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Stock valuation during the COVID-19 pandemic: An explanation using option-based discount rates

Henk Berkman a,*, Hamish Malloch b

a The University of Auckland Business School, New Zealand
b The University of Sydney Business School, Australia

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Changes in short-term expected market returns (discount rates) were a significant driver behind the unprecedented fluctuations in equity markets during the first 4 months of the COVID-19 pandemic. Using option-based estimates of the expected market risk premium for 13 international markets, we find that approximately 40% of the change in market values during the COVID-19 pandemic can be attributed to changes in short-term discount rates. We also document sharply downward sloping term structures of equity risk premia at the start of the pandemic, consistent with Hasler and Marfe (2016). Finally, we document a significant increase in the correlation between index returns and changes in the short-term discount rate during the pandemic compared to the period before the pandemic.

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1. Introduction

The outbreak of the SARS-CoV-2 coronavirus in late 2019, hereafter referred to as the COVID-19 pandemic, significantly impacted economies around the world as efforts to slow the spread of the virus required large scale shut-downs. At the same time, from the early days of the pandemic, there was a widely held belief that the availability of a vaccine would allow economies to be fully operational again within 12 to 18 months (see Hong et al., 2020). Despite this expectation of a relatively fast recovery, stock markets around the world crashed in March 2020, with losses of more than 25%. Equally remarkable was the quick bounce back of stock markets in the next few months, exhibiting returns of around 20%. What explains these extremely large swings in market valuations during the first half of 2020? In answering this question, this study examines the role of changes in short-term expected market returns (discount rates).

Recent advances in asset pricing theory allow us to compute a close proxy for the short-term discount rate. Martin (2017) and Chabi-Yo and Loudis (2020) provide an approach to compute a lower bound to the expected market risk premium (EMRP) based only on the current prices of index options, the underlying index and risk-free rates. In a related model, Bakshi et al. (2019) provide an exact formula for the conditional expected excess return of the market. Using this latter measure, we show that at the start of the pandemic, option markets are pricing in a strong stock market recovery within one year from the beginning of the crisis. An illustration of our main result is in Table 1, which documents stock market returns from the 2nd of January to the 23rd of March 2020, and from the 2nd of January to the 12th of May 2020, for three major indices: the S&P 500, the NIKKEI 225 and the DAX index. This table also provides the one-year discount rate for these indices.1

From Table 1 it is clear that the extreme drop in share prices between early January and the 23rd of March 2020, coincided with a sharp increase in the one-year discount rate from around 3–7% p.a. in early January to 15–30% p.a. on the 23rd of March. Taking the S&P 500 as an example, the remarkable jump in the one-year discount rate between the 2nd of January and the 23rd of March, indicates that as of the 23rd of March, prices in the index options

1 Bakshi et al. (2019) provides an expression for the expected market risk premium in terms of risk neutral moments derived from option prices. This premium is converted into an expected market return by adding the risk-free rate back in. Going forwards we use the term “discount rate”, “expected market return” and “expected return” interchangeably.
market imply that investors in the S&P 500 expect to earn a return of approximately 30% over the next year. In the weeks following the 23rd of March, central banks and governments announced a series of rescue plans, and a large part of the very high expected market return was quickly realized as stock markets rebounded, and the one-year discount rate sharply decreased to 5–18%. These co-movements in market values and short-term discount rates suggest that index returns during the pandemic were heavily influenced by changes in short-term (360-day) discount rates.

Our contention that changes in the short-term discount rates were a primary determinant of index returns at the onset of the pandemic is further illustrated in Fig. 1, which plots daily index returns, $\Delta S_i$, against daily changes in the 360-day discount factor (the inverse of the discount rate), $\Delta \delta_{i,t+1}$, for the S&P 500 index. Our data is split into observations prior to the first lockdown in Italy on the 21st of February 2020 and observations after the lockdown. Fig. 1 clearly shows the significant impact the COVID-19 pandemic had on the joint behavior of these variables. Firstly, we see that the relationship between returns and changes in the 360-day discount factors strengthened considerably, with the correlation coefficient increasing from 42% in the pre-covid period to 87% during the pandemic. Second, we observe that both index returns and discount factor changes become significantly more volatile as the effects of the pandemic set in. This significant and contemporaneous change in the joint behavior of index returns and discount factor changes, suggests that much of the change in market values was driven by the short-term discount rate.

To formally examine the role played by changes in short-term discount rates, we decompose index returns into changes in the one-year discount factor, and a term that reflects changes in longer term discount rates and changes in expected future dividends. We then examine the joint behavior of index returns and changes in short-term discount factors for a set of 13 international indices during the COVID-19 pandemic. We find that prior to the COVID-19 pandemic, index returns were only weakly related to changes in short-term discount factors, with the correlation between both variables averaging 19%. However, when markets around the globe responded to the COVID-19 pandemic, this correlation increased to around 62% on average. We also find that during the pandemic approximately 40% of the change in market value can be attributed to changes in short-term discount factors. These results suggest that during the economic crisis brought on by the pandemic, short-term discount rates became a much more significant driver of realized stock market returns across the globe.

The results in our paper provide strong support for the theory of Hasler and Marfè (2016), who build an equilibrium model.

| Realized Returns from Jan 2, 2020 | 360-day Discount Rate |
|----------------------------------|-----------------------|
| S&P 500  | DAX  | NIKKEI 225 | S&P 500  | DAX  | NIKKEI 225 |
| Jan-2    | 0.0%  | 0.0%       | 0.0%    | 7.3%  | 3.9%       | 2.9%    |
| Mar-23   | -31.3%| -14.7%     | -27.2%  | 30.5% | 19.9%      | 15.4%   |
| May-12   | -10.0%| -19.0%     | -12.1%  | 18.0% | 12.3%      | 5.5%    |
with rare disasters followed by recoveries. Based on this model, the authors predict a downward sloping term structure of equity risk premia because, in the presence of recoveries, the volatility of dividend growth is larger in the short term than in the long term. Importantly, for a situation where disaster intensity is high and expected recovery fast, such as at the start of the pandemic, the authors predict a more steeply downward sloping term structure, where short-term risk premia increase more than long-term risk premia. This is exactly what we find across the markets in our sample. Furthermore, looking back more than 20 years, we document that for the US, the term structure of equity market risk premia was never steeper than during March 2020. We also find that the term structure of equity risk premia, measured as the difference in the 360-day EMRP and the 30-day EMRP, is weakly downward sloping, on average.

Our findings also support those of Gormsen and Koijen (2020) who use dividend futures to conclude that most of the variation in market values during the COVID-19 crisis is due to discount rate fluctuations. These authors also argue that the behavior of dividend futures is consistent with a V-shaped recovery (a quick and sharp decline followed by an equally quick and sharp recovery). Consistent with this evidence, Hong et al. (2020) use analyst earnings forecasts and show that as of mid-May 2020, an effective vaccine is expected in 0.96 years and that corporate earnings are expected to quickly recover when the vaccine is available. Landier and Thesmar (2020) examine analyst earnings revisions during the pandemic and find that long-term forecasts reacted far less dramatically than short-term forecasts, reflecting the perceived short-term nature of the crisis. Our study uses a different source of information, the options market, and shows that a large part of changes in stock valuations during the COVID-19 crisis were due to changes in the one-year discount rates.

Our paper proceeds as follows. In Section 2, we show how to decompose changes in the value of stock markets into changes in the one-year discount factor and a term that reflects changes in longer term discount rates and changes in expected future dividends. Based on this decomposition, we examine how the joint behavior of discount factors and index returns changed as a result of the COVID-19 pandemic. In Section 3, we explain how to obtain estimates of discount factors from options on stock market indices. Since index options are typically written on price indices and not on total return indices, we also discuss the role of expected dividends in our analysis. We also describe the evolution of the COVID-19 crisis and its impact on stock markets and discount rates during the first few months of 2020. Next, in Section 4, we present our main results pertaining to the impact of changes in short-term discount factors on index returns during the COVID-19 pandemic. Section 5 concludes.

2. Analyzing the return-discount rate connection

This section provides a framework to analyze the relative importance of short-term discount rate changes as a driver of changes in the valuation of stocks as the COVID-19 pandemic evolved.

2.1. A decomposition of prices and returns

The definition of the present value of a stock market at time $t$, $S_t$, is the discounted value of all future dividends. Movements in the market value can hence be attributed to changes in discount rates, changes in future expected dividends, or both. To simplify further expressions, define the gross discount rate $R_{t+1} = (1 + r_{t+1})$, which will hereafter be referred to as simply a discount rate. Noting that we may factor out the discount rate at $t+1$ allows us to rewrite index prices via,

$$S_t = \sum_{n=1}^{\infty} \frac{E_t(D_{t+n})}{\Pi_{j=1}^{t+n}(1 + r_{t+n})}$$

$$= \frac{1}{R_{t+1}} \left( \frac{E_t(D_{t+1})}{R_{t+1}} + \sum_{n=2}^{\infty} \frac{E_t(D_{t+n})}{\Pi_{j=2}^{n} R_{t+j}} \right)$$

$$= R_{t+1}^{-1} F_t$$

where $F_t$ is the $t$ conditional one-year forward present value of all future dividends. Note that neither of the terms in (3) can be directly observed and as such analyzing asset prices in this way has received little attention in the literature. However, as we discuss in Section 3.1, recent developments in asset pricing offers us with an option-based estimate for $R_{t+1}$, which we label $\hat{R}_{t+1}$. We assume that

$$\hat{R}_{t+1} = R_{t+1} F_t$$

where $\hat{F}_t$ is a multiplicative error term and hence $\hat{F}_t > 0$. We also assume that this error term is independent of the true discount rate and the unobserved term $F_t$, hence $\text{Cov}[R_{t+1}, \hat{F}_t] = \text{Cov}[\hat{R}_{t+1}, \hat{F}_t] = 0$. We further assume that our proxy is unbiased and hence $\mathbb{E}[\hat{F}_t] = 1^2$. Substituting (4) into (3), we can express the observed stock price in terms of our observed proxy, $\hat{R}_{t+1}$ via

$$S_t = \hat{R}_{t+1}^{-1} R_t F_t$$

where $\hat{F}_t = \epsilon_t$. Taking logs of (5) linearizes the expression to,

$$s_t = \hat{R}_{t+1}^{-1} s_t + f_t + u_t$$

where $s_t = \log(S_t)$, $s_t = \log(\hat{R}_t)$, $u_t = \log(\hat{F}_t)$ and $\delta_{t+1} = \hat{R}_{t+1}^{-1}$. Substituting (4) into (3), we can express the change in log index values over the time period $\Delta t$ as,

$$s_{t+\Delta t} - s_t = (\delta_{t+\Delta t} + \delta_t) + (f_{t+\Delta t} - f_t) + (u_{t+\Delta t} - u_t)$$

$$\Delta s_t = \Delta \delta_{t+1} + \Delta f_t + \Delta u_t.$$  

Eq. (7) provides the basis for our analysis. Our research seeks to understand the relation between changes in short-term discount factor indices and index returns and how this relation changed from the pre-crisis period to the first few months of the COVID-19 pandemic. A typical approach to understand the relation between these variables would involve the estimation of regression coefficients for the variables in Eq. (7). However, in our setting such an approach is inappropriate for two reasons. First, we cannot observe a proxy for the term $\Delta f_t$, which means that estimation via OLS will be impacted by the omitted variable bias. Second, Eqs. (6) and (7) tell us a priori that the regression coefficient between $\Delta s_t$ and $\Delta \delta_{t+1}$ should be 1 when the model is correctly specified, because the sensitivity of index returns to the discount factor is invariant. Our approach instead studies how changes in the distribution of the short-term discount factor, brought on by the pandemic, led to changes in the distribution of index returns. Section 2.2 discusses how we study these changing distributions.

$^2$ In our main results, such an assumption is warranted as we use the exact representation of expected returns provided by Bakshi et al. (2019).
2.2. Changes in short-term discount rates and stock market returns

In this section we first explore what proportion of the index returns observed during the pandemic can be attributed to changes in the short-term discount factor. This is achieved by analyzing the ratio

$$R_{t_1, t_2} = \frac{\sum_{t=t_1}^{t_2} \Delta \delta_{t+1}}{\sum_{t=t_1}^{t_2} \Delta \delta_t}$$

where $t_1$ and $t_2$ represent start and end dates and the terms $\Delta \delta_{t+1}$ and $\Delta \delta_t$ are computed on a daily basis. It is well-known that ratios of random variables often yield complicated distributions which are difficult to study.\(^1\) The main issues we face is that the numerator and denominator of (8) may have a different sign and that the denominator of (8) may be very small relative to the numerator. Both of these problems are exacerbated by the error term $\Delta u_i$. To circumvent these issues, we measure $R_{t_1, t_2}$ over a limited number of intervals with large changes in stock market valuations during the first few months of the pandemic. Computing $R_{t_1, t_2}$ over longer periods of time corresponds to aggregating $\Delta u_i$ across observations. Given $\Delta u_i$, is an error term with zero expected value, this aggregation reduces the impact of this term making the errors relative to the quantity being measured. Additionally, computing $R_{t_1, t_2}$ over a period with a large change in stock valuations means that index returns (denominator) are not too small relative to changes in the discount factor (numerator), which otherwise could perversely impact statistics related to $R_{t_1, t_2}$. Last, since the computed values satisfy $0 \leq R_{t_1, t_2} \leq 1$, we may interpret $R_{t_1, t_2}$ as the proportion of index returns that may be attributed to changes in the short-term discount factor.

We are also interested in the impact of the pandemic on the determinants of index returns. As stated earlier, the relationship between index returns and its drivers, $\Delta \delta_{t+1}$ and $\Delta f_i$, is invariant, but the distributions of these variables are not. Rather, the distributions of $\Delta \delta_{t+1}$, $\Delta f_i$ and, consequently, $\Delta \delta_t$ change through time. We examine how the economic shock provided by the COVID-19 pandemic altered the distribution of these variables around the globe. Defining $T_0$ to be the date at which the effects of the COVID-19 pandemic started impacting financial markets, we split our sample into observations that occur prior to the beginning of the COVID-19 pandemic, $t < T_0$, and those that occur during the COVID-19 pandemic, $t \geq T_0$.\(^4\) Using these two samples, we compute statistics that capture the distributional properties of the main variables both prior to the onset of the COVID-19 pandemic and during the COVID-19 pandemic. We then perform statistical tests to determine the significance of the measured changes.

While some measures are straightforward to calculate (for example, $\text{Var}(\Delta \delta_t)$ can be computed directly), those involving $\Delta f_i$ are complicated by the fact that this variable is unobserved. In order to compute statistics related to $\Delta f_i$, we must make a simplifying assumption. Defining the variable $\Delta f_i^c = \Delta f_i + \Delta u_i$, Eq. (7) implies

$$\Delta f_i^c = \Delta \delta_t - \Delta \delta_{t+1}.$$  

We then use $\Delta f_i^c$ as a proxy for the term $\Delta f_i$. However, since $\Delta f_i^c$ represents the effect of changes in the present value of the future expected dividends and measurement error, we must be careful how we interpret statistics related to this variable. Using the assumed properties of $\Delta u_i$ (zero expectation and independence from all other variables), we have that

$$\text{Cov}(\Delta f_i^c, \Delta \delta_t) = \text{Cov}(\Delta f_i, \Delta \delta_t)$$

and hence that

$$\rho_{\Delta f_i^c, \gamma} = \frac{\text{Cov}(\Delta f_i^c, \gamma)}{\sqrt{\text{Var}(\Delta f_i^c)^2}}$$

is biased towards 0 relative to the correlation $\rho_{\Delta f_i, \gamma}$ where $\gamma \in \{\Delta \delta_t, \Delta \delta_{t+1}\}$. Our analysis will focus on changes in variance using Levene’s test with quadratic variances, and changes in correlation using Fisher’s test. We present results from this analysis in Section 4.1.

3. Variables and data

This section details how short-term discount rates may be computed from option prices. We also discuss the data used in the computation of these discount rates and provide a discussion of how the COVID-19 pandemic evolved in terms of stock market returns and discount rates.

3.1. Computing the short-term discount rate

We use the method developed by Bakshi et al. (2019) to compute expected returns on our selected indices using traded option prices. This approach produces an exact representation of the equity market risk premium, $E_i^R(R_{i,T}) - R_i$, where $E_i^R$ denotes the physical measure and $i = 1, 2, . . . , n$ denotes the index. This is in contrast to Chabi-Yo and Louédiss (2020) and Martin (2017) who provide formulas to compute lower bounds on the equity risk premium under $P$. In what follows, we provide a brief outline of the Bakshi et al. (2019) formula.

To derive their result, Bakshi et al. (2019) assume the projected SDF, $M_T(R_i)$ follows a specific functional form,

$$M_T(R_i) = e^{\alpha_t + \varphi (R_i - R_i)}.$$  

This representation allows the authors to specify the Radon-Nikodym derivative, which enables transition between the physical measure $P$ and risk neutral measure $Q$. Using this result, the authors show that the physical and risk neutral cumulant generating functions, cgf, are related to one another via\(^5\)

$$\text{cgf}_P^\omega(\lambda) = \text{cgf}_Q^{\omega}(\lambda + \varphi) - \text{cgf}_Q^{\omega}(\varphi)$$

and hence the moments under the physical measure, computed by differentiating cgf\(^2\), can be expressed as an infinite series of risk neutral moments and the parameter $\varphi$. These risk neutral moments can be computed using the spanning relation found in Carr and Madan (2001). To compute the EMRP, Bakshi et al. (2019) suggest truncating the infinite series at the fifth cumulant resulting in the expression

$$E_i^R(R_{i,T}) - R_i = \frac{1}{\varphi} \left( (\varphi \text{SD}^0_i(R_{i,T}))^2 + \frac{1}{2} (\varphi \text{SD}^0_i(R_{i,T}))^3 \text{Kurtosis}_i^Q(R_{i,T}) \right) + \frac{1}{\varphi^2} (\varphi \text{SD}^0_i(R_{i,T}))^4 (\text{Kurtosis}_i^Q(R_{i,T}) - 3) + \frac{1}{\varphi^3} (\varphi \text{SD}^0_i(R_{i,T}))^5 (\text{Hskewness}_i^Q(R_{i,T}) - 10 \text{Skewness}_i^Q(R_{i,T}))$$

\(^3\) The reason for this complexity lies in the fact that the denominator can be small relative to the numerator leading to distributions with fat tails among other undesirable properties. For example, the ratio of two standard normal distributions is Cauchy distributed. Cauchy distributions do not have a defined mean or variance among other undesirable properties.

\(^4\) We select the 21st of February 2020, the start of the lockdown in Italy, as the beginning of the COVID-19 period in our sample.

\(^5\) We point out that in this case the cgf is defined as the log of the moment generating function.
where $SD^2 = \sqrt{\text{Var}^2(R_f)}$, Skewness$^0$, Kurtosis$^0$, and Hskewness$^0$ refer to the risk-neutral volatility, skewness, kurtosis, and hyper-skewness, respectively. All these risk neutral moments can be computed through observed option prices.

The parameter $\phi$ plays an important role in setting the equity risk premium as it is key to defining the SDE. This parameter cannot be obtained from options prices and must be estimated from historical data. We describe the procedures to estimate $\phi$ in Appendix A, where we also provide descriptive statistics for these parameters for each of the stock market indices in our sample.

3.2. Dividends and option implied expected returns

Formula (16) refers to the expected return on the asset underlying the option which, in our case, is a market index. Typically, these market indices are price indices and hence do not reflect income an investor receives from dividends. If dividends are known with certainty, there is no difference between the expected return computed from a price index and a total return index. To see this, note that the total return for a dividend paying asset is given by $R_T = R_f + D_T/S_T$ where $D_T$ is all dividend income received between $t$ and $T$. To illustrate our point, say we were to truncate Eq. (16) at the first (variance) term and apply this expression to the total return, $R_T$:

$$E_T^n(R_T) - R_f = \phi \text{Var}^0(R_f) = \phi \left[ \text{Var}^0(R_f) + \text{Var}^0(D_T/S_T) + 2Cov^0(R_f, D_T/S_T) \right].$$

If dividends are known with certainty, then the last two terms on the right-hand side of (17) equal 0 and $E_T^n(R_T) = E_T^n(R_f)$. We can also see from this simplified expression that if dividend uncertainty is small relative to the uncertainty in capital gains, then the expected return derived from index options on a price and total return index should be close.

Based on interview data, Lintner (1956) argues that managers aim to deliver a smooth stream of dividend payments to their shareholders. This dividend smoothing has become even more prevalent in recent times with Chen et al. (2012) showing that the best predictor of the next dividend is the previous one. Hence, in stable economic times, the variance of future dividends is relatively small and the omission of dividends from the underlying index is likely to have little consequence for the calculated option-based expected return. However, during the COVID-19 crisis, many firms were forced to reduce dividends in the short term in an effort to save cash (see Cejnek et al., 2020). Consequently, as the dire short-term implications of the COVID-19 crisis became increasingly clear, the option-based expected return can be expected to increasingly underestimate the true expected return because the uncertainty associated with dividends is not incorporated into expected returns computed from options which have a price index as their underlying.

Hence, we expect that the difference between the true one-year discount rate (reflecting dividend income risk) and our measured one-year discount rate (excluding dividend income risk) for a stock index is larger the higher the dividend yield on the index. Hence, if we were to relate the proportion of the change in the stock index in our sample period that is explained by the contemporaneous change in the one-year discount rate to the dividend yield, we would hypothesize a negative relation.

3.3. Data

We obtain index option prices and underlying index levels for the following markets (country); AEX (Netherlands), ASX 200 (Australia), CAC 40 (France), DAX (Germany), FTSE 100 (UK), Hang Seng (Hong Kong), KOSPI (South Korea), MIB (Italy), NIKKEI 225 (Japan), OMX (Sweden), SMI (Switzerland), S&P 500 (USA) and STOXX 50 (Eurozone). All data is obtained from Datastream. We also require a proxy for the risk-free rate across a range of maturities for each of the currencies in which the index is traded. We use the ICE-LIBOR rates for those currencies that have active rates published (USA, Eurozone, UK, Japan, Switzerland). For those countries for which there are no LIBOR rates, we use the yield on zero-coupon government bonds, again sourced from Datastream.

The date at which our options data begins varies across indices and is presented in the first column of Table 2. All available option prices are obtained until 12th May, 2020 and we select the 21st February, 2020, the start of the first lockdown in Italy, as the beginning of the COVID-19 pandemic. We provide a justification for this choice of start date in Section 3.4. The options data is cleaned to ensure we have accurate and relevant prices. Our data cleaning approach largely follows the procedure used by the CBOE to compute the VIX index, the calculation of which is similar to those

\[^6\] While it is not possible to rule out an over-estimation, it is reasonable to expect that the variance of the dividend yield is the dominant term in its uncertainty (see Bakshi et al., 2019).

\[^7\] The London interbank offer rate (LIBOR) was originally published by the British Bankers Association (BBA). This responsibility has now passed to the Intercontinental Exchange (ICE).
presented in Section 3.1. First, all options with maturities of less than 7 days are omitted to remove potentially confounding microstructure effects. Second, only option prices which have non-zero trade volume are used and we use the last traded price. If the last trade price is not reported, the mid-point of the closing bid and ask prices is used in its place. Expected returns are calculated for a set of standardized maturities of \{30, 60, 90, 180, 360\}-days. To obtain these maturities, we use linear interpolation on the observed set of maturities at each date. Occasionally we are required to extrapolate a standardized maturity and for this we use the nearest neighbour.\(^8\)

Our main results are based on the expected return for the 360-day window, which we refer to as the short-term discount rate. Below, we document the evolution of the expected return for different maturities from 30-days to one year, but our focus is on the one-year measure because this is the maximum maturity for which we can reliably obtain estimates for the expected return from our options data. Longer maturity options are more useful for our purposes because they are likely to be the preferred instrument for informed investors who wish to use leverage and desire a financial instrument with a maturity that matches the time frame over which their expectations about the availability of a vaccine are likely to materialize; early to mid-2021.

3.4. Stock markets and risk premia during the COVID-19 crisis

In this section we discuss how stock markets and investors’ expectations about market risk premiums evolved in response to the COVID-19 outbreak and subsequent policy responses. Fig. 2 plots the price path of thirteen different share market indices from the 2nd of January 2020 through to the 12th of May 2020. We scale each of the indices to 1 at the start of the period.

Markets do not respond to the first reports of the virus outbreak in China in early January and there is no notable reaction to the Wuhan lockdown on January 23, which is indicated by the first vertical line in the graph. However, once it becomes clear that the virus is spreading around the globe and outbreaks are documented in South Korea, Iran and Italy, stock markets start their decline. We use the 21st of February, the date of the lockdown in Italy, as the cut-off date for this next phase where the rest of the world starts to become concerned about the health and economic consequences of the COVID-19 outbreak. At this point, the average decrease in market value since early January is still less than 5%. The next big drop in share prices is observed after the US announces travel restrictions for travelers from the European Union on March 12, and several European governments announce strict lockdowns. At this stage, total share market losses accumulate to about 25%. From March 23, onward, markets start to recover after the US Federal Reserve bank announces a sharp increase in quantitative easing and a drop in interest rates to zero percent. This is followed on March 27, by the US government approving a US$2 trillion relief bill into law (CARES Act). As is typical for crisis periods, market movements were highly correlated with the average 30-day correlation among the 13 indices being 47% during the last quarter of 2019, increasing to 67% over the 3 months from February to April 2020, and reaching a maximum of 84% at the beginning of March. European stock markets (MIB, CAC 40, DAX, FTSE 100, and AEX) experienced the largest losses over the sample period, except for the Swiss market (SMI), which had the best performance.

In Fig. 3 we plot the 5-day moving average of the annualized 30-day EMRP, where the moving average is centered on the third day. Fig. 4 presents a similar plot for the 5-day moving average of the one-year EMRP, centered on the third day. As in Fig. 2, the

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8 Interpolation of the observed maturities to obtain standardized maturities is common in the literature and is used by both Martin (2017) and Chabiy-Yo and Louidis (2020) and in the calculation of the VIX index. The same interpolation/extrapolation method is also used to compute the appropriate risk-free rate for the standardized maturities.
vertical lines in both figures indicate the Wuhan lockdown on January 23, the Italy lockdown on February 21, the EU travel ban on 12 March and the Fed announcements on March 23. Focusing first on Fig. 3, we see that the 30-day EMRP for the KOSPI and OMX are somewhat elevated towards the end of January relative to the other indices. Consistent with the share market decreases seen after the Italy lockdown, the 30-day EMRPs for all indices start to increase sharply and reach their peak in the two weeks before March 23. The highest 5-day moving average annualized 30-day EMRPs are for the OMX on the 11th of March at 149.0% and the S&P 500 at 111% on the 16th of March. After peaking, the 30-day EMRPs decrease sharply to about 15% towards the end of our sample period.

Looking at the one-year EMRPs in Fig. 4, we find a similar pattern but with much lower peaks. The highest 5-day averaged value of the one-year EMRP is 60% for the KOSPI on the 19th of March and the second highest is 34.2% for the ASX 200 on 25th of March. There is an unusual spread in one-year EMRPs towards the end of the sample period, with one-year EMRPs for the ASX 200 and S&P 500 of more than 15%, whereas the EMRPs for the Hang Seng and the NIKKEI 225 are much lower at around 7.5% and 6.3%, respectively.

In Table 2, we provide descriptive statistics for the one-year EMRP for each of the thirteen stock market indices in our sample in both the pre-covid and covid periods. During the pre-covid period, the average one-year EMRP ranges from a low of 2.67% p.a. for the NIKKEI 225 to a high of 6.93% p.a. for the OMX. The average across all indices in this period is 4%. When the COVID-19 pandemic hits markets, we see a marked increase in the EMRP estimates. The average across all indices increases to 13% with a minimum of 7.5% (NIKKEI 225) to a maximum of 21% (KOSPI). For each index, we report the number of daily observations in our sample period in the last column.

In Table 3 we present descriptive statistics for the EMRP for different maturities, averaged across all 13 indices. These statistics are computed for both the pre-covid period and during the pandemic. Pre-covid, the mean EMRP remains stable across all maturities at around 4% p.a. During the covid pandemic however, we observe a downward sloping term structure of the EMRP. This temporal behaviour is typical for turbulent times, whereas a flat/upward sloping term structure of EMRPs is typically observed in stable times (see Chabi-Yo and Loudis, 2020).

To show more detail on how the term structure evolved throughout our sample period, we define the slope of the term structure for each index as the difference between the 360-day EMRP and the 30-day EMRP $(\text{EMRP}_{360} - \text{EMRP}_{30})$. Next, for each day, we compute the mean equity premium term structure by averaging the term structure across all indices in our sample. Fig. 5 presents the results and shows that the slope of the mean equity premia term structure is flat until the 24th of February 2020 and then starts to become increasingly downward sloping. The maximum difference between these risk premia is more than 60% on the 13th of March 2020, 1 day after the European Union travel ban. Following this peak, there is a gradual decline to more normal levels towards the end of our sample period. The results in Fig. 5, are consistent with the model in Hasler and Marfé (2016), which predicts a sharply downward sloping term structure of equity risk premia if the perceived probability of an economic disaster is high, as it was at the onset of the pandemic. The normalisation of the term structure after mid-March 2020, coincides with a stabilisation and subsequent recovery of the share market, consistent with growing confidence that the probability of a major economic disaster is not as high as initially feared.

4. Results and discussion

We first explore what proportion of the index returns observed during the pandemic can be attributed to changes in the short-term discount factor. We compute $R_{x_{1, 2}}$ over three different periods for each index in our sample, all starting on the 2nd of January, 2020. These periods end on the 12th of March, 23rd of March and
12th of May (the end of our sample). The main result, presented in Table 4, is that the proportion of the change in market valuation that can be attributed to changes in the short-term discount factor is approximately 40%.

9 We repeat this analysis for the 8 months during the pre-covid period and find that using these monthly returns, \( \tau_{x, t} \), is significantly lower, averaging 7%. Many of the values for \( \tau_{x, t} \) are negative in the pre-covid period and the standard deviation is 4 times larger. This evidence suggests that the connection between index returns and discount rate changes is much weaker during the pre-covid period than during the pandemic.

To further examine the difference in \( \tau_{x, t} \) across the stock indices, Table 5 presents the proportion of the total return explained by the change in the short-term discount factor for each of the indices in our sample across the three different windows. 10 We find

10 If \( 0 \leq \tau_{x, t} \leq 1 \), then \( \tau_{x, t} \) may be interpreted as the proportion of the index return that can be attributed to the change in the discount factor. These properties are satisfied for all index-window observations, except one (KOSPI) which is greater than 1 over one window in our sample. In this setting, the median is a robust estimator of the central tendency.

Table 3
EMRP term structure. This table presents the EMRP for different maturities both prior to and during the COVID-19 pandemic. The reported EMRP is averaged across all days within each period and across all 13 indices. EMRP estimates are computed using the method developed in Bakshi et al. (2019).

Table 4
Proportion of return attributed to discount factor changes across indices. This table presents the proportion of index returns that can be attributed to contemporaneous changes in the short-term discount factor. We fix the date \( t_1 \) at the 2nd January, 2020 and compute all returns relative to that date. Discount rate estimates are computed using the method of Bakshi et al. (2019).

Fig. 4. Behaviour of the 360-day one-year discount rate during COVID-19. This figure presents a plot of the 5-day moving average of the annualized 360-day expected market return in response to the COVID-19 pandemic from January 2, 2002 to May 12, 2020. All values are computed using the method of Bakshi et al. (2019).
that while the range of estimates for $\mathcal{R}_{t_1, t_2}$ for each of our indices is limited, $\mathcal{R}_{t_1, t_2}$ shows substantial variation across the 13 indices. The wide range of estimates across indices in combination with the relative stability of the estimated $\mathcal{R}_{t_1, t_2}$ across the three different windows for each index, points to structural differences across indices rather than estimation error due to micro-structure frictions.

One possible structural difference is that different indices have different typical levels of dividend yields. We note that the average $\mathcal{R}_{t_1, t_2}$ across all markets is 0.42. Restricting the sample to the 6 stock markets with the lowest dividend yield at the end of 2019, the average $\mathcal{R}_{t_1, t_2}$ is 0.44. If we restrict this group further to the 3 stock markets with the lowest dividend yield, the average ratio increases to 0.55, whereas the US, the country with the lowest dividend yield at the end of January 2019, has a $\mathcal{R}_{t_1, t_2}$ of 0.65. Combining this evidence with the estimate of 0.38 for $\mathcal{R}_{t_1, t_2}$ for the DAX, which is based on a total return index, we conclude that it is reasonable to expect that $\mathcal{R}_{t_1, t_2}$ lies within a range of 0.4 to 0.6.

While the results in Tables 4 and 5 document the relative importance of short-term discount factors in explaining market returns during the COVID-19 pandemic, the results are limited to the specific windows over which we have calculated $\mathcal{R}_{t_1, t_2}$. However, we are also interested in examining the joint distribution of $(\Delta \delta_{t_1}, \Delta f^*_t)$, and therefore the distribution of $\Delta s_t$, as we move from the pre-covid period into a period impacted by COVID-19. In order to understand how these variables change with respect to one another, Section 4.1 provides statistical tests for changes in the variance of and correlations between $\Delta s_t$, $\Delta \delta_{t+1}$ and $\Delta f^*_t$.

4.1. Change in variances and correlations

Panel A of Table 6 presents evidence on the change in variance of the components of Eq. (9) as we move from the pre-covid period into the onset of the pandemic. We observe that, on average, the volatility of all variables increased from approximately 15% p.a. to around 50% p.a. during the pandemic. These increases are statistically significant at the 1% level of significance for all but one index (Hang Seng).

The increases in variances documented in Table 6, Panel A, do not show which source of variation is most responsible for the large shocks in returns observed at the onset of the pandemic. To address this question, we examine correlations among the three variables $\Delta s_t$, $\Delta \delta_{t+1}$ and $\Delta f^*_t$. Note that these correlations can be measured directly via observations for $\Delta s_t$ and $\Delta \delta_{t+1}$ and by using Eq. (9) to compute $\Delta f^*_t$. Panel B of Table 6 presents our results across the 13 indices. Our main result is that $\rho(\Delta s_t, \Delta \delta_{t+1})$, the correlation between $\Delta s_t$ and $\Delta \delta_{t+1}$, increased significantly in response to the economic shock brought on by the COVID-19 pandemic. Prior to the outbreak of COVID-19, this correlation averaged
Table 6
Change in variances and correlations. This table presents the variances (Panel A) of the variables $\Delta t$, $\Delta_{h_{1}}$ and $\Delta f_{t}^*$ and all pairwise correlations (Panel B) measured in both the pre-covid period and during the covid pandemic. In Panel A, all reported figures are annualized volatilities where $\text{Vol}(X) = \sqrt{\text{Var}(X)}$. In Panel B, $\rho(X,Y)$ denotes the correlation between $X$ and $Y$. Differences in variances from the pre-covid to the covid period are tested via Levene’s test using quadratic variation. Differences in correlations from the pre-covid to the covid period are tested via Fisher’s test and differences in means across the 13 indices are tested using the Wilcoxon signed rank test. Statistical significance at the 10, 5 and 1% levels are indicated with *, ** and *** respectively.

Panel A: Change in Variances

|        | Vol($\Delta t$) | Vol($\Delta_{h_{1}}$) | Vol($\Delta f_{t}^*$) |
|--------|-----------------|------------------------|-----------------------|
|        | Pre-Covid       | Covid                  | Pre-Covid             | Covid                  |
| AEX    | 0.1248          | 0.5079***              | 0.0384                | 0.2774***              | 0.1187                | 0.3196***                  |
| ASX 200| 0.1161          | 0.5537***              | 0.1589                | 0.7126***              | 0.1804                | 0.8288***                  |
| CAC 40 | 0.1338          | 0.5857***              | 0.1263                | 0.6359***              | 0.1735                | 0.8300***                  |
| DAX    | 0.1460          | 0.5673***              | 0.0582                | 0.3938***              | 0.1354                | 0.3374***                  |
| FTSE 100| 0.1223         | 0.5160***              | 0.1179                | 0.3729***              | 0.1598                | 0.4628***                  |
| Hang Seng | 0.1755        | 0.3443***              | 0.1993                | 0.2111                 | 0.2743                | 0.2387                     |
| KOSPI  | 0.1436          | 0.4843***              | 0.1665                | 1.2209***              | 0.1992                | 0.5917***                  |
| MIB    | 0.1665          | 0.6438***              | 0.0870                | 0.3254***              | 0.1781                | 0.6262***                  |
| NIKKEI 225 | 0.1601      | 0.4512***              | 0.1323                | 0.2147***              | 0.1974                | 0.3185***                  |
| OMX    | 0.1415          | 0.4925***              | 0.2451                | 0.9770***              | 0.2560                | 0.7938***                  |
| SMI    | 0.1221          | 0.4343***              | 0.1265                | 0.3466                 | 0.1683                | 0.2543***                  |
| S&P 500| 0.1415          | 0.6575***              | 0.0892                | 0.4886***              | 0.1317                | 0.3365***                  |
| STOXX 50 | 0.1323         | 0.5613***              | 0.0432                | 0.2441***              | 0.1266                | 0.3736***                  |
|        |                 |                        |                       |                       |                      |                           |
| Mean   | 0.1405          | 0.5229***              | 0.1222                | 0.4915***              | 0.1769                | 0.5108***                  |

Panel B: Change in Correlations

|        | $\rho(\Delta t, \Delta_{h_{1}})$ | $\rho(\Delta t, \Delta f_{t}^*)$ | $\rho(\Delta_{h_{1}}, \Delta f_{t}^*)$ |
|--------|---------------------------------|---------------------------------|---------------------------------|
|        | Pre-Covid                       | Covid                           | Pre-Covid                       | Covid                           |
| AEX    | 0.3075                          | 0.8259**                        | -0.0004                         | 0.4445**                        |
| ASX    | 0.1677                          | 0.1594                          | -0.7729                         | -0.7538                         |
| CAC    | 0.1110                          | 0.0786                          | -0.6423                         | -0.7107                         |
| DAX    | 0.3748                          | 0.8127**                        | -0.0258                         | 0.1994                          |
| FTSE   | 0.1150                          | 0.4968**                        | -0.6499                         | -0.2519                         |
| Hang Seng | -0.0676       | 0.7301**                        | -0.7696                         | 0.1685**                        |
| KOSPI  | 0.1811                          | 0.7435**                        | -0.7052                         | -0.9359**                       |
| MIB    | 0.1234                          | 0.3061                          | -0.3731                         | -0.2050                         |
| NIKKEI | 0.0988                          | 0.7651**                        | -0.5901                         | 0.4098**                        |
| OMX    | 0.2096                          | 0.5892**                        | -0.8415                         | -0.8653                         |
| SMI    | 0.0837                          | 0.8158**                        | -0.6908                         | 0.1561**                        |
| S&P 500| 0.4214                          | 0.8681**                        | -0.2247                         | 0.2444**                        |
| STOXX 50 | 0.2906        | 0.8577**                        | -0.0376                         | 0.6350**                        |
| Mean   | 0.1659                          | 0.6191**                        | -0.4865                         | -0.3127**                       |

19% but after the pandemic hit, this correlation increased to 62% on average, suggesting that the impact of changes in the short-term discount factor on stock returns increased significantly during the COVID-19 pandemic.

In contrast, the correlation between $\Delta t$ and $\Delta f_{t}^*$ did not change substantially from the pre-covid period into the pandemic. Averaged across all indices, this correlation fell around 72% to 60%. So, even though $\Delta f_{t}^*$ became more volatile during the pandemic, this did not significantly increase the correlation between $\Delta f_{t}^*$ and index returns, suggesting $\Delta f_{t}^*$ did not become a stronger driver of returns throughout the pandemic.

Last, we consider the correlations between $\Delta_{h_{1}}$ and $\Delta f_{t}^*$. Of the indices that yielded statistically different correlations, only one index (KOSPI) had a more negative correlation during the COVID-19 pandemic than in the pre-covid period. In general, we find that the correlation between $\Delta_{h_{1}}$ and $\Delta f_{t}^*$ becomes less negative. This suggests that as the pandemic took hold, changes in the short-term discount factor and the present value of future expected dividends began to decouple, which again points to changes in the short-term discount factor having a more significant impact on index returns during the pandemic than changes in long-term discount rates/expected dividends, consistent with an EMRP term structure that has become significantly downward sloping during this period.

4.2. Changes in the term structure of equity risk premia

In this section, we examine a long time series of the slope of the term structure of equity risk premia in the US to provide further evidence on the predictions based on the model in Hasler and Marfè (2016). These authors derive an equilibrium model with rare disasters followed by recoveries. In their model, short-term dividends are more risky than longer term dividends because of economic recovery following disasters, resulting in a higher risk premium for short-term dividends. The model also predicts that when disaster intensity increases, this difference in volatility of dividends further increases, resulting in more steeply downward-sloping term structures of equity risk premia.

To provide evidence on these predictions, we obtain option prices on the S&P500 from OptionMetrics IvyDB from January 1996 to December 2020 and compute the EMRP at 30 and 360 days (EMRP30 and EMRP60 respectively) using the method of Bakshi et al. (2019). As before, for each day, we define the term structure as the difference between the 360-day EMRP and the 30-
Table 7
Summary statistics of ϕ and m₀. This table provides summary statistics for the bootstrapped estimates of ϕ and m₀. These estimates are obtained by repeating the optimization outlined in Eq. (20) on a subset (80%) of the historical data. R denotes the x-percentile. All data is collected from the start date specified until the 28th February, 2018, prior to the start date of the options series. The number of observations N refers to the number of monthly returns available for bootstrap estimates of the parameters ϕ and m₀.

Panel A: ϕ Summary Statistics

|          | Start Date | N   | Mean  | Med. | Std. Dev. | Skew.   | Kurt. | R1   | R15  |
|----------|------------|-----|-------|------|-----------|---------|-------|------|------|
| AEX      | 11-Apr-94  | 174 | 1.5938| 1.4489| 0.1051    | 0.8878  | 4.0661| 0.2205| 3.4543|
| ASX 200  | 26-Jun-98  | 131 | 2.7085| 2.3745| 1.8519    | 1.0467  | 4.5430| 0.3249| 6.1376|
| CAC 40   | 11-Apr-94  | 163 | 1.5121| 1.4000| 0.9471    | 0.7998  | 3.2843| 0.3267| 3.5068|
| DAX      | 11-Apr-94  | 167 | 1.8678| 1.7598| 1.0205    | 0.7453  | 4.1861| 0.3687| 3.7009|
| FTSE 100 | 2-Jan-86   | 204 | 1.7738| 1.5654| 1.2011    | 1.1330  | 5.0465| 0.2367| 4.0440|
| Hang Seng| 4-Jun-90   | 167 | 1.6414| 1.5650| 0.8611    | 0.6140  | 3.4851| 0.3618| 3.1797|
| KOSPI    | 26-Jul-04  | 89  | 3.4726| 2.9813| 2.4195    | 1.5289  | 6.7416| 0.5628| 8.1908|
| NIKKEI 225 | 6-Jan-86 | 243 | 1.0062| 0.8800| 0.7223    | 1.0566  | 4.5415| 0.0949| 2.3426|
| OMX      | 29-Aug-02  | 104 | 3.6620| 3.3696| 2.0926    | 1.1461  | 6.1817| 0.8070| 7.3848|
| SMI      | 03-Jan-89  | 184 | 2.2938| 2.2002| 1.1893    | 0.5505  | 3.3517| 0.5068| 4.4293|
| S&P 500  | 2-Jan-86   | 238 | 2.9624| 2.8005| 1.5175    | 0.7663  | 3.8157| 0.8094| 5.7910|
| STOXX 50 | 11-Apr-94  | 174 | 1.5004| 1.3630| 0.9591    | 0.7985  | 3.6566| 0.1808| 3.2745|

Panel B: m₀ Summary Statistics

|          | Start Date | N   | Mean  | Med. | Std. Dev. | Skew.   | Kurt. | R1   | R15  |
|----------|------------|-----|-------|------|-----------|---------|-------|------|------|
| AEX      | 11-Apr-94  | 174 | 1.0078| 1.0043| 0.0109    | 2.0811  | 9.2435| 0.9981| 1.0293|
| ASX 200  | 26-Jun-98  | 131 | 1.0091| 1.0041| 0.0142    | 2.2420  | 10.3871| 0.9970| 1.0371|
| CAC 40   | 11-Apr-94  | 163 | 1.0073| 1.0041| 0.0103    | 2.1774  | 10.6482| 0.9982| 1.0281|
| DAX      | 11-Apr-94  | 167 | 1.0141| 1.0099| 0.0150    | 1.8174  | 8.5338 | 0.9986| 1.0437|
| FTSE 100 | 2-Jan-86   | 204 | 1.0048| 1.0020| 0.0090    | 2.0638  | 9.0609 | 0.9966| 1.0228|
| Hang Seng| 4-Jun-90   | 167 | 1.0149| 1.0108| 0.0156    | 1.5234  | 6.0770 | 0.9981| 1.0457|
| KOSPI    | 26-Jul-04  | 89  | 1.0292| 1.0193| 0.0333    | 2.1792  | 10.2771| 0.9984| 1.0953|
| MIB      | 02-Jan-98  | 141 | 1.0027| 1.0003| 0.0062    | 3.0908  | 19.0455| 0.9984| 1.0148|
| NIKKEI 225| 6-Jan-86 | 243 | 1.0032| 1.0011| 0.0058    | 2.8359  | 16.3888| 0.9988| 1.0141|
| OMX      | 29-Aug-02  | 104 | 1.0297| 1.0219| 0.0289    | 1.8979  | 9.2254 | 1.0000| 1.0847|
| SMI      | 03-Jan-89  | 184 | 1.0144| 1.0108| 0.0142    | 1.5181  | 6.1899 | 0.9990| 1.0430|
| S&P 500  | 2-Jan-86   | 238 | 1.0137| 1.0103| 0.0141    | 1.5140  | 6.0911 | 0.9981| 1.0416|
| STOXX 50 | 11-Apr-94  | 174 | 1.0067| 1.0033| 0.0098    | 2.1198  | 9.4946 | 0.9982| 1.0263|

The value of ϕ obtained using daily returns is 2.29 and hence is close to that used in our main analysis (see Table 7).

4.3. Robustness tests

Our main results use the method of Bakshi et al. (2019) to compute the discount rates employed in our analysis. As discussed in Section 3.1, computing these discount factors requires option prices to compute risk neutral moments and historical returns to estimate the parameter ϕ. While this method has the advantage of producing an unbiased estimate of the discount factor, it is not completely forward looking as historical data are used to compute ϕ. Other approaches, such as those developed by Martin (2017) and Chabi-Yo and Loudis (2020), produce estimates of the expected return that do not require historical returns, and hence are completely forward looking. However, these methods have the disadvantage that they provide lower bounds to the true market expected return. To ensure that the use of historical data does not impact our results, we perform all statistical tests in Section 4.1 using discount rates computed with the method of Chabi-Yo and Loudis (2020). In Appendix B we briefly describe the approach Chabi-Yo and Loudis (2020) use to produce their estimates.

The main results using (lower bounds to) expected market returns based on the approach of Chabi-Yo and Loudis (2020) are in Appendix B in Tables 8, 9 and 10. We find that the results obtained using the lower bound estimates of Chabi-Yo and Loudis (2020) are in general agreement with our main results obtained using the

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12 The day with the steepest EMRP term structure slope observed during our sample period was 10th October 2008 coinciding with market crashes across Europe, Asia and the US.
Table 8
Proportion of return attributed to discount factor changes across indices. This table presents the proportion of index returns that can be attributed to contemporaneous changes in the short-term discount factor. We fix the date \( t_1 \) at the 2nd January, 2020 and compute all returns relative to that date. Discount rate estimates are computed using the method of Chabi-Yo and Loudis (2020).

| Date \(( t_2)\) | Variable | Mean  | Median | Std. Dev. | Min   | Max   |
|---------------|----------|-------|--------|-----------|-------|-------|
| March 12,     | Cum. Rtn. | −0.3053 | −0.2909 | 0.0979    | −0.4702 | −0.1592 |
|               | \( R_{t_2-t_1} \) | 0.4232 | 0.4400 | 0.0946 | 0.2284 | 0.5666 |
| March 23,     | Cum. Rtn. | −0.3711 | −0.3758 | 0.0570 | −0.4340 | −0.2709 |
|               | \( R_{t_2-t_1} \) | 0.4016 | 0.3866 | 0.1431 | 0.1316 | 0.6494 |
| May 12,       | Cum. Rtn. | −0.1924 | −0.1635 | 0.0703 | −0.3056 | −0.0947 |
|               | \( R_{t_2-t_1} \) | 0.3247 | 0.2827 | 0.1437 | 0.1211 | 0.6177 |

Table 9
Proportion of return attributed to discount factor changes across time windows. This table presents descriptive statistics for the proportion of the index returns that can be attributed to the changes in short-term discount factors for each of the 13 indices in our sample, computed across all three windows starting on January 2, 2020 and finishing on March 12, March 23, and May 12, 2020. Discount rate estimates are computed using the method of Chabi-Yo and Loudis (2020).

| Index       | Mean  | Median | Std. Dev. | Min   | Max   |
|-------------|-------|--------|-----------|-------|-------|
| AEX         | 0.5343 | 0.5399 | 0.0212 | 0.5108 | 0.5521 |
| ASX 200     | 0.2579 | 0.2284 | 0.1538 | 0.1211 | 0.4243 |
| CAC 40      | 0.3592 | 0.3866 | 0.0977 | 0.2508 | 0.4403 |
| DAX         | 0.3994 | 0.3764 | 0.0435 | 0.3722 | 0.4495 |
| FTSE 100    | 0.2178 | 0.1827 | 0.1082 | 0.1316 | 0.3393 |
| Hang Seng   | 0.4091 | 0.4214 | 0.1885 | 0.2147 | 0.5911 |
| KOSPI       | 0.2572 | 0.2827 | 0.0589 | 0.1898 | 0.2991 |
| MIB         | 0.3389 | 0.3921 | 0.1014 | 0.2220 | 0.4027 |
| NIKKEI 225  | 0.5240 | 0.5257 | 0.1262 | 0.3979 | 0.6484 |
| OMX         | 0.3852 | 0.3694 | 0.0488 | 0.3463 | 0.4400 |
| SMI         | 0.4466 | 0.4345 | 0.0431 | 0.4109 | 0.4944 |
| S&P 500     | 0.5214 | 0.5066 | 0.1252 | 0.3799 | 0.6177 |
| STOXX 50    | 0.3300 | 0.3566 | 0.0802 | 0.2399 | 0.3934 |

Bakshi et al. (2019) method to compute discount rates. This suggests that our results are robust to the method of computing short-term discount rates and we maintain our general conclusion that short-term rates became a more significant driver of index returns as we move from the pre-covid period into the pandemic and that during the pandemic short-term discount rates accounted for around 40% of observed index returns.

5. Conclusion

This paper investigates the change in the joint behavior of option-based expected equity risk premiums and index returns across 13 international markets as the COVID-19 pandemic took hold. By focusing on the impact of variation in short term discount rates on stock market valuations, our study complements existing research that shows that after a sharp decline in earnings in the first 12 to 18 months after the start of the pandemic, earnings were expected to display a quick and sharp recovery (see Hong et al., 2020). We show that approximately 40% of the change in market values during the first few months of the COVID-19 pandemic can be attributed to changes in the short term discount rate. We also document sharply downward sloping term structures of equity risk.
Table 10  
Change in variances and correlations. This table presents the variances (Panel A) of the variables $\Delta x_t$, $\Delta \delta_{t-1}$ and $\Delta f_t^*$ and all pairwise correlations (Panel B) measured in both the pre-covid period and during the covid pandemic. In Panel A, all reported figures are annualized volatilities where $\text{Vol}(X) = \sqrt{\text{Var}(X)}$. In Panel B, $\rho(X, Y)$ denotes the correlation between $X$ and $Y$. Differences in variances from the pre-covid to the covid period are tested via Levene’s test using quadratic variation. Differences in correlations from the pre-covid to the covid period are tested via Fisher’s test and differences in means across the 13 indices are tested using the Wilcoxon signed rank test. Statistical significance at the 10, 5 and 1% levels are indicated with *, ** and *** respectively. Discount rate estimates are computed using the method of Chabi-Yo and Louidis (2020).

Panel A: Change in Variances

|       | Vol($\Delta x_t$) | Vol($\Delta \delta_{t-1}$) | Vol($\Delta f_t^*$) |
|-------|--------------------|-----------------------------|---------------------|
|       | Pre-Covid          | Covid                        | Pre-Covid           | Covid                        | Pre-Covid          | Covid                        |
| AEX   | 0.1248             | 0.5079***                    | 0.0437              | 0.3944***                    | 0.1187             | 0.3269***                    |
| ASX 200 | 0.1161             | 0.5517***                    | 0.1064              | 0.5274***                    | 0.1460             | 0.6394***                    |
| CAC 40 | 0.1338             | 0.5857***                    | 0.1248              | 0.7344***                    | 0.1683             | 0.8467***                    |
| DAX   | 0.1460             | 0.5673***                    | 0.0579              | 0.3858***                    | 0.1368             | 0.3444***                    |
| FTSE 100 | 0.1223            | 0.5160***                    | 0.1040              | 0.4080***                    | 0.1495             | 0.5093***                    |
| Hang Seng | 0.1755            | 0.3443***                    | 0.1774              | 0.3198***                    | 0.2526             | 0.2574                        |
| KOSPI | 0.1436             | 0.4843***                    | 0.0689              | 0.2931***                    | 0.1536             | 0.4376***                    |
| MIB   | 0.1665             | 0.6438***                    | 0.1386              | 0.5220***                    | 0.2001             | 0.6427***                    |
| NIKKEI 225 | 0.1601         | 0.4512***                    | 0.1599              | 0.3787***                    | 0.2084             | 0.2817***                    |
| OMX  | 0.1415             | 0.4925***                    | 0.1123              | 0.6795***                    | 0.1721             | 0.6281***                    |
| SMI   | 0.1221             | 0.4343***                    | 0.0953              | 0.3438***                    | 0.1528             | 0.3935***                    |
| S&P 500 | 0.1415            | 0.6575***                    | 0.0668              | 0.3909***                    | 0.1366             | 0.4374***                    |
| STOXX 50 | 0.1323            | 0.5613***                    | 0.0524              | 0.3842***                    | 0.1269             | 0.3408***                    |
| Mean  | 0.1405             | 0.5229***                    | 0.1006              | 0.4432***                    | 0.1633             | 0.4681***                    |

Panel B: Change in Correlations

|       | $\rho(\Delta x_t, \Delta \delta_{t-1})$ | $\rho(\Delta x_t, \Delta f_t^*)$ | $\rho(\Delta \delta_{t-1}, \Delta f_t^*)$ |
|-------|----------------------------------------|-----------------------------------|------------------------------------------|
|       | Pre-Covid                      | Covid                      | Pre-Covid                             | Covid                      | Pre-Covid                      | Covid                      |
| AEX   | 0.3107                          | 0.7654**                   | 0.9369                                | 0.6301***                  | -0.0412                        | -0.0174                   |
| ASX 200 | 0.1405                          | 0.2985                     | 0.6927                                | 0.6166                     | -0.6167                        | -0.5674                   |
| CAC 40 | 0.1543                          | 0.1924                     | 0.6808                                | 0.5248*                    | -0.0471                        | -0.2649                   |
| DAX   | 0.3523                          | 0.8044***                  | 0.9183                                | 0.7463***                  | -0.0471                        | -0.2649                   |
| FTSE 100 | 0.1339                        | 0.4118*                    | 0.7245                                | 0.6833**                   | -0.586                          | -0.3389*                  |
| Hang Seng | -0.0245                      | 0.7018**                   | 0.7121                                | 0.4656*                    | -0.7193                        | -0.3038**                 |
| KOSPI | 0.0699                          | 0.4543*                    | 0.8545                                | 0.8025*                    | -0.3648                        | -0.167                     |
| MIB   | 0.1491                          | 0.4076*                    | 0.7286                                | 0.6708**                   | -0.5686                        | -0.4039                   |
| NIKKEI 225 | 0.152                         | 0.7832***                  | 0.6519                                | 0.5487*                    | -0.6504                        | -0.0901***                |
| OMX   | 0.0944                          | 0.4628*                    | 0.7604                                | 0.2834*                    | -0.5748                        | -0.7189                   |
| SMI   | 0.0283                          | 0.5089*                    | 0.7817                                | 0.659*                     | -0.6012                        | -0.312*                   |
| S&P 500 | 0.3084                         | 0.7661***                  | 0.8853                                | 0.8186*                    | -0.1693                        | 0.258*                    |
| STOXX 50 | 0.2986                         | 0.8033**                   | 0.919                                 | 0.7411**                   | -0.1018                        | 0.1956*                   |
| Mean  | 0.1683                          | 0.5662***                  | 0.7913                                | 0.6301***                  | -0.4354                        | -0.2339***                |

Applying the method Lagrange multipliers provides the solution

$$M^* = e^{m_0^* + \phi^*(R_t - R_t)}$$  \hspace{1cm} (19)

where $(m_0^*, \phi^*)$ solves

$$\arg\min_{m_0, \phi} (-m_0 \mu_M + E^{\phi^*}(e^{m_0^* - 1 + \phi^*(R_t - R_t)})).$$  \hspace{1cm} (20)

To compute a value of $\phi$ for each index, we perform the optimization procedure outlined in Eq. (20) on a set of historical monthly return data for each index. The returns used to compute $\phi$ all occur prior to the start of our options data period and are presented in Table 7. Using these return series, we perform 10,000 bootstrap estimates using 80% of the observations to create each bootstrap sample to arrive at our estimate of $\phi$, which is taken as the mean of the bootstrapped values. This is the same approach as used by Bakshi et al. (2019). Descriptive statistics for $\phi$ and $m_0$ are provided in Table 7.

Appendix B. Robustness Test

Chabi-Yo and Louidis (2020) demonstrate how to connect physical expected returns with the risk-neutral covariance between re-
turns and the inverted SDF, namely,
\[
E^p_t( R_{t+\tau} ) - R_{t,t} = \text{Cov}_t^p \left( R_{t+\tau}, \frac{E^p_t(M_{t+\tau})}{M_{t+\tau}} \right)
\]
(21)

where \( p \) denotes the physical measure, \( q \) the risk-neutral, \( R_{t+\tau} \) is the \( \tau \)-period gross return on the market and \( M_{t+\tau} \) the \( \tau \)-period stochastic discount factor. The authors show how the Radon-Nikodym derivative can be used to express the inverted SDF, \( E^p_t(M_{t+\tau})/M_{t+\tau} \), in terms of a risk-neutral expectation. This means that the right hand side of (21) can be written entirely in terms of risk-neutral moments. Given that the SDF may be written in terms of a utility function which is assumed to be sufficiently differentiable, Chabi-Yo and Loudis (2020) show that the difference between physical and risk neutral moments can be written as
\[
M^p_n - M^q_n = \frac{\sum_{k=1}^{\infty} \theta_k (M^q_n M^q_k - M^q_{n+k} M^q_k)}{1 + \sum_{k=1}^{\infty} \theta_k M^q_k}
\]
(22)

where
\[
M^q_n = E^q_t((R_{t+\tau} - R_{t,t})^n); \quad M^q_k = E^q_t((R_{t+\tau} - R_{t,t})^k).
\]
(23)

The coefficients \( \theta_k \) correspond to investor preferences with respect to the risk captured by each moment, which Chabi-Yo and Loudis (2020) argue may be bounded. Hence, setting \( n = 1 \) to address the expected excess return, replacing the terms \( \theta_k \) with \( 1/R_{t,t}^k \) for \( k \) even, and \(-1/R_{t,t}^k \) for \( k \) odd (which provides a lower bound), and truncating the infinite sum to three terms, Chabi-Yo and Loudis (2020) show that
\[
E^p_t( R_{t+\tau} ) - R_{t,t} \geq \frac{1}{R_{t,t}} [ M^q_3 - \frac{1}{R_{t,t}} M^q_2 + \frac{1}{R_{t,t}^2} M^q_1 - \frac{1}{R_{t,t}} M^q_2 + \frac{1}{R_{t,t}^2} M^q_1 ]
\]
(24)

Expressions for the value of risk-neutral moments can be obtained by employing spanning relations found in Carr and Madan (2001) and Bakshi et al. (2003). These formulas are provided in Appendix B of Chabi-Yo and Loudis (2020). One of the key assumptions in the derivation of this bound is that the odd risk-neutral moments are negative. Since Eq. (24) is truncated, the only odd moment we have available to empirically test is \( M^q_3 \). We find that the proportion of observations for which \( M^q_3 < 0 \) averages more than 99%, suggesting this is not a restrictive assumption.

In Tables 8, 9 and 10 we provide results that correspond to the results presented in Tables 4, 5 and 6 respectively. These results show that our main conclusions are robust to the method used to compute EMRPs.

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