Earnings Expectations during the COVID-19 Crisis*

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Abstract

We analyze the dynamics of earnings forecasts and discount rates implicit in valuations during the COVID-19 crisis. Forecasts over 2020 earnings have been progressively reduced by 16%. Longer-run forecasts have reacted much less. We estimate an implicit discount rate going from 10% in mid-February to 13% at the end of March and reverting to its initial level in mid-May. Over this period, the unlevered asset risk premium is unchanged, as the risk-free rate drop is compensated by the effect of increased leverage. Hence, analysts’ forecast revisions explain all of the decrease in equity values between January 2020 and mid-May 2020. (JEL G40, G12, G17)

In April 2020, the stock market had fallen dramatically as a result of concerns about the economic impact of COVID-19. This provides a natural laboratory to examine the joint impact of expectations changes and discount rate changes on firm valuations during an episode of extreme market stress. Gormsen and Koijen (2020) use dividend strips to infer the shift in the term structure of expectations of future dividends. We propose instead to directly look at revisions of analysts’ forecasts of firms’ earnings. Both methods offer advantages and disadvantages: dividend futures is purely based on prices, which are more likely to reflect actual investors’ beliefs. However, using dividend futures prices forces the focus on the aggregate, and only provides a lower bound to changes in forecasts as shocks to risk premiums are not directly observed. Using analysts’ forecasts allows for a firm-level analysis and a direct measure of revisions in beliefs. However, to connect

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it to stock prices, we need to assume that analysts’ forecasts are a reliable proxy for investors’ beliefs.

Our work joins a fast-growing set of papers looking at how the stock market has reacted to the COVID-19 outbreak. Gormsen and Koijen (2020) provide a lower bound on the change in expected aggregate S&P 500 dividends. Ramelli and Wagner (2020) and Ding et al. (2020) study in detail how firm-level characteristics, such as leverage, cash holdings, supply chain, and industry, affect the cross-section of returns. Alfaro et al. (2020) show how unanticipated changes in predicted infections forecast aggregate equity market returns. Albuquerque et al. (2020) find a positive correlation between ESG ratings and abnormal returns through the crisis.

We address two main issues that speak to the finance literature. First, we show how the term structure of earnings expectations has evolved over in March, April, and May 2020. Downward revisions have occurred smoothly, but were mostly focused on 2020–2022; longer-term forecasts for 2023 and 2024 have remained quite stable. Analysts’ forecast dispersion has mostly increased for short-term horizons. The smooth reaction of short-term forecasts and the rather muted response of long-term forecasts paint a picture that is somewhat unusual when compared to the available literature on expectations and stock returns. Indeed, this literature shows that (1) analysts’ short-term earnings per share (EPS) forecasts tend to underreact to news (Bouchaud et al. (2019); Ma et al. (2020)), whereas (2) analysts’ long-term growth expectations overreact (Bordalo et al., 2019). The fact that long-term forecasts have reacted less (actually, not at all, beyond 2023) than short-term forecasts might reflect the intrinsic short-term nature of the shock.

Second, using stock prices, we back out the implied change over time in the discount rate for each firm. Assuming constant discount rates between February 15 and May 11, the decline in stock prices implied by forecast revisions would have been very close to realized returns. In other words, the stock price decline can fully be accounted for by earnings forecast revisions. We also show that discount rate shocks are the main driver of the V-shaped evolution of stock-prices. Our exercise is related to the large literature on discount rates movements that was initiated by Shiller (1981). The difference between his analysis and ours is twofold. First, we use forecasts of future cash flows instead of ex post dividend realizations or model-predicted growth. DeLaO and Myers (2020) have performed a related exercise using macro forecasts and a longer time period, and arrive to the similar conclusion that long-run stock-price fluctuations can be essentially explained by earnings forecast fluctuations, instead of discount rate movements. The second difference between a Shiller (1981)-type analysis and ours is that we decompose the change in discount rate into three terms: interest rates, unlevered asset risk premium, and the leverage effect (declining stock prices lead to an increase in expected equity returns). An interesting finding is that the leverage effect, often unmodeled in asset pricing setups, is as large as changes in the unlevered equity premium. Overall, our decomposition suggests that, by mid-May, the 1-ppt reduction in interest rates is fully offset
by a 50-bp increase in the unlevered risk premium and a 50-bp increase due to the leverage effect. Third, we document that the sensitivity of cumulative returns to changes in discount rates is rather low in the cross-section of stocks. This suggests that the term structure of equity discount rates is not flat, and that stock prices, combined with earnings forecasts, can be used to identify it. This also suggests that nonflat equity risk premium term structure should be an important component of firm valuation models (Ang and Liu (2004)). Overall, our analysis suggests that, by mid-May 2020, stock prices had moved in line with expectations. Such a result is consistent with recent findings in the asset pricing literature, which attributes a surprisingly large fraction of medium-term stock price movements to movements in expectations (Engelberg et al. (2018); Loechster and Tetlock (2020); DeLaO and Myers (2020)) rather than movements in discount rates.

1 Data

Using CRSP (via WRDS), we select firms that were traded on NYSE, Nasdaq, or Amex at the end of 2019. Among them, we then retain the top 1,000 by total market capitalization as of December 31, 2019. This gives us a list of CUSIP identifiers, which we use to retrieve historical returns and I/B/E/S forecasts through the Refinitiv-Eikon platform (Thomson Reuters). We use Refinitiv to have up-to-date forecasts and stock returns, which are not yet available on WRDS. We focus on forecasts issued up until May 11, 2020, about EPS for fiscal years 2020 to 2024. We use forecasts averaged across analysts (i.e., the consensus forecast), as updated on the Eikon platform on a daily basis. We also download Long-term growth forecasts (variable LTG), providing expected annual growth in operating earnings over the next full business cycle. We use market betas computed as of December 31, 2019, based on 1 year of daily returns. Data on fundamentals (debt, total assets, GIC sector) are retrieved from COMPUSTAT.

To give a sense of the data, we reproduce in Figure 1 the evolution of average EPS forecasts for two large firms, Facebook and Ford. We show forecasts at all five horizons (2020, . . . , 2024). We show how these forecasts have evolved over time. First, we see that long-term expectations did not react as much as short-term expectations. Second, forecast revisions differ across firms in expected ways: the small impact in the case of Facebook; however, revisions to Ford’s earnings are strongly negative, all the way to 2023.

Can we trust analysts’ forecasts? The literature historically documents an optimistic bias in analysts’ forecasts (Dreman and Berry (1995)), often related to conflicts of interest (see, e.g., Michaely and Womack (1999); Dechow et al. (2000); Hong and Kubik (2003); Cowen et al. (2006)). However, the upward bias of analysts has strongly decreased since the 1990s, a fact already noted in Kothari (2001). The trend has accelerated after the tech bubble. In Figure A.1, we compute
for each year the average normalized difference between forecasted and realized earnings. While this difference was strongly positive in the 1990s, it has become quite close from zero, especially for horizons of 1 and 2 years. One explanation is that regulations of sell-side research introduced after the 2001 have reduced incentives for analysts to provide rosy views on companies (Kadan et al. (2008)). It also might be related to companies’ increased reliance on earnings guidance.

2 Change in the Term Structure of Expectations

2.1 Term structure of implied growth forecasts

For each firm \(i\) at date \(t\) which has positive earnings in 2019, we compute the implicit annualized growth rate of earnings at horizon \(h\) as

\[
g_{i,t,h} = \frac{1}{h - 2019} \left( \frac{F_t EPS_{i,t,h} - EPS_{i,2019}}{EPS_{i,2019}} \right). 
\]

This linearized growth formula allows us to accommodate negative future \(F_t EPS_{i,t,h}\), of which there are many, especially since the COVID-19 crisis. To be in line with analysts’ forecasts,\(^1\) we use realized earnings as reported by I/B/E/S/ for \(EPS_{i,2019}\), but require such earnings to be positive. We focus on annualized growth in this definition to more easily compare forecasts at different horizons.

\(^1\)I/B/E/S/ forecasts typically are about “street earnings” rather than GAAP earnings (reported in, e.g., Compustat). See Abarbanell and Lehavy (2007).
Figure 2 reports median implicit growth across all firms per horizon. We compute the median of this implicit growth measure across firms, for each date $t$ and each horizon. It appears that 2020 EPS growth expectations were slashed down from 12% to nearly -6%, or a 16% reduction. Longer-term growth expectations were reduced but to a much lesser extent. 2024 forecasts decreased from an implicit annual growth of 13% to 10.2%. This confirms the preliminary insights we gained from Figure 1.

Figure 2: Forecasted annualized growth of earnings

This figure shows the evolution of implicit annualized growth at horizons 2020, . . . , 2024. For every day $t$ between February 15, 2020, and May 11, 2020, we define annualized growth expected at time $t$ for firm $i$ at horizon $h$ as $g_{i,t,h} = \frac{1}{h-2019} \left(F_{t, EPS_{i,h}} - EPS_{i,2019}\right)$, where $F_{t, EPS_{i,h}}$ is the average forecast at date $t$ of annual earnings per share for firm $i$ and horizon $h$. We restrict the sample to firms with a positive realized EPS in 2019 ($EPS_{i,2019} > 0$) and report a cross-sectional median at each date $t$.

To visualize the speed of recovery, in Figure A.2, we plot the annualized growth rates $g_{i,t,h}$ per horizon $h$ for just two dates. This is essentially the same information as in Figure 2, except that we show it only for two dates, and report confidence bands. Consistent with Figure 2, we find that forecasts have been revised downward for 2020 (to slightly negative growth). Analysts anticipate the COVID-19 shock to last well into 2022. By 2023–2024, they expect the economy to have returned to trend.

For the sake of comparison, we replicate in Figure 3 the analysis in Figure 2 during the global financial crisis. We use consensus forecasts from I/B/E/S/ and compute the same statistic as

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2To report confidence bands in a simple way, we trim the sample by removing observations within the 5 interquartile range away from the median. On the chart, we report the mean (which after trimming does not differ much from the median) and the confidence band as two times the standard error divided by the square root of the number of observations.
before: the implicit annual growth forecast between 2007 (which was known at the time) and 2009, 2010, 2011, and 2012. We observe in Figure 3 drastic downward adjustments by analysts after the Lehman Bankruptcy, suggesting that conditional on updating, analysts do not hesitate to slash their forecasts substantially. However, Figure 3 also suggests that these adjustments are more pronounced at shorter horizons, and rather progressive. This indication is confirmed by the fact that average forecast errors at all horizons were positive until mid-2009 (see Figure A.3). Hence, in both crises, the term structure of updates has been similar. During the GFC, revisions were big, but not (in hindsight) big enough.

Figure 3: Evolution of implicit growth in forecasts around the Lehman bankruptcy

We focus on firms whose fiscal year ends in December 31, and firms whose EPS realization in 2007 was positive. For each firm, each month and each horizon we compute the implicit growth rate in the forecast as in Equation (1). We do not report the 2008 FY forecast, since FY 2008 was largely completed when Lehman Brothers went bankrupt (so forecasts were not much revised). Reading: In September 2008, the average implicit growth between 2007 and 2009 was about 14% annually. Between 2007 and 2010, 2011 and 2012, it was still about 17% annually.

2.2 Under- versus overreaction

An old debate in the behavioral literature is whether stock analysts underreact or overreact to news. Lakonishok et al. (1994), DeBondt and Thaler (1990), Laporta (1996), and Bordalo et al. (2019) document extrapolative bias by analysts about glamour stocks. Abarbanell and Bernard (1992) and Bouchaud et al. (2019) find evidence that analysts actually underreact, leading to

3In a more general study of analysts’ forecasts in bad times, Loh and Stulz (2018) document that conditional on a crisis, analysts are quite active in producing relevant information: forecast errors per unit of uncertainty fall, and analysts publish more frequent and longer reports.
serial autocorrelation in revisions and predictability in forecast errors. The evidence from Figures 2 and 3 shows that analysts’ consensus forecast is updated downward in a smooth manner, which contrasts with the volatility of prices (see the next section). This is interesting as overreaction is often associated with salient news, and the COVID-19 crisis is indeed salient, to say the least. (For information about the spike in attention to COVID-19, see Ramelli and Wagner (2020).)

In the overreaction literature, research shows that overreaction mostly takes place in long-run expectations. Laporta (1996) and Bordalo et al. (2019) measure long-term expectations using “long-term growth” (LTG) updates by analysts, and show that these forecast tend to update “too much.” This I/B/E/S/ variable corresponds to average growth over the coming business cycle. Figure 4 shows the evolution of median LTG (“long-term growth”) in our sample. We restrict ourselves to firms for which an LTG is continuously present in the data. Evidence from Figure 4 is consistent with evidence from the rest of the term structure of forecasts. Expectations for 2024 suggest a reduction in expected EPS growth until 2024 by about 1.5 ppt (see Figure A.2, for instance). Evidence from revisions in LTG does suggest a reduction of the same amount. Hence, LTG was progressively updated as the crisis grew more severe. This pattern is not obviously related to overreaction, unless the COVID-19 crisis turns out to be a very temporary shock.
2.3 Term structure of analysts’ forecast dispersion

Here, we investigate the term structure of analysts’ disagreement. I/B/E/S/ reports the standard deviation of earnings forecasts (across analysts) at different horizons, $\sigma_{i,t,h}$. This is a measure of disagreement among analysts and can be interpreted as reflecting the level of economic uncertainty. We normalize this dispersion by dividing it by past realized earnings ($EPS_{i,2019}$) when they are positive. Figure 5 plots the median normalized disagreement per horizon among firms in our sample. We observe a sharp increase in disagreement. Interestingly, this increase is, until mid-April, stronger at shorter horizon, so that the term structure of disagreement is flipped over. While prior to the crisis, analyst disagreed more about the long run, at the beginning of April, when the market was in a trough, there was more disagreement about the short run. Note that after April 15, we observe decreasing disagreement about 2020 earnings, reflecting the fact that quarter 1 earnings for 2020 are being published, mechanically limiting uncertainty to the subsequent three quarters.

Figure 5: Dispersion of forecasts

This figure plots the standard deviation of yearly earnings forecasts (across analysts) at different fiscal year horizons, normalized by 2019 realized earnings ($EPS_{i,2019}$). We restrict to firms with $EPS_{i,2019} > 0$ and report the median of this normalized dispersion for each date.

2.4 Revisions across industries

We now ask which industries analysts most revised. We divide our sample of 1,000 firms into GIC sectors and show the median value of $\left(\frac{F_{T_1}EPS_{i,h}}{F_{T_0}EPS_{i,h}} - 1\right)$, where $T_1$ is May 11, 2020, and $T_0$ is February 15, 2020. Figure 6 reports the industry breakdown. Each bar represents the percentage
change in typical forecast of yearly EPS in a given industry for various horizons. The different bars allow to evaluate the relative persistence of the COVID-19 shock across industries: real estate faces the strongest downward revision but only at short horizon. This is in line with Ling et al. (2020). Utilities and Consumer Staples are the sectors that are the least hit by the crisis, in both the short term and the medium term. Some industries, such as Consumer Discretionary, face a very persistent shock (the revisions in their forecasted earnings are similar for 2020, 2021, and 2022). Interestingly, the crisis has led to downward revisions that are still visible at 4 years horizon: analysts significantly downgrade their initial forecasts even for 2023.

Figure 6: Revision by industries

This figure represents the median percentage change in EPS forecasts \(\left(\frac{F_{T_1}^{\text{EPS},i,h}}{F_{T_0}^{\text{EPS},i,h}} - 1\right)\) by industry (GIC sectors). The final date \((T_1)\) is May 11, 2020, and the start date \((T_0)\) is February 15, 2020. We restrict our sample to firms with \(F_{T_0}^{\text{EPS},i,h} > 0\). For each sector, we report forecasts for four horizons \(h\), namely, fiscal years 2020, ..., 2023.

\[\text{Figure 6: Revision by industries}\]

2.5 The leverage effect in analysts’ forecasts

The impact that a given cash flow shock has on earnings should be larger for highly levered companies. This is simply because interest payments are a larger fraction of total cash flows for these companies, hence making earnings more sensitive to the shock. We test whether analysts do indeed anticipate a sharper reduction of earnings for high leverage companies. To do this, we sort companies in five leverage quintiles, using their market leverage as observed on December 31, 2019. We use the total book value of debt from COMPUSTAT and market capitalization from CRSP. For each date \(t\), we compute \(\left(\frac{F_t^{\text{EPS},i,h}}{F_{T_0}^{\text{EPS},i,h}} - 1\right)\), where \(T_0\) is February 15. Figure 7 plots the median by date and quintile of leverage. Consistent with the leverage effect, this figure shows that
downward revisions are much stronger for highly levered companies. For 2020 earnings, companies in the highest leverage quintile experiences a $-27\%$ downward revision as of May 11 versus $-8\%$ for the lowest quintile of leverage. For 2021 earnings, we also observe a large spread between the high and the low leverage quintiles.

Figure 7: Revision by leverage quintiles

This figure represents the median percentage revision in forecasts \(\frac{F_{i,h}^{EPS} - T_{0}^{EPS}_{i,h}}{T_{0}^{EPS}_{i,h}} - 1\) by the quintile of leverage. The reference date \((T_{0})\) for initial forecasts is February 15. We use market leverage computed by the total debt from Compustat (for fiscal year 2019) and market capitalization from CRSP as of the end of 2019. For each date, we plot the median by the quintile of leverage. The sample is restricted to firms with \(F_{T_{0}}^{EPS}_{i,h} > 0\).

3 Forecasts and Market Prices

3.1 Forecast-implied prices versus realized prices

We now conduct an exercise similar to Shiller (1981), except that we use EPS forecast revisions instead of ex post dividend realizations. Our exercise is similar to that of DeLaO and Myers (2020), who look at the past few decades of aggregate returns. An important difference between their analysis and ours is that we look on the cross-section of firms (they look at macro returns).

As a motivating fact, we show in Figure A.4 the strong positive relationship between sector-level revisions in forecasts and cumulative returns over the same period. This figure shows that sectors where analysts have been the most pessimistic also have experienced the sharpest decline in stock prices. We can this expect a connection between forecast revisions and returns in the cross-section of firms.
We then move a more quantitative decomposition of prices into expected earnings and discount rates. First, we ask, assuming constant discount rates, by how much stock prices would have decreased in order to be consistent with forecast revisions. Specifically, for each firm-date, we compute

\[
P_{it} = \frac{b_i F_i EPS_{2020,i}}{1 + r_i} + \frac{b_i F_i EPS_{2021,i}}{(1 + r_i)^2} + \frac{b_i F_i EPS_{2022,i}}{(1 + r_i)^3} + \frac{(1 + g_i)b_i F_i EPS_{2022,i}}{(r_i - g_i)(1 + r_i)^3},
\]

where \( b_i \) is the firm-level payout ratio, \( r_i \) is a firm-specific discount rate, and \( g_i \) the long-term growth rate. All three variables are computed using the following approach. First, for each firm in our sample, we calculate common stock payout, every year between 2010 and 2019, as the sum of dividends (COMPUSTAT item dvc) and common stock repurchases (total buybacks prstkc minus preferred buybacks pstkrv). We then normalize common stock payout by net income (when net income if positive, otherwise we report payout as missing), and compute the average of this number over 2010–2019. We then winsorize these average payout ratios at 0 and 1: This gives us \( b_i \). For growth, we compute \( g_i \) as the average sales growth rate at GICS industry level over 2015–2019. For each GICS sector, we compute the average firm sales growth over 2015–2019, weighted by 2015 sales, after removing outliers. Because of this cleaning procedure, such industry growth is well behaved, goes from 0.2% to 10%, with an average of 3.5%. Finally, we estimate \( r_i \) separately for each firm by computing the IRR on Jan 2 (we remove observations for which the algorithm fails to find an IRR above 30% or below 0%). We show the distribution of these discount rates in Figure A.5 in the appendix.

This analysis yields our first key finding: analysts’ revisions explain the entirety of the stock price decrease between February 15 and May 11. In Figure 8, we compute the mean cumulative PV growth across firms, and plot it alongside unweighted average cumulative returns (after trimming outliers). Forecast-implied returns (i.e., fixed initial discount rates) are down 12% since beginning of 2020, which is very close with the (unweighted) average realized cumulative return which are down 10% since the same date. Put differently, the term structure of forecasts shown above is broadly consistent with the fall in the stock market on the entire period.4

A second key finding is a large temporary increase in discount rates at the end of March and the beginning of April. 5 We now turn to a decomposition of this discount rate to build intuition

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4We note that this result is robust to many of our assumptions. The forecast-implied estimate is, by definition, insensitive to the payout ratio \( b_i \), which does not vary within firm. It is robust to the choice of growth, \( g_i \), or discount rate, \( r_i \). In Figures A.6 and A.7 in the appendix, we compute the implied cumulative return taking alternative values of \( r_i \) and \( g_i \).

5One potential concern with our analysis is that our long-term forecasts might be very stale, and their staleness might bias our DCF exercise. By looking at the subsample of analysts for which Eikon-Refinitiv provides individual data, we find that this bias is limited in scope: by the end of April, a large majority of analysts covering 2020, 2021, and 2022 earnings had renewed their forecasts at all horizons. The proportions range from 88% for the 2022
Figure 8: Forecast implied returns versus realized returns
Assuming a constant (over time) firm-level discount rate
Together, we report (1) the realized cumulative return and (2) the forecast-implied cumulative return \( (PV_t/PV_{T_0} - 1) \). The forecast implied cumulative return is based on the evolution of present values \( (PV_t) \) defined above. The computation of \( PV_t \) employs firm-level average forecasts at date \( t \) and a constant discount rate implied by the initial value of each firm at \( T_0 \). Valuations are performed at the firm level. The start date \( (T_0) \) is January 1, 2020, and the end date May 11, 2020. We focus on 890 firms for which \( PV_t \) is continuously defined throughout the period.

about the drivers of this temporary increase.

### 3.2 Discount rates

In this section, we now seek to understand the drivers of the implicit firm discount rate in market valuation at each point in time. We first construct this number. Namely, for each firm \( i \) at date \( t \), we compute the internal rate of return of buying one stock, which is the \( r_{it} \) that solves

\[
P_{it} = \frac{b_i F_t EPS_{2020,i}}{1 + r_{it}} + \frac{b_i F_t EPS_{2021,i}}{(1 + r_{it})^2} + \frac{b_i F_t EPS_{2022,i}}{(1 + r_{it})^3} + \frac{(1 + g_i)b_i F_t EPS_{2022,i}}{(r_{it} - g_i)(1 + r_{it})^3}.
\] (3)

We set \( b_i \) as before as the average common stock payout ratio over 2010-2019. We set \( g_i \), as before, as the long-term growth rate at the industry level: We assume it is not changed by the crisis. Note that, by definition, \( r_{i0} = r_i \), where \( r_i \) is the discount rate used in Equation (2). We solve Equation (3) for each firm-year observation since January 1, 2020, for which all three forecasts and the CRSP price is available. This gives us a panel of discount rates that is the mirror image of the difference between forecast-implied valuation and market valuation shown in Figure 8.

Figure 9 reports the mean discount rate. The discount rate on stocks increases from 8.5% horizon up to 92% for 2020.
to nearly 11%, then back to its precrisis level. This rapid reversal hinges on our assumption that analysts’ forecasts are a faithful representation of investor forecasts. One possible concern would be that analysts are slower at adjusting their forecasts than are investors. While continuous-time data on investors’ expectations are not available, some scattered evidence indicates that analysts’ forecasts can be trusted. First, as we discuss in Section 1, analysts’ forecasts have become more and more reliable over time, and are now much less overoptimistic than they used to be. Second, Engelberg et al. (2018) offer evidence that earnings surprises correlate with earnings announcement returns: when analysts are positively surprised, announcement returns tend to be positive. This suggests that analysts are surprised in the same direction as the market. Finally, anecdotal accounts of the late March to early April 2020 period are consistent with a lack of arbitrage capital. For instance, Haddad et al. (2020) document a negative liquidity shock on bond market, partly solved by monetary policy announcements.

![Figure 9: Implicit discount rates](image)

This figure plots the evolution of the mean discount rate on stocks (computed as described above), jointly with the realized average stock return from firms in our sample.

We are now set to decompose the dynamics of this IRR. We seek to disentangle three distinct effects: (1) changes in the risk-free rate, (2) changes in risk premium, and (3) the leverage effect. The first two effects are obvious. The leverage effect is often omitted in asset pricing analyses (who focus on the levered equity premium). It arises directly from the economic shock which is hitting unlevered value (be it a discount rate or a cash flow shock). Because debt value responds less than equity value to a reduction in enterprise value, market leverage mechanically goes up. Through the leverage formula, this increases the cost of equity. As a result, the leverage effect hurts equity prices, both through cash flows and through an increase in expected equity returns.
To obtain this decomposition, we write the change of \( IRR \) between time 0 and time \( t \) as

\[
\Delta r_{it} = \frac{r^f_t - r^f_0}{r^f_t} + \frac{1 - \frac{D_{it}}{E_{it}}}{L^f_t} (r^f_{it} - r^f_t) + \frac{\frac{D_{it}}{E_{it}}}{L^f_t} (r^f_{it} - r^f_t) - (r_{i0} - r^f_0),
\]

where \( l_{it} = \frac{E_{it} + D_{it}}{E_{it}} \) is a measure of market leverage at date \( t \). This formula is an exact decomposition. What makes it marginally unusual is that it breaks down movements in (levered) equity premium into a movement in (unlevered equity premium) and the leverage effect.\(^6\)

The leverage effect is captured by the second term of Equation (4), which is equal to zero if leverage has not changed between 0 and \( t \).

We implement this decomposition at the firm-level and after averaging at each date, we plot the results in Figure 10, in which the thin black line (total change in \( IRR \)) is the sum of the three thick gray lines. To compute the leverage variable \( l_{it} \), we use the firm’s market capitalization at time \( t \) and the book value of total debt as of end of 2019.

**Figure 10:** Decomposition of \( IRR \) changes over time

The thin black line is the total change in \( IRR \). It is an average at each time \( t \) over our sample of firms of \( IRR_{it} \) computed above. We decompose this line as the sum of the three thick gray lines, which represent the effects coming from (1) changes in the safe rate, (2) leverage, and (3) changes in the economic risk premium. These effects are measured by taking the cross-sectional average of, respectively, \( (r^f_t - r^f_0) \), \( (1 - \frac{D_{it}}{E_{it}})(r^f_{it} - r^f_t) \), and \( \frac{\frac{D_{it}}{E_{it}}}{L^f_t} (r^f_{it} - r^f_t) - (r_{i0} - r^f_0) \), in line with Equation 4. Firm leverage at time \( t \) is based on equity values retrieved from CRSP and the book value of total debt at the end of 2019.

\(^6\)Formally, the cash flows generated by the firm’s assets serve both debt and equity, leading to the Modigliani-Miller’s “WACC formula”:

\[
r^A_{it} = \frac{E_{it}}{E_{it} + D_{it}} (r^f_{it} - r^f_t) + \frac{D_{it}}{E_{it} + D_{it}} (r^D_{it} - r^f_t).
\]

The interpretation of our decomposition relies on assuming \( \frac{D_{it}}{E_{it} + D_{it}} (r^D_{it} - r^f_t) \approx 0 \). Under this assumption, the economic risk-premium for holding asset risk is \( r^A_{it} - r^f_t = \frac{E_{it}}{E_{it} + D_{it}} (r^E_{it} - r^f_t) \). The forward expectation of this term should not vary unless risk premiums on fundamental risk vary.
Figure 10 contains three main lessons: First, the Federal Reserve's actions have reduced the
discount rates by about 100 bp via the safe rate of return. Second, the increase in unlevered asset
risk premium has sharp but mostly temporary: by mid-May, the unlevered premium stood about
50 bp above its precrisis level. Third, the leverage effect is quantitatively big, and contributes to
a 50-bp increase in the discount rate. Overall, in mid-May, discount rates have returned to their
precrisis level: higher risk premium and leverage effect being fully counteracted by the reduction
in interest rates.

Of course, our estimate of the leverage effect is vulnerable to the fact that we assume that debt
is safe, which is not true during this period. Making this adjustment is an interesting avenue of
future research for researchers interested in estimating the contribution of the leverage effect to
movement in discount rate.

3.3 Cross-sectional variation in discount rates

We find that the security market line implied by the cross-section of discount rates is quite flat and
variable. In Figure A.8 in the appendix, we take the panel of firm-level discount rates, and regress
the cross-section, every date, on firm-level betas supplied by WRDS. The graph makes clear that
the slope of the SML is lower than what the capital asset pricing model (CAPM) implies. It went
up, then when back down, and was never larger than 2%. That the CAPM does not price the
cross-section of stocks is not surprising in light of the large asset pricing literature documenting
the empirical failure of the CAPM (Fama and French (2004)).

There is also considerable cross-industry heterogeneity in discount rates. In Figure A.9 in the
appendix, we report the variation in discount rates across sectors: Energy and Real Estate are
the most affected (the real estate discount rate goes up from 15% to nearly 25%). Information
Technology goes up very slightly from 8% to 9%. Financials are in between, from 13% to 16%.

3.4 Decomposition of returns during the COVID-19 crisis: Discount
rates versus EPS forecasts

In this last section, we try to appraise the share of cross-section variation in returns that comes from
EPS forecast revisions versus discount rates. We do this using the Campbell-Shiller decomposition
(Campbell (2017)). It allows us to write down prices as a function of dividend expectations and
returns expectations, where $t$ is in years:

$$p_t = \frac{k}{1 - \rho} + (1 - \rho) \sum_{j \geq 0} \rho^j E_t d_{t+1+j} - \sum_{j \geq 0} \rho^j E_t r_{t+1+j}$$
so that log returns (between two consecutive dates excluding dividend payout) write

$$r_t = (1 - \rho) \sum_{j \geq 0} \rho^j R_t d_{t+1+j} - \sum_{j \geq 0} \rho^j R_t r_{t+1+j}$$

, where $R_t \equiv E_t - E_{t-1}$ is the revision operator between two consecutive dates (in our data, $2$ consecutive days).

Assume that the term structure of expected returns follows an AR1 process $E_t r_{t+j+1} = r_j^f + \mu + (\mu_t - \mu) \phi^j$. $r_j^f$ is the safe rate of return at horizon $j$. The revision of expected returns becomes

$$R_t r_{t+1+j} = \Delta r_j^f + \phi^j \Delta \mu_t$$

, where $\Delta \mu_t$ is the change in expected next year equity returns. To simplify the algebra—though it is not necessary for the analysis—we assume here that the term structure of the revision of safe returns is flat: $\Delta r_j^f = \Delta r^f$. At the beginning of 2020, the 3-month U.S. Treasury bill and the 10-year Treasury have both decreased by 1.50 ppt.

Thus, the return of firm $i$ follows (adding firm subscripts):

$$r_{it} = (1 - \rho) \sum_{s \geq 0} \rho^s R_t d_{it+1+s} - \frac{1}{1 - \rho \phi} \Delta \mu_{it} - \frac{1}{1 - \rho} \Delta r^f$$

, where $\rho = \frac{1}{1 + e^{-d-p}}$ and $d - p$ is the mean log dividend yield. We assume $\rho$ and $\phi$ are the same for all stocks, but this first pass could be easily extended.

See Table 1 for the results of this regression. We define as sum of revisions for date $d$ and firm $i$:

$$Rev_{id} = \sum_{h=2022}^{2022} \rho_i^{h-2020} (\log F_d EPS_{ih} - \log F_{d-1} EPS_{ih}) + \rho_i^2 (\log F_d EPS_{i2022} - \log F_{d-1} EPS_{i2022})$$

which implicitly assumes that there is no revision in earnings growth beyond 2022. Evidence from Figure A.2 supports this assumption. To simplify the exercise, we assume that $\rho_i = \rho = .96$, which is consistent with a P/D ratio of about 25.

We also compute a risk premium measure as the internal rates of returns obtained from solving Equation (3). This methodology, described in detail in the previous section, assumes a flat term structure, whereas the current decomposition allows for mean reversion in risk premium ($\phi < 1$). We will work on making the two approaches more consistent in future research.

The first key lesson of this table is that the cross-section of cumulative reaction to the crisis
Table 1: Cross-sectional regressions

<table>
<thead>
<tr>
<th></th>
<th>Week 9</th>
<th>Week 9</th>
<th>Week 14</th>
<th>Week 14</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revid</td>
<td>.015***</td>
<td>.019***</td>
<td>.027***</td>
<td>.025***</td>
</tr>
<tr>
<td></td>
<td>(5.1)</td>
<td>(7.9)</td>
<td>(9.1)</td>
<td>(12)</td>
</tr>
<tr>
<td>∆µid</td>
<td>-8.5***</td>
<td></td>
<td></td>
<td>-6***</td>
</tr>
<tr>
<td></td>
<td>(-9.5)</td>
<td></td>
<td></td>
<td>(-16)</td>
</tr>
<tr>
<td>Constant</td>
<td>-.071***</td>
<td>-.031***</td>
<td>-.19***</td>
<td>-.12***</td>
</tr>
<tr>
<td></td>
<td>(-15)</td>
<td>(-6.1)</td>
<td>(-21)</td>
<td>(-14)</td>
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<tr>
<td>N</td>
<td>3071</td>
<td>3039</td>
<td>2612</td>
<td>2571</td>
</tr>
<tr>
<td>r2</td>
<td>.07</td>
<td>.51</td>
<td>.16</td>
<td>.54</td>
</tr>
</tbody>
</table>

We cluster error terms within observations of the same firm.

is mostly explained by the cross-section of discount rate movements. EPS forecast revisions only explain about 10% of the variation.

The second key lesson is that the model is sensitive, but not enough, to discount rate shocks. One possible explanation is that expected returns are badly measured. A second explanation is that ϕ < 1, that is, that discount rate shocks are expected to mean revert at long horizon. Combining the coefficient for ∆µid and the coefficient for Revid, we can back out ρ and ϕ. Looking at the regression in week 14, for instance, we obtain ρ = .968, and ϕ ≈ .91, which corresponds to a persistent, but not perfectly flat, risk premium. This order of magnitude is also consistent with macro estimate of equity premium mean-reversion (Campbell, 2017). It is also consistent with recent work by Keloharju et al. (2020), who suggests that expected returns at the firm level can be forecasted in the short run, but not in the long run. We will study the implication of mean-reverting equity risk premium for corporate valuation in future research (for an earlier approach to this problem, see Ang and Liu (2004)).

4 Conclusion

Firm-level analysts’ consensus forecasts have been sluggishly revised down over March, April, and May 2020 before leveling off. Analysts expect a long-lasting impact of the crisis: even at long horizon, forecasts have been negatively affected. Overall, assuming a constant discount rate, downward revisions are consistent with a mean average return of -12%, very close to the observed fall in equities. The actual discount rate started at 10% before the crisis, went all the way up to
13% in late March, and back down to 10% in mid-May. This stability of the discount rate comes from an increase in the equity premium of about 1 ppt, fully offset by a reduction in interest rates by 1 ppt over the period. We also observe that the entirety of the risk premium increase comes from the leverage effect: adverse news increases the cost of equity. Unlevered asset risk premiums only increased temporarily.
References


Online Appendix to Earnings Expectations and The COVID Crisis

Augustin Landier\textsuperscript{1} and David Thesmar\textsuperscript{2}

\textsuperscript{1}HEC Paris
\textsuperscript{2}MIT Sloan, NBER and CEPR
We obtain the 1,000 largest firms by stock market capitalization for every year from I/B/E/S/. For each firm, we compute the consensus forecast error as the difference between the median EPS forecast and the realized EPS, normalized by median forecast. We ensure that the median forecast is positive, and we trim outliers more than five IQR away from the median. We compute the mean error across all firms over periods of 5 years. A positive value indicates ex post optimism. We implement this exercise for 1-, 2-, and 3-year horizon forecasts.
Figure A.2: Term structure of expected earnings growth before and after readjustment

This figure shows the annualized growth rates $g_{t,h}$ per horizon $h$ for two dates (February 15, 2020, and May 11, 2020), averaged across our sample of firms. We trim the sample by removing observations within the five interquartile range away from the median. Confidence bands are computed as twice the standard error divided by the square root of the number of observations.
Here, we report the average ex post forecast error made by analysts during the GFC. We focus on firms whose EPS in 2007 was positive, and we compute, at each horizon, the average (across firms) of the difference between forecast and eventual realizations normalized by 2007 EPS. In September 2008, the difference between 2012 analysts’ forecasts and 2012 realizations were about 60% of the 2007 EPS on average. By June 2009, average forecasts fell in line with eventual realizations, especially for 2010 and 2011.
Figure A.4: Cumulative returns and forecast revisions by industries

Each dot represents a different GIC sector. The vertical axis represents the average cumulative returns at the industry level over the time period $[T_0, T_1]$. The horizontal axis represents the mean of $\left( \frac{F_{T_1} EPS_{i,h}}{F_{T_0} EPS_{i,h}} - 1 \right)$. The final date $T_1$ is May 11, 2020, and the initial date $T_0$ is January 1, 2020. The sample is restricted to firms with $F_{T_0} EPS_{i,h} > 0$. 

![Diagram showing cumulative returns and forecast revisions by industries]
For each firm, on January 2, we compute the internal rate of return from Equation (2), which uses as inputs the current stock price and the term structure of EPS forecasts. This chart shows the distribution of such IRRs. For about 3% of the observations, the algorithm fails to find a solution below 30%. We omit these observations. Whether or not we include these observations does not materially affect our results.
Figure A.6: Forecast implied cumulative market return as a function of $r$

In this chart, we change the discount rate with which we estimate the PV of each stock using formula (2), which uses as inputs the daily term structure of forecasts. In the main Figure 8, we use as discount rates a firm-specific IRR calculated on January 2, 2020, and an industry-level sales growth rate. In this figure, we use a single $r$ for all firms and vary it from 6% to 14%. We set $g = 4\%$. The effect of $r$ on forecast-implied cumulative return since January 2 is very small. The intuition is that we are looking at price changes, not price levels.
In this chart, we change the discount rate with which we estimate the PV of each stock using formula (2), which uses as inputs the daily term structure of forecasts. In main Figure 8, we use as discount rates a firm-specific IRR calculated on January 2, 2020, and an industry-level sales growth rate. In this figure, we use a single $g$ for all firms and vary it from 0% to 8%. We set $r = 10.5\%$. The effect of $g$ on forecast-implied cumulative return since January 2nd is very small. We are looking at price changes, not price levels.
In this chart, we compute the security market line implicit in the cross-section discount rates and precrisis betas. For each date, we regress the cross-section of IRRs obtained from solving Equation (3) for each firm, on the cross-section of December 31, 2019, betas available from WRDS. The slope of this line is shown in the chart.
For each firm, at each date, we compute the internal rate of return from Equation (3), which uses as inputs the current stock price as well as the term structure of EPS forecasts. This chart shows the evolution of the discount rate for a selected sample of industries, using the GICS classification.