EIEF WORKING PAPER SERIES

EINAUDI INSTITUTE FOR ECONOMICS AND FINANCE

EIEF Working Paper 20/08

May 2020

Disaster Resilience and Asset Prices

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forthcoming in the

Journal of Financial Economics

Abstract

Using the COVID-19 pandemic as a laboratory, we show that asset markets assign a time-varying price to firms' disaster risk exposure. The cross-section of stock returns reflected firms' different exposure to the pandemic, as measured by their vulnerability to social distancing. As predicted by theory, realized and expected return differentials moved in opposite directions, initially widening and then narrowing. When inferred from market outcomes, firm resilience correlates mainly with exposure to social distancing: vulnerability to social distancing is priced in changes of firms' expected returns, while measures of financial and environmental resilience are not.

JEL classification: G01, G11, G12, G13, G14, Q51, Q54.

Keywords: asset pricing, rare disasters, social distance, resilience, pandemics.

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1 Introduction

How do investors take into account disaster risk in pricing assets? One view, dating to Rietz (1988), Barro (2006) and Gabaix (2012), is that rare disasters are pointlike events whose probability is known to investors, and therefore impounded in asset valuations. However, since disasters are rare and heterogeneous events, in reality investors may not know in advance the precise magnitude and persistence of all possible disasters, nor the extent to which different sectors of the economy are resilient to their consequences. Hence, investors are likely to gradually learn about them, especially once a particular disaster materializes and gradually displays its effects on the economy, while society attempts to mitigate them. In this case, asset prices are not only driven by the onset of a disaster, but also by the dynamics of investors' beliefs about it.

In this paper, we draw upon the evidence generated by the COVID-19 pandemic as a laboratory to investigate the implications of the gradual unfolding of a rare disaster for the cross-section of assets. The pandemic is especially suited to this purpose, as it not only inflicted massive social and economic harm, but also created great uncertainty about its persistence, as witnessed by sharp changes in expectations (Coibion et al., 2020b; Hanspal et al., 2021; Coibion et al., 2020a; Giglio et al., 2021) and asset prices (Gormsen and Koijen, 2020). Moreover, its effects have been highly heterogeneous: some firms, especially in high-tech industries, have adapted well to social distancing requirements, by resorting extensively to teleworking, while others, such as those in the food catering, travel and hospitality sectors, could not do so, as the nature of their business requires close contact with customers and between employees. Hence, the pandemic has unearthed a so-far hidden economic watershed between resilient and non-resilient activities. In this paper, we investigate whether asset markets have priced the resilience of different firms to disaster risk and whether such pricing reveals changes in investors' perception of this risk as the disaster unfolded.

To guide the empirical analysis, we present a simple three-period model of stochastic disaster risk in the spirit of Gabaix (2012), where investors can learn about the probability of a disaster before its onset and about its persistence once it has occurred. The main predictions are that more resilient stocks should not only outperform the market when a disaster occurs, but should feature a drop in expected returns relative to the market portfolio, because investors view them as a hedge against the risk of continuation of the disaster. Symmetrically, less resilient stocks should not only underperform when the disaster hits, but also feature an increase in expected returns over the market portfolio relative to the pre-disaster period.

The model also offers predictions about how realized and expected returns of assets respond to investors' changing estimate of the disaster's persistence after its occurrence. If, for instance, investors become more optimistic, the realized return differential between low and high-resilience assets will shrink, and so will the expected market-adjusted return differential between these two classes of assets. Hence, a hallmark of the model is that investors learn about disaster risk both as a disaster strikes and as it develops: rather than point-like events, disasters are gradually unfolding ones, during which investors revise their beliefs, possibly in a persistent way for some assets (Collin-Dufresne et al., 2016; Kozlowski et al., 2020a,b).

We adopt two complementary strategies to take the predictions of the model to the data generated by the COVID-19 disaster. First, we rely on an empirical measure of firm resilience, based on each industry's immunity to social distancing requirements: a firm is defined to be more resilient than others if its operations require less direct physical interaction among employees and/or between customers and employees. Our baseline measure of resilience is drawn from Koren and Pető (2020), but we check whether our results are robust to the use of other measures. We test whether the stock and option prices of firms with different resilience to social distancing respond to the disaster as predicted by the model. This strategy effectively tests the joint hypothesis that the model and the measure of resilience based on social distancing are correct.

Our second strategy identifies the resilience of firms on the basis of the response of their stock and option prices to the disaster, and then investigates which firm characteristics are associated with this market-implied classification of resilience. This strategy allows for disaster resilience to depend on various firm characteristics, rather than on a specific measure of resilience to social distancing requirements. As such, it may also be more robust to possible measurement error in any single measure of resilience, insofar as different characteristics correlate with a common underlying resilience, of which they capture different dimensions. This second approach relies on the predictions of the model to classify firms according to their underlying degree of resilience, without taking a stance on its determinants, and then investigates whether this model-implied classification of firms corresponds to economically plausible resilience criteria.

Hence, the second approach is more agnostic than the first, in that it enables us to investigate whether other dimensions of resilience were priced by asset markets in the wake of COVID-19, beside those related to social distancing. According to many, the pandemic acted as a wake-up call for concerns about environmental disaster risk, as it highlighted how much society depends on a healthy environment.[1] Hence, in the wake of the pandemic companies with a better record on climate protection may have featured higher valuations than others, being perceived as less exposed to environmental disaster risk. Moreover, companies with more cash and less leverage may have been regarded by investors as more financially resilient to disasters, being better positioned to withstand losses arising from disasters without entering distress.

The results from our first empirical strategy, based on a measure of firms' resilience to social distancing rules, are as follows. First, during the so-called 'fever period' (from late February to late March 2020), high-resilience stocks greatly outperformed low-resilience ones, after controlling for market risk and other established risk factors. For example, less resilient firms realized a negative Fama-French 5 factor (FF5) risk-adjusted return of approximately -7% during this period whereas more resilient firms feature a corresponding out-performance by approximately 5%.

Second, the options-implied expected returns of high-resilience stocks in excess of the expected return on the market dropped sharply (by -5.4% p.a. on a 1-month horizon), and those of low-resilience stocks increased (by 4.4% p.a. on a 1-month horizon), which in light of the model is consistent with investors perceiving a high risk of potential persistence of the pandemic.

Third, from late March to December 2020, which we refer to as the 'post-fever' period, the differential between the realized risk-adjusted returns of high and low-resilience stocks reversed in sign, and the differential between their expected returns gradually shrank. Most of this reversal occurred between March and June 2020, when positive news about the development and widespread adoption of effective vaccines started spreading (Acharya et al., 2022). Over this period, the cross-section of firms' expected returns reveals that investors placed a decreasing price on exposure to disaster risk, as measured by firms' vulnerability to social distancing. However, even as late as December 2020, exposure to disaster risk still commanded a positive extra

[1] See for instance the address on "Global Wake-up Call" delivered by UN Secretary-General António Gutierrez on 18 May 2020 (https://www.un.org/en/coronavirus/global-wake-call) and the article "Global Risks in a COVID-19 World" posted by the ISO on 25 March 2021 (https://www.iso.org/news/ref2647.html).

excess return, after adjusting for standard risk factors. In light of the model, this joint pattern of realized and expected returns is consistent with investors reducing their estimate of the persistence of the pandemic and/or increasing their estimate of the resilience of the economy to it, while still assigning a positive market price to disaster risk, especially for the most exposed companies.

While for most firms the measure of resilience based on social distancing is consistent with the model's predictions regarding the realized and expected returns, this is not always the case: for instance, Boeing and Tripadvisor are classified as high-resilience firms based on their resilience to social distancing, while their realized and expected return patterns would be consistent with them being low-resilience firms, probably due to their indirect exposure to the travel and hospitality industry (which however is not reflected by their measured supply-chain linkages). This prompts us to implement the more agnostic approach described above, whereby firm resilience is based on market outcomes and then related to firm characteristics. Using this approach, we find that vulnerability to social distancing contributes more to the identification of low-resilience and high-resilience firms than financial characteristics (such as the cash-asset ratio and leverage) and the environmental score of companies. In particular, it is the only firm characteristic that correlates with changes in expected returns of firms during the pandemic, and the only one that identifies firms persistently scarred by the pandemic.

Our analysis is related to the asset pricing literature on rare disasters, starting with Rietz (1988), who shows that a rare disaster state leads to high equity risk premia and low risk-free returns, even with reasonable time discounting and risk preferences. Barro (2006) and Barro (2009) extend this model and show that empirically calibrated disaster probabilities may suffice to explain the observed high equity premium, low risk-free rate and stock return volatility.

Subsequent models of disaster risk allow for stochastic disaster risk (Gabaix, 2012; Gourio, 2012; Wachter, 2013) and for learning (Veronesi, 2004; Gillman et al., 2014; Wachter and Zhu, 2019; Lu and Siemer, 2016; Collin-Dufresne et al., 2016; Kozlowski et al., 2020b,a). One common feature of these models is that risk premia that would appear abnormally high conditioning on no disaster occurring, are in fact justified, being merely an equilibrium compensation for the expected loss in a disaster, plus a risk premium as this loss occurs when the marginal utility of consumption is high. The distinctive feature of our model and empirical analysis is the focus on the effects of learning about disaster risk on the cross-section of realized and expected stock returns.

Our work is also related to the recent literature on the response of firms' stock returns, balance sheets and operating performance to the COVID-19 pandemic: see Pagano and Zechner (2022) for a survey. Several studies focus on the immediate response of stock returns to the shock. Using textual analysis of news articles, Baker et al. (2020) document that developments related to COVID-19 drove stock market returns and volatility between mid-February and late March. Ramelli and Wagner (2020) show that during the 'fever' period, U.S. firms with high exposure to China and, more generally, to international trade, as well as firms with high leverage and low cash holdings experienced the sharpest stock price declines; also Fahlenbrach et al. (2021) find that firms with greater financial flexibility experienced smaller drops in stock prices. Albuquerque et al. (2020) report that firms with high environmental and social (ES) ratings offered comparably higher returns and lower return volatility in the first quarter of 2020; relatedly, Pástor and Vorsatz (2020) find that sustainable funds perform well during the crisis. Bretscher et al. (2020) provide evidence for supply chain effects in the cross-section of stocks during COVID-19.

Some studies relate the price response of different stocks to the pandemic to the corresponding firms' exposure to the disease. Ramelli and Wagner (2020) and Hassan et al. (20223) analyze conference call data, which the latter use to construct text-based, firm-level measures for exposures to epidemic diseases, and find that stock returns are significantly and negatively related to disease exposures, with demand- and supply-chain related concerns being primary drivers.[2] Some of the results obtained for the response of U.S. stock returns to the pandemic also apply to non-U.S. stock returns.[3]

Our work differs from these papers since it focuses on the asset pricing implications of companies' resilience to the pandemic on the cross-section of stock returns for the

[2]Li et al. (2021) also construct a text-based firm-level exposure measure to COVID-19 based on earnings calls and find that firms with a strong corporate culture outperform their peers without a strong culture during the onset of the pandemic.

[3]Ding et al. (2021) show for a sample of over 50 countries that firms with better financials, less supply chain exposures and more corporate social responsibility (CSR) activities experienced milder stock price reactions in the first quarter of 2020. Other studies focus on the response of country-level stock market indices to COVID-19: Ru et al. (2021) find that stock markets in countries with 2003 SARS experience reacted more quickly to the outbreak than countries without prior experience, while Gerding and Nagler (2022) document that market declines were more severe in countries with lower fiscal capacity, defined as higher debt/GDP ratio. Finally, Arteaga-Garavito et al. (2022) use Twitter news to study the (real-time) COVID-19 caused contagion in global equity markets.

whole of 2020, and documents the key importance of revisions in investors' perception of disaster risk for asset returns. Moreover, a unique feature of our analysis is to show how such learning impacts not only the cross-section of *actual* stock returns, but also the cross-section of *expected* returns. The analysis of expected returns also enables us to identify which firms have been persistently scarred by the pandemic, namely, for which stocks investors kept pricing pandemic risk even as late as late 2020.

The rest of the paper is structured as follows. Section 2 presents a model to interpret the relationship between disaster risk and the realized and expected stock returns of firms with different disaster resilience. Section 4 tests the model's predictions by assuming that firms' resilience depends on their exposure to social distancing restrictions. Section 5 presents an alternative approach where firms' resilience is determined by their model-implied price responses to the pandemic, and such market-implied resilience is correlated with firm characteristics. Section 6 concludes.

2 Disaster Awareness and Risk Premia

This section sketches a simple model where investors learn about the occurrence, magnitude and persistence of a rare disaster, and where firms are differently harmed by the disaster. The predictions of the model, which is presented in the Appendix, will guide our empirical analysis. The model highlights that, while the occurrence of a disaster changes the cross-section of realized returns by affecting differently high-resilience and low-resilience firms, changes in investors' beliefs about the probability or persistence of a disaster affects both the cross-section of realized and of expected returns. For instance, in the wake of a disaster, people may view a new disaster as being more likely to occur than before, or equivalently they may expect the disaster to persist over time, as modeled by Gourio (2012) for the case of a single risky asset. Our model shows that this persistence widens the return differentials between industries differently exposed to disaster risk: realized returns of less resilient firms drop relative to those of more resilient firms, while the opposite is true for their respective expected returns. Return differentials may also change if investors receive news about the future resilience of the economy (e.g., the development of an effective vaccine during a pandemic) or about improved resilience of individual firms.

The timeline of the model, shown in Figure 1, comprises three dates ($t = 1, 2, 3$), in which dividends are paid and consumption occurs. Shares are traded ex-dividend, and output is non-storable. The representative investor maximizes an expected power utility function defined over consumption in the three periods, and is initially endowed with shares of a resilient and of a non-resilient asset, whose number is normalized to 1/2 each, for simplicity. The dividend per share of the two assets is the same in normal states but differs in disaster states, depending on the asset's resilience. Specifically, the dividend of asset i, D_i, equals D in the no-disaster state and $D\phi_i/B$ in the disaster state, for $i = N, R$. The parameter $B > 0$ denotes the intensity of the disaster, while ϕ_i is asset i's resilience to the disaster.

We assume $\phi_R > \phi_N$, i.e., asset R is more resilient than asset N, and may even benefit from disasters, i.e., we allow $\phi_N < B < \phi_R$. Average asset resilience, $\overline{\phi} \equiv (\phi_N + \phi_R)/2$, is low enough that the economy is hurt by a disaster: $\overline{\phi}/B < 1$. The ratio $\overline{\phi}/B$ measures the resilience of the economy, being increasing in average asset resilience $\overline{\phi}$ and decreasing in the disaster's magnitude B. Instead, the cross-industry diversity in the response to a disaster is measured by the percentage difference in resilience $\lambda_R - \lambda_N \equiv (\phi_R - \phi_N)/\overline{\phi}$.

[**Insert Figure 1**]

Period 1 is assumed to feature no disaster, but in periods 2 and 3 a disaster occurs with (low) probabilities p_1 and p_2, respectively. In the model, investors are assumed to learn about the probability of a future disaster both in period 1 and in period 2. Moreover, in period 2 they may also receive news about the resilience of the economy or of individual firms to disasters. Specifically:

- In period 1, the arrival of news may lead investors to update the probability they assign to a period-2 disaster from their prior p_{1^-} to p_1, and reprice assets accordingly. To capture such repricing, trading is assumed to occur both at the start and at the end of period 1: end-of-period prices P_{N1} and P_{R1} may differ from their initial values P_{N1^-} and P_{R1^-}, and the expected returns of the two assets will change accordingly. Consumption occurs simultaneously with this end-of-period trading.

- In period 2, once a disaster occurs, investors revise the probability p_2 of a new disaster occurring in period 3 relative to the no-disaster scenario. In the latter case, $p_2 = p_1$, i.e. the probability of a disaster in period 3 stays the same as before. If instead a disaster occurs in period 2, its probability of persisting (or re-occurring) in period 3 is $p_2 = \rho$. If $\rho > p_1$, disasters are likely to persist, which makes their impact on returns more severe: for instance, in the wake of the Covid-19 outbreak, key concerns have been the duration of the pandemic and its possible resurgence due to virus mutations. However, the model can also accommodate the case of negatively auto-correlated disaster, i.e., $\rho < p_1$: for instance, public health investments may reduce the chances of future pandemics. In either case, a disaster is a "learning experience": upon its occurrence, investors revise their beliefs about disaster risk.

- If a disaster occurs in period 2, investors may also receive news about the average resilience $\overline{\phi}$, the magnitude of the disaster B or the cross-sectional dispersion of resilience $(\phi_R - \phi_N)/\overline{\phi}$. We assume that if such news arrive, investors engage in a new round of trading at $t = 2^+$, resulting in new prices P_{N2^+} and P_{R2^+} that differ from their initial values P_{N2} and P_{R2}. For analytical simplicity, the ex ante probability of such news arrival and re-trading is assumed to be negligible.

In Appendix A, we solve the representative investor's expected utility maximization problem by backward induction and imposing equilibrium. The theoretical results imply four main predictions:

- **Prediction A:** *Controlling for other risk factors, the expected rates of return of resilient assets are lower than those of non-resilient ones.*

  The idea is that disasters, however rare, are rationally anticipated, so that less resilient firms are priced at a discount relative to more resilient ones, since their dividends are comparatively low in disaster stats, when marginal utility of consumption is high. Thus, they offer a higher expected return, consistent with Barro (2006), Barro (2009) and Gabaix (2012). In principle, this idea applies both to the period before and after the COVID breakout: people may have placed a non-zero probability weight on a pandemic even before COVID, and during the pandemic may have assigned a positive probability to its persistence or future re- occurrence. Of course, this statement applies to the differential returns of resilient and non-resilient stocks after controlling for their respective exposures to 'standard' risk factors, which are assumed away in the model for simplicity. Prediction A is formally stated and proved in the Appendix (see Proposition 5 for expected returns at $t = 1$ and Proposition 1 for expected returns at $t = 2$).

- **Prediction B:** *If the perceived probability of a future disaster p_1 is revised upwards from a sufficiently small prior, then the expected return difference at $t = 1$ between less and more resilient assets increases. Moreover, the expected return differential in the disaster state at $t = 2$ exceeds its value in the no-disaster scenario if* *the probability of its persistence ρ exceeds the probability p_1 of first-time disaster occurrence, under plausible parameter restrictions.*

These predictions, based on Propositions 5 and 2 in the Appendix, highlight that the expected differential between less and more resilient stocks widens as soon as investors start placing a positive probability on a disaster – such as COVID-19 – striking for the first time or increase their estimate of its persistence in the future.

- **Prediction C:** *If, upon a disaster occurring, investors unexpectedly learn that the economy's resilience has increased or the cross-industry relative difference in resilience has decreased, then the expected return differences at $t = 2$ between less and more resilient assets decreases.*

  These predictions, which are based on Proposition 3 in the Appendix, imply that the expected differential between less and more resilient stocks should shrink as soon as investors become more optimistic about the resilience of the economy – e.g., upon receiving news of the development of a successful vaccine in a pandemic. The same prediction applies if investors learn that different industries have become more homogeneous in their resilience. Of course, *a fortiori* the same occurs if both developments occur concomitantly.

- **Prediction D:** *Realized return differentials respond similarly to an increase in the perceived disaster probability at $t = 1$ and to the occurrence of a disaster at $t = 2$: both lead to lower realized returns in less resilient firms than in more resilient ones; upon a disaster occurring, the increase in the realized return differential is larger, the greater the disaster's expected persistence.*

  These results correspond to Propositions 6 and 4 of the Appendix. In our model investors may update the probability of a disaster occurring before its onset or the probability of its persistence once a disaster strikes. In the case of COVID-19, as mentioned in the introduction, investors are likely to have revised upwards the probability of a pandemic in the period between the detection of the first clusters in Italy on 21 February and the March 11 declaration of the pandemic by the WHO. In terms of the model, this would be captured by an upward revision of the probability of a disaster at $t = 1$ from a negligible prior to a strictly positive p_1: according to Prediction D, this should have produced an increase in the valuation of resilient stocks relative to non-resilient ones, leading the former to outperform the latter. In turn, the rapid spread of the disease after the WHO declaration can be seen as the actual occurrence of the disaster at $t = 2$ in the model, and the corresponding increase in pessimism about the persistence of the pandemic: in our model, this would be captured by an additional upward revision of the probability of a new disaster at $t = 3$ to $p_2 = \rho > p_1$, leading to further divergence in the performance of resilient and non-resilient assets. Conversely, news about the successful development of vaccines which started spreading between the end of March and May 2020 (see Acharya et al. (2022)) should have the opposite implication, namely, be associated with a recovery in the valuations of non-resilient stocks relative to resilient ones, hence with a convergence in their returns. In our model, this can be interpreted as positive surprises at $t = 2^+$ about the probability of future disasters or the average resilience of the corporate sector to future disasters.

Taking together Predictions B and C about expected returns and Prediction D about realized returns, the overall implications of the model are that the differentials of both expected and actual returns of assets featuring different resilience should *widen* when investors become *more pessimistic* about a disaster occurring or persisting, and *narrow* when they become more optimistic. Specifically, pessimistic belief revisions should trigger higher realized and lower expected returns relative to the market for resilient assets, and the opposite for non-resilient assets; conversely, optimistic belief revisions should trigger lower realized and higher expected returns relative to the market for resilient assets, and again symmetric effects for the returns of non-resilient ones.

3 Empirical Strategy and Data

The theory presented in the previous section predicts that the cross-sectional distribution of *realized* and *expected* stock returns should both react to the onset of a disaster and to investors' updating about its severity and duration. Since the model implies that realized and expected returns of firms featuring high resilience to the disaster respond differently from those of low resilience firms, a key prerequisite to take the theory to the data is a measure of disaster resilience. In the context of the COVID-19 pandemic, a natural measure of resilience is one based on firms' immunity to social distancing requirements: firms whose employees could keep operating and dealing with customers remotely were less affected by the pandemic than those that could not.

Hence, our first strategy to test the model's predictions is to build a measure of resilience to social distancing restrictions by capitalizing on relevant research by labor economists, and study the cross-sectional differences in firms' realized and expected returns associated with differences in this particular resilience measure. In implementing this strategy we control for firms' exposure to standard risk factors: our approach effectively amounts to testing whether the occurrence of the pandemic induced investors to price an additional source of risk, beside those priced in normal times. Importantly, this strategy amounts to a joint test of our model's predictions and of the assumption that immunity to social distancing is an appropriate metric of resilience to pandemic risk.

However, during the pandemic the stock market may also have priced other dimensions of resilience, in addition to immunity to social distancing. To take this into account, we adopt a second, more agnostic empirical strategy: Using the predictions of our model, we first classify stocks as featuring high or low resilience based on their realized and expected returns during the outbreak of the pandemic, and then investigate to what extent different empirical measures of resilience are consistent with such classification. In particular, we consider also variables that capture firms' balance sheet strength, hence their resistance to the financial shock triggered by the pandemic, and their resilience to environmental risk, which has received attention by the media in the wake of the pandemic. Hence, this strategy enables us to very whether indeed social distancing played a key role in defining the responses of asset prices to the COVID-19 disaster.

In what follows, we describe the data and the construction of variables used to implement these two empirical strategies. Both of them require data on firms' realized and expected returns. To generate a consistent sample of realized and expected returns, we focus on S&P 500 firms and follow the approach of Martin and Wagner (2019) to compute firms' options-implied expected returns. Our final sample contains daily risk-adjusted realized and expected returns for horizons ranging from one month to two years for 498 firms. We then merge these data with empirical measures related to social distancing and data on other firm characteristics.

3.1 Realized returns

Daily realized returns are computed for all stocks included in the S&P 500 during the fourth quarter of 2019, accounting for price-adjustments and dividends. The price data are taken from the Compustat Capital IQ North America Daily database for the years 2019 and 2020. Data for daily risk-free, market and standard factor returns are drawn from from Kenneth French's website.

We estimate firms' exposures to common factors by regressing daily stock returns in 2019 on market excess returns (CAPM), the five Fama and French (2015) factors (FF5, i.e. market, size, value, investment, and profitability) or the q-factors proposed by Hou et al. (2015, HXZ, i.e. market, size, investment, and profitability). These exposures are then used to compute factor model-adjusted stock returns for 2020 as the difference between a stock's daily excess return and its CAPM beta multiplied by the daily market excess return. We proceed analogously for the FF5 and the HXZ specification.[4]

3.2 Options-implied expected returns

Prices of index and stock options can be used to compute measures of expected market returns and expected stock returns. Our analysis builds on the approaches suggested by Martin (2017) and Martin and Wagner (2019). Martin (2017) shows that the risk-neutral variance of the market provides a lower bound on the equity premium. He also argues that, empirically, the lower bound is approximately tight, so that the risk-neutral variance of the market directly measures the equity premium. Martin and Wagner (2019) derive a formula for the expected return on a stock in terms of the risk-neutral variance of the market and the stock's excess risk-neutral variance relative to that of the average stock.

We obtain daily S&P 500 index option and individual stock options data from OptionMetrics for the year 2020. Using the index and stock volatility surfaces, we compute the three measures of risk-neutral variance – for the market, the individual stock and the average stock – for maturities of 30, 91, 182, 365, and 730 days.

The risk-neutral market variance, SVIX_t^2, is determined by the prices of index options:

$$\text{SVIX}_t^2 = \frac{2}{R_{f,t+1} S_{m,t}^2} \left[\int_0^{F_{m,t}} \text{put}_{m,t}(K)\, dK + \int_{F_{m,t}}^{\infty} \text{call}_{m,t}(K)\, dK \right],$$

where $R_{f,t+1}$ is the gross riskfree rate, $S_{m,t}$ and $F_{m,t}$ denote the spot and forward

[4]This approach follows Ramelli and Wagner (2020) and other related papers.

(to time $t+1$) prices of the market, and $\text{put}_{m,t}(K)$ and $\text{call}_{m,t}(K)$ denote the time t prices of European puts and calls on the market that expire at time $t+1$ with strike K. The length of the time interval from t to $t+1$ corresponds to the maturity of the options used in the computation.

The risk-neutral variance at the individual stock level, $\text{SVIX}^2_{i,t}$, is defined in terms of individual stock option prices:

$$\text{SVIX}^2_{i,t} = \frac{2}{R_{f,t+1} S^2_{i,t}} \left[\int_0^{F_{i,t}} \text{put}_{i,t}(K)\, dK + \int_{F_{i,t}}^{\infty} \text{call}_{i,t}(K)\, dK \right],$$

where the subscripts i indicate the underlying stock i. Finally, using $\text{SVIX}^2_{i,t}$ for all firms available at time t, one can calculate the risk-neutral average stock variance index as $\overline{\text{SVIX}}^2_t = \sum_i w_{i,t}\, \text{SVIX}^2_{i,t}$.

Using these three risk-neutral variances, we follow Martin and Wagner (2019) and compute the expected return on a stock as

$$\frac{\mathbb{E}_t\, R_{i,t+1} - R_{f,t+1}}{R_{f,t+1}} = \text{SVIX}^2_t + \frac{1}{2} \left(\text{SVIX}^2_{i,t} - \overline{\text{SVIX}}^2_t \right),$$

where $R_{i,t+1}$ denotes the one period gross return on stock i, and the expected return on stock i in excess of the market as

$$\frac{\mathbb{E}_t(R_{i,t+1} - R_{m,t+1})}{R_{f,t+1}} = \frac{1}{2} \left(\text{SVIX}^2_{i,t} - \overline{\text{SVIX}}^2_t \right). \tag{1}$$

Since our model generates predictions for the dynamics of firms' expected returns in excess of the expected return of the market portfolio, Equation (1) appears particularly well-suited for our empirical analysis. For every day in 2020, we therefore compute each firm's expected return in excess of the market for the next 30, 91, 182, 365, and 730 days. Our final sample comprises time series of expected returns in excess of the market for 498 firms for horizons of one month up to two years.

3.3 Empirical measures of resilience to social distancing

Recent research in labor economics provides several proxies for firms' resilience to social distancing. Koren and Pető (2020, KP) use a model of communication showing how social distancing rules can affect production costs and propose empirical proxies for communication based on data from the Occupational Information Net-work (O*Net). They construct three types of industry-level measures of face-to-face interactions, depending on whether these are due to internal communication ('teamwork'), external communication ('customers'), or physical proximity to others ('presence'). They also aggregate 'teamwork' and 'customers' to a measure of 'communication' intensity and construct an industry-level measure of the percentage of employees 'affected' by social distancing regulations due to their occupations being communication-intensive and/or requiring physical proximity to others. We merge stock, options, and KP resilience data using firms' 3-digit NAICS codes.

In our main analysis, we rely on the 'affected share' variable proposed by KP, which, for brevity, we refer to as 'KP score', because, beside capturing reliance on work from home, it also explicitly accounts for physical proximity to others, and therefore is the most complete measure of vulnerability to social distancing. Since the KP score ranges between 0 and 100, resilience to social distancing is defined as the negative of the KP score.

For robustness, we also consider other measures of resilience based on social distancing, namely, the industry-level work-from-home measures proposed by Dingel and Neiman (2020, DN) and Hensvik et al. (2020, HLR), as well as the firm-level work-from-home index proposed by Bai et al. (2021), which combines the industry-level DN measure with firm-level job postings. Table A.1 in the Internet Appendix provides an overview of all these measures and presents their definitions.

3.4 Data on firm characteristics

Our second, more agnostic empirical strategy requires measures of other dimensions of resilience, beside those related to social distancing. To this purpose, we retrieve firms' balance sheet data from the Compustat database as of end of 2019, namely, firms' cash ratios, defined as cash (Compustat item che) divided by total assets (at), and leverage ratios, defined as book debt ($dlc + dltt$) divided by total assets (at). Finally, we obtain the last available environmental score of our sample firms (which in most cases refers to September 2019) from Sustainalytics via WRDS.

4 Pricing Resilience to Social Distancing

In this section, we present the results of the first empirical strategy described in the previous section: we measure firm resilience on the basis of each industry's immunity to social distancing, and study the cross-section of firms' realized and expected returns through 2020. Our focus will be on resilience as measured by the KP score, that is the 'affected_share' defined by Koren and Pető (2020), but we also discuss corroborating evidence from using other resilience measures. Table A.2 in the Internet Appendix presents summary statistics of the KP score for the sample of S&P 500 firms used in our empirical analysis. Our matched sample of realized returns, expected returns, and KP data comprises 466 firms in 61 industries, as classified by their NAICS 3-digit codes.

We distinguish three periods: (i) the period before the COVID-19 outbreak, which we date as starting on February 23, the date of the first Italian lockdown; (ii) the 'fever' period, from February 24 to March 20, and the (iii) 'post-fever' period, from March 23 to the end of 2020. This periodization was first proposed by Ramelli and Wagner (2020), who place the end of the fever period on the last trading day before the Fed's announcement of its expansionary policy against the pandemic.[5] This date was not only associated with a sizable shift in the monetary policy stance, but also with the diffusion of the first news of the development of successful vaccines: between March 15 and 20, the estimate of the expected time to a widespread COVID-19 vaccine deployment reported by Acharya et al. (2022) dropped sharply (by 17%) for the first time since the beginning of 2020, with another sharp drop (21%) occurring between March 29 and April 3. However, below we show that our results are not sensitive to this particular definition of the fever and post-fever period.

4.1 Realized Returns and Firm Resilience

We start by studying the realized returns of S&P 500 firms. The red and green lines in Figure 2 plot the value-weighted cumulative risk-adjusted returns of a low-resilience and a high-resilience portfolio, respectively formed by stocks in industries above and below the median KP score. The figure shows that the performance of these two portfolios differed substantially throughout 2020, in line with Prediction D of our model. During the fever period, marked by the dashed vertical lines, less resilient

[5]On Monday March 23, the Fed unveiled its plan to buy an unlimited amount of bonds with government guarantees, including some commercial mortgage debt. It also established the Secondary Market Corporate Credit Facility (SMCCF), in order to purchase existing investment-grade corporate debt, including exchange-traded funds, as well as the Primary Market Corporate Credit Facility (PMCCF), to purchase newly issued corporate bonds, so as to prevent companies facing pandemic fallout from dismissing employees and terminating business relationships.

firms featured a negative risk-adjusted cumulative return of approximately −6% and −7%, depending on whether the risk adjustment is based on the CAPM, the FF5, or the HXZ model. Resilient firms instead outperformed by approximately 10% and 5% respectively in the two panels: hence, their cumulative differential return relative to low-resilience firms during the fever period reached (rounded values of) 17% and 13% depending on the risk adjustment.

[Insert Figure 2]

The post-fever period featured a strong reversal of these return dynamics: by the end of the year the return differential almost vanished if the risk adjustment is based on the CAPM or on the q-factors, even turning slightly negative if it is based on the FF5 model. In fact, most of the reversal occurred by the end of June, only three months after the end of the fever period. This is precisely the period in which the expected time to a vaccine widespread deployment dropped most markedly: the indicator computed by Acharya et al. (2022) dropped from 3.04 to 0.88 years (a 71% decline) between March 21 and June 30.

Table 1 shows the estimates of the cross-sectional relationship between cumulative risk-adjusted returns and firms' resilience to social distancing, separately for the fever and post-fever period.[6] The 'social distancing resilience' variable used in the regressions of Table 1 is defined as the negative of the are shown below each coefficient estimate: the first one is based on robust standard errors following White (1980), whereas the second is based on standard errors clustered at the (NAICS 3-digit) industry level.

[Insert Table 1]

During the fever period, there is a significant positive correlation between cumulative risk-adjusted returns and industry-level resilience: a 10-point increase in resilience is associated with a 3% to 4% increase in risk-adjusted performance. Comparing the first and fourth columns of the table, or the second and the fifth or the third and the sixth columns, reveals that the relationship between risk-adjusted performance and resilience reversed sharply in the post-fever period: the slope coefficients turn from positive to negative.

[6] Table A.3 in the Internet Appendix provides industry-level summary statistics of firms' risk-adjusted returns during these two periods.

The results are qualitatively unchanged, albeit with varying degrees of significance, when using other proxies of social distancing, as we discuss in Section 4.4. Taken together, when firms are classified on the basis of their resilience to social distancing, their realized return dynamics are consistent with Prediction D of our model: the "fanning out" of realized excess returns during the fever period and their reversal in the post-fever period can be explained by investors initially estimating the pandemic to be quite persistent, and then revising their estimate due to encouraging news about vaccine development.

4.2 Options-Implied Expected Returns and Firm Resilience

Our model's predictions not only concern the dynamics of realized returns of resilient and non-resilient assets during the pandemic, but also their expected returns. To test these predictions, we rely on equity options data. Options prices are observable in real time, are inherently forward-looking, and provide information about the expected returns of the underlying stocks. These features are especially useful when studying the effects of disasters, such as COVID-19, since they are better equipped to detect the sharp changes in expected returns associated with belief revisions during disasters (see, for example, Collin-Dufresne et al., 2016) than alternative methods, such as those based on machine-learning techniques, which usually include low frequency input data and are not refitted at high-frequencies (Gu et al. (2020), Grammig et al. (2021)). Following Martin and Wagner (2019), we derive expected stock returns from risk-neutral variances computed from index and stock options, as described in Section 3.2. In Section IA.B of the Internet Appendix, we discuss the empirical validity of their approach and present evidence for the usefulness of options-implied expected returns to forecast realized returns in 2020. While pre-pandemic forecasts did not anticipate the pandemic outbreak, options-implied expected returns predicted realized returns quite accurately by the end of the fever period, once markets had learned about COVID-19.

In the remainder of this section, we explore how the cross-section of expected excess returns derived from Equation (1) relates to the same measures of resilience used for realized risk-adjusted returns. Recall that, according to Predictions B and C of our model, as investors update their beliefs about the persistence of a disaster, the cross-section of expected returns should change precisely in the opposite way relative to the risk-adjusted realized returns. Namely, when investors revise the disaster probability or persistence upwards, the expected return differential between non-resilient and resilient assets should increase, while their realized risk-adjusted return differential decreases.

We start by looking at the value-weighted expected return in excess of the market for the high- and low-resilience portfolios defined in Section 4.1, respectively. Since we have data for the prices of options with maturities ranging from 30 to 730 days, we can calculate expected returns over all of these horizons, but for brevity in Figure 3 we display only those inferred from 30-days and 2-year maturity option prices.[7]

Figure 3 reveals that, even though at the start of 2020 low-resilience firms featured slightly lower expected returns than resilient ones, during the fever period the expected returns of low-resilience firms peaked at approximately 4.4% p.a. on a 1-month horizon and at 1% p.a. on a 2-year horizon. The opposite dynamics are observed for high-resilience firms: expected returns dropped as much as 5.39% on a 1-month horizon, and 1% on a 2-year horizon. Thus, over the fever period the expected return differential between high- and low-resilience stocks dropped by approximately 10 percentage points on a 1-month horizon and by 2 percentage points an a 2-year horizon.

[Insert Figure 3]

In the post-fever period, there was a strong reversal of these dynamics, similar to that observed for realized returns in Section 4.1, though with opposite signs: by the end of 2020, the expected excess returns of the resilient and non-resilient portfolios almost reverted to their pre-pandemic levels.

To shed light on the cross-section of changes in expected excess returns at the firm-level, we regress them on our resilience measure.[8] Table 2 shows the results separately for the fever and the post-fever period, using option-implied expected returns at 1-month, 3-months, 6-months, 1-year and 2-year horizons. In the fever period, changes in expected returns are negatively and significantly related to resilience: an increase in resilience by 10 (out of 100) is associated with a drop in expected returns by

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[7] In the Internet Appendix, Section IA.A presents details on the risk-neutral variances of the market, the average stock as well as the high-resilience and low-resilience portfolios, which we use to compute expected returns.

[8] Table A.4 in the Internet Appendix provides summary statistics of firms' changes in expected returns in excess of the market during the fever and post-fever periods at the industry level.

5.4% when expected excess returns are measured using 1-month options prices, and by 1.5% when measured at the 2-year horizon. The fact that the coefficients are monotonically decreasing in option maturity indicates that investors expect a gradual resolution of uncertainty regarding the effects of the pandemic. In the post-fever period, instead, the relation between changes in expected excess returns and resilience becomes positive: a 10-point increase in resilience in this period is associated with a 5.1% to 0.9% increase in expected excess returns, depending on the option maturity.

[Insert Table 2]

Again, the results are qualitatively unchanged when using the other proxies for social distancing, with varying degrees of significance, as we discuss in Section 4.4. Overall, the cross-sectional dynamics of realized and expected returns shown in Figures 2 and 3 and in Tables 1 and 2 accord well with Predictions B and C of the model presented in Section 2, if disaster resilience is defined on the basis of exposure to social distancing. The model predicts that both realized and expected returns of resilient and non-resilient firms reflect the combined effects of disaster and learning: their pattern in the initial phase of the pandemic is consistent with investors becoming more pessimistic about the probabilities of future pandemics and/or the severity and persistence of the current one, while their subsequent convergence is consistent with good news about the development of vaccines, and therefore with downward revisions of the probability of future disasters and/or the severity and persistence of COVID-19.

In light of this narrative, the question arises whether the economy fully reverted 'back to normal' by the end of 2020, so that by then the cross-section of asset prices no longer reflected any exposure to pandemic risks. Inspecting the expected returns shown in Figure 3, this may indeed appear to be the case: by the end of 2020, the difference between the expected excess returns of the high and low-resilience portfolios almost disappeared. Yet, this does not necessarily imply that at that date pandemic risks were no longer priced in the cross-section of expected returns, for two reasons. First, grouping stocks in two portfolios respectively featuring above- and below-average resilience hides the considerable cross-industry variation in resilience, and the extent to which it correlates with variation in expected returns during the pandemic. Second, the options-implied excess returns shown in Figure 3 are not adjusted for standard risk factors, so that their convergence by the end of 2020 could still be consistent with a risk-adjusted expected return differential between them.

Indeed, Figure 3 shows that in early 2020, before the outbreak of the pandemic, high-resilience firms featured higher expected returns than low-resilience ones, especially when measured over a 2-year horizon. This suggests that the former may be more exposed to standard risk factors than the latter. Indeed, on average the stocks included in the high-resilience portfolio feature higher CAPM betas and exposure to several FF factors than stocks in the low-resilience portfolio. Hence, even if the expected returns of the two portfolios converge at the end of 2020, exposure to pandemic risk may still be priced in the cross-section of stocks.

To bring evidence from the whole cross-section of individual firms' expected returns to bear on this issue, we estimate regressions of expected returns in excess of the market on their respective KP score, for each trading day in 2020, and in one specification of these regressions we also control for firms' FF5 exposures.[9] Figure 4 displays the estimates of the daily coefficients of the KP score, which measure the extent to which exposure to pandemic risk (as measured by vulnerability to social distancing) was priced in the cross-section of expected returns at each date. Panels A and B respectively show the coefficient estimates obtained using expected excess returns from 1-month and 2-year options. The charts on the left are obtained from regressions without controls, while those on the right are based on regressions that control for FF5 exposures.

[Insert Figure 4]

In all the charts of Figure 4, the coefficients shot up during the fever period, indicating a corresponding increase in the price of pandemic risk exposure, and subsided to lower levels thereafter. But they also show that vulnerability to social distancing was still priced for S&P 500 firms at the end of 2020, especially after controlling for the FF5 factors. Almost one year after the onset of COVID-19, less resilient stocks (i.e., those with a higher KP score) yielded a significantly higher expected return over that of the market portfolio: based on the estimates shown in the lower-right graph of Figure 4, in December 2020 a 1-standard deviation increase in the KP score was associated with an extra expected return in excess of the market of approximately

[9] The KP scores used in the estimation are standardized, i.e. measured as deviations from the cross-sectional mean and divided by their cross-sectional standard deviation of KP scores on the corresponding day. Since expected returns in excess of the market are regressed on these standardized KP scores, the regression coefficient measures the change in expected returns in excess of the market associated with a 1-standard deviation change in the KP score.

1%, after controlling for FF5 factors, down from almost 4% at the peak of the crisis.[10]

4.3 The link between expected and realized returns

Our model implies that disaster risk moves stock prices and expected returns in opposite directions. The empirical evidence in Sections 4.1 and 4.2 supports this prediction: In the fever period, the stock returns (adjusted for standard risk factors) of high resilience firms exceed those of low resilience firms and, at the same time, expected excess market returns of high resilience firms decrease whereas those of low resilience firms increase. The post-fever period is characterized by reversals of both stock prices and expected returns. Now, we explicitly connect the results on realized returns (Figure 2 and Table 1) to those on expected returns (Figure 3 and Table 2) and present a detailed analysis of their relationship.

First, we test for the negative relation between expected and realized returns that is predicted by the model for the fever period. Using firm-level returns, we regress the change in expected returns in excess of the market on realized risk-adjusted returns. Consistent with our theory, Table 3 shows that the estimates of the regression coefficients are significantly negative for all expected return horizons τ, both using robust and industry-clustered standard errors. The results are qualitatively similar for all factor model adjustments, with sizable R^2-values in the range 0.30 to 0.34 for CAPM-adjusted returns, 0.14 to 0.17 for FF5-adjusted returns, and 0.24 to 0.27 for HXZ-adjusted returns.

[Insert Table 3]

Second, we study *when* the relation between realized and expected returns becomes negative. To do so, we estimate regressions of changes in expected on realized returns using rolling 20-day windows. Figure 5 presents results for expected returns in excess of the market with the shortest horizon (30 days) and the longest horizon (730 days) using all three factor model-adjusted realized returns. We find that all coefficient estimates are very close to zero prior to the fever period. Once the fever period starts, the coefficients become markedly negative, and increase in absolute value until the end of the fever period. From then on, the negative relationship weakens,

[10] These results are broadly robust to the use of clustered standard errors, as shown in Figure A.5. They also survive when using the Bai et al. (2021) firm-level resilience measure, both with robust standard errors, as shown in Figure A.6, and with clustered standard errors, as shown in Figure A.7.

but does not completely vanish: the coefficients remain significantly negative for the longer horizon. Hence, realized and expected returns also move in opposite directions in the post-fever period, consistent with the reversals observed in Figures 2 and 3.

[**Insert Figure 5**]

Third, we explore whether the negative relation between expected and realized returns is stronger for low resilience firms than for high resilience ones. Intuitively, this should be the case if the average firm is hurt by a disaster, but low resilience firms are hurt much more than the average, while high resilience ones are barely affected. Then, the prices and expected returns of the former should respond (in opposite directions) more strongly to COVID-19 news than those of the latter. In the limit, if high resilience firms were completely insulated from the pandemic, neither their stock prices nor their expected returns should have reacted to learning about the pandemic, leading to a zero correlation between realized and expected returns, as long as their exposure to other risk factors remained constant.

To test this prediction, we assign firms to quartiles based on their KP score and repeat the regressions of changes in expected returns on realized returns, separately for each resilience quartile. Figure 6 shows that, although the patterns in the rolling-window coefficient estimates are similar across resilience quartiles, the estimates being initially close to zero and becoming negative in the fever period, the pattern is indeed more pronounced for the less resilient firms than for more resilient ones, as expected.[11]

For the fever period, we report coefficient estimates within the respective plots of Figure 6, along with robust and industry-clustered t-statistics. In most cases, the coefficient estimates are significantly negative, and are strongest for Q1 and weakest for Q4, again with Q2 estimates similar to those for Q1, and Q3 estimates similar to those of Q4.

[**Insert Figure 6**]

Overall, the empirical results in this section support the predictions of our model on how disaster risk affects stock prices, expected returns and the relation between the two.

[11] While the difference between high and low resilience firms as a whole is pronounced, there is no clear difference between the estimates for the two low resilience quartiles (Q1 and Q2) and between those of the two high resilience quartiles (Q3 and Q4).

4.4 Robustness checks

This section summarizes results of robustness checks that corroborate our conclusions.

Timing of fever and post-fever periods. First, we show that our results do not rely on precisely choosing March 20 as transition date between the fever and post-fever period. Figure 7 shows that our findings are robust to any different choice of the fever period's ending date ranging between March 13 and April 8. Panel A presents the results for cross-sectional regressions of cumulative risk-adjusted returns and firms' resilience to social distancing (analogous to Table 1); Panel B presents results regarding changes in expected returns in excess of the market (analogous to Table 2).

[Insert Figure 7]

Alternative proxies for social distancing. Second, we verify that our results are qualitatively unchanged, albeit with varying degrees of significance, when using other proxies of social distancing. To this end, we repeat the empirical analysis of cumulative risk-adjusted returns as well as expected returns in excess of the market and report the respective results in the Internet Appendix. The robustness checks using the components underlying the aggregate score of Koren and Pető (2020) are shown in Tables A.5 and A.9; those based on the industry-level work-from-home measures proposed by Dingel and Neiman (2020) are in Tables A.6 and A.10, and those proposed by Hensvik et al. (2020) are in Tables A.7 and A.11. Finally, results based on the firm-level work-from-home index proposed by Bai et al. (2021) are illustrated by Figures A.1 and A.2 and by the estimates shown in Tables A.8 and A.12.

Larger cross-section. As a robustness check, we repeat the analysis for a broader sample of stocks, which includes all firms for which CRSP and Compustat provide price and fundamentals data, respectively, a sufficient number of observations for option prices is available in OptionMetrics, and Koren and Pető (2020) provide their metric of resilience to social distancing. The empirical findings for this larger sample of 2,274 firms are qualitatively similar to those obtained for the sample of S&P 500 firms, as documented in detail in Internet Appendix IA.C.

5 Inferring Resilience from Market Responses

The empirical analysis in Section 4 provides a consistent picture of the pricing of COVID-19 disaster risk on the basis of firm resilience to social distancing. These results support the joint hypothesis that our model and the social distancing measures we employ, in particular the KP score, are useful for understanding asset price behavior during the pandemic. These results, however, do not rule out that other dimensions of resilience may also be priced by asset markets during the pandemic. As discussed in Section 3, this concern can be addressed via a different empirical strategy: first, use the predictions of our model to classify stocks as featuring high or low resilience based on their realized and expected returns during the fever period, and then investigate to what extent different measures of resilience are consistent with such classification. In this section we pursue this more agnostic strategy and let the data speak.

Recall that, according to Predictions B, C and D of the model, high-resilience assets should exhibit positive risk-adjusted realized returns and decreasing expected returns during the onset of the disaster, while the opposite prediction applies to low-resilience assets. These predictions imply that the joint distribution of realized returns and changes in expected returns should be characterized as shown by the left plot of Panel A in Figure 8: resilient firms should lie in the green quadrant whereas non-resilient firms should lie in the red quadrant. The right plot provides the empirical counterpart for the fever period of the pandemic, using the S&P 500 firms' cumulative FF5-adjusted returns and changes in their one-month expected return during the fever period. The joint distribution of realized and expected returns shows that a majority of firms feature stock price responses that are in line with the prediction of the model, that is, their realized returns and changes in expected returns have opposite signs and fall into either the green or red quadrant.

[Insert Figure 8]

To relate this idea to the findings presented in Section 4, Panel B of Figure 8 illustrates how accurately firms are classified in the red and green quadrants based on their KP affected share: the red dots in the left figure correspond to firms that, based on a social distancing criterion, are non-resilient, since they have an above-median KP score, such as United Airlines or Royal Caribbean. These firms are correctly identified as non-resilient, as their red dots are included in the red quadrant. But some firms are misclassified by their KP score: both Amazon and Netflix have an above-median KP score, and are therefore classified as non-resilient, even though their realized and expected returns suggest that they are resilient firms: their red dots are in the green quadrant.

Symmetrically, the right graph in Panel B pictures firms with below-median KP score, and therefore classified as resilient: they are represented as green triangles. Many of them are indeed located in the green quadrant, so that their return patterns conform with the model predictions. But again, some misclassified stocks stick out: both Boeing and Tripadvisor, which are classified as resilient based on their KP score, are in the red quadrant. The KP score classifies them as resilient, since they do not require a high degree of customer proximity and many of their employees' jobs can probably be done from home. But this does not take into account that their customers are tourists or business travellers, so that their business model was seriously disrupted by the onset of COVID-19.

To take into account that social distancing may not be the only dimension of resilience priced by asset markets during the pandemic, we now classify firms based on their asset price responses. To illustrate the idea, we label Apple as resilient, as it exhibits a positive realized risk-adjusted return during the fever period and a decrease in expected excess return (which coincides with its classification on the basis of its KP score). But we also classify Netflix and Amazon as resilient, since they exhibit the same return pattern, hence deviating from the classification implied by the KP scores of these two stocks.

We summarize our classification strategy by referring to Figure 9. For each stock, we calculate (a) its realized risk-adjusted returns and (b) the change in its expected excess return during the fever period, and define firms as low-resilience, if (a) is negative and (b) is positive, i.e. if it lies in the red quadrant of Panel A; symmetrically, we define firms as high-resilience if (a) is positive and (b) negative, i.e. if it lies in the green quadrant of Panel A. Remaining firms are classified as featuring neither high nor low-resilience.

[**Insert Figure 9**]

Table 4 presents summary statistics for the market-based resilience classification illustrated by Figure 9. The first two columns of the table refer to the fever period, which is used to classify firms as low resilience (Panel A), high resilience (Panel

B), and a residual group of firms that do not fit either criterion (Panel C). The subsequent columns show that, in the post-fever period, realized and changes in expected returns switch signs relative to the fever period, for both low- and high-resilience firms. According to our model, this would be consistent with investors updating their beliefs due to good news about the disaster, such as the development of vaccines.[12] Qualitatively, these results are similar to those obtained when firms are classified based on social distancing metrics. Indeed, the scale of the responses of realized returns and changes in expected returns is considerably larger using this market-based classification than that based on social distancing. This is because the market-based classification leaves out 187 firms whose returns do not comply with the criteria for inclusion in either group, and feature more moderate responses to the COVID-19 shock.

[Insert Table 4]

The outcome-based resilience of the firms shown in Figure 9 may arise from a variety of firm characteristics, not only from their resilience to social distancing used to classify them in Section 4. Other potentially relevant characteristics are those that determine firms' financial resilience, for instance their cash-asset ratio and their leverage, and their resilience to environmental disasters, as measured by their Sustainalytics environmental score. Firms that entered the fever period with abundant liquidity and/or low leverage may have been better able to avoid financial distress, translating into higher realized returns and lower increases in the required expected return on their stocks. Similarly, insofar as COVID-19 acted as a 'wake-up call' regarding environmental concerns, the stocks of firms with better environmental record may have responded less negatively to the pandemic in terms of market performance.

These different firm characteristics may be correlated to some extent: for instance, Apple is more resilient to social distancing than other firms, being a high-tech firm, and at the same time has very large cash reserves; on the other hand, oil and mining companies, which tend to score low on environmental issues, also feature low social distancing resilience, as their operations require employees' physical proximity to their plants, wells and mines. Indeed, the social distancing resilience of S&P500

[12] To provide further support for this interpretation, we show that the reversal in post-fever realized returns is positively related to changes in expected returns during the fever period, as shown by Figure A.10 and Table A.16 in the Internet Appendix, whereas expected returns feature a reversal between the fever and the post-fever period, as shown by Table A.17 of the Internet Appendix.

firms correlates positively with their cash ratios and negatively with their leverage, so that on average firms that are more resilient to social distancing also tend to have greater financial resilience. Similarly, social distancing resilience correlates positively with environmental scores, consistent with the idea that firms whose activity is less dependent on physical proximity are also 'greener' in investors' eyes (see Table A.19 in the Internet Appendix). However, these correlations never exceed 0.28 in absolute value, so that to some extent these characteristics may measure different aspects of resilience.

To assess how each of these firm characteristics correlates with the criteria used to measure firm resilience in Figure 9, Table 5 reports the estimates of regressions of the realized and expected returns in the fever and post-fever period on these firm characteristics. These regressions are estimated separately for firms classified as high and low resilience, because Figure 9 shows that the joint distribution of realized and expected returns is quite different for the two subsamples. The regression results indicate that resilience to social distancing stands out as the variable with the greatest explanatory power in accounting for the pattern of both realized and expected returns of low-resilience firms, both in the fever and post-fever period: it correlates both with the increase in their realized risk-adjusted return and the decrease in their expected return in the fever period, as well as the subsequent reversals in the post-fever period. Importantly, it is the only characteristic that appears to explain the change in expected returns during the pandemic. Instead, financial variables and environmental characteristics only play a role for realized returns. Consistent with Fahlenbrach et al. (2021), firms with more cash and less leverage performed better in the immediate aftermath of the COVID-19 shock, but their expected returns do not appear to have been differently affected by the COVID-19 shock. Similarly, high-resilience firms with better environmental scores performed better than other firms in the immediate aftermath of the COVID-19 shock, in line with the findings by Albuquerque et al. (2020), and worse in the post-fever period, but again their expected returns were not differently affected by the pandemic. In conclusion, while financial and environmental resilience may have mitigated investors' reassessment of firms' expected cash flows in the wake of the pandemic, it did not play a role in their assessment of firms' systematic risk exposure, in contrast to social distancing resilience.

[Insert Table 5]

It is worth asking whether the reversal in expected returns observed for firms classified as low-resilience by the market-based criterion is complete by the end of 2020, or whether some of these firms were persistently scarred by the pandemic, in the sense of facing higher expected excess returns than before the COVID-19 shock well after the end of the fever period. Figure 10 sheds light on this point, by plotting the change in stocks' expected excess returns after the fever period (on the vertical axis) against the change in their expected returns during the fever period.[13] The stocks featuring a complete reversal in expected returns by the end of the year are those that lie along the dotted line with slope -1 in the figure. However, many red dots, which correspond to stocks classified as non-resilient based on their fever-period performance, lie on a flatter line, as their expected excess return after the fever period remains higher than before the pandemic. Hence, several low-resilience firms, such as Royal Caribbean and United Airlines, appear to have been persistently scarred. Section IA.D in the Internet Appendix illustrates these results by presenting the dynamics of expected returns in 2020 for some well-known stocks belonging to the S&P 500.

[Insert Figure 10]

To identify the characteristics of the stocks that feature such long-term scarring effects from COVID-19, we calculate the deviation of the expected excess return of low-resilience firms from the dotted line with slope -1 in Figure 10, which is equivalent to calculating the sum of the change in expected returns during the fever period, ΔE^F, and in the post-fever period, ΔE^{PF}. Then, in Table 6 we estimate a regression of these deviations on the firm characteristics used in Table 5.

[Insert Table 6]

Table 6 shows that the coefficients of the cash ratio, leverage and environmental score are not significantly different from zero, and only social distancing resilience has a significant and negative coefficient.[14] Hence, only firms that are vulnerable to social distancing feature persistent increases in their required risk premia after the

[13] For detailed regression results, see Table A.17 in the Internet Appendix.

[14] The leverage coefficient is marginally significant when using 1-year or 2-year expected excess returns, but these coefficients are no longer significant when errors are clustered by industry.

pandemic, whereas financial flexibility and environmental resilience play no role in mitigating the scarring effects of the pandemic. In contrast, firms that are resilient to social distancing feature no persistent change in their expected rate of return relative to their pre-pandemic level.

6 Conclusions

This paper provides a theoretically-guided analysis of the asset pricing implications of disaster risk and learning about it by investors, using the COVID-19 pandemic as a laboratory. We establish three main empirical sets of results.

First, the onset of the COVID-19 disaster triggered a different stock return response depending on companies' resilience to social distancing, which is the most severe constraint imposed by the pandemic on firms' operations. Differently from all other related studies, we focus not only on the response of realized returns to the disaster but also on that of expected returns, which we infer from the respective firms' option prices. The realized returns of less resilient firms greatly underperformed those of more resilient ones, after controlling for conventional risk factors; conversely, as predicted by our model, their expected returns increased steeply above that of the market, and symmetrically those of more resilient firms dropped.

Second, from late March to December 2020, the differential between the realized risk-adjusted returns of high and low-resilience stocks reversed in sign, and that between expected returns of the two asset classes gradually shrank. This occurred mostly while good news about the development and adoption of effective vaccines started to spread. Hence, the cross-section of firms' expected returns reveals that investors gradually priced less exposure to disaster risk. Nevertheless, even as late as the end of year, exposure to disaster risk still commanded a positive extra excess return, after adjusting for standard risk factors. In light of the model, this joint pattern of realized and expected returns is consistent with investors reducing their estimate of the persistence of the pandemic.

Finally, if the resilience of firms is inferred from from realized and expected returns of their stocks, it turns out to be correlated mainly with their vulnerability to social distancing requirements, rather than with other firm characteristics such as their cash-asset ratio, their leverage and their environmental score. In particular, vulnerability to social distancing is the only firm characteristic that significantly correlates with changes in firms' expected returns during the pandemic, and that correctly identifies firms persistently scarred in terms of increased expected returns relative to the pre-disaster period, such as Royal Caribbean and United Airlines. This dovetails with the evidence about the central role that firms' vulnerability to social distancing played in affecting the response of firms' sales, employment, and asset growth to the COVID-19 shock (Pagano and Zechner, 2022).

In conclusion, our findings indicate that asset markets price exposure to disaster risk, and assign to it a time-varying price as investors learn about disaster persistence. The methodology employed in this paper to investigate the asset pricing implications of pandemic risk may be applied more generally to analyze the pricing of different types of disaster risk and the way in which investors learn and revise their views about their magnitude and about the resilience of the economy.

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Figure 1. Timeline of the model

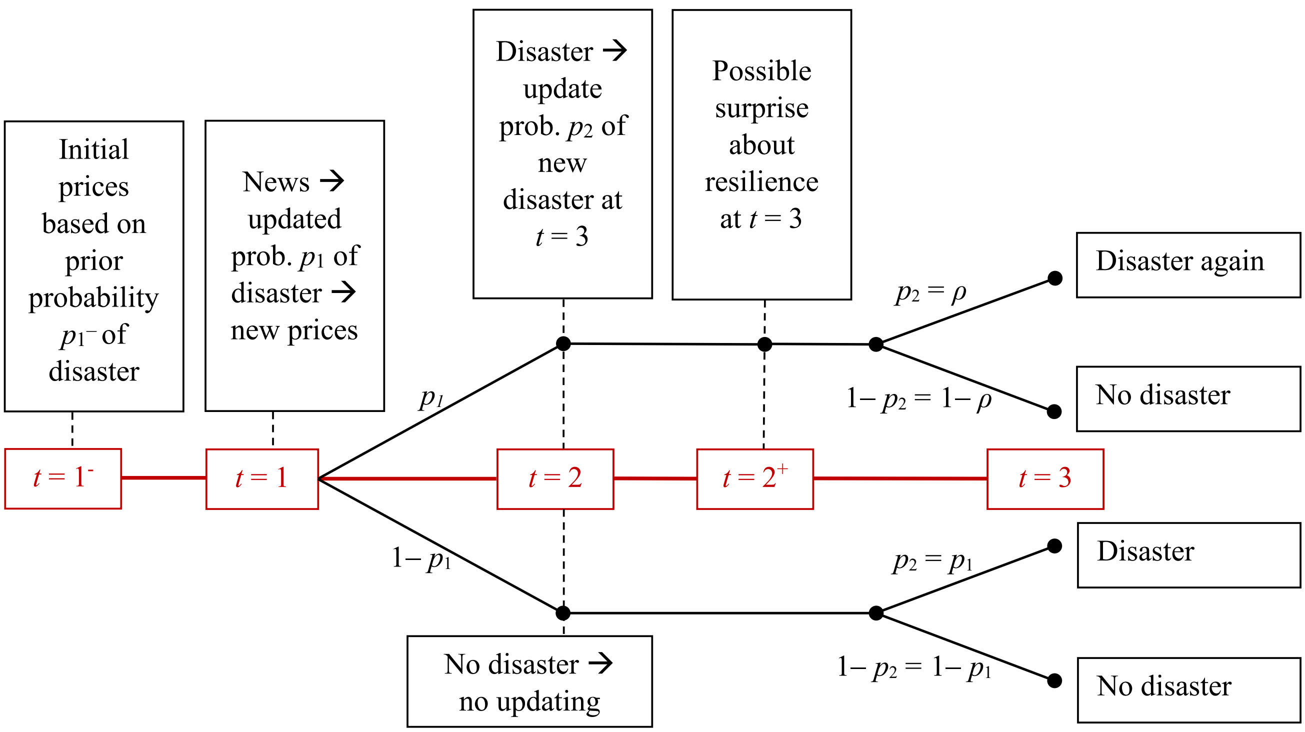


Figure 2. Risk-adjusted returns of stocks with high and low resilience to social distancing

This figure plots the cumulative risk-adjusted returns of portfolios sorted by firms' resilience to disaster risk for 2020. On any given day, we assign a firm to the 'High' portfolio if its 'affected_share' (as defined by Koren and Pető, 2020) is below the median value and to the 'Low' portfolio if it is above. In Panel A, we present CAPM-adjusted returns, i.e. controlling for exposure to market risk. Panel B presents results controlling for the Fama-French five factor model exposures (i.e. market, size, value, investments, profitability). Panel C presents results controlling for the q-factors (i.e. market, size, investments, profitability) proposed by Hou et al. (2015). We plot the cumulative value-weighted portfolio returns for the 'High' portfolio (in green) and the Low portfolio (in red) as well as the High-Low differential return (in blue). The dashed vertical lines mark February 24 and March 20, the beginning and the end of the 'fever-period'.

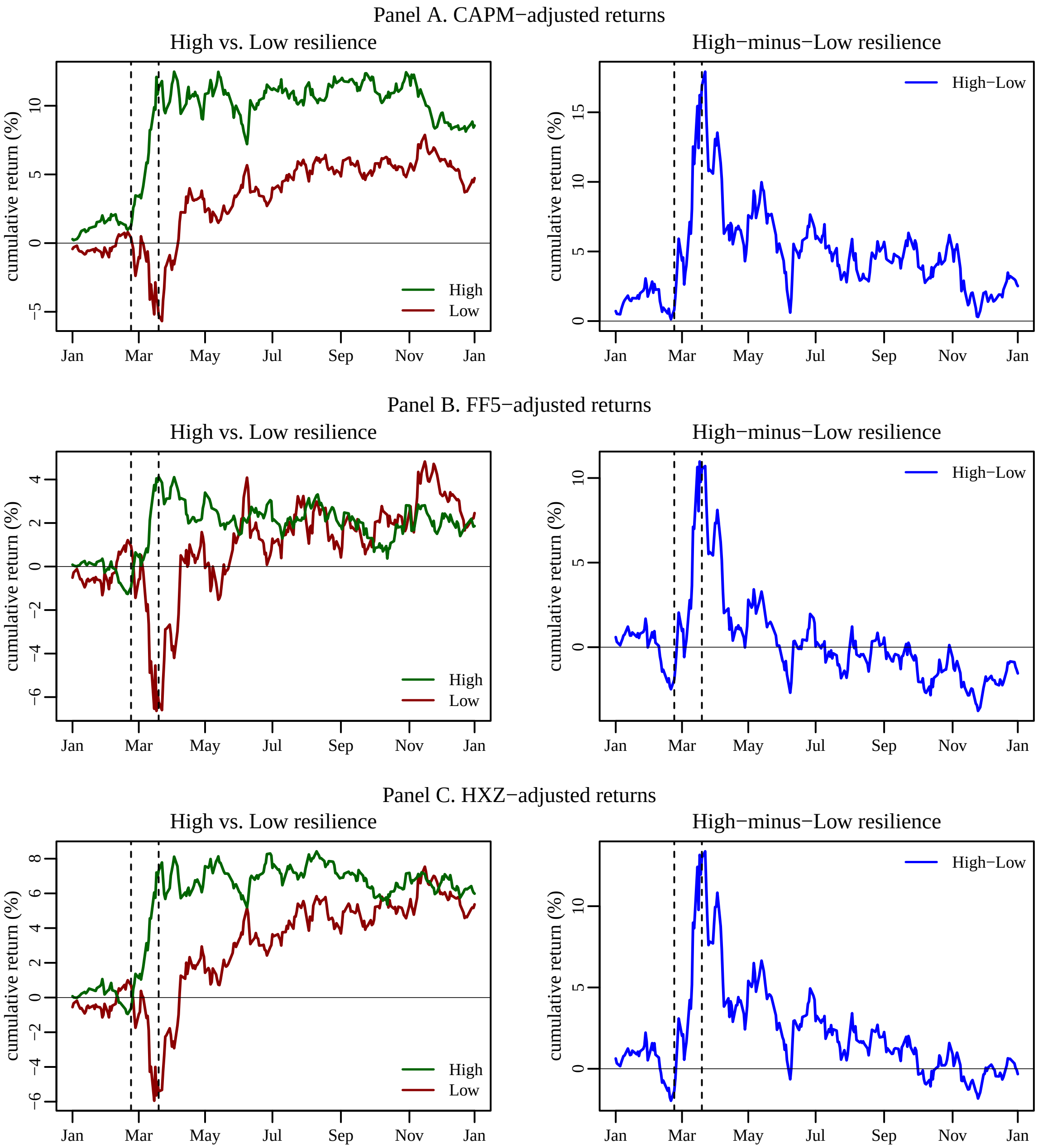


Figure 3. Expected returns in excess of the market of stocks with high and low resilience to social distancing in excess of the market

This figure plots the time-series of expected returns in excess of the market for portfolios sorted by firms' resilience to disaster risk for 2020. On any given day, we compute a firm's expected return in excess of the market from options data, using Equation (1), and assign the firm to the 'High' portfolio if its 'affected_share' (as defined by Koren and Pető, 2020) is below the median value and to the 'Low' portfolio if it is above. In Panel A, we present results for a 30-day horizon. Panel B presents results for a 730-day horizon. We plot the value-weighted portfolio expected returns in excess of the market for the 'High' portfolio (in green) and the Low portfolio (in red) as well as the High-Low differential return (in blue). The dashed vertical lines mark February 24 and March 20, the beginning and the end of the 'fever-period'.

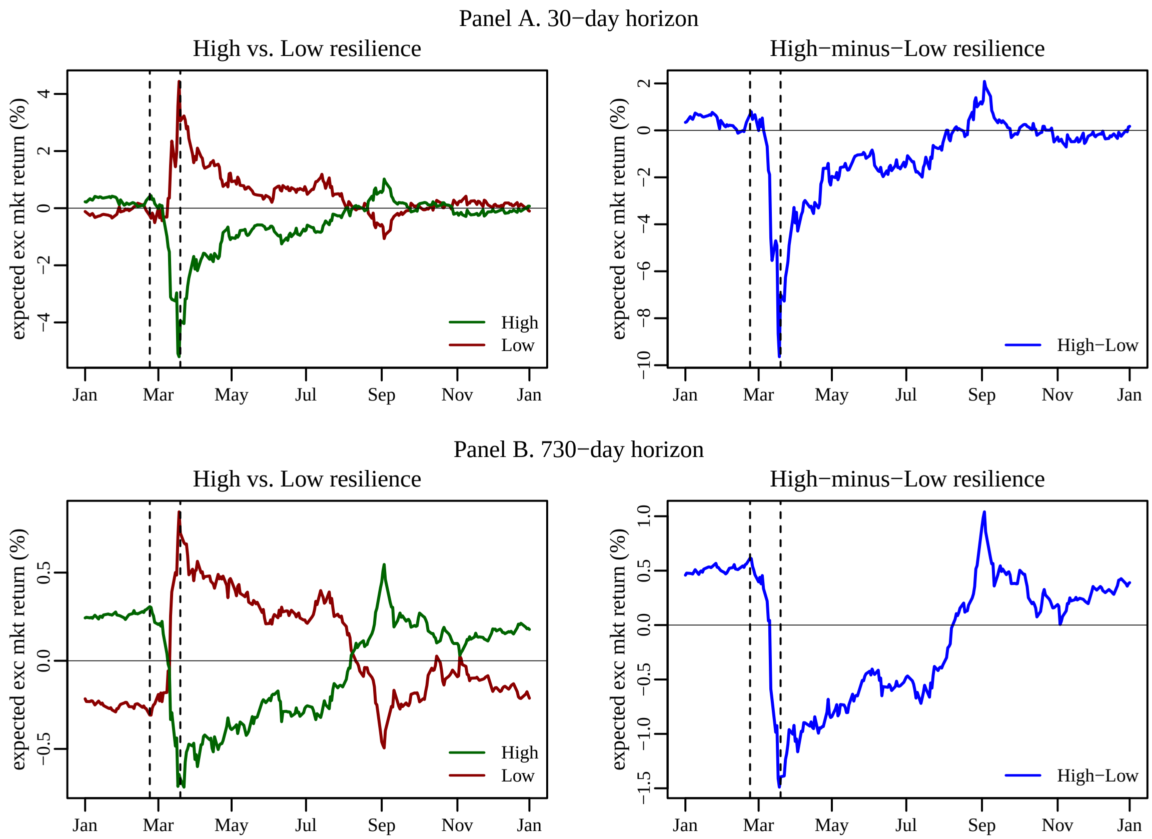


Figure 4. Pandemic risk exposures and expected returns in excess of the market

This figures presents results from cross-sectional regressions of S&P 500 firms expected returns in excess of the market on their pandemic risk exposures, measured by their cross-sectionally standardized KP scores. We run regressions every day of the year 2020 and plot the time series of the pandemic risk exposure coefficient estimate ($\widehat{b}$, bold line) along with 95%-confidence intervals (thin lines) based on robust standard errors following White (1980). Panel A presents results for expected returns in excess of the market for a 30-day horizon ($p.a.$), Panel B results for a 730-day horizon ($p.a.$). Plots on the left represent results from univariate regressions, plots on the right include firms' FF5-exposures as control variables.

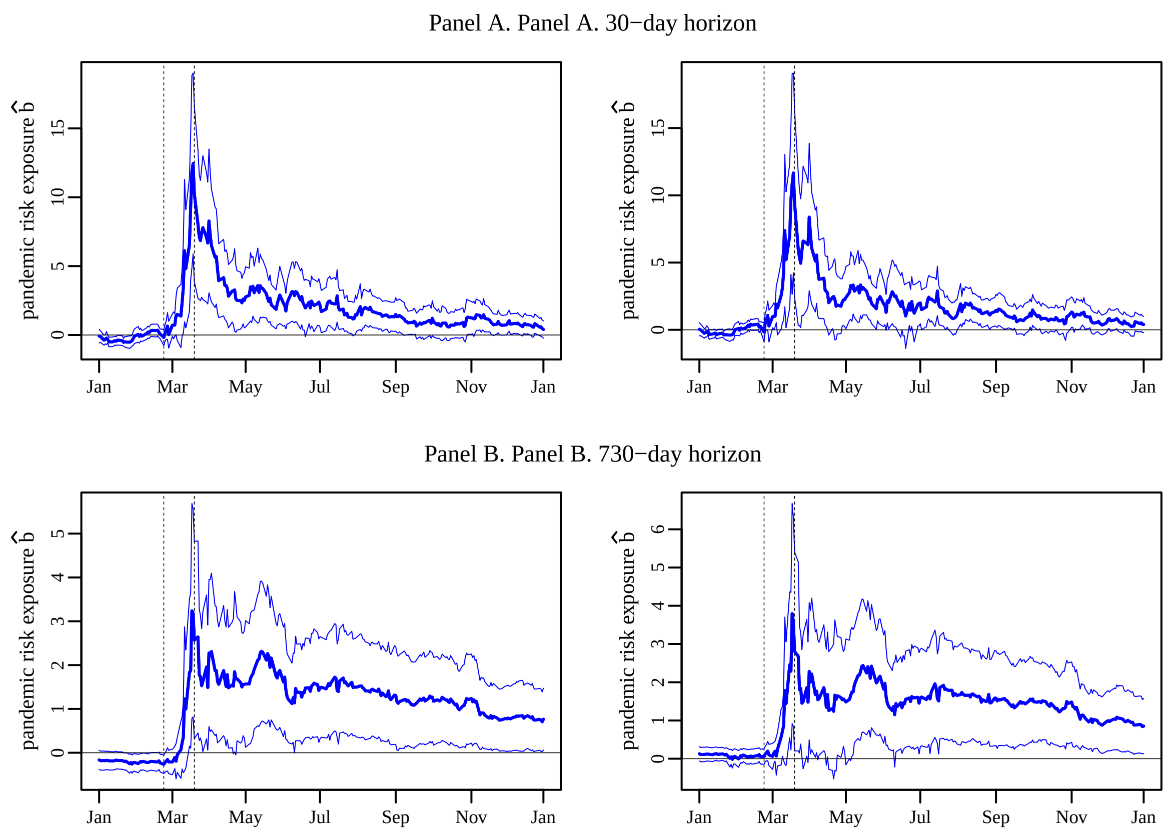


Figure 5. The link between expected returns and realized returns

This figures presents results from cross-sectional regressions of S&P 500 firms' expected returns in excess of the market on their risk-adjusted realized returns. Using 20-day rolling windows, we run regressions every day from February to December 2020. We regress firm i's 20-day changes in expected returns in excess of the market, using options maturities $T \in (30, 730)$, on its cumulative risk-adjusted returns, based on $m \in (CAPM, FF5, HXZ)$,

$$\Delta E^{20d}_{T,i} = b_0 + b_1 cumret^{20d}_{m,i} + e_i,$$

and plot the time series of coefficient estimates along with 95%-confidence intervals based on robust standard errors (following White, 1980, short dash) and based on standard errors clustered at the NAICS 3-digit-code industry level (long dash). Panels A to C presents results for changes in 30-day and 730-day expected returns in excess of the market regressed on CAPM-adjusted returns, i.e. controlling for exposure to market risk, Fama-French five factor model exposures (i.e. market, size, value, investments, profitability), and results controlling for the q-factors (i.e. market, size, investments, profitability) proposed by Hou et al. (2015, HXZ), respectively. The vertical lines mark the fever period from February 24 to March 20.

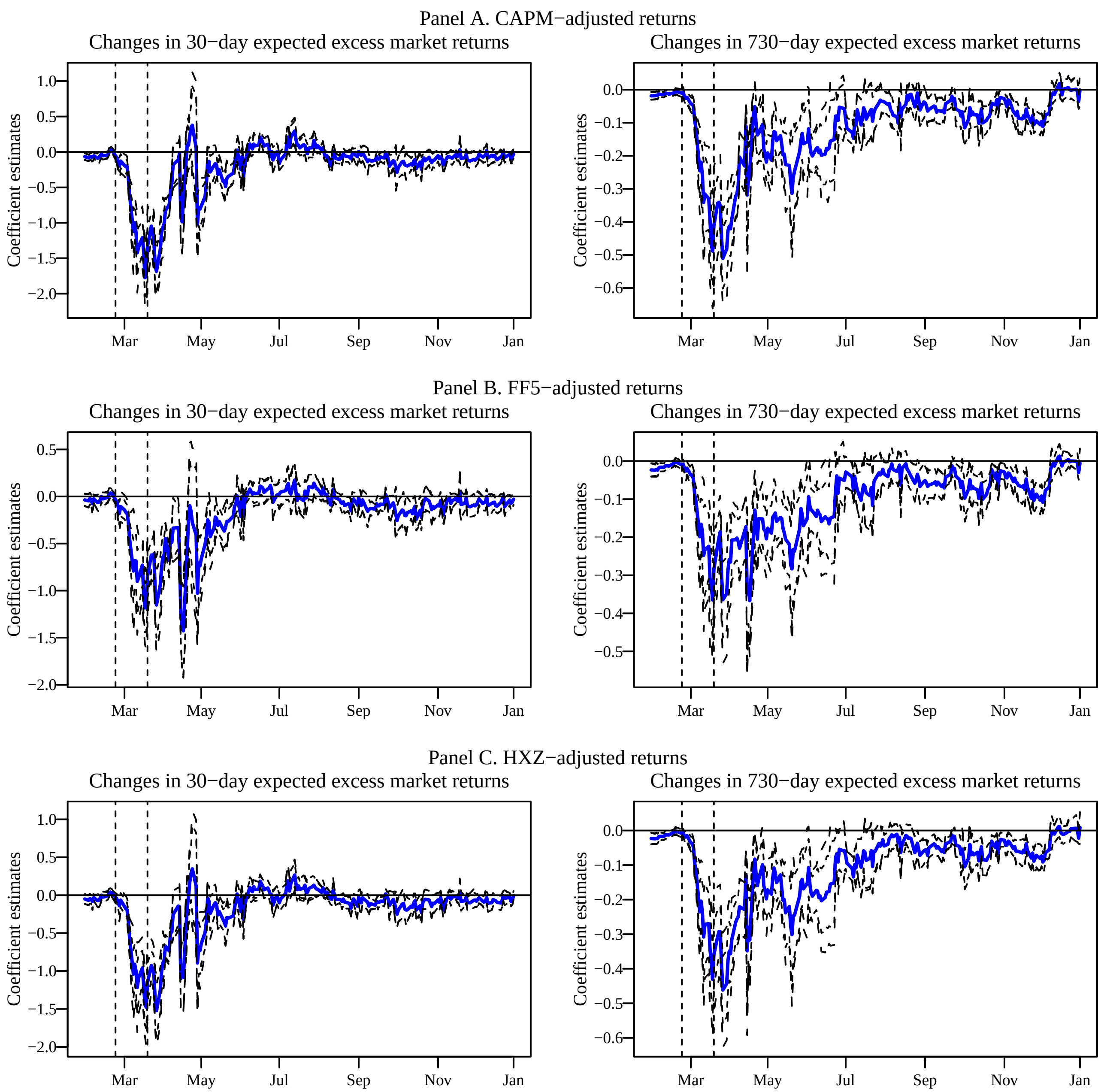


Figure 6. Social distancing and the link between expected returns and realized returns

This figures presents results from cross-sectional regressions of S&P 500 firms' expected returns in excess of the market on their risk-adjusted realized returns. We assign firms to quartiles based on their 'affected_share' (as defined by Koren and Pető, 2020), with the least (most) resilient firms in Q1 (Q4). Using 20-day rolling windows, we run regressions every day of February and March 2020. For each resilience quartile, we regress firm i's 20-day changes in expected returns in excess of the market, using options maturities $T \in (30, 730)$, on its cumulative risk-adjusted returns, based on $m \in (CAPM, FF5, HXZ)$,

$$\Delta E^{20d}_{T,i} = b_0 + b_1 cumret^{20d}_{m,i} + e_i,$$

and plot the time series of the coefficient estimates for the four quartiles. Panels A to C presents results for changes in 30-day and 730-day expected returns in excess of the market regressed on CAPM-adjusted returns, i.e. controlling for exposure to market risk, Fama-French five factor model exposures (i.e. market, size, value, investments, profitability), and results controlling for the q-factors (i.e. market, size, investments, profitability) proposed by Hou et al. (2015, HXZ), respectively. In the plot legends, we report the coefficient estimates for the fever period (from February 24 to March 20, marked by the vertical lines) and two sets of t-statistics: the first is based on robust standard errors following White (1980), whereas the second is based on standard errors clustered at the NAICS 3-digit-code industry level.

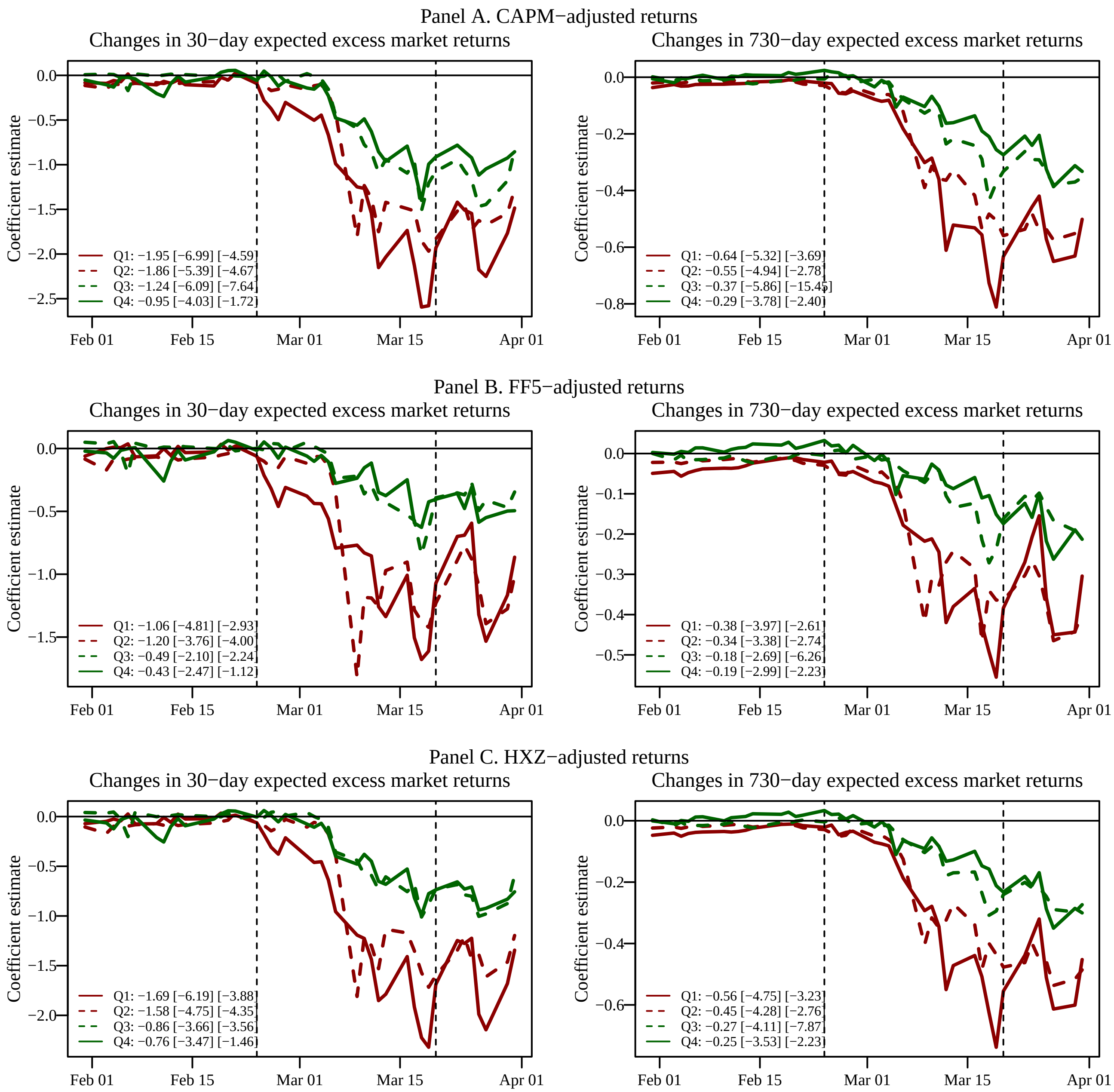


Figure 7. Risk-adjusted returns and resilience to social distancing: different (post-)fever periods

This table summarizes the results of firm-level cross-sectional regressions of cumulative risk-adjusted returns (Panel A) and of changes in expected returns in excess of the market (Panel B) on resilience to social distancing. We present results for two sub-periods of 2020: the 'fever-period' (coefficient estimates in black) and the 'post-fever period' (estimates in grey). The fever period starts from February 24 and ends at the date indicated on the horizontal axis. That date also marks the start of the post-fever period, which goes until the end of 2021. For both periods, we compute each firm's cumulative risk-adjusted returns and as well as the change in its expected return in excess of the market. In Panel A, we use each firm's cumulative CAPM-adjusted return (controlling for exposure to market risk) and its cumulative Fama-French five factor model-adjusted return (controlling for exposures to market, size, value, investments, profitability). In Panel B, we compute each firm's change in its expected return in excess of the market from options data, using Equation (1), with options maturities of 30 and 730 days. The measure of firms' resilience to social distancing is the negative of the 'affected_share' (as defined by Koren and Pető, 2020). We plot regression coefficient estimates and 95%-confidence intervals based on robust standard errors (following White, 1980, short dash) and based on standard errors clustered at the NAICS 3-digit-code industry level (long dash).

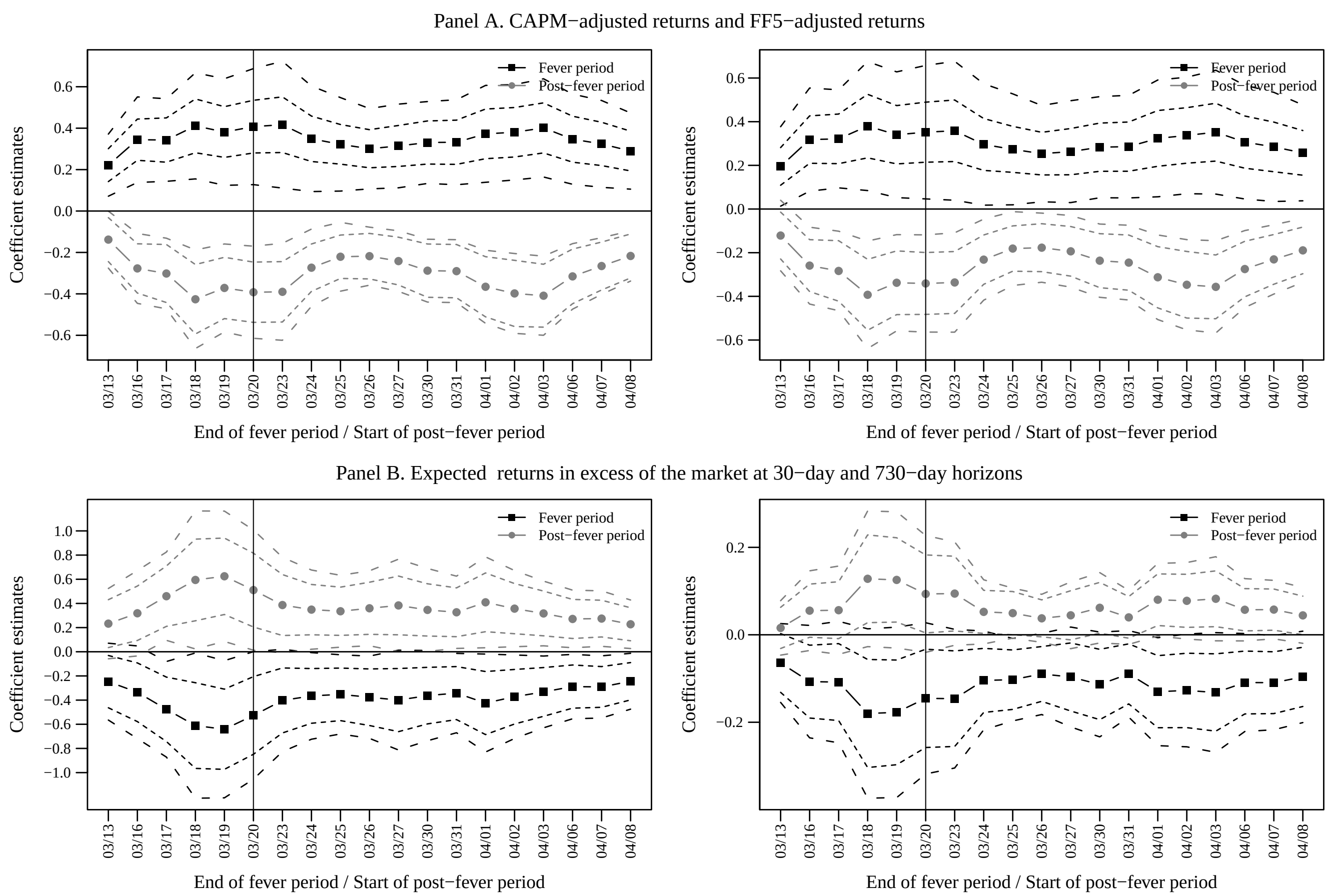


Figure 8. Cross-sectional relation between returns and resilience: Model and data

This figure illustrates the predictions of our model regarding realized and expected returns in excess of the market, and how the sample data relates to these predictions. In Panel A, the left figure illustrates that our model predicts resilient firms should fall into the green quadrant during the fever period (Feb 24 to Mar 20), i.e. have positive realized risk-adjusted returns and decreases in expected returns in excess of the market. Conversely, non-resilient firms should fall in the red quadrant, i.e., realize negative risk-adjusted returns and experience increases in expected returns in excess of the market. The right figure shows the actual fever-period distribution of S&P 500 firms across quadrants, using FF5-adjusted realized returns and changes in one-month expected returns in excess of the market. Panel B illustrates the distribution of low resilience firms (left plot) compared to high resilience firms (right plot), identified as firms with 'affected_share' (as defined by Koren and Pető, 2020) is above and below the sample median value, respectively.

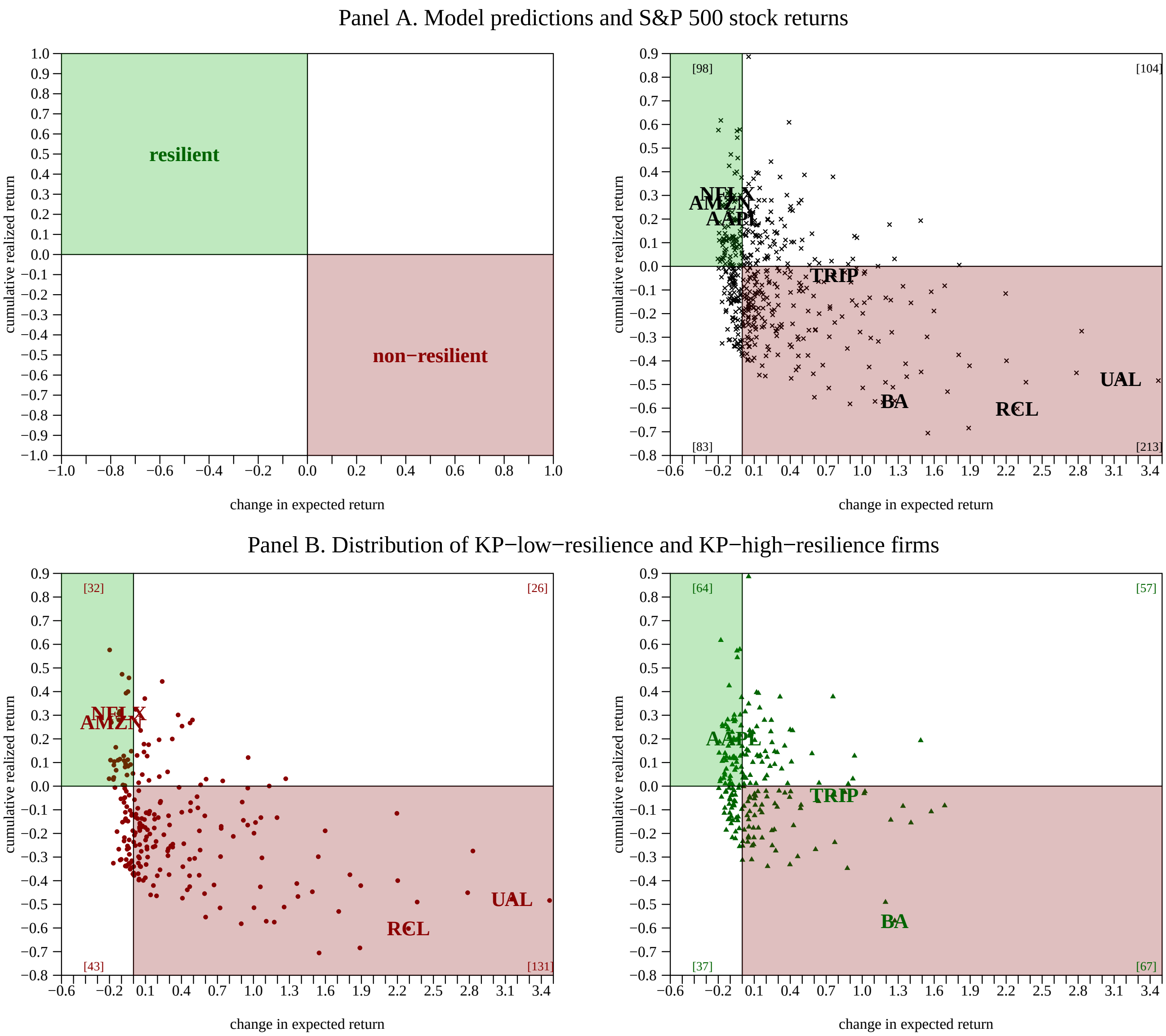


Figure 9. Market-based identification of low- versus high-resilience firms

The figure illustrates our identification of low- versus high-resilience S&P 500 firms based on the firms' asset price responses. The identification is based on firms' cumulatively realized FF5-adjusted returns and changes in one-month expected returns in excess of the market during the fever-period, i.e. from Feb 24 to Mar 20. We identify high-resilience firms (marked by green triangles) as the firms which have realized positive cumulative returns and decreases in expected returns in excess of the market. Conversely, we identify low-resilience firms (marked by red bullets) as the firms which have realized negative cumulative returns and increases in expected returns in excess of the market.

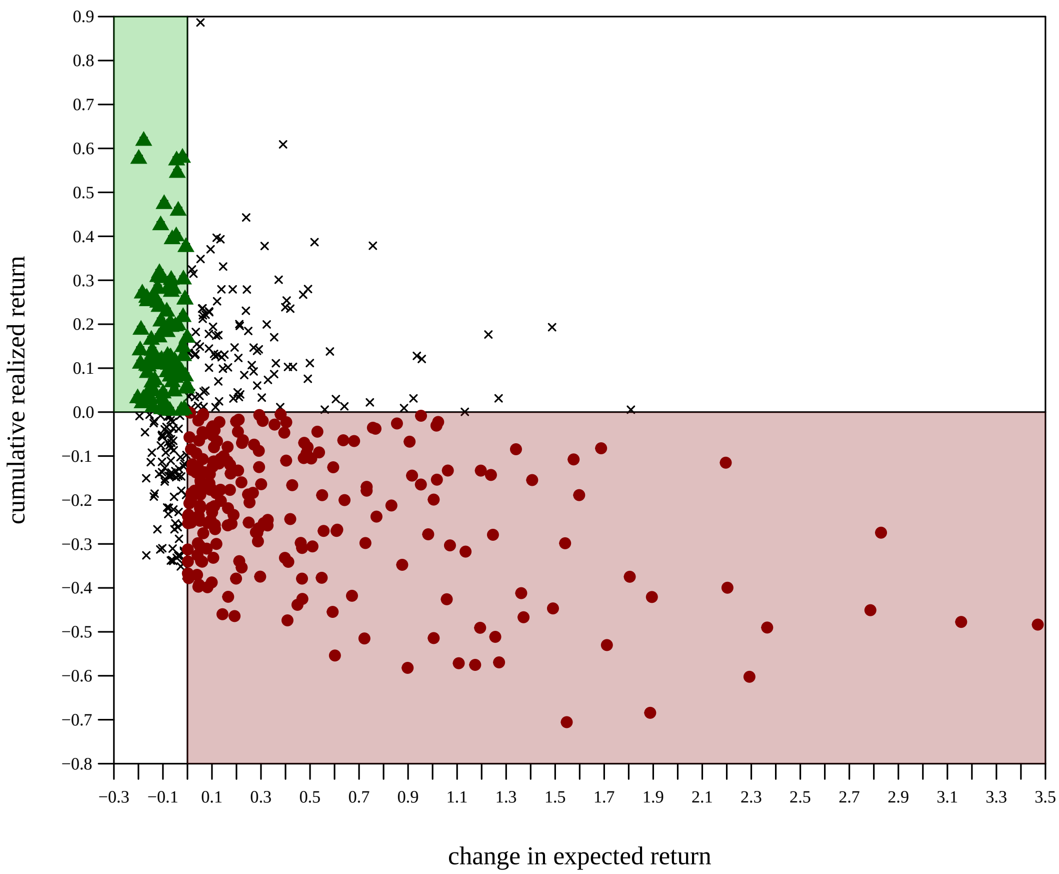


Figure 10. After-fever reversals and persistent scarring of low-resilience firms

This figure plots firms' changes in two-year expected returns in excess of the market during the fever-period, i.e. from February 24 to March 20 (horizontal axis), against changes after the fever-period, i.e. until the end of 2020 (vertical axis). Green triangles represent firms classified as high-resilience by our market-based criterion, and red bullets those classified as low-resilience by that criterion. The green and red lines show the predicted values from regressions (reported in Table A.17 in the Internet Appendix), respectively fitted using the samples of high- and low-resilience firms. Their slope coefficients are −0.79 and −1, respectively, both significantly different from zero. For low-resilience firms, the coefficient is significantly different from −1, whereas this is not the case for high-resilience firms.

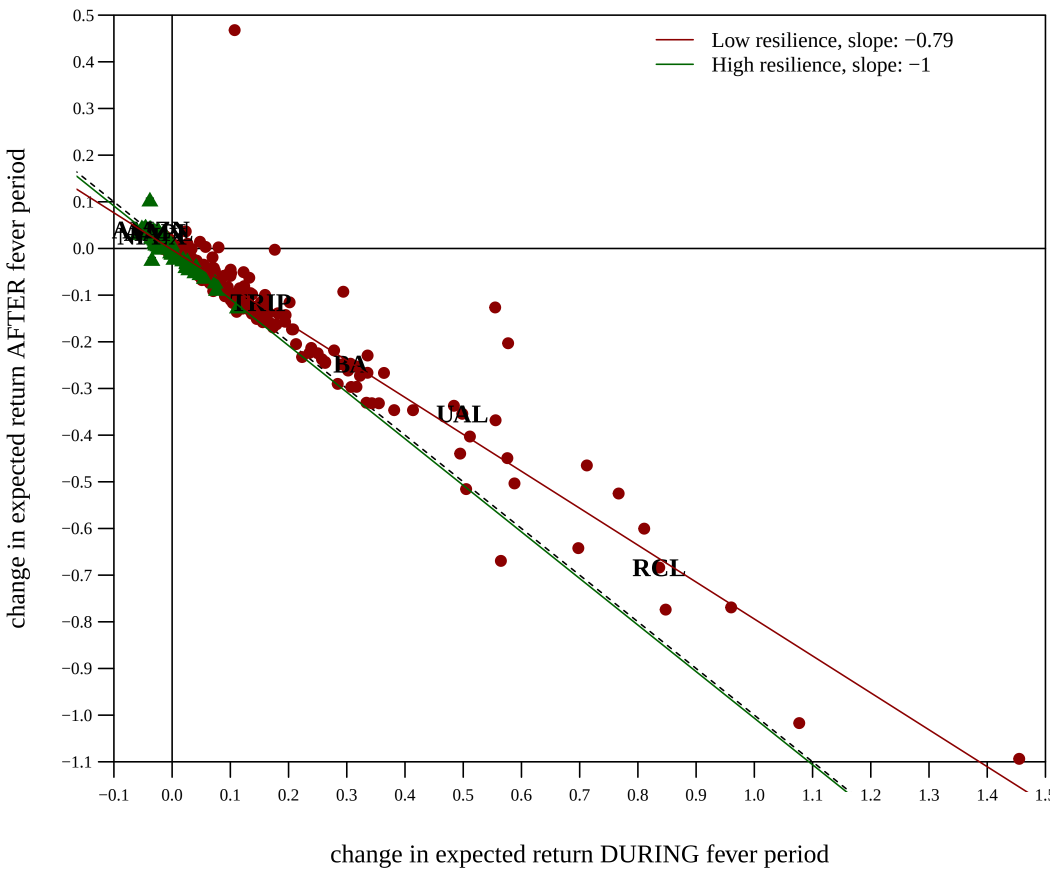


Table 1: Risk-adjusted returns of stocks with high and low resilience to social distancing

This table summarizes the results of firm-level cross-sectional regressions of cumulative risk-adjusted returns on resilience to social distancing. We present results for two sub-periods of 2020: the 'fever-period' (from February 24 to March 20) and the 'post-fever period' (after March 20). For both periods, we compute each firm's cumulative CAPM-adjusted return (controlling for exposure to market risk), its cumulative Fama-French five factor model-adjusted return (controlling for exposures to market, size, value, investments, profitability), and its cumulative q-factor model-adjusted return (controlling for exposures to market, size, investments, profitability) following Hou et al. (2015, HXZ). The measure of firms' resilience to social distancing is the negative of their respective 'affected_share' (as in Koren and Pető, 2020). We regress firm i's cumulative risk-adjusted returns, based on three different models indexed by $m \in (CAPM, FF5, HXZ)$, during the fever (F) and post-fever (PF) periods on the firm's resilience to social distancing:

$$cumret_{m,i}^{\{F,PF\}} = b_0 + b_1 \text{Distancing}_i + e_i,$$

and report coefficient estimates along with two sets of t-statistics: the first is based on robust standard errors following White (1980), whereas the second is based on standard errors clustered at the NAICS 3-digit-code industry level.

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	3.00	3.45	3.73	−6.94	−7.11	−7.02
	[1.59]	[1.76]*	[1.93]*	[−3.41]***	[−3.49]***	[−3.24]***
	[0.57]	[0.70]	[0.70]	[−2.01]**	[−1.89]*	[−1.82]*
Distancing	0.41	0.35	0.39	−0.39	−0.34	−0.41
	[6.28]***	[5.02]***	[5.86]***	[−5.28]***	[−4.72]***	[−5.47]***
	[2.85]***	[2.26]**	[2.65]***	[−3.46]***	[−3.00]***	[−3.41]***
Adj-R^2	0.12	0.08	0.11	0.08	0.07	0.08
Firms	466	466	466	466	466	466

Table 2: Expected returns in excess of the market of stocks with high and low resilience to social distancing

This table summarizes the results of firm-level cross-sectional regressions of changes in expected returns in excess of the market on resilience to social distancing. We present results for two sub-periods of 2020: the 'fever-period' (from February 24 to March 20) and the 'post-fever period' (after March 20). For both periods, we compute each firm's change in its expected return in excess of the market from options data, using Equation (1). We present results for horizons, i.e. options maturities, of 30, 91, 182, 365, and 730 days. The measure of firms' resilience to social distancing is the negative of their respective 'affected_share' (as defined by Koren and Pető, 2020). We regress firm i's changes in expected returns in excess of the market, using options maturities $T \in (30, 91, 182, 365, 730)$, during the fever ($F$) and post-fever ($PF$) periods on the firm's resilience to social distancing:

$$\Delta E_{T,i}^{\{F,PF\}} = b_0 + b_1 \text{Distancing}_i + e_i,$$

and report coefficient estimates along with two sets of t-statistics: the first is based on robust standard errors following White (1980), whereas the second is based on standard errors clustered at the NAICS 3-digit-code industry level.

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	9.18	2.70	2.73	3.94	3.90	−9.65	−3.06	−3.01	−4.28	−4.26
	[2.35]**	[1.60]	[1.92]*	[2.54]**	[2.77]***	[−2.52]**	[−2.05]**	[−2.50]**	[−3.17]***	[−3.63]***
	[1.35]	[0.82]	[1.00]	[1.44]	[1.72]*	[−1.49]	[−1.05]	[−1.31]	[−1.82]*	[−2.33]**
Distancing	−0.54	−0.27	−0.21	−0.17	−0.15	0.51	0.23	0.16	0.12	0.09
	[−3.34]***	[−3.62]***	[−3.44]***	[−2.86]***	[−2.57]**	[3.28]***	[3.41]***	[3.20]***	[2.48]**	[2.05]**
	[−2.03]**	[−2.07]**	[−2.05]**	[−1.79]*	[−1.67]*	[2.01]**	[1.94]*	[1.91]*	[1.55]	[1.37]
Adj-R^2	0.04	0.04	0.04	0.03	0.03	0.04	0.04	0.03	0.02	0.01
Firms	466	466	466	466	466	466	466	466	466	466

Table 3: The relation between expected and realized returns

This table summarizes the results of firm-level cross-sectional regressions of changes in expected returns in excess of the market on cumulative risk-adjusted returns during the 'fever-period' (from February 24 to March 20). We compute each firm's change in its expected return in excess of the market from options data, using Equation (1), for horizons, i.e. options maturities, of 30, 91, 182, 365, and 730 days. In Panel A, we present results for CAPM-adjusted returns, i.e. controlling for exposure to market risk. Panel B presents results controlling for the Fama-French five factor model exposures (i.e. market, size, value, investments, profitability). Panel C presents results controlling for the q-factors (i.e. market, size, investments, profitability) proposed by Hou et al. (2015, HXZ). We regress firm i's fever period changes in expected returns in excess of the market, using options maturities $T \in (30, 91, 182, 365, 730)$, on its cumulative risk-adjusted returns, based on three different models indexed by $m \in (CAPM, FF5, HXZ)$:

$$\Delta E^F_{T,i} = b_0 + b_1 cumret^F_{m,i} + e_i,$$

and report coefficient estimates along with two sets of t-statistics: the first is based on robust standard errors following White (1980), whereas the second is based on standard errors clustered at the NAICS 3-digit-code industry level.

Panel A. CAPM-adjusted returns

	Changes in expected excess market returns				
	30	91	182	365	730
constant	13.03	4.90	4.22	4.66	4.56
	[8.13]***	[6.84]***	[7.38]***	[8.00]***	[9.01]***
	[3.43]***	[2.64]**	[2.83]***	[3.33]***	[3.95]***
Realized return	−1.34	−0.64	−0.51	−0.48	−0.41
	[−10.14]***	[−9.27]***	[−9.07]***	[−8.55]***	[−8.40]***
	[−5.08]***	[−4.70]***	[−4.46]***	[−4.35]***	[−4.65]***
Adj-R^2	0.34	0.34	0.33	0.30	0.31
Firms	466	466	466	466	466

Panel B. FF5-adjusted returns

	Changes in expected excess market returns				
	30	91	182	365	730
constant	18.66	7.46	6.28	6.60	6.16
	[10.09]***	[9.13]***	[9.52]***	[9.82]***	[10.83]***
	[5.26]***	[4.16]***	[4.26]***	[4.83]***	[5.91]***
Realized return	−0.87	−0.44	−0.34	−0.32	−0.29
	[−7.17]***	[−6.75]***	[−6.64]***	[−6.36]***	[−6.35]***
	[−4.08]***	[−4.02]***	[−3.90]***	[−3.88]***	[−3.94]***
Adj-R^2	0.15	0.17	0.16	0.15	0.16
Firms	466	466	466	466	466

Panel C. HXZ-adjusted returns

	Changes in expected excess market returns				
	30	91	182	365	730
constant	15.80	6.17	5.27	5.68	5.39
	[9.17]***	[8.15]***	[8.63]***	[9.08]***	[10.05]***
	[4.49]***	[3.52]***	[3.70]***	[4.29]***	[5.12]***
Realized return	−1.17	−0.57	−0.44	−0.41	−0.36
	[−8.86]***	[−8.22]***	[−8.09]***	[−7.69]***	[−7.50]***
	[−4.58]***	[−4.38]***	[−4.25]***	[−4.19]***	[−4.34]***
Adj-R^2	0.27	0.27	0.26	0.23	0.24
Firms	466	466	466	466	466

Table 4: Market-based resilience classification: realized and expected returns

This table provides summary statistics for the realized and expected returns of S&P 500 firms that we classify as low resilience firms (Panel A), high resilience firms (Panel B), or neither low nor high resilience firms (Panel C) based on the firms' asset price responses during the fever-period, i.e. from Feb 24 to Mar 20, 2020. In each panel, the first two columns present descriptives statistics for the identification. We identify low-resilience firms as the firms which, during the fever period (F), have realized negative cumulative FF5-adjusted returns (i.e., $\text{ff5}^F < 0$) and increases in one-month expected returns in excess of the market (i.e., $\Delta E^F > 0$). Conversely, we identify high-resilience firms as the firms which have realized positive cumulative risk-adjusted returns (i.e., $\text{ff5}^F > 0$) and decreases in expected returns in excess of the market (i.e., $\Delta E^F < 0$). The other columns, present summary statistics for the post-fever period (PF), that is, realized cumulative risk-adjusted returns (ff5^{PF}) and changes in one-month expected returns in excess of the market (ΔE^{PF}) until the end of 2020. We report cross-sectional means and standard deviations as well as two sets of t-statistics: the first is based on robust standard errors following White (1980), whereas the second is based on standard errors clustered at the NAICS 3-digit-code industry level.

Panel A. Low-resilience firms

	Fever period		Post-fever period		
	ff5^F	ΔE^F	ff5^{PF}	ΔE^{PF}	Firms
mean	−22.70	50.87	13.62	−49.23	213
	[−21.78]***	[11.85]***	[7.47]***	[−11.83]***	
	[−9.74]***	[6.97]***	[6.39]***	[−7.02]***	
std. dev.	15.25	62.82	26.68	60.87	

Panel B. High-resilience firms

	Fever period		Post-fever period		
	ff5^F	ΔE^F	ff5^{PF}	ΔE^{PF}	Firms
mean	17.45	−9.46	−13.63	8.34	98
	[11.94]***	[−17.04]***	[−7.22]***	[14.64]***	
	[7.21]***	[−11.04]***	[−5.13]***	[10.15]***	
std. dev.	14.54	5.53	18.79	5.67	

Panel C. Firms neither classified as low- nor as high-resilience

	Fever period		Post-fever period		
	ff5^F	ΔE^F	ff5^{PF}	ΔE^{PF}	Firms
mean	2.21	13.37	−1.27	−13.47	187
	[1.50]	[5.90]***	[−0.82]	[−6.14]***	
	[0.68]	[4.19]***	[−0.46]	[−4.53]***	
std. dev.	20.23	31.06	21.37	30.08	

Table 5: Realized and expected returns of low and high resilience firms

The table presents the estimates of regressions of S&P 500 firms' realized and expected returns on firm characteristics capturing different dimensions of their resilience to disasters. We identify low-resilience firms as those which, during the fever period (F), featured negative realized cumulative FF5-adjusted returns (i.e., $\text{ff5}^F < 0$) and increases in one-month expected returns in excess of the market (i.e., $\Delta E^F > 0$). Conversely, we identify high-resilience firms as those featuring positive realized cumulative risk-adjusted returns (i.e., $\text{ff5}^F > 0$) and decreases in expected returns in excess of the market (i.e., $\Delta E^F < 0$). We present regression results separately for low-resilience firms (on the left) and high-resilience firms (on the right). For both samples, we present estimates of regressions of ff5^F and ΔE^F on firm characteristics during the fever period, and estimates of analogous regressions of ff5^{PF} and ΔE^{PF} on firm characteristics for the post-fever period. The explanatory variables are firms' end-of-2019 cash ratios, leverage ratios, environmental scores, and distancing defined as the negative of 'affected_share' (as in Koren and Pető, 2020). The table reports two sets of t-statistics for each coefficient estimate: the first is based on robust standard errors following White (1980), and the second is based on standard errors clustered at the NAICS 3-digit-code industry level.

	Low resilience firms				High resilience firms			
	Fever period		Post-fever period		Fever period		Post-fever period	
	ff5^F	ΔE^F	ff5^{PF}	ΔE^{PF}	ff5^F	ΔE^F	ff5^{PF}	ΔE^{PF}
Constant	−20.80	25.95	19.56	−24.35	−2.05	−7.13	13.03	4.89
	[−3.62]***	[1.24]	[1.91]*	[−1.20]	[−0.26]	[−2.19]**	[1.30]	[1.38]
	[−2.53]**	[1.00]	[1.87]*	[−0.99]	[−0.31]	[−2.36]**	[1.57]	[1.56]
Cash	0.34	0.59	−0.15	−0.63	0.18	0.02	−0.13	0.00
	[3.15]***	[1.36]	[−0.92]	[−1.48]	[1.66]*	[0.53]	[−1.04]	[0.08]
	[2.25]**	[1.08]	[−0.90]	[−1.22]	[1.77]*	[0.67]	[−1.16]	[0.12]
Leverage	−0.21	0.11	0.12	−0.08	−0.11	0.04	0.17	−0.03
	[−3.70]***	[0.47]	[1.29]	[−0.34]	[−1.58]	[1.49]	[1.51]	[−0.89]
	[−2.77]***	[0.42]	[1.38]	[−0.30]	[−1.38]	[1.10]	[1.26]	[−0.68]
Environment	0.15	−0.15	−0.32	0.12	0.26	−0.04	−0.43	0.04
	[1.64]	[−0.43]	[−1.97]**	[0.35]	[2.40]**	[−0.98]	[−3.27]***	[0.91]
	[1.20]	[−0.32]	[−1.84]*	[0.26]	[1.97]**	[−0.94]	[−3.65]***	[0.86]
Distancing	0.18	−0.80	−0.26	0.76	−0.14	0.04	0.09	−0.05
	[3.15]***	[−2.73]***	[−2.84]***	[2.71]***	[−1.67]*	[1.35]	[0.78]	[−1.78]*
	[1.93]*	[−1.76]*	[−2.73]***	[1.76]*	[−1.53]	[0.97]	[0.61]	[−1.48]
Adj R^2	0.18	0.04	0.05	0.04	0.06	0.00	0.07	0.00
Firms	199	199	199	199	96	96	96	96

Table 6: Persistent changes in expected returns of low and high resilience firms

The table shows regression results about the drivers of persistent changes in S&P 500 firms' expected returns due to the COVID-19 pandemic. The estimates are presented separately for low-resilience firms (on the left) and high-resilience ones (on the right), where the classification is based on firms' asset price responses during the fever period. We identify low-resilience firms as those which, during the fever period (F), featured negative realized cumulative FF5-adjusted returns (i.e., $\text{ff5}^F < 0$) and increases in one-month expected returns in excess of the market (i.e., $\Delta E^F > 0$). Conversely, we identify high-resilience firms as those featuring positive realized cumulative risk-adjusted returns (i.e., $\text{ff5}^F > 0$) and decreases in expected returns in excess of the market (i.e., $\Delta E^F < 0$). Persistent changes in expected returns are measured as the sum of the change in expected returns during the fever period, ΔE^F, and in the post-fever period, ΔE^{PF}. These persistent changes in expected returns are computed with horizons of 30, 91, 182, 365, and 730 days, and are regressed on firms' end-of-2019 cash ratios, leverage ratios, environmental scores, and distancing defined as the negative of 'affected_share' (as in Koren and Pető, 2020). The table reports the estimated coefficients and two sets of t-statistics for each coefficient estimate: the first is based on robust standard errors following White (1980), and the second is based on standard errors clustered at the NAICS 3-digit-code industry level.

	Low resilience firms				High resilience firms			
	91	182	365	730	91	182	365	730
constant	0.91	0.49	0.48	0.55	−1.80	−1.49	−1.26	−1.30
	[0.40]	[0.22]	[0.20]	[0.19]	[−1.69]*	[−2.07]**	[−1.85]*	[−1.84]*
	[0.36]	[0.21]	[0.25]	[0.23]	[−1.74]*	[−2.71]***	[−3.26]***	[−2.91]***
Cash	0.01	0.00	0.01	0.01	0.02	0.01	0.01	0.02
	[0.29]	[0.08]	[0.30]	[0.15]	[1.09]	[1.00]	[1.01]	[1.23]
	[0.22]	[0.06]	[0.23]	[0.12]	[1.75]*	[1.36]	[1.22]	[1.64]
Lev	0.03	0.04	0.05	0.06	−0.00	0.00	0.01	0.00
	[1.40]	[1.45]	[1.67]*	[1.70]*	[−0.14]	[0.49]	[0.99]	[0.69]
	[1.20]	[1.24]	[1.45]	[1.54]	[−0.11]	[0.37]	[0.72]	[0.46]
Env	−0.03	−0.02	−0.03	−0.04	0.01	0.01	0.00	0.00
	[−0.69]	[−0.44]	[−0.66]	[−0.67]	[0.68]	[0.65]	[0.11]	[0.23]
	[−0.69]	[−0.50]	[−0.85]	[−0.85]	[0.62]	[0.80]	[0.16]	[0.36]
Dist	−0.06	−0.06	−0.06	−0.08	−0.00	0.00	0.00	0.00
	[−2.72]***	[−2.65]***	[−2.75]***	[−2.56]**	[−0.43]	[0.24]	[0.35]	[0.59]
	[−1.99]**	[−1.87]*	[−1.94]*	[−1.81]*	[−0.48]	[0.27]	[0.43]	[0.65]
Adj R^2	0.05	0.05	0.05	0.05	−0.02	0.00	0.00	0.02
Firms	199	199	199	199	96	96	96	96

Appendix

A Model

This appendix details the model described in Section 2. In the model, a representative investor maximizes expected utility:

$$\mathrm{E}\left[u(C_1) + \frac{1}{1+\delta}u(C_2) + \left(\frac{1}{1+\delta}\right)^2 u(C_3)\right]$$

where C_t is consumption in period t and $\delta > 0$ is the rate of time preference. For concreteness, the investor's instantaneous utility is assumed to be

$$u(C_t) = \frac{C_t^{1-\gamma}}{1-\gamma}.$$

Denoting the number of shares that the representative investor chooses to hold in period t by n_{Nt} and by n_{Rt}, the consumption levels in the no-disaster state, C_t^{ND}, and in the disaster state, C_t^{D}, are determined by the following budget constraints

$$C_t^{ND} = D(n_{Nt-1} + n_{Rt-1}) - P_{Nt}(n_{Nt} - n_{Nt-1}) - P_{Rt}(n_{Rt} - n_{Rt-1}), \tag{2}$$

and

$$C_t^{D} = \frac{D}{B}(n_{Nt-1}\phi_N + n_{Rt-1}\phi_R) - P_{Nt}(n_{Nt} - n_{Nt-1}) - P_{Rt}(n_{Rt} - n_{Rt-1}). \tag{3}$$

The two states are expected to occur with probabilities $1 - p_{t-1}$ (no-disaster) and p_{t-1} (disaster), respectively, where $p_0 = 0$, i.e. no disaster can occur at $t = 1$. Terminal ex-dividend prices are $P_{N3} = P_{R3} = 0$. In any period t, market clearing requires $n_{Nt} = n_{Rt} = \frac{1}{2}$, so that equilibrium consumption is

$$C_t^* = \begin{cases} C_t^{ND} = D & \text{with probability } 1 - p_{t-1} \text{(no-disaster state)}, \\ C_t^{D} = D\overline{\phi}/B & \text{with probability } p_{t-1} \text{ (disaster state)}, \end{cases} \tag{4}$$

A.1 Prices and expected returns at $t = 2$

We start by solving for the consumption and portfolio choices at $t = 2$, separately for the no-disaster and the disaster state. If no disaster occurs in period 2, investors choose their consumption C_2^{ND} and portfolio (n_{N2}, n_{R2}) to maximize

$$u(C_2^{ND}) + \frac{1}{1+\delta}\mathrm{E}\left[u\left(C_3\right)\right],$$

subject to budget constraint (2) for $t = 2$. The representative investor therefore solves

$$\max_{n_{N2},n_{R2}} u(D(n_{N1}+n_{R1}) - P_{N2}^{ND}(n_{N2}-n_{N1}) - P_{R2}^{ND}(n_{R2}-n_{R1}))$$
$$+\frac{1}{1+\delta}\left[p_1 u\left(D\frac{n_{N2}\phi_N + n_{R2}\phi_R}{B}\right) + (1-p_1)u\left(D(n_{N2}+n_{R2})\right)\right].$$

The first-order conditions with respect to n_{N2} and n_{R2} yield the following expressions for the no-disaster prices at $t = 2$:

$$P_{i2}^{ND} = \frac{1}{1+\delta}\left[p_1\frac{u'\left(C_3^D\right)}{u'(C_2^{ND})}D\frac{\phi_i}{B} + (1-p_1)\frac{u'\left(C_3^{ND}\right)}{u'(C_2^{ND})}D\right], \text{ for } i = N, R.$$

Using $u'(C_t) = C_t^{-\gamma}$ and replacing C_2^{ND}, C_3^D and C_3^{ND} with their equilibrium values in (4), this yields the no-disaster equilibrium share prices of non-resilient and resilient firms at $t = 2$:

$$P_{i2}^{ND} = \frac{D}{1+\delta}\left[p_1\left(\frac{\overline{\phi}}{B}\right)^{-\gamma}\frac{\phi_i}{B} + (1-p_1)\right], \text{ for } i = N, R, \tag{5}$$

i.e., the stochastic discount factor $\frac{1}{1+\delta}\left(\frac{\overline{\phi}}{B}\right)^{-\gamma}$ in the disaster state and $\frac{1}{1+\delta}$ in the no-disaster state, where $\left(\frac{\overline{\phi}}{B}\right)^{-\gamma} > 1$.

If a disaster occurs at $t = 2$, the optimization problem of investors becomes

$$\max u(C_2^D) + \frac{1}{1+\delta}\left[\rho u\left(C_3^D\right) + (1-\rho)u\left(C_3^{ND}\right)\right]$$

subject to budget constraint (3) for $t = 2$. The representative investor therefore solves

$$\max_{n_{N2},n_{R2}} u\left(D\frac{n_{N1}\phi_N + n_{R1}\phi_R}{B} - P_{N2}(n_{N2} - n_{N1}) - P_{R2}(n_{R2} - n_{R1})\right)$$
$$+\frac{1}{1+\delta}\left[\rho u\left(D\frac{n_{N2}\phi_N + n_{R2}\phi_R}{B}\right) + (1-\rho)u\left(D(n_{N2}+n_{R2})\right)\right].$$

The first-order conditions with respect to n_{N2} and n_{R2} yield the following expressions for the disaster prices at $t = 2$:

$$P_{i2}^{D} = \frac{1}{1+\delta}\left[\rho\frac{u'\left(C_3^D\right)}{u'(C_2^D)}D\frac{\phi_i}{B} + (1-\rho)\frac{u'\left(C_3^{ND}\right)}{u'(C_2^D)}D\right], \text{ for } i = N, R.$$

Imposing market clearing yields the following expression for the equilibrium disaster share prices at $t = 2$:

$$P_{i2}^{D} = \frac{D}{1+\delta}\left[\rho\frac{\phi_i}{B} + (1-\rho)\left(\frac{\overline{\phi}}{B}\right)^{\gamma}\right], \text{ for } i = N, R. \tag{6}$$

From the equilibrium prices in (5) and (6), we see that in both the no-disaster and in the disaster state the price of the resilient asset exceeds that of the non-resilient one:

$$P_{R2}^{ND} - P_{N2}^{ND} = \frac{D}{1+\delta}p_1\left(\frac{\overline{\phi}}{B}\right)^{-\gamma}\frac{\phi_R - \phi_N}{B} > 0, \quad P_{R2}^{D} - P_{N2}^{D} = \frac{D}{1+\delta}\rho\frac{\phi_R - \phi_N}{B} > 0.$$

The difference between the two asset prices is larger in the disaster state at time $t = 2$ as long as there is serial correlation in the occurrence of disasters, i.e. $\rho > p_1$, and the prior probability of a disaster, p_1, is sufficiently small, i.e. $p_1 < \rho(\frac{\bar{\phi}}{B})^{\gamma}$.

We next analyze how resilience affects the expected rates of return of the two assets at $t = 2$. Upon no disaster occurring at $t = 2$, their equilibrium expected rates of return are

$$1 + \mathrm{E}(r_{i3}^{ND}) = \frac{\mathrm{E}(D_{i3}^{ND})}{P_{i2}^{ND}} = (1+\delta)\left(\frac{\overline{\phi}}{B}\right)^{\gamma}\frac{p_1\frac{\phi_i}{B} + (1-p_1)}{p_1\frac{\phi_i}{B} + (1-p_1)\left(\frac{\overline{\phi}}{B}\right)^{\gamma}}, \text{ for } i = N, R, \tag{7}$$

whereas upon a disaster occurring at $t = 2$ they are

$$1 + \mathrm{E}(r_{i3}^D) = \frac{\mathrm{E}(D_{i3}^D)}{P_{i2}^D} = (1+\delta)\frac{\rho\frac{\phi_i}{B} + (1-\rho)}{\rho\frac{\phi_i}{B} + (1-\rho)\left(\frac{\overline{\phi}}{B}\right)^{\gamma}}, \text{for } i = N, R. \tag{8}$$

Both expressions (7) and (8) are decreasing in ϕ_i and equal $1+\delta$ for $\gamma = 0$, which implies our second prediction:

Proposition 1 (Expected return differential at $t = 2$) *In both the disaster and no-disaster states, the expected rate of return of the non-resilient asset exceeds that of the resilient one. Both expected return differentials vanish under risk neutrality ($\gamma = 0$). In the no-disaster state, they also vanish in the polar cases of a zero disaster probability ($p_2 = p_1 = 0$) or certainty of a disaster at $t = 3$ ($p_2 = p_1 = 1$), and in the disaster state they vanish in the polar cases of no persistence ($p_2 = \rho = 0$) or maximal persistence of disaster at $t = 3$ ($p_2 = \rho = 1$).*

Proof. For simplicity, let us rewrite expressions (7) and (8) using the short-hand $x \equiv \left(\frac{\overline{\phi}}{B}\right)^{\gamma} < 1$:

$$1 + \mathrm{E}(r_{i3}^{ND}) = (1+\delta)x\frac{p_1\frac{\phi_i}{B} + (1-p_1)}{p_1\frac{\phi_i}{B} + (1-p_1)x}, \text{ for } i = N, R,$$

and

$$1 + \mathrm{E}(r_{i3}^{D}) = (1+\delta)\frac{\rho\frac{\phi_i}{B} + (1-\rho)}{\rho\frac{\phi_i}{B} + (1-\rho)x}, \text{ for } i = N, R.$$

If no disaster occurs at $t = 2$, the expected rate of return of the non-resilient asset exceeds that of the resilient one, i.e. $\mathrm{E}(r_{N3}^{ND}) > \mathrm{E}(r_{R3}^{ND})$, as can be seen by differentiating $1+\mathrm{E}(r_{i3}^{ND})$ with respect to asset resilience ϕ_i (holding $\overline{\phi}$ constant):

$$\frac{\partial\left[1 + \mathrm{E}(r_{i3}^{ND})\right]}{\partial\phi_i} = \frac{(1+\delta)(1-p_1)p_1x}{B}\frac{x-1}{\left[p_1\frac{\phi_i}{B} + (1-p_1)x\right]^2} < 0.$$

Similarly, if a disaster occurs at $t = 2$, then $\mathrm{E}(r_{N3}^{D}) > \mathrm{E}(r_{R3}^{D})$, as can be seen by differentiating expression $1+\mathrm{E}(r_{i3}^{D})$ with respect to asset resilience ϕ_i (holding $\overline{\phi}$ constant):

$$\frac{\partial\left[1 + \mathrm{E}(r_{i3}^{D})\right]}{\partial\phi_i} = \frac{(1+\delta)(1-\rho)\rho}{B}\frac{x-1}{\left[\rho\frac{\phi_i}{B} + (1-\rho)x\right]^2} < 0.$$

■

Hence the presence of a positive expected return differential between non-resilient and resilient assets stems from the presence of disaster risk at $t = 2$, and from the danger of disaster persistence if the economy has already experienced a disaster at $t = 2$. In the case of risk neutrality, this differential vanishes, since disaster risk is not priced and the expected loss from disaster is fully impounded in both asset prices, leaving their expected rates of return unaffected. When no disaster has occurred at $t = 2$, the expected return differential also vanishes if the occurrence of a disaster at $t = 3$ is either considered impossible ($p_1 = 0$) or certain ($p_1 = 1$), as in both cases there is no disaster risk. By the same token it vanishes if, once disaster strikes at $t = 2$, investors rule out its persistence at $t = 3$ ($\rho = 0$) or if they are sure of its persistence ($\rho = 1$).

The following proposition shows that the expected return differential between the two assets is larger in the disaster state if the persistence of disasters is not too large:

Proposition 2 (Expected return differentials in disaster *vs.* normal times) *If disasters are positively autocorrelated ($\rho > p_1$), the expected return differential between non-resilient and resilient assets is larger in the disaster than in the no-disaster state at $t = 2$, i.e., $E(r^D_{N3}) - E(r^D_{R3}) > E(r^{ND}_{N3}) - E(r^{ND}_{R3})$, as long as the persistence of a disaster is below a critical threshold:*

$$\rho < \rho^* = \frac{\left(\frac{\bar{\phi}}{B}\right)^{\frac{\gamma}{2}}}{\left(\frac{\bar{\phi}}{B}\right)^{\frac{\gamma}{2}} + \left(\frac{\phi_N}{B}\frac{\phi_R}{B}\right)^{\frac{1}{2}}}. \tag{9}$$

If disasters are serially uncorrelated ($\rho = p_1$), the expected return differential between non-resilient and resilient assets is the same in a disaster and in nomal times, i.e., $E(r^D_{N3}) - E(r^D_{R3}) = E(r^{ND}_{N3}) - E(r^{ND}_{R3})$.

Proof. Define the relative expected return between the non-resilient and the resilient asset in the disaster state at $t = 2$ as

$$\Delta^D_{NR} \equiv \frac{1 + \mathrm{E}(r^D_{N3})}{1 + \mathrm{E}(r^D_{R3})} = \frac{\rho\frac{\phi_N}{B} + (1-\rho)}{\rho\frac{\phi_R}{B} + (1-\rho)} \times \frac{\rho\frac{\phi_R}{B} + (1-\rho)x}{\rho\frac{\phi_N}{B} + (1-\rho)x} \tag{10}$$

and its analogue in the no-disaster state at $t = 2$ as

$$\Delta^{ND}_{NR} \equiv \frac{1 + \mathrm{E}(r^{ND}_{N3})}{1 + \mathrm{E}(r^{ND}_{R3})} = \frac{p_1\frac{\phi_N}{B} + (1-p_1)}{p_1\frac{\phi_R}{B} + (1-p_1)} \times \frac{p_1\frac{\phi_R}{B} + (1-p_1)x}{p_1\frac{\phi_N}{B} + (1-p_1)x}. \tag{11}$$

If $\rho = p_1$, then Equations (10) and (11) coincide, so that the expected return differential between the two assets is the same irrespective of whether a disaster occurs at $t = 2$ or not.

Next, we derive a sufficient condition for expression (10) to exceed expression (11), i.e. such that the return differential between the non-resilient and resilient asset is larger if the disaster occurs at $t = 2$. Since the two expressions are equal when $\rho = p_1$, it suffices to show that $\partial\Delta^D_{NR}/\partial\rho \geq 0$ over the relevant range of ρ. To compute this derivative, note that Δ^D_{NR} can be written as

$$\Delta^D_{NR} = \frac{1+\mathrm{E}(r^D_{N3})}{1+\mathrm{E}(r^D_{R3})} = \frac{1+\rho(\frac{\phi_N}{B}-1)}{1+\rho(\frac{\phi_R}{B}-1)} \times \frac{x+\rho\left[\frac{\phi_R}{B}-x\right]}{x+\rho\left[\frac{\phi_N}{B}-x\right]}.$$

Hence

$$\begin{aligned}
\frac{\partial\Delta^D_{NR}}{\partial\rho} &= \frac{\partial}{\partial\rho}\left(\frac{1+\rho(\frac{\phi_N}{B}-1)}{1+\rho(\frac{\phi_R}{B}-1)}\right)\frac{x+\rho\left(\frac{\phi_R}{B}-x\right)}{x+\rho\left(\frac{\phi_N}{B}-x\right)} + \frac{1+\rho(\frac{\phi_N}{B}-1)}{1+\rho(\frac{\phi_R}{B}-1)}\frac{\partial}{\partial\rho}\left[\frac{x+\rho\left(\frac{\phi_R}{B}-x\right)}{x+\rho\left(\frac{\phi_N}{B}-x\right)}\right] \\
&= -\frac{\phi_R-\phi_N}{B\left[1-\rho+\rho\frac{\phi_R}{B}\right]^2}\frac{(1-\rho)x+\rho\frac{\phi_R}{B}}{(1-\rho)x+\rho\frac{\phi_N}{B}} + \frac{1-\rho+\rho\frac{\phi_N}{B}}{1-\rho+\rho\frac{\phi_R}{B}}\frac{\phi_R-\phi_N}{B\left[(1-\rho)x+\rho\frac{\phi_N}{B}\right]^2}x \\
&= \frac{(\phi_R-\phi_N)(1-x)}{B\left[1-\rho+\rho\frac{\phi_R}{B}\right]\left[(1-\rho)x+\rho\frac{\phi_N}{B}\right]} \times \frac{(1-\rho)^2x-\rho^2\frac{\phi_N}{B}\frac{\phi_R}{B}}{\left[(1-\rho)x+\rho\frac{\phi_N}{B}\right]\left[1-\rho+\rho\frac{\phi_R}{B}\right]},
\end{aligned}$$

which is positive for

$$\rho < \rho^* = \frac{x^{\frac{1}{2}}}{x^{\frac{1}{2}}+\left(\frac{\phi_N}{B}\frac{\phi_R}{B}\right)^{\frac{1}{2}}} = \frac{\left(\frac{\bar{\phi}}{B}\right)^{\frac{\gamma}{2}}}{\left(\frac{\bar{\phi}}{B}\right)^{\frac{\gamma}{2}}+\left(\frac{\phi_N}{B}\frac{\phi_R}{B}\right)^{\frac{1}{2}}}.$$

■

The above proposition contrasts two cases: serially uncorrelated disasters ($\rho = p_1$) and positively autocorrelated ones ($\rho > p_1$). In the first case, the occurrence of disasters generates no learning about the probability of their repetition: disaster risk remains the same as in normal times, and so does the expected return differential between non-resilient and resilient assets. In the second case, the occurrence of a disaster at $t = 2$ triggers an increase in the difference between expected returns for resilient and non-resilient assets if ρ is below the threshold ρ^* in (9). Such a threshold exists because the relationship between the probability of a future disaster and the riskiness of firms' future cash flows due to disasters is non-monotonic: for instance, if both ρ and p_1 were close to 1, $\rho > p_1$ would imply that, following a disaster at $t = 2$ another disaster is almost certain to occur at $t = 3$, so that there would be *less* disaster uncertainty regarding future cash flows than in a no-disaster state; this would lead to a *reduction* in the expected return differential between non-resilient and resilient assets. This case is ruled out by condition (9), which intuitively requires that if a disaster occurs at $t = 2$, its re-occurrence at $t = 3$ not too likely.[15]

Next, we investigate how the expected return differential Δ^D_{NR} between non-resilient and resilient assets responds to unanticipated news about the economy's resilience at $t = 2^+$. To this purpose, we study how Δ^D_{NR} responds to an increase in the economy's resilience $\overline{\phi}/B$ or to a decrease in the resilience differential $\lambda_N - \lambda_R \equiv (\phi_N - \phi_R)/\overline{\phi}$. We show that:

Proposition 3 (Response of expected return differentials to resilience news) *If at $t = 2^+$ investors unexpectedly learn that the resilience of the economy has increased or the cross-industry difference in resilience has decreased, then the expected return differential between non-resilient and resilient assets decreases if investors are risk averse, and is unaffected if they are risk-neutral.*

Proof. The relative expected return between the non-resilient and the resilient asset in the disaster state at $t = 2$ in expression (10) can be rewritten as

$$\Delta^D_{NR} \equiv \frac{(1-\rho) + \rho\frac{\overline{\phi}}{B}\lambda_N}{(1-\rho) + \rho\frac{\overline{\phi}}{B}\lambda_R} \times \frac{(1-\rho)x + \rho\frac{\overline{\phi}}{B}\lambda_R}{(1-\rho)x + \rho\frac{\overline{\phi}}{B}\lambda_N} \tag{12}$$

using again the short-hand $x \equiv \left(\overline{\phi}/B\right)^{\gamma}$. The derivative of expression (12) with respect to the resilience of the economy $\overline{\phi}/B$ can be written as:

$$\frac{\partial \Delta^D_{NR}}{\partial(\overline{\phi}/B)} = \frac{(1-\rho)\rho(\lambda_R - \lambda_N)}{\left[(1-\rho) + \rho\frac{\overline{\phi}}{B}\lambda_R\right]\left[(1-\rho)x + \rho\frac{\overline{\phi}}{B}\lambda_N\right]}\left[\frac{(1-\rho) + \rho\frac{\overline{\phi}}{B}\lambda_N}{(1-\rho)x + \rho\frac{\overline{\phi}}{B}\lambda_N}x(1-\gamma) - \frac{(1-\rho)x + \rho\frac{\overline{\phi}}{B}\lambda_R}{(1-\rho) + \rho\frac{\overline{\phi}}{B}\lambda_R}\right], \tag{13}$$

For $\gamma > 0$, so that $x < 1$, expression (13) is negative. To show this, note that

$$\frac{(1-\rho) + \rho\frac{\overline{\phi}}{B}\lambda_N}{(1-\rho)x + \rho\frac{\overline{\phi}}{B}\lambda_N}x - \frac{(1-\rho)x + \rho\frac{\overline{\phi}}{B}\lambda_R}{(1-\rho) + \rho\frac{\overline{\phi}}{B}\lambda_R} = \left[(1-\rho)^2 + \rho^2 x^2 \lambda_N \lambda_R\right](x-1) < 0.$$

[15] Note that for $\gamma \leqslant 2$, $\rho^* > 1/2$, so that condition (9) is satisfied by assuming $\rho < 1/2$, although the bound becomes tighter for larger values of risk aversion γ.

which is a sufficient condition for expression (13) to be negative. For $\gamma = 0$, so that $x = 1$, the derivative (13) is zero.

The derivatives of expression (12) with respect to the relative resilience of the non-resilient asset λ_N and of the resilient one λ_R can respectively be expressed as

$$\frac{\partial \Delta_{NR}^{D}}{\partial \lambda_N} = \rho \frac{\overline{\phi}}{B} \frac{(1-\rho)x + \rho\frac{\overline{\phi}}{B}\lambda_R}{(1-\rho) + \rho\frac{\overline{\phi}}{B}\lambda_R} \frac{1-\rho}{\left[(1-\rho)x + \rho\frac{\overline{\phi}}{B}\lambda_N\right]^2}(x-1) < 0, \tag{14}$$

$$\frac{\partial \Delta_{NR}^{D}}{\partial \lambda_R} = \rho \frac{\overline{\phi}}{B} \frac{(1-\rho) + \rho\frac{\overline{\phi}}{B}\lambda_N}{(1-\rho)x + \rho\frac{\overline{\phi}}{B}\lambda_N} \frac{1-\rho}{\left[(1-\rho) + \rho\frac{\overline{\phi}}{B}\lambda_R\right]^2}(1-x) > 0, \tag{15}$$

so that an increase in the relative resilience of the non-resilient industry and a decrease in that of the resilient industry lead to a decrease in the expected return differential in the disaster state for $\gamma > 0$, so that $x < 1$. Hence, under this condition a decrease in the percentage difference in sector resilience, $\lambda_R - \lambda_N$, leads to a decrease in the expected return differential in the disaster state. If instead $\gamma = 0$, so that $x = 1$, both expressions (14) and (15) are zero, so that a change in in the percentage difference in sector resilience , $\lambda_R - \lambda_N$, leaves the expected return differential unaffected. ∎

A.2 Prices and expected returns at $t = 1$

Now we turn to the problem that investors face at $t = 1$, where it is assumed that no disaster occurs:

$$\max u(C_1) + \frac{1}{1+\delta}\left((1-p_1)u(C_2^{ND}) + p_1 u(C_2^{D})\right)$$
$$+ \left(\frac{1}{1+\delta}\right)^2 \left[\left((1-p_1)^2 + p_1(1-\rho)\right)u(C_3^{ND}) + \left((1-p_1)p_1 + p_1\rho\right)u(C_3^{D})\right],$$

subject to the budget constraints (2) and (3), so that the problem becomes

$$\max_{n_{N1}, n_{R1}} u\left(D - P_{N1}\left(n_{N1} - \frac{1}{2}\right) - P_{R1}\left(n_{N1} - \frac{1}{2}\right)\right)$$
$$+ \frac{1}{1+\delta}(1-p_1)u\left(D(n_{N1} + n_{R1}) - P_{N2}(n_{N2} - n_{N1}) - P_{R2}(n_{R2} - n_{R1})\right)$$
$$+ \frac{1}{1+\delta}p_1 u\left(D\frac{n_{N1}\phi_N + n_{R1}\phi_R}{B} - P_{N2}(n_{N2} - n_{N1}) - P_{R2}(n_{R2} - n_{R1})\right) + ...$$

where the probability p_1 is the posterior probability conditional on information at $t = 1$. The first-order conditions with respect to n_{N1} and n_{R1} yield the pricing conditions:

$$
\begin{aligned}
P_{i1} &= \frac{1}{1+\delta} \frac{(1-p_1)(D+P_{i2})\, u'(C_2^{ND}) + p_1 (D\phi_i/B + P_{i2})\, u'(C_2^D)}{u'(C_1)} \\
&= \frac{1}{1+\delta} C_1^{\gamma} \left[(1-p_1)(D+P_{i2})(C_2^{ND})^{-\gamma} + p_1 (D\phi_i/B + P_{i2})(C_2^D)^{-\gamma}\right], \text{ for } i = N, R,
\end{aligned}
$$

Using $u'(C_t) = C_t^{\gamma}$ and replacing C_1, C_2^{ND} and C_2^D with their equilibrium values in (4), this expression yields the equilibrium prices at $t = 1$:

$$
\begin{aligned}
P_{i1} &= \frac{1}{1+\delta} D^{\gamma} \left[(1-p_1)\left(D + P_{i2}^{ND}\right) D^{-\gamma} + p_1 \left(\frac{D\phi_i}{B} + P_{i2}^D\right) \left(\frac{D\overline{\phi}}{B}\right)^{-\gamma}\right] \\
&= \frac{1}{1+\delta} \left[(1-p_1)\left(D + P_{i2}^{ND}\right) + p_1 \left(\frac{D\phi_i}{B} + P_{i2}^D\right) \frac{1}{x}\right], \text{ for } i = N, R.
\end{aligned}
$$

where again $x \equiv \left(\frac{\overline{\phi}}{B}\right)^{\gamma}$. Hence, substituting for P_{i2}^{ND} and P_{i2}^D from (5) and (6), we get

$$
P_{i1} = \frac{D}{1+\delta} \left[(1-p_1)\left(1 + \frac{1}{1+\delta}\left[(1-p_1) + p_1 \frac{\phi_i}{B}\frac{1}{x}\right]\right) + p_1 \left(\frac{\phi_i}{B} + \frac{1}{1+\delta}\left[(1-\rho)x + \rho\frac{\phi_i}{B}\right]\right) \frac{1}{x}\right].
$$

Collecting terms yields the following equilibrium prices at $t = 1$:

$$
P_{i1} = \frac{D}{1+\delta} \left\{\left[(1-p_1) + p_1 \frac{\phi_i}{B}\frac{1}{x}\right] + \frac{1}{1+\delta}\left[(1-p_1)\left((1-p_1) + p_1\frac{\phi_i}{B}\frac{1}{x}\right) + p_1\left((1-\rho) + \rho\frac{\phi_i}{B}\frac{1}{x}\right)\right]\right\}, \tag{16}
$$

for $i = N, R$. Using this expression, it is easy to show that at $t = 1$ in equilibrium there is a positive price differential between the resilient asset and the non-resilient asset:

$$
P_{R1} - P_{N1} = \frac{D}{1+\delta} \frac{\phi_R - \phi_N}{xB} p_1 \left\{1 + \frac{1}{1+\delta}\left[(1-p_1) + \rho\right]\right\} > 0, \tag{17}
$$

which is increasing in the difference between the resilience of the two assets $\phi_R - \phi_N$, in the disaster probability p_1 and persistence ρ.

Equipped with the equilibrium prices at $t = 2$ and at $t = 1$ given by Equations (5), (6) and (16), we can compute and characterize the realized rates of return of the two assets in the disaster and normal state at $t = 2$:

Proposition 4 (Realized return differential at $t = 2$) *The realized return of* *the resilient asset exceeds that of the non-resilient asset in the disaster state, and falls short of it in the normal state, even in the risk-neutral case ($\gamma = 0$). In both states the absolute size of the differential increases in disaster persistence ρ.*

Proof. From the equilibrium prices given by Equations (16), (5), and (6), we can compute the realized rates of return of the two assets in the disaster and normal state at $t = 2$, as well as their expected values as of $t = 1$.

The realized return at $t = 2$ in the disaster state, $1 + r_{i2}^D \equiv \frac{P_{i2}^D + D_{i2}^D}{P_{i1}}$, is

$$\begin{aligned} 1 + r_{i2}^D &= \frac{\rho\frac{\phi_i}{B} + (1-\rho)x + (1+\delta)\frac{\phi_i}{B}}{(1-p_1) + p_1\frac{\phi_i}{B}\frac{1}{x} + \frac{1}{1+\delta}\left[(1-p_1)\left((1-p_1) + p_1\frac{\phi_i}{B}\frac{1}{x}\right) + p_1\left((1-\rho) + \rho\frac{\phi_i}{B}\frac{1}{x}\right)\right]} \\ &= \frac{(1-\rho)x + (1+\delta+\rho)\frac{\phi_i}{B}}{(1-p_1) + \frac{1}{1+\delta}\left[(1-p_1)^2 + p_1(1-\rho)\right] + \frac{1}{1+\delta}p_1\left[(1-p_1) + (1+\delta+\rho)\right]\frac{\phi_i}{B}\frac{1}{x}}, \end{aligned}$$

which is higher for the resilient than for the non-resilient asset (i.e., $r_{R2}^D > r_{N2}^D$), because

$$\frac{\partial r_{i2}^D}{\partial \phi_i} = \frac{1-p_1}{B}\frac{(1+\delta+\rho) + (1-p_1) + \frac{1}{1+\delta}(\rho - p_1)}{\left[(1-p_1) + \frac{1}{1+\delta}\left[(1-p_1)^2 + p_1(1-\rho)\right] + \frac{1}{1+\delta}p_1\left[(1-p_1) + (1+\delta+\rho)\right]\frac{\phi_i}{B}\frac{1}{x}\right]^2} > 0.$$

Note that this expression is positive even with no disaster persistence ($\rho = p_1$) or with negatively autocorrelated disasters ($\rho < p_1$, even in the limiting case $\rho = 0$). However, it is larger with persistence ($\rho > p_1$). Moreover, it is positive even without risk aversion, i.e. with $x = 1$.

Similarly, we can compute the assets' realized returns in the no-disaster state, $1 + r_{i2}^{ND} \equiv \frac{P_{i2}^{ND} + D_{i2}^{ND}}{P_{i1}}$, at $t = 2$:

$$\begin{aligned} 1 + r_{i2}^{ND} &= \frac{p_1\frac{\phi_i}{B}\frac{1}{x} + (1-p_1) + (1+\delta)}{(1-p_1) + p_1\frac{\phi_i}{B}\frac{1}{x} + \frac{1}{1+\delta}\left[(1-p_1)\left((1-p_1) + p_1\frac{\phi_i}{B}\frac{1}{x}\right) + p_1\left((1-\rho) + \rho\frac{\phi_i}{B}\frac{1}{x}\right)\right]} \\ &= \frac{p_1\frac{\phi_i}{B}\frac{1}{x} + (1-p_1) + (1+\delta)}{(1-p_1) + \frac{1}{1+\delta}\left[(1-p_1)^2 + p_1(1-\rho)\right] + \frac{1}{1+\delta}p_1\left[(1-p_1) + (1+\delta+\rho)\right]\frac{\phi_i}{B}\frac{1}{x}}, \end{aligned}$$

which is lower for the resilient than for the non-resilient asset (i.e., $r_{R2}^{ND} < r_{N2}^{ND}$), because

$$\frac{\partial r_{i2}^{ND}}{\partial \phi_i} = -\frac{p_1}{xB}\frac{(1+\delta+\rho) + (1-p_1) + \frac{1}{1+\delta}(\rho - p_1)}{\left[(1-p_1) + \frac{1}{1+\delta}\left[(1-p_1)^2 + p_1(1-\rho)\right] + \frac{1}{1+\delta}p_1\left[(1-p_1) + (1+\delta+\rho)\right]\frac{\phi_i}{B}\frac{1}{x}\right]^2} < 0.$$

Note that this expression is negative even with no disaster persistence ($\rho = p_1$) or with negatively autocorrelated disasters ($\rho < p_1$, even in the limiting case $\rho = 0$). However, it is larger in absolute value with persistence ($\rho > p_1$). ■

This proposition is intuitive: once a disaster strikes, the hedge against disasters implicitly provided by the resilient asset pays off, so that it generates higher returns than the non-resilient asset, the more so the more persistent the disaster. In normal times this hedge is worthless, leading to cross-sectionally lower returns of the more resilient assets. Of these two opposite effects, the first one prevails in the assets' expected rate of return as of $t = 1$, $\mathrm{E}(r_{i2})$:

Proposition 5 (Expected return differential at $t = 1$) *The expected return of the non-resilient asset exceeds that of the resilient one, and the differential is increasing in disaster persistence ρ if risk aversion is sufficiently low, and is increasing in the disaster probability p_1 in a neighborhood of zero.*

Proof. First, we compute the expected returns of the two assets as of $t = 1$:

$$
\begin{aligned}
1+\mathrm{E}(r_{i2}) &= 1 + p_1 r_{i2}^D + (1-p_1) r_{i2}^{ND} \qquad (18)\\
&= \frac{p_1\left[(1-\rho)x + (1+\delta+\rho)\frac{\phi_i}{B}\right] + (1-p_1)\left[p_1\frac{\phi_i}{B}\frac{1}{x} + (1-p_1) + (1+\delta)\right]}{(1-p_1) + \frac{1}{1+\delta}\left[(1-p_1)^2 + p_1(1-\rho)\right] + \frac{1}{1+\delta}p_1\left[(1-p_1)+(1+\delta+\rho)\right]\frac{\phi_i}{B}\frac{1}{x}}
\end{aligned}
$$

for $i = N, R$. This expression is lower for the resilient than for the non-resilient asset, i.e., $\mathrm{E}(r_{R2}) <\mathrm{E}(r_{N2})$, because

$$
\begin{aligned}
\frac{\partial \mathrm{E}(r_{i2})}{\partial \phi_i} &= p_1\frac{\partial r_{i2}^D}{\partial \phi_i} + (1-p_1)\frac{\partial r_{i2}^{ND}}{\partial \phi_i} = \frac{p_1(1-p_1)}{B}\frac{1}{x} \qquad (19)\\
&\times \frac{(1+\delta+\rho)x + (1-p_1)x + \frac{1}{1+\delta}(\rho-p_1)x - (1+\delta+\rho) - (1-p_1) - \frac{1}{1+\delta}(\rho-p_1)}{\left[(1-p_1) + \frac{1}{1+\delta}\left[(1-p_1)^2 + p_1(1-\rho)\right] + \frac{1}{1+\delta}p_1\left[(1-p_1)+(1+\delta+\rho)\right]\frac{\phi_i}{B}\frac{1}{x}\right]^2}\\
&= -\frac{p_1(1-p_1)}{B}\frac{1-x}{x}\\
&\times \frac{(1+\delta+\rho) + (1-p_1) + \frac{1}{1+\delta}(\rho-p_1)}{\left[(1-p_1) + \frac{1}{1+\delta}\left[(1-p_1)^2 + p_1(1-\rho)\right] + \frac{1}{1+\delta}p_1\left[(1-p_1)+(1+\delta+\rho)\right]\frac{\phi_i}{B}\frac{1}{x}\right]^2},
\end{aligned}
$$

which is negative for $p_1 \in (0, 1)$.

Like the corresponding expressions for expected returns at $t = 2$, also this derivative vanishes in the risk-neutral case ($x = 1$), as well as in the two polar cases $p_1 = 0$ and $p_1 = 1$. This implies that, if the probability of a disaster rises from $p_1 = 0$

to $p_1 > 0$, the expected return of the non-resilient asset rises more than that of the resilient one. Numerical simulations reveal that this is true more generally for reasonable prior probabilities.[16]

To analyze the differential impact of disaster persistence on the expected returns of the two assets, we compute the cross-derivative $\partial^2 \mathrm{E}(r_{i2})/\partial\phi_i\partial\rho$:

$$\begin{aligned}\frac{\partial^2 \mathrm{E}(r_{i2})}{\partial\phi_i\partial\rho} &= -\frac{p_1(1-p_1)(1-x)}{Bx(1+\delta)} \\ &\times\left\{\frac{2+\delta+2p_1(1-\frac{\phi_i}{B}\frac{1}{x})\left[(1+\delta+\rho)+(1-p_1)+\frac{1}{1+\delta}(\rho-p_1)\right]}{\left[(1-p_1)+\frac{1}{1+\delta}\left[(1-p_1)^2+p_1(1-\rho)\right]+\frac{1}{1+\delta}p_1\left[(1-p_1)+(1+\delta+\rho)\right]\frac{\phi_i}{B}\frac{1}{x}\right]^2}\right\}.\end{aligned}$$

All of the terms inside the curly bracket are positive if $1 > \frac{\phi_i}{B}\frac{1}{x}$. Hence, a sufficient (but not necessary) condition for $\partial^2 \mathrm{E}(r_{i2})/\partial\phi_i\partial\rho < 0$ is that $x > \frac{\phi_i}{B}$, i.e. $\left(\frac{\bar{\phi}}{B}\right)^\gamma > \frac{\phi_i}{B}$. Hence, for sufficiently low risk aversion γ, an increase in the perceived persistence of a disaster raises the expected return of the non-resilient asset more than that of the resilient one.[17] ■

A.3 Prices at $t = 1^-$ and realized returns at $t = 1$

Assume that at $t = 1$ investors observe a signal about the probability of a disaster occurring at $t = 2$. For simplicity, assume that the signal can take one of two values, leading investors to either revise the probability from a prior p_{1^-} to $p_1 = p_h$ or to revise it down to $p_1 = p_l$. Suppose the former signal realization occurs with probability π_{1^-} and the latter with probability $(1-\pi_{1^-})$. Rational expectations imply that the prior probability of a disaster is

$$p_{1^-} = p_h\pi_{1^-} + p_l(1-\pi_{1^-}).$$

Simply replacing p_1 with p_{1^-} in Equation (16) yields asset i's equilibrium price in the first trading round of period 1, P_{i1^-}, for $i = N, R$. The comparative statics of the price P_{i1^-} with respect to resilience ϕ_i is exactly as that of P_{1i}. Insofar as

[16] For plausible parameter calibrations, numerical simulations show that an increase in the probability of a disaster increases the expected return of the non-resilient asset, as long as the prior disaster probability is below 30%. Since we are interested in the effects of rare disasters, this bound seems non-binding when deriving our empirical hypotheses.

[17] If we restrict preferences such that $\lambda \geq 0$, then this statement only holds for resilience values $\phi_i < B$, i.e. as long as even the resilient firm is not better off in a disaster.

new information arrives at $t = 1$ (i.e., $p_1 \neq p_{1^-}$), the equilibrium price at $t = 1$ in expression (16) will differ from its initial value P_{i1^-}. By the law of iterated expectations P_{i1^-} =E$(P_{i1}|\Omega_0)$ =E[E$(P_{i1}|\Omega_1)|\Omega_0$], so that the expected rate of return between $t = 1^-$ and $t = 1$, conditional on information at $t = 0$, must be zero: $\mathrm{E}(r^*_{i1}|\Omega_0) = 0$.

The revision of the probability of a disaster from p_{1^-} to p_1 affects the realized rates of return of the two assets at $t = 1$, $1 + r_{i1} \equiv \frac{P_{i1}}{P_{i1^-}}$, in the following way:

$$1{+}r_{i1} = \frac{(1-p_1) + p_1\frac{\phi_i}{B}\frac{1}{x} + \frac{1}{1+\delta}\left[(1-p_1)\left((1-p_1) + p_1\frac{\phi_i}{B}\frac{1}{x}\right) + p_1\left((1-\rho) + \rho\frac{\phi_i}{B}\frac{1}{x}\right)\right]}{(1-p_{1^-}) + p_{1^-}\frac{\phi_i}{B}\frac{1}{x} + \frac{1}{1+\delta}\left[(1-p_{1^-})\left((1-p_{1^-}) + p_{1^-}\frac{\phi_i}{B}\frac{1}{x}\right) + p_{1^-}\left((1-\rho) + \rho\frac{\phi_i}{B}\frac{1}{x}\right)\right]}, \tag{20}$$

for $i = N, R$. From this expression, we can compute the impact of an upward revision of the posterior to $p_1 > p_{1^-}$ on the realized rate of return of asset i:

$$\frac{\partial r_{i1}}{\partial p_1} \propto -1 + \frac{\phi_i}{B}\frac{1}{x} + \frac{1}{1+\delta}\left[-(1-p_1) - (\rho - p_1) + (1 - 2p_1 + \rho)\frac{\phi_i}{B}\frac{1}{x}\right],$$

where the positive terms are those multiplied by ϕ_i/B, implying that the increase in the probability of a disaster increases the realized return differential between the more resilient asset and the less resilient one:

$$\frac{\partial^2 r_{i1}}{\partial p_1 \partial \phi_i} \propto \frac{1}{B}\frac{1}{x}\left[1 + \frac{1}{1+\delta}(1 - 2p_1 + \rho)\right] > 0. \tag{21}$$

Hence:

Proposition 6 (Realized return differential at $t = 1$) *The realized return of the resilient asset at $t = 1$ following an upward revision of the probability of a disaster ($p_1 > p_{1^-}$) exceeds that of the non-resilient asset.*

Since our empirical analysis focuses on the response of realized and expected returns in excess of the market portfolio (which for brevity we refer to as market-adjusted returns) to changes in the disaster probability, the following two corollaries provide predictions for market-adjusted returns:

Corollary 1 (Market-adjusted realized returns) *An upward revision of the disaster probability leads to a positive market-adjusted realized return for the resilient asset and a negative market-adjusted realized return for the non-resilient one.*

Proof. We provide the proof for $t = 1$. The proof for an upward revision at time $t = 2$ can be obtained analogously. Recall that the realized gross return on asset i at $t = 1$ is given by $1 + r_{i1} = \frac{P_{i1}}{P_{1^-}}$ and is defined in Equation (20) above. Similarly we can define the gross return on the market at $t = 1$, given by $1 + r_{M1} = \frac{P_{M1}}{P_{M1^-}}$, where $P_{M1^-} = (P_{r1^-} + P_{N1^-})/2$ and $P_{M1} = (P_{r1} + P_{N1})/2$.

Thus, $1 + r_{M1}$ is identical to the right-hand-side of Equation (20), but with $\bar{\phi} = \frac{\phi_R + \phi_N}{2}$ replacing ϕ_i. Next, note that for $\phi_R = \phi_N = \bar{\phi}$, the realized gross return at $t = 1$ on any asset i is equal to the market gross return. Since the cross-derivative $\frac{\partial^2 r_{1i}}{\partial p_1 \partial \phi_i}$ is positive by Equation (21), an upward revision in p_1 leads to an increase in $r_{R1} - r_{M1}$ and a reduction in $r_{N1} - r_{M1}$, i.e., the market-adjusted realized rate of return of the resilient and non-resilient asset, respectively.

Going through the same logic, one can show that an upward revision of p_2, the disaster probability at $t = 2$, has the same qualitative effects on market-adjusted realized returns. ■

Corollary 2 (Change in market-adjusted expected returns) *An upward revision of the disaster probability reduces the market-adjusted expected return of the resilient assets, and raises it for non-resilient assets.*

Proof. We provide the proof for an upward revision of the disaster probability p_1 at $t = 1$. The expected return of asset i is defined above by expression (18), so that replacing ϕ_i by $\bar{\phi}$ in that expression yields the expected market return. In the proof of Proposition 5 we have established that if the probability of a disaster rises from $p_1 = 0$ to $p_1 > 0$, then the expected return of the non-resilient asset rises more than that of the resilient one. Thus, it must also rise more than that of the market portfolio, which is by definition more resilient than the non-resilient asset. This establishes that the market-adjusted expected return of the non-resilient asset must increase in response to an increase of the probability p_1 from zero. A symmetric argument establishes that that the market-adjusted expected return of the resilient asset declines in response to an increase of the probability p_1 from zero.

The proof for the response of expected market-adjusted returns to an upward revision of the disaster probability p_2 at $t = 2$ can be obtained by applying a similar argument. ■

Internet Appendix

This Appendix provides additional results referred to in the paper.

IA.A Risk-neutral variances: SVIX_t^2, $\overline{\mathrm{SVIX}}_t^2$, $\mathrm{SVIX}_{i,t}^2$

The options-implied expected stock returns that we use in the paper are computed from three measures of risk-neutral variance, as described in Section 3.2: the risk-neutral market variance (SVIX_t^2), the risk-neutral average stock variance ($\overline{\mathrm{SVIX}}_t^2$), and the risk-neutral variance of the stock ($\mathrm{SVIX}_{i,t}^2$). We now present some empirical details on these quantities for expected return horizons of 30 and 730 days in Figures A.3 and A.4, respectively.

[Insert Figures A.3 and A.4]

In both figures, Panel A illustrates the time series of the market-wide risk-neutral variance measures. On the left, we start with SVIX_t^2. Martin (2017) shows that $R_{f,t} \cdot \mathrm{SVIX}_t^2$, where $R_{f,t}$ denotes the gross riskfree rate, can be interpreted as the lower bound on the expected excess return on the market and he provides empirical evidence that this bound is tight. Our plots of SVIX_t^2 thus illustrate the dynamics of expected market returns over our sample period (during which $R_{f,t}$ is very close to 1) and show that the expected return on the market peaks towards the end of the fever period, exactly when low resilience firms' expected returns in excess of the market peaked as well (see Figure 3).

The second plot in Panel A shows $\overline{\mathrm{SVIX}}_t^2$, which exhibits very similar time-series dynamics as SVIX_t^2, indicating that the risk-neutral average stock variance peaks toward the end of the fever period as well. The main difference to SVIX_t^2 is the higher level of $\overline{\mathrm{SVIX}}_t^2$, which reflects that a portfolio of options is more valuable than an option on a portfolio; i.e., $\overline{\mathrm{SVIX}}_t^2 > \mathrm{SVIX}_t^2$, for details see Martin and Wagner (2019).

Panel B illustrates the $\mathrm{SVIX}_{i,t}^2$-values for high and low resilience firms, which in terms of the time series patterns look similar to those of $\overline{\mathrm{SVIX}}_t^2$, but with a substantially larger increase and higher peak for the low resilience firms than the high resilience firms. This explains the differential patterns in the expected excess of market returns, computed as $\frac{1}{2}(\mathrm{SVIX}_{i,t}^2 - \overline{\mathrm{SVIX}}_t^2)$, of high compared to low resilience firms in Figure 3.

IA.B Forecasting with options-implied returns in 2020

In our empirical analysis, we follow Martin and Wagner (2019) to compute expected returns from options data. In this appendix, we discuss existing evidence for the empirical validity of this approach and present results for our sample, which verify that options-implied expected returns have significant predictive power for subsequent realized returns, in particular after options markets learnt about COVID19.

IA.B.1 Motivating the MW approach

To provide evidence for the empirical validity of their approach, Martin and Wagner (2019, MW) show that their options-implied expected returns predict realized returns, both in-sample and out-of-sample. Other recently proposed options-based measures of (bounds for) expected stock returns include Kadan and Tang (2020, KT) and Chabi-Yo et al. (2021, CDV). Back et al. (2022) find that some options-implied bounds might not necessarily be tight in conditional settings but also that the stock-level measure suggested by MW performs well out-of-sample.

Grammig et al. (2021) compare the machine learning (ML) techniques for asset pricing proposed by Gu et al. (2020, GKX) to the options-implied expected returns based on MW, KT, and CDV. Their findings can be summarized as follows. First, among the options-implied expected returns, MW dominates KT and performs at least as well as CDV. Second, for the comparison of MW against GKX, the results suggest that MW dominates GKX at the one month horizon and also performs better than most ML approaches at the one-year horizon. Third, they find that MW dominates GKX when risk premia are updated at high frequency.

The onset of the pandemic marked the start of an unprecedented episode for financial markets, with pandemic news continuously affecting market prices and leading market participants to update their expectations. A key feature of the MW-approach is that it only relies on (real- time) options data but does not require any use of historical data or estimation. Therefore, both the above evidence regarding their comparative performance and the need to capture high- frequency learning by investors in our analysis warrant our approach of measuring expected returns based on real-time options information updated at a daily frequency, rather than on approaches that use historical data updated at monthly or quarterly frequency.

IA.B.2 Evaluating of the MW approach in our sample

To study the extent to which options-implied expected returns predict subsequently realized returns in our sample, we focus on the returns in excess of the market according to Martin and Wagner (2019). For each day in 2020, we rely on equation (1) to compute expected returns in excess of the market for forecast horizons of 30 days, 91 days, and 182 days from stock options with corresponding maturities. Next, we compute the stocks' returns in excess of the market subsequently realized in 2020 over the respective forecast horizons.

For each day in our sample, we estimate cross-sectional regressions of T-period realized returns on the appropriately lagged T-horizon expected returns for approximately 500 firms. The null hypothesis is that options-implied expected returns predict subsequently realized returns with a coefficient of one, i.e. $b = 1$. In what follows, we discuss the distribution of the daily coefficient estimates and associated t-statistics based on both robust standard errors following White (1980) and standard errors clustered at the NAICS 3-digit-code industry level.

Figure A.11 reports results obtained using all forecasts made throughout 2020. At first glance, these results appear to suggest that options-implied expected returns may have been of limited usefulness to forecast returns in 2020. The median coefficient estimates range between 0.25 and 0.46 and the corresponding t-statistics suggest that realized returns are not significantly related to expected returns.

[**Insert Figure A.11**]

However, a closer look reveals that the full-year results simply reflect that options markets did not see COVID-19 coming before its breakout. To show this explicitly, we present the results separately for forecasts made before the start of the fever period (February 24) and for forecasts made from the end of the fever period (March 20) onward.

Figure A.12 shows that the coefficient estimates from predictive regressions only using pre-fever forecasts are almost all negative. This is because options- implied expected returns did not anticipate that essentially all stocks would perform badly due to the unexpected COVID-19 shock that hit markets after the forecasts were made. This effect is most pronounced for the 91-day horizon for which all coefficient estimates are negative (the median estimate is -7.64), because the realizations of all three-month forecasts are dominated by the fever period.

[**Insert Figure A.12**]

Once we focus on the period after markets learnt about COVID-19, the results suggest that options-implied expected returns provide a good forecast of realized returns, as shown by Martin and Wagner (2019) and others. Figure A.13 shows that, in regressions of actual returns, the median coefficient estimates of expected returns are in the range between 0.81 and 1.18. As in previous evidence, the estimates appear less precise at the 30-day horizon (median t-statistics of 2.01 and 1.62) than for the longer horizons of 91 days (2.44 and 2.07) and 182 days (3.86 and 2.86).

[**Insert Figure A.13**]

Table A.18 presents detailed cross-sectional regression results for the forecasts made at the end of the fever period, i.e., on March 20. In addition to the 30, 91 and 182-day forecasts, we also include a forecast until the end of the year 2020 (which corresponds to a horizon of 286 days, which we interpolate from the expected returns over 182- and 365-day horizons).

[**Insert Table A.18**]

In line with previous research, we find relatively little cross-sectional predictability at the 30-day horizon. With increasing horizons, the relevant coefficients become significantly different from zero and, consistent with the null hypothesis, are not different from one.

IA.C Empirical results for a larger sample

As a robustness check, we repeat the analysis for a broader sample of stocks, which includes all firms for which we can obtain CRSP stock data, Compustat fundamentals, sufficient options data from OptionMetrics, and the social distancing proxy based on Koren and Pető (2020).

The advantage of this sample is that it includes 2,274 firms, compared to the 466 stocks of S&P 500 firms used in the main analysis. The limitation is that we can neither explicitly quantify firms' expected excess returns over the risk-free rate nor their expected returns in excess of that of the market, as described in Section 3.2. Instead, we assess changes in firms' risk-neutral variances, $\text{SVIX}^2_{i,t}$, which is sufficiently informative in our cross-sectional analysis because firm differences in expected returns in excess of that of the market are entirely driven by $\mathrm{SVIX}^2_{i,t}$, as can be seen from Equation (1), as well as from the discussion in Internet Appendix IA.A.

The empirical findings from analyzing this larger sample of firms are qualitatively the same as for the sample of S&P 500 firms. Figure A.8 and Table A.13 present the results on the link between risk-adjusted returns and resilience to social distancing, which are very similar to those in Figure 2 and Table 1.

[**Insert Figure A.8 and Table A.13**]

The large sample results for changes in $\mathrm{SVIX}^2_{i,t}$ at horizons from 30 to 730 days presented in Figure A.9 and Table A.14, are qualitatively the same as those fore expected returns in excess of the market in Figure 3 and Table 2, as well as very similar to the underlying SVIX- quantities presented in Panel B of Figures A.3 and A.4: see Internet Appendix IA.A.

[**Insert Figure A.9 and Table A.14**]

Finally, Table A.15 reports a significantly negative relation between risk-adjusted realized returns and changes in $\mathrm{SVIX}^2_{i,t}$, which supports our model's prediction that pandemic risk moved stock prices and expected returns in opposite directions during the fever period, thereby corroborating the evidence presented in Table 3.

[**Insert Table A.15**]

IA.D Examples of expected returns dynamics

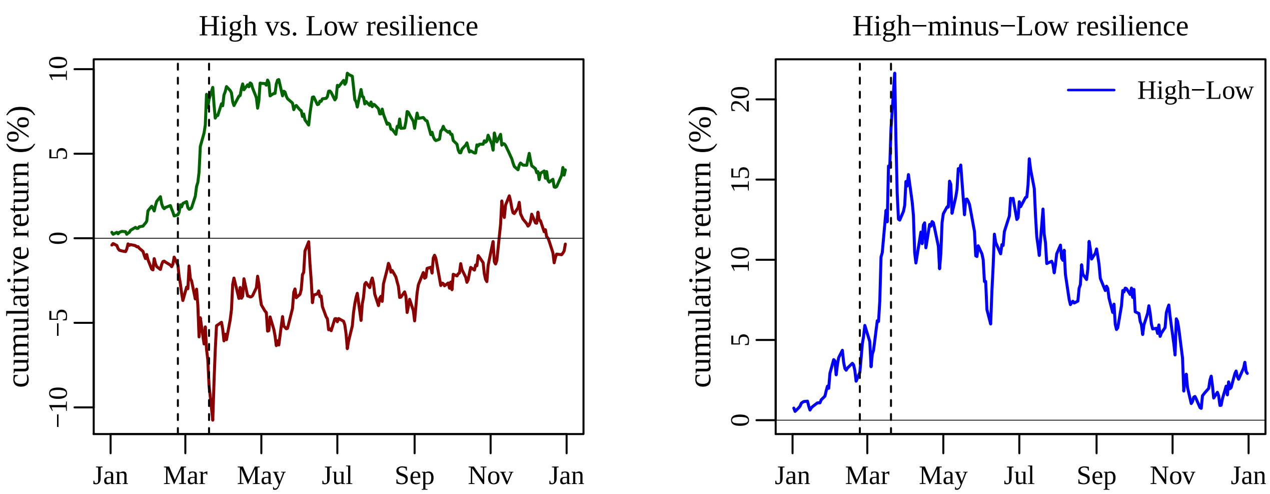
To illustrate the persistence of the impact of the pandemic on expected returns, Figure A.14 presents their dynamics for some well-known stocks belonging to the S&P 500, based on two-year option prices. Panel A shows the time series of expected returns of Google and Microsoft, and Panel B those of United Airlines and Royal Caribbean, respectively meant to illustrate how resilient and non-resilient stocks' expected returns responded to the pandemic. Two results emerge clearly. First, during the fever period, the increase in the expected excess returns of low-resilience stocks was an order of magnitude larger than the corresponding drop of high-resilience ones: at the peak of the crisis, the options-implied expected excess return rose to a staggering 70% p.a. for United Airlines and 90% p.a. for Royal Caribbean, reflecting unprecedented uncertainty about the immediate future of their businesses. Second, this increase is much more persistent for low-resilience stocks than for high-resilience ones: by the end of 2020, the expected returns of United Airlines and Royal Caribbean are still elevated, while for Google and Microsoft they are essentially back to pre-COVID-19 levels.

[**Insert Figure A.14**]

Figure A.1. Risk-adjusted returns of stocks with high and low work-from-home index values

This figure plots the cumulative risk-adjusted returns of portfolios sorted by firms' work-from-home index values for 2020. On any given day, we assign a firm to the 'High' portfolio if its 'work-from-home' index value (as defined by Bai et al., 2021) is above the median value and to the 'Low' portfolio if it is below. In Panel A, we present CAPM-adjusted returns, i.e. controlling for exposure to market risk. Panel B presents results controlling for the Fama-French five factor model exposures (i.e. market, size, value, investments, profitability). We plot the cumulative value-weighted portfolio returns for the 'High' portfolio (in green) and the Low portfolio (in red) as well as the High-Low differential return (in blue). The dashed vertical lines mark February 24 and March 20, the beginning and the end of the 'fever-period'.

Panel A. CAPM-adjusted



Panel B. FF5-adjusted

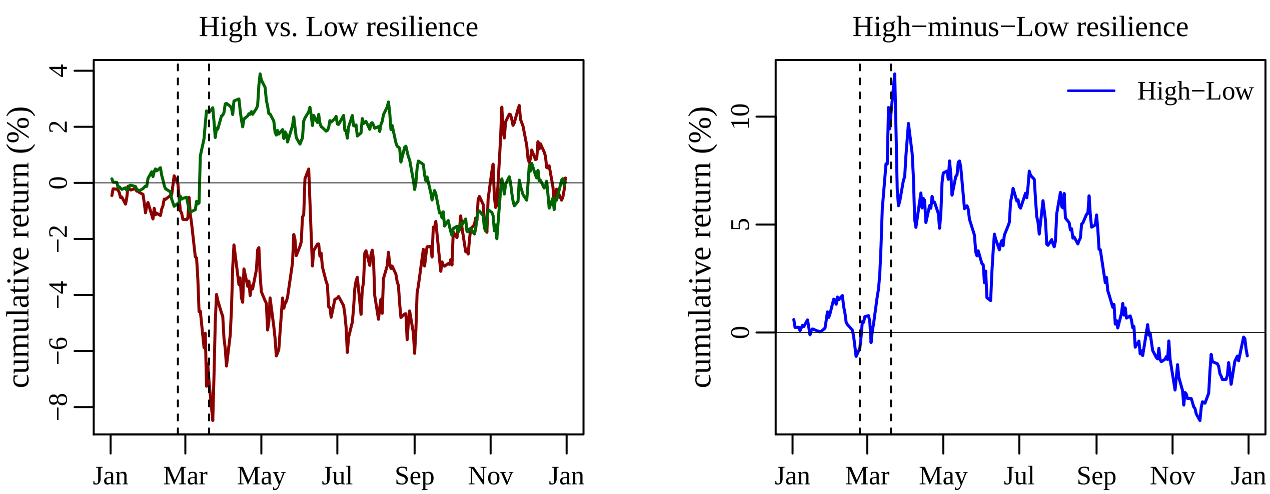
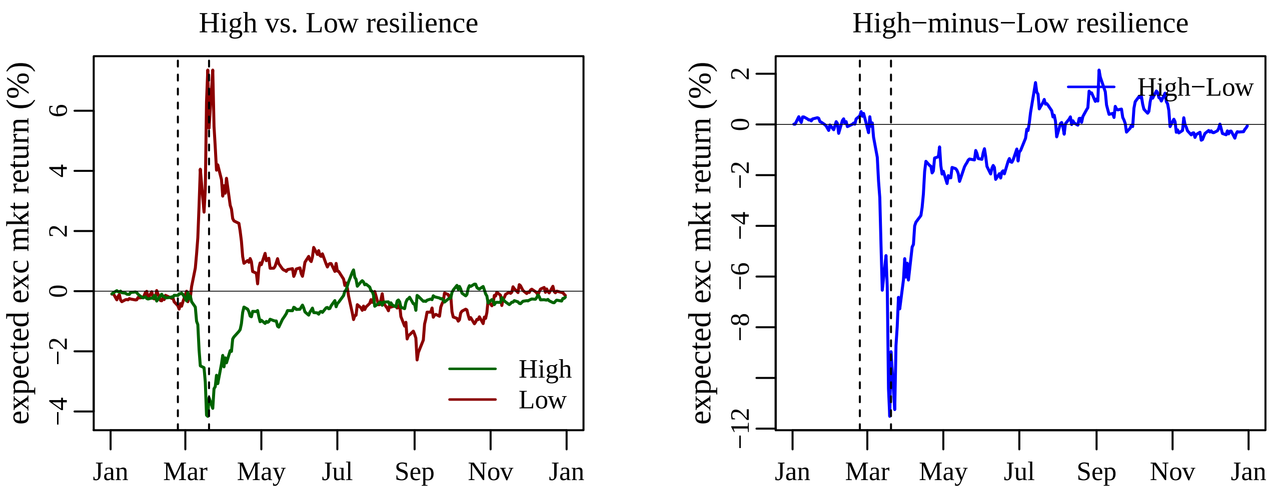


Figure A.2. Expected returns in excess of the market of stocks with high and low work-from-home index values

This figure plots the time-series of expected returns in excess of the market of portfolios sorted by firms' work-from-home index values for 2020. On any given day, we compute a firm's expected return in excess of the market from options data, using Equation (1), and assign the firm to the 'High' portfolio if its 'work-from-home' index value (as defined by Bai et al., 2021) is above the median value and to the 'Low' portfolio if it is below. In Panel A, we present results for a 30-day horizon. Panel B presents results for a 730-day horizon. We plot the value-weighted portfolio expected returns in excess of the market for the 'High' portfolio (in green) and the Low portfolio (in red) as well as the High-Low differential return (in blue). The dashed vertical lines mark February 24 and March 20, the beginning and the end of the 'fever-period'.

Panel A. 30-day horizon



Panel B. 730-day horizon

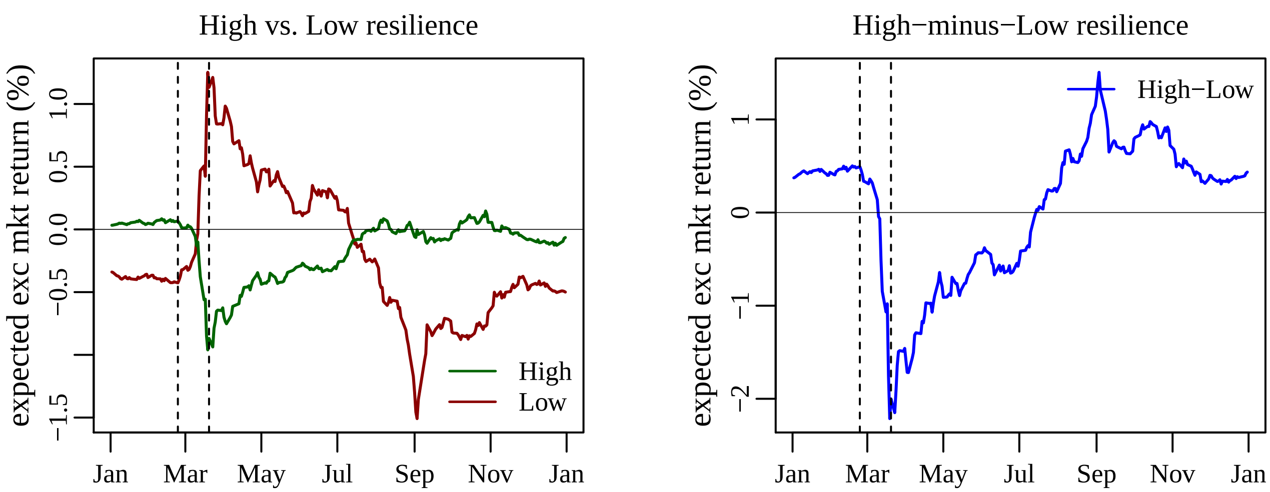
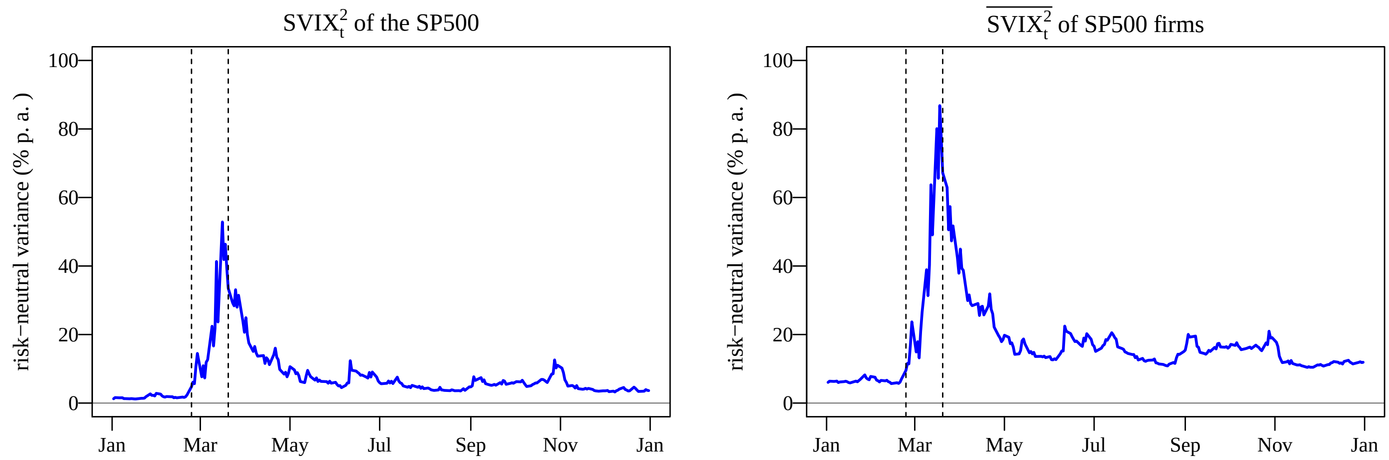


Figure A.3. Risk-neutral variances: 30-day horizon

This figure presents time series plots of the risk-neutral variances required to compute the options-implied expected return on a stock as described in Section 3.2: the risk-neutral market variance, SVIX_t^2; the risk-neutral average stock variance, $\overline{\text{SVIX}}_t^2$; and the risk-neutral variance of the stock, $\text{SVIX}_{i,t}^2$. In Panel A, we plot the time series of SVIX_t^2 and $\overline{\text{SVIX}}_t^2$. Panel B illustrates $\text{SVIX}_{i,t}^2$. for the portfolios of high resilience and low resilience firms, i.e. firms with 'affected_share' (as defined by Koren and Pető, 2020) below and above median value, respectively. All quantities are computed from options with a maturity of 30 days. $\overline{\text{SVIX}}_t^2$ and $\text{SVIX}_{i,t}^2$ are used as to compute the 30-day expected returns in excess of the market in Panel A of Figure 3.

Panel A. Market-wide risk-neutral variances



Panel B. Risk-neutral variances of high and low resilience firms

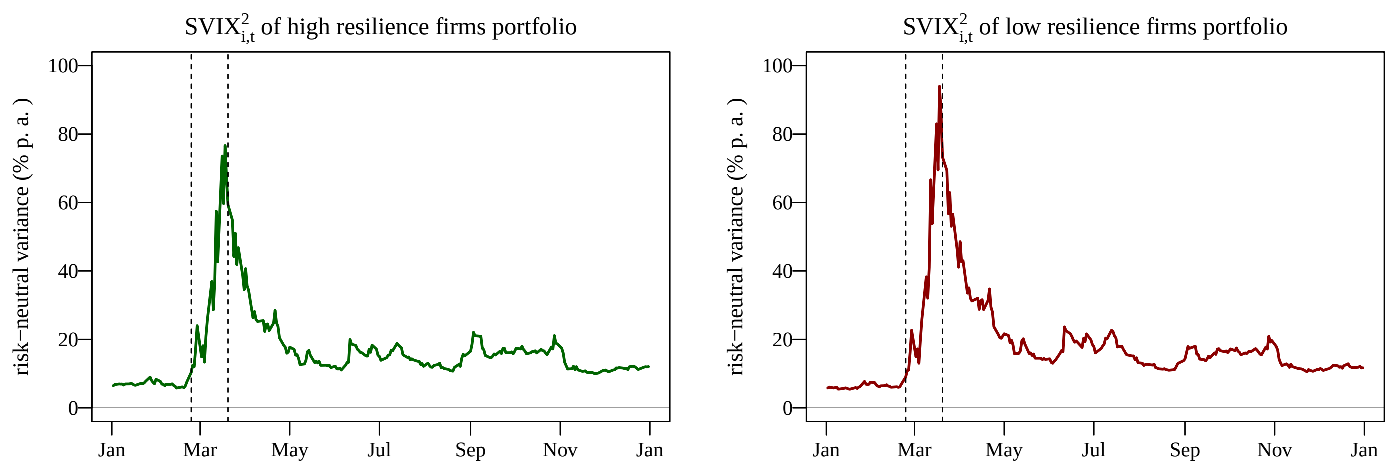
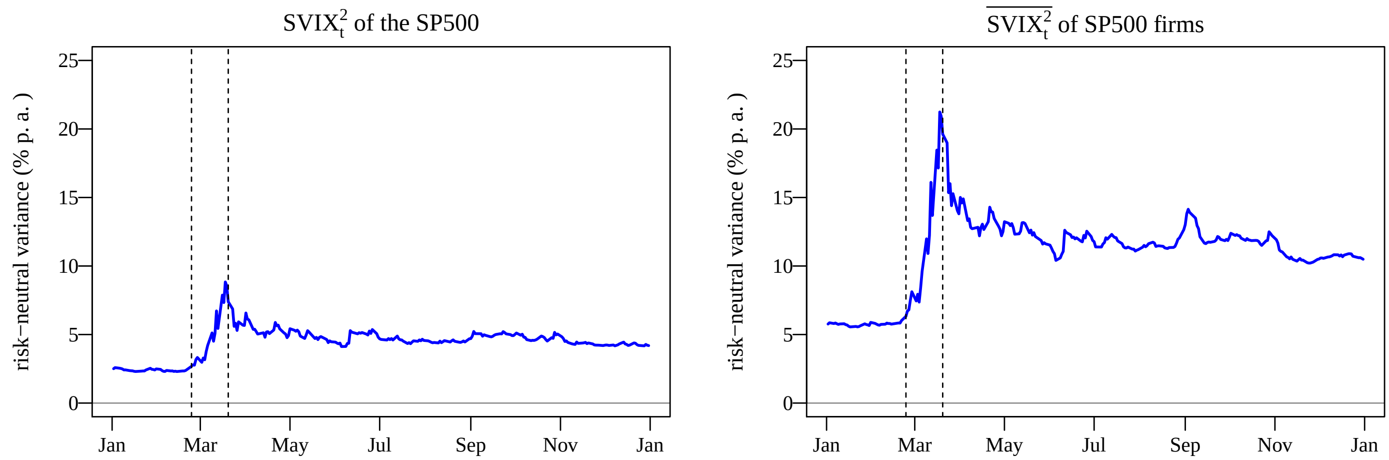


Figure A.4. Risk-neutral variances: 730-day horizon

This figure presents time series plots of the risk-neutral variances required to compute the options-implied expected return on a stock as described in Section 3.2: the risk-neutral market variance, SVIX_t^2; the risk-neutral average stock variance, $\overline{\text{SVIX}}_t^2$; and the risk-neutral variance of the stock, $\text{SVIX}_{i,t}^2$. In Panel A, we plot the time series of SVIX_t^2 and $\overline{\text{SVIX}}_t^2$. Panel B illustrates $\text{SVIX}_{i,t}^2$. for the portfolios of high resilience and low resilience firms, i.e. firms with 'affected_share' (as defined by Koren and Pető, 2020) below and above median value, respectively. All quantities are computed from options with a maturity of 730 days. $\overline{\text{SVIX}}_t^2$ and $\text{SVIX}_{i,t}^2$ are used as to compute the 730-day expected returns in excess of the market in Panel B of Figure 3.

Panel A. Market-wide risk-neutral variances



Panel B. Risk-neutral variances of high and low resilience firms

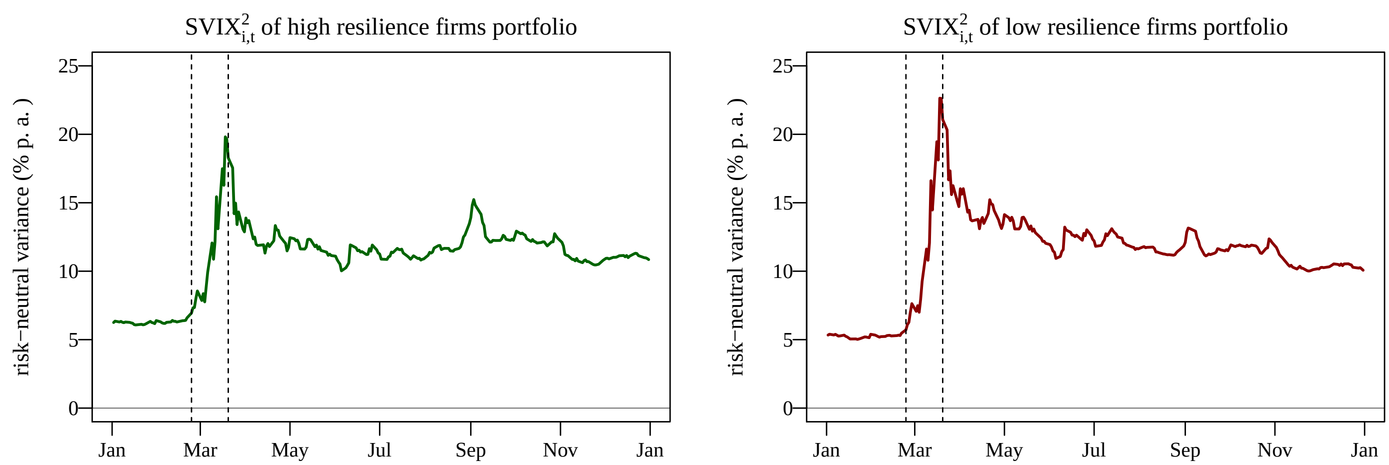
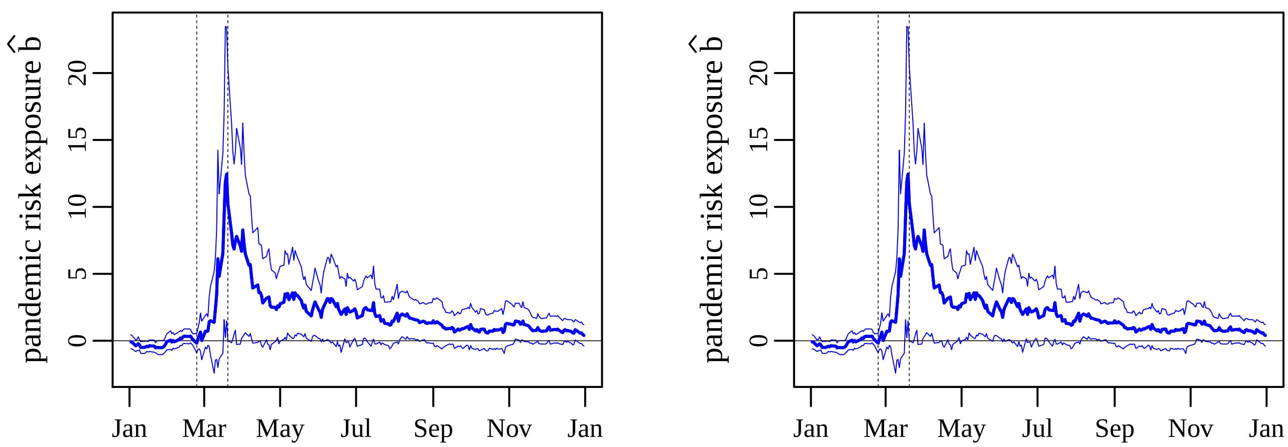


Figure A.5. Pandemic risk exposures and expected returns in excess of the market

This figures presents results from cross-sectional regressions of S&P 500 firms expected returns in excess of the market on their pandemic risk exposures, measured by their cross-sectionally standardized KP scores. We run regressions every day of the year 2020 and plot the time series of the pandemic risk exposure coefficient estimate ($\widehat{b}$, bold line) along with 95%-confidence intervals (thin lines) based on standard errors clustered by industries. Panel A presents results for expected returns in excess of the market for a 30-day horizon (*p.a.*), Panel B results for a 730-day horizon (*p.a.*). Plots on the left represent results from univariate regressions, plots on the right include firms' FF5-exposures as control variables.

Panel A. 30-day horizon



Panel B. 730-day horizon

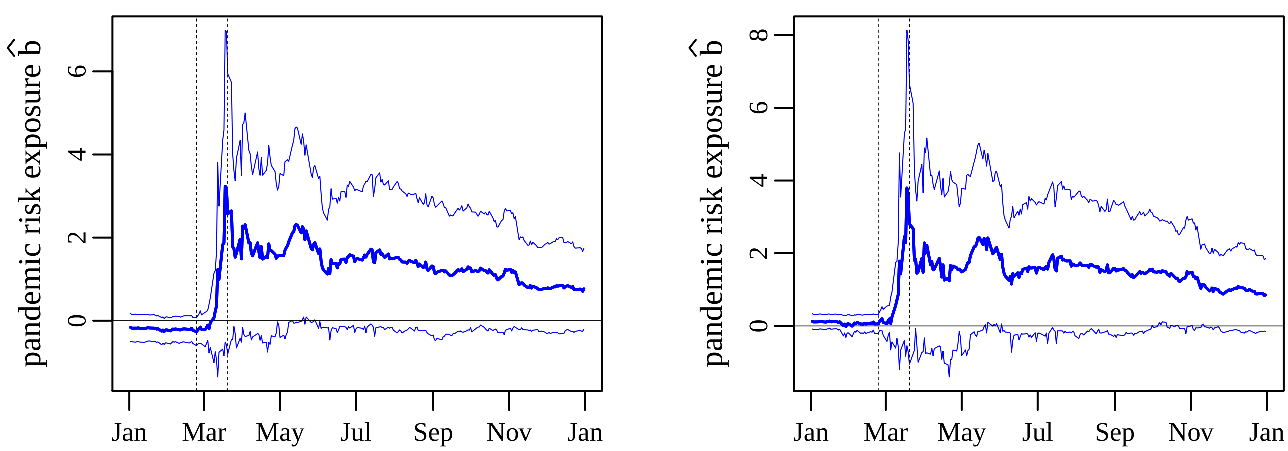
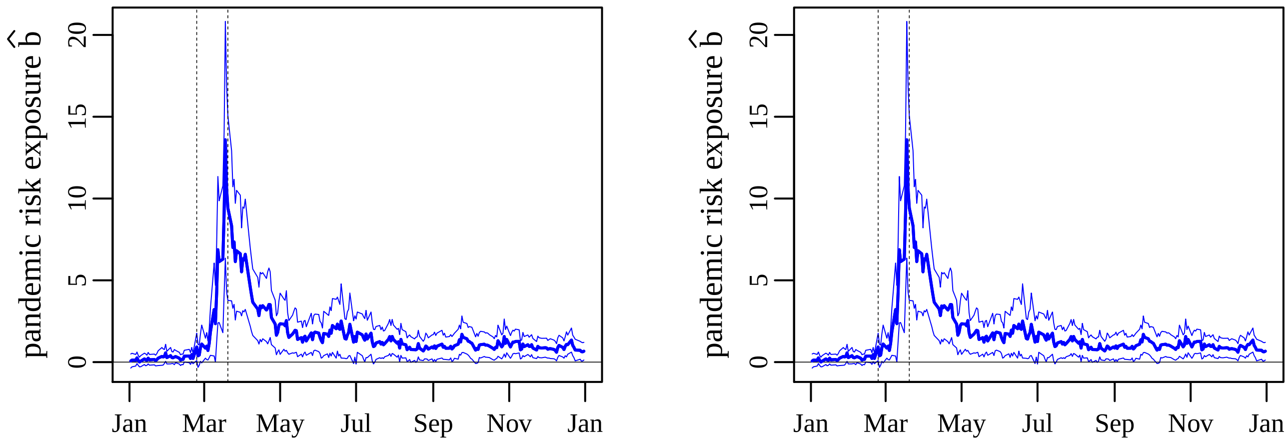


Figure A.6. Pandemic risk exposures and expected returns in excess of the market

This figures presents results from cross-sectional regressions of S&P 500 firms expected returns in excess of the market on their pandemic risk exposures, measured by their cross-sectionally standardized work-from-home index provided by Bai et al. (2021). We run regressions every day of the year 2020 and plot the time series of the pandemic risk exposure coefficient estimate ($\widehat{b}$, bold line) along with 95%-confidence intervals (thin lines) based on robust standard errors following White (1980). Panel A presents results for expected returns in excess of the market for a 30-day horizon (*p.a.*), Panel B results for a 730-day horizon (*p.a.*). Plots on the left represent results from univariate regressions, plots on the right include firms' FF5-exposures as control variables.

Panel A. 30-day horizon



Panel B. 730-day horizon

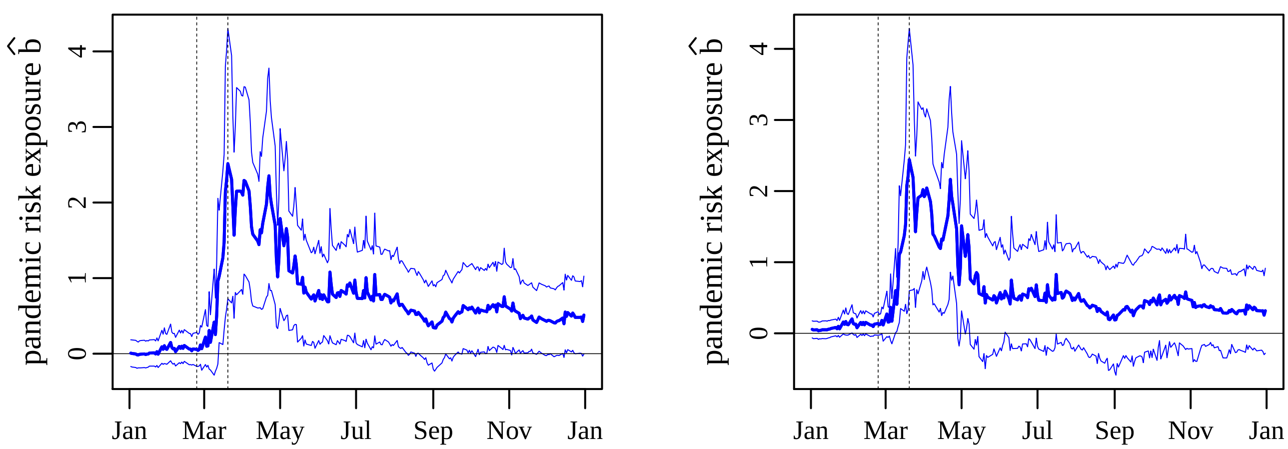
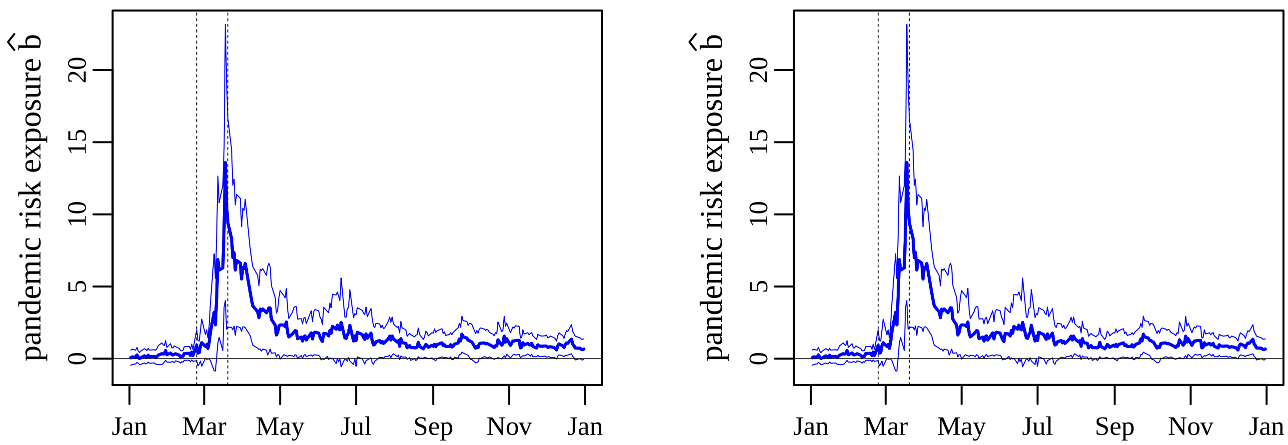


Figure A.7. Pandemic risk exposures and expected returns in excess of the market

This figures presents results from cross-sectional regressions of S&P 500 firms expected returns in excess of the market on their pandemic risk exposures, measured by their cross-sectionally standardized work-from-home index provided by Bai et al. (2021). We run regressions every day of the year 2020 and plot the time series of the pandemic risk exposure coefficient estimate ($\widehat{b}$, bold line) along with 95%-confidence intervals (thin lines) based on standard errors clustered by industries. Panel A presents results for expected returns in excess of the market for a 30-day horizon (*p.a.*), Panel B results for a 730-day horizon (*p.a.*). Plots on the left represent results from univariate regressions, plots on the right include firms' FF5-exposures as control variables.

Panel A. 30-day horizon



Panel B. 730-day horizon

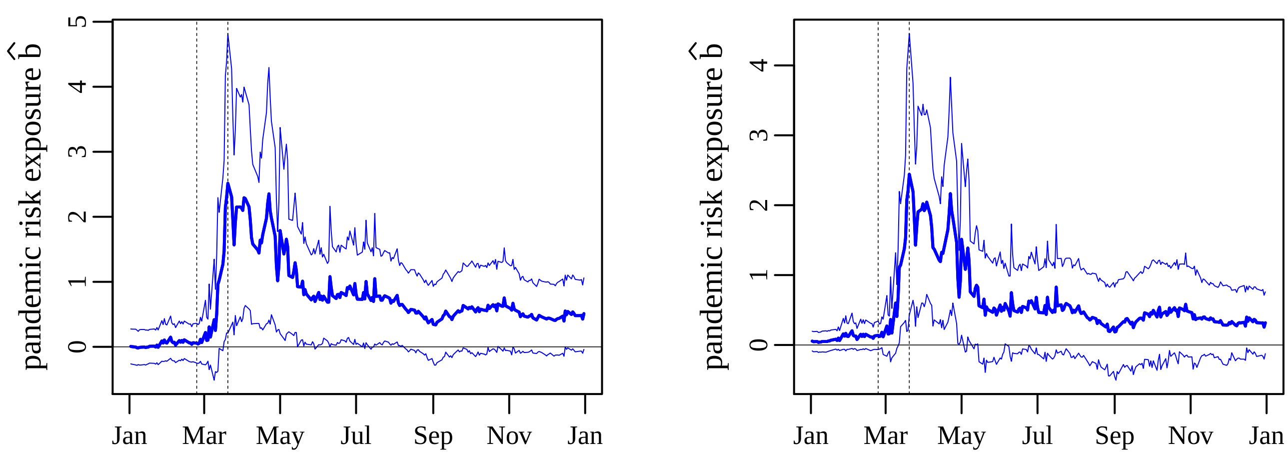
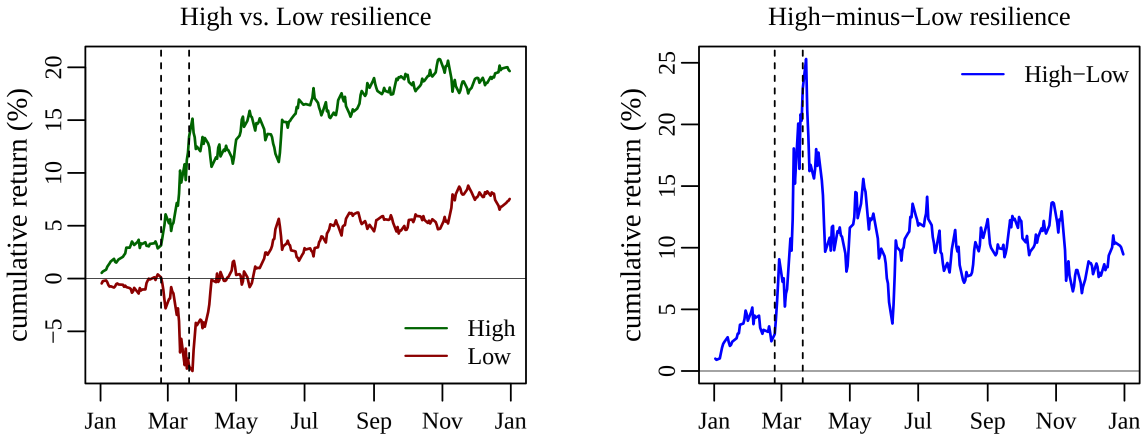


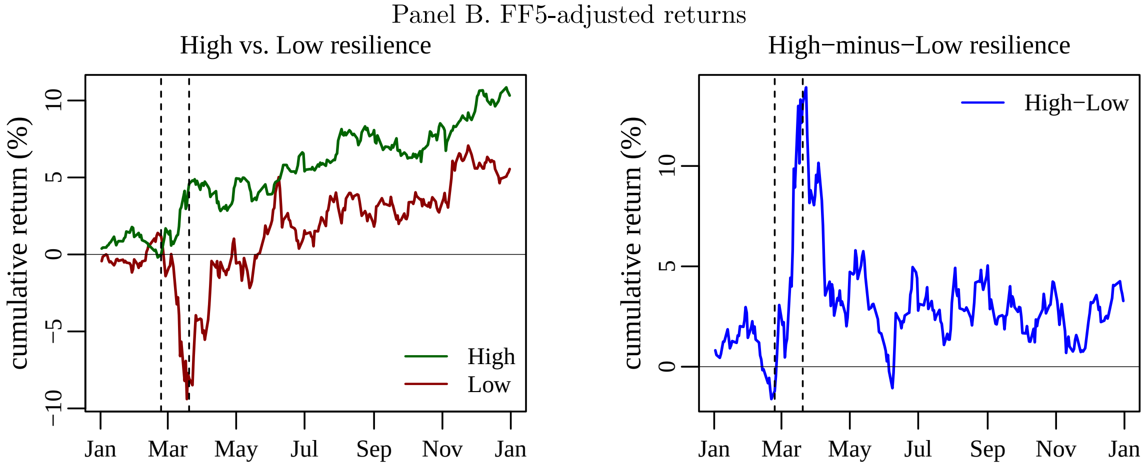
Figure A.8. Risk-adjusted returns of high and low resilience stocks: large sample

This figure plots the cumulative risk-adjusted returns of portfolios sorted by firms' resilience to disaster risk for 2020. The sample covers all firms for which we have CRSP, COMPUSTAT, OptionMetrics, and resilience data. On any given day, we assign a firm to the 'High' portfolio if its 'affected_share' (as defined by Koren and Pető, 2020) is below the median value and to the 'Low' portfolio if it is above. In Panel A, we present CAPM-adjusted returns, i.e. controlling for exposure to market risk. Panel B presents results controlling for the Fama-French five factor model exposures (i.e. market, size, value, investments, profitability). Panel C presents results controlling for the q-factors (i.e. market, size, investments, profitability) proposed by Hou et al. (2015). We plot the cumulative value-weighted portfolio returns for the 'High' portfolio (in green) and the Low portfolio (in red) as well as the High-Low differential return (in blue). The dashed vertical lines mark February 24 and March 20, the beginning and the end of the 'fever-period'.

Panel A. CAPM-adjusted returns



Panel B. FF5-adjusted returns



Panel C. HXZ-adjusted returns

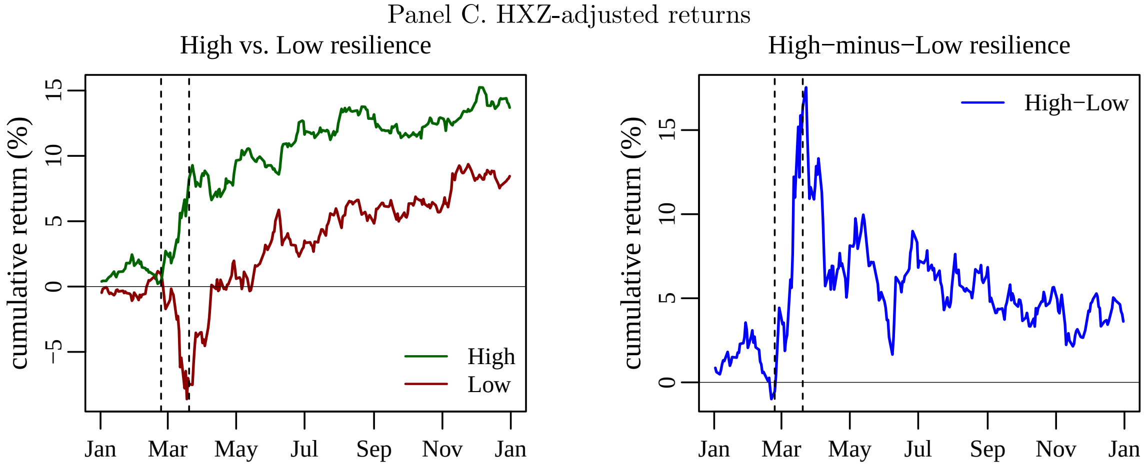
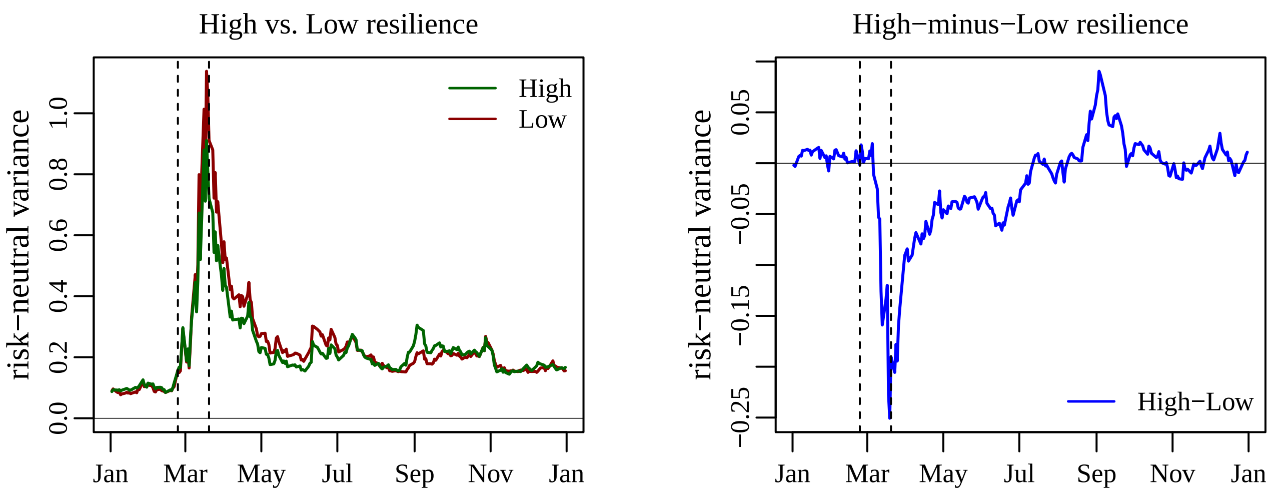


Figure A.9. Risk-neutral variances of high and low resilience stocks: large sample

This figure plots the time-series of risk-neutral variances $\text{SVIX}^2_{i,t}$ of portfolios sorted by firms' resilience to disaster risk for 2020. The sample covers all firms for which we have CRSP, COMPUSTAT, OptionMetrics, and resilience data. On any given day, we compute a firm's $\text{SVIX}^2_{i,t}$ from options data and assign the firm to the 'High' portfolio if its 'affected_share' (as defined by Koren and Pető, 2020) is below the median value and to the 'Low' portfolio if it is above. In Panel A, we present results for a 30-day horizon. Panel B presents results for a 730-day horizon. We plot the value-weighted portfolio $\text{SVIX}^2_{i,t}$ for the 'High' portfolio (in green) and the Low portfolio (in red) as well as the High-Low differential return (in blue). The dashed vertical lines mark February 24 and March 20, the beginning and the end of the 'fever-period'.

Panel A. 30-day horizon



Panel B. 730-day horizon

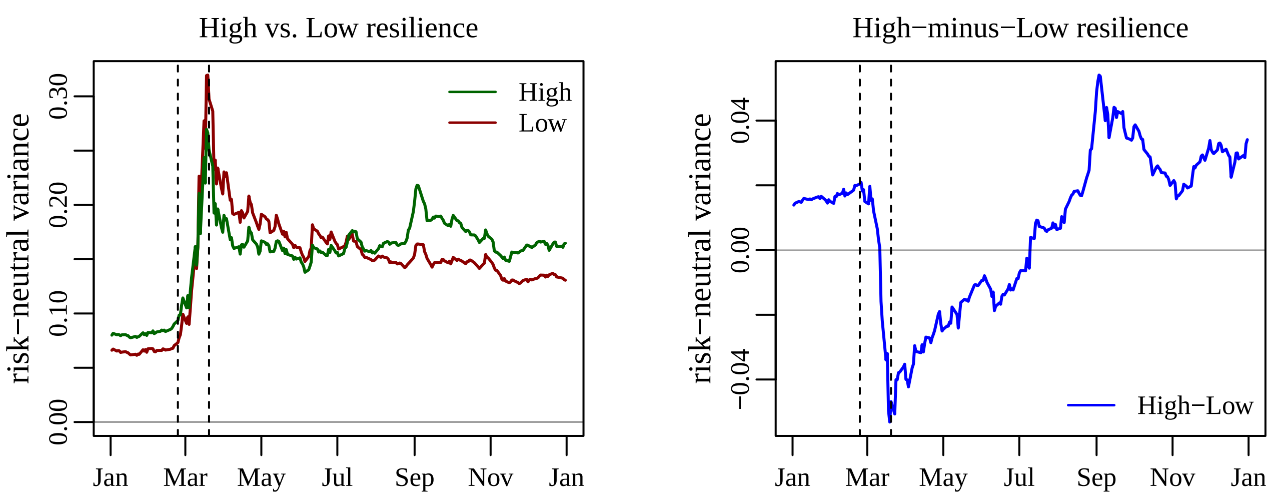


Figure A.10. Post-fever realized returns of low and high resilience firms

This figure plots firms' cumulatively realized FF5-adjusted returns in the post-fever period (y-axis) against changes in their expected returns during the fever period (x-axis). Green triangles and red bullets indicate firms that our market-based resilience classification has identified as high resilience and low resilience, respectively.

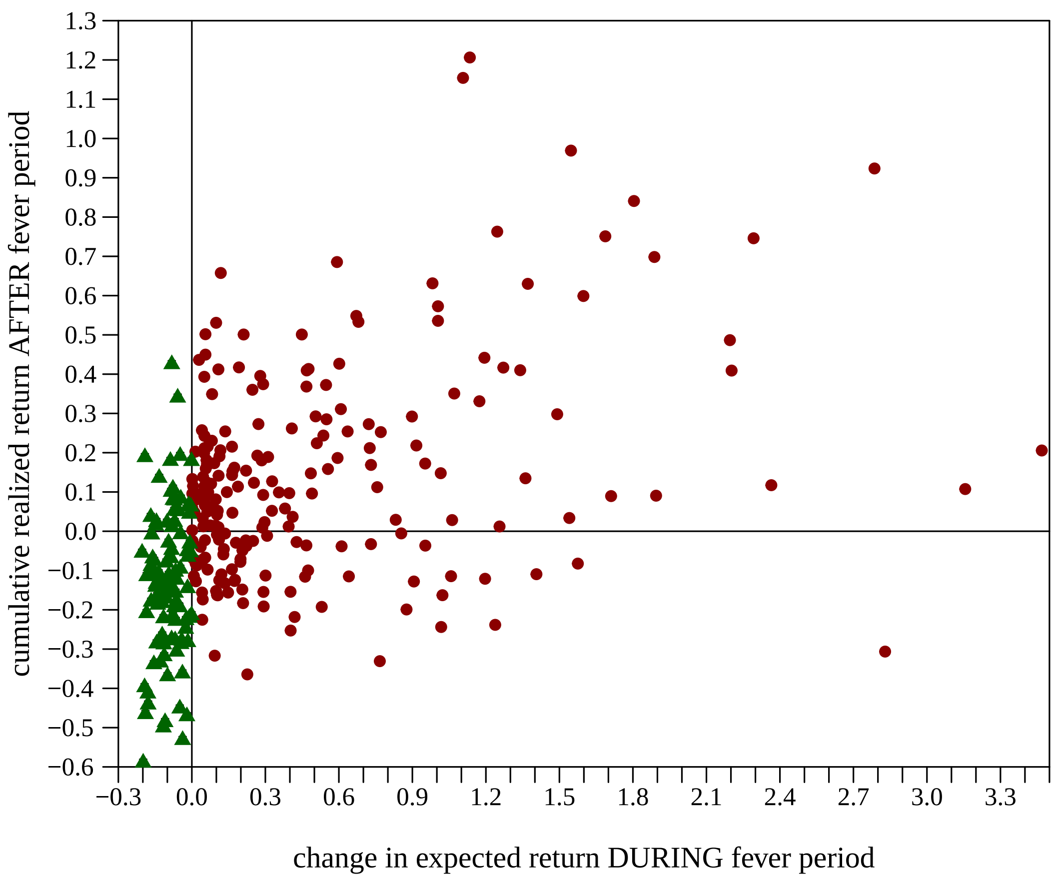
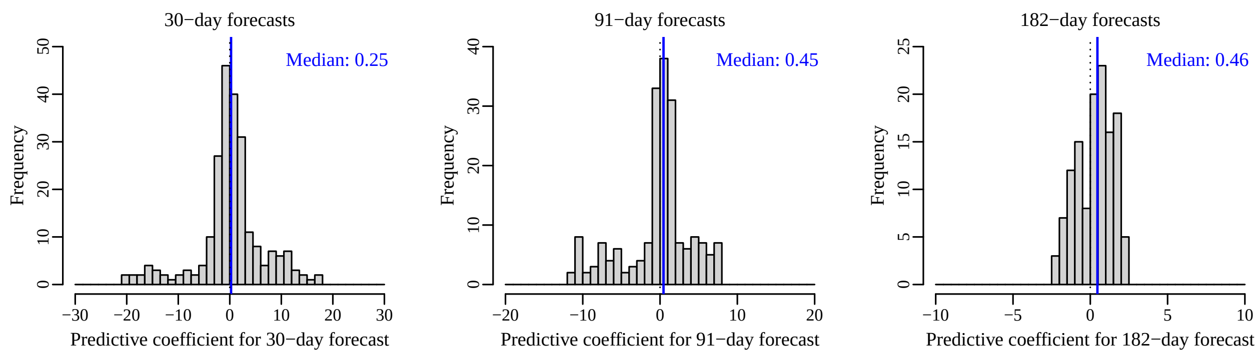


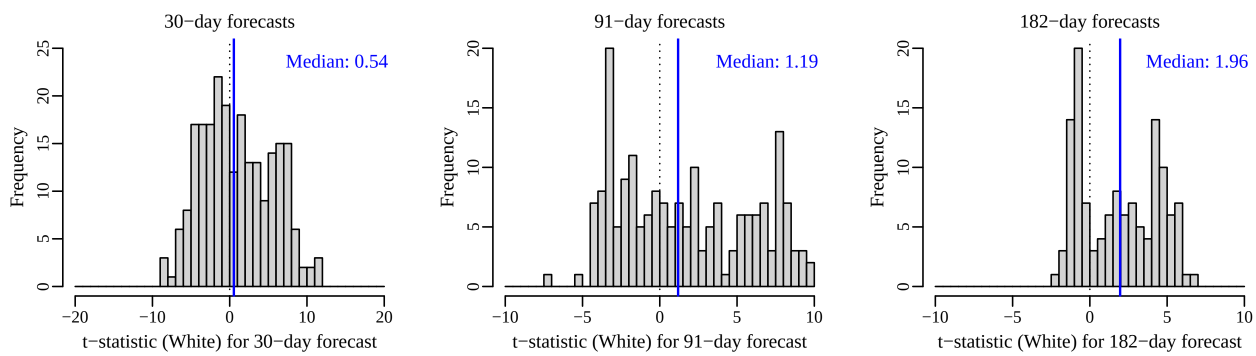
Figure A.11. Predictive regressions: all forecasts made in 2020

This figure summarizes regression results of predicting realized stock returns with options-implied expected returns. Every day in the year 2020, we compute expected returns in excess of the market of S&P 500 firms' stocks (following Martin and Wagner, 2019) for forecast horizons of 30 days, 91 days, and 182 days. Next, we compute the stocks' realized returns in excess of the market over the respective forecast horizons. This provides us with 232 forecasts made and returns realized in 2020 for the 30-day horizon, 190 forecasts for the 91-day horizon, and 127 forecasts for the 182-day horizon. On each day, we run cross-sectional regressions of T-period realized returns on the appropriately lagged T-horizon expected returns. Panel A presents the distribution of the daily coefficient estimates, for the 30-day horizon on the left, the 91-day horizon in the middle, and the 182-day horizon on the right. Panel B reports the distribution of t-statistics based on robust standard errors following White (1980) and Panel C presents t-statistics based on standard errors clustered at the NAICS 3-digit-code industry level.

Panel A. Coefficient estimates



Panel B. t-statistics based on standard errors following White (1980)



Panel C. t-statistics based on standard errors clustered by industries

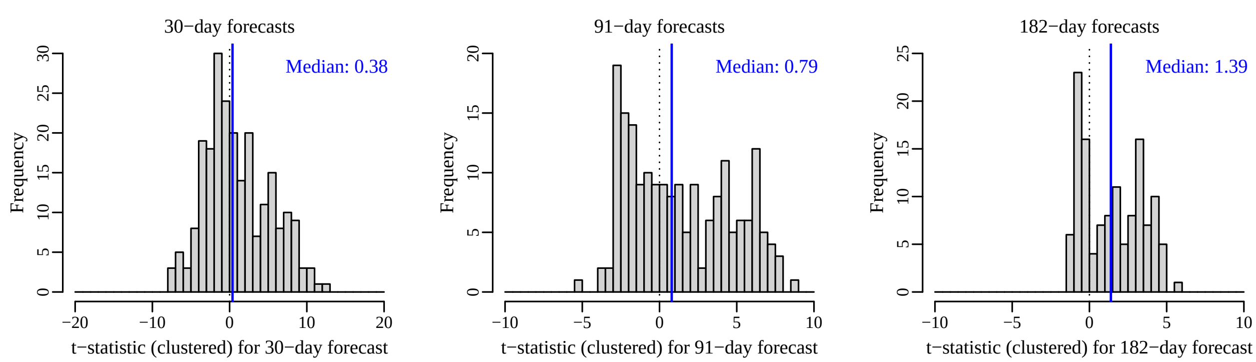
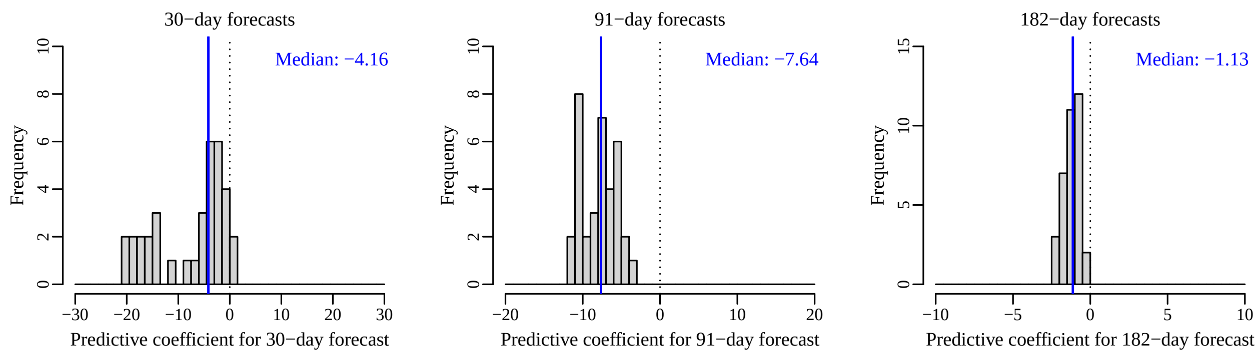


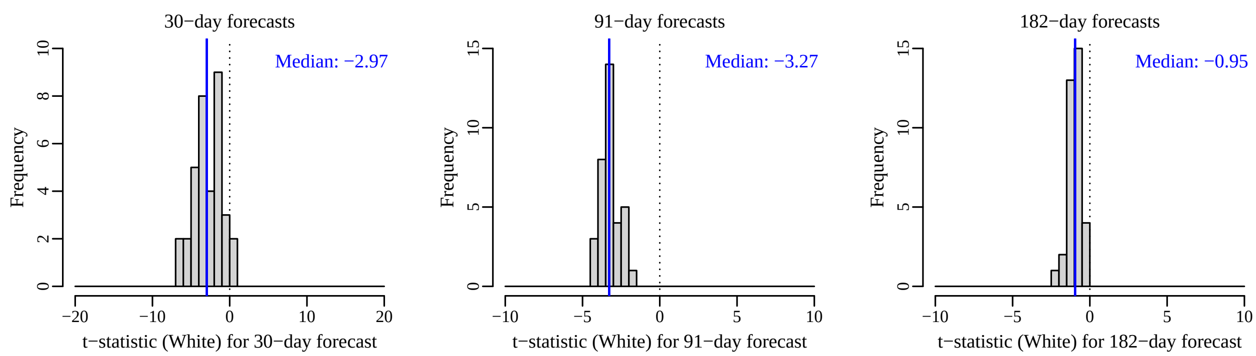
Figure A.12. Predictive regressions: forecasts made prior to the fever period

This figure summarizes regression results of predicting realized stock returns with options-implied expected returns. Every day prior to the start of the fever period on 24 February 2020, we compute expected returns in excess of the market of S&P 500 firms' stocks (following Martin and Wagner, 2019) for forecast horizons of 30 days, 91 days, and 182 days. Next, we compute the stocks' realized returns in excess of the market over the respective forecast horizons. This provides us with 35 forecasts made and returns realized for the 30-day, 91-day horizon, and 182-day horizons. On each day, we run cross-sectional regressions of T-period realized returns on the appropriately lagged T-horizon expected returns. Panel A presents the distribution of the daily coefficient estimates, for the 30-day horizon on the left, the 91-day horizon in the middle, and the 182-day horizon on the right. Panel B reports the distribution of t-statistics based on robust standard errors following White (1980) and Panel C presents t-statistics based on standard errors clustered at the NAICS 3-digit-code industry level.

Panel A. Coefficient estimates



Panel B. t-statistics based on standard errors following White (1980)



Panel C. t-statistics based on standard errors clustered by industries

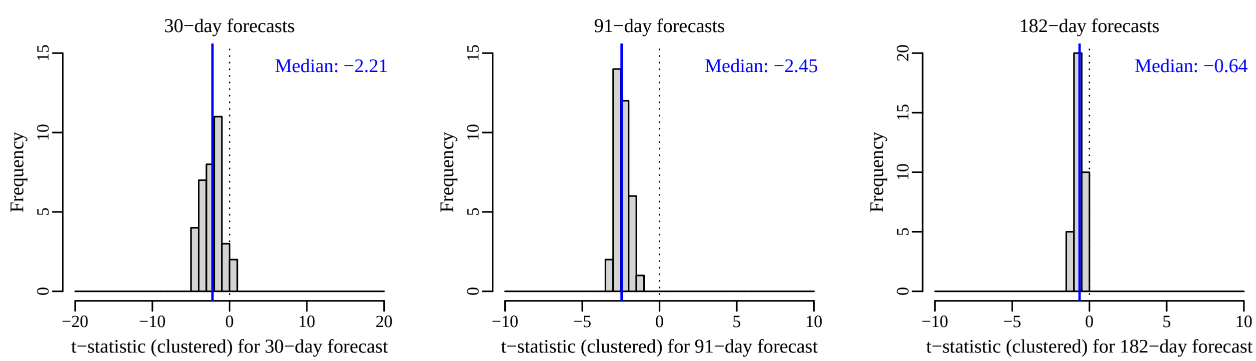
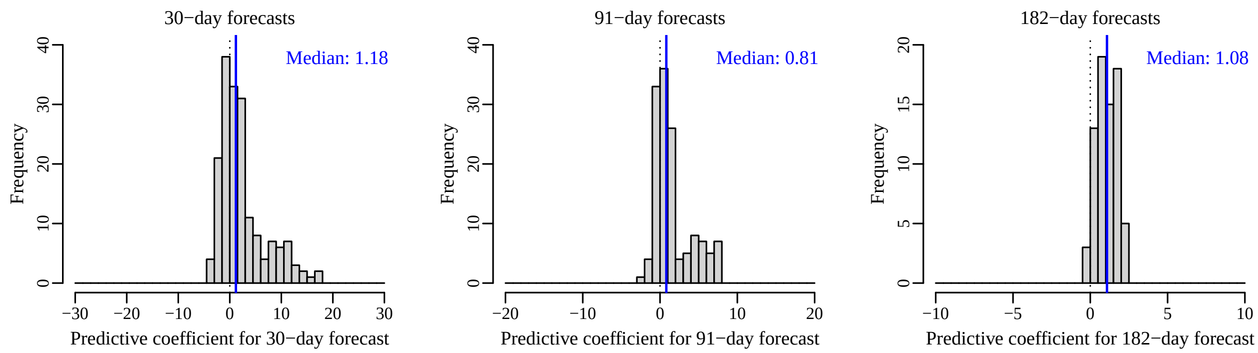


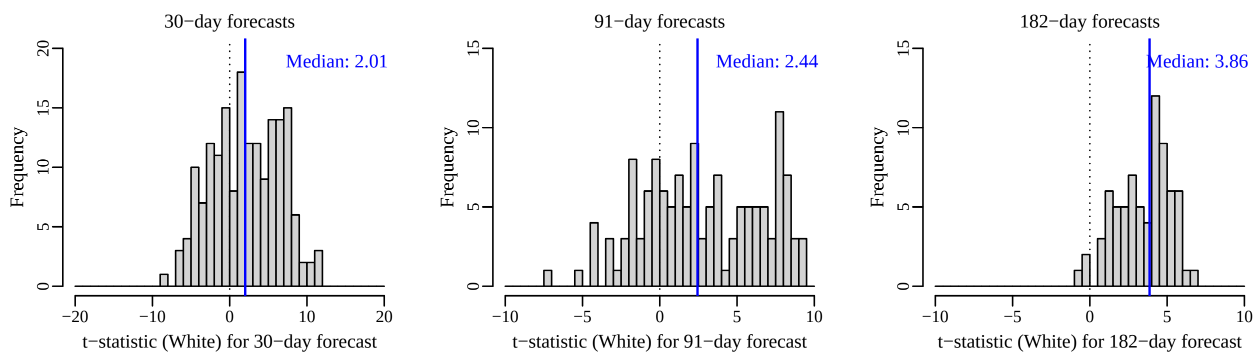
Figure A.13. Predictive regressions: forecasts made from the end of the fever period

This figure summarizes regression results of predicting realized stock returns with options-implied expected returns. Every day from the end of the fever period on 20 March 2020, we compute expected returns in excess of the market of S&P 500 firms' stocks (following Martin and Wagner, 2019) for forecast horizons of 30 days, 91 days, and 182 days. Next, we compute the stocks' realized returns in excess of the market over the respective forecast horizons. This provides us with 178 forecasts made and returns realized in 2020 for the 30-day horizon, 136 forecasts for the 91-day horizon, and 73 forecasts for the 182-day horizon. On each day, we run cross-sectional regressions of T-period realized returns on the appropriately lagged T-horizon expected returns. Panel A presents the distribution of the daily coefficient estimates, for the 30-day horizon on the left, the 91-day horizon in the middle, and the 182-day horizon on the right. Panel B reports the distribution of t-statistics based on robust standard errors following White (1980) and Panel C presents t-statistics based on standard errors clustered at the NAICS 3-digit-code industry level.

Panel A. Coefficient estimates



Panel B. t-statistics based on standard errors following White (1980)



Panel C. t-statistics based on standard errors clustered by industries

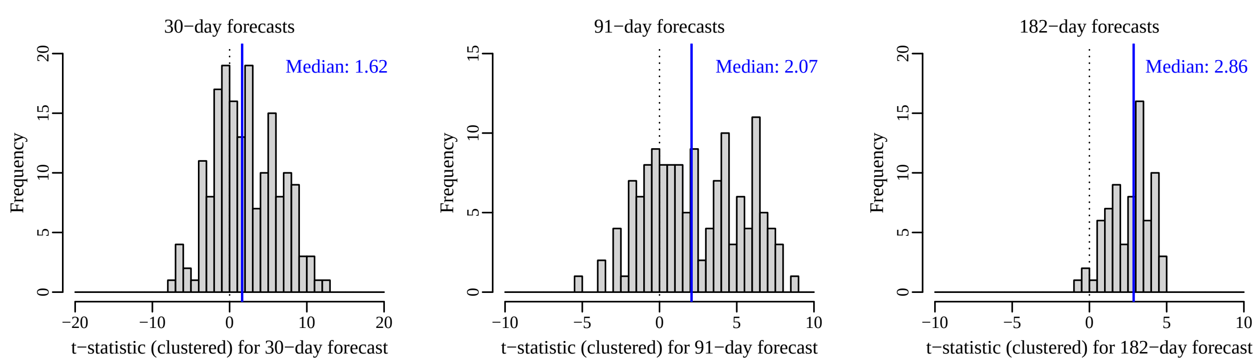
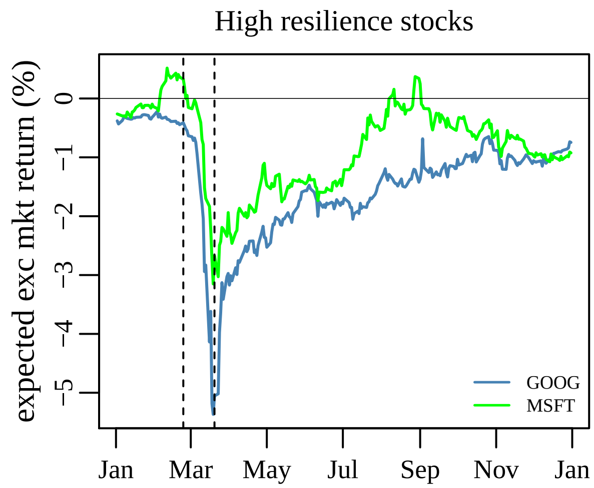


Figure A.14. Expected two-year returns in excess of the market for selected stocks

This figure plots the time-series of two-year expected returns in excess of the market for selected S&P 500 firms during the year 2020. The high resilience stocks we consider are Google (GOOG) and Microsoft (MSFT), the low resilience stocks are United Airlines (UAL) and Royal Caribbean (RCL). We compute stocks' expected return in excess of the market from options with two-year maturity using Equation (1). The dashed vertical lines mark the 'fever-period' from February 24 to March 20, 2020.



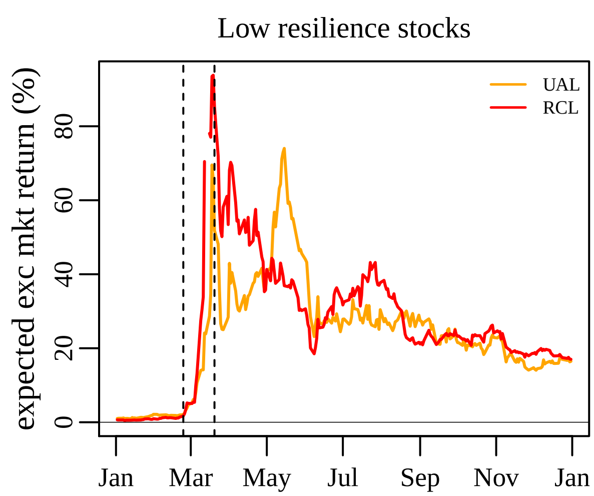


Table A.1: Measures of teleworkability, working at home and at the workplace, and business face-to-face interactions

This Table provides an overview of the empirical measures on which we base our analysis of stocks' disaster resilience. Panel A lists the communication-intensity and physical proximity measures suggested by Koren and Pető (2020) for 84 industries at the NAICS 3-digit level. Panel B lists the teleworkability measures provided by Dingel and Neiman (2020) for 24 industries at the NAICS 2-digit level and for 88 industries at the NAICS 3-digit level. Panel C lists the work at home and work at the workplace measures provided by Hensvik et al. (2020) for 310 industries at the NAICS 4-digit level. Panel D refers to the firm-level work-from-index proposed by Bai et al. (2021).

Panel A. Koren and Pető (2020)

'teamwork_share'	percentage of workers in teamwork-intensive occupations, i.e. internal communication
'customer_share'	percentage of workers in customer-facing occupations, i.e. external communication
'communication_share'	percentage of workers in teamwork-intensive and/or customer-facing occupations
'presence_share'	percentage of workers whose jobs require physical presence in close proximity to others
'affected_share'	percentage of workers in occupations that are communication-intensive and/or require physical presence in close proximity to others

Panel B. Dingel and Neiman (2020):

'teleworkable_emp'	fraction of jobs that can be done from home estimated from O*Net data
'teleworkable_wage'	fraction of wages to jobs that can be done from home estimated from O*Net data
'teleworkable_manual_emp'	fraction of jobs that can be done from home based on manual classification by the authors
'teleworkable_manual_wage'	fraction of wages to jobs that can be done from home based on manual classification by the authors

Panel C. Hensvik et al. (2020)

'home'	fraction of respondents that work at home, based on the 'American Time Use Survey' (2011-2018)
'workplace'	fraction of respondents that work at workplace
'dur_home'	hours worked at home per day
'dur_workplace'	hours worked at workplace per day
'share_home'	hours worked at home divided by hours worked at home and at workplace

Panel D. Bai et al. (2021)

'wfh_index_qtr'	firm-level work-from-home index, based on merging job postings data from Burning Glass Technologies (BGT) with the data of Dingel and Neiman (2020)

Table A.2: Industry composition of our sample

This table summarizes the industry composition of our sample of S&P 500 firms. For each industry we report its 3-digit NAICS code, its description, the number of firms in the respective industry and their average market capitalization (end of 2019, in billion), and the industry's 'affected_share' as defined by Koren and Pető (2020).

NAICS	Description	Firms	Mkt Cap	KP score
211	Oil and gas extraction	12	23.31	24
212	Mining, except oil and gas	4	22.69	70
213	Support activities for mining	4	24.71	52
221	Utilities	29	31.35	43
236	Construction of buildings	3	15.16	22
237	Heavy and civil engineering construction	1	9.54	47
238	Specialty trade contractors	1	5.85	42
311	Food manufacturing	13	26.49	22
312	Miscellaneous nondurable goods manufacturing	8	93.32	35
314	Textile product mills	1	9.65	16
315	Apparel	7	10.46	12
321	Wood products	1	21.90	21
322	Paper and paper products	6	33.40	24
324	Petroleum and coal products	6	111.17	29
325	Chemicals	39	70.69	18
326	Plastics and rubber products	2	11.61	19
331	Primary metals	1	16.71	32
332	Fabricated metal products	5	16.50	20
333	Machinery	17	30.57	18
334	Computer and electronic products	52	76.58	9
335	Electrical equipment and appliances	3	13.24	15
336	Transportation equipment	16	53.16	17
337	Furniture and related products	2	7.89	13
339	Miscellaneous durable goods manufacturing	12	28.59	14
423	Wholesale trade: Durable goods	5	15.64	28
424	Wholesale trade: Nondurable goods	4	25.09	25
425	Electronic markets and agents and brokers	1	21.73	18
441	Motor vehicle and parts dealers	4	21.72	65
443	Electronics and appliance stores	1	22.59	61
444	Building material and garden supply stores	2	165.97	69
445	Food and beverage stores	1	22.94	63
446	Health and personal care stores	3	54.50	90
448	Clothing and clothing accessories stores	6	24.96	90
452	General merchandise stores	7	86.42	74
453	Miscellaneous store retailers	1	11.02	71
454	Nonstore retailers	1	941.03	36
481	Air transportation	5	22.18	57
482	Rail transportation	4	62.54	48
483	Water transportation	3	22.59	72
484	Truck transportation	3	12.79	72
486	Pipeline transportation	2	38.06	36
488	Support activities for transportation	1	13.34	43
492	Couriers and messengers	2	61.17	26
511	Publishing industries, except Internet	14	120.79	8
515	Broadcasting, except Internet	8	80.18	21
517	Telecommunications	4	154.42	47
518	Data processing, hosting and related services	11	138.68	14
519	Other information services	10	102.25	11
523	Securities, commodity contracts, investments, and funds and trusts	17	36.47	9
524	Insurance carriers and related activities	26	42.40	22
531	Real estate	31	24.70	39
532	Rental and leasing services	2	78.61	54
541	Professional and technical services	16	23.29	13
561	Administrative and support services	6	27.44	32
562	Waste management and remediation services	2	38.56	54
621	Ambulatory health care services	4	22.06	67
622	Hospitals	2	30.73	62
711	Performing arts and spectator sports	1	15.35	29
721	Accommodation	5	33.62	43
722	Food services and drinking places	5	65.05	53
812	Personal and laundry services	1	28.08	52

Table A.3: Summary statistics for realized returns at the industry level

For each industry, we report firms' average realized cumulative risk-adjusted returns during the fever and the post-fever period. For details on the industries, see Table A.2. The computation of risk-adjusted returns follows Table 1.

		Fever period		Post-fever period	
NAICS	Description	CAPM-adj	FF5-adj	CAPM-adj	FF5-adj
211	Oil and gas extraction	-29.76	-9.77	-6.32	-6.11
212	Mining, except oil and gas	-19.32	-16.38	53.84	44.23
213	Support activities for mining	-37.94	-18.57	16.16	21.94
221	Utilities	-28.39	-32.49	20.77	17.66
236	Construction of buildings	-41.34	-45.69	68.27	54.07
237	Heavy and civil engineering construction	-32.36	-15.38	-29.60	-24.38
238	Specialty trade contractors	-3.48	12.72	51.49	50.52
311	Food manufacturing	-5.64	-7.07	7.83	4.43
312	Miscellaneous nondurable goods manufacturing	-12.68	-12.22	7.29	6.67
314	Textile product mills	-36.18	-27.35	41.31	39.55
315	Apparel	-15.38	0.37	8.07	7.52
321	Wood products	-28.35	-27.04	43.41	31.09
322	Paper and paper products	9.81	17.37	-11.74	-14.68
324	Petroleum and coal products	-24.55	-15.24	-14.17	-7.81
325	Chemicals	4.22	4.98	-7.41	-10.25
326	Plastics and rubber products	-6.67	-5.24	21.01	21.03
331	Primary metals	2.55	19.95	-11.69	-14.61
332	Fabricated metal products	-9.49	-5.48	7.11	3.48
333	Machinery	-1.66	8.26	-4.69	-5.00
334	Computer and electronic products	15.16	14.49	-12.56	-14.10
335	Electrical equipment and appliances	-1.50	11.00	4.64	-0.70
336	Transportation equipment	-16.45	-7.62	3.41	1.96
337	Furniture and related products	-15.22	-5.40	10.71	4.04
339	Miscellaneous durable goods manufacturing	-5.26	-11.17	7.04	-0.75
423	Wholesale trade: Durable goods	-9.63	-3.82	3.72	0.24
424	Wholesale trade: Nondurable goods	-7.23	-6.01	3.89	-4.51
425	Electronic markets and agents and brokers	-15.18	-18.74	38.57	36.02
441	Motor vehicle and parts dealers	-25.44	-24.56	32.37	28.73
443	Electronics and appliance stores	-8.21	4.03	0.30	-4.08
444	Building material and garden supply stores	-16.66	-14.54	26.06	26.80
445	Food and beverage stores	27.83	39.33	-27.30	-30.67
446	Health and personal care stores	2.10	8.52	-17.98	-24.95
448	Clothing and clothing accessories stores	-13.25	0.20	13.09	8.04
452	General merchandise stores	-4.64	2.03	7.77	10.82
453	Miscellaneous store retailers	5.26	8.43	12.34	8.29
454	Nonstore retailers	37.93	26.98	-15.83	-11.44
481	Air transportation	-39.04	-34.11	-0.67	3.60
482	Rail transportation	-4.59	6.11	1.76	1.90
483	Water transportation	-62.06	-59.22	49.93	52.05
484	Truck transportation	13.13	27.36	-7.53	-14.21
486	Pipeline transportation	-23.56	-20.41	-2.84	-2.30
488	Support activities for transportation	7.00	17.78	-5.25	-9.22
492	Couriers and messengers	25.63	43.66	2.90	-1.84
511	Publishing industries, except Internet	18.34	6.90	-6.94	-4.56
515	Broadcasting, except Internet	-16.84	-12.91	14.65	13.74
517	Telecommunications	-1.94	3.04	-8.85	-11.87
518	Data processing, hosting and related services	-1.70	-9.83	-1.74	0.99
519	Other information services	7.19	0.49	-11.95	-11.57
523	Securities, commodity contracts, investments, and funds and trusts	-0.18	10.50	-1.42	5.32
524	Insurance carriers and related activities	-16.05	-13.41	2.81	7.11
531	Real estate	-29.58	-34.80	18.64	10.13
532	Rental and leasing services	21.47	28.06	-12.41	-14.27
541	Professional and technical services	-10.26	-11.18	-0.37	-1.62
561	Administrative and support services	-5.36	-9.26	9.85	8.29
562	Waste management and remediation services	-11.36	-17.64	3.23	2.76
621	Ambulatory health care services	-11.12	-10.21	14.88	7.49
622	Hospitals	-27.33	-26.35	28.77	18.48
711	Performing arts and spectator sports	-31.80	-41.20	26.27	13.48
721	Accommodation	-17.92	-11.23	2.98	8.46
722	Food services and drinking places	-29.06	-34.46	58.94	55.86
812	Personal and laundry services	-13.31	-18.44	22.13	20.62

Table A.4: Summary statistics for changes in expected returns at the industry level

For each industry, we report averages of firms' changes in expected returns in excess of the market for 30- and 730-day horizons during the fever and the post-fever period. All values reported are *p.a.* For details on the industries, see Table A.2. The computation of changes in expected returns in excess of the market follows Table 2.

		Fever period		Post-fever period	
NAICS	Description	30-day	730-day	30-day	730-day
211	Oil and gas extraction	98.18	37.27	-88.01	-28.50
212	Mining, except oil and gas	19.29	10.34	-17.96	-8.80
213	Support activities for mining	115.65	42.21	-109.73	-37.75
221	Utilities	10.95	4.70	-11.19	-4.90
236	Construction of buildings	70.82	11.70	-67.96	-8.47
237	Heavy and civil engineering construction	101.75	48.40	-100.13	-33.71
238	Specialty trade contractors	11.40	8.96	-11.98	-8.07
311	Food manufacturing	-5.37	-0.92	4.78	-0.33
312	Miscellaneous nondurable goods manufacturing	-2.73	-0.38	1.20	-0.64
314	Textile product mills	27.92	12.38	-23.66	-8.07
315	Apparel	91.19	14.40	-90.50	-10.25
321	Wood products	60.82	13.16	-58.95	-12.40
322	Paper and paper products	7.75	1.72	-8.74	-2.34
324	Petroleum and coal products	28.71	6.50	-23.26	-3.73
325	Chemicals	5.27	2.65	-4.77	-2.14
326	Plastics and rubber products	64.37	9.90	-75.34	-10.99
331	Primary metals	32.35	1.60	-33.34	-2.14
332	Fabricated metal products	6.57	3.96	-6.80	-4.11
333	Machinery	21.32	7.61	-20.94	-7.29
334	Computer and electronic products	3.25	1.67	-3.75	-2.16
335	Electrical equipment and appliances	1.62	2.44	-6.76	-3.72
336	Transportation equipment	34.07	10.42	-32.75	-8.88
337	Furniture and related products	29.92	10.00	-36.97	-8.77
339	Miscellaneous durable goods manufacturing	8.61	3.56	-8.84	-3.87
423	Wholesale trade: Durable goods	17.24	8.96	-19.15	-8.69
424	Wholesale trade: Nondurable goods	6.96	0.04	-7.56	-0.20
425	Electronic markets and agents and brokers	24.72	11.08	-28.09	-13.58
441	Motor vehicle and parts dealers	23.67	6.98	-24.40	-7.55
443	Electronics and appliance stores	21.53	3.57	-27.81	-4.11
444	Building material and garden supply stores	1.92	-0.91	-4.93	-0.05
445	Food and beverage stores	-6.22	-2.79	1.44	0.60
446	Health and personal care stores	7.53	1.32	-9.32	-1.44
448	Clothing and clothing accessories stores	60.82	13.67	-60.13	-8.39
452	General merchandise stores	17.94	4.17	-17.63	-0.86
453	Miscellaneous store retailers	-4.51	-0.60	8.23	0.38
454	Nonstore retailers	-18.42	-3.67	18.72	3.99
481	Air transportation	225.59	39.22	-218.25	-27.93
482	Rail transportation	-2.88	-1.55	3.81	0.25
483	Water transportation	218.17	101.95	-204.17	-76.75
484	Truck transportation	-5.54	-0.26	5.81	-0.99
486	Pipeline transportation	68.58	10.80	-57.67	-10.20
488	Support activities for transportation	8.73	3.83	-9.22	-4.89
492	Couriers and messengers	-7.04	-1.99	6.35	1.91
511	Publishing industries, except Internet	2.41	11.09	-9.18	-11.79
515	Broadcasting, except Internet	26.75	6.05	-23.01	-4.65
517	Telecommunications	-5.35	-0.59	0.54	-0.33
518	Data processing, hosting and related services	8.28	2.95	-6.61	-2.30
519	Other information services	4.04	1.82	-4.19	-1.66
523	Securities, commodity contracts, investments, and funds and trusts	16.51	6.64	-17.03	-6.94
524	Insurance carriers and related activities	27.08	7.76	-26.84	-7.84
531	Real estate	31.72	12.71	-30.94	-8.34
532	Rental and leasing services	14.18	4.42	-12.99	-4.66
541	Professional and technical services	18.33	6.81	-18.55	-6.25
561	Administrative and support services	27.27	7.28	-28.45	-7.15
562	Waste management and remediation services	-3.09	-1.62	3.43	0.45
621	Ambulatory health care services	-2.23	3.34	2.03	-3.96
622	Hospitals	29.81	7.97	-29.79	-6.57
711	Performing arts and spectator sports	136.16	35.51	-137.25	-33.17
721	Accommodation	119.45	27.29	-116.32	-23.80
722	Food services and drinking places	28.41	4.32	-28.16	-4.18
812	Personal and laundry services	11.66	9.18	-15.31	-10.06

Table A.5: Risk-adjusted returns of stocks with high and low resilience to social distancing: KP

This table summarizes the results of firm-level cross-sectional regressions of cumulative risk-adjusted returns on resilience to disaster risk as in Table 1 but using the components of 'affected_share' as defined by Koren and Pető (2020). For details on the variable definitions, see Table A.1.

Measuring resilience as the negative of 'teamwork_share'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	3.77	2.99	3.13	−4.29	−4.49	−1.17
	[1.72]*	[1.38]	[1.43]	[−1.81]*	[−1.86]*	[−0.47]
	[0.62]	[0.52]	[0.51]	[−0.96]	[−0.99]	[−0.22]
Distancing	1.37	1.05	1.16	−0.93	−0.77	−0.63
	[6.06]***	[4.69]***	[5.23]***	[−3.57]***	[−2.97]***	[−2.37]**
	[2.90]***	[2.17]**	[2.45]**	[−2.32]**	[−1.97]**	[−1.23]
Adj-R^2	0.10	0.05	0.07	0.03	0.02	0.01
Firms	466	466	466	466	466	466

Measuring resilience as the negative of 'customer_share'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	−5.42	−3.63	−4.15	0.48	−0.85	0.21
	[−3.92]***	[−2.51]**	[−2.95]***	[0.31]	[−0.56]	[0.12]
	[−1.18]	[−0.82]	[−0.90]	[0.14]	[−0.26]	[0.06]
Distancing	0.20	0.18	0.20	−0.24	−0.22	−0.29
	[2.90]***	[2.49]**	[2.87]***	[−2.76]***	[−2.63]***	[−3.20]***
	[1.63]	[1.38]	[1.59]	[−2.00]**	[−1.84]*	[−2.12]**
Adj-R^2	0.02	0.02	0.02	0.02	0.02	0.03
Firms	466	466	466	466	466	466

Measuring resilience as the negative of 'communication_share'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	−3.22	−2.19	−2.26	−1.22	−2.50	−1.28
	[−1.99]**	[−1.29]	[−1.35]	[−0.67]	[−1.40]	[−0.67]
	[−0.64]	[−0.44]	[−0.44]	[−0.33]	[−0.69]	[−0.32]
Distancing	0.28	0.22	0.27	−0.28	−0.26	−0.31
	[3.66]***	[2.81]***	[3.39]***	[−3.10]***	[−2.98]***	[−3.30]***
	[1.91]*	[1.48]	[1.77]*	[−2.18]**	[−2.02]**	[−2.17]**
Adj-R^2	0.04	0.02	0.04	0.03	0.03	0.03
Firms	466	466	466	466	466	466

Measuring resilience as the negative of 'presence_share'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	−1.89	−0.61	−1.12	−1.24	−1.80	−0.31
	[−1.35]	[−0.42]	[−0.79]	[−0.78]	[−1.13]	[−0.18]
	[−0.45]	[−0.16]	[−0.27]	[−0.40]	[−0.55]	[−0.09]
Distancing	0.59	0.52	0.55	−0.47	−0.38	−0.43
	[6.05]***	[4.74]***	[5.66]***	[−4.38]***	[−3.55]***	[−4.08]***
	[2.68]***	[2.03]**	[2.43]**	[−2.70]***	[−2.16]**	[−2.31]**
Adj-R^2	0.11	0.08	0.09	0.05	0.03	0.04
Firms	466	466	466	466	466	466

Table A.6: Risk-adjusted returns of stocks with high and low resilience to social distancing: DN

This table summarizes the results of firm-level cross-sectional regressions of cumulative risk-adjusted returns on resilience to disaster risk as in Table 1, but instead using the measures provided by Dingel and Neiman (2020) to gauge the prevalence of work-from-home (WFH) relative to work-from-the-office/workplace (WFO). For details on the variable definitions, see Table A.1.

Measuring resilience by 'teleworkable_emp'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	−13.66	−8.49	−10.86	11.02	6.60	11.64
	[−7.64]***	[−4.38]***	[−5.91]***	[4.60]***	[2.77]***	[4.58]***
	[−3.14]***	[−1.83]*	[−2.39]**	[2.65]***	[1.61]	[2.49]**
Distancing	11.83	6.88	8.44	−17.07	−8.88	−17.33
	[3.54]***	[2.02]**	[2.57]**	[−4.20]***	[−2.11]**	[−3.93]***
	[1.48]	[0.90]	[1.09]	[−2.76]***	[−1.32]	[−2.39]**
Adj-R^2	0.02	0.00	0.01	0.03	0.01	0.02
Firms	497	497	497	497	497	497

Measuring resilience by 'teleworkable_wage'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	−16.72	−11.38	−13.81	15.23	9.99	16.23
	[−7.83]***	[−4.86]***	[−6.31]***	[5.24]***	[3.47]***	[5.29]***
	[−3.52]***	[−2.16]**	[−2.77]***	[3.16]***	[2.08]**	[2.99]***
Distancing	15.56	11.15	12.56	−22.07	−13.74	−23.00
	[4.34]***	[2.99]***	[3.52]***	[−4.95]***	[−3.01]***	[−4.79]***
	[1.70]*	[1.26]	[1.39]	[−3.05]***	[−1.73]*	[−2.73]***
Adj-R^2	0.03	0.01	0.02	0.05	0.02	0.04
Firms	497	497	497	497	497	497

Measuring resilience by 'teleworkable_manual_emp'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	−16.15	−11.18	−13.33	13.67	8.52	14.18
	[−8.57]***	[−5.42]***	[−6.90]***	[5.43]***	[3.43]***	[5.34]***
	[−3.61]***	[−2.22]**	[−2.84]***	[3.23]***	[2.10]**	[2.98]***
Distancing	18.42	13.70	14.80	−24.30	−13.93	−24.31
	[4.81]***	[3.48]***	[3.89]***	[−5.28]***	[−2.93]***	[−4.92]***
	[1.78]*	[1.40]	[1.45]	[−3.22]***	[−1.65]*	[−2.79]***
Adj-R^2	0.04	0.02	0.02	0.05	0.02	0.04
Firms	497	497	497	497	497	497

Measuring resilience by 'teleworkable_manual_wage'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	−19.70	−14.68	−16.81	18.20	12.27	19.01
	[−8.71]***	[−5.87]***	[−7.27]***	[6.07]***	[4.16]***	[6.04]***
	[−3.74]***	[−2.48]**	[−3.05]***	[3.73]***	[2.54]**	[3.48]***
Distancing	21.99	18.03	18.92	−28.71	−18.73	−29.30
	[5.52]***	[4.30]***	[4.73]***	[−5.98]***	[−3.81]***	[−5.73]***
	[2.01]**	[1.76]*	[1.74]*	[−3.73]***	[−2.07]**	[−3.32]***
Adj-R^2	0.06	0.03	0.04	0.07	0.03	0.06
Firms	497	497	497	497	497	497

Table A.7: Risk-adjusted returns of stocks with high and low resilience to social distancing: HLR

This table summarizes the results of firm-level cross-sectional regressions of cumulative risk-adjusted returns on resilience to disaster risk as in Table 1, but instead using the measures provided by Hensvik et al. (2020) to gauge the prevalence of work-from-home (WFH) relative to work-from-the-office/workplace (WFO). For details on the variable definitions, see Table A.1.

Measuring resilience as the negative of 'workplace'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	13.42	−3.20	7.87	−17.24	−15.68	−15.69
	[2.02]**	[−0.51]	[1.21]	[−2.45]**	[−2.25]**	[−2.05]**
	[0.94]	[−0.21]	[0.54]	[−1.49]	[−1.44]	[−1.16]
Distancing	26.88	3.21	18.57	−25.53	−22.59	−24.16
	[3.44]***	[0.43]	[2.43]**	[−3.00]***	[−2.69]***	[−2.61]***
	[1.71]*	[0.19]	[1.18]	[−1.93]*	[−1.82]*	[−1.54]
Adj-R^2	0.03	−0.00	0.01	0.02	0.01	0.01
Firms	475	475	475	475	475	475

Measuring resilience by 'home'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	−16.14	−6.41	−12.70	10.10	9.68	10.34
	[−8.87]***	[−3.08]***	[−6.84]***	[4.14]***	[4.11]***	[3.98]***
	[−3.58]***	[−1.12]	[−2.65]***	[2.24]**	[2.36]**	[2.01]**
Distancing	30.07	2.34	21.37	−25.67	−27.31	−24.91
	[4.47]***	[0.33]	[3.19]***	[−3.21]***	[−3.63]***	[−2.92]***
	[1.45]	[0.10]	[1.00]	[−1.47]	[−1.85]*	[−1.30]
Adj-R^2	0.04	−0.00	0.02	0.02	0.02	0.02
Firms	475	475	475	475	475	475

Measuring resilience by the negative of 'dur_workplace'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	8.56	−4.68	3.98	−13.18	−12.87	−10.87
	[1.66]*	[−0.91]	[0.78]	[−2.30]**	[−2.38]**	[−1.79]*
	[0.60]	[−0.30]	[0.27]	[−1.13]	[−1.31]	[−0.83]
Distancing	2.54	0.17	1.68	−2.49	−2.32	−2.22
	[3.54]***	[0.23]	[2.36]**	[−3.01]***	[−2.98]***	[−2.52]**
	[1.36]	[0.08]	[0.89]	[−1.57]	[−1.76]*	[−1.22]
Adj-R^2	0.02	−0.00	0.01	0.02	0.01	0.01
Firms	475	475	475	475	475	475

Measuring resilience by 'dur_home'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	−14.29	−7.88	−11.81	8.20	7.10	8.63
	[−9.96]***	[−5.27]***	[−8.35]***	[4.68]***	[4.13]***	[4.59]***
	[−3.88]***	[−1.85]*	[−3.07]***	[2.55]**	[2.27]**	[2.33]**
Distancing	5.99	2.14	4.69	−4.77	−4.50	−4.77
	[5.01]***	[2.17]**	[4.30]***	[−3.93]***	[−3.83]***	[−3.61]***
	[2.30]**	[0.80]	[1.78]*	[−2.31]**	[−2.22]**	[−1.96]**
Adj-R^2	0.06	0.00	0.03	0.03	0.02	0.02
Firms	475	475	475	475	475	475

Measuring resilience by 'share_home'

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	−14.97	−7.42	−12.08	9.19	8.07	9.53
	[−9.91]***	[−4.42]***	[−7.86]***	[4.71]***	[4.22]***	[4.53]***
	[−4.03]***	[−1.70]*	[−3.14]***	[2.64]***	[2.41]**	[2.37]**
Distancing	36.39	9.08	27.07	−31.59	−30.00	−31.08
	[4.99]***	[1.24]	[3.73]***	[−3.82]***	[−3.74]***	[−3.45]***
	[1.94]*	[0.43]	[1.40]	[−2.02]**	[−2.11]**	[−1.74]*
Adj-R^2	0.05	0.00	0.02	0.03	0.02	0.02
Firms	475	475	475	475	475	475

Table A.8: Risk-adjusted returns of stocks with high and low resilience to social distancing: Bai et al.

This table summarizes the results of firm-level cross-sectional regressions of cumulative risk-adjusted returns on resilience to disaster risk as in Table 1, but instead using the work-from-home measure provided by Bai et al. (2021) to gauge the prevalence of work-from-home (WFH) relative to work-from-the-office/workplace (WFO). For details on the variable definitions, see Table A.1.

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	−21.81	−16.57	−19.06	19.55	13.88	20.20
	[−7.19]***	[−4.74]***	[−6.13]***	[4.29]***	[3.21]***	[4.14]***
	[−5.09]***	[−3.18]***	[−4.25]***	[3.25]***	[2.39]**	[2.89]***
Distancing	20.30	16.39	17.58	−24.82	−16.82	−24.71
	[4.54]***	[3.29]***	[3.87]***	[−3.88]***	[−2.70]***	[−3.59]***
	[3.35]***	[2.68]***	[2.88]***	[−3.11]***	[−1.92]*	[−2.63]***
Adj-R^2	0.05	0.03	0.04	0.06	0.03	0.05
Firms	347	347	347	347	347	347

Table A.9: Expected returns in excess of the market for stocks with high and low resilience to social distancing: KP

This table summarizes the results of firm-level cross-sectional regressions of changes in expected returns in excess of the market on resilience to disaster risk as in Table 2, but using the components of 'affected_share' as defined by Koren and Pető (2020). For details on the variable definitions, see Table A.1.

Measuring resilience as the negative of 'teamwork_share'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	10.10	2.76	1.68	2.33	3.35	−11.03	−3.01	−1.81	−2.37	−3.21
	[1.91]*	[1.08]	[0.80]	[1.09]	[1.84]*	[−2.17]**	[−1.31]	[−1.00]	[−1.25]	[−2.07]**
	[1.00]	[0.57]	[0.43]	[0.63]	[1.10]	[−1.15]	[−0.70]	[−0.54]	[−0.76]	[−1.31]
Distancing	−1.59	−0.85	−0.77	−0.71	−0.52	1.45	0.72	0.64	0.60	0.41
	[−2.77]***	[−2.99]***	[−3.17]***	[−2.91]***	[−2.63]***	[2.64]***	[2.82]***	[3.05]***	[2.78]***	[2.44]**
	[−1.53]	[−1.57]	[−1.61]	[−1.56]	[−1.51]	[1.50]	[1.52]	[1.59]	[1.54]	[1.48]
Adj-R^2	0.02	0.03	0.04	0.03	0.02	0.02	0.03	0.04	0.03	0.02
Firms	466	466	466	466	466	466	466	466	466	466

Measuring resilience as the negative of 'customer_share'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	19.32	7.85	7.13	8.05	7.65	−18.91	−7.23	−6.46	−7.43	−6.89
	[6.61]***	[6.07]***	[6.37]***	[6.84]***	[7.54]***	[−6.69]***	[−6.42]***	[−6.88]***	[−7.35]***	[−8.26]***
	[3.31]***	[2.63]***	[2.76]***	[3.14]***	[3.81]***	[−3.46]***	[−2.82]***	[−3.00]***	[−3.44]***	[−4.42]***
Distancing	−0.33	−0.16	−0.09	−0.04	−0.02	0.34	0.14	0.07	0.02	−0.00
	[−1.87]*	[−2.18]**	[−1.58]	[−0.81]	[−0.47]	[1.95]*	[2.12]**	[1.46]	[0.43]	[−0.10]
	[−1.22]	[−1.27]	[−0.98]	[−0.52]	[−0.34]	[1.28]	[1.21]	[0.88]	[0.27]	[−0.07]
Adj-R^2	0.01	0.01	0.00	−0.00	−0.00	0.01	0.01	0.00	−0.00	−0.00
Firms	466	466	466	466	466	466	466	466	466	466

Measuring resilience as the negative of 'communication_share'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	15.17	5.83	5.49	6.72	6.70	−15.00	−5.49	−5.09	−6.35	−6.21
	[4.54]***	[4.07]***	[4.63]***	[5.48]***	[6.03]***	[−4.61]***	[−4.36]***	[−5.11]***	[−6.05]***	[−6.78]***
	[2.52]**	[1.96]**	[2.26]**	[2.81]***	[3.37]***	[−2.63]***	[−2.12]**	[−2.50]**	[−3.15]***	[−4.00]***
Distancing	−0.49	−0.24	−0.16	−0.10	−0.07	0.48	0.21	0.13	0.07	0.03
	[−2.60]***	[−2.98]***	[−2.68]***	[−2.07]**	[−1.45]	[2.62]***	[2.86]***	[2.54]**	[1.76]*	[0.90]
	[−1.69]*	[−1.75]*	[−1.71]*	[−1.41]	[−1.09]	[1.72]*	[1.64]	[1.57]	[1.16]	[0.69]
Adj-R^2	0.02	0.03	0.02	0.01	0.00	0.02	0.02	0.02	0.00	−0.00
Firms	466	466	466	466	466	466	466	466	466	466

Measuring resilience as the negative of 'presence_share'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	18.05	7.00	5.33	5.36	4.80	−18.45	−6.81	−5.09	−5.14	−4.52
	[5.57]***	[4.55]***	[4.33]***	[4.17]***	[4.05]***	[−5.85]***	[−4.96]***	[−4.85]***	[−4.63]***	[−4.67]***
	[2.97]***	[2.36]**	[2.33]**	[2.45]**	[2.51]**	[−3.16]***	[−2.61]***	[−2.65]***	[−2.78]***	[−3.01]***
Distancing	−0.56	−0.30	−0.28	−0.30	−0.29	0.49	0.23	0.22	0.23	0.21
	[−2.10]**	[−2.13]**	[−2.43]**	[−2.43]**	[−2.42]**	[1.94]*	[1.92]*	[2.25]**	[2.26]**	[2.28]**
	[−1.19]	[−1.19]	[−1.36]	[−1.41]	[−1.45]	[1.11]	[1.08]	[1.28]	[1.34]	[1.42]
Adj-R^2	0.02	0.02	0.03	0.04	0.05	0.01	0.02	0.03	0.03	0.04
Firms	466	466	466	466	466	466	466	466	466	466

Table A.10: Expected returns in excess of the market for stocks with high and low resilience to social distancing: DN

This table summarizes the results of firm-level cross-sectional regressions changes in expected returns in excess of the market on resilience to disaster risk as in Table 2, but instead using the measures provided by Dingel and Neiman (2020) to gauge the prevalence of work-from-home (WFH) relative to work-from-the-office/workplace (WFO). For details on the variable definitions, see Table A.1.

Measuring resilience by 'teleworkable_emp'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	34.82	14.02	11.34	10.24	9.02	−33.73	−12.47	−9.80	−8.67	−7.09
	[6.80]***	[5.87]***	[6.31]***	[6.25]***	[5.91]***	[−6.78]***	[−5.78]***	[−6.36]***	[−6.25]***	[−5.74]***
	[3.61]***	[3.10]***	[3.43]***	[3.62]***	[3.63]***	[−3.62]***	[−3.05]***	[−3.46]***	[−3.69]***	[−3.68]***
WFH vs WFO	−0.23	−0.08	−0.06	−0.03	−0.02	0.21	0.07	0.05	0.02	0.00
	[−2.68]***	[−2.14]**	[−2.15]**	[−1.12]	[−0.82]	[2.56]**	[1.94]*	[1.96]**	[0.74]	[0.15]
	[−1.53]	[−1.20]	[−1.29]	[−0.81]	[−0.60]	[1.50]	[1.10]	[1.19]	[0.55]	[0.12]
Adj-R^2	0.01	0.01	0.01	0.00	−0.00	0.01	0.00	0.00	−0.00	−0.00
Firms	497	497	497	497	497	497	497	497	497	497

Measuring resilience by 'teleworkable_wage'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	36.18	14.67	11.82	10.51	9.26	−34.99	−12.97	−10.15	−8.82	−7.18
	[6.17]***	[5.34]***	[5.61]***	[5.30]***	[4.92]***	[−6.16]***	[−5.25]***	[−5.65]***	[−5.24]***	[−4.70]***
	[3.45]***	[2.93]***	[3.19]***	[3.24]***	[3.16]***	[−3.47]***	[−2.87]***	[−3.22]***	[−3.27]***	[−3.15]***
WFH vs WFO	−0.21	−0.08	−0.06	−0.03	−0.02	0.20	0.07	0.05	0.02	0.00
	[−2.47]**	[−2.02]**	[−1.97]**	[−1.03]	[−0.77]	[2.37]**	[1.83]*	[1.79]*	[0.68]	[0.18]
	[−1.42]	[−1.12]	[−1.13]	[−0.67]	[−0.53]	[1.40]	[1.03]	[1.05]	[0.46]	[0.13]
Adj-R^2	0.01	0.01	0.00	0.00	−0.00	0.01	0.00	0.00	−0.00	−0.00
Firms	497	497	497	497	497	497	497	497	497	497

Measuring resilience by 'teleworkable_manual_emp'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	36.02	14.86	12.17	11.22	9.78	−34.83	−13.04	−10.38	−9.41	−7.60
	[7.10]***	[6.27]***	[6.62]***	[6.41]***	[6.05]***	[−7.06]***	[−6.12]***	[−6.58]***	[−6.28]***	[−5.72]***
	[3.96]***	[3.42]***	[3.68]***	[3.76]***	[3.73]***	[−3.98]***	[−3.35]***	[−3.69]***	[−3.77]***	[−3.74]***
WFH vs WFO	−0.27	−0.11	−0.09	−0.06	−0.04	0.25	0.09	0.07	0.04	0.02
	[−3.06]***	[−2.71]***	[−2.80]***	[−1.78]*	[−1.38]	[2.90]***	[2.37]**	[2.48]**	[1.29]	[0.60]
	[−1.76]*	[−1.53]	[−1.69]*	[−1.26]	[−0.97]	[1.72]*	[1.37]	[1.52]	[0.95]	[0.45]
Adj-R^2	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.00	−0.00
Firms	497	497	497	497	497	497	497	497	497	497

Measuring resilience by 'teleworkable_manual_wage'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	36.36	15.16	12.49	11.60	10.12	−35.07	−13.17	−10.57	−9.64	−7.79
	[6.39]***	[5.67]***	[5.92]***	[5.59]***	[5.16]***	[−6.36]***	[−5.51]***	[−5.86]***	[−5.43]***	[−4.84]***
	[3.73]***	[3.19]***	[3.40]***	[3.38]***	[3.25]***	[−3.76]***	[−3.12]***	[−3.41]***	[−3.36]***	[−3.20]***
WFH vs WFO	−0.22	−0.09	−0.08	−0.06	−0.04	0.21	0.07	0.06	0.04	0.02
	[−2.56]**	[−2.31]**	[−2.41]**	[−1.63]	[−1.28]	[2.42]**	[1.97]**	[2.10]**	[1.19]	[0.61]
	[−1.46]	[−1.27]	[−1.39]	[−1.06]	[−0.84]	[1.42]	[1.11]	[1.24]	[0.80]	[0.42]
Adj-R^2	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.00	−0.00
Firms	497	497	497	497	497	497	497	497	497	497

Table A.11: Expected returns in excess of the market for stocks with high and low resilience to social distancing: HLR

This table summarizes the results of firm-level cross-sectional regressions of changes in expected returns in excess of the market on resilience to disaster risk as in Table 2, but instead using the measures provided by Hensvik et al. (2020) to gauge the prevalence of work-from-home (WFH) relative to work-from-the-office/workplace (WFO). For details on the variable definitions, see Table A.1.

Measuring resilience as the negative of 'workplace'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	30.44	14.32	10.96	10.89	11.03	−30.61	−12.75	−9.14	−9.00	−8.59
	[1.84]*	[1.79]*	[1.68]*	[1.63]	[1.79]*	[−1.94]*	[−1.82]*	[−1.66]*	[−1.58]	[−1.77]*
	[1.09]	[1.02]	[0.98]	[0.99]	[1.09]	[−1.16]	[−1.06]	[−0.99]	[−0.99]	[−1.13]
WFH vs WFO	0.07	0.05	0.03	0.03	0.04	−0.08	−0.04	−0.02	−0.01	−0.02
	[0.38]	[0.51]	[0.39]	[0.34]	[0.51]	[−0.45]	[−0.48]	[−0.29]	[−0.22]	[−0.34]
	[0.23]	[0.29]	[0.22]	[0.20]	[0.31]	[−0.27]	[−0.27]	[−0.17]	[−0.13]	[−0.22]
Adj-R^2	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00
Firms	475	475	475	475	475	475	475	475	475	475

Measuring resilience by 'home'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	34.49	14.97	12.26	12.09	11.05	−33.08	−13.67	−10.97	−10.95	−9.68
	[6.63]***	[6.22]***	[6.32]***	[6.41]***	[6.36]***	[−6.63]***	[−6.42]***	[−6.67]***	[−6.89]***	[−7.05]***
	[4.02]***	[3.32]***	[3.28]***	[3.39]***	[3.73]***	[−4.12]***	[−3.49]***	[−3.55]***	[−3.73]***	[−4.43]***
WFH vs WFO	−0.40	−0.18	−0.15	−0.13	−0.12	0.37	0.16	0.13	0.12	0.11
	[−2.36]**	[−2.39]**	[−2.48]**	[−2.25]**	[−2.21]**	[2.24]**	[2.44]**	[2.61]***	[2.40]**	[2.39]**
	[−1.73]*	[−1.52]	[−1.56]	[−1.43]	[−1.39]	[1.67]*	[1.65]*	[1.77]*	[1.69]*	[1.76]*
Adj-R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Firms	475	475	475	475	475	475	475	475	475	475

Measuring resilience by the negative of 'dur_workplace'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	29.11	13.44	9.57	9.79	10.21	−30.21	−11.87	−7.75	−7.82	−7.80
	[2.35]**	[2.23]**	[1.90]*	[1.83]*	[2.18]**	[−2.54]**	[−2.24]**	[−1.81]*	[−1.68]*	[−2.04]**
	[1.39]	[1.22]	[1.05]	[1.08]	[1.32]	[−1.55]	[−1.28]	[−1.04]	[−1.05]	[−1.38]
WFH vs WFO	0.01	0.00	0.00	0.00	0.00	−0.01	−0.00	−0.00	−0.00	−0.00
	[0.41]	[0.53]	[0.22]	[0.22]	[0.49]	[−0.57]	[−0.46]	[−0.04]	[−0.01]	[−0.22]
	[0.23]	[0.27]	[0.11]	[0.12]	[0.28]	[−0.34]	[−0.25]	[−0.02]	[−0.00]	[−0.14]
Adj-R^2	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00
Firms	475	475	475	475	475	475	475	475	475	475

Measuring resilience by 'dur_home'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	29.02	13.02	10.64	10.81	9.91	−28.07	−11.80	−9.39	−9.62	−8.52
	[7.00]***	[7.31]***	[7.39]***	[8.08]***	[8.29]***	[−7.09]***	[−7.45]***	[−7.71]***	[−8.57]***	[−9.08]***
	[4.05]***	[3.64]***	[3.64]***	[3.92]***	[4.51]***	[−4.13]***	[−3.73]***	[−3.80]***	[−4.14]***	[−5.04]***
WFH vs WFO	−0.05	−0.03	−0.02	−0.02	−0.02	0.04	0.02	0.02	0.02	0.02
	[−1.42]	[−2.27]**	[−2.34]**	[−2.71]***	[−2.70]***	[1.35]	[2.19]**	[2.30]**	[2.78]***	[2.79]***
	[−1.17]	[−1.56]	[−1.59]	[−1.75]*	[−1.85]*	[1.11]	[1.54]	[1.61]	[1.84]*	[2.05]**
Adj-R^2	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01
Firms	475	475	475	475	475	475	475	475	475	475

Measuring resilience by 'share_home'

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	29.29	12.76	10.56	10.71	9.92	−28.21	−11.58	−9.36	−9.59	−8.57
	[7.50]***	[6.98]***	[7.02]***	[7.36]***	[7.55]***	[−7.57]***	[−7.19]***	[−7.39]***	[−7.84]***	[−8.30]***
	[4.11]***	[3.44]***	[3.40]***	[3.60]***	[4.23]***	[−4.22]***	[−3.57]***	[−3.60]***	[−3.84]***	[−4.80]***
WFH vs WFO	−0.28	−0.13	−0.12	−0.11	−0.10	0.25	0.11	0.10	0.10	0.09
	[−1.67]*	[−1.78]*	[−1.97]**	[−1.99]**	[−2.12]**	[1.54]	[1.73]*	[1.97]**	[2.03]**	[2.16]**
	[−1.21]	[−1.15]	[−1.27]	[−1.31]	[−1.43]	[1.13]	[1.16]	[1.32]	[1.42]	[1.65]*
Adj-R^2	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01
Firms	475	475	475	475	475	475	475	475	475	475

Table A.12: Expected returns in excess of the market for stocks with high and low resilience to social distancing: Bai et al.

This table summarizes the results of firm-level cross-sectional regressions of changes in expected returns in excess of the market on resilience to disaster risk as in Table 2, but instead using the work-from-home measure provided by Bai et al. (2021) to gauge the prevalence of work-from-home (WFH) relative to work-from-the-office/workplace (WFO). For details on the variable definitions, see Table A.1.

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	44.89	19.41	16.86	16.05	13.75	−45.24	−18.07	−15.07	−14.19	−11.66
	[5.57]***	[4.91]***	[5.40]***	[5.08]***	[5.23]***	[−5.71]***	[−4.97]***	[−5.45]***	[−4.90]***	[−4.87]***
	[4.17]***	[3.40]***	[3.80]***	[3.67]***	[3.84]***	[−4.25]***	[−3.48]***	[−3.91]***	[−3.59]***	[−3.71]***
WFH vs WFO	−0.34	−0.15	−0.14	−0.12	−0.10	0.35	0.14	0.13	0.11	0.08
	[−3.08]***	[−2.91]***	[−3.44]***	[−3.03]***	[−2.86]***	[3.24]***	[2.99]***	[3.50]***	[2.92]***	[2.59]***
	[−2.42]**	[−2.18]**	[−2.62]***	[−2.33]**	[−2.21]**	[2.52]**	[2.21]**	[2.64]***	[2.21]**	[1.99]**
Adj-R^2	0.03	0.03	0.04	0.03	0.03	0.03	0.03	0.04	0.03	0.02
Firms	347	347	347	347	347	347	347	347	347	347

Table A.13: Risk-adjusted returns of high and low resilience stocks: large sample

This table summarizes the results of firm-level cross-sectional regressions of cumulative risk-adjusted returns on resilience to social distancing. The sample covers all firms for which we have CRSP, COMPUSTAT, OptionMetrics, and resilience data. We present results for two sub-periods of 2020: the 'fever-period' (from February 24 to March 20) and the 'post-fever period' (after March 20). For both periods, we compute each firm's cumulative CAPM-adjusted return (controlling for exposure to market risk), its cumulative Fama-French five factor model-adjusted return (controlling for exposures to market, size, value, investments, profitability), and its cumulative q-factor model-adjusted return (controlling for exposures to market, size, investments, profitability) following Hou et al. (2015, HXZ). The measure of firms' resilience to social distancing is the negative of their respective 'affected_share' (as defined by Koren and Pető, 2020). We report regression coefficient estimates and two sets of t-statistics: the first is based on robust standard errors following White (1980), whereas the second is based on standard errors clustered at the NAICS 3-digit-code industry level.

	Fever period			Post-fever period		
	CAPM-adj	FF5-adj	HXZ-adj	CAPM-adj	FF5-adj	HXZ-adj
constant	−0.16	0.10	4.10	0.90	−4.77	−5.24
	[−0.15]	[0.08]	[3.48]***	[0.36]	[−2.11]**	[−2.32]**
	[−0.04]	[0.02]	[0.72]	[0.14]	[−0.69]	[−0.69]
Distancing	0.31	0.17	0.30	−0.57	−0.50	−0.56
	[8.41]***	[3.81]***	[7.32]***	[−6.30]***	[−6.25]***	[−7.11]***
	[2.60]***	[1.25]	[2.17]**	[−2.11]**	[−2.09]**	[−2.45]**
Adj-R^2	0.04	0.01	0.03	0.03	0.03	0.03
Firms	2274	2274	2274	2274	2274	2274

Table A.14: Risk-neutral variances of high and low resilience stocks: large sample

This table summarizes the results of firm-level cross-sectional regressions of changes in risk-neutral variances on resilience to social distancing. The sample covers all firms for which we have CRSP, COMPUSTAT, OptionMetrics, and resilience data. We present results for two sub-periods of 2020: the 'fever-period' (from February 24 to March 20) and the 'post-fever period' (after March 20). For both periods, we compute each firm's change in its risk-neutral variance for horizons, i.e. options maturities, of 30, 91, 182, 365, and 730 days. The measure of firms' resilience to social distancing is the negative of their respective 'affected_share' (as defined by Koren and Pető, 2020). We report regression coefficient estimates and two sets of t-statistics: the first is based on robust standard errors following White (1980), whereas the second is based on standard errors clustered at the NAICS 3-digit-code industry level.

	Fever period					Post-fever period				
	30	91	182	365	730	30	91	182	365	730
constant	111.41	78.37	68.85	72.05	67.72	−133.27	−77.13	−62.91	−65.53	−59.01
	[21.74]***	[20.88]***	[19.57]***	[19.27]***	[22.47]***	[−26.37]***	[−19.59]***	[−17.40]***	[−17.29]***	[−19.39]***
	[12.23]***	[15.99]***	[14.15]***	[14.27]***	[15.61]***	[−13.01]***	[−14.69]***	[−13.80]***	[−14.22]***	[−14.92]***
Distancing	−0.79	−0.47	−0.33	−0.34	−0.31	0.82	0.42	0.26	0.26	0.22
	[−4.62]***	[−4.29]***	[−3.23]***	[−3.06]***	[−3.30]***	[5.12]***	[3.70]***	[2.51]**	[2.28]**	[2.37]**
	[−2.42]**	[−2.40]**	[−1.98]**	[−1.93]*	[−1.90]*	[2.38]**	[2.11]**	[1.57]	[1.44]	[1.39]
Adj-R^2	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
Firms	2274	2274	2274	2274	2274	2274	2274	2274	2274	2274

Table A.15: Link between risk-neutral variances and realized returns: large sample

This table summarizes the results of firm-level cross-sectional regressions of changes in risk-neutral variances on cumulative risk-adjusted returns during the 'fever-period' (from February 24 to March 20). The sample covers all firms for which we have CRSP, COMPUSTAT, OptionMetrics, and resilience data. We compute each firm's change in its risk-neutral variance from options data for horizons, i.e. options maturities, of 30, 91, 182, 365, and 730 days. In Panel A, we present results for CAPM-adjusted returns, i.e. controlling for exposure to market risk. Panel B presents results controlling for the Fama-French five factor model exposures (i.e. market, size, value, investments, profitability). Panel C presents results controlling for the q-factors (i.e. market, size, investments, profitability) proposed by Hou et al. (2015). We report regression coefficient estimates and two sets of t-statistics: the first is based on robust standard errors following White (1980), whereas the second is based on standard errors clustered at the NAICS 3-digit-code industry level.

Panel A. CAPM-adjusted returns

	Changes in risk-neutral variances ($SVIX^2_{i,t}$)				
	30	91	182	365	730
constant	120.82	81.79	70.27	72.83	68.93
	[32.71]***	[21.79]***	[23.08]***	[28.45]***	[39.32]***
	[20.17]***	[15.30]***	[13.84]***	[13.67]***	[15.25]***
Realized return	−1.40	−1.09	−0.88	−0.99	−0.83
	[−5.57]***	[−3.53]***	[−3.72]***	[−5.93]***	[−10.20]***
	[−4.44]***	[−3.53]***	[−3.68]***	[−4.81]***	[−6.40]***
Adj-R^2	0.08	0.08	0.06	0.07	0.08
Firms	2274	2274	2274	2274	2274

Panel B. FF5-adjusted returns

	Changes in risk-neutral variances ($SVIX^2_{i,t}$)				
	30	91	182	365	730
constant	128.86	88.15	75.65	78.87	74.06
	[41.61]***	[34.42]***	[33.28]***	[35.23]***	[42.33]***
	[22.39]***	[20.38]***	[18.52]***	[18.60]***	[20.61]***
Realized return	−0.84	−0.64	−0.46	−0.52	−0.43
	[−5.22]***	[−3.31]***	[−3.12]***	[−4.80]***	[−6.64]***
	[−4.30]***	[−3.29]***	[−3.23]***	[−4.55]***	[−5.50]***
Adj-R^2	0.04	0.04	0.02	0.03	0.03
Firms	2274	2274	2274	2274	2274

Panel C. HXZ-adjusted returns

	Changes in risk-neutral variances ($SVIX^2_{i,t}$)				
	30	91	182	365	730
constant	128.59	87.91	75.44	78.67	73.85
	[41.47]***	[33.82]***	[32.89]***	[35.17]***	[42.69]***
	[21.27]***	[18.50]***	[16.45]***	[16.32]***	[17.80]***
Realized return	−1.04	−0.79	−0.58	−0.65	−0.54
	[−5.39]***	[−3.37]***	[−3.27]***	[−5.13]***	[−8.12]***
	[−3.83]***	[−3.30]***	[−3.10]***	[−3.61]***	[−4.20]***
Adj-R^2	0.05	0.05	0.03	0.04	0.04
Firms	2274	2274	2274	2274	2274

Table A.16: Predictive regressions for realized returns during the post-fever period

The table presents results of regressing S&P 500 firms' post-fever period realized returns on changes in their fever period expected returns. We present results separately for low resilience firms (Panel A) and high resilience firms (Panel B), where the resilience classification is based on firms' asset price responses during the fever-period. We identify low-resilience firms as those which, during the fever period (F), featured negative realized cumulative FF5-adjusted returns (i.e., $\text{ff5}^F < 0$) and increases in one-month expected returns in excess of the market (i.e., $\Delta E^F > 0$). Conversely, we identify high-resilience firms as those featuring positive realized cumulative risk-adjusted returns (i.e., $\text{ff5}^F > 0$) and decreases in expected returns in excess of the market (i.e., $\Delta E^F < 0$). We present results for predictive regressions of firms' post-fever FF5-adjusted returns on their fever period changes in expected returns in excess of the market, using horizons of 30, 91, 182, 365, and 730 days. We report regression coefficient estimates and two sets of t-statistics: the first is based on robust standard errors following White (1980), whereas the second is based on standard errors clustered at the NAICS 3-digit-code industry level.

Panel A. Low-resilience firms

	30	91	182	365	730
constant	6.27	7.70	7.85	8.75	8.63
	[3.20]***	[3.96]***	[4.20]***	[4.81]***	[4.47]***
	[2.56]**	[3.12]***	[3.41]***	[4.08]***	[3.62]***
ΔE_T^F	0.14	0.27	0.33	0.28	0.31
	[3.54]***	[3.08]***	[3.20]***	[3.13]***	[3.20]***
	[2.84]***	[2.41]**	[2.58]***	[2.70]***	[2.95]***
Adj R^2	0.11	0.10	0.09	0.07	0.06
Firms	213	213	213	213	213

Panel B. High-resilience firms

	30	91	182	365	730
constant	−8.35	−8.10	−9.63	−11.23	−12.84
	[−2.15]**	[−2.74]***	[−3.73]***	[−5.24]***	[−6.60]***
	[−1.84]*	[−3.09]***	[−3.71]***	[−4.51]***	[−5.26]***
ΔE_T^F	0.56	1.41	1.54	1.40	0.54
	[1.56]	[2.38]**	[2.04]**	[1.94]*	[0.98]
	[1.22]	[2.17]**	[1.82]*	[1.63]	[0.90]
Adj R^2	0.02	0.04	0.03	0.02	−0.00
Firms	98	98	98	98	98

Table A.17: Predictive regressions for changes in expected returns during the post-fever period

This table presents results of regressing S&P 500 firms' post-fever period changes in expected returns on changes in their fever period expected returns. We present results separately for low resilience firms (Panel A) and high resilience firms (Panel B), where the resilience classification is based on firms' asset price responses during the fever-period, i.e. from Feb 24 to Mar 20, 2020. We identify low-resilience firms as those which, during the fever period (F), featured negative realized cumulative FF5-adjusted returns (i.e., $\text{ff5}^F < 0$) and increases in one-month expected returns in excess of the market (i.e., $\Delta E^F > 0$). Conversely, we identify high-resilience firms as those featuring positive realized cumulative risk-adjusted returns (i.e., $\text{ff5}^F > 0$) and decreases in expected returns in excess of the market (i.e., $\Delta E^F < 0$). We present results for predictive regressions of firms' post-fever changes in expected returns in excess of the market on their fever period changes in expected returns in excess of the market, using horizons of 30, 91, 182, 365, and 730 days. We report regression coefficients and two sets of t-statistics: the first is based on robust standard errors following White (1980), whereas the second is based on standard errors clustered at the NAICS 3-digit-code industry level. For both types of standard errors, we also present p-values for testing the null hypothesis that the regression coefficient equals -1.

Panel A. Low-resilience firms

	30	91	182	365	730
constant	-0.35	0.08	-0.03	0.12	-0.27
	[-0.68]	[0.26]	[-0.12]	[0.30]	[-0.62]
	[-0.64]	[0.21]	[-0.09]	[0.32]	[-0.56]
ΔE_T^F	-0.96	-0.88	-0.84	-0.85	-0.79
	[-142.88]***	[-56.14]***	[-50.98]***	[-38.04]***	[-26.06]***
	[-110.99]***	[-49.80]***	[-56.21]***	[-37.94]***	[-22.55]***
$p(H_0 : b = -1)$	0.00	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	0.00	0.00
Adj R^2	0.98	0.98	0.97	0.95	0.89
Firms	213	213	213	213	213

Panel B. High-resilience firms

	30	91	182	365	730
constant	-0.12	-0.96	-0.98	-0.85	-0.87
	[-0.25]	[-5.91]***	[-8.97]***	[-8.82]***	[-8.78]***
	[-0.30]	[-7.89]***	[-8.85]***	[-8.08]***	[-5.93]***
ΔE_T^F	-0.89	-1.04	-1.04	-0.99	-1.00
	[-15.49]***	[-21.26]***	[-25.17]***	[-21.35]***	[-30.04]***
	[-15.19]***	[-23.64]***	[-33.04]***	[-23.56]***	[-40.95]***
$p(H_0 : b = -1)$	0.07	0.43	0.36	0.90	0.95
	0.08	0.38	0.23	0.89	0.93
Adj R^2	0.76	0.77	0.82	0.82	0.86
Firms	98	98	98	98	98

Table A.18: Predicting post-fever realized returns with options-implied expected returns

This table presents cross-sectional regression results of predicting post-fever realized returns with options-implied expected returns measured at the end of the fever period. On March 20, 2020, we compute expected returns in excess of the market (following Martin and Wagner, 2019) for forecast horizons of 30 days, 91 days, 182 days and until the end of the year 2020. We compute realized returns in excess of the market over the same horizons and present results for cross-sectional regressions of T-period realized returns on the appropriately lagged T-horizon expected returns. The table reports the coefficient estimates (b) along with two sets of t-statistics; the first is based on robust standard errors following White (1980), whereas the second is based on standard errors clustered at the NAICS 3-digit-code industry level. Additionally, we present two sets of p-values (White and clustered) for the null hypothesis that the predictive regression coefficient is equal to one. The last two rows report the adjusted R-squared of the regressions and the number of firms included in the sample.

	30 days	91 days	182 days	End of 2020
b	0.30	1.49	0.78	0.93
	[1.74]*	[6.56]***	[4.77]***	[7.13]***
	[1.34]	[4.24]***	[4.82]***	[5.74]***
$p(H_0 : b = 1)$	0.00	0.03	0.18	0.58
	0.00	0.16	0.17	0.65
Adj-R^2	0.01	0.25	0.12	0.23
Firms	498	498	498	498

Table A.19: Summary statistics of firm characteristics

This table presents summary statistics and pairwise correlations of S&P 500 firms' characteristics that may proxy for disaster resilience. The cash ratio is defined as cash (Compustat item *che*) divided by total assets (*at*). We measure leverage as book debt ($dlc + dltt$) divided by total assets (*at*). For all quantities we use the latest data available at the end of 2019. 'Environment' denotes the latest via WRDS available environmental score from Sustainalytics, which is for most firms from September 2019. Distancing refers to the negative of 'affected_share' (as defined by Koren and Pető, 2020).

	Cash	Lev	Env	Dist
Summary statistics				
mean	10.81	31.46	59.66	72.39
std. dev.	12.75	17.78	13.32	19.29
Correlations				
Cash		-0.21^{***}	0.10^{**}	0.28^{***}
Leverage	-0.21^{***}		0.13^{**}	-0.20^{***}
Environment	0.10^{**}	0.13^{**}		0.13^{***}
Distancing	0.28^{***}	-0.20^{***}	0.13^{***}	