Online Appendix to: Revealing Downturns

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March 29, 2015

Abstract

This appendix (i) shows how dispersion, correlation, and volatility are related, (ii) shows that the theoretical results are robust to state-dependent uncertainty, (iii) presents supplementary summary statistics, (iv) shows robustness of the main paper’s OLS results to subsamples, (v) provides alternative theoretical and empirical measures of earnings response coefficients (ERCs), (vi) distinguishes the “revealing downturns” effect from a “bad news” effect empirically, (vii) shows that the model can quantitatively account for the magnitude of ERC differences across upturns and downturns, and (viii) evaluates empirically how much of return skewness can be attributed to the “Revealing Downturns” mechanism. The main text of the paper can be downloaded here.

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1 Relation of Correlation, Dispersion, and Volatility

The following example shows that increased dispersion in downturns does not conflict with the established fact that correlations increase in downturns. Consider a vector of stock returns \( r \) that is normally distributed, with mean vector \( \mu \) and variance-covariance matrix \( \Sigma \). The individual returns \( r_i \) are distributed normally with mean \( a_i \) and variance \( \sigma_i^2 \). The covariance between two stock returns \( r_i \) and \( r_j \) is \( \text{Cov}(r_i, r_j) = \rho \sigma^2 \), where \( \rho \) is the correlation coefficient. The cross-sectional variance, or dispersion, is then \( \text{Disp} = (1 - \rho)\sigma^2 \). In downturns, correlations \( \rho \) are high, as are idiosyncratic volatilities \( \sigma^2 \). Nothing is said about the effect on cross-sectional dispersion. The present paper shows that the joint effect is such that cross-sectional dispersion is higher in downturns because individual stocks react more strongly to news.

2 Robustness of Theoretical Predictions to State-Dependent Ex-Ante Uncertainty

In the above results, we assumed the variance of idiosyncratic noise, \( \sigma^2 \), is constant and does not depend on the business cycle. If, however, it changes with the business cycle in the data, it could affect our empirical results. To alleviate that concern, we now derive an additional proposition that predicts how ERCs depend on the state of the economy if we control for the effect ex-ante uncertainty about earnings news, \( \text{var} [Y_t] \), has on earnings response coefficients. ERCs as a function of the variance of earnings surprises can be written as

\[
\lambda(\xi_t, \text{var} [Y_t]) = \frac{\sigma_a^2 - \phi \sigma_{ab} - (\phi \sigma_b^2 - \sigma_{ab}) \xi_t}{\sqrt{\text{var} [Y_t]}}.
\]

(2.1)

**Proposition 1.** If we consider \( \lambda \) as function of \( \text{var} [Y_t] \) and \( \xi_t \), then a positive cutoff \( \tilde{\sigma}_{ab}^\lambda = \phi \sigma_b^2 > 0 \) exists such that

1. \( \lambda \) is decreasing in \( \xi_t \) if \( \sigma_{ab} < \tilde{\sigma}_{ab}^\lambda \), and
2. \( \lambda \) is increasing in \( \xi_t \) if \( \sigma_{ab} > \tilde{\sigma}_{ab}^\lambda \).

The prediction says that the inclusion of an additional control that proxies for the uncertainty of an announcement does not qualitatively change the results. Thus, we still expect to see an asymmetry in ERCs across downturns and upturns, similar to the earlier predictions.

3 Supplements to Summary Statistics

We refer in the main text to histograms of cumulative announcement returns (\( \text{CARs} \)) and earnings surprises (\( \text{ESs} \)), and present them in Figure 1. The top row shows the histograms for
the unfiltered data, used for the results presented in the main text. The bottom row restricts
the sample to observations with a standard deviation of earnings surprises larger than 0.05,
which eliminates “discretization noise” that is caused by observations with very low standard
deviations. IBES reports the measure in discrete steps of size 0.01. The results presented in
the next section of this online appendix are based on the filtered sample.

4 Robustness Tests of OLS Estimation Results to a Restricted
Sample

This section establishes robustness of the main theoretical results to an alternative defini-
tion of ERCs, used in some of the existing literature. Here, we use the same definition as in
the main text again, and provide robustness tests along several other dimensions.

Table 2 normalizes earnings responses by the standard deviation of analyst forecasts, as
reported by IBES. One potential concern with this measure is a high frequency of reported
standard deviations of 0.01, simply as a result of IBES reporting that variable in discrete
steps of size 0.01. As a result, the coefficient of the interaction between earnings surprise and
standard deviation of earnings surprises reported in row 4 of Table 2 has a different sign
depending on the specification. Table 3 in the online appendix shows that this feature of the
data does not affect our main results. The results in the table are based on a sample that
eliminates all observations with a standard deviation of earnings surprises of less than 0.05.
This filter reduces the number of observations to 50,103. Other than the change of sample, the
specifications are unchanged and the table retains the same structure as the previous two.

The results show that the ERCs are in fact more precisely estimated. The highly signifi-
cantly positive estimates range between 0.00353 and 0.00993. Speaking more specifically to the
key predictions of the proposed theory, the downturn-upturn difference is slightly larger than
in the full sample reported in the main text. The difference ranges from 0.0006 to 0.00356.
The relative difference ranges from 15% (column 9) to 48% (column 3). All differences are
statistically significant at the 1% level, except in the final specification, which also yields the
lowest point estimate. In sum, we conclude that the upturn-downturn differences are larger
and more precisely estimated in the restricted sample, consistent with the hypothesis that
measurement noise in the full sample leads to attenuation bias.

5 Alternative Definition of Earnings Response Coefficient

The main text derives ERCs that are normalized by the standard deviation of earnings
surprises, because that measure most directly and simply links theory to empirics. The liter-
ature has previously used other definitions of ERCs. The purpose of this appendix is to show
robustness of all key results to that alternative definition, both theoretically and empirically.
5.1 Theoretical Alternative Definition of Earnings Response Coefficient

Starting with theory, the earnings response can alternatively be written as follows:

**Lemma 1.** The price change of asset $i$ from time $t-1$ to time $t$, when the realization of the market-wide shock is $\xi_t$, is

$$p_t^i - p_{t-1}^i = \frac{\lambda(\xi_t)}{R-1} \cdot (Y_t^i - E[Y_t^i]),$$

where

$$\lambda(\xi_t) = \frac{\sigma_a^2 - \phi \sigma_{ab} - (\phi \sigma_b^2 - \sigma_{ab}) \xi_t}{\sigma_a^2 + 2\sigma_{ab} \xi_t + \sigma_b^2 \xi_t^2 + \sigma_\varepsilon^2}.$$  

(5.2)

$\lambda$ is a measure of how strongly prices react to the given surprise in earnings ($Y_t^i - E[Y_t^i]$). (Recall the notation $E[Y_t^i] = E[Y_t^i|I_{t-1}, \xi_t]$.) Its empirical analogue is the standard ERC used in the traditional literature. Equation (5.2) predicts that $\lambda$ depends on the factor realization, or state of the economy, $\xi_t$.

When we set $\sigma_b^2 = 0$, which also implies $\sigma_{ab} = 0$, the ERC depends only on the ratio of variation in idiosyncratic cash-flow strength, $\sigma_a^2$, to noise, $\sigma_\varepsilon^2$:

$$\lambda = \frac{\sigma_a^2}{\sigma_a^2 + \sigma_\varepsilon^2} = \frac{1}{1 + \frac{\sigma_\varepsilon^2}{\sigma_a^2}},$$

(5.3)

and the usual intuition for a signal-to-noise ratio obtains: the signal-to-noise ratio decreases with idiosyncratic noise. When only $\sigma_{ab}$ is set to zero, we have

$$\lambda(\xi_t; \sigma_{ab} = 0) = \frac{\sigma_a^2 - \phi \sigma_b^2 \xi_t}{\sigma_a^2 + \sigma_b^2 \xi_t^2 + \sigma_\varepsilon^2}.$$  

(5.4)

Compared to the case of no uncertain risk loadings $(\sigma_b^2 = 0)$, introducing uncertainty about $b^i$ $(\sigma_b^2 \neq 0)$ makes the price reaction to a given piece of news depend on the state of the economy, $\xi_t$. The higher the uncertainty about risk exposure, the stronger the dependence of the earnings response on the realization of $\xi_t$. The dependence, however, is not symmetric with respect to $\xi_t = 0$. The analogue to proposition 1 for ERCs is as follows.

**Proposition 2.** For the case of $\sigma_{ab} = 0$, the strongest stock price reaction to fundamental news occurs for negative realizations of the market factor.

ERCs are highest at

$$\xi_{max} = -\phi \left( \frac{\sigma_a^2 + \sigma_\varepsilon^2}{\sigma_a^2 + \sqrt{\sigma_a^4 + \phi^2 (\sigma_a^2 + \sigma_\varepsilon^2) \sigma_b^2}} \right) < 0.$$

(5.5)

We will test these propositions with non-parametric estimation techniques.
We can derive a proposition similar to proposition 3, showing asymmetries in the ERCs, \( \lambda \), as well. The proposition is slightly more involved than proposition 3 because the correlation between \( a \) and \( b \) affects not only how prices respond to news, but also the variability of the observed signal (\( \lambda \) is approximately the ratio of the two).

**Proposition 3.** For any positive \( \sigma_a^2 \) and \( \sigma_b^2 \), and any positive number \( x \), only one of the following contingencies is possible:

1. \( \lambda(\xi_t = -x) \geq \lambda(\xi_t = +x) \) for any \( \sigma_{ab} \).

2. There exists \( \sigma_{ab}^p \), with \( 0 < \sigma_{ab}^p < \sigma_a \sigma_b \), such that
   \[ \lambda(\xi_t = -x) > \lambda(\xi_t = +x) \text{ for } -\sigma_a \sigma_b < \sigma_{ab} < \sigma_{ab}^p \]
   \[ \lambda(\xi_t = -x) < \lambda(\xi_t = +x) \text{ for } \sigma_{ab}^p < \sigma_{ab} \leq \sigma_a \sigma_b. \]

3. There exists \( \sigma_{ab}^p \), with \( -\sigma_a \sigma_b < \sigma_{ab}^p < 0 \), such that
   \[ \lambda(\xi_t = -x) > \lambda(\xi_t = +x) \text{ for } \sigma_{ab}^p < \sigma_{ab} \leq \sigma_a \sigma_b \]
   \[ \lambda(\xi_t = -x) < \lambda(\xi_t = +x) \text{ for } -\sigma_a \sigma_b < \sigma_{ab} < \sigma_{ab}^p. \]

Given the above observations of likely values of \( \sigma_{ab} \), this proposition predicts that higher ERCs more likely obtain in downturns \((\xi_t < 0)\) than in upturns \((\xi_t > 0)\).

### 5.2 Empirical Alternative Definition of Earnings Response Coefficient

#### 5.2.1 Variable Definitions

Some of the literature defines an earnings surprise, \( ES_{i,t} \), of firm \( i \) at time \( t \) as

\[
ES_{i,t} = \frac{EPS_{i,t} - E[EPS_{i,t}]}{BVPS_{i,t}},
\]

where \( EPS_{i,t} \) is stock \( i \)'s actual earnings per share reported at an announcement at time \( t \); \( E[EPS_{i,t}] \) is the expected earnings per share averaged across all analysts from the last pre-announcement set of forecasts for the given fiscal quarter. We obtain these forecasts as well as the date of the earnings announcement from the IBES unadjusted detail files. \( BVPS_{i,t} \) is firm \( i \)'s last recorded book value per share before the time \( t \) announcement from the CRSP/Compustat merged files. This measure corresponds to \( \lambda \) in the theoretical propositions provided in this online appendix.
5.2.2 Data Sources and Restrictions

In general, we use the same data sources and filters here as in the main text, covering January 1984 to December 2012. We obtain 147,474 observations from 4,876 firms for traditional ERCs. The difference in the number of observations compared to the main text obtains because book equity is missing for more firms than the standard deviation of analyst forecasts.

5.2.3 Summary Statistics

Table 1 presents summary statistics for cumulative announcement returns \((CAR)\) and earnings surprises \(ES\)s as traditionally calculated. Table 1 presents summary statistics for the same variables for the sample in which the earnings surprise is normalized by the standard deviation of analyst forecasts. We report the mean, standard deviation, and several percentiles of both \(CAR\) and \(ES\) separately for the different downturn and upturn definitions. Whereas the “market” and “GDP” definitions roughly split the sample in half, only about 10% of observations fall in an NBER downturn.

Table 1, consistent with the existing literature, shows that unconditional \(CAR\)s are slightly positive on average (“unconditional” here refers to the sign of the earnings surprise), which is true throughout all market states. (Point estimates of the the announcement return are slightly smaller in downturns, according to all three alternative definitions.) The most important observation is that \(ES\) are centered at zero both in downturns and in upturns. News in downturns are not significantly worse than news in upturns; according to the GDP definition of a downturn, the point estimate even indicates are higher in downturns than in upturns. We interpret this evidence as consistent with the notion that analysts adjust their earnings expectations to the state of the economy very well. An implication for the interpretation of our results is that a larger earnings response in downturns cannot be driven by a stronger response to bad news than good news. (We also show direct evidence rejecting the earnings response to good and bad news hypothesis in section 6 of this online appendix.)

5.3 Empirical Results

5.3.1 Non-parametric Estimation Results

Figure 2 and Figure 3 give non-parametric estimates of ERC as a function of the economic state, whereas the market return and GDP growth are used as proxies for the state of the economy, respectively. (They are the empirical analogue to equation (5.2) in this online appendix.) The ERCs are significantly positive throughout their domain, with point estimates between 0.95 and 1.15 for the market return specification and between 0.9 and 1.3 for the GDP specification. More specifically, the figures show, consistent with the model predictions, that the relationship between ERCs and the state of the economy is not linear, and not monotonic.
ERCs tend to be much higher in downturns than in upturns on average, and they have a distinct peak left of zero market returns or GDP growth. Specifically, ERCs peak at about -25% market return and -4% GDP growth. The change in magnitude of ERCs across economic states is highly significant, both statistically and economically. The point estimate of the ERC at -25% market return is about 1.15, with a 95% confidence band smaller than 0.1 in either direction, whereas the point estimate of ERCs at +20% market return is 0.95, with confidence bands smaller than 0.05 in either direction. Similarly, ERCs are 1.3 at -4% GDP growth and 0.9 at 5% GDP growth, respectively. These point estimates are similarly precise as in the graph using market returns as the state variable. Thus, ERCs are about 20% to 45% higher at their peak in downturns than at their low in upturns. In sum, both hypotheses 1 and 2 find support also under the alternative measure of ERCs: the null hypothesis of a flat relationship between ERCs and market state is rejected, as is the null hypothesis that ERCs are similarly large on average in downturns and in upturns.

5.3.2 OLS Estimation Results

We now provide additional evidence from simple OLS regressions for the second hypothesis. We formally test whether ERCs for upturns are significantly lower than for downturns. One can think of these results as formal tests of the hypothesis that ERCs in the halves right of zero of Figures 2 and 3 are indeed significantly lower than those in the halves left of zero. Note that we force the ERC to jump at the midpoint, rather than using only more extreme upturn or downturn realizations. This specification of course makes it more difficult for the OLS tests to reject the null hypothesis that there is no difference in ERCs between upturns and downturns.

Table 4 reports the main results. The dependent variable in all specifications is the cumulative announcement return. Columns (1) to (3) report results using the NBER downturns definition. Columns (4) to (6) report results using the “market” downturn definition. Columns (7) to (9) report results using the “GDP” downturn definition. In all cases, we expect a positive earnings response coefficient, that is, a significantly positive coefficient on the earnings surprise, $ES$, reported in the second column. The key hypothesis to test is whether the coefficient on the interaction of $ES$ with the downturn dummy ($DT$) is significantly positive. The first specification of each set of results only has the $ES$, the $DT$, and their interaction as explanatory variables. The second specification also includes the variance of $ES$s and its interaction with $ES$. This specification tests the proposition in the main text according to which the interaction of $ES$ and $DT$ should persist even after controlling for the variance of $ES$s. The last specification also allows for a linear time trend, as well as the interaction of $ES$ with the time trend. Controlling for a time trend in ERCs ensures that the effect we identify comes from a business cycle of shorter frequency and not from secular trends in earnings quality or
other time trends that may affect ERCs. (Similar results obtain when we take into account only the interaction of time and earnings surprise.)

The second row of the first specification reports a highly significant and positive coefficient of 0.950 on the explanatory variable $ES$, the earnings surprise. This coefficient is the ERC in the baseline, that is, in upturns, when $DT$ takes the value zero. It is comparable in magnitude to those reported in the literature. The coefficient reported in the first row, 0.351, indicates the ERC in downturns increases to 1.301 in downturns. The significance of the coefficient reported in the first row indicates the 37% increase in the ERCs in downturns relative to upturns is statistically significant at the 1% level. Notice also that the magnitude of this increase is consistent with the one that can be read out of Figures 2 and 3, namely, the non-parametric estimation approach. The second NBER specification that controls for the standard deviation of the $ES$ yields an ERC in upturns of 1.251. It increases by 0.480 in downturns. Again, the difference is highly statistically significant. Column (3) reports the results that also control for a time trend in ERCs as well as for a time trend in unconditional announcement returns. The upturn ERC is 0.795. It increases by 0.340 in downturns, and the difference is highly statistically significant. The specifications using the market return definition of a downturn in columns (4) to (6) report similar upturn ERCs, ranging from 0.658 to 1.145, and statistically significant increases of the ERC in downturns, ranging from 0.122 to 0.149. The specifications using the GDP definition of downturns in columns (7) to (9) show a similar pattern. Upturn ERCs range from 0.731 to 1.138, and they increase by 0.122 to 0.266 during downturns. The downturn-upturn difference is also highly statistically significant here, albeit only at the 5% level in the last specification. The difference between downturn ERCs and upturn ERCs is slightly smaller in specifications (4) to (9) compared to specifications (1) to (3), because more earnings announcements qualify as a downturn according to these definitions – i.e., also those during less strong economic contractions, compared to NBER recessions. The non-parametric plots make clear that whereas the function of ERC as a function of the economic state is non-monotonic, the highest ERCs occur in quite strong downturns. As a result, allowing states of the economy to enter the downturn definition that also comprises weaker contractions will attenuate the measurement of differences between the peak and trough of the ERC function.

In sum, depending on the definition of downturns, ERCs range from 0.658 to 1.251, similar to the estimates from the non-parametric specifications. In downturns, ERCs increase by up to 45%. The differences between downturn ERCs and upturn ERCs are statistically significant, in most cases at the 1% level. These results provide strong support for the unique predictions of the theoretical model about ERCs. For an intuition about the economic magnitude of the effects, consider the following example based on the first specification. Think of a company with a book value per share of $10 that reports earnings of $1.10, while $1 was expected. The earnings surprise is 0.01. The stock reacts with a $CAR$ of 0.9%. In downturns, the reaction increases to 1.3%, an increase of more than 40%.
6 Distinction from the Overreaction-to-Bad-News Effect

As previously discussed, some authors have argued that a higher incidence of bad news in downturns, combined with a stronger reaction to bad news than to good news, might explain stronger reactions to news in downturns. In addition, agents need to be unaware of the state of the economy. We already showed with summary statistics that, conditional on the state of the economy (which we allow agents to know), downturns do not produce more bad news in the sense of negative unexpected earnings in our data, which means that effect cannot drive our results. In addition, here we provide direct evidence that the reaction to bad news as measured by ERCs is not stronger than the reaction to good news. Formally, we estimate the equation $\text{CAR}_{i,t} = \lambda(ES_{i,t}) \cdot ES_{i,t} + \varepsilon_{i,t}$ using local polynomial regressions of order zero with an Epanechnikov kernel of optimal bandwidth. If the “overreaction-to-bad-news” effect was the driver of higher ERCs in downturns, $\lambda(ES_{i,t})$ should have higher values to the left of zero $ES$. The results are presented in Figure 4. The reaction to good and bad news is almost perfectly symmetric. If anything, it is stronger for good news. Further tests with OLS also reject the hypothesis that the reaction to good news is stronger, both (separately) in upturns and downturns. We omit reporting these OLS results, because they are not the focus of the paper.

7 Test of Quantitative Predictions

The main paper focuses on qualitative differences across the market cycle in investors’ reaction to news. This appendix provides evidence that the theoretical explanation we propose can indeed produce quantitatively important predictions for the the relationship between earnings response and market state.

7.1 General idea

For a quantitative evaluation, we need estimates of how uncertain investors are about the parameters $a$ and $b$, that is, $\sigma^2_a$, $\sigma^2_b$, and $\sigma_{ab}$. Also, we need an estimate of the residual noise $\sigma^2_\varepsilon$. To arrive at these estimates, for every given earnings announcement, we regress earnings per share $Y^i_t$ on realizations of the market return $\xi_t$ during the reference period:

$$Y^i_t = a^i + b^i \xi_t + \varepsilon^i_t.$$  

(7.1)

The covariance matrix

$$\Sigma_t = \begin{pmatrix} \sigma^2_{a,t} & \sigma_{ab,t} \\ \sigma_{ab,t} & \sigma^2_{b,t} \end{pmatrix}.$$  

(7.2)
estimated from the above regression then contains the required estimates, one for each announcement. We use the previous 10 years of quarterly observations for each earnings announcement. If for some announcement, we do not have 10 years of previous data or if gaps between any two consecutive announcements in the previous 10 years of data is more than six months, we code the estimates $\sigma_a^2$, $\sigma_b^2$, and $\sigma_{ab}$ as missing for this announcement.

The reason we cut off the length of the estimating sample at 10 years is that the parameters $a$ and $b$ in reality may change over time, because of changes in firm leadership, strategy, the product market, and so on. As a result, more data do not necessarily lead to more precise estimates. In addition, requiring longer samples would lead to more missing observations.

7.2 Size-neutral ERCs

The next step is to normalize ERCs, because the raw parameters of the $\Sigma_t$ matrix depend on firm size. Thus, to make our predictions comparable across firms, we calculate the announcement return as

$$R_t^i = \frac{p_t^i - p_{t-1}^i}{p_{t-1}^i} = \frac{\lambda(\xi_t)}{E[a^i - \phi b^i]} \cdot \frac{Y_t^i - E[Y_t^i]}{\sqrt{\text{Var}[Y_t^i]}}. \quad (7.3)$$

The ERC then becomes

$$\text{ERC} = \frac{\lambda(\xi_t)}{E[a^i - \phi b^i]} = \frac{1}{E[a^i - \phi b^i]} \cdot \frac{\sigma_a^2 - \phi \sigma_{ab} - (\phi \sigma_b^2 - \sigma_{ab}) \xi_t}{\sqrt{\sigma_a^2 + 2 \sigma_{ab} \xi_t + \sigma_b^2}} = \frac{1}{E[a^i] \left(1 - \frac{\text{E}[b]}{\text{E}[a^i]}\right)} \cdot \left(1 - \frac{\phi \sigma_{ab}}{\sigma_a^2} - \left(\frac{\phi \sigma_b^2}{\sigma_a^2} - \frac{\sigma_{ab}}{\sigma_a^2}\right) \xi_t\right), \quad (7.4)$$

Notice first that this size-neutral ERC definition only depends on ratios of $\sigma$’s, but no longer on their absolute values. Second, the first term is independent of the precision of beliefs about $a$ and $b$. As a result, the first term does not depend on the speed of learning. At the same time, the second term does not depend on the particular realizations of $Y_t^i$; it depends only on the $\xi_t$ vector. Thus, the second term is not firm specific; it is time specific.

$^1$Strictly speaking, we need include the current dividend in the announcement return $R_t^i = \frac{p_t^i + Y_t^i - E[p_t^i + Y_t^i]}{E[p_t^i + Y_t^i]}$. However, we verified empirically that this return definition is quantitatively similar to the one we use (if the interest rate $R$ is not too large, one dividend payment does not considerably affect valuations). Thus, we decide to focus on the simpler one.
7.3 Calibrating $\phi$

The parameter $\phi$ measures how strongly investors need to be compensated for taking risks. We use 1.5% as a standard estimate of the quarterly market risk premium.

7.4 Quantitative Predictions (Given Market State)

For each announcement with a sufficient number of prior observations, we estimate $\frac{E[a^t]}{\sigma_\varepsilon}$, $\frac{E[b^t]}{E[a^t]}$, $\frac{\sigma_{ab}^2}{\sigma_a^2}$, and $\frac{\sigma_{ab}^2}{\sigma_a^2}$ for all announcements and then calculate the average values for each ratio. From these average values, we can predict how ERCs depend on $\xi_t$. Lastly, we make an adjustment to reflect that the variance of analyst forecasts is just a proxy for uncertainty of the announcement, yet the two quantities are likely proportional. Because the theoretically predicted variance of earnings surprises is 1, we take the standard deviation of earnings surprises to be the proportionality factor, which we estimate to be $st.dev(ES) = \sqrt{Var(ES)} \approx 2.784795$, and adjust theoretically predicted ERCs by this factor.

Figure 6 presents the results. The predicted values for the ERC as a function of the market state are indeed quantitatively similar to the empirically observed values, presented in the main text’s Figure 2. The predicted difference between upturns and downturns is even larger than what we can empirically measure. (Of course, empirically, investors process news other than quarterly announcements as well, which the theoretical model does not attempt to capture.)

7.5 Quantitative Predictions (Averaged across Market States)

In the above prediction exercise, we generated the instantaneous ERC curve corresponding to the current hypothetical aggregate shock $\xi_t$. In reality, the learning coefficients do not stay constant over time. An important reason is that $\sigma_{ab}$ changes over time, depending on recent realizations of $\xi_t$. In particular, $\sigma_{ab}$ can be either positive or negative, depending on previous observations. (After a downturn, investors know more about how the stock behaves in downturns, and $\sigma_{ab}$ becomes more positive; after an upturn, investors know about how the stock behaves in upturns, and $\sigma_{ab}$ becomes more negative.) In Figure 5, we show how $\sigma_{ab}$, estimated using 10 years of past quarterly observations up the announcement, changes over time.

In the empirical analysis, we estimate not the instantaneous ERC curve, but the average over-time ERC curve. In this second quantification exercise, we want to get closer to this empirical equivalent. To that end, we take the ratios that do not depend on learning $\frac{E[a^t]}{\sigma_\varepsilon}, \frac{E[b^t]}{E[a^t]}$ to be the averages over histories (as in the previous quantitative exercise). The other ratios $\frac{\sigma_{ab}^2}{\sigma_a^2}, \frac{\sigma_{ab}^2}{\sigma_a^2}, \frac{\sigma_{ab}^2}{\sigma_a^2}$ are calculated for each moment of time (they do not depend on the realizations of $Y$, so for each month, we calculate them only once). Then for each month, we calculate the predicted ERC using the formula from the “ERC Normalization” part above, equation (7.5).
After that, for each moment of time \( t \), we have \( ERC_t^{model} \) and \( \xi_t \). Using these data, we estimate a non-parametric regression:

\[
ERC_t^{model} = \lambda^{model}(\xi_t) + \varepsilon,
\]

similar to the equivalent in the empirical part of the paper. Now we can compare \( \lambda^{model}(\xi_t) \) with \( \lambda(\xi_t) \) from the empirical results, displayed in the main text’s Figure 2. The point estimates continue to be similar, and the predicted difference in ERCs across market states is at least as large as the empirics. Thus, the model proves to be able to make quantitatively important predictions across market states. The exercise presented here corresponds to taking weighted averages across the different calibrations presented in the main text’s Figure 1. The differences in ERC predictions are much further apart on the left tail of the curves than on the right.

8 Skewness

In the literature, the fact that volatility is higher in downturns and that stock returns exhibit negative skewness is well known (e.g., Bollerslev, Engle, and Wooldridge, 1988; Campbell and Hentschel, 1992; Chen, Hong, and Stein, 2001). Here we provide support for the notion that uncertainty about fundamental risk loadings is an important mechanism generating these patterns. That is, the Bayesian learning mechanism proposed in this paper serves as a “skewness accelerator,” as discussed in the context of proposition 5.

To see this effect, let us decompose the stock return into two random variables:

\[
\tilde{r} = \beta \cdot \tilde{\xi} + \tilde{u},
\]

where \( \tilde{\xi} \) corresponds to the market return component, \( \tilde{u} \) is the idiosyncratic return component, and \( \beta \) is the idiosyncratic risk loadings. Suppose \( E[\xi] = 0 \) and \( E[u|\xi] = 0 \), and denote the variance of \( \tilde{u} \) (which depends on the realization of \( \tilde{\xi} \) endogenously) as \( E[u^2|\xi] =: Var_u(\xi) \). Omitting tildes for notational simplicity, note the third moment of returns can be written as

\[
E[r^3] = E[(\beta \xi + u)^3] = E[\beta^3 \xi^3 + 3\beta^2 \xi^2 \cdot u + 3\beta \xi \cdot u^2 + u^3]
\]

\[
= \beta^3 E[\xi^3] + 3\beta^2 \cdot E[\xi^2 \cdot u] + 3\beta \cdot E[\xi \cdot u^2] + E[u^3]
\]

\[
= \beta^3 E[\xi^3] + 3\beta \cdot cov[\xi, Var_u(\xi)] + E[u^3].
\]

Hence, three components determine skewness of a stock return: the skewness of the market return, the individual return skewness, and the covariance between dispersion and market
return:

\[ E[r^3] = \beta^3 \cdot E[\xi^3] + E[u^3] + 3\beta \cdot \text{cov} [\xi, \text{Var}_u(\xi)] \quad . \quad (8.3) \]

A key prediction of our paper is that uncertainty about fundamental risk loadings causes the covariance term to be negative; that is, dispersion of stock returns increases when market returns are low. As a result, the mechanism the present paper proposes generates skewness of returns even if the first two components are zero, that is, even when fundamentals are not negatively skewed. Moreover, when fundamentals are negatively skewed, our mechanism increases the negative skewness.

To show that the covariance component is indeed an empirically important determinant of skewness, we estimate the average magnitude of each component, using quarterly stock returns. In particular, for each stock, we decompose returns \( r \) into the systematic part \( \beta \cdot \xi \) and idiosyncratic part \( u \) by regressing the stock return \( r \) on the quarterly market return. Then we calculate the average skewness of the systematic part \( E[\beta^3 \xi^3] \approx -0.00336 \) (over time and across stocks), the average skewness of the idiosyncratic part \( E[u^3] \approx -0.01197 \), and the average overall skewness \( E[r^3] \approx -0.02392 \). The difference between these terms represents the covariance component \( E[3\beta \cdot \text{cov} [\xi, \text{Var}_u(\xi)]] \approx -0.03253 \). The fraction of skewness explained by the skewness of market returns is thus 14%, and the fraction explained by the skewness of individual returns is 50%; the covariance term explains the remaining 36%. We conclude that our Bayesian learning mechanism is not the only reason for negative skewness of stock returns, but it is a quantitatively important driver.
Appendix

Proof of Lemma 1.

In the defined notation,

\[ \text{var} \left[ Y^i_t \right] = \sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_{\xi}^2 \]

\[ \text{cov} \left[ \left( a^i b^i \right), Y^i_t \right] = \begin{pmatrix} \sigma_a^2 + \sigma_{ab}\xi_t \\ \sigma_{ab} + \sigma_b^2\xi_t \end{pmatrix} \]

\[ \mu_t = \mu_{t-1} + \frac{Y^i_t - E\left[Y^i_t\right]}{\text{var} \left[ Y^i_t \right]} \left( \frac{\sigma_a^2 + \sigma_{ab}\xi_t}{\sigma_{ab} + \sigma_b^2\xi_t} \right). \]

Therefore,

\[ p_t - p_{t-1} = (1 - \phi) (\mu_t - \mu_{t-1}) = \frac{Y^i_t - E\left[Y^i_t\right]}{\text{var} \left[ Y^i_t \right]} \left( \frac{\sigma_a^2 + \sigma_{ab}\xi_t - \phi (\sigma_a^2 + \sigma_b^2\xi_t)}{\sigma_{ab} + \sigma_b^2\xi_t} \right) \]

and we get the following expression for \( \lambda(\xi_t) \):

\[ \lambda(\xi_t) = \frac{\sigma_a^2 - \sigma_{ab}\phi - \xi_t \left( \phi\sigma_b^2 - \sigma_{ab} \right)}{\sigma_a^2 + \sigma_b^2\xi_t^2 + \sigma_{\xi}^2 + 2\sigma_{ab}\xi_t}. \]

Proof of Proposition 2.

The derivative of \( \lambda \) with respect to \( \xi_t \) is

\[ \frac{d\lambda(\xi_t)}{d\xi_t} = \frac{\sigma_a^2 \left( -\phi \left( \sigma_a^2 + \sigma_{\xi}^2 \right) - 2\xi_t\sigma_a^2 + \phi\sigma_b^2\xi_t^2 \right)}{\left( \sigma_a^2 + \sigma_b^2\xi_t^2 + \sigma_{\xi}^2 \right)^2}. \]

The maximum is reached at the smallest root of the equation \(-\phi \left( \sigma_a^2 + \sigma_{\xi}^2 \right) - 2\xi_t\sigma_a^2 + \phi\sigma_b^2\xi_t^2 = 0\); therefore,

\[ \xi_{\lambda_{\text{max}}} = \frac{\sigma_a^2 \sqrt{\sigma_a^4 + \phi^2(\sigma_a^2 + \sigma_{\xi}^2)\sigma_b^2}}{\phi\sigma_b^2} = -\phi \left( \frac{\sigma_a^2 + \sigma_{\xi}^2}{\sigma_a^2 + \sqrt{\sigma_a^4 + \phi^2(\sigma_a^2 + \sigma_{\xi}^2)\sigma_b^2}} \right). \]

Proof of Proposition 3.

\[ \lambda(\xi_t) = \frac{\sigma_a^2 - \phi\sigma_{ab} - \left( \phi\sigma_b^2 - \sigma_{ab} \right) \xi_t}{\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_{\xi}^2} = \frac{A + B\xi_t}{C + D\xi_t}, \]

where \( A = \frac{\sigma_a^2 - \phi\sigma_{ab} - \left( \phi\sigma_b^2 - \sigma_{ab} \right) \xi_t}{\sigma_a^2 + \sigma_b^2\xi_t^2 + \sigma_{\xi}^2} \) and \( B = \frac{2\sigma_{ab}\xi_t}{\sigma_a^2 + \sigma_b^2\xi_t^2 + \sigma_{\xi}^2} \) and \( C = \frac{\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_{\xi}^2}{\sigma_a^2 + \sigma_b^2\xi_t^2 + \sigma_{\xi}^2} \).
where

\[ A = \sigma_a^2 - \phi \sigma_{ab} \quad B = \sigma_{ab} - \phi \sigma_b^2 \]

\[ C = \sigma_a^2 + \sigma_b^2 \xi_t + \sigma_z^2 \]

\[ D = 2\sigma_{ab} . \]

Therefore,

\[ \lambda_{\xi,+} > \lambda_{\xi,-} \iff A \cdot D < B \cdot C, \]

which is equivalent to

\[ (\sigma_a^2 - \phi \sigma_{ab}) 2\sigma_{ab} < (\sigma_{ab} - \phi \sigma_b^2) (\sigma_a^2 + \sigma_b^2 x^2 + \sigma_z^2) \iff \]

\[ \phi \sigma_b^2 (\sigma_a^2 + \sigma_b^2 x^2 + \sigma_z^2) + \sigma_{ab} (\sigma_a^2 - \sigma_b^2 x^2 - \sigma_z^2) - 2\phi \sigma_{ab}^2 < 0. \]

The left-hand side is a quadratic function of \( \sigma_{ab} \)

\[ f(\sigma_{ab}) = \phi \sigma_b^2 (\sigma_a^2 + \sigma_b^2 x^2 + \sigma_z^2) + \sigma_{ab} (\sigma_a^2 - \sigma_b^2 x^2 - \sigma_z^2) - 2\phi \sigma_{ab}^2. \]

The statement of the proposition follows from the following two facts:

1. \( f(\sigma_{ab} = 0) = \phi \sigma_b^2 (\sigma_a^2 + \sigma_b^2 x^2 + \sigma_z^2) > 0, \) and

2. \( f(\sigma_{ab} = -\sigma_a \sigma_b) + f(\sigma_{ab} = \sigma_a \sigma_b) = 2\phi (\sigma_b^2 x^2 + \sigma_z^2) > 0 \Rightarrow \) either \( f(\sigma_{ab} = -\sigma_a \sigma_b) > 0, \)

or \( f(\sigma_{ab} = \sigma_a \sigma_b) > 0, \) or both conditions hold.
References


Figure 1: Histograms of cumulative announcement returns (CAR) and earnings surprises (ES) for different subsamples.

The cumulative announcement returns (CAR) are calculated using CRSP daily returns from January 1984 to December 2012 from the close on the day before the announcement to the close on the day after the announcement. Earnings per share comes from the IBES unadjusted detail files. Earnings Surprises ES are computed as described in the paper. Because the standard deviation of earnings surprises is reported by IBES in large discrete steps, “discretization noise” is introduced. The second row is based on the same sample as the second row, but excludes observations with a reported standard deviation of earnings surprises less than 0.05, which mutes the discretization noise.
Figure 2: Non-parametric estimate of the earnings response coefficient as a function of the market return (earnings surprises normalized by book equity).

We estimate the equation \( CAR_{i,t} = \lambda_t (\xi_t) ES_{i,t} + \varepsilon_{i,t} \) using local polynomial regressions of order zero with an Epanechnikov kernel of 0.1 bandwidth. The cumulative announcement returns (CAR) are calculated using CRSP daily returns from January 1984 to December 2012 from the close on the day before the announcement to the close on the day after the announcement. The earnings surprises (ES) are defined as \( ES = EPS - E[EPS] \), where \( EPS \) is a stock actual announced earnings per share; \( E[EPS] \) is the expected earnings per share averaged across analysts from the IBES unadjusted detail files; \( BVPS \) is a firm’s last recorded book value per share before the announcement from the CRSP/Compustat merged files. The graph shows how the ERC \( \lambda_t \) depends on the state of the economy \( \xi_t \), which is represented by the market return in the reference period (i.e., the period during which earnings are earned).
Figure 3: Non-parametric estimate of the earnings response coefficient as a function of GDP growth (earnings surprises normalized by book equity).

We estimate the equation \( CAR_{i,t} = \lambda (\xi_t) ES_{i,t} + \epsilon_{i,t} \) using local polynomial regressions of order zero with an Epanechnikov kernel of 1.5 bandwidth. The cumulative announcement returns (CAR) are calculated using CRSP daily returns from January 1984 to December 2012 from the close on the day before the announcement to the close on the day after the announcement. The earnings surprises (ES) are defined as \( ES = \frac{EPS - E[EPS]}{BV/PS} \), where \( EPS \) is a stock actual announced earnings per share; \( E[EPS] \) is the expected earnings per share averaged across analysts from the IBES unadjusted detail files; \( BV/PS \) is a firm’s last recorded book value per share before the announcement from the CRSP/Compustat merged files. The graph shows how the ERC \( \lambda \) depends on the state of the economy \( \xi_t \), which is represented by the real US GDP growth rate in the quarter with the largest intersection with the reference period (i.e., the period during which earnings are earned).
Figure 4: Earnings response coefficients (ERC, $\lambda$) as a function of unexpected quarterly earnings (ES).

We estimate the equation $\text{CAR}_{i,t} = \lambda(ES_{i,t}) \cdot ES_{i,t} + \varepsilon_{i,t}$ using local polynomial regressions of order zero with an Epanechnikov kernel of optimal bandwidth. The cumulative announcement returns (CAR) are calculated using CRSP daily returns from January 1984 to December 2012 from the close on the day before the announcement to the close on the day after the announcement. The earnings surprises (ES) are defined as $ES = \frac{EPS - E[EPS]}{\text{st.dev.}[EPS]}$ and then demeaned, where $EPS$ is a stock’s actual announced earnings per share; $E[EPS]$ is the expected earnings per share averaged across analysts from the IBES unadjusted detail files, and $\text{st.dev.}[EPS]$ is the standard deviation of earnings per share.
Figure 5: Empirically estimated correlation for investors’ beliefs about $a$ and $b$. For each moment of time, we calculate the estimated correlation coefficient $\rho_{ab} = \frac{\sigma_{ab}}{\sigma_a \sigma_b}$ from the covariance matrix

$$
\begin{pmatrix}
\sigma_a^2 & \sigma_{ab} \\
\sigma_{ab} & \sigma_b^2
\end{pmatrix}
$$

that comes from the regression $Y_{it} = a_i + b_i \xi_t + \epsilon_{it}$ estimated for the 10 years of the previous quarterly observations. Note the ratio $\rho = \frac{\sigma_{ab}}{\sigma_a \sigma_b}$ does not depend on the realization $Y_{it}$ but only on past $\xi_t$, and thus it is time specific and not firm specific.
Figure 6: Predicted earnings response coefficients for a given aggregate shock.

For each announcement, we estimate the investors’ pre-announcement beliefs \( \left( \frac{E[a_i]}{E[b_i]} \right) \) and the corresponding covariance matrix \( \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix} \) from the regression \( Y_i^t = a^i + b^i \xi_t + \varepsilon_i^t \) using the previous 10 years of quarterly observations. Then we calculate the averages of the ratios \( \frac{E[a^i]}{\sigma_a}, \frac{E[b^i]}{\sigma^i_b}, \frac{\sigma_{ab}}{\sigma_a^2}, \frac{\sigma_{ab}}{\sigma_b^2}, \) and \( \frac{\sigma^2}{\sigma_a^2} \) over all announcements. From these average values, we can predict how ERCs depend on \( \xi_t \) according to equation (7.5).
Figure 7: Predicted average earnings response coefficients for a given aggregate shock.

For each moment of time, we calculate the estimated ratios \( \frac{\sigma_i^2}{\sigma_a^2}, \frac{\sigma_{un}}{\sigma_a^2}, \) and \( \frac{\sigma_{un}}{\sigma_a^2} \) from the covariance matrix \( \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix} \) that comes from the regression \( Y_t^i = a_i + b_i \xi_t + \epsilon_t^i \) estimated for the 10 years of the previous quarterly observations. Note the ratios do not depend on the realization \( Y_t^i \) but only on past \( \xi_t \), and thus they are time specific and not firm specific. Using these ratios for each moment of time, we calculate the predicted \( ERC_{t,model} \) from equation (7.5) (The remaining ratios \( E[a_i^2] \), \( E[b_i^2] \), which are independent from learning are the same as in the caption for Figure (6)). Finally, we estimate the equation \( ERC_{t,model} = \lambda_{model}(\xi_t) + \epsilon \) using local polynomial regressions of order zero with an Epanechnikov kernel of optimal bandwidth.
Table 1: Summary statistics (earnings surprises normalized by book equity).

The table contains summary statistics (means, standard deviations, percentiles) for all earnings announcements in our sample from January 1984 to December 2012. The cumulative announcement returns (CAR) are calculated using CRSP daily returns from the close on the day before the announcement to the close on the day after the announcement. The earnings surprises (ES) are defined as $ES = \frac{EPS - E[EPS]}{BVPS}$, where $EPS$ is a stock’s actual announced earnings per share; $E[EPS]$ is the expected earnings per share averaged across analysts from the IBES unadjusted detail files; $BVPS$ is a firm’s last recorded book value per share before the announcement from the CRSP/Compustat merged files. The statistics are presented separately for upturns and downturns, using three different downturn definitions: (i) NBER recessions, (ii) market return net of risk-free rate less than sample average, (iii) real GDP growth is less than average in 1947-2013.

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<th>p50</th>
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Table 2: Summary statistics (earnings surprises normalized by standard deviation of earnings surprises), restricted sample.

The table contains summary statistics (means, standard deviations, percentiles) for all earnings announcements in our sample from January 1984 to December 2012. The cumulative announcement returns (CAR) are calculated using CRSP daily returns from the close on the day before the announcement to the close on the day after the announcement. The earnings surprises (ES) are defined as $ES = \frac{EPS - E[EPS]}{\text{st.dev.}[EPS]}$, where $EPS$ is a stock’s actual announced earnings per share; $E[EPS]$ is the expected earnings per share averaged across analysts from the IBES unadjusted detail files. The statistics are presented separately for upturns and downturns, using three different downturn definitions: (i) NBER recessions, (ii) market return net of risk-free rate less than sample average, (iii) real GDP growth is less than average in 1947-2013.

<table>
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<tr>
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Table 3: Earnings response coefficients as a function of the macroeconomic state (earnings surprises normalized by standard deviation of analyst forecasts, restricted sample).

ERC is the coefficient $\beta_2$ in a regression of cumulative abnormal earnings announcement returns ($CAR_i,t$) on earnings surprises ($ES = \frac{EPS - \mu[EPS]}{\text{st.dev.}[EPS]}$) $CAR_{i,t} = \alpha + \beta_1 \cdot ES_{i,t} \times DT_{t} + \beta_2 \cdot ES_{i,t} + \beta_3 \cdot DT_{t} + \epsilon_{i,t}$. The regression specifications allows for a higher coefficient in downturns ($DT$) than in upturns. While the null hypothesis is that $\beta_1 = 0$ our theory predicts that $\beta_1 > 0$. The three sets of columns differ in the definition of downturn: (i) NBER recessions, (ii) market return net of risk-free rate less than sample average, (iii) real GDP growth is less than average in 1947-2013. The second specification in each set controls also for the variance of earnings surprises $\text{Var}(ES)$ and its interaction with $ES$. The third specification allows also for a time trend in ERCs. Data are from January 1984 to December 2012, restricted to observations with $\text{st.dev.}[E[EPS]] \geq 0.05$. Earnings surprises are from the IBES unadjusted detail files, corresponding returns are from CRSP. Standard errors are heteroskedasticity robust and clustered by the month of the earnings announcement.

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<td>0.00582*</td>
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<td>-0.000357</td>
<td>-0.000438</td>
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<td>0.000968</td>
<td>0.000628</td>
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<td>(1.80)</td>
<td>(2.22)</td>
<td>(-0.23)</td>
<td>(-0.29)</td>
<td>(0.02)</td>
<td>(0.63)</td>
<td>(0.42)</td>
</tr>
<tr>
<td>$ES \times \text{Var}(ES)$</td>
<td>-0.000325**</td>
<td>-0.000277**</td>
<td>-0.000200</td>
<td>-0.000196*</td>
<td>-0.000235*</td>
<td>-0.000199*</td>
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<td>$\text{Var}(ES)$</td>
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<td>0.000344</td>
<td>0.000654*</td>
<td>0.000699*</td>
<td>0.000565</td>
<td>0.000597</td>
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<td>(0.84)</td>
<td>(1.67)</td>
<td>(1.76)</td>
<td>(1.46)</td>
<td>(1.53)</td>
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</tr>
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<td>0.000000809***</td>
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<td>-0.00522**</td>
<td>-0.00161</td>
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$t$ statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Table 4: Earnings response coefficients as a function of the macroeconomic state (earnings surprises normalized by book equity).

ERC is the coefficient $\beta_2$ in a regression of cumulative abnormal earnings announcement returns ($CAR$) on earnings surprises ($ES = \frac{\text{EPS} - \text{E}[\text{EPS}]}{\text{BVPS}}$). $\text{CAR}_{i,t} = \alpha + \beta_1 \cdot ES_{i,t} \times DT_t + \beta_2 \cdot ES_{i,t} + \beta_3 \cdot DT_t + \varepsilon_{i,t}$. The regression specifications allows for a higher coefficient in downturns ($DT$) than in upturns. The null hypothesis is that $\beta_1 = 0$. Our theory predicts that $\beta_1 > 0$. The three sets of columns differ in the definition of downturn: (i) NBER recessions, (ii) market return net of risk-free rate less than sample average, (iii) real GDP growth is less than average in 1947-2013. The second specification in each set controls also for the variance of earnings surprises $\text{Var}(ES)$ and its interaction with $ES$. The third specification allows also for a time trend in ERCs. Data are from January 1984 to December 2012. Earnings surprises are from the IBES unadjusted detail files, corresponding returns are from CRSP, and $\text{BVPS}$ is from Compustat. Standard errors are heteroskedasticity robust and clustered by the month of the earnings announcement.

<table>
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<tr>
<th></th>
<th>(1) NBER</th>
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<th>(3) NBER</th>
<th>(4) Market</th>
<th>(5) Market</th>
<th>(6) Market</th>
<th>(7) GDP</th>
<th>(8) GDP</th>
<th>(9) GDP</th>
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<td>0.480***</td>
<td>0.340***</td>
<td>0.122**</td>
<td>0.143**</td>
<td>0.149***</td>
<td>0.219***</td>
<td>0.266***</td>
<td>0.122**</td>
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<td></td>
<td>(2.86)</td>
<td>(4.04)</td>
<td>(3.20)</td>
<td>(1.97)</td>
<td>(2.35)</td>
<td>(2.77)</td>
<td>(3.26)</td>
<td>(4.07)</td>
<td>(2.21)</td>
</tr>
<tr>
<td>ES</td>
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<td>1.251***</td>
<td>0.795***</td>
<td>0.928***</td>
<td>1.145***</td>
<td>0.658***</td>
<td>0.891***</td>
<td>1.138***</td>
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<td>(29.01)</td>
<td>(16.75)</td>
<td>(9.58)</td>
<td>(26.73)</td>
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<td>0.00239</td>
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<td>(1.77)</td>
<td>(1.97)</td>
<td>(1.48)</td>
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<td>(0.96)</td>
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<td>-1766.1***</td>
<td>-1015.4***</td>
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<td>-1544.8***</td>
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<td>(-3.79)</td>
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<td>(0.87)</td>
<td>(0.97)</td>
<td>(0.78)</td>
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<td>0.00349***</td>
<td>0.00215</td>
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<td>0.00427***</td>
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<td>(1.20)</td>
<td>(1.57)</td>
<td>(3.88)</td>
<td>(1.66)</td>
<td>(2.16)</td>
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</table>

$N$ = 147474

$t$ statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$