru, 2009). Maheshwari (2012) found the Indian market to be semistrong-form efficient. However, most of the studies are based on either broad indices or a relatively small number of stocks.

We use data on options traded at NSE, unique in having a liquid SSO and SSF market, with matching timestamped quotes. NSE started derivatives trading in index derivatives contracts in 2000 and single stock derivatives in 2001. By 2020, it became the world’s largest derivatives market by volume. The trading volume at NSE grew at the rate of 48.7% to reach 8.85 trillion futures and options contracts, with the corresponding numbers for the CME group and Korea Exchange being 4.82 trillion and 2.18 trillion, respectively

(Futures Industries Association, 2021). As per the World Federation of Exchanges report in 2019, NSE ranked sixth and second in the world by SSO and SSF volumes, with the number of contracts traded being 201.9 million and 255.1 million, respectively. Regarding index options, it ranked first with 4.16 billion contracts, with BANKNIFTY and NIFTY contracts being ranked 1st and 2nd in the world by trade volume, respectively (World Federation of Exchanges, 2019).

Including both SSO and SSF contracts, NSE had listed single stock derivatives for about 250 stocks in 2018, but in 2019, the list of underlying stocks for derivatives contracts was pruned to exclude less-liquid stocks. In 2020, single stock derivatives traded for 148 underlying stocks, which were mostly large-size and liquid and included all the stocks that are part of the two most liquid and highly traded indices globally—NIFTY and BANKNIFTY. Both the single stock and the index options that trade at NSE are European. In a recent study, Jain et al. (2019) found that the Indian equity options market is microefficient with low relative mispricing.

This study considers trading data of all SSOs traded at the NSE from January 01, 2020, to May 31, 2020 (the latest available data at the commencement of the study). We provide the details in Section 4.1.1, but our estimation technique of volatility smile parameters requires that we use high-frequency trade data to avoid using stale prices. In all, we use high-frequency data for all near-month and next-month SSOs and SSFs for 101 trading days for 146 of the largest stocks in NSE and the two indices (NIFTY and BANKNIFTY). As the NIFTY index comprises mostly large-capitalization stocks, the constituent stocks are part of the 146 stocks included in our sample. From the list of all available stocks on which options were listed at the time of the study, two were removed because of the lack of observations.<sup>1</sup> To avoid issues around the expiration-day effects (Agarwalla & Pandey, 2013; Bollen & Whaley, 1999), we used the near-month smiles up to 5 days before the expiry date and the next-month smiles after that. The stocks were classified into 11 industries based on the Global Industry Classification Standard (GICS) to analyse the industry-wise impact.<sup>2</sup>

### 3.2 | COVID-19 and Indian financial markets

In India, the WHO reported the first COVID-19 case on January 30, 2020.<sup>3</sup> The disease spread slowly over the next few weeks, and as of March 24, 2020, the WHO reported that the country had only 434 cases and 9 deaths from COVID-19. However, on that date, the Indian government imposed a stringent nationwide lockdown<sup>4</sup> for 3 weeks: all nonessential government offices, industrial and commercial establishments, hotels and lodges, educational institutions and places of worship were closed, and public gatherings were barred. The lockdown was extended twice, but each extension came with significant relaxations. While specific agriculture, construction, and other activities were permitted on April 15, some economic activities were permitted on May 1 in green zones having a low prevalence of COVID-19.

Central banks and governments worldwide have struggled to cope with the economic impact of COVID-19 (BIS, 2020). The Indian central bank, the Reserve Bank of India (RBI), responded to the COVID-19 situation with an interest rate cut<sup>5</sup> and a package of liquidity and credit interventions.<sup>6</sup> On March 27, RBI announced an INR 1 trillion Targeted Long Term Repos Operations (TLTRO) to be deployed in investment-grade corporate bonds, commercial paper and nonconvertible debentures. It also permitted lending institutions to allow a moratorium of 3 months on payment of term loan installments and defer payment of interest on working capital loans. On May 12, India's Prime

<sup>1</sup>SSO were listed on 148 stocks at the time of writing. See [https://www1.nseindia.com/products/content/derivatives/equities/contract\\_info.htm](https://www1.nseindia.com/products/content/derivatives/equities/contract_info.htm) for selection criteria laid down by India's regulator, SEBI, and the list of stocks as on date. We dropped SSO contracts of two underlying stocks—"TATAMTRDVR" because there is another set of contracts on the same underlying, and "RAMCOCEM" because of the lack of enough observations. For more details about the liquidity and specifics of India's SSO and index options traded at NSE, see Jain et al. (2019).

<sup>2</sup>The GICS classification was developed jointly by MSCI Inc. and S&P Dow Jones Indices in 1999. The industry classification for our sample firms was obtained from the Bloomberg database. See <https://www.msci.com/gics> for more information about GICS.

<sup>3</sup>The WHO announcements are sourced from various WHO situation reports available at <https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports>, and they were accessed on July 30, 2020.

<sup>4</sup>The announcements by the Indian government are available at: <https://ndma.gov.in/en/media-public-awareness/mha-orders-guidelines.html>. They were accessed on July 30, 2020.

<sup>5</sup>RBI (March 27, 2020). Seventh Bi-monthly Monetary Policy Statement, 2019-20 Resolution of the Monetary Policy Committee (MPC) Reserve Bank of India. Retrieved July 30, 2020 from [https://www.rbi.org.in/Scripts/BS\\_PressReleaseDisplay.aspx?prid=49581](https://www.rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx?prid=49581).

<sup>6</sup>RBI (March 27, 2020). Statement on Developmental and Regulatory Policies. Retrieved July 30 from [https://www.rbi.org.in/Scripts/BS\\_PressReleaseDisplay.aspx?prid=49582](https://www.rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx?prid=49582).



Minister announced an INR 20 trillion package to support the economy. The period in the study is divided into different subperiods keeping that in mind.

### 3.3 | Key dates and periods

Before January 30, when the WHO declared the outbreak a Public Health Emergency of International Concern (PHEIC),<sup>7</sup> the discussion on COVID in the global media was almost negligible. Therefore, we use January 1–29 as the *control* period.<sup>8</sup> We ignore the period from January 30 (after the first Indian COVID-19 case) to February 23 (the Italian lockdown) from the control period to avoid contamination. Till the Italian lockdown, investors tended to think of COVID-19 as being essentially confined to China.

The period between February 23 and March 11, when the WHO announced COVID as a pandemic and when the severity of the disease became increasingly apparent, is referred to as the *buildup* period. The WHO declaration of a pandemic on March 11 signifies the beginning of the peak period. As discussed earlier, on March 24, the Indian government enforced a complete three-week lockdown, and on March 27, RBI announced a relief package. The aggressive health intervention and the aggressive credit/liquidity intervention ended the peak of the crisis. Hence, we refer to the period between March 12 and March 26 as *peak*.

Finally, given the developments in the Indian financial markets, we divide the recovery period into two subperiods—the period from March 27 to April 14 (the end of the first lockdown) as the *early recovery* period<sup>9</sup> and the period from April 14 to May 12 as the *further recovery* period. On May 12, the Prime Minister announced an INR 20 trillion stimulus package for the economy, and the lockdown was significantly relaxed. The period from May 12 to the end of the sample (end May) is referred to as the *new normal*. During this period, the financial markets were getting used to the uncertainty surrounding COVID-19, and businesses started to reopen, but with still heightened volatility. For ready reference, Table 1 summarizes the key dates along with period names used in the study.

## 4 | RESEARCH METHODOLOGY

### 4.1 | Measuring uncertainty based on volatility smile attributes

One of the most popular ways of quantifying uncertainty in the financial markets is the use of some measure/function of sample variance, be it unconditional standard deviation based on a large sample or a conditional measure based on GARCH (Bollerslev, 1986) or exponentially weighted moving average (EWMA) models of volatility. Christensen and Prabhala (1998) showed that implied volatility outperforms historical volatility in forecasting future volatility. Since then, other researchers have confirmed the evidence across markets (Poon & Granger, 2003), including for India (Jain et al., 2019; Panda et al., 2008).

The standard EWMA model (and as also implemented in the study) estimates variance for any day ( $\sigma_t^2$ ) as a weighted average of the variance estimate for the previous day ( $\sigma_{t-1}^2$ ) and square of returns ( $r_t^2$ ) observed on that day. In particular, the model estimates volatility  $\sigma_t$  for any day  $t$  as follows:

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1 - \lambda)r_t^2 \quad (1)$$

The value of the weight  $\lambda$  determines the speed with which the volatility estimate responds to changing daily returns. Following JP Morgan's original RiskMetrics document and the literature cited earlier, the value of  $\lambda$  was set at 0.94. The starting value to seed EWMA was based on the unconditional variance of returns for the full sample under study (January–May 2020).

Traders in options markets are known to quote not the options prices but the volatility *implied* by them (Reiswich & Uwe, 2012), which in terms of the (Black, 1976) formula can be written as follows:

<sup>7</sup>The major announcements from the WHO are sourced from <https://www.who.int/news-room/detail/29-06-2020-covidtimeline>, and the major policy-level announcements by the Government of India are sourced from [https://en.wikipedia.org/wiki/COVID-19\\_pandemic\\_lockdown\\_in\\_India](https://en.wikipedia.org/wiki/COVID-19_pandemic_lockdown_in_India).

<sup>8</sup>While there is some evidence of the January effect for returns, there is none so for volatility in the Indian market (Kumar & Kumar 2014).

<sup>9</sup>The first phase was followed by three subsequent phases (2–4) till May 3, May 17, and May 31 and two unlock phases (Unlock 1.0 and 2.0) till June 30 and July 31. The subsequent phases of the lockdown were progressively milder.

TABLE 1 Key dates and periods

Start	Period
01-Jan-2020	Control
30-Jan-2020	Ignore
23-Feb-2020	Buildup
11-Mar-2020	Peak
27-Mar-2020	Early_recovery
14-Apr-2020	Further_recovery
12-May-2020	New_normal

Note: The table describes the various periods used in the paper. We divide the 5 months between January 1 and May 31, 2020 into seven periods based on various announcements/interventions relating to COVID and discussed in Section 3.3. The first column specifies the starting date of each of these periods, while the second column gives the nomenclature we use for the period.

$$\text{Implied volatility } (\sigma) \equiv \sigma^{-1}(C, F, K, r, T - t)$$

where  $C$ ,  $F(t, T)$ ,  $K$ ,  $r$ ,  $T - t$  and  $\sigma$ , respectively, denote the options price, the forward price at  $t$ , the strike/exercise price, the domestic risk-free rate, the time to maturity, and volatility. Empirically, it has been observed that implied volatility is not a constant but varies systematically with strike and time to maturity. The shape of the relationship between implied volatility and strike is often referred to as a “volatility smile.” The methodology followed for fitting the volatility smiles and quantifying the uncertainty measures from the fitted smiles is described in Sections 4.1.1 and 4.1.2.

As Figure 1 shows, for Nifty, it takes backward-looking EWMA a few days to catch up to the heightened level of volatility captured by forward-looking measures like India VIX and ATM volatility. While the computation of ATM volatility is described later in the context of information implied from the volatility smile (see Section 4.1.2), India VIX is a volatility index based on the Nifty index options prices. It is licensed by the Chicago Board of Exchange (CBOE) and computed using the same methodology as used by CBOE for computing VIX based on the S&P 500 Index.<sup>10</sup> To substantiate the qualitative results shown in Figure 1, we later report the results of the lead-lag relationship between EWMA and ATM volatility during COVID-19 using formal Granger causality tests. Accordingly, given that the implied volatility measures lead the volatility based on historical data (EWMA), all our measures to capture heightened uncertainty after COVID-19 are based on implied volatility in one way or another.

#### 4.1.1 | Fitting daily volatility smiles

For fitting the daily volatility smiles for the SSO and the index options, we use the same methodology as used in Jain et al. (2019). For this, we first filter out the illiquid SSO contracts by removing all contracts that traded less than five times during a day and then construct the smile only for those underlying stock-day where we have at least five liquid contracts being traded on the underlying stocks.<sup>11</sup> We prefer the Black (1976) model, based on prices of futures contracts instead of the Black and Scholes (1973) model based on spot prices to avoid estimating dividend yields and cost of carry.

While our analysis requires us to estimate smile for each underlying-day, we realize that all the options contracts traded on a given underlying were not equally liquid, leading to stale prices being reported as closing prices. The use of stale SSO closing prices of some contracts could lead to an incorrect estimation of the implied volatility (IV) of such contracts and the overall smile for the underlying-day. Therefore, to avoid using stale prices, we used high-frequency data to match the SSO and the SSF price at the same timestamp. More specifically, we match the minute-wise SSO prices with SSF prices and use the prices from the last-matched SSO/SSF trade of the day for each particular options contract.

<sup>10</sup>See [https://www.cboe.com/tradable\\_products/vix/for\\_methodology\\_of\\_VIX](https://www.cboe.com/tradable_products/vix/for_methodology_of_VIX) and [https://www1.nseindia.com/content/indices/India\\_VIX\\_Fact\\_Sheet.pdf](https://www1.nseindia.com/content/indices/India_VIX_Fact_Sheet.pdf) for details about India VIX.

<sup>11</sup>Mixon (2009) followed a similar methodology.

The range of the smile deltas was confined between 0 and 1 by converting all the put deltas into call deltas. The smile for each underlying-day is estimated by fitting a quadratic function of the following form:  $IV = a\Delta^2 + b\Delta + c$ , where  $IV$  is the implied volatility of the options contracts and  $\Delta$  is the options delta. To ensure that the smile lies above the X-axis in the interval  $[0,1]$ , we suitably constrain the value of  $c$  during estimation.<sup>12</sup> Jain et al. (2019) find that the quadratic smile-adjusted Black model fits the options prices well. The optimization was done using the popular and robust Nelder Mead (Nelder & Mead, 1965) simplex optimization function. Unlike Jain et al. (2019), while fitting the smile for each underlying-day, our model aims at minimizing the weighted-mean squared errors (using the log of the traded value as weights) between the options market price and the estimated prices using  $IV$  from the volatility smile recursively. The evidence from properties of the three coefficients suggests that smile in Indian markets can be approximated adequately by a quadratic function and for some stocks/days by a negatively sloped straight line (both the median and the mean for  $a$  are near 0.1, with the corresponding statistics for  $b$  being  $-0.4$  and  $-0.2$ , respectively).

#### 4.1.2 | Quantifying uncertainty measures from the volatility smile

Our first set of measures for quantifying uncertainty from the fitted smiles is based on the construction of popular trades based on implied volatility, namely ATM straddle, RR, and BF. These measures describe the properties of the estimated smiles and are used for analysing the changes over a period. Even though Indian equity markets do not have such derivatives traded on the exchange, the liquidity of traded SSO in India allows us to extract their values based on a fitted volatility smile. Options markets quote the three products most commonly in terms of  $\Delta$  around ATM. Although their definitions are well known in the options markets literature (Wystup, 2006), we describe it here for the sake of completeness: (a) ATM, which represents the level of implied volatility, is computed as  $IV_{\Delta=0.5}$ , (b) RR, which represents the slope of the options smile, is computed as  $IV_{\Delta=0.25} - IV_{\Delta=0.75}$  and (c) BF, which represents the curvature of the options smile, is computed as  $0.5(IV_{\Delta=0.25} + IV_{\Delta=0.75}) - ATM$ .<sup>13</sup> Finally, we use the EWMA to measure the realized volatility. The EWMA method is used by major clearing corporations (including by the NSE clearing) for setting margin requirements and is one of the most popularly used measures of realized volatility in practice. Also, the EWMA quickly reflects the change in the environment, making it more relevant during turbulence like in COVID-19. We use these three variables precisely as defined above to analyse the stock- and industry-specific difference through the onset of the COVID-19 pandemic and ensuing government-imposed lockdowns.

#### 4.1.3 | Measuring tail risk using risk-neutral density (RND)

The martingale valuation principle (Hull, 2003) describes the price of a call option as an expectation under the risk-neutral measure:

$$C = e^{-r(T-t)} \mathbb{E}^Q[(S_T - K)^+] = e^{-r(T-t)} \int_K^\infty (S_T - K)q(S_T, T; S_t, t)dS_T$$

where the superscript  $Q$  denotes that the expectation is under the risk-neutral probability measure and  $q(S_T, T; S_t, t)$  represents the risk-neutral (transition) probability density for the spot price at  $T$  being  $S_T$  given that it was  $S_t$  at  $t$ .

Even since Breeden and Litzenberger (1978), it is well known that given a continuum of options prices, one can extract this model-free risk-neutral probability distribution as

$$q(S_T = K) = e^{rT} \frac{\partial^2 C}{\partial K^2}$$

The above result of RND is described in terms of partial derivatives concerning the strike. However, as described earlier, option prices are quoted in terms of implied volatility, and the volatility smile in equity derivatives markets is more often constructed in terms of the option  $\Delta$ . Also, as we are already using smile construction based on  $\Delta$ , it is natural for us to extract RND in terms of  $\Delta$ . Since the computation of density requires smooth second-order partial

<sup>12</sup>As the quadratic function attains its minimum at  $x = -b/2a$ , where the corresponding minimum value of the function is  $b^2/4a$ , we shift the estimated  $c$  by  $b^2/4a$  when  $-b/2a \in [0, 1]$ . For other values of the function, the minimum value of the function is at one of the endpoints (0 or 1). Therefore, we shift the estimated  $c$  by  $\min(0, a + b)$ .

<sup>13</sup>All these are used in the literature. For example, see Wystup (2006), Carr and Wu (2007), and Mixon (2009).



derivatives, a smoothing function is usually fitted to the smile to extract the RND (Malz, 2014). To achieve that, we use the methodology developed recently by Hayashi (2020) for analytically deriving RND from a smile fitted to option  $\Delta$ .<sup>14</sup>

## 4.2 | Relationship across various measures of uncertainty

The principal motivation for using all the components of volatility smile to measure uncertainty is that uncertainty has several dimensions. Uncertainty about the tail risks is not the same as uncertainty about the middle of the distribution, and uncertainties about the left and right tails are also not the same. This multidimensional nature of uncertainty is all the more important during periods like the COVID-19 pandemic when the risks of extreme outcomes are more salient. However, before using the various uncertainty measures derived from SSOs, we first have to demonstrate that these different dimensions of uncertainty are indeed distinct and cannot be subsumed into a single measure of uncertainty.

We follow a two-step approach for this. First, we look at the change in different smile parameters in each subperiod relative to each stock's control period. This procedure controls for stock-specific characteristics that influence its smile parameters. Then within each subperiod, we measure the cross-sectional association between the different smile parameters using Kendall's  $\tau$ . We use a nonparametric measure because the relationships could be nonlinear but are expected to be monotonic. Kendall's  $\tau$  requires only ordinal data and does not need a functional-form specification. We also cross-check our results by computing the time-series correlation between the ATM, BF, and RR for each stock.

## 4.3 | Measuring the lead-lag relationship across various uncertainty measures

To verify whether the options markets lead the realized volatility even during the extreme uncertainty of the COVID-19 pandemic, we use the standard Granger causality tests to measure the lead-lag relationship between the daily estimates of the three parameters describing the options smiles—ATM, RR, and BF—and the realized volatility (EWMA). To be more specific, to test whether a variable  $x$  predicts another variable  $y$ , two regression models—unrestricted and restricted—are estimated. In the unrestricted model,  $y$  is regressed on its own lagged value as well as lagged values of  $x$ , and in the restricted model,  $y$  is regressed only on its own lagged value. In the context of our analysis, this translates to, for example, regressing daily ATM volatility on its lagged value and lagged values of EWMA (or RR or BF). To use this test, we need to specify the maximum order of the lags in the regressions. Since these are nested models, the Wald test is used to determine whether lagged values of  $x$  add any predictive power to the model. We report the test results for three values for this (10, 5, and 3) for robustness.

## 4.4 | Repricing of uncertainty—period, industry, and interaction effects

The extent and pattern of variation in uncertainty during the COVID-19 pandemic are investigated using standard ANOVA and regression frameworks. Our models are described below.

### 4.4.1 | ANOVA model

We use a standard ANOVA framework to disentangle the effects of three variations—period, industry, and interaction effects. The period effect captures the change in the uncertainty over the different phases, and the industry effect captures whether some industries witnessed a greater increase in uncertainty than others. The interaction effect captures whether the time path of changes in uncertainty (e.g., the sharpness of the spike or the speed of recovery) is different between two industries with similar average changes in uncertainty during the sample period. The ANOVA model containing all three effects is modeled as follows:

<sup>14</sup>In particular, we use Equations (10)–(19) of his paper to extract smooth estimates of RND for all stocks and indices studied in the paper.

$$\mu_{pi}^k = \mu^k + \beta_p^k + \gamma_i^k + \delta_{pi}^k \quad (2)$$

where  $\mu_{pi}^k$  is the mean value of the  $k$ th smile variable (ATM, BF, and RR) for all stocks in industry  $i$  in period  $p$ ,  $\mu^k$  is the grand mean (across industries and periods),  $\beta_p^k$  is the period effect,  $\gamma_i^k$  is the industry effect and  $\delta_{pi}^k$  is the interaction effect between the period and industry. For ease of interpretation, we subtract  $\mu_{1i}^k$  from  $\mu_{pi}^k$  (period 1 is the control period) so that the period effects and period-industry interactions represent changes from the control period.

#### 4.4.2 | Regression model

To capture the variation in greater detail, we use the following regression models underlying the above ANOVA. While Equation (3) includes only the period effect, Equation (4) includes period and industry effects in the regression. Equation (5) describes the full model.

$$Y_{mt}^k = \alpha^k + \sum_{p=2}^7 \beta_p^k D_p^p + \epsilon_{mt}^k \quad (3)$$

$$Y_{mt}^k = \alpha^k + \sum_{p=2}^7 \beta_p^k D_p^p + \sum_{s=2}^{11} \gamma_i^k D_i^I + \epsilon_{mt}^k \quad (4)$$

$$Y_{mt}^k = \alpha^k + \sum_{p=2}^7 \beta_p^k D_p^p + \sum_{s=2}^{11} \gamma_i^k D_i^I + \sum_{p=2}^7 \sum_{s=2}^{11} \delta_{pi}^k D_{pi}^{PI} + \epsilon_{mt}^k \quad (5)$$

where  $Y_{mt}^k$  is the mean value of the  $k$ th smile variable (ATM, BF, and RR) for stock  $m$  in period  $t$ ,  $\alpha^k$  is the intercept and, as earlier,  $\beta_p^k$ ,  $\gamma_i^k$ , and  $\delta_{pi}^k$  are the coefficients of the period-effect, industry-effect and period-industry interaction effect, respectively. The  $D$ 's are dummy variables:  $D_p^p$  equals 1 if the period  $t$  equals period  $p$ ,  $D_i^I$  equals 1 if the stock  $m$  belongs to industry  $i$  and  $D_{pi}^{PI}$  equals 1 if the period  $t$  belongs to period  $p$  and the stock  $m$  belongs to industry  $i$ . For ease of interpretation, we subtract  $Y_{m1}^k$  from  $Y_{mt}^k$  (period 1 is the control period) so that the period effects and period-industry interactions represent changes from the control period. The control period data (which has now become identically zero) is dropped before running the regressions.

## 5 | RESULTS AND DISCUSSION

Here, we present our findings, which put together address our three research questions stated at the beginning of the study: (i) Whether the rapid crash and recovery in the stock market index during the first few months of the COVID-19 pandemic were consistent with a rational response to uncertainty, (ii) whether different moments of the returns distribution behaved differently, and (iii) whether there was variation in uncertainty observed for stocks in different industries.

Since our research methodology is based on information implied by the volatility smile of single stocks, we begin by establishing that the different smile parameters indeed capture different dimensions of uncertainty. Next, we show that the forward-looking volatility smile parameters lead the realized volatility measures (corroboration of evidence noted in Figure 1). This is not merely a confirmation of evidence already established in the literature on the level of volatility; we also demonstrate that this holds for options-implied skewness and convexity. Having laid the ground on properties of our uncertainty measures, the subsequent sections then present results that address our research questions more directly, albeit in the reverse order.

### 5.1 | Smile parameters measure different dimensions of uncertainty

As explained in Section 4.2, we measure the relationship across different uncertainty measures using Kendall's  $\tau$  and time-series correlations to check whether they are distinct. The results are tabulated in Table 2. The Kendall's  $\tau$  between each pair of smile parameters for each subperiod (top panel) indicates that the correlations are generally quite low and not always statistically significant. The highest correlation (in absolute value) between ATM and RR

TABLE 2 Cross-sectional and time-series correlations (Kendall's  $\tau$ ) between different smile parameters

Period	ATM_RR	ATM_BF	BF_RR
<i>Panel A: Cross-sectional correlation (Kendall's <math>\tau</math>)</i>			
Buildup	-0.1675**	0.0658	-0.4468***
Early_recovery	-0.2576***	0.2042**	-0.4633***
Further_recovery	-0.0237	0.2737***	-0.3357***
Ignore	0.0011	0.0791	-0.3081***
New_normal	0.1909**	0.2735***	-0.0136
Peak	-0.4126***	0.3775***	-0.6455***
<i>Panel B: Time-series correlation between ATM, BF and IRR (Percentage of stocks with <math>\tau &lt; 0.3</math>)</i>			
Including the peak period	33.11	56.08	39.86
Excluding the peak period	70.27	91.89	80.41

Note: Panel A shows the cross-sectional correlations between the different smile parameters (ATM, BF, and RR) during different periods as defined in Table 1. Panel B shows the percentage of stocks with time-series correlation  $\tau$  between the different smile parameters less than 0.3. The results indicate low correlations between different smile parameters in general and more so during the peak period. \*\*\* and \*\* indicate significance at 1% and 5% levels, respectively.

Abbreviations: ATM, at-the-money; BF, butterfly; RR, risk reversal.

is -0.41 and between ATM and BF is 0.37. Both of these are in the peak period, and outside the peak period, the largest correlation in the absolute value between ATM and BF or ATM and RR is 0.27. The correlation between BF and RR is higher (-0.65 in the peak period and -0.46 outside the peak period). The time-series correlations (bottom panel) also show that most of the correlations are quite low. Excluding the peak period, 70%–92% of the correlations are less than 0.3 in absolute value. Even if we include the peak correlation, 33%–56% of the correlations are less than 0.3 in absolute value. These results establish that each of the ATM, RR, and BF components measures an aspect of uncertainty not captured by the other components. To our understanding, this property of smile attributes has not been addressed in the literature. However, broadly, these findings are consistent with what has been reported by Bartsch (2019) for studying the relationship between economic policy uncertainty and dollar–pound exchange rate volatility and by Wong (2019) for quantifying dollar–euro crash risk from 2007 to 2015.

## 5.2 | Forward-looking measures lead realized volatility

We used the standard Granger causality tests to verify whether option-market implied uncertainty parameters are indeed forward-looking. Table 3 presents the results from the Granger causality tests, as explained in Section 4.3, for the options on the Nifty index. The key inferences from the Granger test results are as follows. First, the ATM parameter of the smile predicts the realized (EWMA) volatility with a statistical significance better than 0.01% (in line with Jain et al., 2019). There is no reverse causation from EWMA to ATM. Second, the smile's BF parameter also predicts the realized (EWMA) volatility with a statistical significance better than 0.01%. There is weak evidence of reverse causation from EWMA (the results are significant for order 10 but not for orders 3 and 5 at the 1% level). Third, the smile's RR parameter also predicts the realized (EWMA) volatility with a statistical significance better than 0.01%. There is weak evidence of reverse causation from EWMA (the results are significant for orders 3 and 5 but not for order 10 at the 1% level).

Panel B shows the results of the Granger tests for the three components of the smile among themselves. We find that the smile's ATM component predicts BF (0.01%  $p$ -value), and there is no reverse causation from BF to ATM. There is very weak evidence of ATM predicting RR with no reverse causation. RR and BF do not predict each other.

Overall, all smile components predict the realized volatility, and within the three components, the ATM seems to lead the others. This is consistent with Christensen and Prabhala (1998), Poon and Granger (2003) and Jain et al. (2019). Our study has shown that the relationship holds at the single stock level during stressful events like pandemics. We verify these conclusions by looking at the smile components for individual stocks. We find that at the 1% significance level, the ATM component predicts the EWMA volatility in 75%–82% of the stocks with reverse causation in only 16%–27% of cases (Panel C of Table 3).

**TABLE 3** Lead-lag relationship between different smile parameters and realized volatility for Nifty index: Granger causality tests results

Test	Order_10	Order_5	Order_3
<i>Panel A: Smile predicts realized volatility</i>			
ATM predicts EWMA	0.0000	0.0000	0.0000
EWMA predicts ATM	0.3151	0.1978	0.3584
BF predicts EWMA	0.0001	0.0000	0.0000
EWMA predicts BF	0.0073	0.0975	0.0218
RR predicts EWMA	0.0000	0.0000	0.0002
EWMA predicts RR	0.1247	0.0033	0.0006
<i>Panel B: ATM predicts BF and RR</i>			
ATM predicts BF	0.0001	0.0000	0.0000
BF predicts ATM	0.1881	0.2962	0.7335
ATM predicts RR	0.0588	0.0302	0.0026
RR predicts ATM	0.4477	0.2909	0.0387
RR predicts BF	0.1217	0.0237	0.0058
BF predicts RR	0.0875	0.0122	0.2157
<i>Panel C: Stock-wise Granger tests: percentage with <math>p &lt; 0.01</math></i>			
ATM predicts EWMA	75.00	80.41	82.43
EWMA predicts ATM	27.03	22.97	16.22

Note: The table shows the results from the Granger causality tests between the daily estimates of different smile parameters (ATM, BF, and RR) for options on the Nifty index and the realized volatility (EWMA) of the Nifty index (panels A and B). Panel C summarizes the stock-wise Granger causality tests and shows the percentage of firms with  $p < 0.01$ . The results are reported over three lag values (10, 5, and 3). The EWMA and the three smile parameters are estimated using the methodology explained in Sections 4.1 and 4.1.2, respectively. The methodology of testing the lead-lag relationship is explained in Section 4.3.

Abbreviations: ATM, at-the-money; BF, butterfly; EWMA, exponentially weighted moving average; RR, risk reversal.

**TABLE 4** Industry, period and interaction effects: ANOVA results

	Df	Sum <sup>2</sup>	Mean <sup>2</sup>	F value	Pr(>F)
<i>Panel A: ATM</i>					
Period	5	43.36	8.67	356.45	0.0000
Industry	10	3.93	0.39	16.14	0.0000
Period:industry	50	3.10	0.06	2.55	0.0000
Residuals	723	17.59	0.02		
<i>Panel B: RR</i>					
Period	5	10.08	2.02	196.97	0.0000
Industry	10	0.41	0.04	4.01	0.0000
Period:industry	50	1.32	0.03	2.58	0.0000
Residuals	723	7.40	0.01		
<i>Panel C: BF</i>					
Period	5	0.77	0.15	204.04	0.0000
Industry	10	0.03	0.00	4.24	0.0000
Period:industry	50	0.10	0.00	2.64	0.0000
Residuals	723	0.55	0.00		

Note: The table shows the estimates from the ANOVA model described in Equation (2) and explained in Section 4.4.1. The model disentangles the period, industry and interaction effects for the three smile parameters—ATM, RR, and BF. The analysis is done using the three smile parameters for all SSO-days from January 1, 2020, to May 31, 2020. The entire period is divided into seven subperiods as explained in Table 1 and the underlying firms are classified into 11 industries based on the GICS.

Abbreviations: ATM, at-the-money; BF, butterfly; RR, risk reversal.

### 5.3 | Industry-wise differences in uncertainty

The output of the ANOVA model described in Equation (2) is given in Table 4. The results show that all three effects are significant at the 0.01% level for each of the three measures of uncertainty—ATM, RR, and BF. The interaction effect's high significance in all the three variables shows that some industries were affected more than the others in a

**TABLE 5** Regression results with period, industry and interaction effects

Dependent variable	ATM	RR	BF
<i>Panel A: Period effects</i>			
period_buildup	0.097 (0.022)***	−0.038 (0.013)***	0.002 (0.004)
period_peak	0.688 (0.022)***	−0.318 (0.013)***	0.089 (0.004)***
period_early_recovery	0.496 (0.022)***	−0.111 (0.014)***	0.026 (0.004)***
period_further_recovery	0.389 (0.022)***	−0.030 (0.013)**	0.011 (0.004)***
period_new_normal	0.264 (0.022)***	0.006 (0.013)	0.007 (0.004)*
<i>Panel B: Period and industry effects</i>			
period_buildup	0.097 (0.020)***	−0.038 (0.013)***	0.002 (0.004)
period_peak	0.688 (0.020)***	−0.318 (0.013)***	0.089 (0.004)***
period_early_recovery	0.494 (0.021)***	−0.113 (0.013)***	0.027 (0.004)***
period_further_recovery	0.389 (0.020)***	−0.030 (0.013)**	0.011 (0.004)***
period_new_normal	0.264 (0.020)***	0.006 (0.013)	0.007 (0.004)*
industry_ConsumerDiscret	−0.040 (0.031)	0.004 (0.020)	−0.001 (0.006)
industry_ConsumerStaples	−0.159 (0.033)***	0.020 (0.021)	−0.008 (0.006)
industry_Energy	−0.085 (0.036)**	0.032 (0.023)	−0.008 (0.006)
industry_Financials	0.066 (0.029)**	−0.010 (0.019)	0.006 (0.005)
industry_Healthcare	−0.091 (0.032)***	0.034 (0.021)	−0.006 (0.006)
industry_Industrials	−0.056 (0.031)*	−0.018 (0.020)	0.006 (0.005)
industry_InfoTech	−0.152 (0.037)***	−0.014 (0.024)	−0.002 (0.006)
industry_Materials	−0.070 (0.030)**	0.001 (0.020)	−0.004 (0.005)
industry_Real Estate	−0.027 (0.072)	−0.060 (0.047)	0.009 (0.013)
industry_Utilities	−0.078 (0.035)**	−0.060 (0.022)***	0.015 (0.006)**
<i>Panel C: Period, industry and interaction effects (only coefficients with <math>p &lt; 0.1</math>)</i>			
period_buildup	0.140 (0.083)*		
period_peak	0.917 (0.083)***	−0.352 (0.054)***	0.087 (0.015)***
period_early_recovery	0.456 (0.091)***		
period_further_recovery	0.354 (0.083)***		
period_new_normal	0.210 (0.083)**		
period_peak:industry_ConsumerDiscret	−0.297 (0.100)***		
period_peak:industry_ConsumerStaples	−0.518 (0.107)***	0.134 (0.069)*	
period_peak:industry_Energy	−0.241 (0.114)**	0.182 (0.074)**	−0.034 (0.020)*
period_early_recovery:industry_Financials	0.266 (0.100)***		
period_further_recovery:industry_Financials	0.204 (0.093)**		
period_new_normal:industry_Financials	0.183 (0.093)**		
period_peak:industry_Healthcare	−0.336 (0.106)***	0.137 (0.069)**	
period_peak:industry_Industrials	−0.296 (0.100)***		
period_peak:industry_InfoTech	−0.367 (0.118)***		
period_peak:industry_Materials	−0.271 (0.098)***		
period_peak:industry_Utilities	−0.253 (0.111)**	−0.277 (0.072)***	0.094 (0.020)***
Observations	789	789	789

*Note:* The table presents the regression estimates for regression models explained in Equation (3) (panel A), Equation (4) (panel B) and Equation (5) (panel C). In panel C, we report only those estimates that are statistically significant at <10% level. The full regression output for the period, industry and interaction effects is provided in the Appendix Table A1. \*\*\*, \*\*, and \* indicate significance at 1%, 5%, and 10% levels, respectively.

Abbreviations: ATM, at-the-money; BF, butterfly; RR, risk reversal.



certain period but not in other periods. This indicates the stock market performing very fine-grained analysis of the uncertainty of each stock at each point in time rather than just using an additive model involving a period effect and an industry effect. This could (with several caveats) be interpreted as evidence of market efficiency even during times of extreme stress.

The output of the regression model described in Equations (3)–(5) is presented in Table 5. The top panel includes only the period effect, and the middle panel includes the period and industry effects. The bottom panel of the table shows the regression results of the full model with interaction effects. To conserve space and improve readability, we have included only the significant variables (at the 10% level) for the full model with interaction effects and provided the complete output in the Appendix Table A1.

For ATM, the results indicate that it rose by nearly 10 percentage points in the buildup period (relative to the control period) and by almost another 50% in the peak period (to reach a level 68 percentage points above the control period) before it started falling. The ATM level fell nearly 20 percentage points during the early recovery and another 10 percentage points during the late recovery. It fell more than 10 percentage points during the new normal but remained more than 25 percentage points above the control period levels, indicating the persistence of elevated uncertainty levels. Our results are in line with those of Phan and Narayan (2020) and Narayan et al. (2020).

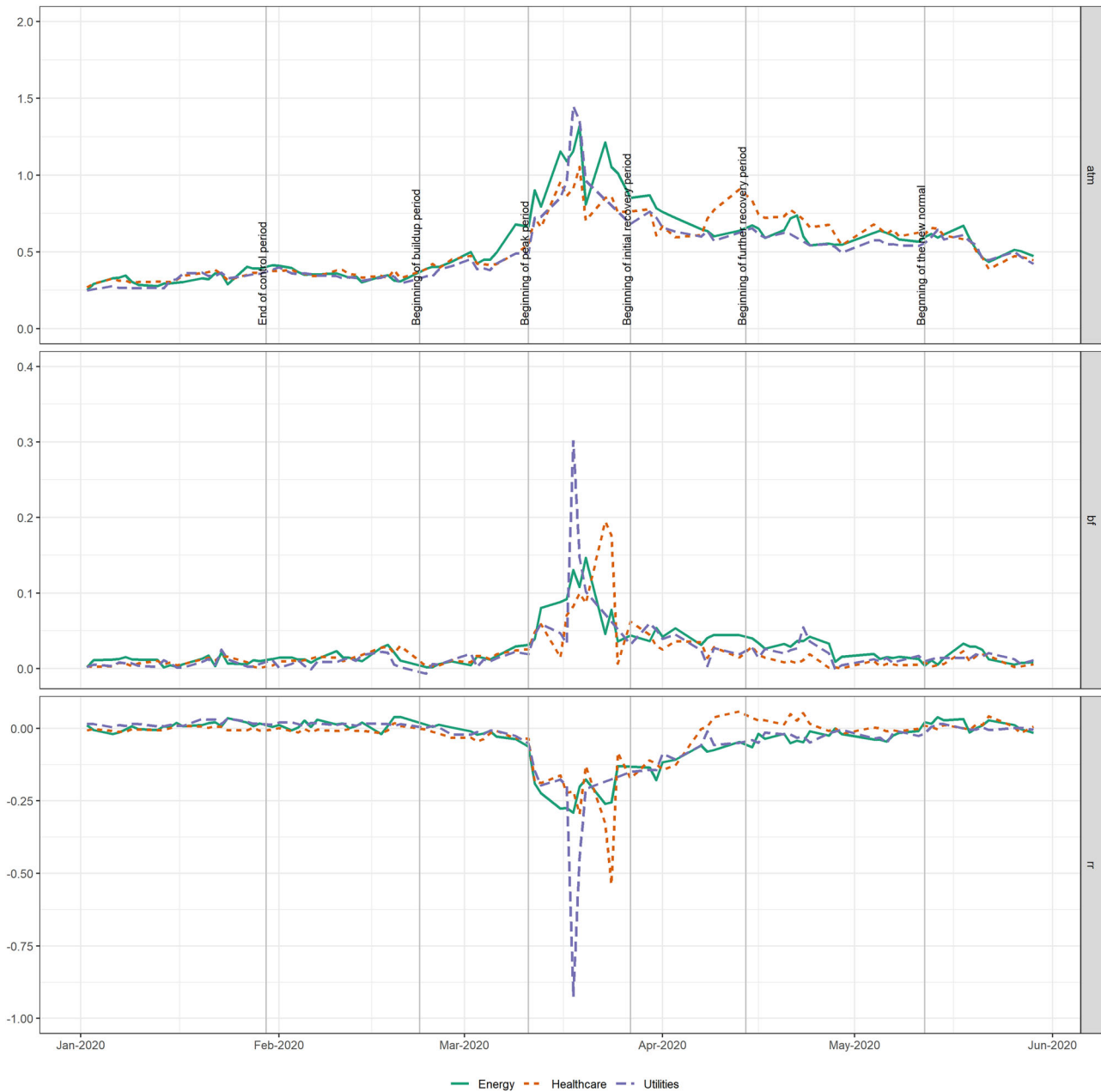
The middle panel shows that adding the industry effect to the regression leaves the period effects unchanged from earlier. However, the increase in ATM uncertainty was much less than average in consumer staples and information technology (Bansal et al., 2020, also noticed low fragility in these industries); somewhat lower than average in energy, utilities, and healthcare; and somewhat higher than average in financials. Finally, the bottom panel shows that adding the interaction effects to the model changes all the earlier regression coefficients. The results are quite interesting: with one exception, all the industry effects identified in the earlier model are confined to the peak period. Consumer staples, information technology, energy, utilities, and healthcare all had lower-than-average increases in ATM uncertainty during the peak period but not in other periods. The exception is financials, whose an above-average increase in uncertainty is entirely in the post-peak period. Another way of putting it is that financials experienced only an average increase in uncertainty during the peak, but this increased uncertainty failed to come down as much as that of other industries during the recovery and normalization, as the uncertainty about future loan losses could last for an extended period (Akhtaruzzaman et al., 2020).

For the measure of tail uncertainty (BF), from the top panel, we note that as in ATM (uncertainty about the middle of the distribution), the tail uncertainty also rose sharply in the peak and fell during the recovery. In this case, the difference is that the recovery is complete, and the new normal does not differ from the control period in terms of tail uncertainty. The other two panels show that the only statistically significant industry is the utilities, which had higher-than-average tail risk and that too mainly in the peak period.

The measure of asymmetric tail risk (RR) is similar to BF as far as period effects are concerned. The left tail uncertainty (low-probability event of catastrophic losses) became very pronounced during the peak period, as evidenced in the large *negative* value of the RR. This left tail uncertainty attenuated during the recovery and completely normalized in the new normal period. The industry-wise differentiation is entirely in the peak period during which energy and healthcare had significantly higher right tail uncertainty than average. In comparison, utilities had significantly higher left tail uncertainty than average. This is also illustrated in Figure 2, which plots the time series of the industry-wise median of ATM, BF, and RR in energy and healthcare versus utilities, along with markers for key dates/periods. To the best of our knowledge, this is the first study exploring industry-wise differences in uncertainty and tail risk during a pandemic, but He et al. (2020) and Gu et al. (2020) have reported similar results for returns.

## 5.4 | Risk-neutral densities

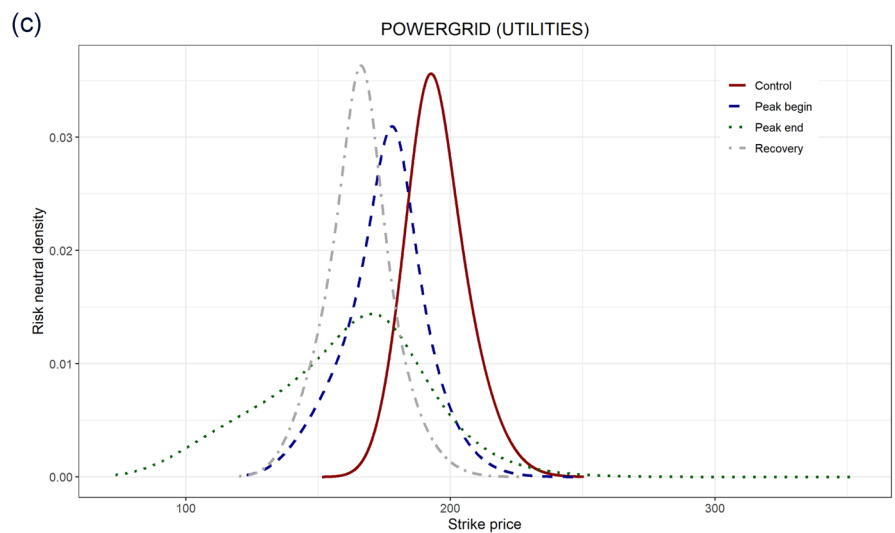
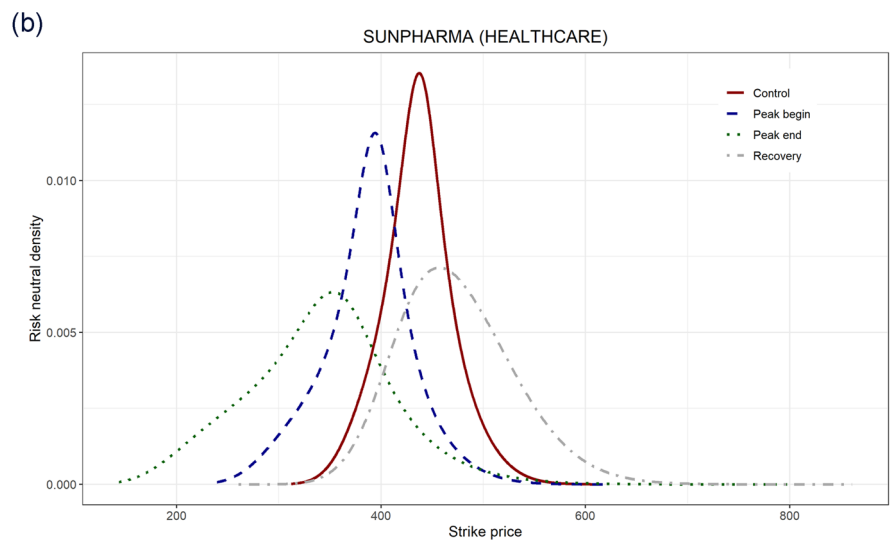
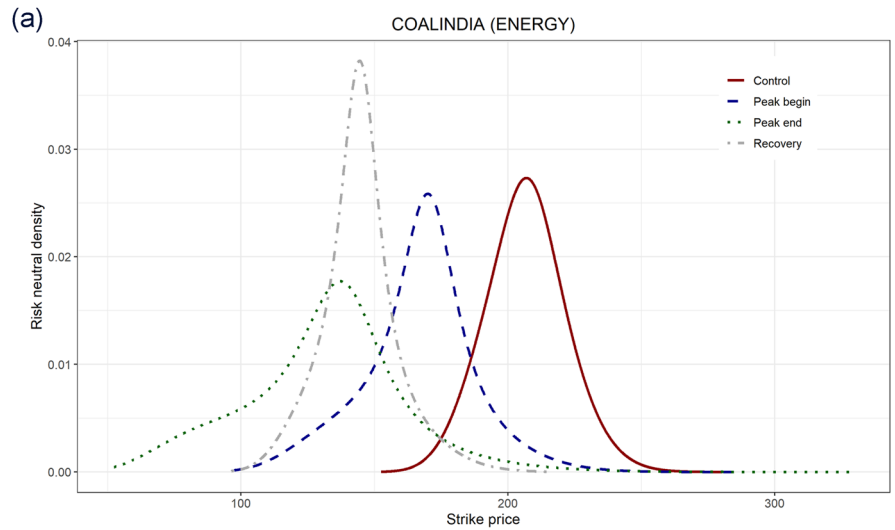
We then turn our attention to implied RND from the fitted volatility smile in terms of  $\Delta$  using the analytical approach devised by Hayashi (2020). We get a different RND for each stock-day, whose domains (strike levels) differ. To make their comparison tractable, we use our findings on the difference in response of stocks in different industries and follow the style of Hanke et al. (2020) and Jackwerth (2020), both of whom provide a comparison of densities on important days. We arbitrarily select a large stock from each of the three industries—energy (COALINDIA), healthcare (SUNPHARMA) and utilities (POWERGRID)—with a visible difference in response and compare their densities on dates around the different periods defined in Table 1. Figure 3 plots the estimated RND on January 1 (beginning of the “control” period), March 11 (beginning of the “peak”), March 27 (beginning of “recovery”), and April 20 (just after “further recovery”).

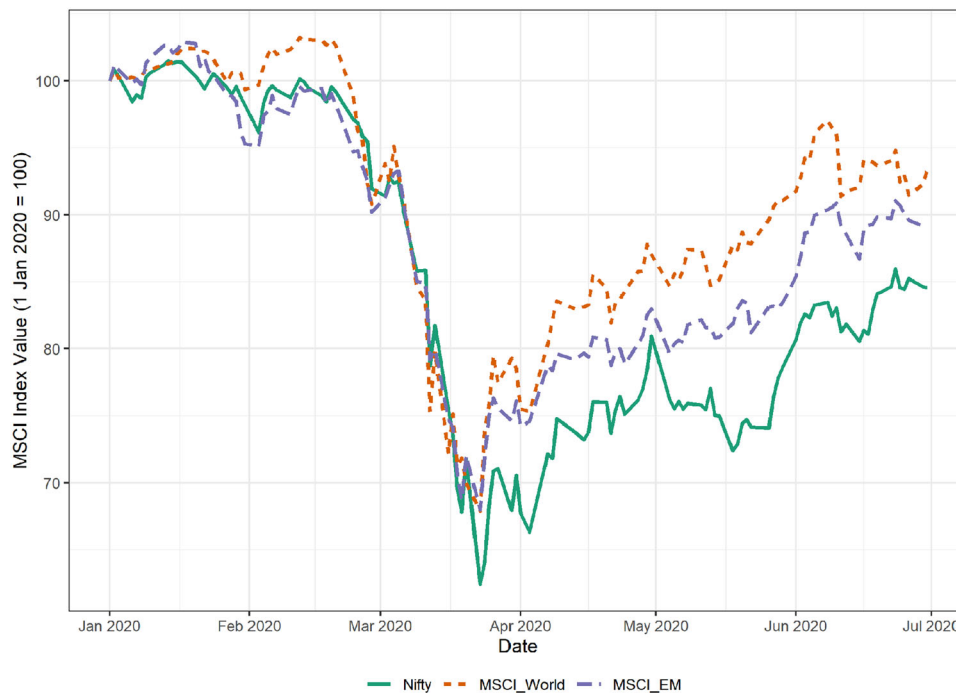


**FIGURE 2** Time series of median ATM, BF, and RR of energy, healthcare and utilities industries. The figure shows the time series of the median ATM, BF, and RR across all the eight firms in the energy industry (green line), all 12 firms in the healthcare industry (red line) and all nine firms in the utilities industry (blue line) from January 1 to May 31, 2020. The industry-wise medians were computed considering all the stocks belonging to the industry in the sample. The vertical lines mark the end/beginning of different periods described in Table 1. The plots show that while the ATM remain elevated for a long period, the BF and RR levels were restored to pre-COVID levels immediately after the policy interventions. ATM, at-the-money; BF, butterfly; RR, risk reversal [Color figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

We begin by highlighting the commonalities between the response of the three selected stocks. After the control period, as the peak period arrives, the density shifts leftward for all three stocks as the Indian financial markets plunged downwards along with the rest of the world (Figure 4 plots India's Nifty index with comparable indices published by MSCI Inc.). From the beginning till the end of the peak, the density shifts further backward. The width of the RNDs has also become relatively wider, signifying an increase in ATM volatility and convexity. Consistent with what was remarked earlier in the regression results, the widening is the largest in POWERGRID, where the right tail uncertainty was significantly higher than average. The observed behavior is also in line with the industry-wise median of ATM, RR, and BF given in Figure 2.

**FIGURE 3** Comparison of RND on four different days for randomly drawn stocks from three different industries. Each subfigure shows the RND on four different days belonging to different periods for a large firm from each of the three industries. The periods are classified as per the dates given in Exhibit I. The figures indicate that the market response to the pandemic was different across the three industries: (a) COALINDIA (energy), (b) SUNPHARMA (healthcare), and (c) POWERGRID (utilities). RND, risk-neutral density [Color figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]





**FIGURE 4** Comparison of Nifty with indices developed by MSCI Inc. The figure shows a comparison of the Nifty, MSCI-World and MSCI-Emerging Market indices from January 1 to May 31, 2020. The indices are rebased to January 1, 2020 = 100. The figure indicates that the pandemic had a more severe downward effect on the prices, and the recovery is slower for the Nifty stocks compared to that for their global peers. The data source for the MSCI indices is MSCI Inc. (<https://www.msci.com>) and the source for the Nifty index is NSE. MSCI, MSCI Inc. [Color figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

However, what was not apparent from the earlier plots of median and period/industry-controlled regression results is the change in the skewness of the distribution of individual securities over time. For both SUNPHARMA and POWERGRID, the shape of the RNDs changes from being a bell-shaped curve to first left-skewed at the beginning of the crisis and then right-skewed as the further recovery period begins.<sup>15</sup> While the right skewness may seem surprising in times of falling expectations and confidence, as Jackwerth (2020) also points out in the context of S&P index options in the US, RND captures the market *forecast of future/terminal spot prices*.<sup>16</sup> Therefore, the rightward shift of the distribution from the peak-end to the beginning of further-recovery signals discounting of future news, just as the shift from the beginning of the peak to the end of the peak signals market distress. After the recovery period, the fat right tail captures the low-probability event of a better-than-expected recovery. In terms of shifting risk aversion in times of extreme distress, it is as if the market or stock investment is now a lottery ticket—the negative mode is the ticket price, and the fat right tail is the prize (Barberis & Huang, 2008).

While the broad pattern observed here is similar to what was observed by Hanke et al. (2020) in their cross-country comparison for indices, the data here is richer in providing a comparison of the differential response of different industries. Such stock-specific estimates of *future* uncertainty can only be understood via the option-implied RND. COVID-19 is also a stark reminder of Jensen's inequality for convex functions that options on a basket of stocks (index options) are not the same as a basket of options. Moreover, the density implied by the index options is only of limited use in inferring stock- or industry-specific uncertainty, especially those affected the most by the pandemic.<sup>17</sup>

Our results of the shift in risk-neutral densities are robust to smile computed with respect to delta or different measures of moneyness and use of more commonly used statistical measures like skewness and kurtosis (results available on request). Our preference for the use of delta is because of its popularity in the options market and in the modern literature (Hayashi, 2020; Malz, 2014).

<sup>15</sup>The evidence from RND plots with respect to log moneyness ( $\ln(K/F)$ ) makes the increased dispersion during the peak period starker, but that requires suitably scaling the density so that the area under the curve adds up to 1. Those results are not presented here and are available on request.

<sup>16</sup>With the times coinciding with the maturity of the options used to derive the density.

<sup>17</sup>While the evidence here is presented only for a few stocks, for other stock-days across industries, comparisons are qualitatively in line with expectations and intuition reported here. The results for other days/stocks are available on request.

## 6 | CONCLUSIONS

Our results demonstrate the advantages of forward-looking measures of uncertainty derived from the options market. First, they outperform backward-looking realized volatility measures from the stock market. Second, the information from options with different strikes (the volatility smile) can be summarized into measures that enable uncertainty about the tails of the distribution to be distinguished from uncertainty about the middle of the distribution. Both forms of uncertainties rose sharply during the peak of the COVID-19 crisis in the Indian stock market (March 11–27). However, the tail uncertainty quickly reverted to the precrisis level, while the mid-distribution uncertainty remains elevated. With some timing difference, the evidence here is in line with the recent findings of Jackwerth (2020) and Hanke et al. (2020) in the context of index options markets in the United States and Europe, respectively.

Our study, however, focuses on divergent behavior of different dimensions of uncertainty across industries. The results indicate that the options market does not merely reprice risk indiscriminately; instead, it arrives at different risk assessments for each stock in each period while also distinguishing between mid and tail uncertainties. Our results demonstrate that unidimensional uncertainty measures are inadequate to capture the multifaceted impact of an event like a pandemic. Our work contributes to the literature in many ways. First, it demonstrates the benefits of measuring mid and tail uncertainties separately using options prices. This methodology is easy to operationalize and could be applied to measure time-varying risk aversion in response to other stressful events. Second, it contributes to our understanding of how financial markets can process information rationally under extreme uncertainty and stressful situations. Finally, we show the importance of higher moments like skewness and kurtosis in asset pricing during a pandemic.

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## CONFLICT OF INTERESTS

The authors declare that there are no conflict of interests.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the National Stock Exchange of India Limited (NSE). Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of NSE. The option smile parameters data that support the findings of this study are available from the authors upon reasonable request.

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## APPENDIX A

TABLE A1 Regression results with period, industry and interaction effects

Dependent variable	ATM	RR	BF
period_buildup	0.140 (0.083)*	−0.011 (0.054)	−0.007 (0.015)
period_peak	0.917 (0.083)***	−0.352 (0.054)***	0.087 (0.015)***
period_early_recovery	0.456 (0.091)***	−0.060 (0.059)	0.017 (0.016)
period_further_recovery	0.354 (0.083)***	0.017 (0.054)	−0.001 (0.015)
period_new_normal	0.210 (0.083)**	0.043 (0.054)	−0.004 (0.015)
industry_Consumer Discret	−0.014 (0.071)	0.024 (0.046)	−0.011 (0.012)
industry_Consumer Staples	0.002 (0.075)	0.019 (0.049)	−0.007 (0.013)
industry_Energy	−0.008 (0.081)	0.032 (0.052)	−0.007 (0.014)

(Continues)

TABLE A1 (Continued)

Dependent variable	ATM	RR	BF
industry_Financials	-0.035 (0.065)	0.016 (0.042)	-0.006 (0.012)
industry_Healthcare	-0.014 (0.074)	0.015 (0.048)	-0.004 (0.013)
industry_Industrials	-0.012 (0.071)	0.016 (0.046)	-0.006 (0.012)
industry_InfoTech	-0.046 (0.083)	0.020 (0.054)	-0.010 (0.015)
industry_Materials	-0.021 (0.069)	0.019 (0.045)	-0.008 (0.012)
industry_Real Estate	-0.012 (0.167)	0.012 (0.108)	0.004 (0.029)
industry_Utilities	-0.007 (0.079)	0.012 (0.051)	-0.007 (0.014)
period_buildup:industry_Consumer Discret	-0.033 (0.100)	-0.030 (0.065)	0.013 (0.018)
period_peak:industry_Consumer Discret	-0.297 (0.100)***	0.062 (0.065)	-0.005 (0.018)
period_early_recovery:industry_Consumer Discret	0.063 (0.108)	-0.042 (0.070)	0.022 (0.019)
period_further_recovery:industry_ConsumerDiscret	0.057 (0.100)	-0.058 (0.065)	0.015 (0.018)
period_new_normal:industry_Consumer Discret	0.075 (0.100)	-0.060 (0.065)	0.012 (0.018)
period_buildup:industry_Consumer Staples	-0.100 (0.107)	-0.019 (0.069)	0.008 (0.019)
period_peak:industry_Consumer Staples	-0.518 (0.107)***	0.134 (0.069)*	-0.027 (0.019)
period_early_recovery:industry_Consumer Staples	-0.178 (0.114)	-0.016 (0.074)	-0.009 (0.020)
period_further_recovery:industry_Consumer Staples	-0.103 (0.107)	-0.052 (0.069)	0.010 (0.019)
period_new_normal:industry_Consumer Staples	-0.060 (0.107)	-0.049 (0.069)	0.008 (0.019)
period_buildup:industry_Energy	-0.041 (0.114)	-0.016 (0.074)	0.001 (0.020)
period_peak:industry_Energy	-0.241 (0.114)**	0.182 (0.074)**	-0.034 (0.020)*
period_early_recovery:industry_Energy	-0.097 (0.122)	-0.065 (0.079)	0.010 (0.022)
period_further_recovery: industry_Energy	-0.079 (0.116)	-0.073 (0.075)	0.014 (0.020)
period_new_normal:industry_Energy	-0.005 (0.116)	-0.056 (0.075)	0.007 (0.020)
period_buildup:industry_Financials	-0.019 (0.093)	-0.028 (0.060)	0.007 (0.016)
period_peak:industry_Financials	-0.004 (0.093)	-0.008 (0.060)	0.017 (0.016)
period_early_recovery:industry_Financials	0.266 (0.100)***	-0.067 (0.065)	0.009 (0.018)
period_further_recovery:industry_Financials	0.204 (0.093)**	-0.048 (0.060)	0.017 (0.016)
period_new_normal:industry_Financials	0.183 (0.093)**	-0.014 (0.060)	0.020 (0.016)
period_buildup:industry_Health care	-0.065 (0.105)	-0.007 (0.068)	0.006 (0.019)
period_peak:industry_Health care	-0.336 (0.106)***	0.137 (0.069)**	-0.019 (0.019)
period_early_recovery:industry_Healthcare	-0.043 (0.111)	0.017 (0.072)	0.002 (0.020)
period_further_recovery:industry_Healthcare	0.014 (0.105)	-0.006 (0.068)	-0.001 (0.019)
period_new_normal:industry_Healthcare	-0.020 (0.105)	-0.034 (0.068)	0.001 (0.019)
period_buildup:industry_Industrials	-0.036 (0.100)	-0.065 (0.065)	0.018 (0.018)
period_peak:industry_Industrials	-0.296 (0.100)***	0.049 (0.065)	0.003 (0.018)
period_early_recovery:industry_Industrials	0.035 (0.108)	-0.098 (0.070)	0.024 (0.019)
period_further_recovery:industry_Industrials	-0.002 (0.100)	-0.056 (0.065)	0.016 (0.018)
period_new_normal:industry_Industrials	0.052 (0.100)	-0.047 (0.065)	0.013 (0.018)
period_buildup:industry_Info Tech	-0.052 (0.118)	-0.028 (0.076)	0.010 (0.021)

TABLE A1 (Continued)

Dependent variable	ATM	RR	BF
period_peak:industry_Info Tech	-0.367 (0.118)***	-0.0002 (0.076)	0.001 (0.021)
period_early_recovery:industry_Info Tech	-0.087 (0.129)	-0.050 (0.084)	0.012 (0.023)
period_further_recovery:industry_Info Tech	-0.071 (0.118)	-0.066 (0.076)	0.013 (0.021)
period_new_normal:industry_Info Tech	-0.049 (0.118)	-0.066 (0.076)	0.012 (0.021)
period_buildup:industry_Materials	-0.062 (0.098)	-0.031 (0.063)	0.010 (0.017)
period_peak:industry_Materials	-0.271 (0.098)***	0.067 (0.063)	-0.011 (0.017)
period_early_recovery:industry_Materials	0.002 (0.106)	-0.079 (0.068)	0.006 (0.019)
period_further_recovery:industry_Materials	0.016 (0.098)	-0.049(0.063)	0.013 (0.017)
period_new_normal:industry_Materials	0.036 (0.098)	-0.030 (0.063)	0.008 (0.017)
period_buildup:industry_Real Estate	-0.042 (0.236)	-0.036 (0.153)	-0.002 (0.042)
period_peak:industry_Real Estate	-0.109 (0.236)	-0.106 (0.153)	-0.006 (0.042)
period_early_recovery:industry_Real Estate	0.007 (0.239)	-0.174 (0.155)	0.024 (0.042)
period_further_recovery:industry_Real Estate	0.032 (0.236)	-0.063 (0.153)	0.014 (0.042)
period_new_normal:industry_Real Estate	0.037 (0.236)	-0.061 (0.153)	0.003 (0.042)
period_buildup:industry_Utilities	-0.051 (0.111)	-0.014 (0.072)	0.008 (0.020)
period_peak:industry_Utilities	-0.253 (0.111)**	-0.277 (0.072)***	0.094 (0.020)***
period_early_recovery:industry_Utilities	-0.114 (0.123)	-0.029 (0.080)	0.002 (0.022)
period_further_recovery:industry_Utilities	-0.065 (0.111)	-0.050 (0.072)	0.013 (0.020)
period_new_normal:industry_Utilities	0.040 (0.111)	-0.048 (0.072)	0.010 (0.020)
Observations	789	789	789
Adjusted $R^2$	0.718	0.580	0.589

Note: The table presents the regression estimates for the regression model explained in Equation (5). \*\*\*, \*\*, and \* indicate significance at 1%, 5%, and 10% levels, respectively.

Abbreviations: ATM, at-the-money; BF, butterfly; RR, risk reversal.