

Earnings Expectations during the COVID-19 Crisis*

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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 8.5% in mid-February to 11% at the end of March and reverting to its initial level in mid-May. Over the period, the unlevered asset risk premium increases by 50bp, the leverage effect also increases by 50bp, while the risk free rate decreases by 100bp. Hence, analysts' forecast revisions explain all of the decrease in equity values between January 2020 and mid-May 2020. (*JEL* G40, G12, G17)

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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 Kojen \(2020\)](#) 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

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are not directly observed. Using analysts' forecasts allows for a firm-level analysis and a direct measure of revisions in beliefs. However, to connect 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 Kojien \(2020\)](#) 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. [de la O 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; de la O 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.

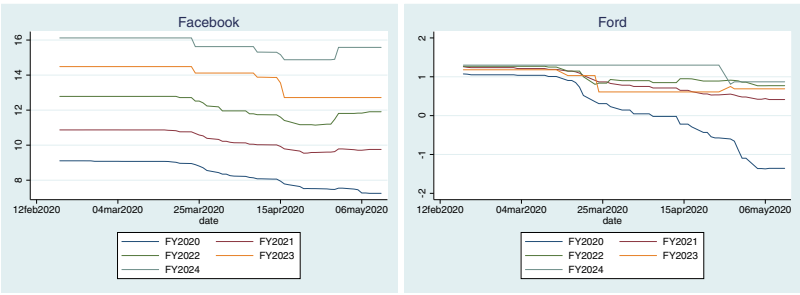


Figure 1

Two examples of forecast revisions

This figure shows the evolution of average forecasts of annual earnings per share for Ford and Facebook between February 15, 2020, and May 11, 2020. We report forecasts for fiscal years 2020, ..., 2024. I/B/E/S/ forecasts come from Refinitiv-Eikon's platform (Thomson Reuters).

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

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

This linearized growth formula allows us to accommodate negative future $F_t EPS_{i,h}$, 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).

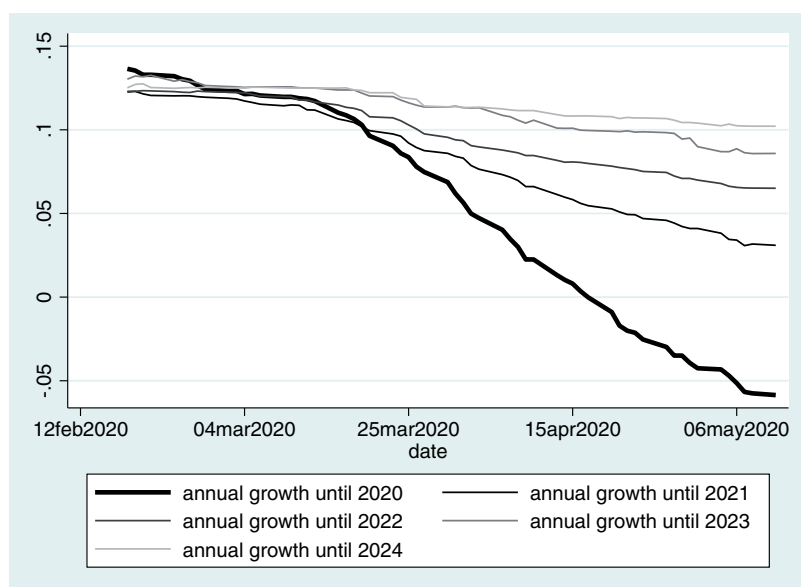


Figure 2

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

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.

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.² 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.

² To 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.

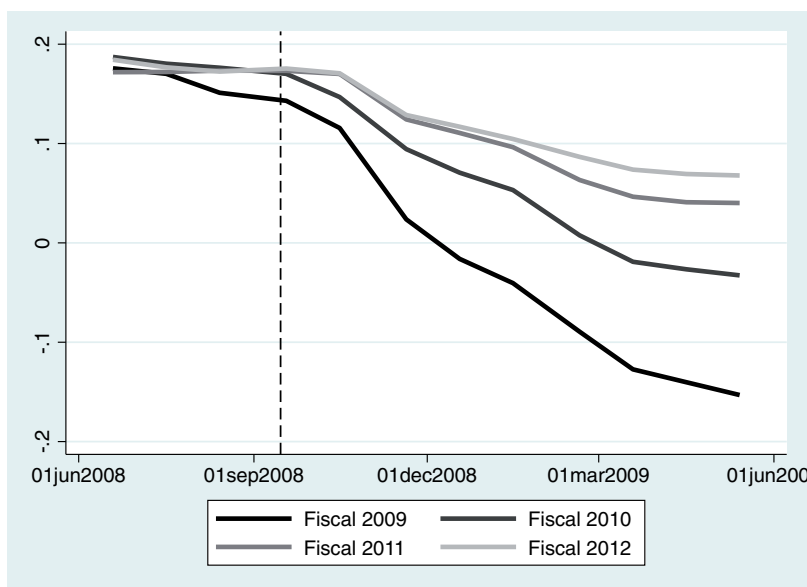


Figure 3

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.

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 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.³ 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.

³ In 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.

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 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

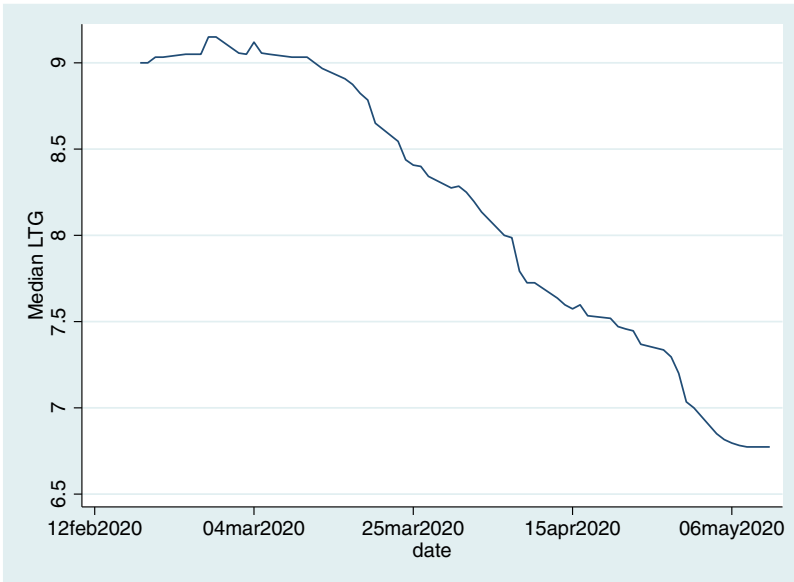


Figure 4
Long-term growth

This figure plots the evolution of the LTG forecast (“long-term growth”) over time in our sample. We report the median (as a percentage) across all firms of the consensus LTG forecast reported by I/B/E/S/ (which is an average across analysts for each firm).

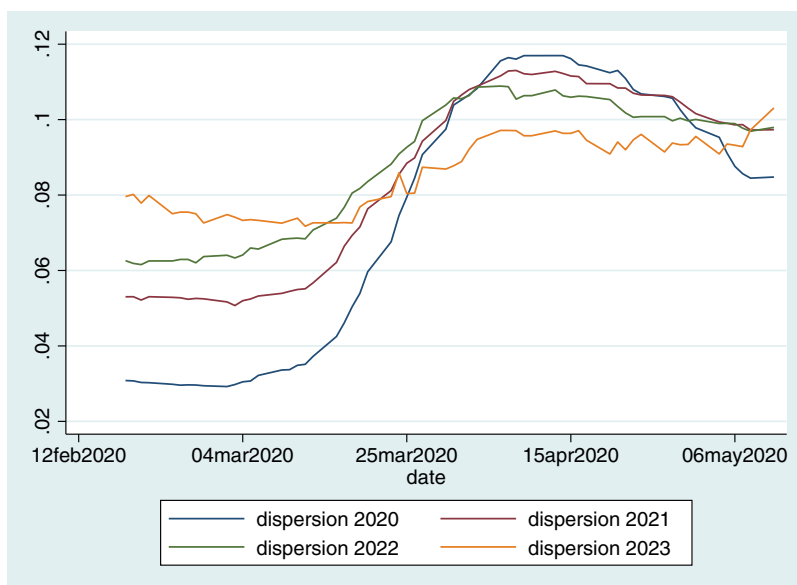


Figure 5

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.

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

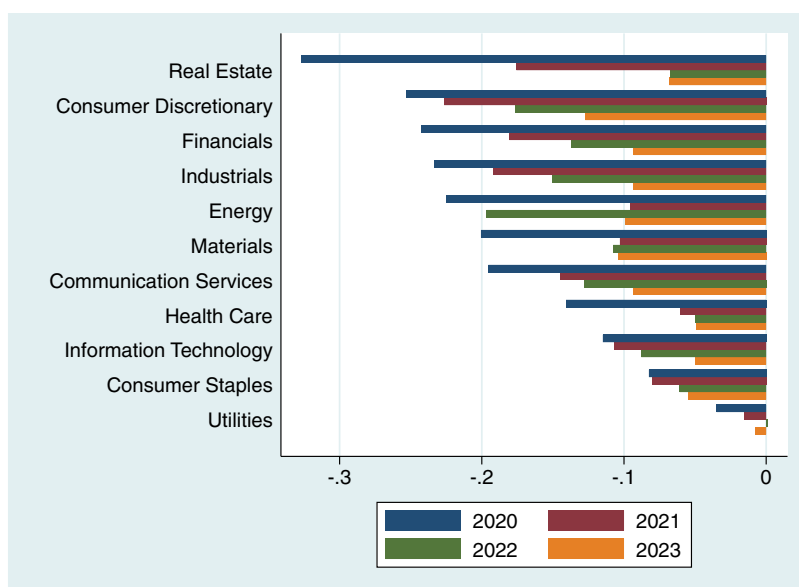


Figure 6
Revision by industries

This figure represents the median percentage change in EPS forecasts $\left(\frac{F_{T_1}EPS_{i,h}}{F_{T_0}EPS_{i,h}} - 1\right)$ 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 $F_{T_0}EPS_{i,h} > 0$. For each sector, we report forecasts for four horizons h , namely, fiscal years 2020, ..., 2023.

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.

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

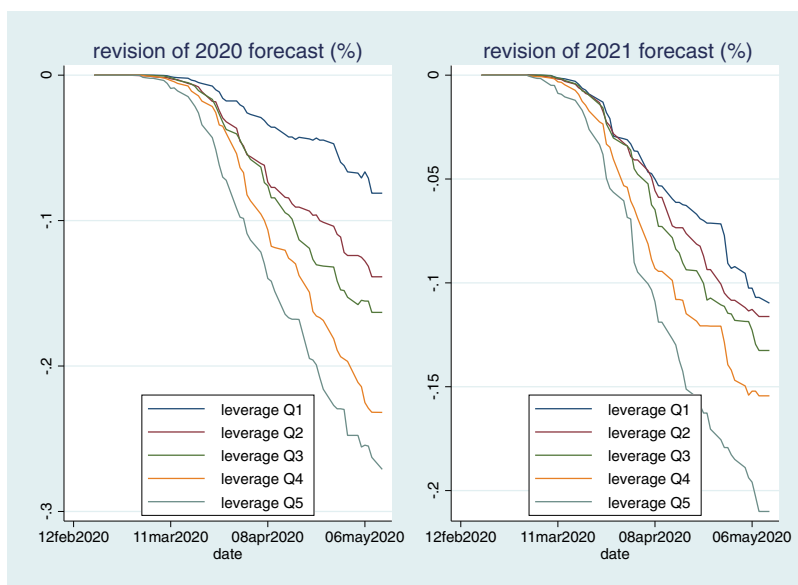


Figure 7
Revision by leverage quintiles

This figure represents the median percentage revision in forecasts $\left(\frac{F_t EPS_{i,h}}{F_{T_0} EPS_{i,h}} - 1\right)$ 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 $F_{T_0} EPS_{i,h} > 0$.

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.

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 $\left(\frac{F_t EPS_{i,h}}{F_{T_0} EPS_{i,h}} - 1\right)$, 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.

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 [de la O 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 thus expect a connection between forecast revisions and returns in the cross-section of firms.

We then move to 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

$$PV_{it} = \frac{b_i F_t EPS_{2020,i}}{1 + r_i} + \frac{b_i F_t EPS_{2021,i}}{(1 + r_i)^2} + \frac{b_i F_t EPS_{2022,i}}{(1 + r_i)^3} + \frac{(1 + g_i) b_i F_t EPS_{2022,i}}{(r_i - g_i)(1 + r_i)^3}, \quad (2)$$

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 *prstk* minus preferred buybacks *pstkrv*). We then normalize common stock payout by net income (when net income is 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

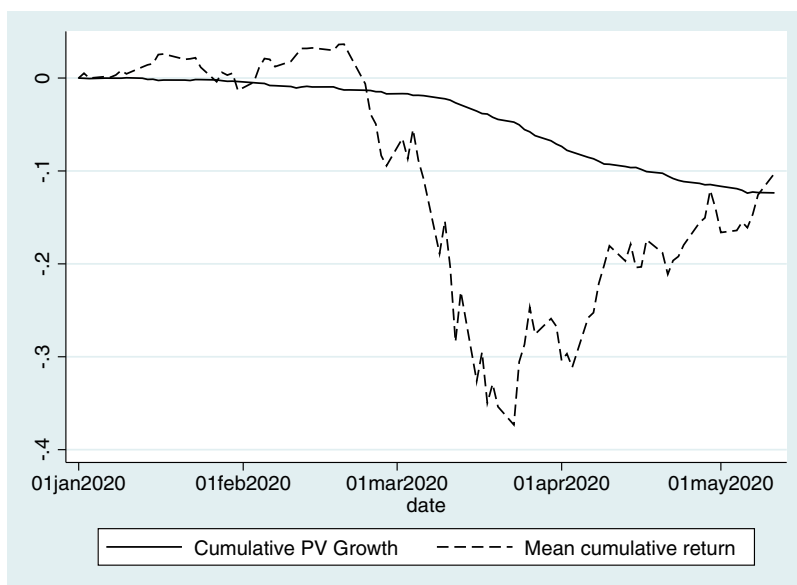


Figure 8

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 ($PV_{it}/PV_{iT_0} - 1$). The forecast implied cumulative return is based on the evolution of present values (PV_{it}) defined above. The computation of PV_{it} 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_{it} is continuously defined throughout the period.

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

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

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 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

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

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% 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.

⁵ One 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 horizon up to 92% for 2020.

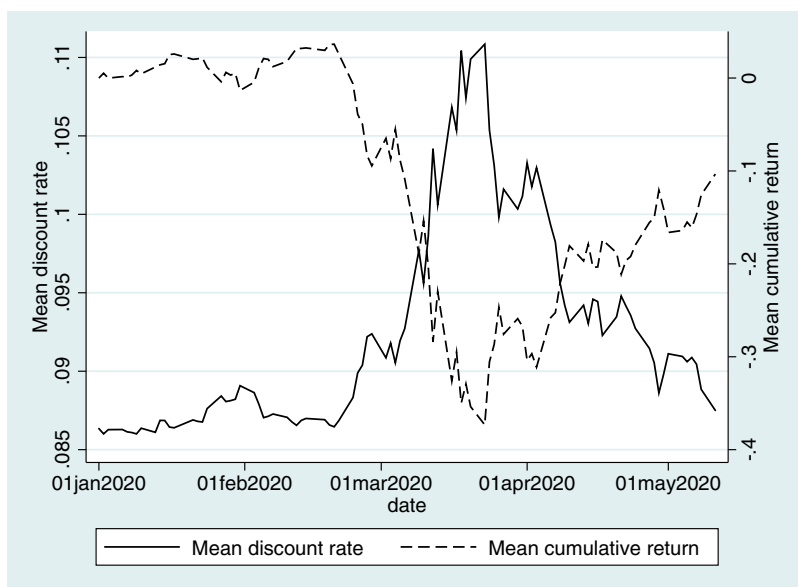


Figure 9

Implicit discount rates

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

$$r_{it} - r_{i0} = \underbrace{(r_t^f - r_0^f)}_{\text{risk-free rate effect}} + \underbrace{\left(1 - \frac{l_{i0}}{l_{it}}\right)(r_{it} - r_t^f)}_{\text{leverage effect}} + \underbrace{\frac{l_{i0}}{l_{it}}(r_{it} - r_t^f) - (r_{i0} - r_0^f)}_{\text{risk-premium effect}}, \quad (4)$$

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

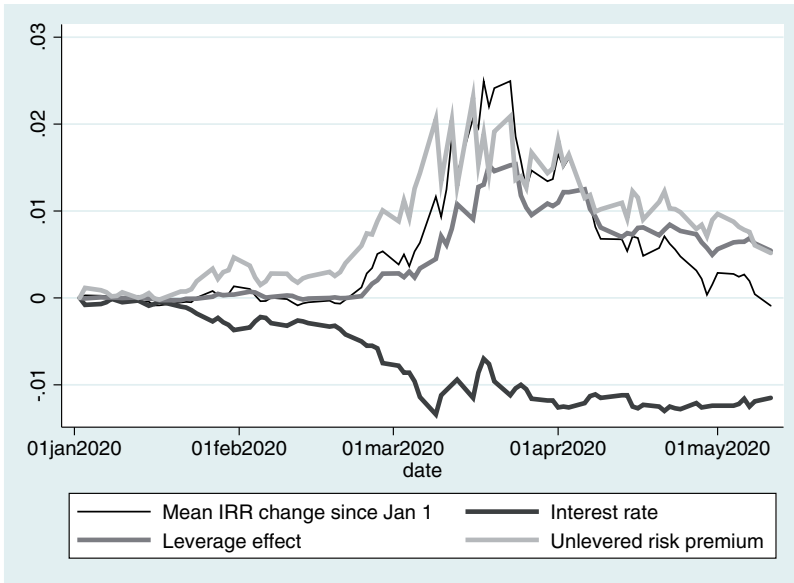


Figure 10
Decomposition of IRR changes over time

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, $(r_t^f - r_0^f)$, $(1 - \frac{l_{it}}{l_{it}})(r_{it} - r_t^f)$, and $\frac{l_{it}}{l_{it}}(r_{it} - r_t^f) - (r_{it} - r_0^f)$, in line with Equation 4. Firm leverage at time t is based on equity values retrieved from CRSP and the book value of debt at the end of 2019 from Compustat.

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 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

⁶ Formally, the cash flows generated by the firm's assets serve both debt and equity, leading to the Modigliani-Miller's "WACC formula": $r_{it}^A - r_t^f = \frac{E_{it}}{E_{it} + D_{it}}(r_{it} - r_t^f) + \frac{D_{it}}{E_{it} + D_{it}}(r_{it}^D - r_t^f)$. The interpretation of our decomposition relies on assuming $\frac{D_{it}}{E_{it} + D_{it}}(r_{it}^D - r_t^f) \simeq 0$. Under this assumption, the economic risk-premium for holding asset risk is $r_{it}^A - r_t^f = \frac{E_{it}}{E_{it} + D_{it}}(r_{it}^E - r_t^f)$. The forward expectation of this term should not vary unless risk premiums on fundamental risk vary.

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

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

where $\mathbb{R}_t \equiv E_t - E_{t-1}$ is the revision operator between two consecutive dates (in our data, 2 consecutive days). Assume that the term structure of expected

Table 1
Cross-sectional regressions

	Cumulative daily log returns since January 1			
	Week 9	Week 9	Week 14	Week 14
Rev_{id}	.015*** (5.1)	.019*** (7.9)	.027*** (9.1)	.025*** (12)
$\Delta\mu_{id}$		-8.5*** (-9.5)		-6*** (-16)
Constant	-.071*** (-15)	-.031*** (-6.1)	-.19*** (-21)	-.12*** (-14)
N	3071	3039	2612	2571
r2	.07	.51	.16	.54

We cluster error terms within observations of the same firm.

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

$$\mathbb{R}_t r_{t+1+j} = \Delta r_j^f + \phi^j \Delta \mu_t,$$

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):

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

where $\rho = \frac{1}{1+e^{d-p}}$ and $d - p$ is the mean log dividend yield. We assume ρ and ϕ 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 :

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

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 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 $\phi < 1$, that is, that discount rate shocks are expected to mean revert at long horizon. Combining the coefficient for $\Delta\mu_{id}$ and the coefficient for Rev_{id} , we can back out ρ and ϕ . Looking at the regression in week 14, for instance, we obtain $\rho = .968$, and $\phi \approx .91$, 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

- Abarbanell, J. S., and R. Lehavy. 2007. Letting the tail wag the dog: The debate over GAAP versus street earnings revisited. *Contemporary Accounting Research* 24:675–723.
- Abarbanell, J. S., and V. L. Bernard. 1992. Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior. *Journal of Finance* 47:1181–207.
- Albuquerque, R. A., Y. Koskinen, S. Yang, and C. Zhang. 2020. The resiliency of environmental and social stocks: An Analysis of the Exogenous COVID-19 Market Crash". *Review of Corporate Finance Studies* 9:593–621.
- Alfaro, L., A. Chari, A. N. Greenland, and P. K. Schott. 2020. Aggregate and firm-level stock returns during pandemics, in real time. Working Paper, Harvard Business School.

- Ang, A., and J. Liu. 2004. How to discount cash-flows with time-varying expected returns. *Journal of Finance* 59:2745–83.
- Bordalo, P., N. Gennaioli, R. Laporta, and A. Shleifer. 2019. Diagnostic expectations and stock returns. *Journal of Finance* 74:2839–74.
- Bouchaud, J.-P., P. Krueger, A. Landier, and D. Thesmar. 2019. Sticky expectations and the profitability anomaly. *Journal of Finance* 74:639–74.
- Campbell, J. 2017. *Financial decisions and markets*. Princeton, NJ: Princeton University Press.
- Cowen, A., B. Groysberg, and P. Healy. 2006. Which types of analyst firms are more optimistic? *Journal of Accounting and Economics* 41:119–46.
- de la O, R., and S. Myers. 2020. Search results web results subjective cash flow and discount rate expectations. Technical Report, Stanford University.
- DeBondt, W. F. and R. H. Thaler. 1990. Do security analysts overreact? *American Economic Review* 80:52–57.
- Dechow, P. M., A. P. Hutton, and R. G. Sloan. 2000. The relation between analysts' forecasts of long-term earnings growth and stock price performance following equity offerings. *Contemporary Accounting Research* 17:1–32.
- Ding, W., R. Levine, C. Lin, and W. Xie. 2020. Corporate immunity to the COVID-19 pandemic. Working Paper, University of Hong Kong.
- Dreman, D. N., and M. A. Berry. 1995. Analyst forecasting errors and their implications for security analysis. *Financial Analysts Journal* 51:30–41.
- Engelberg, J., R. D. McLean, and J. Pontiff. 2018. Anomalies and news. *Journal of Finance* 73:1971–2001.
- Fama, E., and K. French. 2004. The capital asset pricing model: Theory and evidence. *Journal of Economic Perspectives* 18:25–46.
- Gormsen, N., and R. Kojen. 2020. How to interpret financial market movements to predict the impact of coronavirus on GDP. Working Paper, University of Chicago.
- Haddad, V., A. Moreira, and T. Muir. 2020. When selling becomes viral: Disruptions in debt markets in the COVID crisis and the Fed's response. Working Paper, University of California, Los Angeles.
- Hong, H., and J. D. Kubik. 2003. Analyzing the analysts: Career concerns and biased earnings forecasts. *Journal of Finance* 58:313–51.
- Kadan, O., L. Madureira, R. Wang, and T. Zach. 2008. Conflicts of interest and stock recommendations: The effects of the global settlement and related regulations. *Review of Financial Studies* 22:4189–217.
- Keloharju, M., J. Linainmaa, and P. Nyberg. 2020. Long-term discount rates do not vary across firms. Working Paper, Aalto University.
- Kothari, S. P. 2001. Capital markets research in accounting. *Journal of Accounting Research* 31:105–231.
- Lakonishok, J., A. Shleifer, and R. Vishny. 1994. Contrarian investment, extrapolation and risk. *Journal of Finance* 49:1541–78.
- Laporta, R. 1996. Expectations and the cross-section of stock returns. *Journal of Finance* 51:1715–42.
- Ling, D. C., C. Wang, and T. Zhou. 2020. A first look at the Impact of COVID-19 on commercial real estate prices: Asset level evidence. *Review of Asset Pricing Studies* 10:669–704.
- Loechster, L., and P. Tetlock. 2020. What drives anomaly returns? *Journal of Finance* 75:1417–55.
- Loh, R. K., and R. M. Stulz. 2018. Is sell-side research more valuable in bad times? *Journal of Finance* 73:959–1013.

Ma, Y., T. Ropele, D. Sraer, and D. Thesmar. 2020. A quantitative analysis of distortions in managerial forecasts. Working Paper, University of Chicago.

Michaely, R., and K. L. Womack. 1999. Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies* 12:653–86.

Ramelli, S., and A. F. Wagner. 2020. Feverish stock price reactions to COVID-19. *Review of Corporate Finance Studies* 9:622–55.

Shiller, R. 1981. Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review* 71:421–36.