# Revealing Downturns

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**Abstract**

When a Bayesian risk-averse investor is uncertain both about individual assets' expected cash flows and about their exposure to systematic risk, then stock prices react more to news in downturns than in upturns, implying negatively skewed returns. The reason is that, in good times, less desirable assets with low average cash flows and high loading on market risk perform similar to more desirable assets with high average cash flows and low market risk, but their relative performance diverges in downturns. Consistent with these predictions, stocks' reaction to earnings news is up to 80% stronger in downturns than in upturns.

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# 1 Introduction

Accounting scandals, Ponzi schemes, and other investment frauds are typically revealed in downturns. In Warren Buffett's words: "you only find out who is swimming naked when the tide goes out" (Buffett, 2001). Interestingly, downturns are also the times during which Buffett has made some of his most memorable and profitable investment decisions, such as his \$5bn Goldman Sachs equity injection in the fall of 2008. Such asymmetries between upturns and downturns arise in many domains. For example, active mutual funds over-perform the index only in downturns, boards fire CEOs more frequently in bad times than in good times, and stock prices tend to rise slow but fall fast, leading to negatively skewed returns.[1] The common theme is that investors are better at discerning good from bad projects in downturns than in upturns.

This paper proposes a model that provides a simple rationale to explain why rational Bayesian investors are better at distinguishing the relative quality of alternative investment projects in downturns than in upturns. The key insight is that uncertainty about individual projects' fundamental risk loadings, combined with positive risk premia, are sufficient to understand such asymmetries. Contrary to common belief, no behavioral distortions, time-varying earnings manipulation, asymmetric information, or other frictions are necessary. We show that when risk premia are positive, then project-specific fundamental news in downturns carries more relevant information about the utility that investors derive from investing in the project than news pertaining to performance in upturns does. The reason is that what risk-averse investors see in downturns is more aligned with what they care about, which is risk-adjusted performance. While this insight applies also to corporate finance and other fields, we focus our predictions on an asset pricing application. We show that even when all model parameter distributions are symmetric and stable across states of the economy, there is an asymmetry across economic states in the price response to fundamental news. The model predicts that stocks react more to earnings news in downturns on average. More specifically, the sensitivity of the stock price to news is a function that is non-monotonic with respect to the underlying macro-economic state, i.e., the risk factor realization. Empirical tests confirm these predictions.

The intuition of the model is as follows. A firm's cash-flow realizations depend on a

[1] On fund performance, see Sun, Wang, and Zheng (2009) and Kosowski (2006); see also Moskowitz (2000) discussing Wermers (2000). See Jenter and Kanaan (forthcoming) and Eisfeldt and Kuhnen (2013) on forced CEO turnover. See Campbell and Hentschel (1992) on negatively skew in stock returns.

firm-specific time-fixed parameter for good idiosyncratic performance ("cash-flow alpha" – henceforth, $a$), and the realization of a market-wide factor. The correlation with that risk factor is firm-specific as well, and referred to as "cash-flow beta" (henceforth, $b$). Risk-averse investors like good idiosyncratic performance but dislike correlation with the market, so the stock price increases in $a$ and decreases in $b$. Investors do not know the exact values of the two parameters for a given firm, but they know the distributions from which the parameters are drawn. They attempt to learn the firms' parameters by observing fundamental performance, and conditioning that news on the state of the world in which they were observed. Unexpectedly high cash-flows in good times are a signal for both high $a$ and high $b$. Higher-than-expected $a$ means the stock price should rise; higher-than-expected $b$ means the stock price should fall. In sum, a mixed signal obtains. Intuitively, while generally content with higher-than-expected earnings, investors sense that over-performance in upturns was quite possibly achieved with exceptionally high market risk exposure. Good news in good times is therefore a somewhat ambiguous signal about firm value, and is thus weighted less heavily. The low information content is symmetric with respect to the sign of the news surprise: Unexpectedly low cash flows in good times can be either due to low idiosyncratic performance ($a$), which is bad news, or due to low market exposure ($b$), which is good news. Because of the ambiguity of the signal, investors do not attach high confidence to *either good or bad* news in good times. As a result, prices do not react strongly to any piece of firm-specific news in good times.

In contrast, unexpectedly high earnings in bad times can be due to either unexpectedly high cash-flow alpha ($a$) or unexpectedly low cash-flow beta ($b$). Both interpretations are good news for firm value. Similarly, bad performance in bad times is clearly a bad signal about firm value: it can be due to either bad idiosyncratic performance ($a$) or due to high market correlation ($b$), both of which are undesirable attributes. In sum, cash flow news in downturns provides less ambiguous signals about firm value, irrespective of the direction. Therefore, Bayesian investors place higher weight on news pertaining to firm performance in downturns than to performance in upturns, no matter whether the news is good or bad conditional on the market state. As a result, prices react more strongly to fundamental news in downturns than in upturns.[2]

[2]Figure 1 illustrates the conclusions investors draw from observing good and bad earnings surprises in good and bad times. A more technical description of the intuition is as follows. Investors update their beliefs more swiftly when the stochastic discount factor is high because news in such states is (i) more important to them and (ii) more informative about future states with high discount factors, compared to news obtained during states connected to low stochastic discount factor. In other words,

A direct result of a stronger reaction in downturns to both good news (as realized by some firms) and bad news (as realized by other firms), dispersion of returns increases in bad times. Further, a consequence of higher dispersion in downturns combined with lower average returns in downturns is that the unconditional return distribution is negatively skewed. This prediction of our model is a well-known fact. What was not known before is that a model without frictions other than parameter uncertainty is able to generate this pattern.

Empirically, we measure the price response to unexpected earnings changes ("earnings news") first with earnings response coefficients (ERC) as used in the previous literature, and then confirm the results with a new measure of earnings response coefficients that more literally reflects the model equivalent. In all specifications, the ERCs are positive. Moreover, consistent with the model's predictions, ERCs change with the state of the economy. Using non-parametric techniques, we find that ERCs are highest at about -25% market return or -5% GDP growth, and are up to 80% higher at such times than in upturns of similar magnitudes. The fact that ERCs peak at a negative market return (rather than decrease monotonically with market returns) is a unique empirical result, confirming the unique theoretical prediction. We then test a second key prediction with ordinary least squares (OLS), finding that ERCs are up to 65% higher on average in downturns compared to upturns.

The insights from this paper contribute to the literature by establishing that symmetric asset return distributions only obtain in the special case when market risk premia are zero, or when investors are not uncertain about *cash flow* risk loadings of individual assets. Given the low frequency of observations of such fundamental data, this special case is less likely to be relevant in practice. Conversely, the likely case of imperfect knowledge of risk loadings amid positive risk premia implies asymmetric price reactions and negatively skewed returns. As such, we simplify the intuition for several empirically observed asymmetries over the business cycle, compared to the intuition provided by the extant literature.

The paper proceeds as follows. Section 2 discusses the related literature. Section 3

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the estimates of $a$ and $b$ are more positively correlated in upturns, and negatively in downturns. As a result, investors are better able to distinguish in bad times between "good firms" that have high $a$ and low $b$ and "bad firms" that have low $a$ and high $b$.

The results crucially rely on uncertainty about the fundamental parameters governing the firms' reduced-form cash flow processes, and in particular on these cash flows' risk loadings. It is well known since Merton (1980) that second moments can be learned arbitrarily fast when a stochastic process is continuously observed. This assumption may be satisfied for stock prices, but not for firms' cash flows, which are reported only at a quarterly frequency.

presents the model. Section 4 explains the empirical results. Section 5 concludes.

## 2 Related Literature

The present paper is closely related to several models of learning in financial markets; see Pastor and Veronesi (2009) for a review of the literature. Existing papers explain asymmetries in asset pricing and the intermediation sector over the business cycle with a combination of (a subset of) Bayesian learning, limited channel capacity of the decision maker, costly effort, information asymmetry and exogenous variation of risk aversion or other parameters over the business cycle. Examples include Veldkamp (2005); Van Nieuwerburgh and Veldkamp (2006); Kacperczyk, van Nieuwerburgh, and Veldkamp (2013, Forthcoming). While these papers generally address distinct phenomena from the present one, the conceptual difference is that the only necessary assumptions of the present model are a positive risk premium and parameter uncertainty, while additional assumptions are used to derive the results in the previous papers. An interesting contrast in terms of mechanism also occurs in comparison with Ilut, Kehrig, and Schneider (2013), who generate asymmetries across upturns and downturns by employing agents who overweight bad news relative to good news, while being unaware of the state of the economy. In contrast, our model does not assume overweighting of bad news, and we allow the decision maker to rationally infer the state of the economy in our model. Compared to Banerjee and Green (2013), the agents in our model are all identical. As a result, there is no asymmetric information, and prices contain no more information than fundamentals. A difference in terms of predictions is that we generate an asymmetry across upturns and downturns but not across good and bad news. Relatedly, Veronesi (1999) explains asymmetric reactions to good and bad news in any state of the economy, while we explain the asymmetric reaction to any type of news in good and bad times. In contrast to Veronesi (1999), our agent is cognizant about the aggregate state and in our model there are no regime switches. Veronesi and Ribeiro (2002) predict higher co-movement of stock returns in recessions, while we explain higher cross-sectional dispersion in recessions, which leads to negatively skewed returns.[3] The difference in assumptions is that in Veronesi and Ribeiro (2002), the state of the world is uncertain, but firm parameters are known. In our case, the state of the

[3]There is no contradiction between these predictions. Dispersion and correlations can both increase at the same time when volatility increases as well. See Figure 2 for an illustration. The appendix provides an analytic explanation.

world is known, but firm parameters are uncertain.[4]

Empirically, the present paper is most closely related to a literature in accounting that documents time-variation in earnings response coefficients. Johnson (1999) finds that the state of the business cycle explains a considerable portion of that variation. Our paper differs from Johnson (1999) in several dimensions. One is that we use 1984-2012 IBES data whereas she uses earnings announcements by Value Line firms over the period January 1970–September 1987. Another is that we follow the method of calculating earnings response coefficients (ERCs) that is accepted in the finance literature (Pástor, Taylor, and Veronesi, 2009), which normalizes earnings responses by book equity rather than market equity. The reason for this choice is that market value of equity varies with the business cycle and can therefore generate a mechanical relationship between ERCs and the state of the economy. We also contribute non-linear estimation results that do not impose discrete changes in the state of the economy on the econometric model. Lastly, our hypotheses are derived from a formal rational model, whereas Johnson (1999)'s hypothesis development is less constrained. Relatedly, Collins and Kothari (1989) find that ERCs are negatively related to risk-free interest rates. A distinction is that their hypotheses are developed as a partial equilibrium argument loosely tied to the CAPM, while our hypotheses are closely tied to a formal equilibrium model. Mian and Sankaraguruswamy (2012) investigate the impact of investor sentiment (Baker and Wurgler, 2006) on the reaction to news. In contrast, we investigate rational reasons for the variation of ERCs over time.

Franzoni and Schmalz (2013) use the same multidimensional filtering problem employed in the present paper to derive how mutual funds' flow-performance sensitivity depends on the state of the economy. Compared to their model, the model presented here is more general in that it allows for arbitrary prior-period beliefs.

[4] Savor and Wilson (2011); Patton and Verardo (2012); Collin-Dufresne, Johannes, and Lochstoer (2012) and many others study the effects of uncertainty about the macro state, or political uncertainty, with implications for risk premia. We discuss at the end of section 3 why our model is largely orthogonal to models of learning about aggregate states. Fernández-Villaverde, Garicano, and Santos (2013) invoke a behavioral friction in addition to Bayesian learning to explain asymmetries over the business cycle in the replacement of politicians in office. By contrast, Schmalz (2012) and Zhuk (2012) explain asymmetries in involuntary CEO turnover over the business cycle Jenter and Kanaan (forthcoming) with a Bayesian model without additional frictions.

# 3 Model

This section describes a model of Bayesian learning by a mass of identical risk-averse agents about the value of several assets. The assets experience idiosyncratic shocks; in addition, they are subject to economy-wide systemic shocks. The key ingredient of the model is that the assets' risk exposure to a systemic shock differs across assets and is not perfectly known by investors. More specifically, each asset's cash flow is affected by two time-fixed but uncertain idiosyncratic parameters that can be thought of as cash-flow alpha and cash-flow beta. The former is the asset's average payoff. The latter stands for the exposure of the asset to a market-wide risk factor.[5] Risk-averse agents dislike such exposure and needs to be compensated for it. Under these assumptions, how much the agents learns from a piece of fundamental information about her utility from holding a particular asset depends on the state of the economy. As the agents prices the assets, the price reaction to news also depends on the state of the economy. In particular, news pertaining to firm performance in a downturn contains more relevant information than news pertaining to firm performance in an upturn. As a result, asset prices react more strongly to cash flow news in downturns than in upturns. The striking feature of the model is that although all parameter distributions are symmetric and stable across states of the economy and shocks are *iid*, there is an asymmetry across states of the economy in the price response to fundamental news.

## 3.1 Economy

There is a large number of stocks $i = 1, 2, \ldots, N$ in the economy. A risk-free asset is available in unlimited supply and generates return $R$ every period. Assets are priced by an overlapping generations mass of identical agents with von Neumann-Morgenstern utility index $u$.[6] Each stock $i$ pays dividends $Y_t^i$ at time $t = 1, 2, \ldots$. These dividend realizations can be projected on realizations of an aggregate shock, $\xi_t$, that is identical for all assets. Then, the reduced-form cash flow process can we written as

$$Y_t^i = a^i + b^i \xi_t + \varepsilon_t^i. \tag{3.1}$$

[5]We focus on market risk for simplicity and because it is likely to be highly correlated with other risk factors; the same argument, however, also applies to other risk factors.

[6]We use the overlapping generations structure and the normality of distributions for tractability of our main results. We explain below why these assumptions are not driving the results.

$a^i$ and $b^i$ represent firm-specific parameters capturing average cash flows and the cash flows' sensitivity to the aggregate shock, respectively. Investors are uncertain about the precise value of both of them. We refer to the parameters as cash-flow alpha and cash-flow beta. While the exact distribution of $\xi_t$ including its mean is irrelevant, for concreteness we assume that the market shocks $\xi_t$ are *iid* and have mean zero $E[\xi_t] = 0$. The idiosyncratic shocks $\varepsilon_t^i \sim N(0, \sigma_\varepsilon^2)$ are normally distributed and independent across firms and over time.[7]

Initially the true cash flow parameters $a^i$ and $b^i$ are independently drawn from a known distribution. For analytical tractability, we assume that the distribution is mutually normal,

$$\begin{pmatrix} a^i \\ b^i \end{pmatrix} \sim \mathcal{N}\left( \begin{pmatrix} \bar{a} \\ \bar{b} \end{pmatrix}, \begin{pmatrix} \bar{\sigma}_a^2 & \bar{\sigma}_{ab} \\ \bar{\sigma}_{ab} & \bar{\sigma}_b^2 \end{pmatrix} \right). \tag{3.2}$$

We assume $\bar{a}, \bar{b} > 0$. No other restrictions are necessary; the precise values of the means are immaterial for our results.

## 3.2 Beliefs

The investors do not know the exact realizations of $a^i$ and $b^i$ for a given firm $i$, but they do know the distribution from which the parameters were drawn (3.2). We require that the agents' initial prior beliefs correspond to that true distribution. We denote $\Omega_0^i = \mathcal{N}(\mu_0^i, \Sigma_0)$ for initial prior beliefs, with

$$\mu_0^i = \begin{pmatrix} \bar{a} \\ \bar{b} \end{pmatrix} \qquad \Sigma_0 = \begin{pmatrix} \bar{\sigma}_a^2 & \bar{\sigma}_{ab} \\ \bar{\sigma}_{ab} & \bar{\sigma}_b^2 \end{pmatrix}. \tag{3.3}$$

Every period, investors observe new dividend realizations and use that news to update their prior beliefs about the parameters of each asset. Formally, denote by $I_t =$

[7] We fix $\sigma_\varepsilon^2$ to be a constant to emphasize that the stock price response to news varies with the aggregate shock even when no asymmetry in parameter distributions is assumed. Empirically, we show that non-monotonicity is important by providing non-parametric estimates of how earnings response coefficients depend on the state of the economy, and we offer specifications in our OLS results that control for variance of earnings surprises to mitigate the concern that variation in the parameter distributions over time drive our results. Similarly, the assumption that systemic shocks, $\xi_t$, are *iid*, is a deliberate choice for similar reasons: our results might be viewed as less surprising if time-series correlation of the shocks were the driver. For this reason, Banerjee and Green (2013) also view *iid* shocks as a desirable property of their model. Note that the non-monotonic predictions of the model cannot be generated by simply assuming that $\sigma_\varepsilon^2$ is a decreasing function of $\xi_t$, i.e., that volatility is higher in downturns.

$\{\{Y_1^i\}, \xi_1, \{Y_2^i\}, \xi_2 \ldots, \{Y_t^i\}, \xi_t\}$ the information set that becomes available at time $t$. Note that the realization of $\xi_t$ is known at the time the inference is made.[8] As a result, the conditional distribution of beliefs remains normal despite the multiplicative form of the cash flow process. We will use the following notation for conditional posterior beliefs $\Omega_t$ about parameters $\psi^i = \begin{pmatrix} a^i \\ b^i \end{pmatrix}$ at the end of time $t$,

$$\psi^i | I_t = \Omega_t^i \sim \mathcal{N}(\mu_t^i, \Sigma_t) \tag{3.4}$$

where

$$\mu_t^i = \begin{pmatrix} a_t^i \\ b_t^i \end{pmatrix} \qquad \Sigma_t = \begin{pmatrix} \sigma_{a,t}^2 & \sigma_{ab,t} \\ \sigma_{ab,t} & \sigma_{b,t}^2 \end{pmatrix}. \tag{3.5}$$

The conditional variance remains the same across firms, so we omit the $i$-superscript for variance.

## 3.3 Valuation

Investors have identical, risk-averse preferences, and live for two periods. In such an OLG economy, a stochastic discount factor (*sdf*), $m_t$, prices the uncertain dividend stream $\{Y^i\}_t$ as follows,

$$p_t^i = E_t[m_{t+1}(p_{t+1}^i + Y_{t+1}^i)] \qquad E_t[m_{t+1}] = \frac{1}{R}. \tag{3.6}$$

Importantly, the *sdf* depends only on the realization of the aggregate dividend $Y_t = \sum Y_t^i$, but not on individual stock returns or current beliefs about the stocks' parameters. (As $N$ is large, there is no learning about the aggregate dividend.) We contrast this feature of the model with models in the existing literature at the end of this section.

[8] If $\xi_t$ were not directly observable, it could be easily inferred from the aggregate dividend $Y_t = \sum Y_t^i = N(\bar{a} + \bar{b} \cdot \xi_t)$ and knowledge about $\bar{a}$ and $\bar{b}$. The fact that investors condition the signal they see on the state of the market is a point of distinction of our notion of "news" from several existing approaches, as discussed in the literature review. A positive cash flow surprise means that cash flows are higher than expected, given the current state of the economy. Merely positive cash flows are not necessarily good news. To clarify, we give an example each for bad news and good news. Suppose current beliefs about an asset's parameters are $a_t = 0$, $b_t = 1$, and the market shock $\xi_t$ is $\xi_t = 4$ (recall $\xi_t$ has mean zero.) A cash flow of $Y_t^i = 3$ is higher than the average cash flow that the stock generates, 0, but the investor is nevertheless negatively surprised, as the expected cash flow in the current state of the economy is $E[Y_t^i] = a^i + b^i \cdot \xi_t = 0 + 1 \cdot 4 = 4$. As a result, the investor downward-adjusts her beliefs about both $a^i$ and $b^i$, maybe to $-0.1$ and $+0.75$, respectively. In contrast, when the cash flow realization is higher than expected given current beliefs and given the state of the market, e.g., $Y_t^i = 5$, the investor will upward-adjust beliefs about both $a^i$ and $b^i$.

**Lemma 1.** *The stochastic discount factor is iid and given by*

$$m_{t+1} = \frac{1}{R} \frac{u'(C + Y_{t+1})}{E_t[u'(C + Y_{t+1})]}. \tag{3.7}$$

*(C is a constant defined in the appendix.)*

All proofs are in the appendix. Because there is no learning about $Y_t$, and as result no learning about $m_t$, we can solve recursively for the price of asset $i$:

$$p_t^i = \sum_{k=1}^{\infty} E_t \left[ (m_{t+1} \cdot \dots \cdot m_{t+k}) \cdot Y_{t+k}^i \right]$$

$$= \sum_{k=1}^{\infty} E_t (m_{t+1}) \cdot \dots \cdot E_t (m_{t+k-1}) \cdot E_t \left[ m_{t+k} \cdot Y_{t+k}^i \right]$$

$$= \sum_{k=1}^{\infty} \frac{1}{R^{k-1}} E_t \left[ m_{t+k} \cdot Y_{t+k}^i \right] = \sum_{k=1}^{\infty} \frac{1}{R^{k-1}} E_t \left[ m_{t+1} \cdot Y_{t+1}^i \right]$$

$$= \frac{R}{R-1} E_t \left[ m_{t+1} \cdot Y_{t+1}^i \right]. \tag{3.8}$$

Using the functional form (3.1) for the reduced-form cash flow process, the price takes a simple form,

$$p_t^i = \frac{R}{R-1} E_t \left[ m_{t+1} \cdot Y_{t+1}^i \right] = \frac{R}{R-1} E_t \left[ m_{t+1} \left( a^i + b^i \cdot \xi_{t+1} + \varepsilon_{t+1}^i \right) \right]$$

$$= \frac{R}{R-1} \left( E_t \left[ a^i \right] \cdot E_t \left[ m_{t+1} \right] + E_t \left[ b^i \right] \cdot E_t \left[ m_{t+1} \xi_{t+1} \right] \right).$$

The following lemma immediately follows.

**Lemma 2.** *The price of stock $i$ increases in beliefs about $a^i$ and decreases in beliefs about $b^i$. Specifically,*

$$p_t^i = \frac{1}{R-1} E_t \left[ a^i - \phi b^i \right], \tag{3.9}$$

*where $\phi = -R \cdot E_t \left[ m_{t+1} \xi_{t+1} \right] > 0$.*

Note that for a risk-averse investor, the stochastic discount factor $m_{t+1}$ is decreasing in the realization of the aggregate shock $\xi_{t+1}$, i.e., $m_{t+1}$ and $\xi_{t+1}$ are negatively correlated. $\phi > 0$ captures the effect of risk aversion, and reflects the utility cost of bearing the economy-wide market risk. As a result, a risk-averse investor's willingness to pay for the asset increases in the asset's cash-flow alpha and decreases in its cash-flow beta, as equation (3.9) conveys. For CARA utility we can explicitly solve for the utility cost of bearing economy-wide risk, $\phi$. We give this result to help with the intuition of why $\phi$ is positive.

**Lemma 3.** *If investors have CARA utility, $u(Y) = -exp(-\gamma Y)$ with risk aversion parameter $\gamma$, then $\phi = \gamma N\bar{b} \cdot \sigma_{\xi}^2$.*

The lemma illustrates that the utility cost of bearing economy-wide risk, $\phi$, can be thought of as the product of the price of risk ($\gamma$) multiplied with the quantity of macro-economic risk ($N\bar{b} \cdot \sigma_{\xi}^2$). Note that CARA utility is not an assumption that drives the following results.

## 3.4 Intuition of the Main Results

This subsection gives the intuition behind our main result that prices respond stronger to news in downturns than in upturns, which we present in the next subsection. First, instead of thinking about learning about $a^i$ and $b^i$, let us think more generally about learning the properties of the cash flow process $Y_t^i$. Since risk-averse agents derive greater value from cash flows in downturns than from cash flows in upturns, in order to value the asset it is more important to know how the asset performs in downturns. As a consequence, they put more weight on observations pertaining to asset performance in downturns compared to observations pertaining to performance in upturns. The driver of the asymmetry is not a higher amount of information in downturns. The driver is that information is more important for gauging the value from holding the asset. In order to illustrate this intuition more formally, consider equation (3.8). In an *iid* environment, we can approximate the conditional expectation with a weighted sum of past observations,

$$p_t^i = \frac{R}{R-1} E_t \left[ m_{t+1} \cdot Y_{t+1}^i \right] \approx \frac{R}{R-1} \frac{1}{t} \sum_{\tau=1}^{t} m_\tau Y_\tau^i. \tag{3.10}$$

In this estimator, the price corresponds to the weighted sum of observed cash flows, where the weights are the stochastic discount factors in the states in which the cash flows were generated. To gain further intuition, let us decompose the weighted sum in the above expression analogously to the decomposition $E_t \left[ m_{t+1} \cdot Y_{t+1}^i \right] = E_t \left[ m_{t+1} \right] E_t \left[ Y_{t+1}^i \right] +$

$Cov\left(m_{t+1}, Y_{t+1}^i\right)$,

$$p_t^i \approx \frac{R}{R-1}\left[\frac{1}{t}\sum_{\tau=1}^{t} m_\tau \cdot \frac{1}{t}\sum_{\tau=1}^{t} Y_\tau^i + \frac{1}{t}\sum_{\tau=1}^{t}\left(m_\tau - \frac{1}{t}\sum_{s=1}^{t} m_s\right)\left(Y_\tau^i - \frac{1}{t}\sum_{s=1}^{t} Y_s^i\right)\right]. \tag{3.11}$$

A higher-than-average observation of $Y_\tau^i$ always increases the first component of the price (the "average" term - notice that $m$ is equal to one on average), but when it occurs when $m_\tau$ has a below-average realization, it decreases the second component of the price (the "covariance" term) at the same time, thus dampening the positive value implication of the observation. By contrast, when the above-average observation of $Y_\tau^i$ occurs amid an above-average realization of $m_\tau$, then the covariance term also increases, strengthening the value implication of the good news. Symmetrically, bad news in bad times has a negative effect on both the first and the second term, while bad news in good times has a negative effect on the "average" term but increases the "covariance" term, thus leading to a dampened reaction. In sum, irrespective of whether the news is good or bad, the magnitude of the value implication of the news covaries with the stochastic discount factor.

The following alternative way to illustrate our main result adds to this intuition that the relationship between reaction to news and the state of the economy is not monotonic, as the above intuition may have suggested. Here, we compare in which state of the economy, $\xi_t$, the alignment between what the investor cares about and what she observes is greatest. From lemma 2, the quantity that the investor is interested in learning about is $a^i - \phi b^i$, and we take from equation (3.1) what she observes, $Y_t^i = a^i + b^i \cdot \xi_t + \varepsilon_t^i$. The asset value conditional on observed cash flows is,

$$p_t^i = \frac{1}{R-1} E\left[a^i - \phi b^i \quad | \quad a^i + b^i \cdot \xi_t + \varepsilon_t^i\right]. \tag{3.12}$$

Subtracting and adding $\phi b^i$, the conditioning information can be rewritten as

$$p_t^i = \frac{1}{R-1} E\left[a^i - \phi b^i \quad | \quad a^i - \phi b^i + b^i(\xi_t + \phi) + \varepsilon_t^i\right]. \tag{3.13}$$

The investor is interested in $a^i - \phi b^i$, but observes $a^i - \phi b^i + b^i(\xi_t + \phi) + \varepsilon_t^i$. The first two terms agree; the remainder of what the investor observes is noise that obfuscates the inference about what she cares about. This noise is minimized and the object of interest and the conditioning information are most aligned when $\xi_t + \phi$ is close to zero, or when

$\xi_t$ is close to $-\phi$, which is smaller than 0 because $\phi > 0$ because of risk aversion. Thus, the signal-to-noise ratio is highest when $\xi_t$ is a *moderately* negative number. But when the market-wide shock is extremely negative, e.g., $\xi_t \approx -2 \cdot \phi$, there is more "noise" in the observation than when $\xi_t \approx -\phi$. Thus the non-monotonicity.

## 3.5 Formal Results

### 3.5.1 Updating Beliefs

Each period, investors observe new realizations of dividends of all assets and update their beliefs about parameters accordingly,

$$\Omega_t^i = \psi^i | I_t \sim \mathcal{N}(\mu_t, \Sigma_t). \tag{3.14}$$

Conditional on the state of the economy, $\xi_t$, the dividend $Y_t^i$ is a linear function of the parameters. Therefore the standard equations for Bayesian updating of beliefs apply. The posterior beliefs in period $t$ about means and variances, conditional on beliefs that were formed in period $t-1$, dividend observations $Y_t^i$, and the market shock $\xi_t$, are calculated as

$$\mu_t = \mu_{t-1} + \frac{cov\left[\psi^i, Y_t^i\right]}{var\left[Y_t^i\right]}(Y_t^i - E[Y_t^i]), \tag{3.15}$$

and

$$\Sigma_t = \Sigma_{t-1} - \frac{cov\left[\psi^i, Y_t^i\right] cov\left[\psi^i, Y_t^i\right]^T}{var\left[Y_t^i\right]}. \tag{3.16}$$

Regarding notation, here all expectations are conditional on information available at $t-1$ and $\xi_t$. For example, $cov\left[\psi^i, Y_t^i\right] = cov\left[\psi^i, Y_t^i | I_{t-1}, \xi_t\right]$. Also, current beliefs depend on the beliefs in the previous period $\mu_{t-1}, \Sigma_{t-1}$. To make the results more readable we omit the $t-1$ subscript in the conditional variance for the previous period,

$$\Sigma_{t-1} = \begin{pmatrix} \sigma_{a,t-1}^2 & \sigma_{ab,t-1} \\ \sigma_{ab,t-1} & \sigma_{b,t-1}^2 \end{pmatrix} = \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix}. \tag{3.17}$$

With this notation,

$$var\left[Y_t^i\right] = var\left[Y_t^i | I_{t-1}, \xi_t\right] = \sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2 \tag{3.18}$$

and

$$cov\left[\psi^i, Y_t^i\right] = cov\left[\psi^i, Y_t^i | I_{t-1}, \xi_t\right] = \begin{pmatrix} \sigma_a^2 + \sigma_{ab}\xi_t \\ \sigma_{ab} + \sigma_b^2\xi_t \end{pmatrix}. \tag{3.19}$$

In words, the variance of the news, $Y_t^i$, which investors use as an input to their learning problem, depends on the factor realization, $\xi_t$. By contrast, the asset parameters that investors wish to infer, do not depend on $\xi_t$. Necessarily then, signal-to-noise ratios will depend on $\xi_t$. We derive a closed-form expression of this dependence below.

### 3.5.2 Measures of the Price Response to News

To derive a precise statement of the price response to news, it is useful to rewrite the asset price in vector notation

$$p_t^i = \frac{1}{R-1} E_t\left[a^i - \phi b^i\right] = \frac{1}{R-1}\left(1 \ \ -\phi\right) \cdot \mu_t. \tag{3.20}$$

With that notation in place, we can use equation (3.15) to derive the price change in response to a piece of news, our key result.

**Lemma 4.** *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*

$$p_t^i - p_{t-1}^i = \frac{\lambda(\xi_t)}{R-1} \cdot \left(Y_t^i - E\left[Y_t^i\right]\right), \tag{3.21}$$

*where*

$$\lambda(\xi_t) = \frac{\sigma_a^2 - \phi\sigma_{ab} - \left(\phi\sigma_b^2 - \sigma_{ab}\right)\xi_t}{\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2}. \tag{3.22}$$

$\lambda$ is a measure of how strongly prices react to the given surprise in earnings ($Y_t^i - E[Y_t^i]$). (Recall the notation $E\left[Y_t^i\right] = E\left[Y_t^i|\xi_t\right]$.) Its empirical analogue is the standard earnings response coefficient. Equation (3.22) predicts that $\lambda$ depends on the factor realization, or state of the economy, $\xi_t$.

Traditional theories do not recognize such a dependence, because they do not consider uncertainty about risk exposure of individual assets, $\sigma_b^2 > 0$. To appreciate the impact of this assumption, set $\sigma_b^2 = 0$, which also implies $\sigma_{ab} = 0$. In that case, the earnings response coefficient depends only on the ratio of variation in idiosyncratic cash flow strength, $\sigma_a^2$, to noise, $\sigma_\varepsilon^2$:

$$\lambda = \frac{\sigma_a^2}{\sigma_a^2 + \sigma_\varepsilon^2} = \frac{1}{1 + \frac{\sigma_\varepsilon^2}{\sigma_a^2}} \tag{3.23}$$

and the usual intuition for a signal-to-noise ratio obtains: the signal-to-noise ratio decreases with idiosyncratic noise. The key contribution of the present paper is to show that the signal-to-noise ratio also depends on the state of the economy, $\xi_t$, when risk loadings are uncertain, $\sigma_b^2 > 0$. We discuss similar special cases below to understand equation (3.22) better. In addition to the earnings response coefficient, $\lambda$, derived above, we also derive the variance of price changes in response to news,

$$\begin{aligned} Var_p(\xi_t) = Var\left[p_t^i - p_{t-1}^i\right] &= \frac{(\lambda(\xi_t))^2}{(R-1)^2} \cdot Var\left[Y_t^i\right] \\ &= \frac{1}{(R-1)^2} \cdot \frac{\left(\sigma_a^2 - \phi\sigma_{ab} - \left(\phi\sigma_b^2 - \sigma_{ab}\right)\xi_t\right)^2}{\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2}. \end{aligned} \tag{3.24}$$

The difference between $\lambda$ and $Var_p$ is as follows. $\lambda$ measures how strongly prices react to a concrete news event with information content $Y_t^i - E\left[Y_t^i\right]$. In contrast, the variance of prices $Var_p$ shows how strongly prices react to one additional cash flow observation given the macro state $\xi_t$, independent of how surprising the particular news is. $Var_p$ is more directly related to our main intuition that news received in downturns are more relevant for learning about the utility derived from holding the asset. In addition the propositions for $Var_p$ are simpler. Nevertheless, $\lambda$ represent the earnings response coefficients that are traditionally used in the literature to measure the sensitivity to news. We want to ascertain comparability of our results and results based on traditional measures. Therefore, we derive theoretical results and conduct the empirical tests for both measures.

### 3.5.3 The role of $\sigma_{ab}$

The formulas above show that the price reaction to news depends on beliefs formed in previous periods, which serve as the prior belief in the current period's inference. (Unless otherwise noted, we use "prior beliefs" to denote beliefs before period-$t$ information is observed.) In particular, the reaction to news depends on beliefs about the correlation between $a^i$ and $b^i$. This correlation changes over time as learning proceeds. For example, after an observation during an upturn ($a^i + b^i|\xi_t|$), the beliefs about $a^i$ and $b^i$ will tend to be more negatively correlated compared to the correlation between these beliefs before that observation. In contrast, after an observation in a downturn ($a^i - b^i|\xi_t|$), $a^i$ and $b^i$ will be believed to be more positively correlated than they were believed to be before the observation.

Laying out explicitly how our results depend on the history of systematic shocks leads to a more complicated analysis, which is presented later. First, to gain a simpler intuition, we begin by presenting results for the special case of $\sigma_{ab} = 0$: this case, despite its symmetric belief distribution, already generates an asymmetry in price responses across states of the economy.[9] After that, we address the general case $\sigma_{ab} \neq 0$ and show robustness of the intuition to this generalization.

### 3.5.4 Results for uncorrelated beliefs $\sigma_{ab}$

To highlight the dependence of the earnings response to the state variable, $\xi_t$, we first discuss the case in which the prior belief about the correlation of $a^i$ and $b^i$ is zero, $\sigma_{ab,t-1} = \sigma_{ab} = 0$. In this case, the expressions for price sensitivity, $\lambda$, and the variance of the price responses, $Var_p$, look much simpler than above, and the asymmetry in the price response to earnings news with respect to positive and negative realizations of $\xi_t$ is easier to see:

$$Var_p\left(\xi_t; \sigma_{ab} = 0\right) = \frac{1}{\left(R-1\right)^2} \cdot \frac{\left(\sigma_a^2 - \phi\sigma_b^2\xi_t\right)^2}{\sigma_a^2 + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2}, \tag{3.25}$$

$$\lambda\left(\xi_t; \sigma_{ab} = 0\right) = \frac{\sigma_a^2 - \phi\sigma_b^2\xi_t}{\sigma_a^2 + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2}. \tag{3.26}$$

Compared to the case of no uncertain risk loadings ($\sigma_b^2 = 0$) that we discussed above, 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 $\xi_t = 0$. We prove below that $\lambda$ and $Var_p$ tend to be lower for negative realizations of the market shock $\xi_t$ than for positive realizations of the same magnitude. Note also that the strength of the reaction is also not monotonous in $\xi_t$. For example, for large $\xi_t$, $Var_p$ and $\lambda$ are small because the variance of earnings surprises (the denominator) increases with $\xi_t^2$. Most importantly, the peaks of both $\lambda$ and $Var_p$ are bounded above by zero, i.e., the $\xi_t$'s that maximize $\lambda$ and $Var_p$ are always negative. The following proposition makes this claim formally.

**Proposition 1.** *The strongest stock price reaction to fundamental news occurs for negative realizations of the market factor.*

[9] The distribution of $\sigma_{ab}$ is "symmetric" in the following sense. If in the initial prior distribution, $a^i$ and $b^i$ are not correlated and the distribution of $\xi_t$ is symmetric, then positive and negative realizations of $\sigma_{ab}$ are equally likely to appear, and $\sigma_{ab} = 0$ in expectation in all periods.

*The variance of price changes is highest at*

$$\xi_{max}^{Var} = -\phi\left(1 + \frac{\sigma_\varepsilon^2}{\sigma_a^2}\right) < 0. \tag{3.27}$$

*Earnings response coefficients are highest at*

$$\xi_{max}^{\lambda} = -\phi\left(\frac{\sigma_a^2 + \sigma_\varepsilon^2}{\sigma_a^2 + \sqrt{\sigma_a^4 + \phi^2(\sigma_a^2 + \sigma_\varepsilon^2)\sigma_b^2}}\right) < 0. \tag{3.28}$$

We will test these propositions with non-parametric estimation techniques.

### 3.5.5 Results for general beliefs $\sigma_{ab} \neq 0$

In this subsection we describe the asymmetries for the general beliefs. When $\sigma_{ab} \neq 0$, there is an additional factor that affects how strongly stock prices react to news, which may make price reactions to news stronger in downturns or in upturns. The two cases are as follows. $\sigma_{ab} > 0$ corresponds to a case in which most observations in the decision maker's sample occurred in downturns. Investors then already know quite well how the asset behaves in downturns ($a^i - b^i|\xi_t|$), but know less about how the asset performs in upturns ($a^i + b^i|\xi_t|$). As a result, prices may respond more strongly to news received in market upturns. In contrast, $\sigma_{ab} < 0$ means that investors already know quite precisely the asset payoff in market upturns ($a^i + b^i|\xi_t|$), whereas there is great uncertainty about the payoff in a downturn ($a^i - b^i|\xi_t|$). In that case, the price response in the downturn will be stronger than in corresponding upturns – even more so than if $\sigma_{ab} = 0$.

We now show that prices are more likely to respond more strongly to news received in market downturns than in upturns. We start with the prediction about the peak of the market reaction to news that allows for $\sigma_{ab} \neq 0$.

**Proposition 2.** *The strongest stock price reaction to fundamental news occurs at*

$$\xi_{max}^{Var} = -\phi\left(1 + \frac{\sigma_\varepsilon^2\sigma_b^2}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2}\right) + \frac{\sigma_\varepsilon^2}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2}\sigma_{ab}, \tag{3.29}$$

*which is a negative number for the majority of prior beliefs $\sigma_{ab}$.*

We can see that there are two terms that affect the maximum. The first reflects the original intuition discussed previously. The second term reflects the effect of information that investors received prior to the current observation – for example, if investors have seen many downturns, they do not learn much from additional ones, as described above. We explain the notion of "majority of prior beliefs" in several ways below. In the next proposition we directly compare downturns and upturns of the same size and we show that, for a majority of prior beliefs about the correlation between $a$ and $b$, $\sigma_{ab}$, the response to downturn news is stronger than in upturns.

**Proposition 3.** *For any positive $\sigma_a^2$ and $\sigma_b^2$, and any positive number $x$ there exists $0 < \bar{\sigma}_{ab}^p < \sigma_a \sigma_b$ such that*

$Var_p(\xi_t = -x) > Var_p(\xi_t = +x)$ *for* $-\sigma_a \sigma_b \leq \sigma_{ab} < \bar{\sigma}_{ab}^p$

$Var_p(\xi_t = -x) < Var_p(\xi_t = +x)$ *for* $\bar{\sigma}_{ab}^p < \sigma_{ab} \leq \sigma_a \sigma_b$.

Figure 3 illustrates the proposition. Unless the correlation between $a^i$ and $b^i$ is higher than some cutoff $\bar{\sigma}_{ab}^p$ (which means that investors already know a lot about how the asset's cash flows behave in downturns), prices react more strongly to news that pertain to performance in market downturns. This is true for the "majority of prior beliefs" because the cutoff is guaranteed to be a positive number, $\bar{\sigma}_{ab}^p > 0$, and the distribution of beliefs $\sigma_{ab}$ is symmetric and centered at zero. Figure 4 shows how the variance of price changes depends on the correlation between beliefs about parameters. It shows that only for extreme positive correlations, $\sigma_{ab} >> 0$, prices respond stronger to news in the upturns. For negative correlations, the response in downturns is stronger. Also, the response is stronger in downturns for the zero-correlation case, $\sigma_{ab} = 0$. The key message is that the graphs are not symmetric with respect to zero, and on average (across beliefs resulting from previous periods' learning $\sigma_{ab}$), the responses in downturns are higher.

We can derive a proposition similar to proposition 3 showing asymmetries in the earnings response coefficients, $\lambda$, 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 4.** *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 $0 < \bar{\sigma}^p_{ab} < \sigma_a \sigma_b$ such that

$$\begin{aligned} \lambda(\xi_t = -x) > \lambda(\xi_t = +x) \ \text{ for } -\sigma_a\sigma_b < \sigma_{ab} < \bar{\sigma}^p_{ab} \\ \lambda(\xi_t = -x) < \lambda(\xi_t = +x) \ \text{ for } \bar{\sigma}^p_{ab} < \sigma_{ab} \leq \sigma_a\sigma_b. \end{aligned}$$

3. There exists $-\sigma_a\sigma_b < \bar{\sigma}^p_{ab} < 0$ such that

$$\begin{aligned} \lambda(\xi_t = -x) > \lambda(\xi_t = +x) \ \text{ for } \bar{\sigma}^p_{ab} < \sigma_{ab} \leq \sigma_a\sigma_b \\ \lambda(\xi_t = -x) < \lambda(\xi_t = +x) \ \text{ for } -\sigma_a\sigma_b < \sigma_{ab} < \bar{\sigma}^p_{ab}. \end{aligned}$$

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

#### 3.5.6 Results Conditional on Variance of Earnings Surprises

In the above results, we assumed that the variance of idiosyncratic noise, $\sigma^2_\varepsilon$, 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.[10] To alleviate that concern, we now derive an additional proposition. It makes a prediction about how earnings response coefficients depend on the state of the economy if we control for the effect that ex ante uncertainty about earnings news, $var[Y^i_t]$, has on earnings response coefficients. ERCs as a function of the variance of earnings surprises can be written as

$$\lambda\left(\xi_t, var\left[Y^i_t\right]\right) = \frac{\sigma^2_a - \phi\sigma_{ab} - \left(\phi\sigma^2_b - \sigma_{ab}\right)\xi_t}{var\left[Y^i_t\right]}. \tag{3.30}$$

**Proposition 5.** *If we consider $\lambda$ as function of $var[Y^i_t]$ and $\xi_t$, then there exists a positive cutoff $\bar{\sigma}^\lambda_{ab} = \phi\sigma^2_b > 0$ such that*

1. *$\lambda$ is decreasing in $\xi_t$ if $\sigma_{ab} < \bar{\sigma}^\lambda_{ab}$, and*

2. *$\lambda$ is increasing in $\xi_t$ if $\sigma_{ab} > \bar{\sigma}^\lambda_{ab}$.*

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

[10]Notice that increased volatility in downturns would in fact predict a lower earnings response coefficient in downturns than in upturns, a prediction opposite to the one made in the present paper.

### 3.5.7 Results about Average Prices Responses

So far we have documented the asymmetry in the reaction to news only for specific beliefs. However, we do not directly observe beliefs in the data, and the empirical tests measure asymmetries between upturns and downturns that arise on average. Therefore, we now make formal claims about the average reaction to news by deriving propositions for "average beliefs" resulting from learning in previous periods. The challenge is that the prior beliefs, $\sigma_{ab}$, depend on previous periods' realizations of the market shock, $\xi_t$. We therefore derive propositions that hold for an average across possible histories of market shocks.

**Lemma 5.** *Suppose $a^i$ and $b^i$ are uncorrelated in the prior distribution ($\bar{\sigma}_{ab} = 0$) and the distribution of $\xi_t$ is symmetric. Then in any period $t$, the distribution of beliefs $\sigma^2_{a,t}$, $\sigma^2_{b,t}$, and $\sigma_{ab,t}$ is symmetric with respect to $\sigma_{ab,t}$.*

Now we derive how the variance of price changes depends on the state of the economy for an average history of market shocks (i.e., an average prior belief $\sigma_{ab}$). Consider a period $t$. We calculate the average price response to news in this period over all possible realizations of beliefs that could arise from market shocks previous to $t$,

$$\overline{Var}_p\left(\xi_t\right) = E_{(\xi_1,\ldots,\xi_{t-1})}\left[Var_p\left(\xi_t\right)\right] \tag{3.31}$$

The above expectation is over all possible realizations of past shocks, $\xi_1, \xi_2, \ldots \xi_{t-1}$. These shocks affect beliefs in the period $t-1$, and therefore our quantity of interest, $Var_p(\xi_t)$.

**Proposition 6.** *Suppose $a^i$ and $b^i$ are uncorrelated in the prior distribution ($\bar{\sigma}_{ab} = 0$) and the distribution of $\xi_t$ is symmetric. Then for any positive number $x$*

$$\overline{Var}_p\left(\xi_t = +x\right) < \overline{Var}_p\left(\xi_t = -x\right). \tag{3.32}$$

This is the formal statement of the claim that, *on average*, prices react more strongly to news in downturns than in upturns.

### 3.5.8 Dispersion and Skewness

A direct consequence of the above predictions is that returns are more dispersed in downturns than in upturns. A consequence is that returns are negatively skewed, although distributions of parameters and shocks are assumed to be symmetric and shocks are *iid*.[11] Since prices do not change as much in upturns as in downturns, the unconditional distribution of returns is negatively skewed. To show this formally, consider the return between periods $t-1$ and $t$

$$R_t^i = \frac{p_t^i + Y_t^i - p_{t-1}^i}{p_{t-1}^i}. \tag{3.33}$$

Skewness is defined as

$$E_3 = E_{t-1}\left[\left(R_t^i - E_{t-1}\left[R_t^i\right]\right)^3\right]. \tag{3.34}$$

As the following proposition shows, for the majority of prior beliefs, returns are negatively skewed.

**Proposition 7.** *For any beliefs $\sigma_a^2$ and $\sigma_b^2$ there exists $\bar{\sigma}_{ab}^s > 0$ such that $E_3 < 0$ for any $\sigma_{ab} < \bar{\sigma}_{ab}^s$.*

This proposition shows that the only ingredients needed to generate negatively skewed returns are positive risk premia (which in our model are endogenously generated by risk aversion) and uncertainty about risk loadings. A symmetric return distribution can only arise in the special (and unlikely) case that firms' cash flow risk loadings are perfectly known.

## 3.6 Model Limitations and Extensions

This section discusses several modeling choices, the rationale behind them, and how alternative choices would change the model predictions. To start, the model uses an overlapping generations structure. This modeling choice is only for simplicity and tractability. The mechanism still works for a general representative agent that maximizes expected utility in an infinite-horizon setup,

$$U_t = \sum_{k=0}^{\infty} \beta^t u\left(C_{t+k}\right), \tag{3.35}$$

where $C_t$ is aggregate consumption in period $t$. The following lemma gives the valuation formula for this case.

**Lemma 6.** *The price of an asset in an economy with representative agent (3.35) is*

$$p_i^t = \frac{1}{R-1} E_t\left[a^i - \phi\left(\xi\right) b^i\right] \tag{3.36}$$

[11] We thank Valerio Poti for suggesting that we investigate this direction.

*where*

$$\phi\left(\xi\right)=\frac{R-1}{R}\sum_{k=1}^{\infty}\beta^{k}\frac{E_{t}\left[u'(C_{t+k})\xi_{t+k}\right]}{u'\left(C_{t}\right)}>0. \tag{3.37}$$

The only difference compared to the OLG setup is that $\phi$ is not constant here, but depends on the realization of the observed aggregate shocks, $\xi_1, \xi_2 \ldots, \xi_t$. Nevertheless, because of risk aversion, $\phi\left(\xi\right)$ is always positive. The price change in response to news retains the structure

$$p_i^t - E_{t-1,\xi_t}\left[p_i^t\right] = \frac{\lambda\left(\xi_t\right)}{R-1}\cdot\left(Y_t^i - E\left[Y_t^i\right]\right).$$

The structure of the expression for the ERC under symmetric beliefs is also retained,

$$\lambda\left(\xi_t;\sigma_{ab}=0\right)=\frac{\sigma_a^2-\phi\left(\xi_1,\ldots,\xi_t\right)\sigma_b^2\xi_t}{\sigma_a^2+\sigma_b^2\xi_t^2+\sigma_\varepsilon^2}.$$

Since $\phi(\xi_1, \ldots, \xi_t)$ is always positive, prices respond stronger to news in downturns than in upturns.

Relatedly, we focus only on cross sectional learning; the model does not feature learning about the stochastic discount factor. This is a key distinction from a substantial part of the learning literature that focuses on precisely that problem, see Pastor and Veronesi (2009). News about one stock carrying information about another (see Savor and Wilson (2011) and also Patton and Verardo (2012)) are well-known examples; see also Collin-Dufresne, Johannes, and Lochstoer (2012). The reason we shut off this channel is twofold. First, we are able to more simply solve for the earnings response $\lambda$ in closed form this way. Second, learning about the stochastic discount factor is largely orthogonal to cross-sectional learning and does not essentially change our results. In our setup, the parameters $\bar{a}$ and $\bar{b}$ represent beliefs of consumers about the overall economy. If we endogenized aggregate learning, the beliefs about these means would depend on the realizations of past shocks. For example, investors would update beliefs about $\bar{a}$ upwards after a positive shock. The only way aggregate parameters like $\bar{a}$ and $\bar{b}$ can affect the sensitivity of individual stocks' earnings response is through the risk premium, $\phi$. Similar to the infinite-horizon economy above, it is easy to show that $\phi$ always remains positive for a risk-averse agent. Therefore, the asymmetry between price responses in downturns and upturns persists. Because the intuition remains the same, we present the simpler model without learning about the stochastic discount factor.

As is common in learning models, we can solve the model explicitly only for the special case in which parameters are normally distributed. It should be clear from the intuitive explanations at the beginning of the model section, however, that normality is not driving the qualitative results. Next, our parameters $a^i$ and $b^i$ are fixed and do not change over time. As a result, infinitely-lived investors would eventually learn the true values. In the real world, however, the parameters change over time in response to changes of corporate leadership, the competitive landscape, and innovations. As a result, investors never perfectly learn the true values. To extend our base case to a simple dynamic setting that reflects this consideration, assume that each period a share $\delta$ of firms dies and is replaced by new firms for which the unknown parameters are drawn from the initial prior distribution. In such a setup the above propositions continue to hold, they only need to be applied separately to each generation of firms.

# 4 Empirical Results

This section describes the empirical methodology, variable definitions, data sources, and empirical results. We test the two key predictions of the theoretical model: 1. Earnings response coefficients (ERCs) peak in downturns, and 2. ERCs are higher in downturns than in upturns, on average. While prediction 2 is key for the "revealing downturns" intuition, prediction 1 of a non-monotonic relationship between ERCs and market state is a more specific prediction of our particular model. We also test the prediction that controlling for ex ante uncertainty of the earnings news event does not qualitatively change the results. We omit providing evidence for the prediction that stock returns are negatively skewed, which is a well-known fact.

## 4.1 Empirical Methodology, Variable Definitions, and Data Sources

### 4.1.1 Empirical Methodology

Our goal is to measure how strongly stock prices react to a given news about unexpected earnings, or "earnings surprise," and how the strength of this reaction depends on the state of the economy. Earnings response coefficients (ERCs, see Ertimur, Livnat, and Martikainen (2003); Jegadeesh and Livnat (2006)) are the standard solution to measure the strength of the reaction to a given piece of news while filtering out noise, and have been used to similar ends in the recent finance literature, see for example Pástor, Taylor, and Veronesi (2009). The basic idea of an ERC is illustrated by the following regression,

$$CAR_{i,t} = \alpha + \lambda ES_{i,t} + \varepsilon_{i,t}. \tag{4.1}$$

In this regression, $CAR_{i,t}$ is the cumulative announcement return of stock $i$ around an announcement at time $t$, $ES_{i,t}$ is the earnings surprise (defined below), and $\lambda$ is the ERC.[12] Note that equation (4.1) is the exact empirical analogue of equation (3.21) in the theory. The theoretical predictions derived in propositions 1 / 2 and propositions 3 / 4 therefore translate into the following two statistical hypotheses.

1. The highest ERCs occur in downturns.

2. On average, ERCs are higher in downturns than in upturns on average.

The null hypothesis in each case is that ERCs do not depend on the state of the economy. To investigate these predictions, we run two sets of tests, one non-parametric and one with OLS. The reason for running non-parametric tests is that we need non-linear methods to test hypothesis 1, which is a non-monotonic prediction. Non-linear tests also provide the most direct link between the model, which makes non-linear predictions, and the empirical analysis. The reason to test hypothesis 2 with OLS is twofold. First, the main effect and thus the intuition emphasized in the paper is between upturns and downturns, a monotonic comparison. Second, the existing empirical literature on the stock market reaction to earnings news uses OLS. Doing likewise makes our results more comparable to that literature. Comparing estimates from our non-parametric estimation and the OLS tests also serves as a consistency check between the two sets of results.

The non-parametric tests estimate a version of equation (4.1) that allows ERCs to vary with the state of the economy $\xi_t$,

$$CAR_{i,t} = \lambda\left(\xi_t\right) ES_{i,t} + \varepsilon_{i,t}. \tag{4.2}$$

We use local polynomial regressions of order zero with an Epanechnikov kernel of optimal bandwidth. What this method does is to calculate the best fit of $\lambda(\xi)$ without assuming a specific functional form.[13] The null hypothesis here is that the ERC, $\lambda\left(\xi_t\right)$, is

[12] In contrast to Pástor, Taylor, and Veronesi (2009) (PTV), we always estimate ERCs in a regression. We never calculate ERCs by dividing returns by earnings surprises. The reason is that a majority of earnings surprises is very close to zero, leading to a large number of outliers in terms of ERCs. PTV deal with this by winsorizing at 5% levels. Our method does not require us to winsorize the ERCs and thus allows to use more variation in the data.

[13] Similar methods have been used in the finance literature at least since Stanton (1997). To perform the estimation, instead of manually calculating smooth coefficient models (Hastie and Tibshirani, 1993;

positive, but flat and does not depend on the state of the economy, $\lambda(\xi_t) = \lambda = const.$, whereas the model predicts a positive ERC with a non-monotonic shape with a peak for negative shocks, $\xi_t < 0$.

We use OLS to test the second key prediction, which is that ERCs on average are larger in downturns with OLS. Specifically, we estimate the following regression across all firm-quarter observations

$$CAR_{i,t} = \alpha + \beta_1 ES_{i,t} \times DT_{i,t} + \beta_2 ES_{i,t} + \beta_3 DT_{i,t} + \varepsilon_{i,t}, \tag{4.4}$$

where $DT_{i,t}$ is a downturn dummy that takes unity if the reference period corresponding to a given observation (defined below) is a downturn according to several definitions given below, and zero otherwise. $\beta_2$ of the above regression equation is the ERC in upturns; $\beta_1 + \beta_2$ is the ERC in downturns. The null hypothesis is that there is no difference in ERCs between upturns and downturns, whereas our model predicts the difference, i.e., $\beta_1$, to be positive, in addition to a positive $\beta_2$. To account for time-changing volatility, including the empirically relevant case that volatility is higher in downturn periods, we cluster the standard errors by the month of the announcement.

We furthermore provide specifications that add two additional controls to regression (4.4): the variance of earnings surprises, $Var(ES)$, and the variance of earnings surprises interacted with the earnings surprise, $Var(ES) \times ES$. The latter inclusion allows ERCs to vary with $Var(ES)$. These specifications mitigate the concern that the variation in ERCs across states of the economy is driven by variation in earnings quality over these states.

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Li and Racine, 2007), we use the following trick. We divide equation (4.2) by $ES_{i,t}$

$$\frac{CAR_{i,t}}{ES_{i,t}} = \lambda(\xi_t) + \frac{\varepsilon_{i,t}}{ES_{i,t}} \tag{4.3}$$

and then use Stata's standard polynomial smoothing command with corresponding weights for the standard errors. Specifically, for each $\xi$ this command calculates a weighted average value of the ratios $\frac{CAR_{i,t}}{ES_{i,t}}$, where the weights decrease with the distance between $\xi$ and $\xi_t$ (the realization of the aggregate shock corresponding to the observation). Different non-parametric techniques use different weighting functions with $|\xi_t - \xi_i|$ as their argument. With an Epanechnikov kernel, weights are assigned quadratically, proportional to an inverse-U shape. They are most frequently used because of their efficiency properties. The bandwidths we choose, 0.1 and 1.5 for the "market" and "GDP" specifications, respectively, correspond to the average of the respective optimal bandwidths across the traditional and modified ERC measures defined below.

### 4.1.2 Variable Definitions

We calculate cumulative announcement returns, $CAR_{i,t}$, over a three-day window using CRSP daily returns from the close on the day before the announcement to the close on the day after the announcement.[14] We use two ways to define earnings surprises. The first one is the standard earnings surprise used in the existing literature. There, the earnings surprise, $ES_{i,t}$, of firm $i$ at time $t$ is defined as

$$ES_{i,t} = \frac{EPS_{i,t} - E\left[EPS_{i,t}\right]}{BVPS_{i,t}}, \tag{4.5}$$

where $EPS_{i,t}$ is stock $i$'s actual earnings per share reported at an announcement at time $t$; $E\left[EPS_{i,t}\right]$ 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. The estimates from the first measure correspond to $\lambda$ in our theoretical propositions.

The second definition of earnings surprises is

$$ES_{i,t} = \frac{EPS_{i,t} - E\left[EPS_{i,t}\right]}{st.dev.\left[EPS_{i,t}\right]}, \tag{4.6}$$

where $st.dev.\left[EPS_{i,t}\right]$ is the standard deviation of expected earnings per share averaged across all analysts from the last pre-announcement set of forecasts for the given fiscal quarter as reported by IBES (not the standard deviation of actual earnings per share) and is meant to proxy for the ex ante uncertainty of an announcement. The other definitions are identical to the above. We report results using this second measure because of two main reasons. First is a closer link to the main theoretical results. ERCs estimated using the second definition of earnings surprises represent the square root of the variance of price changes $Var_p$.[15] Second, we are concerned that accounting

[14] There is some disagreement in the literature about which dependent variable to use. While significant results are often more easily obtained with abnormal returns than with raw returns, the reduction in noise comes at the expense of assuming a pricing model and a loss of transparency. To avoid such additional assumptions and loss of transparency, we use raw cumulative announcement returns.

[15] We can rewrite the equations (3.21) and (3.22) as

$$p_t^i - p_{t-1}^i = \frac{\tilde{\lambda}\left(\xi_t\right)}{R-1} \cdot \frac{\left(Y_t^i - E\left[Y_t^i\right]\right)}{\sqrt{Var\left[Y_t^i\right]}} \tag{4.7}$$

practices may vary over the business cycle, or that book equity changes mechanically over the business cycle for other reasons. This could lead to mechanical changes in earnings response coefficients over the business cycle. The specifications that use our alternative definition of the earnings response avoid this potential pitfall.

We use the variance of earnings surprises in the month of the announcement as a control in some regressions. It is defined as the average of the squared earnings surprises for all announcements (by all firms) in a given month.

The reference period pertaining to an earnings announcement at date $t$ is the period during which the firm earns the earnings it reports at time $t$. The announcement date is typically a few weeks after the end of the reference period, and is available from IBES. We measure the state of the economy, $\xi_t$, for the nonlinear tests and assign downturn dummies for the linear tests according to the state of the economy in the reference period, not the state during the announcement date. Figure 5 illustrates the timing of reference period and earnings announcement.

For the non-linear tests, we measure the state of the economy, $\xi_t$, with GDP growth from the Bureau of Economic Analysis (BEA) in one specification and with market returns from CRSP in a second specification. Downturn dummies for the OLS regressions are constructed in three alternative ways to ensure robustness of the results. They are based on NBER recessions, market return, and GDP growth, respectively. We say that an earnings announcement falls in an NBER downturn if the middle point of the reference period falls into an NBER recession, or, equivalently, if two out of three months of the reference quarter fall into an NBER recession. We say that an earnings announcement falls in a market-return downturn if the cumulative value-weighted market return net of the risk-free rate over the three months of the reference period is lower than its sample average. Lastly, we say an earnings announcement falls in a GDP downturn if the 2009-chained quarterly real seasonally adjusted GDP growth rate (again from BEA) in the quarter with the largest intersection with the reference period is lower than the average real GDP growth rate in the period 1984-2012. Upturns are all periods that are not defined as downturns.

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where

$$\tilde{\lambda}(\xi_t) = \lambda(\xi_t) \cdot \sqrt{Var\left[Y_t^i\right]} = \frac{\sigma_a^2 - \phi\sigma_{ab} - \left(\phi\sigma_b^2 - \sigma_{ab}\right)\xi_t}{\left(\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2\right)^{\frac{1}{2}}} = \sqrt{Var_p}. \tag{4.8}$$

### 4.1.3 Data Sources and Restrictions

We use data from IBES, CRSP, and the CRSP/Compustat merged files. We start with all earnings announcements available from IBES, which cover January 1984 to December 2012. We drop an observation if less than three analysts cover a stock. For the first definition of earnings surprises that normalizes by book equity, we also drop an observation if the latest reported value for book equity occurred more than one year before the announcement date or if the book equity is negative. We truncate the observations at 1% levels. After these filters, we are left with 147,871 observations from 4,876 firms for traditional ERCs. For the earnings surprises normalized by the standard deviation of analyst forecasts, we drop observations where the standard deviation is missing or reported as zero, and then also truncate the observations at 1% levels. We end up with 195,924 observations in that case. The difference in the number of observations obtains because book equity is missing for more firms than the standard deviation of analyst forecasts.

### 4.1.4 Summary Statistics

Table 1 presents summary statistics for cumulative announcement returns ($CAR$) and earnings surprises ($ES$) as traditionally calculated. Table 2 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. While 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 cumulative announcement returns are slightly positive on average. ("Unconditional" here refers to the sign of the earnings surprise.) This 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 earnings surprises 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 that earnings surprises 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 on the earnings response to good and bad news at the end of the empirical results section.)

Table 2 Panel A shows a similar picture for the sample for the alternative measure of earnings surprises. The point estimate of the average $CAR$ is positive unconditionally, and also in the different market states. The mean earnings surprises are not significantly different from zero either, but the point estimates are positive across subsamples. Moreover, the percentiles show an accumulation of the same value of earnings surprises at particular values. The reason is the discreteness of the variable standard deviation of analyst forecasts, as reported by IBES: both means and standard deviations of the analyst forecasts are rounded to nearest hundredth. To illustrate the effect of this feature of the data, we present histogramms of the sample in Figure 6. The two plots in the first row give the distribution of $CAR$ and $ES$ as traditionally calculated, corresponding to Table 1. The distributions are roughly symmetric. Consistent with the tabulated summary statistics, there is a slight mass at zero returns and earnings surprises, which is consistent with the existing literature. The second row presents the same histrogramms according the the alternative definition in which the earnings surprise is normalized by the standard deviation of analyst forecasts, corresponding to Table 2. The $CAR$ distribution looks similar to the $CAR$ distribution in the first row, indicating that the change in sample does not change the distribution of earnings announcement returns considerably. The earnings surprises distribution to the right, however, clearly shows the mechanical pattern caused by the discreteness of the IBES standard deviation variable.[16] This pattern does not seem to change the overall shape of the distribution, however. Its main effect seems to be the introduction of noise. Because the alternative measure of earnings surprises has other desirable properties discussed previously, we decide to report corresponding results despite the "discretization noise" in the data. Moreover, for transparency, we report results based on the full sample first, instead of discarding parts of the sample that are subject to discretization noise from the start. To ascertain that the mechanical noise does not drive our results, we then filter out observations with standard deviations smaller than 0.05 to obtain a sample with a smoother distribution. Its characteristics are reported in Table 2 Panel B, and its distributions of $CA$R and $ES$ are given in the third row of Figure 6. The $CAR$ retains its distributional properties, while the $ES$ in the restricted sample shows much less discretization noise.

[16]The effect is particularly driven by observations with values of 0.01 for the standard deviation.

The empirical results below are consistent across the full and the restricted sample, whereas slightly more significant results obtain with the restricted sample. This difference is consistent with less attenuation bias due to measurement noise in the estimates based on the restricted sample.

## 4.2 Empirical Results

### 4.2.1 Non-parametric Estimation Results

Figure 7 and Figure 8 give non-parametric estimates of ERC as a function of the economic state, whereas the market return and GDP growth is used as proxies for the state of the economy, respectively. (They are the empirical analogue to the simulations presented in Figure 4.) 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 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 of 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, while 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.

Figure 9 and Figure 10 give non-parametric estimates of the modified ERC that normalizes by the standard deviation as a function of the economic state, whereas the market return and GDP growth is used as proxies for the state of the economy, respectively. (They are the empirical analogue to the simulations presented in Figure 4.) The ERCs are significantly positive throughout their domain, with point estimates between 0.07 and 0.09 for the market return specification and between 0.07 and 0.12 for the GDP specification. More specifically, the figures show, consistent with the model predictions, that the relationship between ERCs and 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 -5% GDP growth. The change of magnitude of ERCs across economic states is significant, both statistically and economically. The point estimate of the ERC at -25% market return is about 0.09 with a 95% confidence band smaller than 0.005 in either direction, while the point estimate of ERCs at +20% market return is just over 0.073, with confidence bands smaller than 0.003 in either direction. Similarly, ERCs at -5% GDP growth are 0.012 and 0.07 at 5% GDP growth. Thus, ERCs according to our new definition are about 30% to 80% higher at their peak in downturns than at their low in upturns. These results not only provide strong support for the model predictions, they also distinguish the model from other potential explanations why ERCs could be higher in downturns than in upturns on average (proposition 1): The non-monotonic shape predicted by Lemma 4 is a unique prediction of our model. In sum, both Hypothesis 1 and 2 find support: 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.

#### 4.2.2 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 7 and 8 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 3 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, i.e. 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 earnings surprise, $ES$, the downturn dummy, $DT$, and their interaction as explanatory variables. The second specification also includes the variance of earnings surprises and its interaction with the earnings surprise. This specification tests proposition 5, according to which the interaction of earnings surprise ($ES$) and downturn dummy ($DT$) should persist even after controlling for the standard deviation of earnings surprises. The last specification also allows for a linear time trend, as well as the interaction of earnings surprise with the time trend. Controlling for a time trend in earnings response coefficients makes sure 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 earnings response coefficients. (Similar results obtain when only the interaction of time and earnings surprise is taken into account.)

The second row of the first specification reports a highly significant and positive coefficient of 0.943 on the explanatory variable $ES$, the earnings surprise. This is the earnings response coefficient in the baseline, i.e., in upturns, when the downturn dummy $DT$ takes the value zero. It is comparable in magnitude to those reported in the literature. The coefficient reported in the first row, 0.356, indicates that the earnings response coefficient in downturns increases to 1.299 in downturns. The significance of the coefficient reported in the first row indicates that the 38% increase in the earnings response coefficients in downturns relative to upturns is statistically significant at the 1 percent level. Notice also that the magnitude of this increase is consistent with the one that can be read out of Figures 7 and 8, i.e., the non-parametric estimation approach. The second NBER-specification that controls for the standard deviation of the earnings surprise yields an ERC in upturns of 1.247. It increases by 0.484 in downturns. Again, the difference is highly statistically significant. Column (3) reports the results that also control for a time trend in earnings response coefficients as well as for a time trend in unconditional announcement returns. The upturn-ERC is 0.789. It increases by 0.342 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 0.652 to 1.140, and statistically significant increases of the ERC in downturns, ranging from 0.128 to 0.151. The specifications using the GDP definition of downturns in columns (7) to (9) show a similar pattern. Upturn-ERCs range from 0.725 to 1.133, and they increase by 0.123 to 0.222 during downturns. The downturn-upturn difference is highly statistically significant also here; albeit in the last specification only at the 5% level. 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 while the function of ERC as a function of 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 comprise also less strong contractions will attenuate the measurement of differences between peak and trough of the ERC function.

In sum, depending on the definition of downturns, earnings response coefficients range from 0.652 to 1.247, 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 earnings response coefficients. To get 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%.

Table 4 presents the results for the alternative earnings response coefficient that utilizes the definition of the earnings surprise that normalizes by the standard deviation of analyst forecasts rather than by book equity. The structure of the table is identical to that of Table 3. The coefficients are on a different scale because of the alternative normalization of the earnings surprise. However, the relative increase of the ERCs in downturns compared to upturns has the same interpretation. The second row's estimates indicate that the ERCs range from 0.352% to 0.744% in upturns. The estimates in the first row indicate that they are 0.067 percentage points to 0.24 percentage points higher in downturns. The relative increases comparing downturn-ERCs to upturn-ERCs range from 14% (column 4) to 44% (column 2). The difference in coefficients is again caused by the more generous definition of a "downturn" in specifications (4) through (9); the strongest downturn-upturn differences occur in specifications (1) through (3) also in this table.

Table 4 introduced a new measure of earnings responses that normalizes earnings surprises 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 4 had a different sign depending on the specification. Table 5 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, as previously described. 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 significantly positive estimates range between 0.00310 and 0.0103. The downturn-upturn difference is slightly larger, though of a similar magnitude as estimated with the full sample. It ranges from 0.0008 to 0.00295. The relative difference ranges from 20% (column 9) to 65% (column 6). 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 key result, the difference in ERCs between upturns and downturns, is less likely to be driven by the quality of the standard deviation of analyst forecasts variable reported by IBES. To the contrary, 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.

### 4.3 Empirical Distinction from the Overreaction-to-bad-news Effect

As previously discussed, some authors have argued that stronger reactions to news in downturns may be explained by a higher incidence of bad news in downturns, combined with a stronger reaction to bad news than good news. 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), there are no more bad news in downturns in the sense of negative unexpected earnings in our data, which makes it impossible that our results are driven by that effect. 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 $CAR_{i,t} = \lambda\left(ES_{i,t}\right) \cdot ES_{i,t} + \varepsilon_{i,t}$ 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 11. 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. This is true separately in upturns and downturns. We omit reporting these OLS results, as they are not the focus of the paper.

# 5 Conclusion

This paper provides a new and simple rationale for empirically observed asymmetries in investors' reaction to news over the business cycle and for negative skewness of stock returns. Specifically, a Bayesian learning model predicts that risk-averse investors react more strongly to news in downturns than in upturns when they are uncertain about individual assets' risk loadings and risk premia are positive. The theoretical predictions are supported by two sets of empirical results, one non-parametric and one estimated with linear econometric techniques. Both strongly support the theoretical predictions: stocks react up to 60% more strongly to earnings news when the respective news pertains to firm performance in downturns than when the news pertains to performance in upturns.

While the present paper focuses on an asset pricing application, the principle that Bayesian agents react more strongly to news in downturns than in upturns is more general. Adaptions of the model also correctly predicts the dynamics of capital allocation to mutual funds over the business cycle (Franzoni and Schmalz, 2013), it explains why forced CEO turnover is higher in downturns than in upturns (Schmalz, 2012; Zhuk, 2012), and applies to all other situations in which risk loadings of projects are less than perfectly known.

# Appendix

## Correlation and Dispersion Are Not Equivalent

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 $a$ and variance-covariance matrix $\Sigma$. The individual returns $r_i$ are distributed normally with mean $a_i$ and variance $\sigma^2$. The covariance between two stock returns $r_i$ and $r_j$ is $Cov(r_i, r_j) = \rho\sigma^2$, where $\rho$ is the correlation coefficient. The cross-sectional variance, or dispersion, is then $Disp = (1-\rho)\sigma^2$. 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.

## Proof of Lemma 1. (Stochastic Discount Factor for OLG models)

Assume an agent consuming $C_{t+1}$ at $t+1$ is buying $x$ units of an asset that pays $Z_{t+1}$ at $t+1$ and cost $p_z$ at $t$. Then, the expected utility of the agent

$$U(x) = E_t\left[u\left(C_{t+1} + x\left(Z_{t+1} - Rp_z\right)\right)\right].$$

It should be maximized when $x = 0$,

$$0 = U'(x)|_{x=0} = E_t\left[u'\left(C_{t+1}\right)\left(Z_{t+1} - Rp_z\right)\right]$$

$$0 = E_t\left[u'\left(C_{t+1}\right)Z_{t+1}\right] - E_t\left[u'\left(C_{t+1}\right)\right]Rp_z$$
$$p_z = \frac{1}{R}\cdot\frac{E_t\left[u'\left(C_{t+1}\right)Z_{t+1}\right]}{E_t\left[u'\left(C_{t+1}\right)\right]}.$$

Therefore,

$$p_z = \frac{1}{R}E_t\left[\frac{u'\left(C_{t+1}\right)}{E_t\left[u'\left(C_{t+1}\right)\right]}Z_{t+1}\right]$$

and the $SDF$ is equal to

$$m_{t+1} = \frac{1}{R}\frac{u'\left(C_{t+1}\right)}{E_t\left[u'\left(C_{t+1}\right)\right]}.$$

Suppose $W_0$ is the initial wealth of the young generation in OLG model, and $p$ is the the price of the whole economy (it is a constant, since there is no learning about the aggregate state), then the agents' consumption at $t+1$ is

$$C_{t+1} = (W_0 - p) \cdot R + Y_{t+1} + p = C + Y_{t+1}$$

where $C = W \cdot R - p \cdot (R-1)$. As a result the $SDF$ is equal to

$$m_{t+1} = \frac{1}{R} \frac{u'(C + Y_{t+1})}{E_t[u'(C + Y_{t+1})]}.$$

## Proof of Lemma 3. (Valuation for CARA utility)

For normally distributed $Y$,

$$E\left[e^{\gamma Y}\right] = e^{\gamma E[Y] + \frac{\gamma^2}{2} V[Y]},$$

$$E\left[Y \cdot e^{\gamma Y}\right] = (E[Y] + \gamma V[Y]) \cdot e^{\gamma E[Y] + \frac{\gamma^2}{2} V[Y]} = (E[Y] + \gamma V[Y]) \cdot E\left[e^{\gamma Y}\right].$$

Therefore, for the exponential utility $(u'(Y_{t+1}) = \gamma e^{-\gamma Y_{t+1}})$

$$\phi = -E_t[m_{t+1}\xi_{t+1}] = -\frac{1}{E_t\left[e^{-\gamma Y_{t+1}}\right]} E_t\left[e^{-\gamma Y_{t+1}} \xi_{t+1}\right].$$

Given that aggregate consumption is $Y_{t+1} = N\left(\bar{a} + \bar{b} \cdot \xi_{t+1}\right)$

$$E_t\left[e^{-\gamma Y_{t+1}} \xi_{t+1}\right] = E_t\left[e^{-\gamma N\left(\bar{a} + \bar{b} \cdot \xi_{t+1}\right)} \xi_{t+1}\right] = -\gamma N \bar{b} \sigma_\xi^2 \cdot E_t\left[e^{-\gamma Y_{t+1}}\right].$$

Thus, $\phi = \gamma N \bar{b} \cdot \sigma_\xi^2$.

## Proof of Lemma 4.

In the defined notation,

$$var\left[Y_t^i\right] = \sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2 \xi_t^2 + \sigma_\varepsilon^2$$

$$cov\left[\begin{pmatrix} a^i \\ b^i \end{pmatrix}, Y_t^i\right] = \begin{pmatrix} \sigma_a^2 + \sigma_{ab}\xi_t \\ \sigma_{ab} + \sigma_b^2 \xi_t \end{pmatrix}$$

$$\mu_t = \mu_{t-1} + \frac{Y_t^i - E[Y_t^i]}{var[Y_t^i]} \begin{pmatrix} \sigma_a^2 + \sigma_{ab}\xi_t \\ \sigma_{ab} + \sigma_b^2 \xi_t \end{pmatrix}.$$

Therefore,

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

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

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

## Proof of Proposition 1.

The derivative of $Var_p$ with respect to $\xi_t$ is

$$\frac{dVar_p}{d\xi_t} = -\frac{2\left(\sigma_a^2 - \phi\sigma_b^2\xi_t\right)\sigma_b^2}{\left(\sigma_a^2 + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2\right)^2}\left(\phi\left(\sigma_a^2 + \sigma_\varepsilon^2\right) + \xi_t\sigma_a^2\right)$$

The maximum is reached at the point $\xi_t$ at which

$$\phi\left(\sigma_a^2 + \sigma_\varepsilon^2\right) + \xi_t\sigma_a^2 = 0 \qquad \Rightarrow$$

$$\xi_{max}^{Var} = -\phi\left(1 + \frac{\sigma_\varepsilon^2}{\sigma_a^2}\right).$$

The derivative of $\lambda$ with respect to $\xi_t$ is

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

The maximum is reached at the smallest root of the equation $-\phi\left(\sigma_a^2 + \sigma_\varepsilon^2\right) - 2\xi_t\sigma_a^2 + \phi\sigma_b^2\xi_t^2 = 0$ therefore

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

## Proof of Proposition 2.

The derivative of log of $Var_p$ with respect to $\xi_t$ is

$$\frac{dlog(Var_p)}{d\xi_t} = \frac{-2\left(\phi\sigma_b^2 - \sigma_{ab}\right)}{\sigma_a^2 - \phi\sigma_{ab} - (\phi\sigma_b^2 - \sigma_{ab})\xi_t} - \frac{2\sigma_{ab} + 2\sigma_b^2\xi_t}{\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2}$$

$$= \frac{-2 \cdot M}{\left(\sigma_a^2 - \phi\sigma_{ab} - (\phi\sigma_b^2 - \sigma_{ab})\xi_t\right)\left(\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2\right)},$$

where

$$M = \left(\phi\sigma_b^2 - \sigma_{ab}\right)\cdot\left(\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2\right) + \left(\sigma_a^2 - \phi\sigma_{ab} - \left(\phi\sigma_b^2 - \sigma_{ab}\right)\xi_t\right)\left(\sigma_{ab} + \sigma_b^2\xi_t\right) =$$

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

The maximum is at the value for $\xi_t$ at which $M$ is equal to 0. Therefore,

$$\xi_{max}^{Var} = -\frac{\phi\left(\sigma_a^2\sigma_b^2 - \sigma_{ab}^2\right) + \sigma_\varepsilon^2\left(\phi\sigma_b^2 - \sigma_{ab}\right)}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2} = -\phi\left(1 + \frac{\sigma_\varepsilon^2\sigma_b^2}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2}\right) + \frac{\sigma_\varepsilon^2}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2}\sigma_{ab}.$$

## Proof of Proposition 3.

Although we know that

$$Var_p = \frac{\left(\sigma_a^2 - \sigma_{ab}\phi - \xi_t\left(\phi\sigma_b^2 - \sigma_{ab}\right)\right)^2}{\sigma_a^2 + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2 + 2\sigma_{ab}\xi_t},$$

it is easier to get to the result indirectly. The updated conditional variance

$$\Sigma_t = \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix} - \frac{1}{var\left[Y_t^i\right]}\begin{pmatrix} \sigma_a^2 + \sigma_{ab}\xi_t \\ \sigma_{ab} + \sigma_b^2\xi_t \end{pmatrix}\begin{pmatrix} \sigma_a^2 + \sigma_{ab}\xi_t \\ \sigma_{ab} + \sigma_b^2\xi_t \end{pmatrix}^T =$$

$$= \frac{1}{var\left[Y_t^i\right]}\begin{pmatrix} \sigma_a^2\sigma_\varepsilon^2 + (\sigma_a^2\sigma_b^2 - \sigma_{ab}^2)\xi_t^2 & \sigma_{ab}\sigma_\varepsilon^2 - (\sigma_a^2\sigma_b^2 - \sigma_{ab}^2)\xi_t \\ \sigma_{ab}\sigma_\varepsilon^2 - (\sigma_a^2\sigma_b^2 - \sigma_{ab}^2)\xi_t & \sigma_b^2\sigma_\varepsilon^2 + (\sigma_a^2\sigma_b^2 - \sigma_{ab}^2) \end{pmatrix}.$$

Then (here $\Phi = (1, -\phi)$),

$$Var\left[p_t - p_{t-1}\right] = Var\left[\Phi\left(\mu_t - \mu_{t-1}\right)\right] = \Phi Var\left[\mu_t - \mu_{t-1}\right]\Phi^T =$$

$$= \Phi\left(\Sigma_{t-1} - \Sigma_t\right)\Phi^T.$$

Since $\Sigma_{t-1}$ does not depend on $\xi_t$, we can consider only the second term,

$$H := \Phi\Sigma_t\Phi^T = \frac{\sigma_\varepsilon^2\left(\sigma_a^2 - 2\phi\sigma_{ab} + \phi^2\sigma_b^2\right) + \left(\sigma_a^2\sigma_b^2 - \sigma_{ab}^2\right)\left(\phi^2 + 2\phi\xi_t + \xi_t^2\right)}{\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2}.$$

If we denote

$$A = \sigma_\varepsilon^2 \left(\sigma_a^2 - 2\phi\sigma_{ab} + \phi^2\sigma_b^2\right) + \left(\sigma_a^2\sigma_b^2 - \sigma_{ab}^2\right)\left(\phi^2 + \xi_t^2\right),$$

$$B = 2\phi\left(\sigma_a^2\sigma_b^2 - \sigma_{ab}^2\right),$$

$$C = \sigma_a^2 + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2,$$

and

$$D = 2\sigma_{ab},$$

then $H(\xi_t) = \frac{A+B\xi_t}{C+D\xi_t}$ and

$$H_{\xi=+x} > H_{\xi=-x} \quad \Leftrightarrow \quad A \cdot D < B \cdot C.$$

The last equation is equivalent to

$$\left(\sigma_\varepsilon^2 \left(\sigma_a^2 - 2\phi\sigma_{ab} + \phi^2\sigma_b^2\right) + \left(\sigma_a^2\sigma_b^2 - \sigma_{ab}^2\right)\left(\phi^2 + x^2\right)\right) \cdot 2\sigma_{ab}$$

$$< 2\phi\left(\sigma_a^2\sigma_b^2 - \sigma_{ab}^2\right) \cdot \left(\sigma_a^2 + \sigma_b^2 x^2 + \sigma_\varepsilon^2\right)$$

$$\Leftrightarrow \sigma_{ab}\left(\sigma_\varepsilon^2 \frac{\sigma_a^2 - 2\phi\sigma_{ab} + \phi^2\sigma_b^2}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2} + \left(\phi^2 + x^2\right)\right) < \phi\left(\sigma_a^2 + \sigma_b^2 x^2 + \sigma_\varepsilon^2\right).$$

We can rewrite the left hand side as

$$\sigma_{ab}\left(\sigma_\varepsilon^2 \frac{\sigma_a^2 - 2\phi\sigma_{ab} + \phi^2\sigma_b^2}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2} + \left(\phi^2 + x^2\right)\right) =$$

$$\sigma_{ab}\left(\sigma_\varepsilon^2 \frac{\left(\sigma_a - \phi\sigma_b\right)^2}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2} + \left(\phi^2 + x^2\right)\right) + \frac{2\phi\sigma_{ab}}{\sigma_a\sigma_b + \sigma_{ab}}.$$

The expression is negative for negative $\sigma_{ab}$, is equal to zero when $\sigma_{ab} = 0$, and is an increasing function of $\sigma_{ab}$ for positive $\sigma_{ab}$. Moreover, $H\left(\xi_t = -x\right) > H\left(\xi_t = x\right)$ for $\sigma_{ab} = \sigma_a\sigma_b$. Thus, there exists a positive cutoff $0 < \bar{\sigma}_{ab}^p < \sigma_a\sigma_b$ such that

- $Var_p\left[\xi_t = -x\right] > Var_p\left[\xi_t = +x\right]$ for $-\sigma_a\sigma_b \leq \sigma_{ab} < \sigma_{ab}^p$ , and
- $Var_p\left[\xi_t = -x\right] < Var_p\left[\xi_t = +x\right]$ for $\sigma_{ab}^p < \sigma_{ab} \leq \sigma_a\sigma_b$.

## Proof of Proposition 4.

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

where

$$A = \sigma_a^2 - \phi\sigma_{ab} \qquad B = \sigma_{ab} - \phi\sigma_b^2$$
$$C = \sigma_a^2 + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2 \qquad D = 2\sigma_{ab}.$$

Therefore,

$$\lambda_{\xi=+x} > \lambda_{\xi=-x} \quad \Leftrightarrow \quad A \cdot D < B \cdot C,$$

which is equivalent to

$$\left(\sigma_a^2 - \phi\sigma_{ab}\right) 2\sigma_{ab} < \left(\sigma_{ab} - \phi\sigma_b^2\right)\left(\sigma_a^2 + \sigma_b^2 x^2 + \sigma_\varepsilon^2\right) \quad \Leftrightarrow$$

$$\phi\sigma_b^2\left(\sigma_a^2 + \sigma_b^2 x^2 + \sigma_\varepsilon^2\right) + \sigma_{ab}\left(\sigma_a^2 - \sigma_b^2 x^2 - \sigma_\varepsilon^2\right) - 2\phi\sigma_{ab}^2 < 0.$$

The left hand side is a quadratic function of $\sigma_{ab}$

$$f(\sigma_{ab}) = \phi\sigma_b^2\left(\sigma_a^2 + \sigma_b^2 x^2 + \sigma_\varepsilon^2\right) + \sigma_{ab}\left(\sigma_a^2 - \sigma_b^2 x^2 - \sigma_\varepsilon^2\right) - 2\phi\sigma_{ab}^2.$$

The statement of the proposition follows from the following two facts

1. $f(\sigma_{ab} = 0) = \phi\sigma_b^2\left(\sigma_a^2 + \sigma_b^2 x^2 + \sigma_\varepsilon^2\right) > 0$, and
2. $f\left(\sigma_{ab} = -\sigma_a\sigma_b\right) + f\left(\sigma_{ab} = \sigma_a\sigma_b\right) = 2\phi\left(\sigma_b^2 x^2 + \sigma_\varepsilon^2\right) > 0 \Rightarrow$ either $f\left(\sigma_{ab} = -\sigma_a\sigma_b\right) > 0$, or $f\left(\sigma_{ab} = \sigma_a\sigma_b\right) > 0$, or both conditions hold.

## Proof of Lemma 5.

The formulas for updating beliefs from proposition 3 are symmetric with respect to $\xi_t$. Since the distribution of $\xi_t$ and the initial prior are symmetric, then for each of the following periods the distribution of beliefs is also symmetric.

## Proof of Proposition 6.

The variance of price changes $Var_p$ is a function of $\xi_t$ and previous-period beliefs $\sigma_a^2, \sigma_b^2, \sigma_{ab}$. From lemma 5, it follows that the distribution $\sigma_{ab}$ is symmetric. As a result, to prove the proposition it is sufficient to show that

$$\frac{1}{2}Var_p\left(\xi_t = -x, \sigma_{ab} = +y\right) + \frac{1}{2}Var_p\left(\xi_t = -x, \sigma_{ab} = -y\right) >$$

$$\frac{1}{2}Var_p\left(\xi_t = x, \sigma_{ab} = +y\right) + \frac{1}{2}Var_p\left(\xi_t = x, \sigma_{ab} = -y\right),$$

or equivalently,

$$X = \left(Var_p\left(\xi_t = +x, \sigma_{ab} = +y\right) - Var_p\left(\xi_t = -x, \sigma_{ab} = -y\right)\right) -$$

$$\left(Var_p\left(\xi_t = -x, \sigma_{ab} = +y\right) - Var_p\left(\xi_t = x, \sigma_{ab} = -y\right)\right) < 0.$$

Given that

$$Var_p = \frac{\left(\sigma_a^2 - \sigma_{ab}\phi - \xi_t\left(\phi\sigma_b^2 - \sigma_{ab}\right)\right)^2}{\sigma_a^2 + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2 + 2\sigma_{ab}\xi_t},$$

we get

$$Var_p\left(\xi_t = +x, \sigma_{ab} = +y\right) - Var_p\left(\xi_t = -x, \sigma_{ab} = -y\right) =$$

$$\frac{\left(\sigma_a^2 - y\phi - x\left(\phi\sigma_b^2 - y\right)\right)^2 - \left(\sigma_a^2 + y\phi + x\left(\phi\sigma_b^2 + y\right)\right)^2}{\sigma_a^2 + \sigma_b^2x^2 + \sigma_\varepsilon^2 + 2xy} =$$

$$\frac{-4\phi\left(\sigma_a^2 + xy\right)\left(y + x\sigma_b^2\right)}{\sigma_a^2 + \sigma_b^2x^2 + \sigma_\varepsilon^2 + 2xy} = -4\phi\frac{\sigma_a^2y + yx^2\sigma_b^2 + x\left(y^2 + \sigma_a^2\sigma_b^2\right)}{\sigma_a^2 + \sigma_b^2x^2 + \sigma_\varepsilon^2 + 2xy}$$

and

$$Var_p\left(\xi_t = -x, \sigma_{ab} = +y\right) - Var_p\left(\xi_t = +x, \sigma_{ab} = -y\right) =$$

$$-4\phi\frac{\sigma_a^2y + yx^2\sigma_b^2 - x\left(y^2 + \sigma_a^2\sigma_b^2\right)}{\sigma_a^2 + \sigma_b^2x^2 + \sigma_\varepsilon^2 - 2xy}.$$

As a result,

$$-\frac{X}{4\phi} = \frac{\sigma_a^2y + yx^2\sigma_b^2 + x\left(y^2 + \sigma_a^2\sigma_b^2\right)}{\sigma_a^2 + \sigma_b^2x^2 + \sigma_\varepsilon^2 + 2xy} - \frac{\sigma_a^2y + yx^2\sigma_b^2 - x\left(y^2 + \sigma_a^2\sigma_b^2\right)}{\sigma_a^2 + \sigma_b^2x^2 + \sigma_\varepsilon^2 - 2xy} =$$

$$= \frac{2 \cdot Y}{\left(\sigma_a^2 + \sigma_b^2x^2 + \sigma_\varepsilon^2\right)^2 - 4x^2y^2},$$

where

$$Y = x\left(\sigma_a^2\sigma_b^2 + y^2\right)\left(\sigma_a^2 + \sigma_b^2 x^2 + \sigma_\varepsilon^2\right) - \left(x^2\sigma_b^2 y + \sigma_a^2 y\right)\cdot 2xy =$$

$$= x\sigma_a^2\left(\sigma_a^2\sigma_b^2 - y^2\right) + x^3\sigma_b^2\left(\sigma_a^2\sigma_b^2 - y^2\right) > 0.$$

It follows that $X > 0$.

## Proof of Proposition 7

Stock $i$'s return between periods $t-1$ and $t$, and the expected return at $t-1$, respectively, are

$$R_t^i = \frac{p_t^i + Y_t^i - p_{t-1}^i}{p_{t-1}^i}, \qquad E_{t-1}\left[R_t^i\right] = \frac{a_{t-1}^i}{p_{t-1}^i}.$$

Therefore, the skewness

$$E_3 = E_{t-1}\left[\left(R_t^i - E_{t-1}\left[R_t^i\right]\right)^3\right] =$$

$$= \frac{1}{\left(p_{t-1}^i\right)^3} E_{t-1}\left[X^3\right]$$

where

$$X = \left(\tilde{\lambda} + 1\right)\left(Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]\right) + b_{t-1}^i \xi_t$$

$$E_{t-1,\xi_t}\left[Y_t^i\right] = a_{t-1}^i + b_{t-1}^i \xi_t$$

$$\tilde{\lambda} = \frac{\lambda}{R-1} = \frac{1}{R-1}\cdot\frac{\sigma_a^2 - \phi\sigma_{ab} - \left(\phi\sigma_b^2 - \sigma_{ab}\right)\xi_t}{\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2}.$$

We can calculate $E_{t-1}\left[X^3\right]$ in the following way

$$E_{t-1}\left[X^3\right] = E_{t-1}\left[\left(\tilde{\lambda} + 1\right)^3\left(Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]\right)^3\right]$$

$$+3\cdot E_{t-1}\left[\left(\tilde{\lambda} + 1\right)^2\left(Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]\right)^2\cdot b_{t-1}^i\xi_t\right]$$

$$+3\cdot E_{t-1}\left[\left(\tilde{\lambda} + 1\right)\left(Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]\right)\cdot\left(b_{t-1}^i\xi_t\right)^2\right]$$

$$+3E_{t-1}\left[\left(b_{t-1}^i\xi_t\right)^3\right].$$

Only the second term in the above expression is different from 0. Note that $E_{t-1}[\dots] = E_{t-1}[E_{t-1,\xi_t}[\dots]]$ and that conditional on $\xi_t$ the random variable $Y_t^i - E_{t-1,\xi_t}[Y_t^i]$ is normally distributed with 0 mean. The second term is

$$E_{t-1}\left[X^3\right] = 3E_{t-1}\left[\left(\tilde{\lambda}+1\right)^2\left(Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]\right)^2 \cdot b_{t-1}^i \xi_t\right] =$$

$$3E_{t-1}\left[\left(\tilde{\lambda}+1\right)^2 Var\left[Y_t^i\right] \cdot b_{t-1}^i \xi_t\right],$$

where $Var[Y_t^i] = Var_{t-1,\xi_t}[Y_t^i] = \sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2$ (here we as usual omit $t-1$ subscripts for variance). As a result,

$$E_{t-1}\left[X^3\right] = 3b_{t-1}^i\left(\frac{E_{t-1}[\lambda^2 Var[Y_t^i]\xi_t]}{(R-1)^2} + \frac{2E_{t-1}[\lambda Var[Y_t^i]\xi_t]}{R-1} + E_{t-1}\left[Var\left[Y_t^i\right]\xi_t\right]\right).$$

Consider each term separately

$$E_{t-1}\left[Var\left[Y_t^i\right]\xi_t\right] = E_{t-1}\left[\left(\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2\right)\xi_t\right] = 2\sigma_{ab}\cdot\sigma_\xi^2$$

$$E_{t-1}\left[\lambda Var\left[Y_t^i\right]\xi_t\right] = E_{t-1}\left[\left(\sigma_a^2 - \phi\sigma_{ab} - \left(\phi\sigma_b^2 - \sigma_{ab}\right)\xi_t\right)\xi_t\right] = -\left(\phi\sigma_b^2 - \sigma_{ab}\right)\cdot\sigma_\xi^2$$

$$E_{t-1}\left[\lambda^2 Var\left[Y_t^i\right]\xi_t\right] = \frac{1}{R-1}E_{t-1}\left[Var_p(\xi_t)\xi_t\right]$$

If $\sigma_{ab} \le 0$, the sum of the first two terms is negative. From proposition 3 we know that $Var_p(\xi_t)$ is larger for negative $\xi_t$ when $\sigma_{ab} \le 0$. Thus the last term is negative as well for $\sigma_{ab} \le 0$. Therefore $E_{t-1}[X^3] < 0$ for $\sigma_{ab} \le 0$, which is equivalent to the statement of the proposition.

## Proof of Lemma 6.

The stochastic discount factor is

$$m_{t,t+k} = \beta^k \frac{u'(C_{t+k})}{u'(C_t)},$$

such that assets prices are determined by

$$p_t^i = \sum_{k=1}^{\infty} E_t\left[m_{t,t+k}Y_{t+k}^i\right]$$

$$= \sum_{k=1}^{\infty} E_t \left[ \beta^k \frac{u'\left(C_{t+k}\right)}{u'\left(C_t\right)} \left( a^i + b^i \xi_{t+k} + \varepsilon_{t+k}^i \right) \right] =$$

$$E_t[a^i] \cdot \sum_{k=1}^{\infty} E_t \left[ \beta^k \frac{u'\left(C_{t+k}\right)}{u'\left(C_t\right)} \right] + E_t[b^i] \cdot \sum_{k=1}^{\infty} E_t \left[ \beta^k \frac{u'\left(C_{t+k}\right)}{u'\left(C_t\right)} \xi_{t+k} \right].$$

Since there exists a risk-free asset, we can write

$$E_t \left[ \beta^k \frac{u'(C_{t+k})}{u'(C_t)} \right] = \frac{1}{R^k}$$

and

$$\sum_{k=1}^{\infty} E_t \left[ \beta^k \frac{u'(C_{t+k})}{u'(C_t)} \right] = \frac{R}{R-1}.$$

Therefore

$$p_t^i = \frac{R}{R-1} E \left[ a^i - \phi \left( \xi^t \right) b^i \right],$$

where

$$\phi = \frac{R-1}{R} \sum_{k=1}^{\infty} \beta^k \frac{E_t \left[ u'(C_{t+k}) \xi_{t+k} \right]}{u'\left(C_t\right)}.$$

The consumption in period $t+k$ is positively correlated with the aggregate shock in the current period (because of consumption smoothing). As a result $E_t \left[ u'(C_{t+k}) \xi_{t+k} \right] < 0$ for each $k$ and thus $\phi > 0$.

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| Macro State | Good News<br>Higher than expected performance | Bad News<br>Lower than expected performance | Price Reaction |
|---|---|---|---|
| *Good Times* | *high a or high b* | *low a or low b* | ? $\vert$ ? |
| *Bad Times* | *high a or low b* | *low a or high b* | $\uparrow$ $\vert$ $\downarrow$ |

Figure 1: Intuition of the main results.

In good times, better-than-expected cash flows can be attributed either to desirable higher-than-expected idiosyncratic performance, $a$, or due to undesirable higher-than-expected correlation, $b$, with a market-wide factor. A similar logic holds for bad news in good times. As a result, the price response to news in good times is ambiguous. In contrast, in bad times, better-than-expected performance is either due to higher-than-expected idiosyncratic performance, or due to lower-than-expected correlation with a market-wide factor, both of which are desirable properties. As a result, the price response to news in downturns is unambiguous.

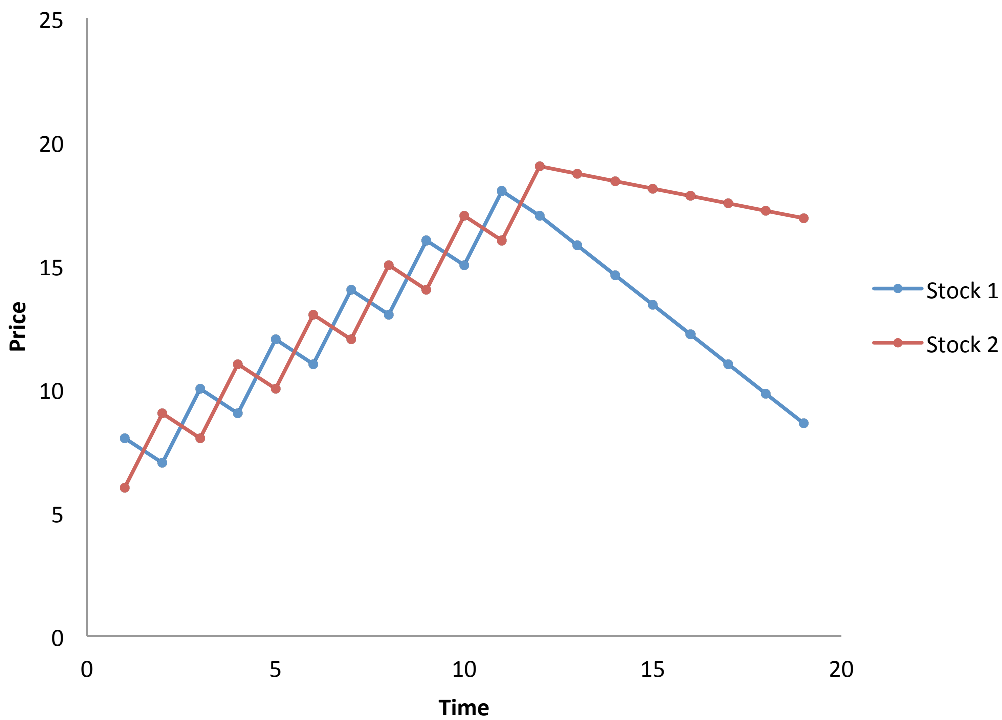



Figure 2: Illustration of the relationship between correlation and dispersion.

Stock returns can be uncorrelated or negatively correlated in upturns and positively correlated in downturns, while relative valuations do not diverge in upturns, but diverge strongly in downturns. Thus, an increase in correlations in downturns does not imply a decrease in dispersion. Conversely, an increase in dispersion is consistent with an increase of correlations. The appendix provides a proof.

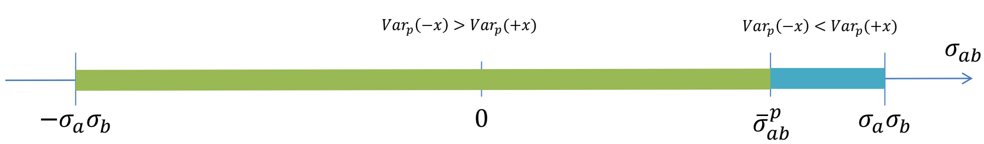



Figure 3: Illustration of Proposition 3.

The figure shows the set of beliefs in green for which the variance of prices changes in market downturns is higher than in market upturns. This set of beliefs is defined by all beliefs $\sigma_{ab}$ that fall below a cutoff $\bar{\sigma}^p_{ab}$, which is always positive. The opposite result holds for the beliefs $\sigma_{ab}$ that fall above the cutoff. That set is colored blue. The distribution of beliefs $\sigma_{ab}$ is symmetric, and on average, $\sigma_{ab}$ is zero. As a result, beliefs fall into the green set most of the time as well as on average.

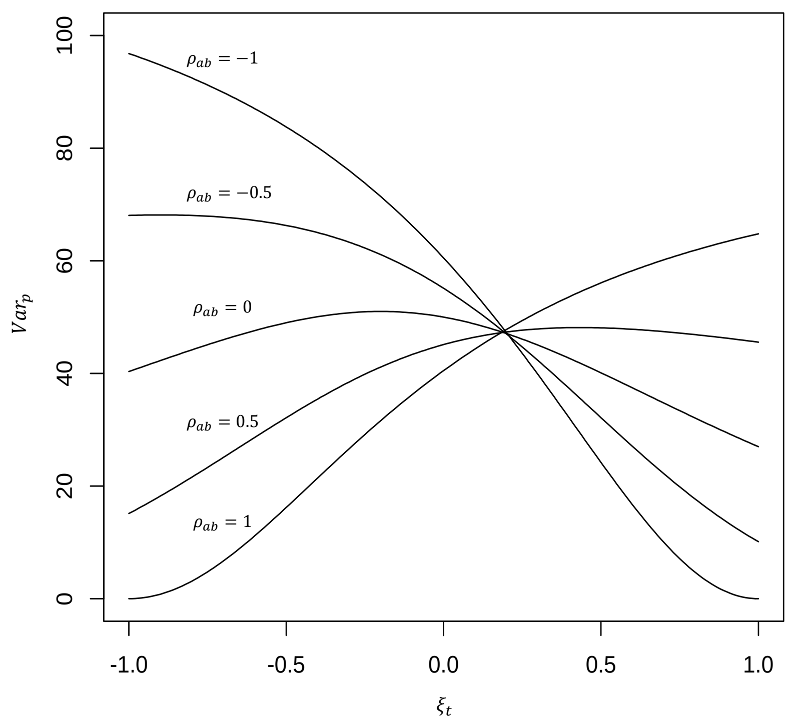



Figure 4: Illustration how the market reaction to news depends on prior beliefs.

Simulation plot of the variance of the price changes over the realization of the market-wide shock $\xi$, for different values of $\rho = \frac{\sigma_{ab}}{\sigma_a \sigma_b}$. Unless $\rho_{ab}$ is strongly positive, the part of the graph left of $\xi = 0$ tends to be higher than the part to the right of $\xi = 0$, i.e., variance is higher in downturns than in upturns, i.e., unless $\sigma_{ab}$ is very high, the variance of price response to an observation is higher in downturns then in upturns. Simulation results for $\phi = 0.1$, $\sigma_a^2 = 1$, $\sigma_b^2 = 1$, $\sigma_{ab} = 0$, $\sigma_\varepsilon = 1$, and $R = 1$.

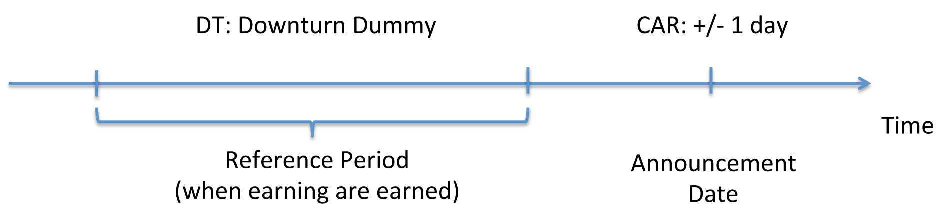
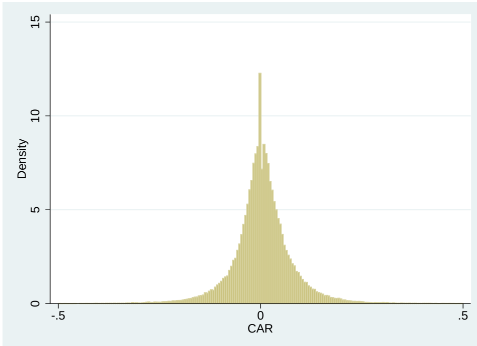
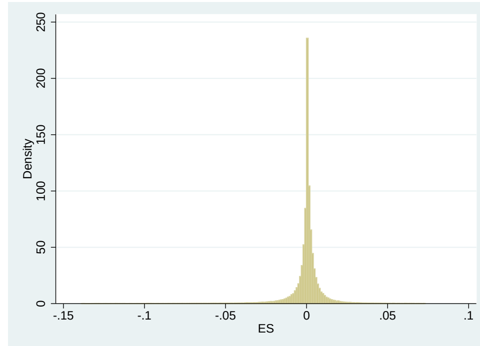


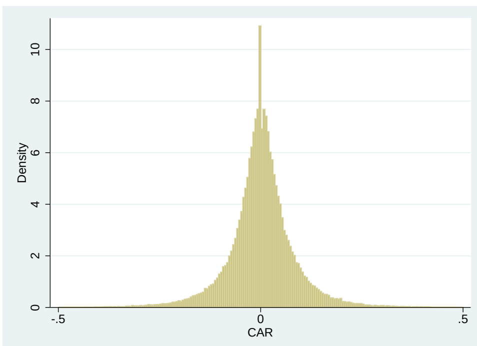

Figure 5: Illustration of the timing of reference period and earnings announcement.
The reference period pertaining to an earnings announcement at date $t$ is the period during which the firm earns the earnings it reports at time $t$. The announcement date is typically a few weeks after the end of the reference period, and is available from IBES. We measure the market state $\xi_t$ for the nonlinear tests and assign downturn dummies for the linear tests according to the market state in the reference period, not the market state during the announcement date.



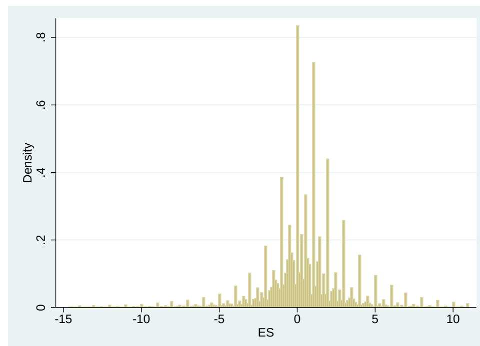

(a) CAR (book equity, full sample)



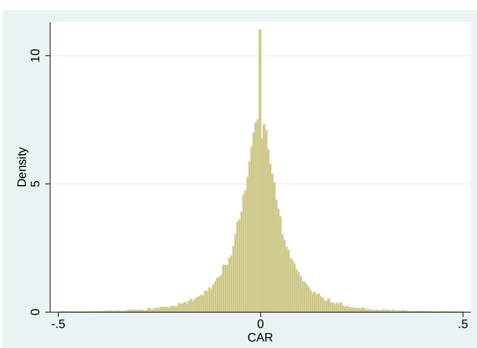

(b) ES (book equity, full sample)



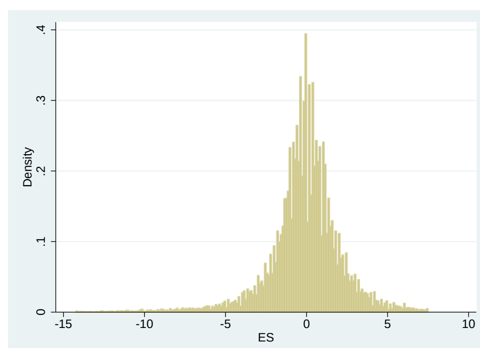

(c) CAR (st. dev., full sample)




(d) ES (st. dev., full sample)




(e) CAR (st. dev., restricted sample)




(f) ES (st. dev., restricted sample)

Figure 6: Histogramms of cumulative announcement returns ($CAR$) and earnings surprises ($ES$) for different definitions of the earnings response and different subsamples. "book equity" refers to earnings response coefficients based on the traditional notion of earnings surprises that are normalized by book equity. "st. dev." refers to an alternative calculation of the earnings surprise that normalizes by the standard deviation of analyst forecasts. The first row is based on a sample in which the earnings surprise $ES$ is calculated as in the literature. The second row calculates $ES$ by normalizing by the standard deviation of analyst forecasts. Because that variable is reported by IBES in large discrete steps, "discretization noise" is introduced. The third row is base 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. 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.

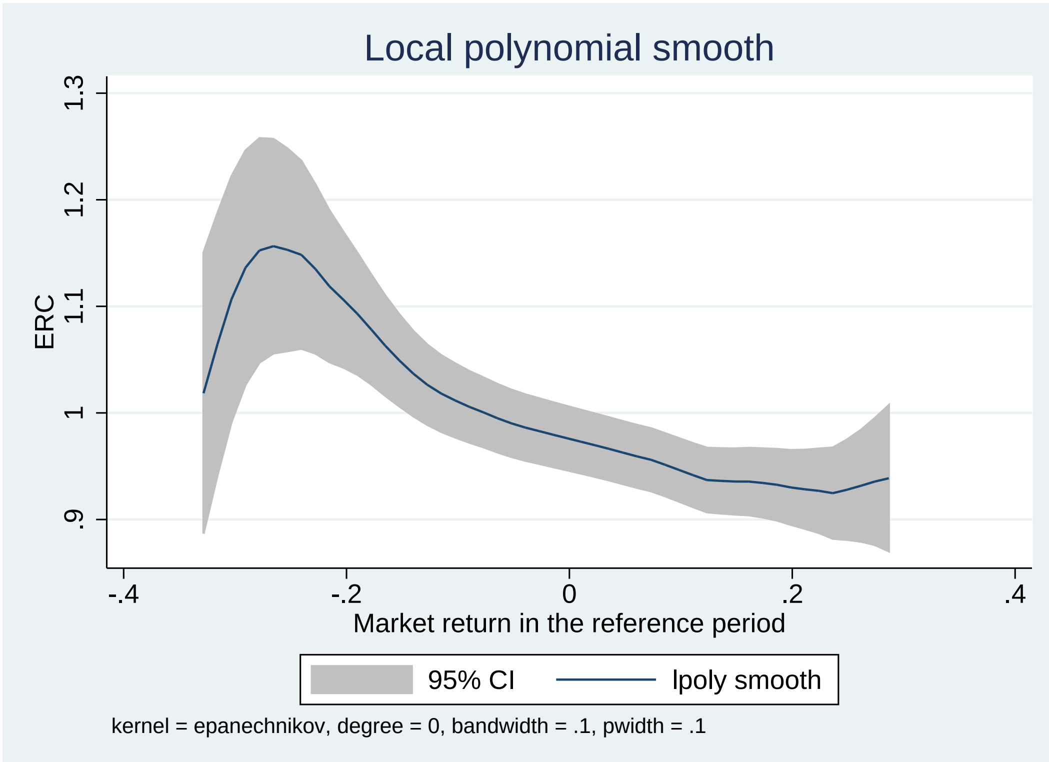



Figure 7: Non-parametric estimate of the earnings response coefficient as a function of the market return (earnings surprises normalized by book equity).

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 $ES = \frac{EPS - E[ESP]}{BVPS}$ 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 earnings response coefficient $\lambda$ 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).

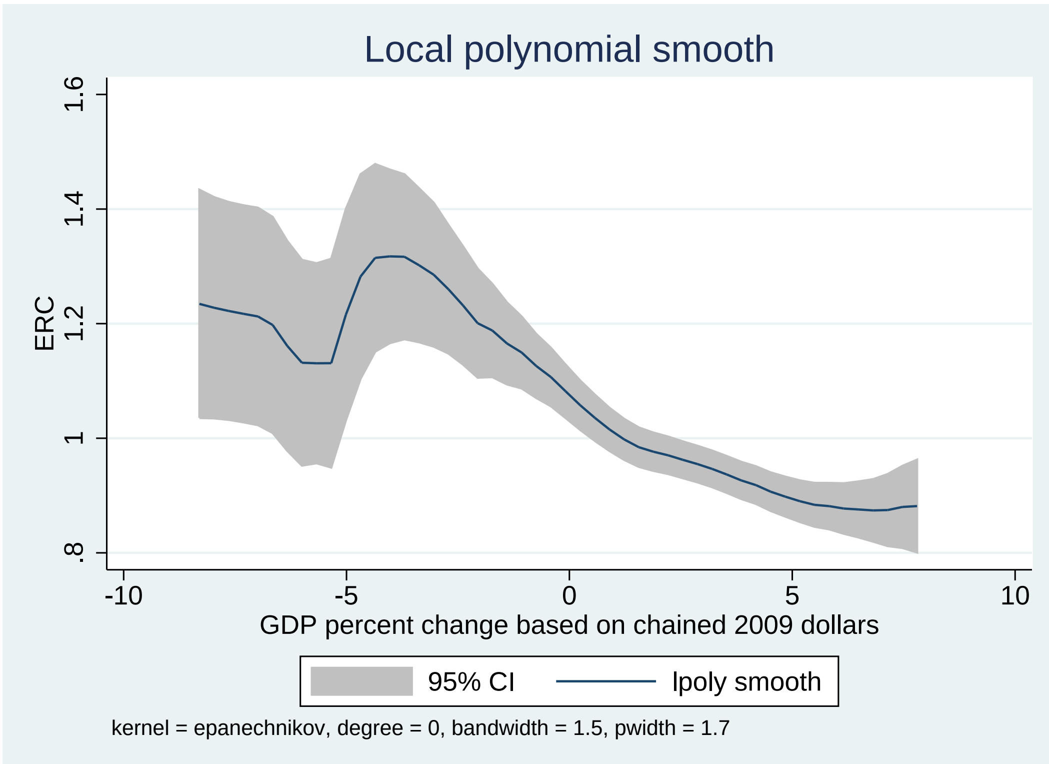



Figure 8: Non-parametric estimate of the earnings response coefficient as a function of GDP growth (earnings surprises normalized by book equity).

We estimate the equation $CAR_{i,t} = \lambda(\xi_t)\, ES_{i,t} + \varepsilon_{i,t}$ 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 $ES = \frac{EPS - E[ESP]}{BVPS}$ 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 earnings response coefficient $\lambda$ depends on the state of the economy $\xi_t$, which is represented by 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).

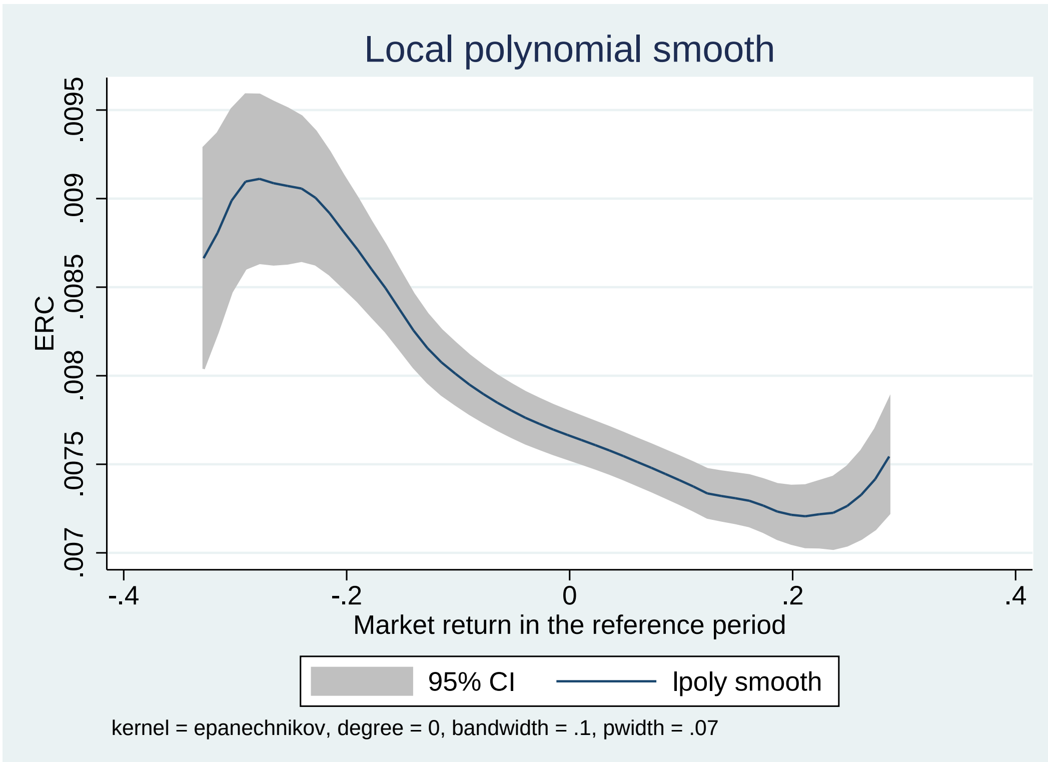



Figure 9: Non-parametric estimate of the earnings response coefficient as a function of the market return (earnings surprises normalized by standard deviation of analyst forecasts).

We estimate the equation $CAR_{i,t} = \lambda(\xi_t)\, ES_{i,t} + \varepsilon_{i,t}$ 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 $ES = \frac{EPS - E[ESP]}{st.dev.[ESP]}$ 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; $st.dev.[ESP]$ is the standard deviation of expected earnings per share across analysts from from the IBES unadjusted detail files. The graph shows how the earnings response coefficient $\lambda$ 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).

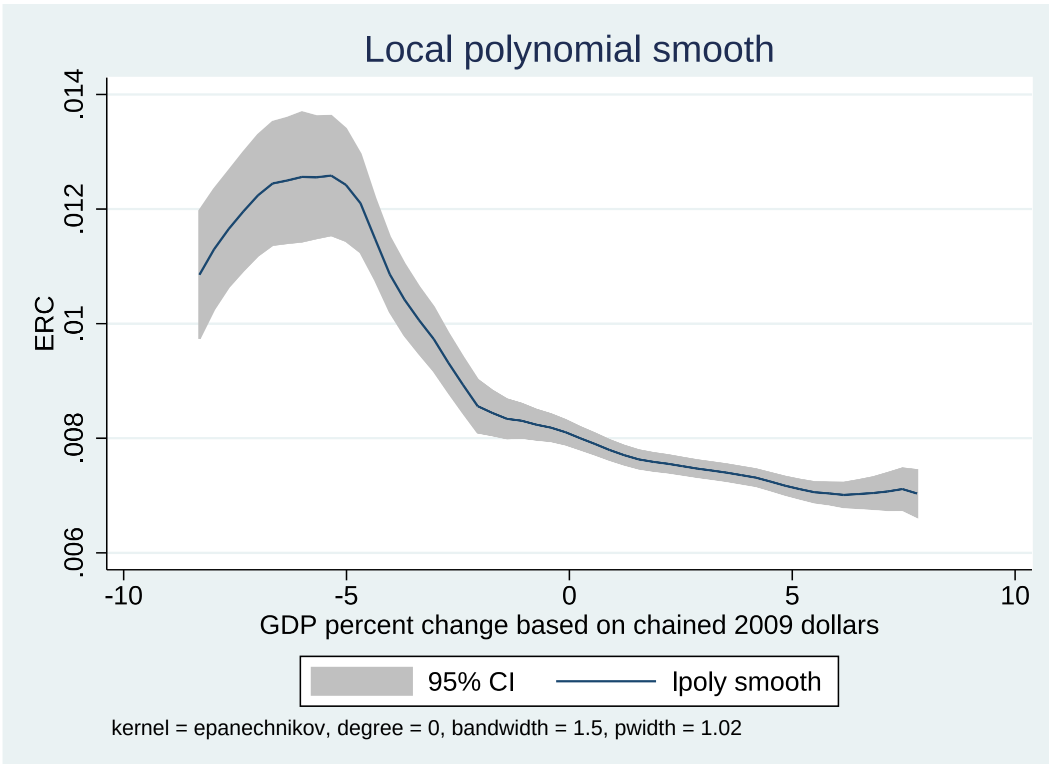



Figure 10: Non-parametric estimate of the earnings response coefficient as a function of GDP growth (earnings surprises normalized by standard deviation of analyst forecasts).

We estimate the equation $CAR_{i,t} = \lambda(\xi_t) ES_{i,t} + \varepsilon_{i,t}$ 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 $ES = \frac{EPS - E[ESP]}{st.dev.[ESP]}$ 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; $st.dev.[ESP]$ is the standard deviation of expected earnings per share across analysts from from the IBES unadjusted detail files. The graph shows how the earnings response coefficient $\lambda$ depends on the state of the economy $\xi_t$, which is represented by 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).

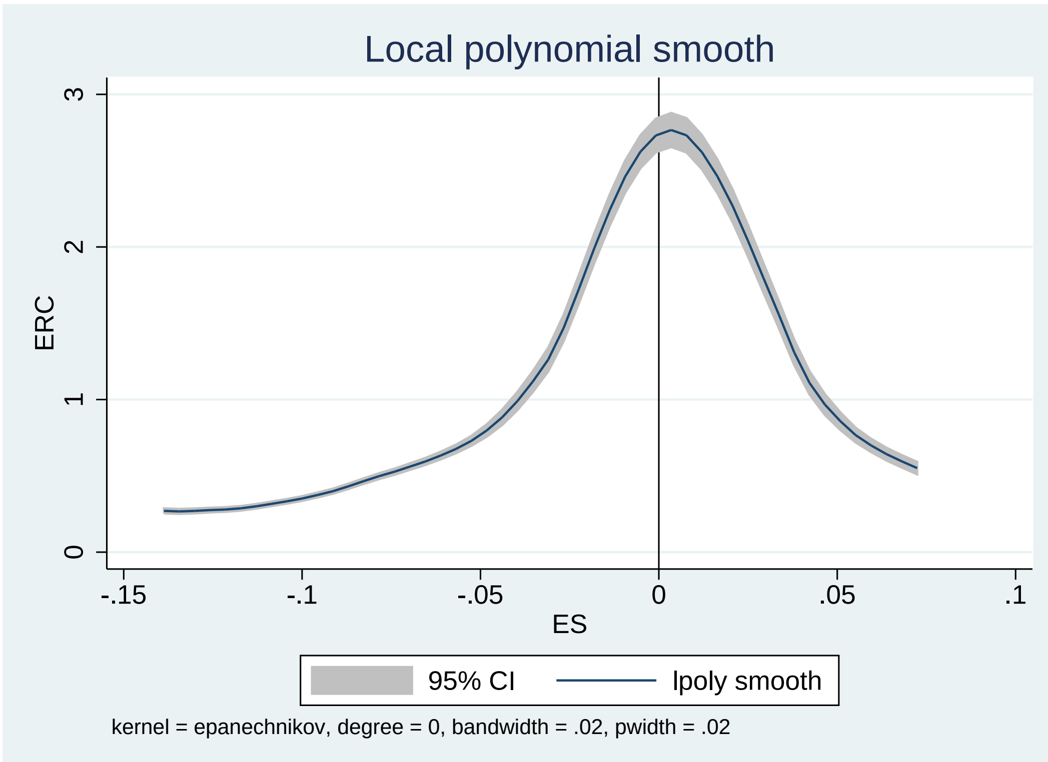



Figure 11: Earnings response coefficients (ERC, $\lambda$) as a function of unexpected quarterly earnings (ES).

We estimate the equation $CAR_{i,t} = \lambda(ES_{i,t}) \cdot ES_{i,t} + \varepsilon_{i,t}$ 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 $ES = \frac{EPS - E[ESP]}{BVPS}$ 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.

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 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 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 statics 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.

| | N | Mean | St.Dev. | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| CAR | 147667 | 0.0044 | 0.0780 | -0.0294 | 0.0019 | 0.0377 |
| CAR, NBER, DT = 1 | 15505 | 0.0081 | 0.1050 | -0.0379 | 0.0055 | 0.0514 |
| CAR, NBER, DT = 0 | 132162 | 0.0040 | 0.0742 | -0.0286 | 0.0015 | 0.0364 |
| CAR, Market, DT = 1 | 64476 | 0.0053 | 0.0856 | -0.0312 | 0.0034 | 0.0414 |
| CAR, Market, DT = 0 | 83191 | 0.0038 | 0.0715 | -0.0284 | 0.0004 | 0.0350 |
| CAR, GDP, DT = 1 | 66189 | 0.0051 | 0.0842 | -0.0317 | 0.0025 | 0.0411 |
| CAR, GDP, DT = 0 | 81478 | 0.0038 | 0.0726 | -0.0278 | 0.0014 | 0.0353 |
| ES | 147667 | -0.0004 | 0.0134 | -0.0013 | 0.0003 | 0.0026 |
| ES, NBER, DT = 1 | 15505 | -0.0009 | 0.0155 | -0.0022 | 0.0003 | 0.0031 |
| ES, NBER, DT = 0 | 132162 | -0.0003 | 0.0132 | -0.0012 | 0.0003 | 0.0026 |
| ES, Market, DT = 1 | 64476 | -0.0005 | 0.0135 | -0.0013 | 0.0003 | 0.0026 |
| ES, Market, DT = 0 | 83191 | -0.0004 | 0.0134 | -0.0012 | 0.0003 | 0.0026 |
| ES, GDP, DT = 1 | 66189 | -0.0003 | 0.0139 | -0.0014 | 0.0004 | 0.0030 |
| ES, GDP, DT = 0 | 81478 | -0.0005 | 0.0130 | -0.0012 | 0.0003 | 0.0024 |

Table 2: Summary statistics (earnings surprises normalized by standard deviation of analyst forecasts).

The table contains summary statistics (means, standard deviations, percentiles) for all earnings announcements in our sample from 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 $ES = \frac{EPS - E[EPS]}{st.dev.[EPS_{i,t}]}$ where $EPS$ is a stock actual announced earnings per share; $E[EPS]$ is the expected earnings per share averaged across analysts and $st.dev.[EPS_{i,t}]$ is the standard deviation of expected earnings per share across all analysts as reported in the IBES unadjusted detail files. The statics 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 1984-2012.

| Panel A: Full sample | | | | | | |
|---|---|---|---|---|---|---|
| | N | Mean | St.Dev. | p25 | p50 | p75 |
| CAR | 195924 | 0.0023 | 0.0889 | -0.0354 | 0.0000 | 0.0396 |
| CAR, NBER, DT = 1 | 25172 | 0.0070 | 0.1198 | -0.0476 | 0.0038 | 0.0578 |
| CAR, NBER, DT = 0 | 170752 | 0.0016 | 0.0833 | -0.0339 | 0.0000 | 0.0375 |
| CAR, Market, DT = 1 | 109847 | 0.0031 | 0.0962 | -0.0369 | 0.0014 | 0.0427 |
| CAR, Market, DT = 0 | 86077 | 0.0013 | 0.0785 | -0.0338 | 0.0000 | 0.0359 |
| CAR, GDP, DT = 1 | 97605 | 0.0031 | 0.0973 | -0.0386 | 0.0010 | 0.0440 |
| CAR, GDP, DT = 0 | 98319 | 0.0015 | 0.0797 | -0.0323 | 0.0000 | 0.0359 |
| ES | 195924 | 0.3990 | 2.7848 | -0.7500 | 0.3333 | 1.6667 |
| ES, NBER, DT = 1 | 25172 | 0.2803 | 2.9592 | -1.0000 | 0.2616 | 1.6667 |
| ES, NBER, DT = 0 | 170752 | 0.4165 | 2.7577 | -0.7500 | 0.3350 | 1.6667 |
| ES, Market, DT = 1 | 109847 | 0.3584 | 2.8033 | -0.8000 | 0.3333 | 1.6250 |
| ES, Market, DT = 0 | 86077 | 0.4508 | 2.7602 | -0.7200 | 0.4000 | 1.7471 |
| ES, GDP, DT = 1 | 97605 | 0.4333 | 2.8638 | -0.8000 | 0.4000 | 1.8333 |
| ES, GDP, DT = 0 | 98319 | 0.3650 | 2.7036 | -0.7500 | 0.3333 | 1.5000 |

| Panel B: Restricted sample: excludes observations with SD(ES)<0.05 | | | | | | |
|---|---|---|---|---|---|---|
| | N | Mean | St.Dev. | p25 | p50 | p75 |
| CAR | 50103 | -0.00155 | 0.09679 | -0.04040 | -0.00000 | 0.03602 |
| CAR, NBER, DT = 1 | 8168 | 0.00531 | 0.13935 | -0.05556 | 0.00000 | 0.05841 |
| CAR, NBER, DT = 0 | 41935 | -0.00288 | 0.08602 | -0.03838 | -0.00047 | 0.03303 |
| CAR, Market, DT = 1 | 27790 | -0.00082 | 0.10797 | -0.04286 | -0.00000 | 0.03961 |
| CAR, Market, DT = 0 | 22313 | -0.00246 | 0.08072 | -0.03797 | -0.00173 | 0.03205 |
| CAR, GDP, DT = 1 | 26766 | -0.00038 | 0.10845 | -0.04434 | -0.00000 | 0.04042 |
| CAR, GDP, DT = 0 | 23337 | -0.00288 | 0.08137 | -0.03644 | -0.00044 | 0.03217 |
| ES | 50103 | -0.13386 | 2.34075 | -1.06250 | 0.00000 | 1.00000 |
| ES, NBER, DT = 1 | 8168 | -0.29423 | 2.51891 | -1.27273 | -0.12500 | 1.00000 |
| ES, NBER, DT = 0 | 41935 | -0.10262 | 2.30318 | -1.00000 | 0.00000 | 1.00000 |
| ES, Market, DT = 1 | 27790 | -0.17738 | 2.33716 | -1.11111 | 0.00000 | 1.00000 |
| ES, Market, DT = 0 | 22313 | -0.07965 | 2.34414 | -1.00000 | 0.00000 | 1.06250 |
| ES, GDP, DT = 1 | 26766 | -0.12268 | 2.39909 | -1.11111 | 0.00000 | 1.10000 |
| ES, GDP, DT = 0 | 23337 | -0.14668 | 2.27198 | -1.00000 | 0.00000 | 1.00000 |

Table 3: 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 ($ES = \frac{EPS-E[EPS]}{BVPS}$) $CAR_{i,t} = \alpha+\beta_1 \cdot ES_{i,t} \times DT_t + \beta_2 \cdot ES_{i,t} + \beta_3 \cdot DT_t + \varepsilon_{i,t}$. The regression specifications allows for a higher coefficient in downturns ($DT$) than in upturns. 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 $Var(ES)$ and its interaction with $ES$. The third specification allows also for a time trend in ERCs. Data are from January 1984-December 2012. 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.

| | Dependent variable: cumulative announcement returns, $CAR_{i,t}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | NBER | NBER | NBER | Market | Market | Market | GDP | GDP | GDP |
| ES x DT | 0.356*** | 0.484*** | 0.342*** | 0.128** | 0.147** | 0.151*** | 0.222*** | 0.267*** | 0.123** |
| | (2.91) | (4.08) | (3.23) | (2.06) | (2.42) | (2.82) | (3.31) | (4.11) | (2.23) |
| ES | 0.943*** | 1.247*** | 0.789*** | 0.920*** | 1.140*** | 0.652*** | 0.885*** | 1.133*** | 0.725*** |
| | (28.92) | (16.94) | (9.60) | (26.42) | (15.13) | (7.21) | (23.24) | (15.17) | (8.44) |
| DT | 0.00496* | 0.00479* | 0.00535** | 0.00237 | 0.00232 | 0.00241 | 0.00121 | 0.00106 | 0.00160 |
| | (1.75) | (1.78) | (1.98) | (1.47) | (1.44) | (1.50) | (0.72) | (0.64) | (0.97) |
| ES x Var(ES) | | -1431.4*** | -1746.5*** | | -1021.2*** | -1503.0*** | | -1197.3*** | -1529.5*** |
| | | (-4.48) | (-6.06) | | (-3.16) | (-5.33) | | (-3.90) | (-5.50) |
| Var(ES) | | 2.855 | 3.241 | | 7.023 | 7.430 | | 6.074 | 6.630 |
| | | (0.38) | (0.45) | | (0.85) | (0.95) | | (0.76) | (0.86) |
| ES x Time | | | 0.0000932*** | | | 0.000101*** | | | 0.0000939*** |
| | | | (10.05) | | | (10.30) | | | (10.10) |
| Time | | | -0.000000464 | | | -0.000000394 | | | -0.000000469 |
| | | | (-1.62) | | | (-1.34) | | | (-1.61) |
| Intercept | 0.00432*** | 0.00375** | 0.00602*** | 0.00350*** | 0.00221 | 0.00405 | 0.00427*** | 0.00317* | 0.00527** |
| | (4.96) | (2.23) | (2.64) | (3.31) | (1.24) | (1.60) | (3.88) | (1.70) | (2.19) |
| $N$ | 147667 | 147667 | 147667 | 147667 | 147667 | 147667 | 147667 | 147667 | 147667 |

$t$ 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 standard deviation of analyst forecasts, full sample).

ERC is the coefficient $\beta_2$ in a regression of cumulative abnormal earnings announcement returns ($CAR$) on earnings surprises ($ES = \frac{EPS - E[EPS]}{st.dev.[EPS]}$) $CAR_{i,t} = \alpha + \beta_1 \cdot ES_{i,t} \times DT_t + \beta_2 \cdot ES_{i,t} + \beta_3 \cdot DT_t + \varepsilon_{i,t}$. 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 $Var(ES)$ and its interaction with $ES$. The third specification allows also for a time trend in ERCs. Data are from January 1984-December 2012. 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.

| | Dependent variable: cumulative announcement returns, $CAR_{i,t}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | NBER | NBER | NBER | Market | Market | Market | GDP | GDP | GDP |
| ES x DT | 0.00244*** | 0.00198*** | 0.00179*** | 0.00100*** | 0.000915*** | 0.00107*** | 0.00152*** | 0.00118*** | 0.000677** |
| | (4.14) | (3.56) | (3.48) | (3.10) | (3.02) | (4.06) | (4.44) | (3.55) | (2.35) |
| ES | 0.00744*** | 0.00447*** | 0.00468*** | 0.00721*** | 0.00352*** | 0.00369*** | 0.00697*** | 0.00414*** | 0.00435*** |
| | (43.77) | (6.61) | (7.53) | (38.93) | (5.03) | (5.92) | (33.05) | (5.90) | (6.80) |
| DT | 0.00577 | 0.00713* | 0.00757** | 0.00209 | 0.00233 | 0.00210 | 0.000453 | 0.00148 | 0.00255 |
| | (1.46) | (1.87) | (1.97) | (1.00) | (1.13) | (1.02) | (0.21) | (0.71) | (1.22) |
| ES x Var(ES) | | 0.000370*** | -0.000175* | | 0.000454*** | -0.000127 | | 0.000366*** | -0.000137 |
| | | (4.39) | (-1.91) | | (5.36) | (-1.42) | | (4.14) | (-1.47) |
| Var(ES) | | -0.00120** | 0.000181 | | -0.000941 | 0.000385 | | -0.00106* | 0.000289 |
| | | (-2.25) | (0.28) | | (-1.64) | (0.56) | | (-1.96) | (0.45) |
| ES x Time | | | 0.000000649*** | | | 0.000000679*** | | | 0.000000633*** |
| | | | (12.23) | | | (12.65) | | | (11.59) |
| Time | | | -0.00000157*** | | | -0.00000148*** | | | -0.00000160*** |
| | | | (-3.39) | | | (-3.07) | | | (-3.37) |
| Intercept | -0.00151 | 0.00775* | 0.00659 | -0.00197 | 0.00532 | 0.00420 | -0.00105 | 0.00682 | 0.00567 |
| | (-1.36) | (1.89) | (1.64) | (-1.59) | (1.22) | (0.99) | (-0.73) | (1.63) | (1.37) |
| $N$ | 195924 | 195924 | 195924 | 195924 | 195924 | 195924 | 195924 | 195924 | 195924 |

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

Table 5: 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 ($CAR$) on earnings surprises ($ES = \frac{EPS-E[EPS]}{st.dev.[EPS]}$) $CAR_{i,t} = \alpha + \beta_1 \cdot ES_{i,t} \times DT_t + \beta_2 \cdot ES_{i,t} + \beta_3 \cdot DT_t + \varepsilon_{i,t}$. 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 $Var(ES)$ and its interaction with $ES$. The third specification allows also for a time trend in ERCs. Data are from January 1984-December 2012, restricted to observations with $st.dev.[E[EPS]] > 0.05$. 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.

| | Dependent variable: cumulative announcement returns, $CAR_{i,t}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | NBER | NBER | NBER | Market | Market | Market | GDP | GDP | GDP |
| ES x DT | 0.00392*** | 0.00432*** | 0.00295*** | 0.00211*** | 0.00217*** | 0.00204*** | 0.00234*** | 0.00244*** | 0.000824 |
| | (3.69) | (3.97) | (2.97) | (3.35) | (3.45) | (3.81) | (3.59) | (3.81) | (1.52) |
| ES | 0.00803*** | 0.0103*** | 0.00488*** | 0.00756*** | 0.00886*** | 0.00310*** | 0.00741*** | 0.00901*** | 0.00419*** |
| | (26.24) | (11.46) | (5.29) | (21.22) | (8.88) | (2.90) | (18.18) | (9.29) | (4.28) |
| DT | 0.0109** | 0.0107* | 0.0123** | 0.00276 | 0.00271 | 0.00303 | 0.00261 | 0.00226 | 0.00421 |
| | (2.00) | (1.94) | (2.24) | (0.97) | (0.95) | (1.06) | (0.89) | (0.80) | (1.46) |
| ES x Var(ES) | | -0.000383*** | -0.000327** | | -0.000211 | -0.000207 | | -0.000267* | -0.000225* |
| | | (-2.61) | (-2.51) | | (-1.33) | (-1.56) | | (-1.76) | (-1.68) |
| Var(ES) | | 0.000161 | 0.000243 | | 0.000755 | 0.000834 | | 0.000581 | 0.000657 |
| | | (0.26) | (0.38) | | (1.16) | (1.25) | | (0.94) | (1.03) |
| ES x Time | | | 0.000000801*** | | | 0.000000866*** | | | 0.000000820*** |
| | | | (10.21) | | | (10.69) | | | (10.09) |
| Time | | | -0.00000107** | | | -0.000000841* | | | -0.00000107** |
| | | | (-2.31) | | | (-1.67) | | | (-2.11) |
| Intercept | -0.00206 | -0.00301 | 0.00294 | -0.00186 | -0.00603 | -0.00157 | -0.00180 | -0.00487 | 0.000340 |
| | (-1.49) | (-0.81) | (0.81) | (-1.16) | (-1.55) | (-0.36) | (-0.96) | (-1.20) | (0.09) |
| $N$ | 50103 | 50103 | 50103 | 50103 | 50103 | 50103 | 50103 | 50103 | 50103 |

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