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Pandemic tail risk☆

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ABSTRACT

This paper studies the measurement of forward-looking tail risk in US equity markets around the COVID-19 outbreak. We document that financial markets are informative about how pandemic risk has spread in the economy in advance of the actual outbreak. While the tail risk of the market index did not respond before the outbreak, investors identified less pandemic-resilient economic sectors whose tail risk boomed in advance of both the market drawdown and the implementation of social distancing provisions. This pattern is consistent across different methodologies for measuring forward-looking tail risk, using option contracts, and across various horizons.

1. Introduction

The ongoing COVID-19 crisis highlights the importance of predicting and assessing the severity of a global pandemic. Timely indicators of pandemic risk could help decision-makers—such as politicians, firm executives, and investors—to take appropriate and prompt protective actions. This calls for forward-looking measures that are timely and informative about the severity of an upcoming or ongoing pandemic.

We investigate whether financial markets embed informative signals about pandemic risk and its evolution. Under informational efficiency, prices should reflect both private and public information (Hayek, 1945; Grossman and Stiglitz, 1980). However, the simple observation of the US equity index suggests that financial markets did not react promptly to the spread of the COVID-19 pandemic. Notably, when the S&P 500 and Dow Jones reached a high on February 19, 2020, the COVID-19 virus had already caused the death of more than 2000 people in China and infected thousands in several countries, including the United States.

This paper analyzes the extent to which asset prices beyond the market index capture the risk of the COVID-19 pandemic well before the index's decline in late February 2020. In particular, we study whether and how financial markets assess tail risk (i.e., the risk of extreme events) in relation to the COVID-19 outbreak.

We shed light on (i) investors' assessment of pandemic tail risk, exploiting information embedded in option contracts, (ii) the spread of pandemic tail risk across economic sectors, and (iii) the evolution of pandemic tail risk around the market turmoil due to the COVID-19 outbreak.

Specifically, we uncover a novel pattern: Pandemic tail risk is highly heterogeneous across economic sectors. We document that some sectors exhibited a significant increase in tail-risk measures in early February. Pandemic tail risk spread through some economic sectors well before the rise in market tail risk and ahead of the realized market crash. Our evidence underscores the importance of recognizing tail-risk heterogeneity to better understand the economic impact of a pandemic. The results of our study on ex-ante tail risk align with the heterogeneous response of realized stock returns across different groups of firms documented by the recent literature.

In our empirical approach, we analyze equity option prices for the US market index and nine economic sectors to investigate tail risk heterogeneity. We compute two key tail risk measures: the Slope, which captures the steepness in the implied volatility (IV) curve for out-of-the-money put options, and Implied Skewness, reflecting the asymmetry in the perceived risk of significant market moves. Applying

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this methodology to option data from the S&P 500 and economic sector indices, we aim to reveal how different market segments perceived risk during the COVID-19 pandemic.

Specifically, we document that pandemic resilience is key to understanding tail-risk heterogeneity. To this end, we further aggregate sectors' tail risk into three groups based on the sectors' pandemic resilience measure of Dingel and Neiman (2020)—that is, a measure of proneness to social distancing provisions.

We find that option-implied tail risk measures spiked before the first market crash only for the less resilient sectors. Thus, investors recognized a pandemic risk related to resilience to social distancing provisions before these were adopted. Our results attest to the reliability of real-time market-based measures in gauging the severity and spread of economic risks—even in the face of exogenous and unprecedented shocks.

The analysis focuses on out-of-the-money (OTM) options because OTM options serve as insurance against equity risk and, therefore, should reflect investors' fear of a significant drop in stock prices. We extract tail risk information from option prices by measuring the costliness of large drop protection — that is, the Slope measure of Kelly et al. (2016) — and the asymmetry in the risk-neutral distribution of equity returns, a measure of Implied Skewness. We study the evolution of these measures — both graphically and through panel regressions — around two key events: the COVID-19 outbreak on February 19, 2020, and the release of positive vaccine news on August 12, 2020.

Additionally, we find that tail-risk measures capture pandemic risk even earlier when considering their term spreads. We demonstrate that investors' perception of risk shifted towards the short term as the large drawdown in February 2020 approached. The opposite effect is observed in anticipation of positive vaccine news. This supports our hypothesis that tail risk measures were able to detect pandemic risk much earlier than aggregate measures.

Finally, we repeat the analysis using traditional (non-tail risk) measures of risk, including implied volatility and the variance risk premium. We find that our effects disappear when resorting to these traditional non-tail risk measures. This underscores the importance of analyzing the relevant parts of the complete distribution of asset prices and shows that crucial forward-looking information regarding the COVID-19 pandemic was primarily contained in the tail of the distribution.

Our study contributes to the literature on the COVID-19 pandemic's impact on financial markets. Alfaro et al. (2020) link unexpected COVID-19 infection rate changes to stock market returns, while Baker et al. (2020) find the pandemic's impact on markets surpasses any other, including the Spanish Flu. Croce et al. (2020) quantify the pandemic infection risk's financial value. Focusing on firm resilience, Pagano et al. (2023) observe that during the outbreak, firms more resilient to social distancing outperformed less resilient ones. Bretscher et al. (2020) use the first reported U.S. COVID-19 cases to study the pandemic's effect on equity returns, noting significant downturns in labor-intensive firms due to reduced labor mobility. Our paper extends this inquiry, examining *ex-ante* tail risk and its timing across economic sectors.

In addition, our research enhances the understanding of market-implied information. We investigate option-implied tail-risk measures as early indicators of significant events, resonating with studies by Leahy and Thomas (1996) and Hanke et al. (2018), who relate option prices to major political events such as the Quebec referendum and Brexit. Studies by Gemmill and Saflekos (2000) and Coutant et al. (2001) further underscore options' predictiveness in electoral contexts, and Gkionis et al. (2021) demonstrate their utility in detecting Brexit-related political risks.

Unlike Gormsen and Koijen (2020)'s exploration of dividend futures for assessing economic growth expectations during the COVID-19 pandemic, our study delves into the variability of tail risk across different economic sectors. This perspective is reinforced by the findings of Jackwerth (2020) and Cheng (2020) regarding market behaviors and the VIX index's responses, as well as the insights from Hanke et al. (2020) on the risk-neutral densities in equity index options. Our analysis uncovers that investors were able to detect sectors with lower resilience to the pandemic, as evidenced by an early increase in tail risk in these sectors, preceding both the overall market downturn and the onset of social distancing measures.

The remainder of this paper is organized as follows: Section 2 describes our data and methodology. Section 3 presents empirical results, exploring how financial markets assessed tail risk during the COVID-19 pandemic, particularly its spread across economic sectors. Section 4 examines the robustness of our results using various measures and scenarios. Section 5 concludes by summarizing key insights and their implications for financial markets amidst global health crises.

2. Data and methodology

This section describes the key measures that we adopt to conduct our empirical analysis. First, we employ a measure of pandemic *resilience* in order to aggregate economic sectors into homogeneous groups with respect to the impact of social distancing rules on their operating activity. Second, we formally describe our tail-risk measures.

2.1. Economic sectors and pandemic resilience

Constituents of the S&P 500 index are classified into nine economic sectors based on their industry classification. The family of exchange-traded funds (ETFs) tracking the returns of the individual sectors are denoted as SPDR.[1]

We compute a measure of pandemic *resilience* following the approach of Dingel and Neiman (2020). This measure is based on the capability of a company to implement remote working. In particular, Dingel and Neiman (2020) classify the occupations that can be conducted at home ("teleworkable employment" and "teleworkable manual employment") and compute the percentage of wages associated with these teleworkable occupations ("teleworkable wage" and "teleworkable manual wage") for industries based on the NAICS classification.

We then map companies from the NAICS code to the respective sector (GICS codes) using COMPUSTAT, and we aggregate companies at the SPDR sector level. The aggregate ranking of the sectors across the four resilience metrics is displayed in Table 1 and is almost identical for each metric. Sectors, ranked from low to high resilience, are Consumer Staples (CST), Materials (MAT), Consumer Discretionary (CDI), Industrial (IND), Energy (ENE), Health Care (HEA), Utilities (UTL), Technology (TEC), and Financial (FIN).[2]

During the pandemic, industries with long-duration cash flows were less affected compared to those with short-duration cash flows (Dechow et al., 2021). Notably, our resilience categories are not aligned with typical measures of cash-flow duration (see Dechow et al. (2004), Weber (2018), and Mohrschladt and Nolte (2018)). For instance, Healthcare typically has a high duration but medium resilience. In contrast, banking (Financial) exhibits a low duration but high resilience. Utilities fall into a middle ground with medium duration and high resilience, while the petroleum and natural gas sector (Energy) features a low duration but displays a medium resilience. The industrial sector also shows low duration but medium resilience. This suggests that conditioning on cash-flow duration does not subsume our measure of pandemic resilience to social distancing provisions. Therefore, our investigation captures a distinct risk feature of the cross-section of S&P 500 index constituents.

[1] SPDR is a trademark of Standard and Poor's Financial Services LLC, a subsidiary of S&P Global.

[2] Table A.1 of the Appendix shows the resilience categorization of sectors in detail.

Table 1
SPDR sectors and pandemic resilience. This table reports the tickers, names, IDs, classification, resilience rank, and the overall resilience group extracted as in Dingel and Neiman (2020).

Ticker	Name	ID	Resilience rank	Resilience group
SPX	S&P 500	SPX		
XLP	Consumer Staples	CST	1	Low
XLB	Materials	MAT	2	Low
XLY	Consumer Discretionary	CDI	3	Low
XLI	Industrial	IND	4	Medium
XLE	Energy	ENE	5	Medium
XLV	Health Care	HEA	6	Medium
XLU	Utilities	UTL	7	High
XLK	Technology	TEC	8	High
XLF	Financial	FIN	9	High

2.2. Option-implied tail risk measures

We construct option-implied tail risk measures from the surface files of iVolatility.com, which provides a range of implied volatilities for each day, with their corresponding maturity and delta levels. Moneyness is implied by the Black–Scholes delta. In particular, deltas (Δ) are provided for OTM puts and calls and range from −0.5 to 0.5 in steps of 0.05.[3]

We use out-of-the-money (OTM) options with 30 and 365 days to maturity and deltas lower than 0.5 in magnitude to construct the tail-risk measures. Additionally, we gather information for both the S&P 500 index and the nine SPDR sectors. In doing so, we align with literature such as DeMiguel et al. (2013) and Driessen et al. (2005), which document the high informational content of the options surface.

We are particularly interested in extracting forward-looking information, which is crucial in understanding how the distribution of equity returns has been impacted during the COVID-19 pandemic. To this end, we compute two main option-implied measures of tail risk: (i) the *Slope*, in line with Kelly et al. (2016) and Ilhan et al. (2020), and (ii) the *Implied Skewness* (IS), following the approach of Bakshi et al. (2003).

The $Slope$ identifies the slope coefficient obtained by regressing, for a given maturity (τ), the implied volatilities ($IV_t^{\tau,m}$) of the OTM puts at time t on their deltas ($\Delta_t^{\tau,m}$), across the moneyness (m) dimension, as follows:

$$IV_t^{\tau,m} = \alpha_t^{\tau} + Slope_t^{\tau} \times \Delta_t^{\tau,m} + \epsilon_t^{\tau,m}, \qquad \forall m. \tag{1}$$

A positive slope indicates that options that are deeper out-of-the-money (OTM) are relatively more expensive than those that are less OTM. Kelly et al. (2016) emphasize that a positive value of the $Slope$ suggests that investors are willing to pay a substantial price for protection against the downside tail risk associated with a near-future event. As outlined by Branger and Schlag (2004), Dennis et al. (2006), Bakshi et al. (2003), and Bollen and Whaley (2004), the buying pressure on OTM puts on the index serves as an insurance device against market crashes. This buying pressure increases the prices of these options, and consequently, their implied volatilities. These studies also demonstrate that the slope measure for the S&P Index is significantly steeper than for individual options.

An alternative measure of tail risk is the *Implied Skewness* (IS), which captures the asymmetry of the underlying risk-neutral distribution. Negative skewness commonly indicates that tail events are more likely on the left side of the distribution, while a positive skewness indicates the opposite. Actually, IS is the difference in the cost of buying protection against left-tail events and the cost of protection against right-tail events. IS is obtained by translating the regular skewness formula into the risk-neutral space as the third standardized risk-neutral moment of future log returns at horizon τ (Bakshi et al., 2003); thus we compute the Implied Skewness as follows:

$$IS_{t,\tau} = \frac{e^{r t} W_{t,\tau} - 3\mu_{t,\tau} e^{r t} V_{t,\tau} + 2\mu_{t,\tau}^3}{[e^{r t} V_{t,\tau} - \mu_{t,\tau}^2]^{3/2}}, \tag{2}$$

where $V_{t,\tau}$ and $W_{t,\tau}$ denote the risk-neutral discounted volatility and cubic contracts, $\mu_{t,\tau}$ denotes a Taylor approximation of the first risk-neutral moment at horizon τ (as a function of $V_{t,\tau}$ and $W_{t,\tau}$), and r represents the constant instantaneous interest rate.

[3] We choose iVolatility.com for data procurement due to its cost-effective customization options for individual tickers and desired time horizons, supported by its status as a trusted data provider with a broad client base of over 70,000 users in the global financial industry, including prominent hedge funds and institutional investors.

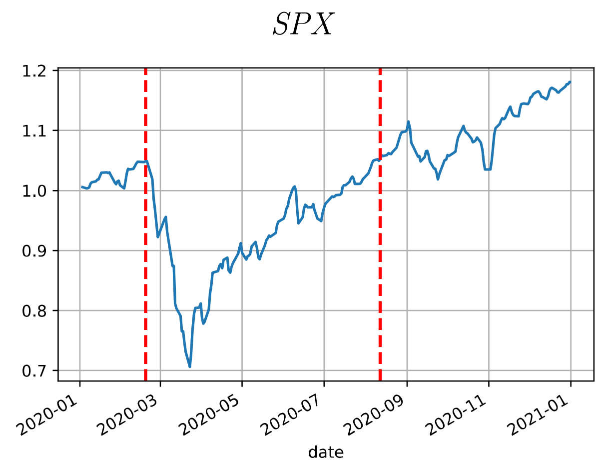

Fig. 1. Cumulative return for the SPX. The figure displays the cumulative return in 2020, for the S&P 500. The vertical dashed lines indicate the two events: (i) the first market drawdown on February 19, 2020; (ii) the positive news covering vaccines released on August 12, 2020.

3. Empirical analysis

We now study the tail risk embedded in the option-implied measures before, during, and after the burst of the COVID-19 pandemic in the US. We explore how tail risk evolves with the pandemic across the economic sectors, over different resilience groups, and over different time windows. In particular, we consider the following two events:

1. **Pandemic Outbreak**, which coincided with the first market drawdown on February 19, 2020,
2. **Positive Vaccine News**, which was released on August 12, 2020 (see Mulligan et al. (2021)).

We compute the realized equity returns for the market index (Fig. 1) and for the nine sectors that are sorted by level of resilience (Fig. 2). As of April 2019, the share of market capitalization by sector ranges from approximately 5% for Materials (MAT), Utilities (UTL), and Energy (ENE) to more than 20% for Technologies (TEC).

We find that for both the market index and the individual sectors, there is no significant reaction before the first drawdown (indicated by the left vertical dashed line in the figures). After the first drawdown, however, the aggregate market drops by around 35%. Moreover, all sectors experienced large negative returns that ranged from −20% for Technology (TEC) to approximately −50% for Energy (ENE). This finding is especially interesting because Technology (TEC) is classified as a cyclical sector, while Energy (ENE) represents a defensive sector.

We find that the cumulative return on the low-resilience sectors is in line with the market return. In contrast, the mid-and high-resilience sectors exhibited pronounced and dampened downturns during the crisis, respectively. In general, the gap between the returns of the different resilience groups materializes in the first two periods and remains generally constant afterward.

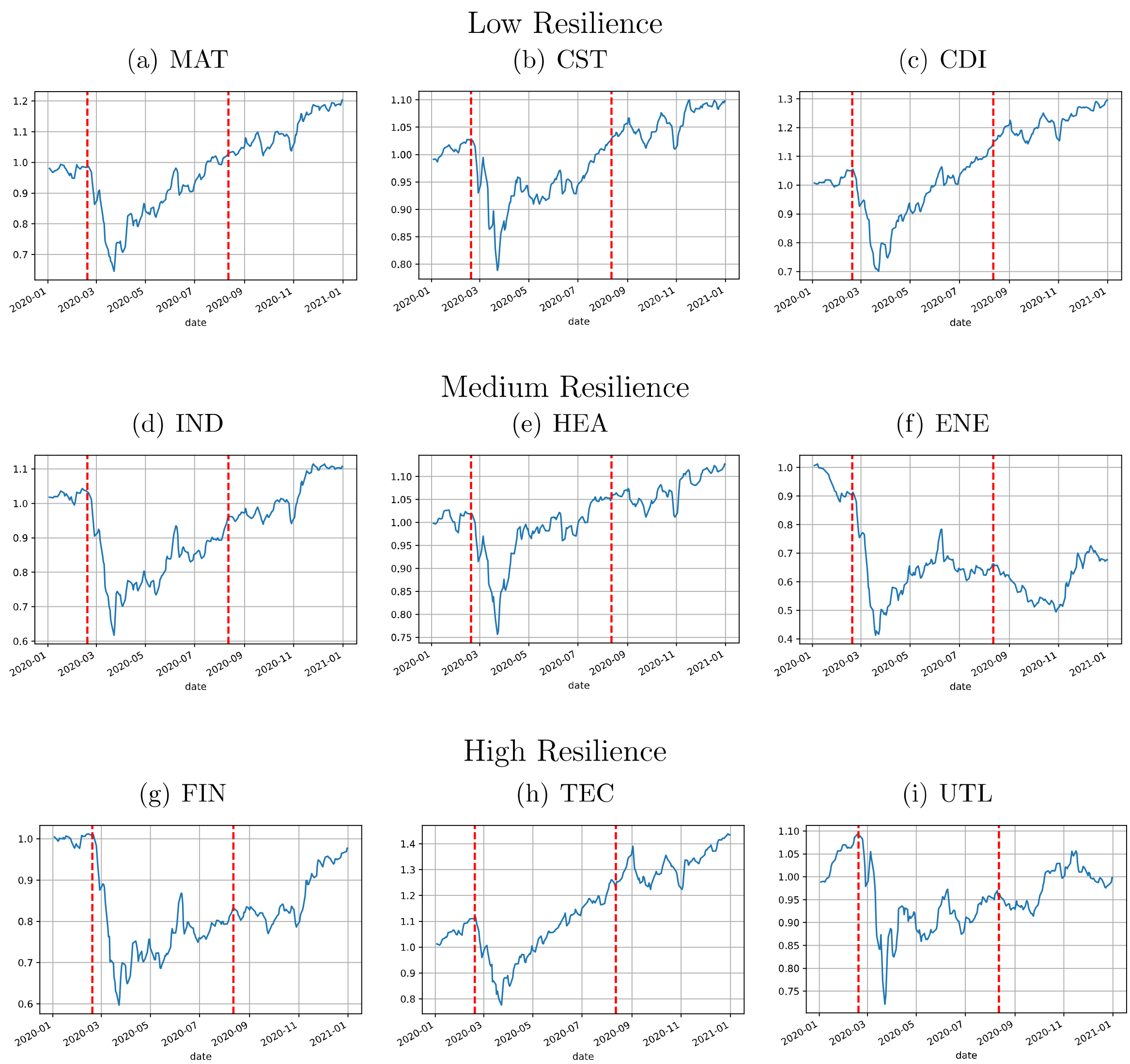

Fig. 2. Cumulative return for the nine SPDR sectors. The figure displays the cumulative returns in 2020, for the nine equity sectors. SPDR sectors are named as indicated in Table 1: Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the two-day moving average. The vertical dashed lines indicate the two events: (i) the first market drawdown on February 19, 2020; (ii) the positive news covering vaccines released on August 12, 2020.

Overall, our results show that financial markets did not capture pandemic risk before the first drawdown if we consider returns only. The goal of this paper is to show that when considering tail-risk measures, financial markets anticipated the COVID-19 outbreak, in particular by comparing tail-risk measures of the high versus low resilience groups.

3.1. Option-implied tail risk

We now focus on the option-implied measures of tail risk. We study both the *Slope* and the IS measures for the market index, the nine economic sectors, and the three resilience groups. In Table 2, we present summary statistics for our option-implied tail-risk measures from options with time to maturity of 30 days, over four different time windows (before the pandemic outbreak, after the pandemic outbreak, before positive vaccines news, and after positive vaccine news). We show that our tail-risk measures capture forward-looking information regarding the upcoming pandemic.

We plot the $Slope$ measure for the market index and the three resilience groups around the pandemic outbreak event (February 19, 2020). Panel (a) of Fig. 3 displays the levels of the $Slope$ measure on a four-month window centered around the event. We observe that the $Slope$ measure barely increases for the market index, from 0.157 to 0.167, before the first market drawdown. To clearly visualize the behavior of the $Slope$ measure across resilience groups right before the pandemic outbreak, Panel (b) of Fig. 3 displays the relative change in the $Slope$ measure one month before the event.

Indeed, we observe that the tail risk of the low-resilience group, as measured by the $Slope$ measure, increases much more than the tail risk of the high-resilience group. From the observation of the market index alone, one could infer that the fear of investors started in late February 2020, after the market crashed for the first time. Specifically, at this time, we begin to observe pandemic tail-risk for the market index. The *Slope* computed for the market index increases from 0.17 to 0.54.

This paper demonstrates that the information from the three resilience groups provides a much better understanding of tail-risk evolution. We document that the $Slope$ measure increases for all three groups and that the $Slope$ measure computed for the low-resilience group increases significantly more than the medium- and high-resilience groups. The latter shows only a moderate increase before the first market drawdown. Importantly, the rise of tail risk for the low-resilience group begins at the start of February 2020, well in advance of the first market drawdown.

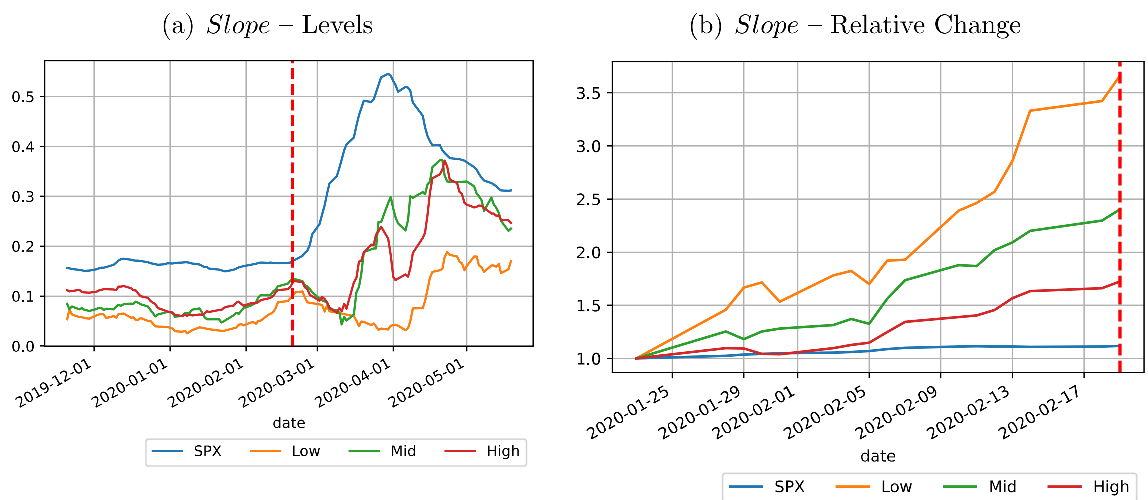

Fig. 3. *Slope* measure for the SPX and the resilience groups - Pandemic Outbreak. The figure displays the levels (left panel) and relative changes (right panel) in the tail-risk measure *Slope* for an option maturity of 30 days associated with the first drawdown (February 19, 2020). The *Slope* measure is constructed following Kelly et al. (2016) and denotes the slope coefficient from the regression of OTM puts' implied volatilities on the same options' deltas. Table 1, the SPDR sectors are aggregated into the three resilience groups: Low, Mid, and High. The plots report the 10-day moving average. The vertical dashed lines indicate the first market drawdown.

Table 2
Summary statistics: *Slope* measure. The table reports the summary statistics (time-series mean and standard deviation) for the SPX, the nine SPRD sectors, and the three resilience groups, for different time periods: (i) Before the Pandemic Outbreak (2019-07-30 to 2020-01-20); (ii) After the Pandemic Outbreak (2020-01-20 to 2020-07-10); (iii) Before Positive Vaccine Trials (2020-02-24 to 2020-08-12); (iv) After Positive Vaccine Trials (2020-08-12 to 2021-02-02) for the option-implied tail-risk measure *Slope* calculated as in Section 2.2. We use an option maturity of one month, sampled on a daily frequency. The tickers for the nine equity sectors are given in Table 1 (Panel A). Table 1, the SPDR sectors are aggregated into the three resilience groups: Low, Mid, and High.

Event	1. Pandemic outbreak				2. Positive vaccine news			
Period	Before		After		Before		After	
Stats	Mean	Std	Mean	Std	Mean	Std	Mean	Std
SPX	0.163	0.020	0.324	0.113	0.342	0.092	0.259	0.037
MAT	0.098	0.069	0.135	0.150	0.124	0.159	0.128	0.104
CST	0.037	0.045	0.071	0.090	0.076	0.093	0.068	0.054
CDI	0.078	0.058	0.132	0.117	0.139	0.116	0.150	0.067
IND	0.105	0.066	0.154	0.121	0.152	0.121	0.154	0.055
HEA	0.083	0.054	0.118	0.094	0.114	0.096	0.137	0.059
ENE	0.101	0.044	0.315	0.289	0.333	0.278	0.129	0.064
FIN	0.149	0.043	0.274	0.190	0.278	0.187	0.170	0.048
TEC	0.116	0.078	0.217	0.145	0.235	0.138	0.210	0.055
UTL	0.058	0.044	0.105	0.141	0.113	0.142	0.077	0.069
Resilience:								
Low	0.070	0.040	0.111	0.090	0.112	0.090	0.115	0.051
Mid	0.097	0.038	0.198	0.119	0.202	0.117	0.140	0.043
High	0.108	0.037	0.198	0.112	0.208	0.106	0.153	0.034

Table 3
Summary statistics: Implied Skewness (IS) over time. The table reports the summary statistics (time-series mean and standard deviation) for the SPX, the nine SPRD sectors, and the three resilience groups, for different time periods: (i) Before the Pandemic Outbreak (2019-07-30 to 2020-01-20); (ii) After the Pandemic Outbreak (2020-01-20 to 2020-07-10); (iii) Before Positive Vaccine Trials (2020-02-24 to 2020-08-12); (iv) After Positive Vaccine Trials (2020-08-12 to 2021-02-02) for the option-implied tail-risk measure IS calculated as in Section 2.2. We use an option maturity of one month, sampled on a daily frequency. The tickers for the nine equity sectors are given in Table 1 (Panel A). Table 1, the SPDR sectors are aggregated into the three resilience groups: Low, Mid, and High.

Event	1. Pandemic outbreak				2. Positive vaccine news			
Period	Before		After		Before		After	
Stats	Mean	Std	Mean	Std	Mean	Std	Mean	Std
SPX	−1.513	0.155	−1.364	0.146	−1.343	0.124	−1.395	0.189
MAT	−0.636	0.417	−0.461	0.445	−0.359	0.414	−0.503	0.367
CST	−0.289	0.360	−0.324	0.355	−0.318	0.382	−0.396	0.267
CDI	−0.567	0.415	−0.499	0.397	−0.490	0.357	−0.596	0.279
IND	−0.668	0.423	−0.552	0.420	−0.462	0.328	−0.602	0.197
HEA	−0.640	0.398	−0.598	0.419	−0.530	0.372	−0.723	0.273
ENE	−0.646	0.220	−0.678	0.319	−0.654	0.322	−0.306	0.207
FIN	−1.005	0.230	−0.769	0.327	−0.703	0.285	−0.666	0.167
TEC	−0.768	0.472	−0.813	0.465	−0.824	0.434	−0.860	0.240
UTL	−0.494	0.372	−0.363	0.342	−0.373	0.360	−0.376	0.352
Resilience:								
Low	−0.494	0.272	−0.420	0.294	−0.384	0.265	−0.498	0.201
Mid	−0.651	0.230	−0.610	0.288	−0.550	0.249	−0.544	0.158
High	−0.756	0.220	−0.648	0.289	−0.633	0.278	−0.634	0.162

The implication of these plots is remarkable. Based on our analysis, before the first market drop, a downturn was more likely for some specific sectors than for the whole market. In reality, investors were concerned about less pandemic-resilient sectors.

Thus, by extracting a forward-looking measure of tail risk from option prices, we document that markets anticipated the potential economic impact of social distancing provisions before they were adopted. This sheds light on the importance of the information embedded in financial markets about the timely understanding of the severity of an exogenous and unprecedented shock to the economy, as well as its propagation across economic sectors.

We obtain similar insights for the IS measure (for which we provide summary statistics in Table 3). We plot the IS measure for the market index and the three resilience groups in Fig. 4, between January 2020 and March 2020. Note that negative values of the IS measure stand for a heavier left-skewed distribution, thus signaling that investors consider extreme negative events more likely than extreme positive events.

Fig. 4 documents the slow reaction of the market index to pandemic risk and a substantial heterogeneity across the three resilience groups. Although the IS measure of the market index exhibits a flat pattern over our sample, the IS measure computed for the three resilience groups drops even before the first market crash. Importantly, the IS measure of the low-resilience group plunges sharply before the first market drawdown on February 20, 2020, while the tumble of the IS measure of the high-resilience group is much less pronounced. After the drawdown, the IS measure rebounds and begins to increase. Although the market and the high- and mid-resilience groups converge back

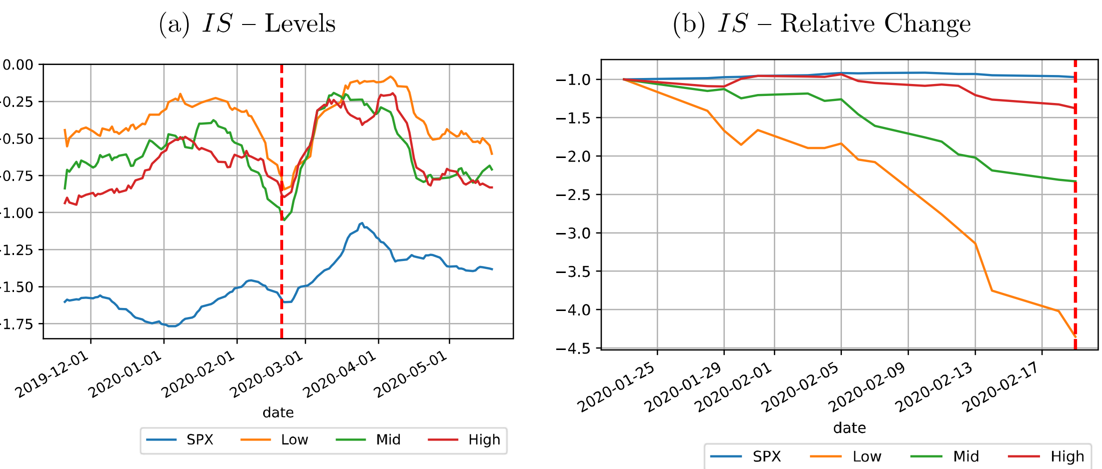

Fig. 4. IS measure for the SPX and the resilience groups - Pandemic Outbreak. The figure displays the levels (left panel) and relative changes (right panel) in the tail-risk measure IS for an option maturity of 30 days associated with the first drawdown (February 19, 2020). *IS*, as a proxy for tail risk, is constructed as in Bakshi et al. (2003) and quantifies the asymmetry of the risk-neutral distribution. Table 1, the SPDR sectors are aggregated into the three resilience groups: Low, Mid, and High. The plots report the 10-day moving average. The vertical dashed lines indicate the first market drawdown.

to the same level, the IS measure of the low-resilience group only partially recovers.[4]

The reversal in the IS measure is also visible, to a smaller extent, in the $Slope$ measure for individual sectors (see Fig. 3). However, the IS measure reverses more strongly than the Slope since $Slope$ and IS analyze implied volatilities (IVs) differently. In fact, The $Slope$ relates put IVs to their moneyness, while IS compares the IVs of out-of-the-money (OTM) calls and puts, normalized by the IV of at-the-money (ATM) options. IS usually shows a negative value, as put IVs are often higher than those of equivalent calls. The notable post-outbreak reversal in IS, compared to the $Slope$, is largely due to an increase in ATM IV. This increase in IV, detailed in Fig. 11, leads to a rise in IS. However, this does not suggest a reduction in tail risk. Instead, the high Slope measure post-event indicates that deep protection, particularly OTM puts, remains expensive.

Next, we investigate option-implied measures of tail risk around the second event: the positive vaccine news in August 2020. In Fig. 5, we plot the $Slope$ measure for the three resilience groups, where we observe that the tail risk of the low-resilience group decreases much more than that of the high-resilience group.

We obtain similar insights when turning our attention to the IS measure, the plots of which we provide in Fig. 6, around the event of the positive vaccine news. From panel (b), in which we display the relative changes, it is easy to observe that the low-resilience group's IS measure increases substantially. Meanwhile, the IS measure of the market index exhibits a flat pattern over this period.

In summary, our option-implied measures of tail risk allow us to disentangle the heterogeneous effect on the financial markets of the upcoming pandemic. Moreover, they provide forward-looking information that (i) anticipates the crash of the stock market index, as well as the adoption of social distancing provisions, and (ii) provides insights about the propagation of the pandemic across the economic sectors.

3.2. Regression analysis

We corroborate our graphical evidence using a panel regression analysis. We study the behavior of the option-implied tail risk measures at the sector level to test heterogeneity across resilience groups. Specifically, we test whether a significant increase or decrease in the option-implied tail risk measures occurs around specific relevant COVID-19 events. In particular, we focus on both negative and positive events using several different time windows that are symmetric around the event date: 30 days, 60 days, 90 days, and 120 days.[5] Then, we use the $Slope$ and the IS measures as our dependent variable in the regression equation, respectively, and the following independent variables: a time-series dummy for the pre-event days and a cross-sectional dummy for the low-resilience sectors. Our main variable of interest is the interaction term between the time series and the cross-section dummies. We include additional controls, such as the daily number of COVID-19 cases in the US, the level of daily (log)-trading volume, and implied volatility in all regressions. Moreover, we use industry-fixed effects to account for sector heterogeneity. Our main regression specification is the following:

$$Y_{i,t} = c + \alpha D_{i,t} + \gamma X_{i,t} + \epsilon_{i,t},$$

where i denotes the sector, c is the constant term, $X_{i,t}$ is a vector of control variables including the number of COVID-19 daily cases, the sectors' implied volatilities, trading volumes, and the sector fixed-effects. Finally, $D_{i,t}$ is a vector of dummies containing the main independent variables of interest. In particular, we consider the dummy variable *Resilience*, equal to 1 if the sector belongs to the low-resilience group and zero otherwise; the dummy variable *Pre-Outbreak*, equal to 1 if the observation is before the event date, and zero otherwise; and their interaction. Our main object of interest is the vector of coefficients α. We also account for both heteroskedasticity and autocorrelation in the error structure of our panel data using (Driscoll and Kraay, 1998) standard errors.

As in the previous section, we use two key events as our analysis framework: the pandemic outbreak (February 19, 2020) and the positive outcome of the COVID-19 vaccine test (August 12, 2020). These events serve as representative examples of negative and positive impacts, respectively. Some related papers (e.g., Pagano et al. (2023)) follow Ramelli and Wagner (2020) in using February 24 as a critical date for their empirical analysis. However, Ramelli and Wagner (2020) adopt February 24 as the initial date of the *Fever* period, while they indeed include February 19 in the *Pandemic Outbreak*. Thus, we have re-done our regression analysis using February 24 as the critical event date instead of February 19, and our results are substantially unaltered.

[4] As visible from Fig. 11 the IV increased after the event leading to an increase in IS.

[5] We also use additional time windows to check the robustness of our findings, such as 45 days and 75 days, and we obtain consistent results. However, we do not report the results in the Table to save in space.

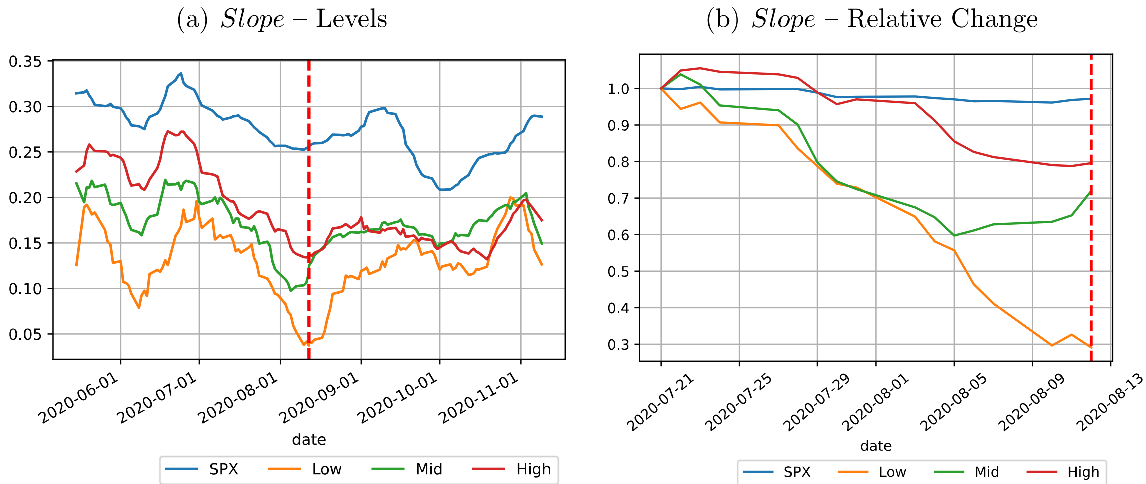

Fig. 5. *Slope* measure for the SPX and the resilience groups - Positive vaccine trials. The figure displays the levels (left panel) and relative changes (right panel) in the tail-risk measure *Slope* for an option maturity of 30 days associated to the release of positive vaccine news (August 12, 2020). *Slope* is constructed following Kelly et al. (2016) and denotes the slope coefficient from the regression of OTM puts' implied volatilities on the same options' deltas, where the option maturity corresponds to one month. Table 1, the SPDR sectors are aggregated into the three resilience groups: Low, Mid, and High. The plots report the 10-day moving average. The vertical dashed line indicates the positive news covering vaccines.

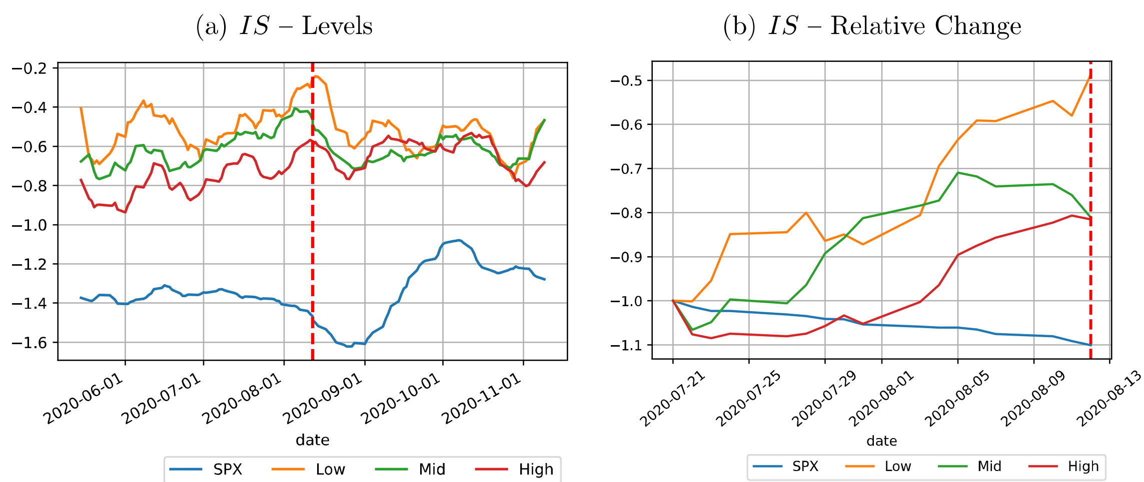

Fig. 6. *IS* measure for the SPX and the resilience groups – Positive vaccine trials. The figure displays the levels (left panel) and relative changes (right panel) in the tail-risk measure *IS* for an option maturity of 30 days associated to the release of positive vaccine news (August 12, 2020). *IS*, as a proxy for tail risk, is constructed as in Bakshi et al. (2003) and quantifies the asymmetry of the risk-neutral distribution. Table 1, the SPDR sectors are aggregated into the three resilience groups: Low, Mid, and High. The plots report the 10-day moving average. The vertical dashed line indicates the positive news covering vaccines.

We present our regression results in Table 4. We find that the *Slope* measure significantly increases for the low-resilience firms even before the first stock market crash and significantly decreases for the low-resilience firms even before the positive news about the COVID-19 vaccine trials, thus confirming the visual insights obtained from our previous graphical analysis. Consistently, we also find that the *IS* measure drops for the low-resilience firms before the first stock market crash and increases for the low-resilience firms before the positive news about the COVID-19 vaccine trials. The statistical significance of our results about the interaction dummy is robust for both the *Slope* and the *IS* across the event dates and all the time windows, with the only exception of the shortest window. While the 30-day window does not yield significant results, it is important to note that this window encompasses fewer observations that are used to estimate a considerable number of parameters. This limitation naturally affects the robustness of findings within this narrower time frame. It is important to highlight, however, that the sign and coefficient magnitudes for the 30-day window are similar to those of longer windows.[6] Moreover, the regression analysis supports the graphical evidence that the low-resilience sectors display lower *Slope* and higher *IS* compared to other sectors across different event dates and time windows–that is, less pandemic-resilient sectors, unconditionally, bear lower tail risk. This finding is also consistent with the sector-level evidence provided in Appendix C, in which we show that the low-resilience sectors have generally lower tail risk compared to other sectors. The simple rationale behind this result is that low-resilience industries (i.e., MAT, CST, CDI) are generally considered defensive sectors in the stock market context, unlike those in mid- and high-resilience groups, such as the Financial

[6] We also explored additional time frames, including 45-day and 75-day windows, and asymmetrical periods surrounding key events, to validate our findings further. These extended analyses have reinforced our main results, with minor exceptions in the 45-day windows related to vaccine announcements and the pandemic's onset. These insights, consistent with our broader narrative, are available upon request.

Table 4
Regression analysis. The table reports results from the OLS regression. In Panel A (B), the dependent variable is the daily level of the *Slope* (resp., *IS*) obtained by following the methodology described in Section 2.2. The main independent variables are the dummy variable *Resilience*, equal to 1 if the sector belongs to the low-resilience group and zero otherwise, the dummy variable *Pre-Event*, equal to 1 if the observation is before the event day and zero otherwise, and their interaction. Among the independent variables, we also include the logarithm of the traded *Volume*, the *Implied Volatility* computed following Bakshi et al. (2003), the daily number of new COVID-19 cases in the US, and sector fixed-effects. Columns (1)–(4) report results using a symmetric time window of 30 days around the event. Columns (2)–(5) report results using a symmetric time window of 60 days around the event. Columns (3)–(6) report results using a symmetric time window of 90 days around the event. Columns (4)–(8) report results using a symmetric time window of 120 days around the event. The events are specified in the first line of the table and are the following: the outbreak of the pandemic in Europe (February 19, 2020) and the positive news covering vaccines (August 12, 2020). We report (Driscoll and Kraay, 1998) standard errors below the regression coefficients to account for both heteroskedasticity and autocorrelation in the error structure.

Event	Pandemic outbreak				Positive vaccine trials			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time window	30-days	60-days	90-days	120-days	30-days	60-days	90-days	120-days
	Panel A: Slope							
Constant	0.932*	1.671**	1.584***	0.995*	0.429	0.904***	0.860***	0.859***
	(0.458)	(0.731)	(0.577)	(0.559)	(0.268)	(0.222)	(0.176)	(0.318)
Low-Resilience	−0.172**	−0.360***	−0.348***	−0.237***	−0.063*	−0.110**	−0.118***	−0.162***
	(0.067)	(0.098)	(0.080)	(0.077)	(0.033)	(0.026)	(0.023)	(0.040)
Pre-Outbreak	0.023	0.002	0.015	0.041	−0.015	0.002	0.008	0.058***
	(0.036)	(0.056)	(0.055)	(0.053)	(0.011)	(0.007)	(0.008)	(0.017)
Pre * Resilience	0.022	0.104***	0.093***	0.065***	−0.015	−0.028**	−0.033***	−0.047***
	(0.030)	(0.023)	(0.019)	(0.018)	(0.017)	(0.013)	(0.010)	(0.011)
Volume	−0.045*	−0.085**	−0.082***	−0.050*	−0.013	−0.034***	−0.031***	−0.046***
	(0.026)	(0.039)	(0.030)	(0.029)	(0.010)	(0.011)	(0.009)	(0.017)
Implied Vol	0.386***	0.028	0.232***	0.263***	0.697***	0.989***	0.967***	0.301***
	(0.052)	(0.070)	(0.056)	(0.048)	(0.216)	(0.128)	(0.144)	(0.041)
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES
Covid cases	YES	YES	YES	YES	YES	YES	YES	YES
N	286	535	796	1057	504	1035	1563	2084
R^2	0.372	0.364	0.355	0.320	0.351	0.377	0.463	0.292
	Panel B: Implied Skewness							
Constant	−5.305**	−6.452***	−6.299***	−4.707***	−3.421***	−4.219***	−4.067***	−3.735***
	(2.449)	(1.398)	(1.137)	(1.206)	(1.136)	(0.812)	(0.608)	(0.703)
Low-Resilience	0.778	1.140***	1.174***	0.898***	0.374 ***	0.529***	0.546***	0.618***
	(0.272)	(0.157)	(0.131)	(0.146)	(0.131)	(0.091)	(0.072)	(0.085)
Pre-Outbreak	−0.069	−0.029	−0.039	−0.110	0.033	0.005	0.001	−0.104**
	(0.165)	(0.137)	(0.133)	(0.137)	(0.052)	(0.034)	(0.033)	(0.044)
Pre * Resilience	0.023	−0.154**	−0.172***	−0.108*	0.101	0.122***	0.114***	0.124***
	(0.073)	(0.058)	(0.057)	(0.056)	(0.065)	(0.043)	(0.032)	(0.029)
Volume	0.254*	0.316***	0.310***	0.224***	0.086*	0.153***	0.144***	0.181***
	(0.129)	(0.072)	(0.058)	(0.062)	(0.047)	(0.039)	(0.031)	(0.037)
Implied Vol	−0.279***	0.118	0.166	0.112	0.201	−1.227***	−1.029***	0.014
	(0.079)	(0.121)	(0.114)	(0.097)	(0.826)	(0.406)	(0.381)	0.082
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES
Covid cases	YES	YES	YES	YES	YES	YES	YES	YES
N	286	535	796	1057	504	1035	1563	2084
R^2	0.364	0.319	0.322	0.271	0.280	0.279	0.307	0.245

and Technology sectors. Lastly, we do not find any significant impact of the *Pre-Outbreak* time-series dummy on the tail risk measures.

3.3. Additional evidence: Tail risk across the horizon

We next provide supportive evidence that tail-risk measures are capable of capturing pandemic risk well in advance of other non-tail-risk measures. Specifically, we examine investors' fear about the pandemic across various horizons, demonstrating that the term spread of tail-risk measures adjusts well before key pandemic events. Notably, the price of short-term tail risk increased as we approached the February drawdown (negative news), while the long-term risk was priced higher in the period leading up to the release of positive news about vaccine trials.

To do so, we focus on the term spread in tail risk, that is, the difference between a long (360 days) and a short (30 days) horizon measure of tail risk. Fig. 7 displays the term spread of the $Slope$ and IS measures for different resilience groups. We document two main patterns. First, Panels (a) and (b) show that the term spread for the $Slope$ and IS measures decreases and increases, respectively. This suggests that investors' perception of tail risk shifted towards the short run following the outbreak of the pandemic.

Second, we observe that this shift primarily concerns the low-resilience group, while the term spread of the high-resilience group is almost unaffected. Overall, the impending pandemic increased the transient risk for firms less resilient to social distancing provisions.

Finally, we find that the opposite effect is evident in anticipation of positive vaccine trial news. Fig. 8 displays the term spread of the $Slope$ and IS measures for different resilience groups prior to the release of positive vaccine news on August 12, 2020. The patterns observed previously now reverse. Panels (a) and (b) illustrate that the term spread for the $Slope$ *increases* and for the IS *decreases*, respectively. Consistent with our previous findings, we observe that investors' perception of tail risk shifted towards the *long run* in anticipation of *positive* news.

4. Robustness

To verify the robustness of our main findings to various specifications, we carry out a series of additional tests, the results of which are reported in Appendix. Overall, the results in the main part of the paper are robust.

4.1. Testing additional events

While the focus of this paper is on the pandemic events, we test the general validity of our approach by using additional, different events. Specifically, we use the collapse of the Lehman Brothers bank (September 15, 2008), the presidential election of Donald Trump (November

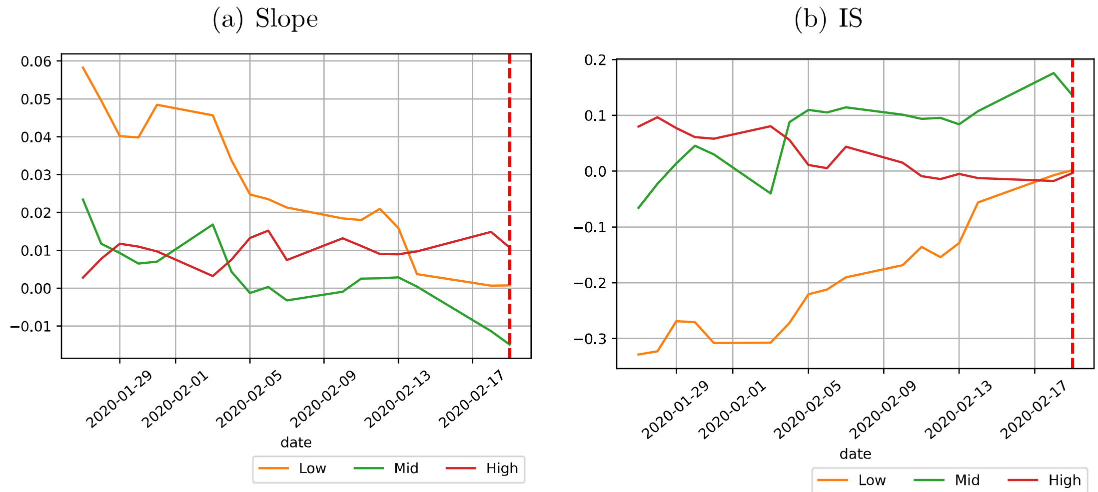

Fig. 7. Term spreads and resilience groups - Pandemic Outbreak. The figure displays the term spread between long-horizon and short-horizon tail-risk measures associated with the first market drawdown (February 19, 2020), starting one month before the event. The figure displays the difference between the respective measures extracted from 360- and 30-day maturity options. Table 1, the SPDR sectors are aggregated into the three resilience groups: Low, Mid, and High. The plots report the 10-day moving average. The vertical dashed lines indicate the market drawdown.

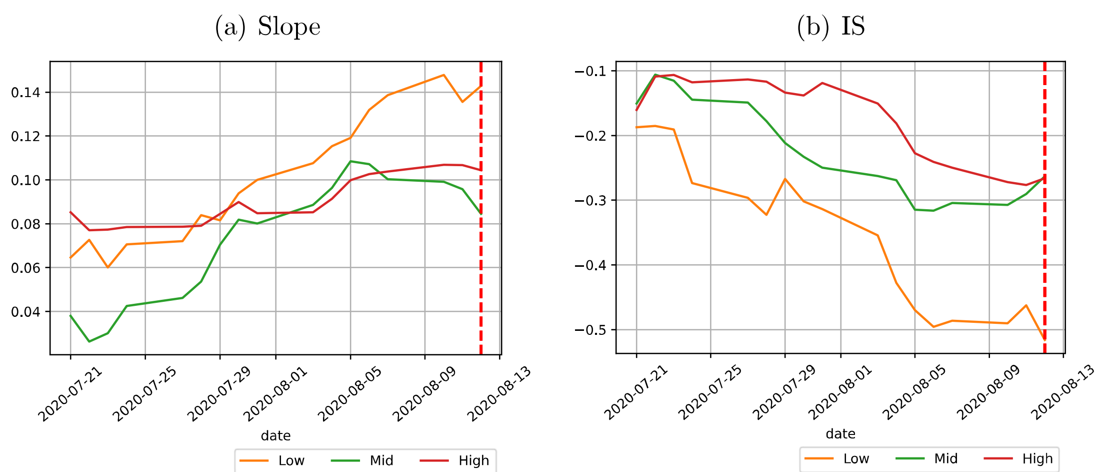

Fig. 8. Term spreads and resilience groups - Positive vaccine trials. The figure displays the term spread between long-horizon and short-horizon tail-risk measures associated with the positive vaccine news (August 12, 2020). The figure displays the difference between the respective measures extracted from 360- and 30-day maturity options starting from one month before the event. Table 1, the SPDR sectors are aggregated into the three resilience groups: Low, Mid, and High. The plots report the 10-day moving average. The vertical dashed line indicates the positive news covering vaccines.

8, 2016), and the burst of the Ukraine War (February 24, 2022) as a further laboratory of our study. We conduct a similar analysis as in Table 4, however, we do not group sectors into resilience groups. Instead, while keep controlling for the *Pre-Event* period and industry-fixed effects, we now interact the time-series *Pre-Event* dummy with a sector-specific dummy and run a different regression for each sector. We use three time windows that are symmetric around the event date: 60 days, 90 days, and 120 days. As in Table 4, we use the level of daily (log)-trading volume and implied volatility as additional controls in all the regressions. Furthermore, we also include in the set of control variables the following quantities with daily frequency: the sector returns, the *Daily News Sentiment Index*, the *S&P Dividend Yield*, and the *Economic Policy Uncertainty Index for the United States*.[7]

Because we obtain consistent results across the three time windows, we present only results about the shortest time window to save in space. In Table 5, we show that both the Slope significantly increases and the IS significantly decreases before the event date only for two sectors, namely the *Consumers Staples* industry and the *Financial* sectors, in line with the prior that financial firms, in particular banks, were strongly affected by the collapse of Lehman Brothers. On the 15th of September 2008, the bank officially filed for bankruptcy and its stock fell by 80%, leading the Dow Jones down to the largest drop since September 11, 2001. For all the remaining sectors, the interaction dummy between the Pre-Event period and the industry dummy displays either no statistical significance or the opposite sign of the regression coefficient for at least one of the two tail risk measures (i.e., negative sign for the Slope and positive sign for the IS). This reflects the financial sector's relative sensitivity to anticipating tail risks associated with significant financial events like the Lehman Brothers collapse.

[7] The Economic Policy Uncertainty Index (FRED, St. Louis Fed) provides insights into the uncertainty surrounding economic policies in the US. The sector returns are calculated as the daily percentage change in the underlying SPDR ETF prices. The Daily News Sentiment Index offers a real-time gauge of economic sentiment, derived from lexical analysis of news articles related to economics (Federal Reserve Bank of San Francisco). The S&P Dividend Yield is the annual dividend payments of S&P 500 companies as a percentage of the index's current price.

Table 5
Regression analysis: Lehman Brothers' collapse. The table reports results from the OLS regression at the sector level. In Panel A (B), the dependent variable is the daily level of the *Slope* (resp., *IS*) obtained by following the methodology described in Section 2.2. In each column-regression, the main independent variables are the dummy variable *Pre-Event*, equal to 1 if the observation is before the event day, and zero otherwise; the interaction dummy *Pre*Sector*, equal to 1 if the observation is before the event day and the sector is the one specified in the column label (e.g., it is *Material* in regression of column (1)), and zero otherwise. Among the independent variables, we also include the logarithm of the traded *Volume*, the *Implied Volatility* computed following Bakshi et al. (2003), and sector fixed-effects. In the Table, we report results using a symmetric time window of 60 days around the event. The event is the collapse of the Lehman Brothers bank (September 15, 2008). We include in the set of *Controls* the following variables: the daily sector returns, the Daily News Sentiment Index (Federal Reserve Bank of San Francisco), the S&P Dividend Yield, and the Economic Policy Uncertainty Index for the United States (FRED, St. Louis Fed). A short description of the additional *Controls* is reported in footnote 7. We report (Driscoll and Kraay, 1998) standard errors below the regression coefficients to account for both heteroskedasticity and autocorrelation in the error structure.

Event	Lehman Brothers collapse								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sector	MAT	CST	CDI	IND	HEA	ENE	FIN	TEC	UTL
	Panel A: Slope								
Constant	1.083***	0.988***	1.072***	1.102***	1.094***	1.027***	1.195***	1.106***	1.073***
	(0.351)	(0.348)	(0.352)	(0.343)	(0.353)	(0.349)	(0.344)	(0.357)	(0.346)
Pre-Event	−0.126***	−0.146***	−0.126***	−0.123***	−0.127***	−0.122***	−0.133***	−0.125***	−0.137***
	(0.046)	(0.050)	(0.045)	(0.046)	(0.045)	(0.045)	(0.045)	(0.044)	(0.046)
Pre * Sector	−0.027	0.111**	−0.023	−0.051*	−0.012	−0.101**	0.094**	−0.030	0.057***
	(0.037)	(0.046)	(0.019)	(0.029)	(0.032)	(0.042)	(0.044)	(0.024)	(0.020)
Volume	−0.045***	−0.039**	−0.045***	−0.047***	−0.046***	−0.042***	−0.052***	−0.047***	−0.045***
	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)	(0.015)
Implied Vol	0.649***	0.612***	0.650***	0.653***	0.654***	0.620***	0.697***	0.653***	0.641***
	(0.135)	(0.143)	(0.135)	(0.134)	(0.140)	(0.141)	(0.127)	(0.135)	(0.135)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	1062	1062	1062	1062	1062	1062	1062	1062	1062
R^2	0.637	0.644	0.637	0.639	0.637	0.643	0.642	0.637	0.639
	Panel B: Implied Skewness								
Constant	−1.590**	−1.229*	−1.580**	−1.600**	−1.703**	−1.497**	−1.754***	−1.616**	−1.604**
	(0.653)	(0.664)	(0.657)	(0.651)	(0.654)	(0.650)	(0.669)	(0.656)	(0.652)
Pre-Event	0.156	0.222**	0.157	0.157	0.130	0.147	0.166*	0.155	0.155
	(0.097)	(0.107)	(0.097)	(0.097)	(0.088)	(0.097)	(0.095)	(0.095)	(0.096)
Pre * Sector	0.035	−0.406***	0.023	0.017	0.203**	0.166***	−0.140**	0.034	0.032
	(0.045)	(0.082)	(0.047)	(0.061)	(0.080)	(0.055)	(0.065)	(0.041)	(0.053)
Volume	0.033	0.011	0.034	0.035	0.042	0.030	0.044	0.036	0.035
	(0.036)	(0.038)	(0.036)	(0.036)	(0.035)	(0.036)	(0.036)	(0.036)	(0.036)
Implied Vol	−0.348**	−0.208	−0.350**	−0.351**	−0.402***	−0.299*	−0.419***	−0.353**	−0.356**
	(0.147)	(0.158)	(0.146)	(0.146)	(0.147)	(0.153)	(0.142)	(0.147)	(0.145)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	1062	1062	1062	1062	1062	1062	1062	1062	1062
R^2	0.371	0.411	0.371	0.371	0.381	0.377	0.375	0.371	0.371

In Table 6, we report results about the unexpected victory of Donald Trump in the presidential election of 2016 and document that both the Slope significantly increases and the IS significantly decreases before the event date only for the *Industrial* and *Health-Care* sectors.[8] Intuitively, healthcare companies were particularly sensitive to the well-known Donald Trump's threat of repealing and replacing the previous Democrats' reform. Once more, the regression coefficient on the interaction dummy between the Pre-Event period and the industry dummy is either not significant or of opposite sign for at least one of the two tail risk measures for all the other sectors. Finally, not surprisingly, we show in Table 7 that both the Slope significantly increases and the IS significantly decreases before the event date only for the Industrial and the Energy sectors, which is consistent with the dramatic oil and gas crisis following the burst of the Ukraine war.

4.2. Index tail risk and market segmentation

We have explored the possibility that the market index might exhibit a reaction in options far out of the money, a phenomenon not visible in our initial analysis. This further examination, as shown in Fig. 9, was conducted to uncover potential hidden effects in the deeper

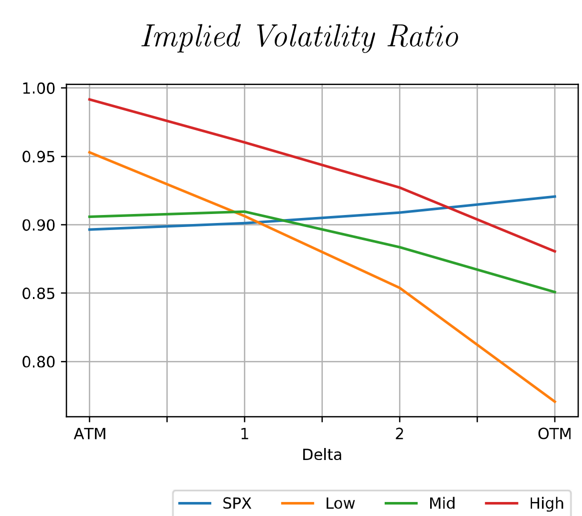

Fig. 9. Anticipated Market vs. Sector reaction. This figure illustrates the ratio of implied volatility on January 2, 2020, to that on February 18, 2020, for put options with a maturity of 30 days on the S&P 500 Index and the three resilience groups, by computing the withing-group average across sectors. A lower value of the ratio indicates a more significant reaction before the outbreak.

[8] The presidential election of Donald Trump can be truly considered as a shock for the financial markets. For instance, the New York Times assigned Hillary Clinton a 98.5% chance of success at the beginning of election night.

Table 6
Regression analysis: Trump's election. The table reports results from the OLS regression at the sector level. In Panel A (B), the dependent variable is the daily level of the *Slope* (resp., *IS*) obtained by following the methodology described in Section 2.2. In each column-regression, the main independent variables are the dummy variable *Pre-Event*, equal to 1 if the observation is before the event day, and zero otherwise; the interaction dummy *Pre*Sector*, equal to 1 if the observation is before the event day and the sector is the one specified in the column label (e.g., it is *Material* in regression of column (1)), and zero otherwise. Among the independent variables, we also include the logarithm of the traded *Volume*, the *Implied Volatility* computed following Bakshi et al. (2003), and sector fixed-effects. In the Table, we report results using a symmetric time window of 60 days around the event. The event is the presidential election of Donald Trump (November 8, 2016). We include in the set of *Controls* the following variables: the daily sector returns, the Daily News Sentiment Index (Federal Reserve Bank of San Francisco), the S&P Dividend Yield, and the Economic Policy Uncertainty Index for the United States (FRED, St. Louis Fed). A short description of the additional *Controls* is reported in footnote 7. We report (Driscoll and Kraay, 1998) standard errors below the regression coefficients to account for both heteroskedasticity and autocorrelation in the error structure.

Event	Trump's election								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sector	MAT	CST	CDI	IND	HEA	ENE	FIN	TEC	UTL
	Panel A: Slope								
Constant	0.475***	0.448***	0.448***	0.453***	0.457***	0.451***	0.539***	0.448***	0.466***
	(0.170)	(0.169)	(0.169)	(0.170)	(0.169)	(0.165)	(0.159)	(0.169)	(0.167)
Pre-Event	0.062**	0.054*	0.054*	0.049	0.049*	0.053*	0.062**	0.052*	0.049
	(0.030)	(0.030)	(0.030)	(0.029)	(0.029)	(0.029)	(0.030)	(0.029)	(0.030)
Pre * Sector	−0.066***	−0.004	0.003	0.049***	0.042**	0.005	−0.092*	0.016	0.044***
	(0.016)	(0.023)	(0.011)	(0.015)	(0.016)	(0.026)	(0.054)	(0.016)	0.015)
Volume	−0.038***	−0.038***	−0.038***	−0.038***	−0.038***	−0.038***	−0.044***	−0.038***	−0.039***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Implied Vol	8.686***	8.670***	8.670***	8.672***	8.672***	8.669***	8.668***	8.671***	8.671***
	(0.526)	(0.522)	(0.521)	(0.517)	(0.518)	(0.520)	(0.473)	(0.521)	(0.519)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	1061	1061	1061	1061	1061	1061	1061	1061	1061
R^2	0.908	0.907	0.907	0.907	0.907	0.907	0.909	0.907	0.907
	Panel B: Implied Skewness								
Constant	0.462	0.512	0.542	0.505	0.505	0.487	0.485	0.526	0.565
	(0.595)	(0.606)	(0.598)	(0.607)	(0.605)	(0.598)	(0.632)	(0.605)	(0.603)
Pre-Event	−0.332**	−0.323**	−0.321**	−0.291**	−0.302**	−0.305**	−0.318**	−0.304**	−0.324**
	(0.140)	(0.143)	(0.138)	(0.138)	(0.140)	(0.141)	(0.139)	(0.144)	(0.142)
Pre * Sector	0.156*	0.092	0.069	−0.199***	−0.099**	−0.068	0.043	−0.083	0.091
	(0.080)	(0.106)	(0.055)	(0.067)	(0.049)	(0.076)	(0.152)	(0.206)	(0.092)
Volume	−0.063	−0.062	−0.064*	−0.062	−0.062	−0.061	−0.060	−0.063	−0.065*
	(0.038)	(0.039)	(0.038)	(0.039)	(0.039)	(0.038)	(0.040)	(0.038)	(0.038)
Implied Vol	3.569***	3.617***	3.610***	3.599***	3.602***	3.615***	3.607***	3.598***	3.608***
	(1.265)	(1.278)	(1.274)	(1.261)	(1.268)	(1.270)	(1.259)	(1.263)	(1.274)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	1061	1061	1061	1061	1061	1061	1061	1061	1061
R^2	0.464	0.463	0.462	0.466	0.463	0.462	0.462	0.462	0.463

tail segments of the market. However, the analysis indicates that the S&P 500 Index did not exhibit a reaction, even for options that are far out of the money (OTM). This lack of response persists across the spectrum of OTM options prior to the outbreak. In stark contrast, individual sectors, particularly those with lower resilience, show a more pronounced reaction. Notably, the strength of these reactions increases as the options move further out of the money, highlighting a distinct behavioral pattern in these sectors compared to the overall index.

We have also investigated trading volume as depicted in Fig. 10. It is observed that for the aggregate index, there was no abnormal trading volume before the outbreak. However, for the resilience groups, particularly the low resilience group, there was abnormal trading volume in the days before the outbreak. This suggests that there was some form of market segmentation, where sector traders did not extensively trade in the index. This could justify the absent reaction of the index before the outbreak, adding further insight into the dynamics of market responses in the face of emerging risks.

4.3. Alternative option-implied risk measures

In this section, we discuss alternative option-implied variables, such as the Implied Volatility (IV), Variance Risk Premium (VRP), and the Implied Correlation. The IV is defined as the option-implied variance which captures total quadratic variation, typically using variance swaps, as outlined in Bakshi et al. (2003). We compute the associated risk premia, particularly the ex-ante variance risk premium $VRP(t,\tau)$, calculated as the difference between the day-t implied variance from options with maturity τ and the realized variance for the period $t-\tau$ to t. For the estimation of realized variances (RV), we use the sum of squared daily returns. We emphasize that IV and VRP are not the main focus of our paper but we nonetheless provide a basic analysis, briefly discussing their roles and implications in the context of our research.

The results are displayed in Fig. 11. The IV measure, representing market volatility implied by observed option prices, showed a strong correlation (0.998) with the VIX index in our sample from January 2019 to March 2021. However, despite this correlation, we found that the IV and traditional VRP measures were not as effective in capturing pandemic risk in a timely manner, particularly because they do not focus on tail risk. The IV did not show a significant increase before the first market drawdown, with a more noticeable rise only several weeks later, across different resilience groups.

We also explored another definition of the VRP, updating our approach in line with advancements in the literature. The traditional VRP measure, as previously introduced, has been refined and we have conducted our analysis using the state-of-the-art measure from Bekaert and Hoerova (2014). This updated measure aligns more closely with advanced risk measurement techniques, effectively capturing the intricacies of variance risk dynamics, particularly in the context of tail risks.

To illustrate this, we examined the Conditional Variance (CV) and the new VRP for the SPX, following Bekaert and Hoerova (2014)'s

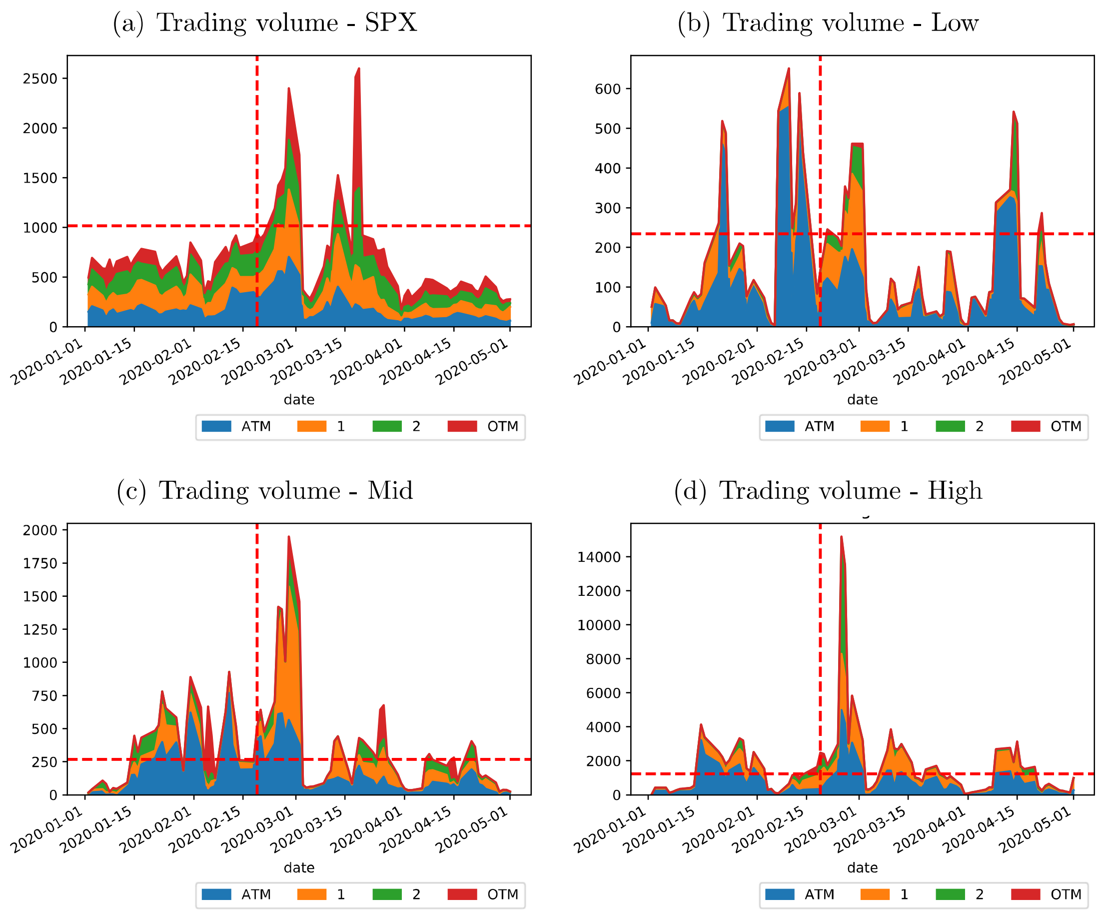

Fig. 10. Trading volume around the outbreak. This figure displays the daily trading volumes of ATM and OTM put options (delta between −0.5 and 0) with a maturity of 30 days. In each plot, the dotted horizontal red line indicates the long-term average, computed over the entire 2019, and the dotted vertical red line indicates the first market drawdown (February 19, 2020).

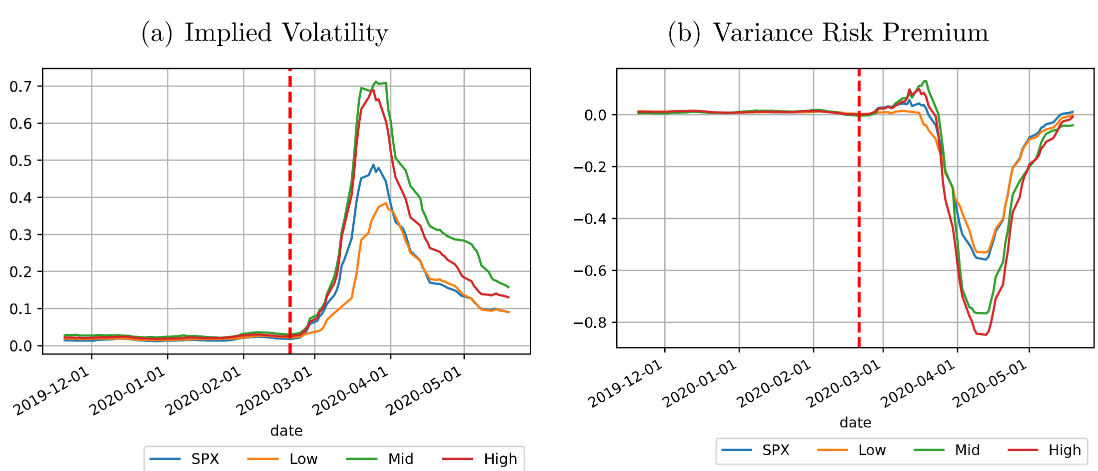

Fig. 11. IV and VRP measures for SPX and resilience groups. The left panel displays the IV extracted for an option maturity of 30 days three months before and after the event day (February 19, 2020). As described in Section 2.2, implied variance is constructed as in Bakshi et al. (2003) and quantifies the risk-neutral expectation of the realized variance over the future horizon of 30 days. The right panel displays the relative changes of the VRP extracted for an option maturity of 30 days, from December 2019 to May 2020. As described in Section 2.2, the variance risk premium (VRP) is computed as risk-neutral variance (IV) observed at the end of the day t minus the realized variance (RV) from $t - \Delta t$ to t. To compute realized variances, we use daily returns for a window length corresponding to the maturity of the considered options. Table 1, the SPDR sectors are aggregated into the three resilience groups: Low, Mid, and High. The plots report the 10-day moving average. The vertical dashed line indicates the first market drawdown (February 19, 2020).

Table 7
Regression analysis: Ukraine War. The table reports results from the OLS regression at the sector level. In Panel A (B), the dependent variable is the daily level of the *Slope* (resp., *IS*) obtained by following the methodology described in Section 2.2. In each column-regression, the main independent variables are the dummy variable *Pre-Event*, equal to 1 if the observation is before the event day, and zero otherwise; the interaction dummy *Pre*Sector*, equal to 1 if the observation is before the event day and the sector is the one specified in the column label (e.g., it is *Material* in regression of column (1)), and zero otherwise. Among the independent variables, we also include the logarithm of the traded *Volume*, the *Implied Volatility* computed following Bakshi et al. (2003), and sector fixed-effects. In the Table, we report results using a symmetric time window of 60 days around the event. The event is the burst of the Ukraine War (February 24, 2022). We include in the set of *Controls* the following variables: the daily sector returns, the Daily News Sentiment Index (Federal Reserve Bank of San Francisco), the S&P Dividend Yield, and the Economic Policy Uncertainty Index for the United States (FRED, St. Louis Fed). A short description of the additional *Controls* is reported in footnote 7. We report (Driscoll and Kraay, 1998) standard errors below the regression coefficients to account for both heteroskedasticity and autocorrelation in the error structure.

Event	Ukraine war burst								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sector	MAT	CST	CDI	IND	HEA	ENE	FIN	TEC	UTL
	Panel A: Slope								
Constant	2.171***	2.144***	2.161***	2.255***	2.194***	2.156***	2.178***	2.213***	2.198***
	(0.350)	(0.346)	(0.367)	(0.348)	(0.354)	(0.339)	(0.351)	(0.356)	(0.349)
Pre-Event	0.048**	0.057***	0.043*	0.039*	0.047**	0.034*	0.049***	0.047**	0.042*
	(0.022)	(0.021)	(0.023)	(0.023)	(0.023)	(0.018)	(0.018)	(0.022)	(0.022)
Pre * Sector	−0.020	−0.104	0.027	0.050**	−0.018	0.095**	−0.034	−0.020	0.027
	(0.020)	(0.066)	(0.024)	(0.023)	(0.027)	(0.043)	(0.059)	(0.028)	(0.021)
Volume	−0.130***	−0.129***	−0.130***	−0.136***	−0.132***	−0.129***	−0.131***	−0.133***	−0.132***
	(0.023)	(0.022)	(0.023)	(0.023)	(0.023)	(0.022)	(0.023)	(0.023)	(0.023)
Implied Vol	7.922***	7.898***	7.945***	7.993***	7.944***	7.811***	7.925***	7.944***	7.909***
	(1.247)	(1.201)	(1.241)	(1.247)	(1.234)	(1.222)	(1.246)	(1.235)	(1.240)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	1062	1062	1062	1062	1062	1062	1062	1062	1062
R^2	0.499	0.507	0.499	0.500	0.499	0.505	0.499	0.499	0.499
	Panel B: Implied Skewness								
Constant	−2.237*	−2.375**	−2.444**	−3.015***	−2.309**	−2.277**	−2.306**	−2.353*	−2.287*
	(1.146)	(1.142)	(1.193)	(1.127)	(1.140)	(1.110)	(1.117)	(1.197)	(1.159)
Pre-Event	−0.217***	−0.198**	−0.192**	−0.136*	−0.172**	−0.142**	−0.241***	−0.185**	−0.227***
	(0.071)	(0.080)	(0.074)	(0.072)	(0.077)	(0.066)	(0.060)	(0.075)	(0.083)
Pre * Sector	0.218***	0.071	0.021	−0.441***	−0.176*	−0.411***	0.467**	−0.053	0.294
	(0.063)	(0.187)	(0.072)	(0.130)	(0.095)	(0.133)	(0.208)	(0.112)	(0.207)
Volume	0.044	0.061	0.064	0.101	0.056	0.050	0.057	0.058	0.056
	(0.070)	(0.069)	(0.072)	(0.069)	(0.069)	(0.066)	(0.068)	(0.072)	(0.070)
Implied Vol	−4.644**	−4.798**	−4.822**	−5.305**	−4.777**	−4.269*	−4.627*	−4.815**	−5.149**
	(2.338)	(2.304)	(2.325)	(2.325)	(2.341)	(2.189)	(2.430)	(2.350)	(2.228)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	1062	1062	1062	1062	1062	1062	1062	1062	1062
R^2	0.272	0.269	0.268	0.283	0.271	0.281	0.285	0.269	0.275

approach. As can be seen from Fig. 12, both CV and the revised VRP displayed an increase in January, similar to the VIX index, but notably reverted before the pandemic outbreak. This observation underscores the effectiveness of the revised VRP measure in capturing nuances in variance risk that traditional measures may overlook.

In contrast to these traditional measures, our selected metrics, such as Slope and Implied Skewness, did not exhibit this reversion. This indicates their greater efficacy in anticipating the market impact of the COVID-19 pandemic, highlighting the importance of employing tail risk-focused measures in financial analysis, particularly when examining market dynamics during unprecedented events.

In sum, our findings suggest that the alternative measures IV and VRP do not timely capture pandemic risk, in contrast to our tail-based measures. Moreover, we show that the IV and VRP measures of risk are not able to capture the heterogeneity among different sectors and resilience groups with respect to tail risk.

Next, as shown in Fig. 13, we construct an option-implied correlation using the implied volatilities from the sectors. We, therefore, follow Buss et al. (2016) and construct the "reduced sector-based correlation" for the S&P 500 Index using only nine sector ETFs ($N = 9$):

$$\rho(t) = \frac{\sigma_I^2(t) - \sum_{i=1}^{N} w_i(t)^2 \sigma_i^2(t)}{\sum_{i=1}^{N} \sum_{j \neq i} w_i(t) w_j(t) \sigma_i(t) \sigma_j(t)}. \tag{3}$$

As visible from the plot, the sector correlation indeed increased at the beginning of February 2020 which suggests that the correlation risk matters. However, the sector correlation reversed before the drawdown. The strongest increase is visible after the outbreak in March 2020 where the average correlation across sectors reaches almost 0.9.

The main determinants of the sector correlation are the respective option-implied volatilities (i.e., of the nine sectors and the index). As argued before, implied volatilities do not increase before the outbreak, therefore, the sector correlation (as a function of the volatilities) does not increase either. Overall, our results indicate that correlation risk does not anticipate tail risk to the same extent that tail risk measures such as Slope and IS do.

In the next step, we also construct the downside and upside IV. We, therefore, split the IV considering only puts or calls following Kilic and Shaliastovich (2019), and Feunou et al. (2017). We added the respective plots for the pandemic outbreak and the vaccine trials on a sector level in the Appendix (Figs. D.3–D.8). As for the total implied volatility, the up and down volatilities do not show any movement before the pandemic outbreak. In contrast, one can infer a strong decline in the volatility measures before the positive vaccine trials.

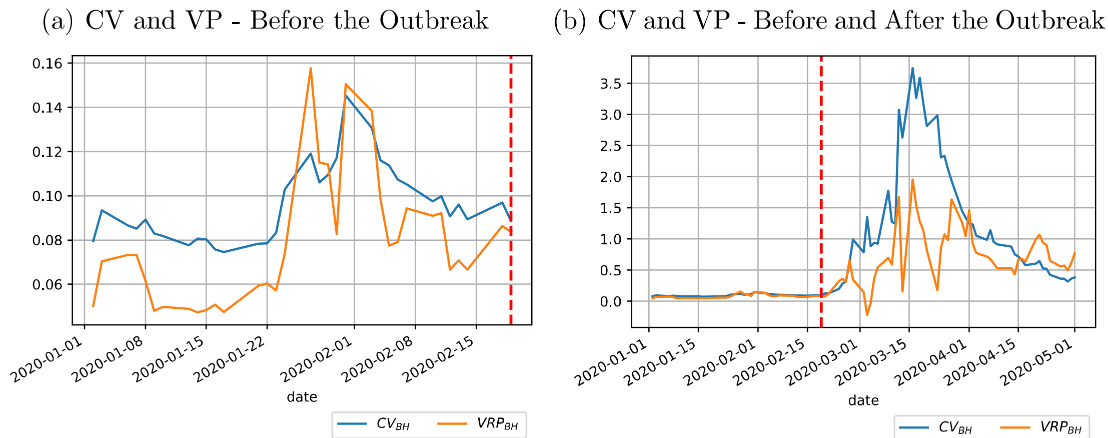

Fig. 12. CV and VP measures for the SPX from Bekaert and Hoerova (2014). The figure displays the conditional variance (CV) and variance premium (VP), computed by following Bekaert and Hoerova (2014), before the pandemic outbreak (February 19, 2020) (Panel (a)), and over a longer period (Panel (b)). The vertical dashed line indicates the first market drawdown (February 19, 2020).

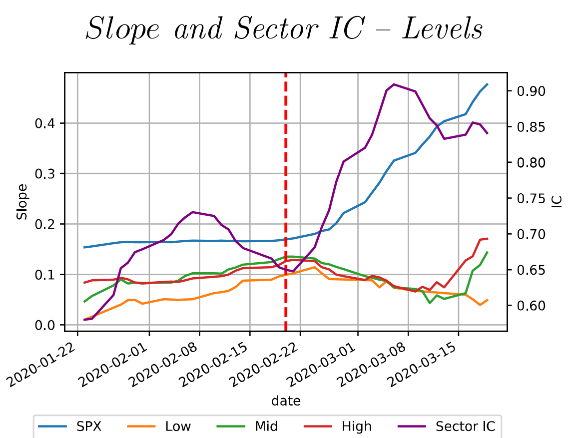

Fig. 13. *Slope* measure and Sector IC for the SPX and the resilience groups - Pandemic Outbreak. The figure displays the tail-risk measure *Slope* (left axis) and the option-implied sector correlation (*Sector IC*, right axis) for an option maturity of 30 days associated with the first drawdown (February 19, 2020). The *Slope* measure is constructed following Kelly et al. (2016) and denotes the slope coefficient from the regression of OTM puts' implied volatilities on the same options' deltas. The option maturity is one month. Table 1, the SPDR sectors are aggregated into the three resilience groups: Low, Mid, and High. The *Sector IC* is constructed following Buss et al. (2016) by applying Eq. (3) using the IVs for the index and the individual sectors. The plots report the 10-day moving average. The vertical dashed lines indicate the first market drawdown.

4.4. Shift in risk aversion

The dynamics of risk aversion, particularly during the COVID-19 crisis, present a compelling aspect of financial market behavior. Incorporating the Risk Aversion Index (BEX) from Bekaert et al. (2022) into our analysis, we observed notable patterns that align with historical movements in other risk measures such as the VIX and IV.

Our findings, depicted in Fig. 14, illustrate that the BEX experienced an increase in mid-February, preceding the pandemic's global impact. However, this uptick was temporary and reversed even before the outbreak's escalation on February 19th, reaching a low of 2.65. This pattern of initial rise and subsequent decline mirrors the movements in the VIX and IV indices, suggesting a common underlying market sentiment.

Interestingly, the sectorial Slope and IS measures, which are central to our analysis, displayed a different trajectory. These measures started increasing in mid-February but continued their upward trend until the pandemic's outbreak, only beginning to revert afterward. This divergence indicates that while general market risk aversion, as captured by the BEX, did react to the onset of COVID-19, it did not predominantly drive the dynamics of our primary focus - the tail risk measures (Slope and IS).

Our examination suggests that the movement in these tail risk measures is more closely tied to the sectors' resilience to social distancing provisions, rather than being primarily driven by aggregate risk aversion.

4.5. Value-weighted resilience groups

Results remain unchanged if we consider a value-weighted aggregation of the individual sectors' *Slope* and IS into the corresponding resilience groups as displayed in Figs. B.1 and B.2 for the pandemic outbreak and in Figs. B.3 and B.4 for the news associated to the positive vaccine trials.

4.6. Option-implied tail risk: SPDR sectors

The *Slope* (IS) measure for each of the nine SPDR sectors before the pandemic outbreak is shown in Fig. C.1 (Fig. C.2) of the Appendix, where it displays an increase (decrease) in terms of levels over time, especially for low- and mid-resilient sectors. For the positive vaccine trials, the situation is the opposite: the *Slope* (IS) measure is decreasing (increasing) before the event, as visible in Fig. C.3 (Fig. C.4).

4.7. Information search

We next investigate the ability of Google searches (Google Trends) to forecast pandemic risk. Google Trends data is typically used as an information search or attention-based measure (for example, in Da et al. (2011)). Importantly, Preis et al. (2013) demonstrated that Google Trends not only aggregates financial market information but also contains (fundamental) information that is not (yet) captured in financial markets. This suggests that Google Trends could be an important statistic capturing investors' information set.

As seen in Fig. 15, Google searches for pandemic-related search terms spiked only well after the first drawdown. This finding is in line with other non-tail-risk measures. This suggests that the pandemic was

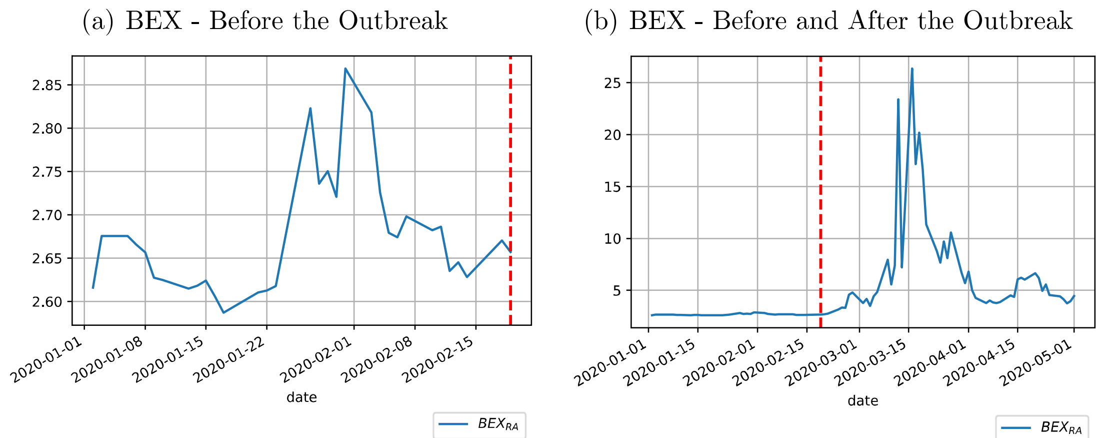

Fig. 14. Risk aversion index from Bekaert et al. (2022). The figure displays the risk aversion index (BEX_{RA}), computed by following Bekaert et al. (2022), before the pandemic outbreak (February 19, 2020) (Panel (a)), and over a longer period (Panel (b)). The vertical dashed line indicates the market drawdown (February 19, 2020).

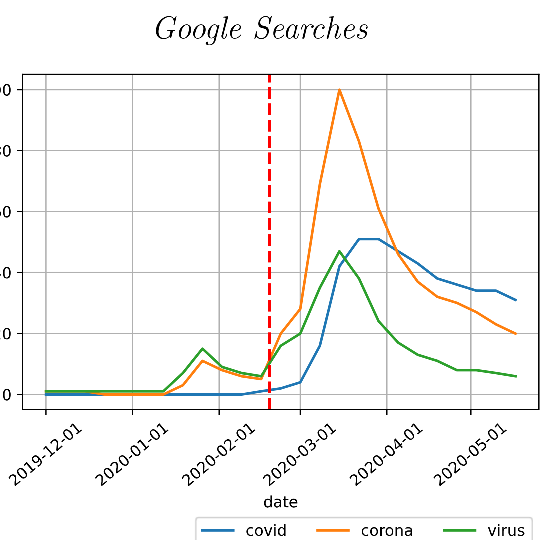

Fig. 15. Google searches. The figure displays the worldwide search intensity for the keywords "covid", "corona" and "virus" from Google Trends between December 2019 and May 2020. The figures are normalized w.r.t. the peak search intensity for expositional simplicity.

not considered of main interest by financial market participants, which is consistent with our finding that on an aggregate level, financial markets did not price pandemic risk before the drawdown of February 19, 2020.[9]

4.8. Alternative difference-in-differences approach

We next explore "A Local Projections Approach to Difference-in-Differences Event Studies" by Dube et al. (2023) as a means to further validate the robustness of our baseline findings. This method enhances the traditional DiD analysis by addressing biases and refining control and treatment group definitions using local projections. Its adaptability across different estimands and the incorporation of pre-treatment controls underscores its utility and efficiency. Here, we articulate the application of Dube et al. (2023)'s methodology to our study, highlighting the process and findings derived from this approach.

Our primary analysis diverges from the classical DiD model in two significant ways. Firstly, the conventional DiD method assesses the post-event effect to estimate the differential impact across treatment and control groups, assuming parallel trends pre-event. Our interest, conversely, lies in examining significant differences in option-implied risk measures before the event. Secondly, traditional DiD identifies the event as the point at which the treatment group receives treatment, with pre-event similarity between treatment and control groups. Our scenario, however, presents pre-event differences between the Low-Resilience and Non-Low-Resilience groups, notably during the Pandemic Outbreak.

We have incorporated the methodology developed by Dube et al. (2023) into our study, tailoring it to fit our specific framework. Our approach unfolded in two directions:

Approach 1

Utilizing the newly developed Stata command "lpdid" by Dube et al. (2023), we adapted their DiD estimator for our analysis, which accommodates both absorbing and non-absorbing treatments. In their demonstration with a simulated dataset, the treatment variable "treat" is defined in a manner that parallels our "*Pre-Event * Low-Resilience*" interaction dummy, albeit with a crucial distinction in the pre-treatment assignment. We thus replicated their variable to align with our interaction dummy and interpreted the post-event coefficient as the DiD effect. This analysis, conducted across various event dates and symmetrical time windows, is documented in Panel A of Table 8. The sign and magnitude of the estimated coefficients are generally consistent with those reported in Table 4 for both event dates and both option-implied tail risk measures, across all the time windows. Also, the estimated coefficients are significant at least at the 10% level, except for (i) the 30-day time window, and (ii) the 60-, 90-, and 120-day time windows for the Implied Skewness around the Positive Vaccine News. Nonetheless, the magnitude and direction of the estimates are consistent with our main results.

Approach 2

Next, we undertake an approach that may appear more conventional and comparable with the usual DiD framework. We consider the event (i.e., the Pandemic Outbreak and the Positive Vaccine News) in the standard format (i.e., the treatment event). Conversely, we consider the Non-Low-resilience group (i.e., the High-Resilience group and the Mid-Resilience group) as the treated group. Then, we build a treatment

[9] It should be noted, however, that towards the end of January, there was a slight increase in search intensity. However, financial markets did not react so early (neither on an aggregate level nor in the tail) and potentially considered the risk of an outbreak too small for it to affect asset prices.

Table 8
Regression analysis: Local Projection-DiD. The table reports results from the difference-in-differences regression analysis. The dependent variable is the daily level of the *Slope* (resp., *IS*) obtained by following the methodology described in Section 2.2. To estimate the DiD effect we use the local projection method developed by Dube et al. (2023). Panel A (Panel B) reports results obtained by following Approach 1 (Approach 2) outlined in the paper. Columns (1)–(4) report results using a symmetric time window of 30 days around the event. Columns (2)–(5) report results using a symmetric time window of 60 days around the event. Columns (3)–(6) report results using a symmetric time window of 90 days around the event. Columns (4)–(8) report results using a symmetric time window of 120 days around the event. The events are specified in the first line of the table and are the following: the outbreak of the pandemic in Europe (February 19, 2020) and the positive news covering vaccines (August 12, 2020). In all the regressions, we include the same set of control variables described in Table 4.

Event	Pandemic outbreak				Positive vaccine trials			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time window	30-days	60-days	90-days	120-days	30-days	60-days	90-days	120-days
Panel A: Approach 1	DiD effect							
Slope	0.102	0.109**	0.088**	0.076**	−0.072	−0.080*	−0.073*	−0.077*
	(0.066)	(0.051)	(0.038)	(0.031)	(0.045)	(0.043)	(0.044)	(0.044)
Implied Skewness	−0.263	−0.314*	−0.293*	−0.296*	0.265	0.281	0.266	0.246
	(0.214)	(0.182)	(0.171)	(0.163)	(0.200)	(0.197)	(0.191)	(0.195)
Panel B: Approach 2	DiD effect							
Slope	0.107	0.115**	0.095**	0.078**	−0.074*	−0.079*	−0.095*	−0.154**
	(0.071)	(0.060)	(0.048)	(0.038)	(0.043)	(0.048)	(0.054)	(0.070)
Implied Skewness	−0.247	−0.273	−0.252	−0.223	0.270	0.300	0.325	0.380
	(0.218)	(0.185)	(0.169)	(0.165)	(0.213)	(0.213)	(0.242)	(0.269)

variable that is equal to 1 for the Non-Low-resilience group after the treatment event, and zero otherwise. By following this approach, we thus test whether the High-Resilience group and the Mid-Resilience group display a higher (lower) Slope and lower (higher) Implied Skewness only after the treatment event—that is, the Pandemic Outbreak (Positive Vaccine News). We report the results in Table 8 (Panel B).

We find results similar to those obtained with approach 1. It is important to note that approach 2 is further from our main analysis compared to approach 1, and we observe a slight decrease in the significance of the results. The significance of the implied skewness results decreases slightly, dropping to around 10%–11% for most estimates of implied skewness. Nevertheless, the size and magnitude of the results remain consistent.

5. Conclusion

This paper offers broad evidence about investors' perception of pandemic risk, both before and during the large market drops that followed the COVID-19 outbreak.

Using information conveyed by both equity options, we uncover a novel pattern, that is, tail risk heterogeneity across different economic sectors in reaction to the pandemic.

On the one hand, we document that the tail risk of the market index did not rise before the upcoming market crash. On the other hand, firms suffering more from social distancing provisions display a dramatic increase in the tail-risk indicators in advance of the first market drop of late February 2020.

Our findings suggest that investors were coherently accounting for the tail risk of firms more exposed to the pandemic's effects, such as social distancing provisions that have been subsequently adopted. Thus, investors were hedging the risk of a near downturn.

Overall, our analysis delivers insights about the importance of forward-looking tail-risk measures encapsulated in equity derivatives. These measures seem to respond rationally and promptly to exceptional and unprecedented events. Moreover, tail-risk heterogeneity is informative about the economic impact of such events and their propagation patterns in the economy.

CRediT authorship contribution statement

Matthijs Breugem: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Raffaele Corvino:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Roberto Marfè:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Lorenzo Schönleber:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Data availability

Data will be made available on request.

Appendix A. Individual SPDR sector resilience

The measure from Dingel and Neiman (2020) provides a resilience score for each NAICS code. From Compustat we can extract a table that gives us for each firm (gvkey) the NAICS codes (NAICS3) and the corresponding economic sector (gsector). In the first step, we identify for each NAIC code the economic sectors. In the best case the mapping is unique: for example, the NAIC code 113 which represents "Forestry and Logging" is always associated with the gsector 15 (Materials). Nevertheless, the mapping can be not unique as well: For example, the NAIC code 812 which represents "Personal and Laundry Services" is, depending on the firm, associated with the gsector 20 (Industrials) or gsector 25 (consumer discretionary). We then attribute for each NAIC code the metric (for example "teleworkable emp") to the sectors in which the NAIC code appears. In order to obtain one aggregated measure per sector we then simply average the metrics across the NAICS codes.

Appendix B. Resilience groups - Value weighted

See Figs. B.1–B.4.

Appendix C. Individual SPDR sectors

See Figs. C.1–C.4.

Appendix D. Alternative risk measures

See Figs. D.1–D.8.

Table A.1
Resilience measure of sectors. The table reports the resilience measure provided by Dingel and Neiman (2020). "Teleworkable emp (wage)" denotes the fraction of (wages to) jobs that can be done from home, estimated from O*Net data, and "teleworkable manual emp (wage)" denotes the fraction of (wages to) jobs that can be done from home, based on manual classification by the authors. Panel B displays the relative rank of each sector based on the absolute values in Panel A. The mapping from NAICS to the respective sector can be inferred from COMPUSTAT (gsector). SPDR sectors are named as in Table 1, that is, Materials (MAT), Energy (ENE), Consumer Staples (CST), Industrial (IND), Health Care (HEA), Consumer Discretionary (CDI), Financial (FIN), Technologies (TEC), and Utilities (UTL).

Panel A: Sectors – Resilience

Metrics sector	teleworkable emp	teleworkable wage	teleworkable manual emp	teleworkable manual wage
MAT	0.312	0.392	0.271	0.353
ENE	0.353	0.438	0.331	0.419
FIN	0.553	0.631	0.495	0.578
IND	0.344	0.421	0.303	0.383
TEC	0.534	0.620	0.496	0.588
CST	0.294	0.372	0.256	0.335
UTL	0.467	0.578	0.439	0.546
HEA	0.454	0.530	0.406	0.484
CDI	0.330	0.406	0.285	0.364

Panel B: Sectors – Resilience – Rank

Metrics sector	teleworkable emp	teleworkable wage	teleworkable manual emp	teleworkable manual wage
MAT	2	2	2	2
ENE	5	5	5	5
FIN	9	9	8	8
IND	4	4	4	4
TEC	8	8	9	9
CST	1	1	1	1
UTL	7	7	7	7
HEA	6	6	6	6
CDI	3	3	3	3

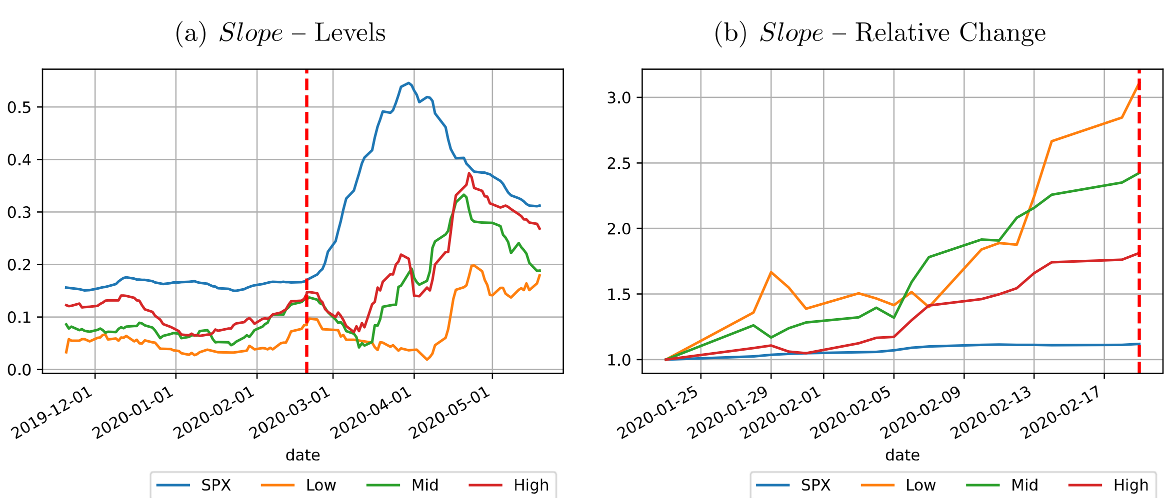

Fig. B.1. *Slope* measure for the SPX and the resilience groups – Pandemic Outbreak – Value-weighted. The figure displays the levels and relative changes in the tail-risk measure *Slope* for an option maturity of 30 days associated with the first drawdown, which occurred on February 19, 2020. *Slope* is constructed following Kelly et al. (2016) and denotes the slope coefficient from the regression of OTM puts' implied volatilities on the same options' deltas, where the option maturity corresponds to one month. Table 1, the SPDR sectors are aggregated by their market capitalization (value-weighted) into the three resilience groups: Low, Mid, and High. The plots report the 10-day moving average. The vertical dashed lines indicate the first market drawdown.

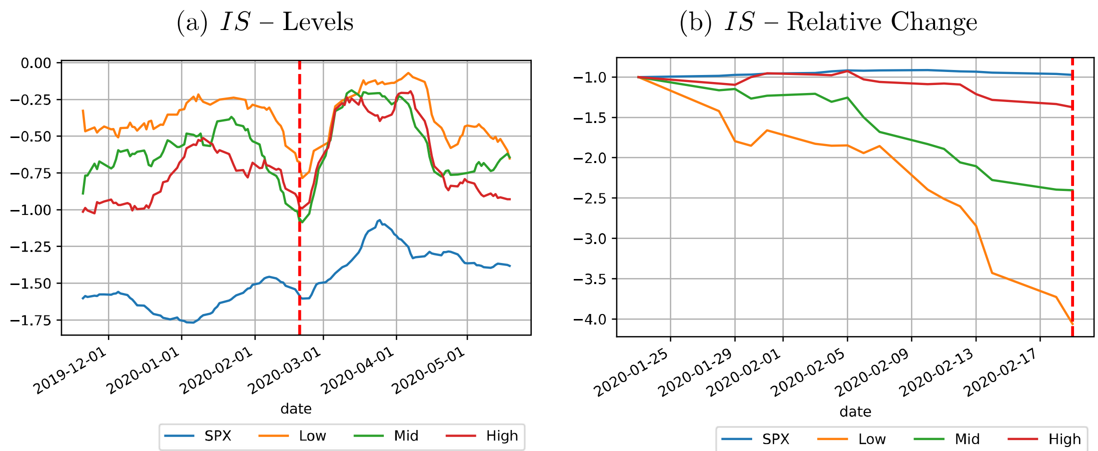

Fig. B.2. IS measure for the SPX and the resilience groups – Pandemic Outbreak – Value weighted. The figure displays the levels and relative changes of the tail-risk measure IS extracted for an option maturity of 30 associated with the first market drawdown, which occurred on February 19, 2020. *IS*, as a proxy for tail risk, is constructed as in Bakshi et al. (2003) and quantifies the asymmetry of the risk-neutral distribution. Table 1, the SPDR sectors are aggregated by their market capitalization (value-weighted) into the three resilience groups: Low, Mid, and High. The plots report the 10-day moving average. The vertical dashed lines indicate the first market drawdown.

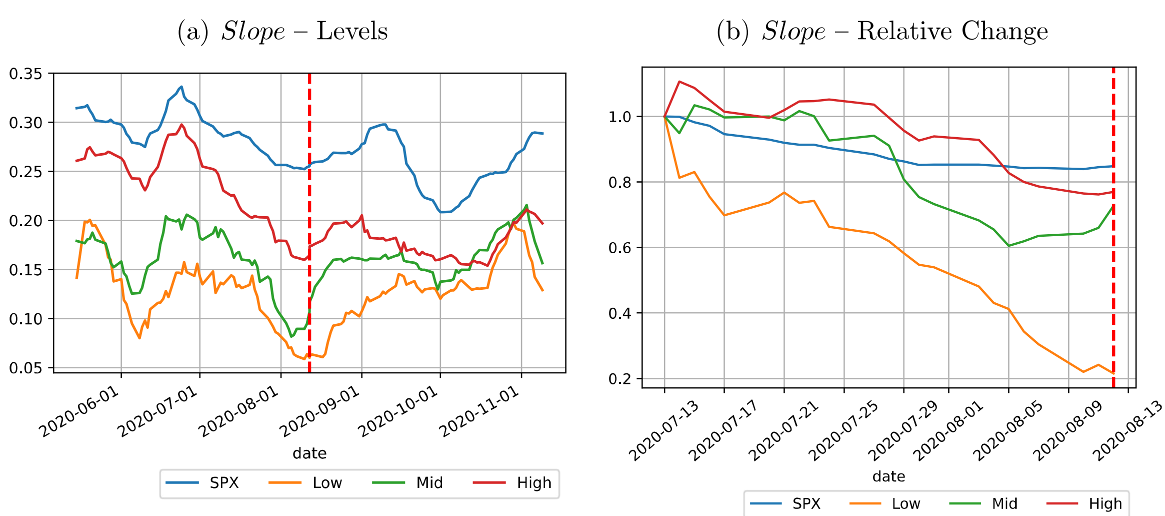

Fig. B.3. $Slope$ measure for the SPX and the resilience groups – Positive vaccine trials – Value weighted. The figure displays the relative changes in the tail-risk measure $Slope$ extracted for an option maturity of 30 days associated with the positive vaccine news, which was released on August 12, 2020. $Slope$ is constructed following Kelly et al. (2016) and denotes the slope coefficient from the regression of OTM puts' implied volatilities on the same options' deltas, where the option maturity corresponds to one month. Table 1, the SPDR sectors are aggregated by their market capitalization (value-weighted) into the three resilience groups: Low, Mid, and High. The plots report the 10-day moving average. The vertical dashed line indicates the positive news covering vaccines.

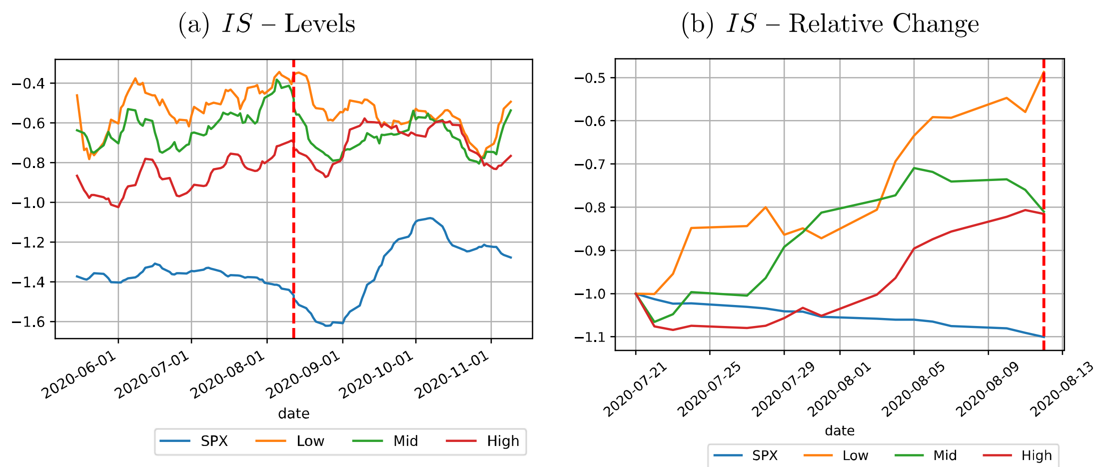

Fig. B.4. IS measure for the SPX and the resilience groups – Positive vaccine trials – Value weighted. The figure displays the relative changes of the tail-risk measure IS extracted for an option maturity of 30 days, associated with the positive vaccine news, which were released on August 12, 2020. *IS*, as a proxy for tail risk, is constructed as in Bakshi et al. (2003) and quantifies the asymmetry of the risk-neutral distribution. Table 1, the SPDR sectors are aggregated by their market capitalization (value-weighted) into the three resilience groups: Low, Mid, and High. The plots report the 10-day moving average. The vertical dashed line indicates the positive news covering vaccines.

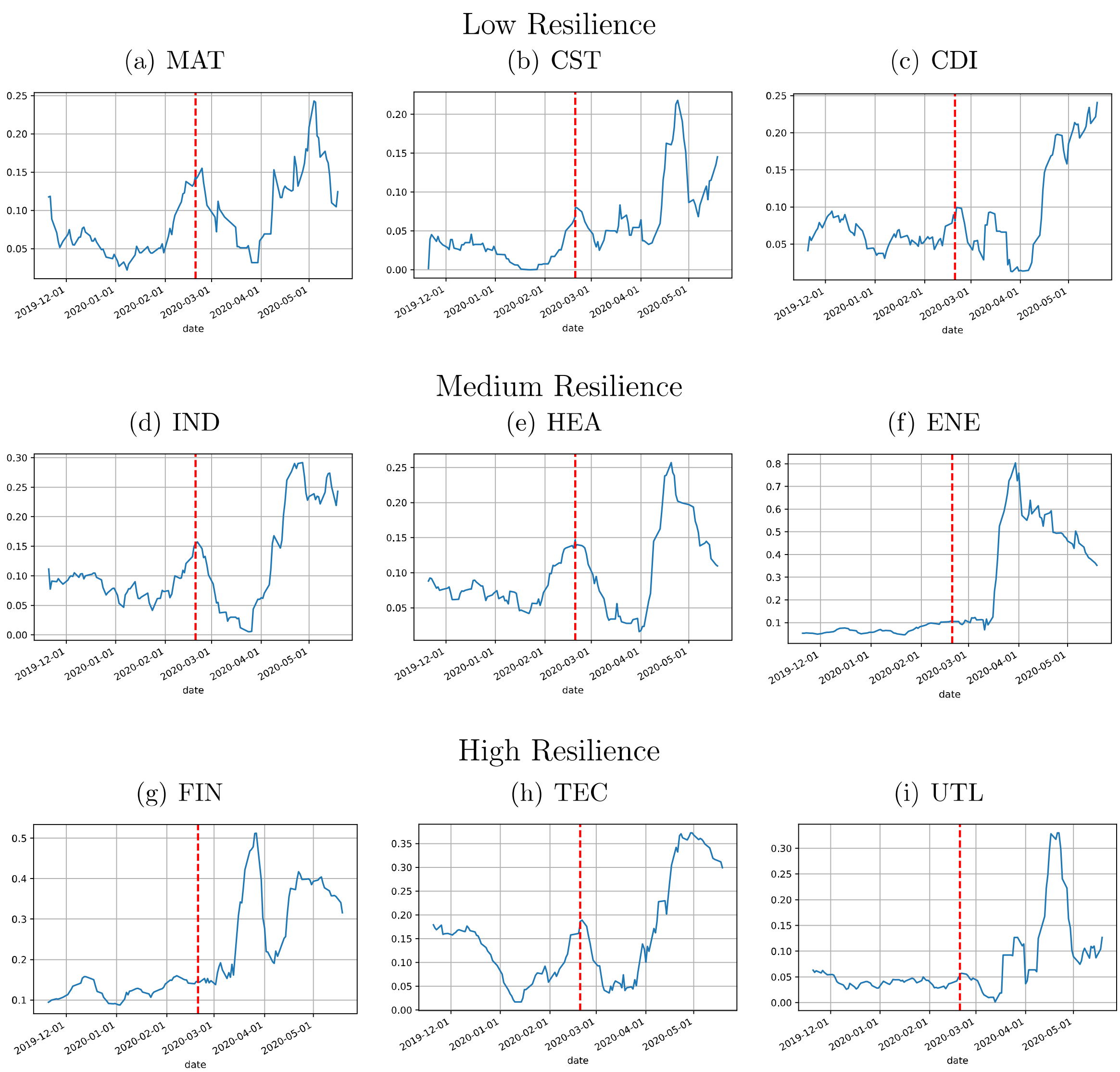

Fig. C.1. *Slope* measure for the nine SPDR sectors – Pandemic Outbreak. The figure displays the tail-risk measure *Slope* extracted for an option maturity of 30 days three months before and after the event (February 19, 2020). As described in Section 2.2, *Slope* is constructed following Kelly et al. (2016) and denotes the slope coefficient from the regression of OTM puts' implied volatilities on the same options' deltas, where the option maturity corresponds to one month. SPDR sectors are named as in Table 1, that is, Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the 10-day moving average. The vertical dashed lines indicate the market drawdown.

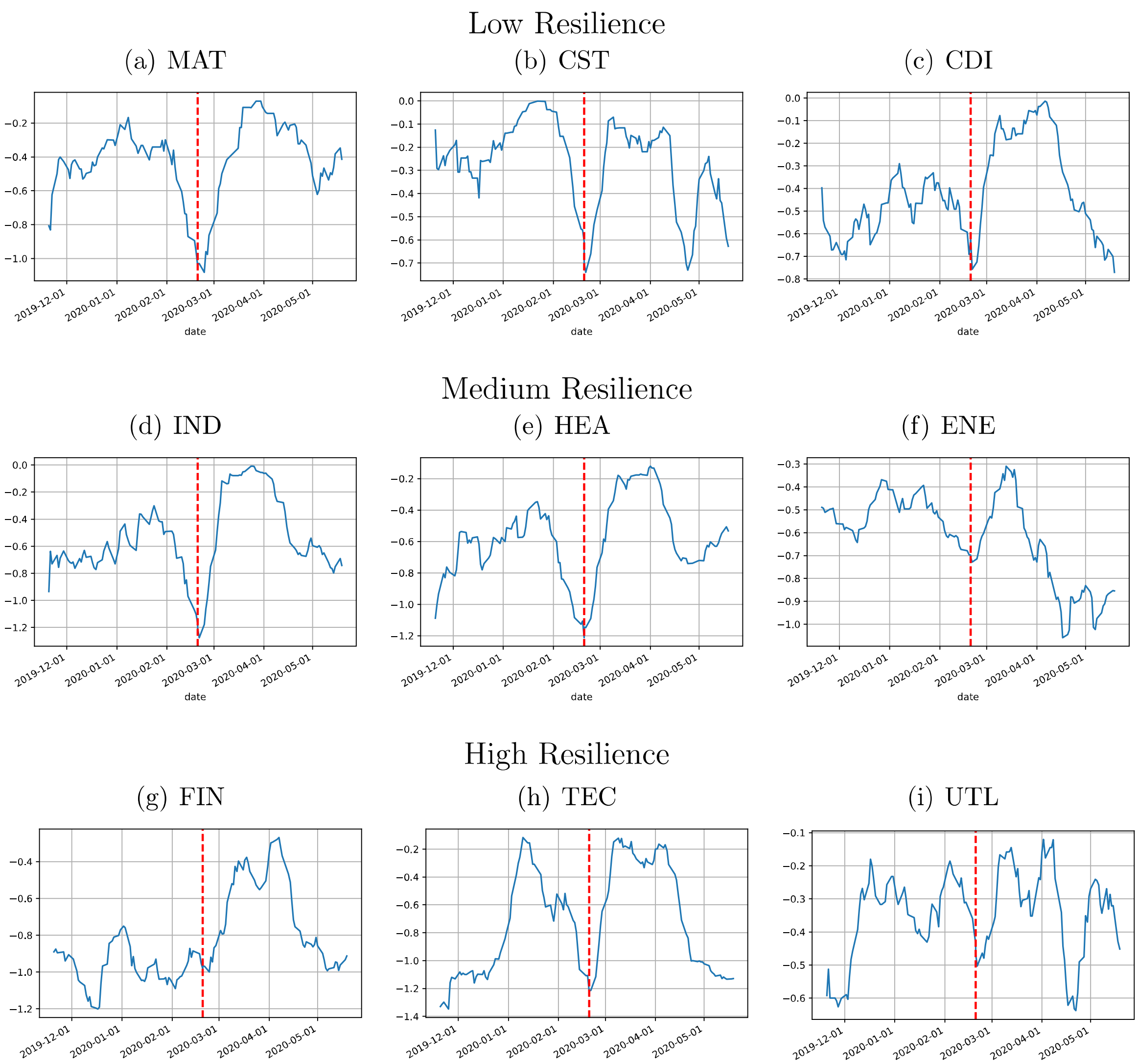

Fig. C.2. IS measure for the nine SPDR sectors – Pandemic Outbreak. The figure displays the IS extracted for an option maturity of 30 days three months before and after the event (February 19, 2020). As described in Section 2.2, *IS*, as a proxy for tail risk, is constructed as in Bakshi et al. (2003) and quantifies the asymmetry of the risk-neutral distribution. SPDR sectors are named as in Table 1, that is, Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the 10-day moving average. The vertical dashed lines indicate the market drawdown.

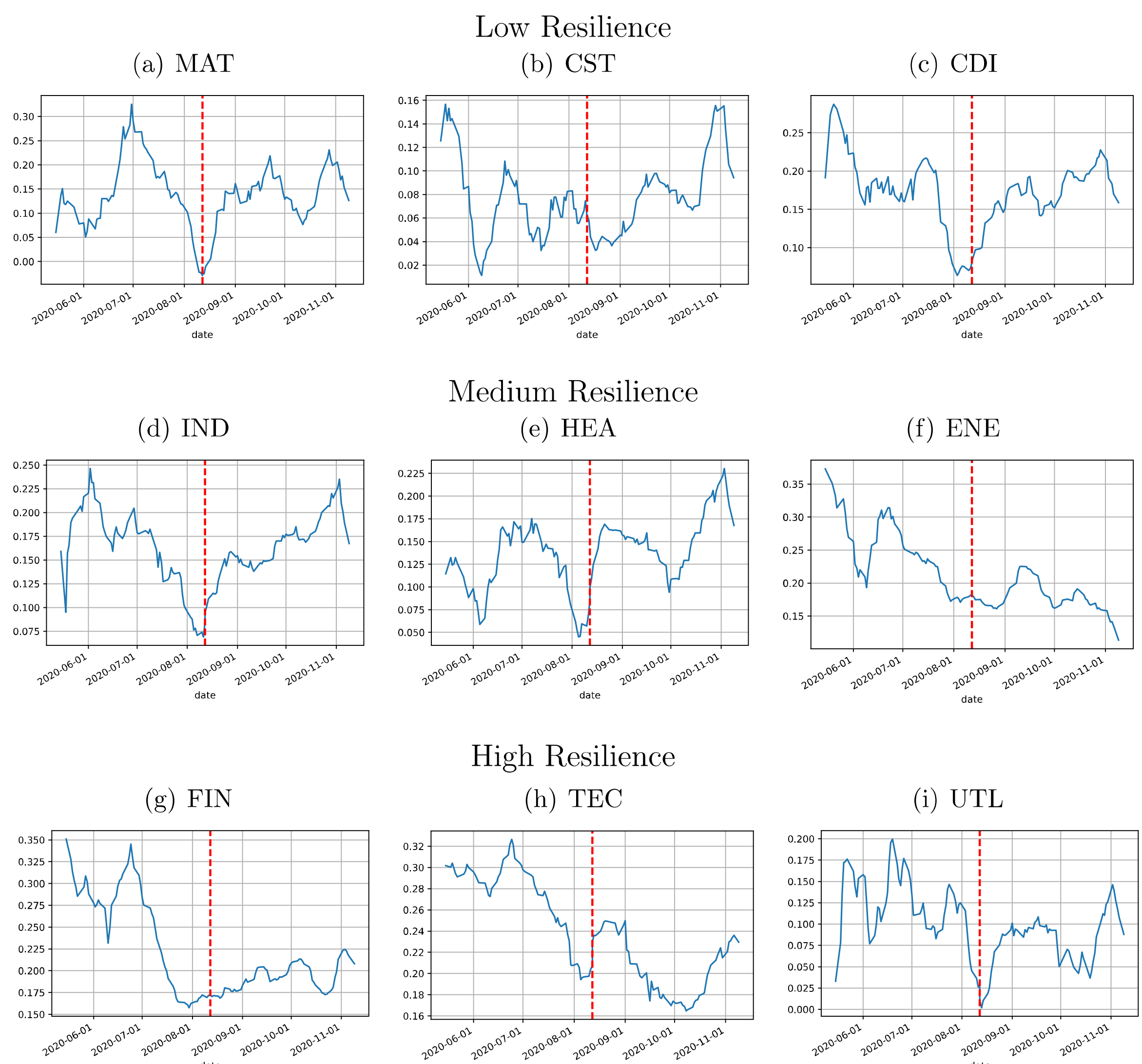

Fig. C.3. *Slope* measure for the nine SPDR sectors – Positive vaccine trials. The figure displays the tail-risk measure *Slope* extracted for an option maturity of 30 days three months before and after the event (August 12, 2020). As described in Section 2.2, *Slope* is constructed following Kelly et al. (2016) and denotes the slope coefficient from the regression of OTM puts' implied volatilities on the same options' deltas, where the option maturity corresponds to one month. SPDR sectors are named as in Table 1, that is, Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the 10-day moving average. The vertical dashed line indicates the positive news covering vaccines.

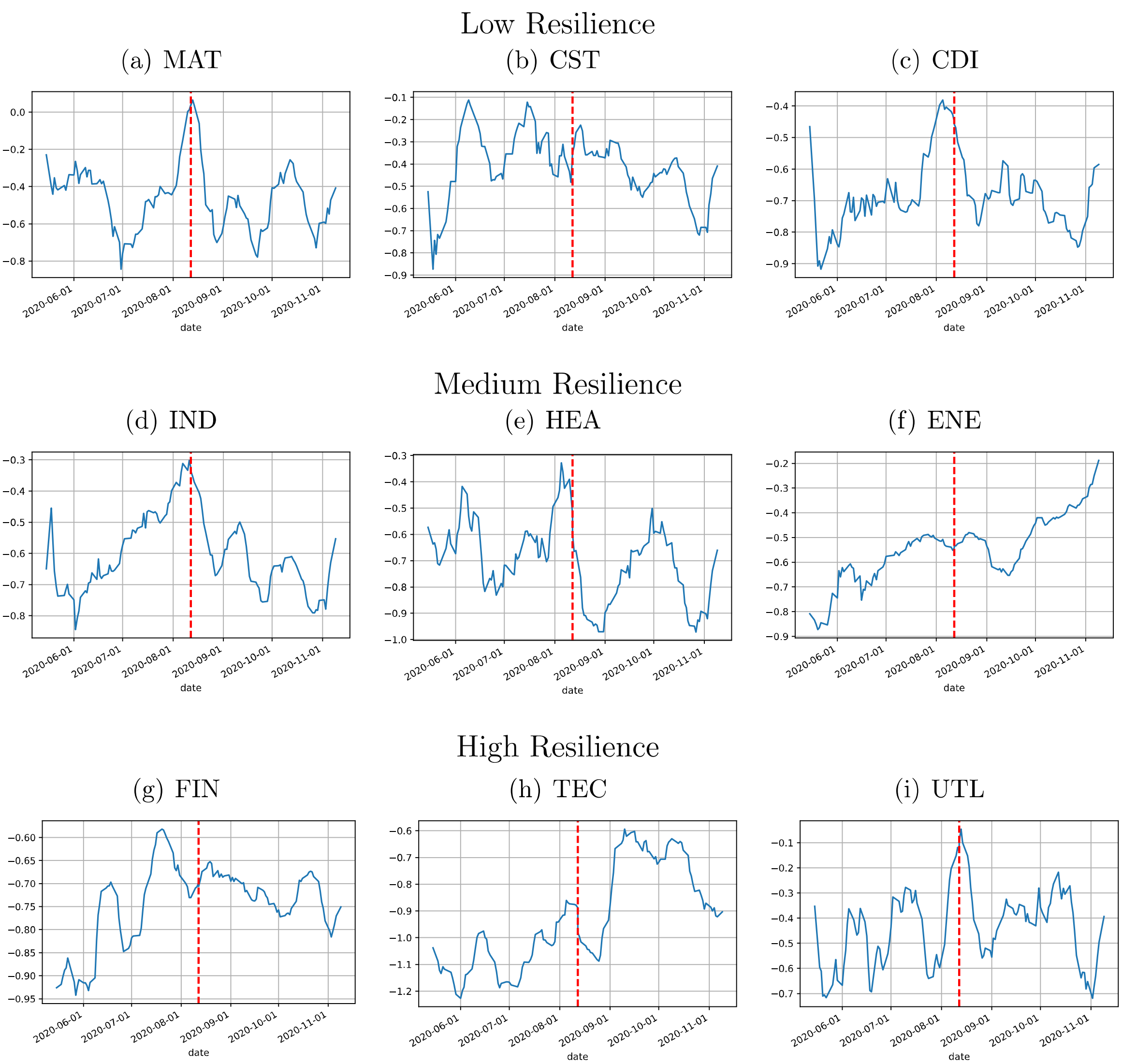

Fig. C.4. IS measure for the nine SPDR sectors – Positive vaccine trials. The figure displays the IS extracted for an option maturity of 30 days three months before and after the event (August 12, 2020). As described in Section 2.2, *IS*, as a proxy for tail risk, is constructed as in Bakshi et al. (2003) and quantifies the asymmetry of the risk-neutral distribution. SPDR sectors are named as in Table 1, that is, Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the 10-day moving average. The vertical dashed line indicates the positive news covering vaccines.

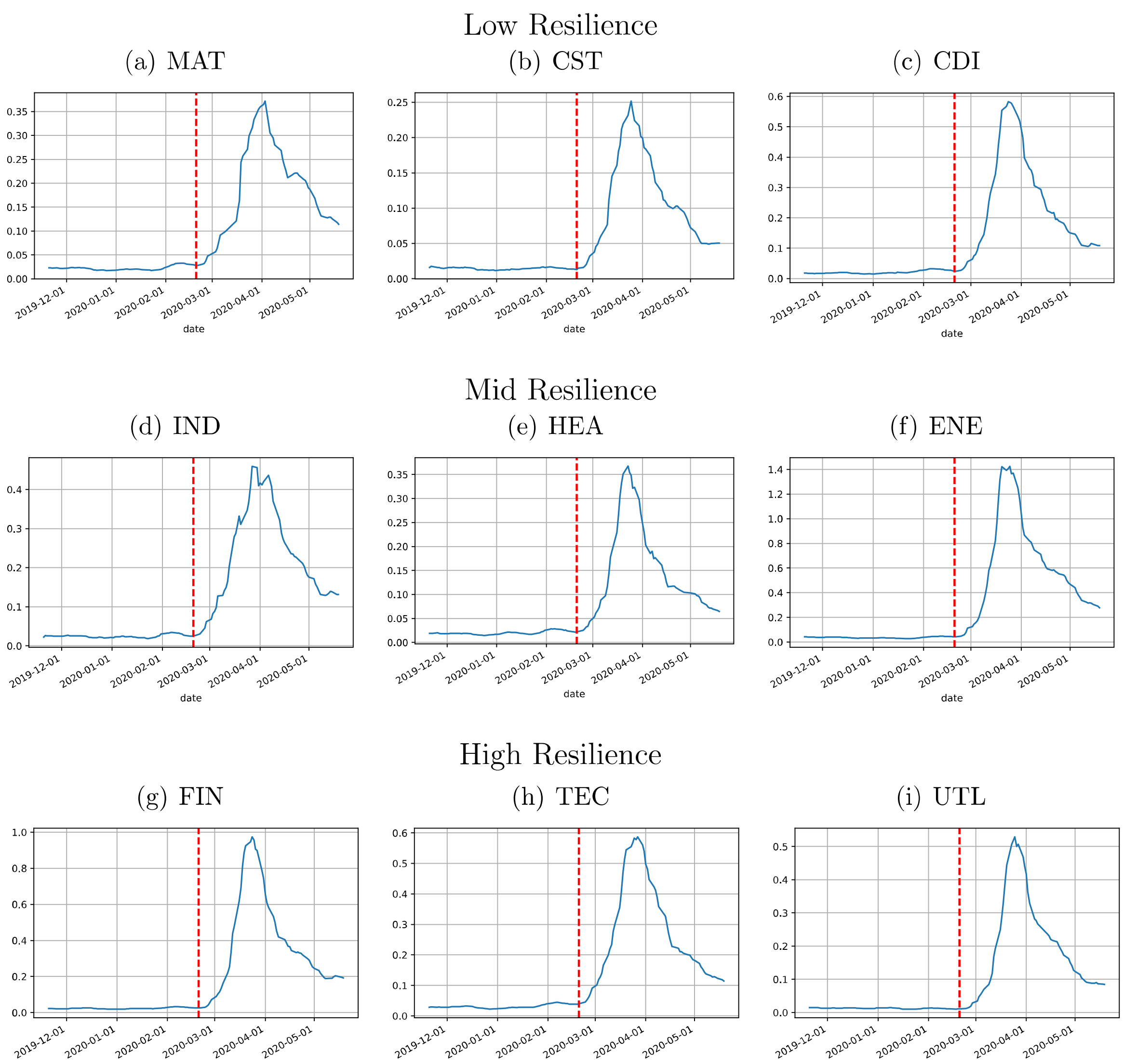

Fig. D.1. IV measure for the nine SPDR sectors – Pandemic Outbreak. The figure displays the IV extracted for an option maturity of 30 days three months before and after the event (February 19, 2020). As described in Section 2.2, implied variance is constructed as in Bakshi et al. (2003) and quantifies the risk-neutral expectation of the realized variance over the future horizon of 30 days. SPDR sectors are named as in Table 1, that is, Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the 10-day moving average. The vertical dashed lines indicate the market drawdown.

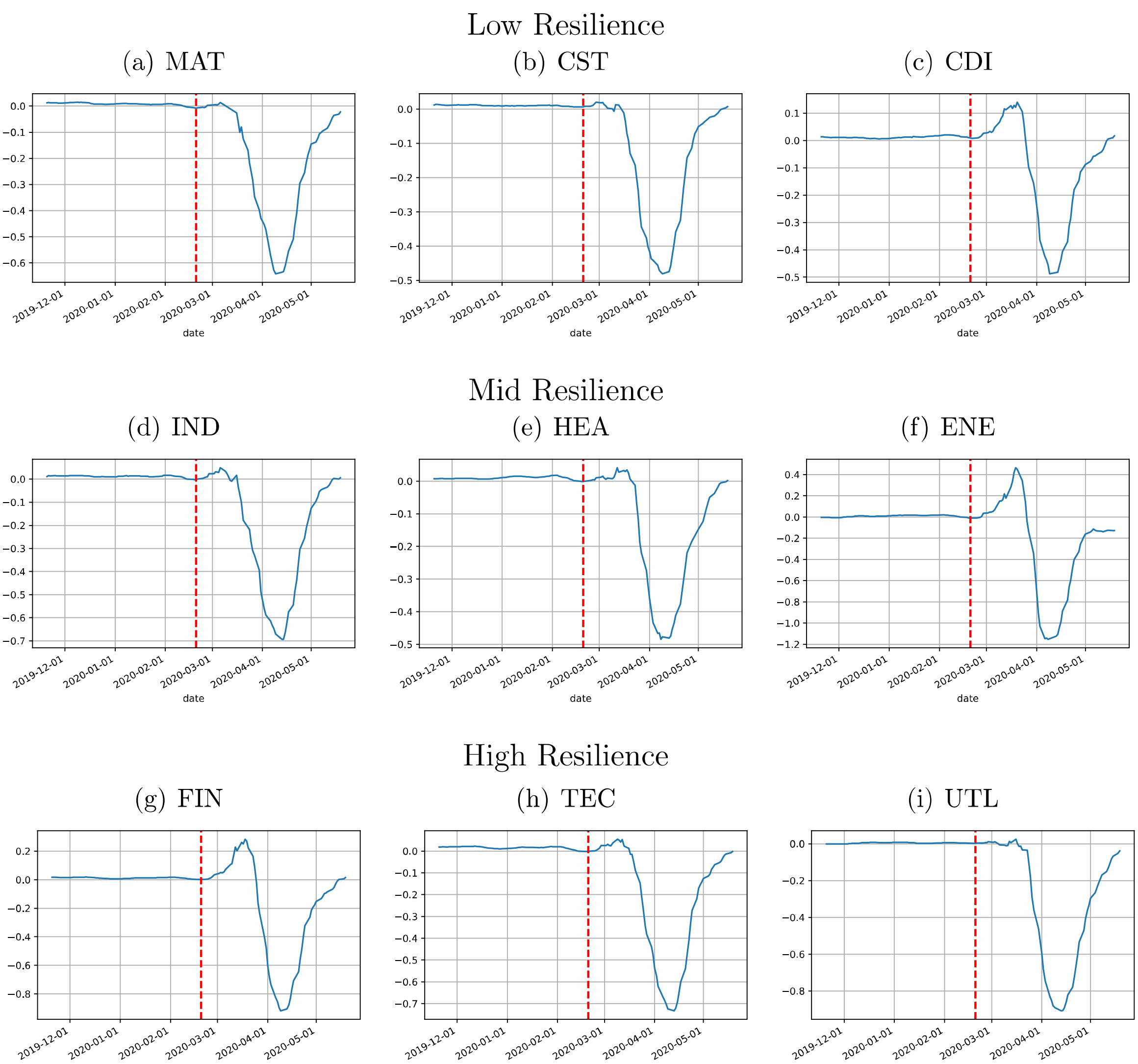

Fig. D.2. VRP measure for the nine SPDR sectors – Pandemic Outbreak. The figure displays the VRP extracted for an option maturity of 30 days three months before and after the event (February 19, 2020). As described in Section 2.2, the variance risk premium (VRP) is computed as risk-neutral variance (IV) observed at the end of the day t minus the realized variance (RV) from $t - \Delta t$ to t. To compute realized variances, we use daily returns for a window length corresponding to the maturity of the considered options. SPDR sectors are named as in Table 1, that is, Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the 10-day moving average. The vertical dashed lines indicate the market drawdown.

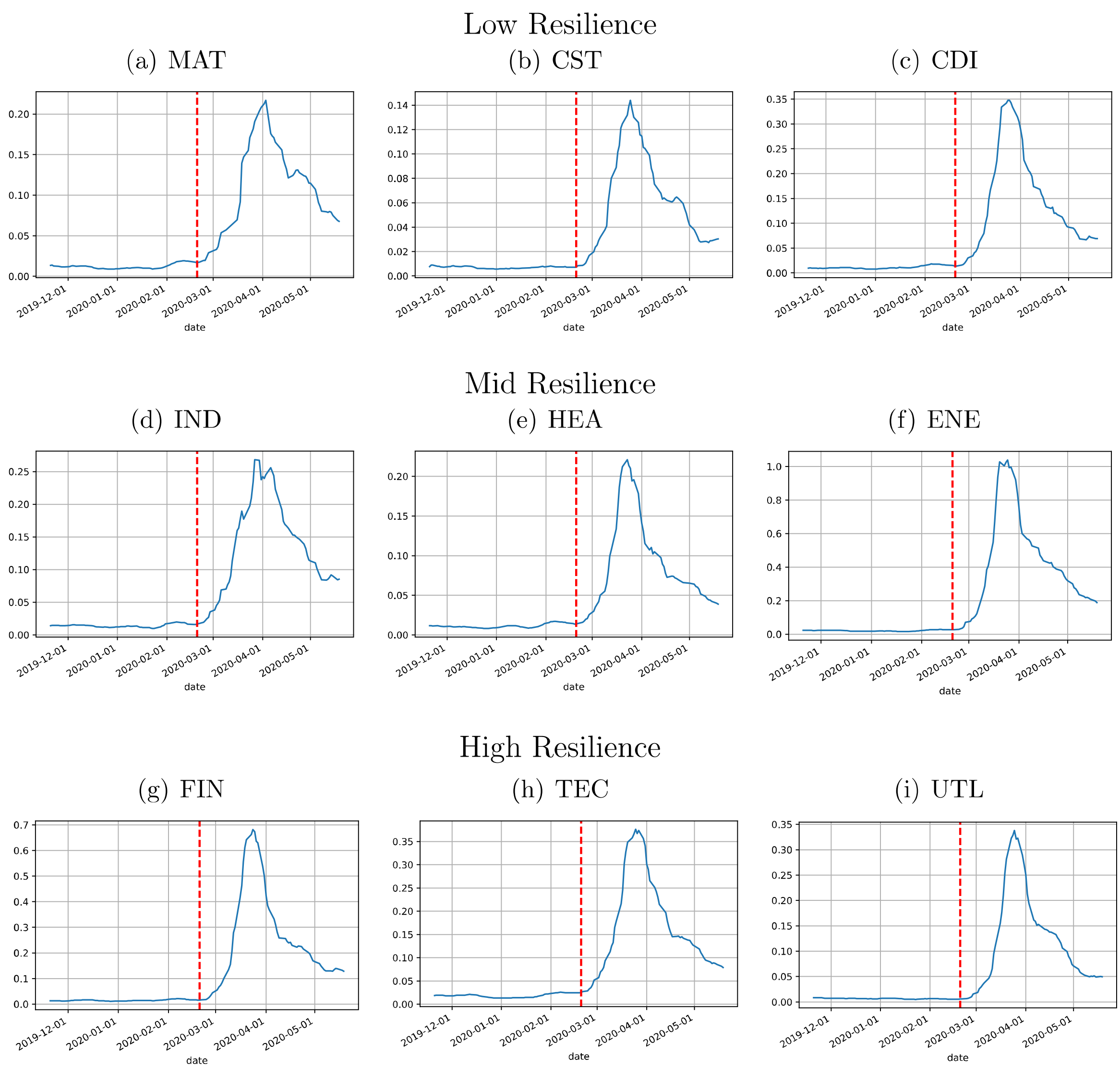

Fig. D.3. IV_{dn} measure for the nine SPDR sectors – Pandemic Outbreak. The figure displays the IV_{dn} extracted for an option maturity of 30 days three months before and after the event (February 19, 2020). Implied downside variance is constructed as in Kilic and Shaliastovich (2019) and Feunou et al. (2017). SPDR sectors are named as in Table 1, that is, Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the 10-day moving average. The vertical dashed lines indicate the market drawdown.

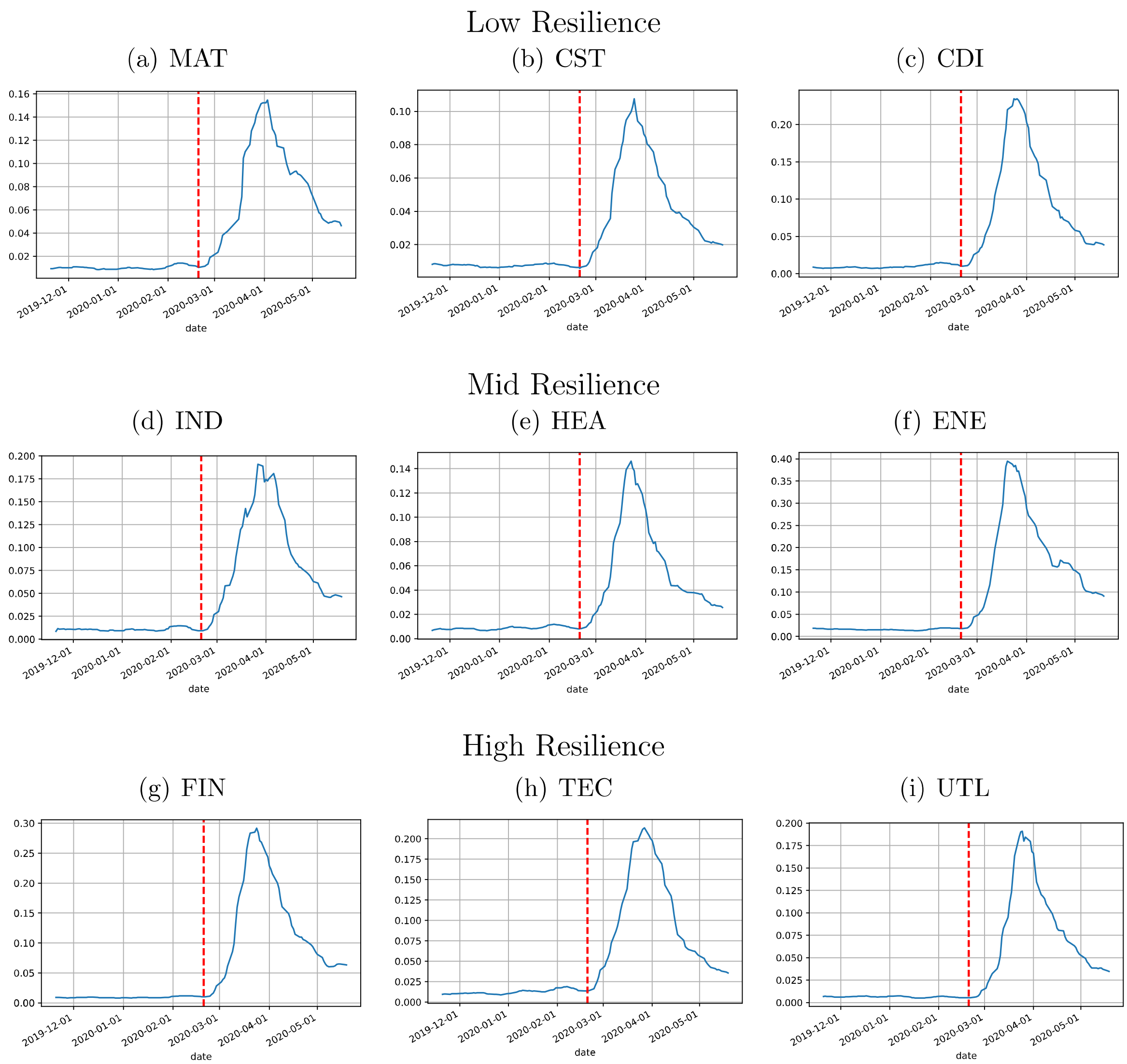

Fig. D.4. IV_{up} measure for the nine SPDR sectors – Pandemic Outbreak. The figure displays the IV_{up} extracted for an option maturity of 30 days three months before and after the event (February 19, 2020). Implied upside variance is constructed as in Kilic and Shaliastovich (2019) and Feunou et al. (2017). SPDR sectors are named as in Table 1, that is, Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the 10-day moving average. The vertical dashed lines indicate the market drawdown.

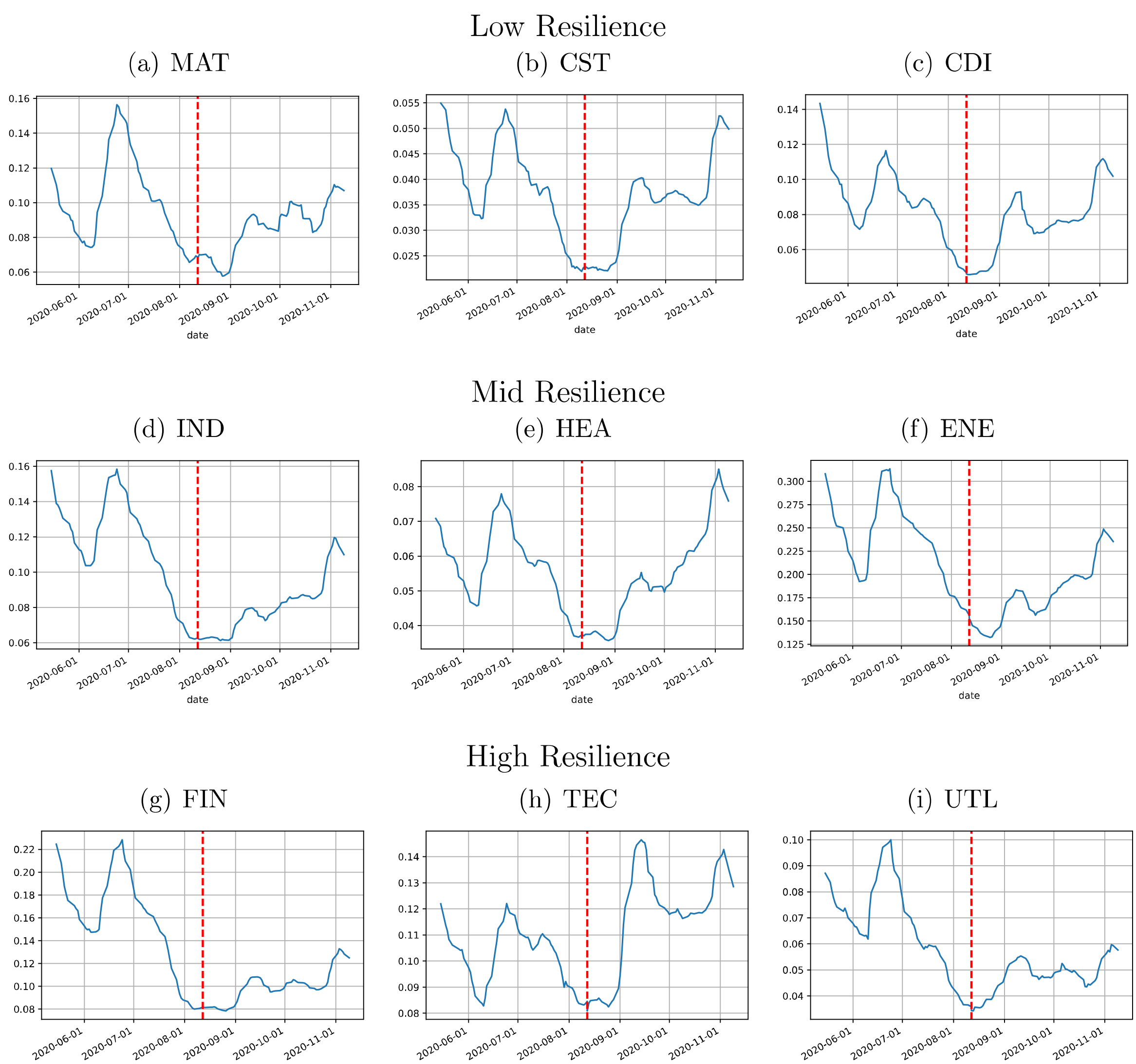

Fig. D.5. IV measure for the nine SPDR sectors – Positive Vaccine Trials. The figure displays the IV extracted for an option maturity of 30 days three months before and after the event (August 12, 2020). As described in Section 2.2, implied variance is constructed as in Bakshi et al. (2003) and quantifies the risk-neutral expectation of the realized variance over the future horizon of 30 days. SPDR sectors are named as in Table 1, that is, Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the 10-day moving average. The vertical dashed line indicates the positive news covering vaccines.

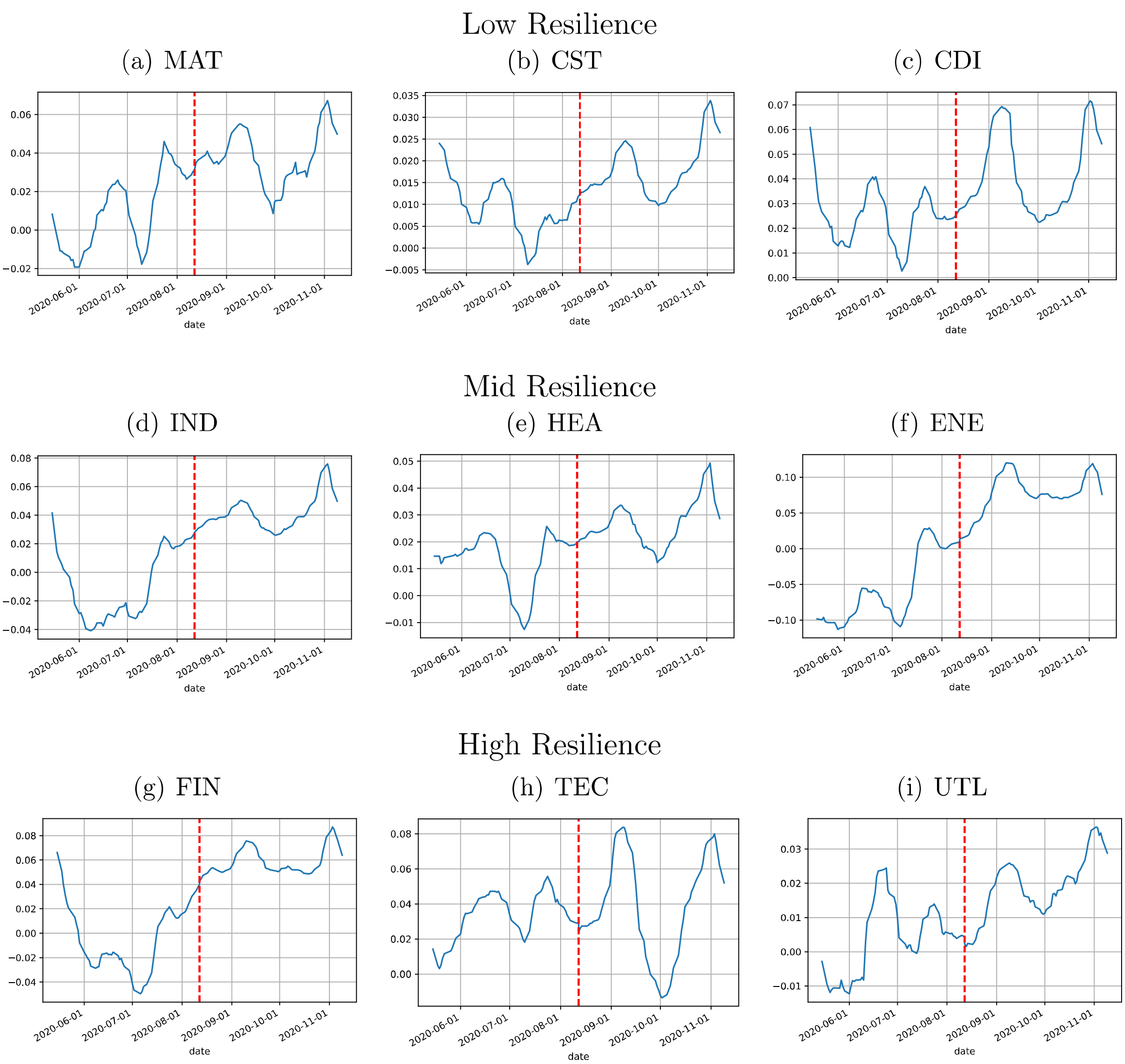

Fig. D.6. VRP measure for the nine SPDR sectors – Positive vaccine trials. The figure displays the VRP extracted for an option maturity of 30 days three months before and after the event (August 12, 2020). As described in Section 2.2, the variance risk premium (VRP) is computed in an *ex-ante* version as risk-neutral variance (IV) observed at the end of the day t minus the realized variance (RV) from $t - \Delta t$ to t. For realized variances, we use daily returns for a window length corresponding to the maturity of the considered options. SPDR sectors are named as in Table 1, that is, Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the 10-day moving average. The vertical dashed line indicates the positive news covering vaccines.

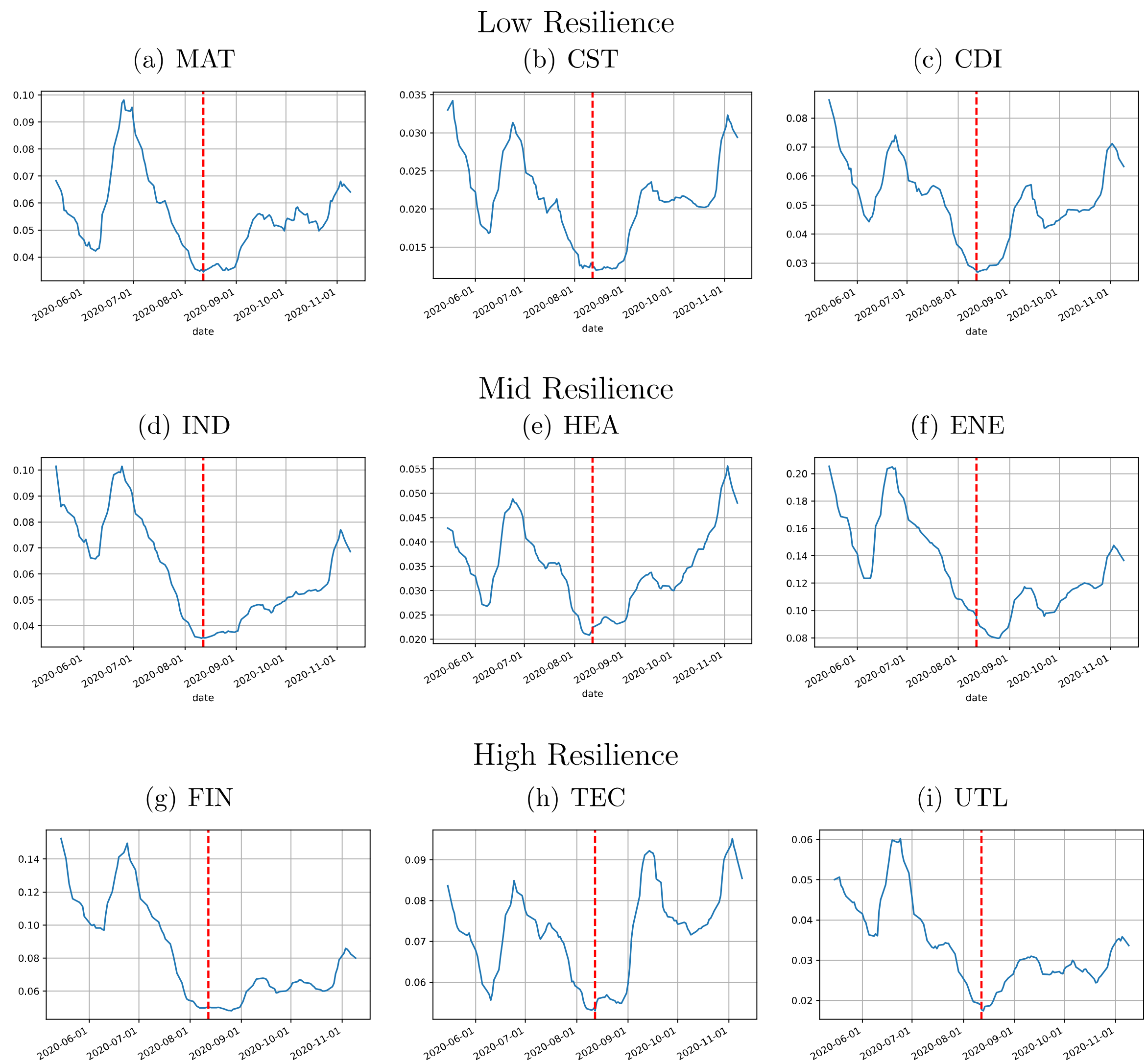

Fig. D.7. IV_{dn} measure for the nine SPDR sectors – Positive vaccine trials. The figure displays the IV_{dn} extracted for an option maturity of 30 days three months before and after the event (August 12, 2020). Implied downside variance is constructed as in Kilic and Shaliastovich (2019) and Feunou et al. (2017). SPDR sectors are named as in Table 1, that is, Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the 10-day moving average. The vertical dashed line indicates the positive news covering vaccines.

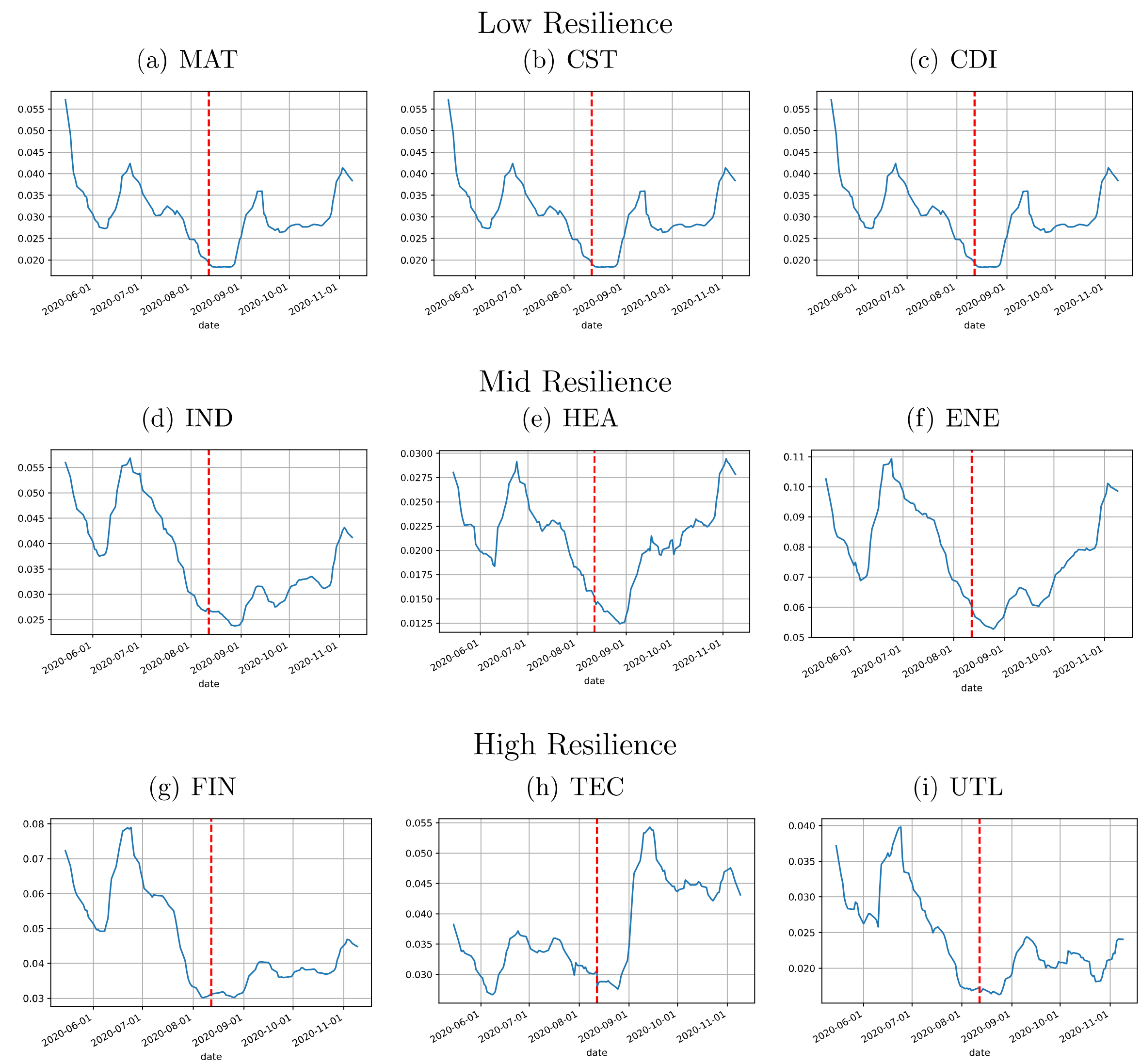

Fig. D.8. IV_{up} measure for the nine SPDR sectors – Positive Vaccine Trials. The figure displays the IV_{up} extracted for an option maturity of 30 days three months before and after the event (August 12, 2020). Implied upside variance is constructed as in Kilic and Shaliastovich (2019) and Feunou et al. (2017). SPDR sectors are named as in Table 1, that is, Materials (MAT), Consumer Staples (CST), Consumer Discretionary (CDI), Industrial (IND), Health Care (HEA), Energy (ENE), Financial (FIN), Technologies (TEC), and Utilities (UTL). The plots report the 10-day moving average. The vertical dashed line indicates the positive news covering vaccines.

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