CESifo WORKING PAPERS

6879
2018

January 2018

Revealing Downturns

Martin C. Schmalz, Sergey Zhuk

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
www.cesifo-group.org/wp

An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: www.CESifo-group.org/wp

CESifo *Working Paper No. 6879*
Category 13: Behavioural Economics

Revealing Downturns

Abstract

When Bayesian risk-averse investors are uncertain about their assets' cash flows' exposure to systematic risk, stock prices react more to news in downturns than in upturns, implying higher volatility in downturns and 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, rendering them difficult to distinguish. However, their relative fundamental performance diverges in downturns, enabling better inference. Consistent with these predictions, stocks' reaction to earnings news is up to 70% stronger in downturns than in upturns.

Keywords: financial economics, finance.

Martin C. Schmalz
Stephen M. Ross School of Business
University of Michigan
USA - 48109-1234 Ann Arbor MI
schmalz@umich.edu

Sergey Zhuk
Department of Finance
University of Vienna
Austria – 1090 Wien
sergey.zhuk@univie.ac.at

January 15, 2018
For helpful comments and discussions, we thank Tobias Adrian (discussant), Sugato Bhattacharyya, Markus Brunnermeier, Robert Dittmar, David Hirshleifer, Matthias Kehrig, John Laitner (discussant), Antonietta Mira, Stephen Morris, Venky Nagar, Valerio Poti, Uday Rajan, David Sraer, Laura Starks (the editor), Günter Strobl, Johannes Stroebel, Fabio Trojani, Pietro Veronesi, Luis Viceira, Christopher Williams, and especially Stefan Nagel, an outstanding referee, the audience at the 2015 AFA Meetings (Boston), 2013 European Meeting of the Econometric Society (Gothenburg), 7th International Conference on Computational and Financial Econometrics (London), 10th Christmas Meeting of German Economists Abroad (Konstanz), 2nd University of Michigan Economics & Finance Conference, New Economic School 20th Anniversary Conference, as well as seminar participants at the Federal Reserve Board of Governors, Frankfurt School of Finance and Management, Princeton University, and the University of Vienna. Shruthi Nayak and Christina Zafeiridou provided excellent research assistance.

"You only find out who is swimming naked when the tide goes out" (Buffett, 2001)

1 Introduction

Asymmetries between upturns and downturns arise in many domains. For example, evidence indicates that actively managed mutual funds tend to "underperform" in good times but tend to perform abnormally well when the economy is doing poorly (Moskowitz, 2000; Kosowski, 2006; Sun, Wang, and Zheng, 2009; Glode, 2011). Jenter and Kanaan (2015) show that boards fire CEOs more frequently after negative market shocks. Equity returns are negatively skewed, implying that stocks are slow to rise in expansions but quick to fall in market downturns (see e.g. Bollerslev, Engle, and Wooldridge, 1988; Campbell and Hentschel, 1992; Chen, Hong, and Stein, 2001). Perhaps one common theme across these domains is that decision makers (such as investors or company boards) are better at discerning good from bad projects (i.e., investments/managers/stocks) 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 between the relative quality of different 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. No behavioral distortions, time-varying earnings manipulation, asymmetric information, or other frictions are necessary. In particular, we show that when risk premia are positive, project-specific fundamental news in downturns carries more relevant information about the utility investors derive from investing in the project than news pertaining to performance in upturns.

Although the insight applies also to corporate finance and other fields, we focus our predictions on an asset-pricing application. We show that even when all parameter distributions are both symmetric and stable across states, prices can nevertheless react more sensitively to news in some states than in others. Specifically, on average, stocks react more to earnings news in downturns, which implies negative skew in the return distribution. More precisely, the sensitivity of the stock price to news is a function that is non-monotonic with respect to the underlying macro-economic state. The precise shape depends on the history of aggregate shocks, but its peak is guaranteed to tend to be at below-average market returns.

We offer a variety of empirical approaches to test these predictions. In particular, we first use non-parametric techniques to discern the shape of earnings response coefficients as a function of the market return in the quarter of the announcement. We then offer various OLS regressions to formally show that earnings response coefficients are statistically significantly different in various measures of downturns and upturns, even after controlling for potential confounding variables.

The model's key features are as follows. A firm's cash-flow realizations depend on an uncertain, firm-specific time-fixed parameter capturing idiosyncratic performance ("cash-flow alpha" – henceforth, a), as well as the realization of a market-wide factor. The correlation of the firm's cash flows with that risk factor is uncertain and 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.[1] They attempt to learn the parameters by observing updates to firms' fundamental performance, and conditioning that news on the state of the world in which the news was observed.

The inference investors make is quite intuitive. 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, although generally content with higher-than-expected earnings, investors also sense that over-performance in upturns may have been achieved with the aid of 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 associated with upturn observations is symmetric with respect to the sign of the news surprise: unexpectedly low cash flows in good times can be either due to

[1] It is well known since Merton (1980) that second moments can be learned arbitrarily quickly when a stochastic process is quasi-continuously observed. This assumption is satisfied for stock returns but not for firms' cash flows, which are reported only at a quarterly frequency.

low idiosyncratic performance (low a), which is bad news, or due to low market exposure (low 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.

By contrast, unexpectedly high earnings in bad times can be due to either unexpectedly high cash-flow alpha (high a) or unexpectedly low cash-flow beta (low b). Both interpretations imply 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 (low a) or due to high market correlation (high b), both of which are undesirable attributes. In sum, cash-flow news in downturns provides less ambiguous signals about firm value, irrespective of the sign of the earnings surprise. Therefore, Bayesian investors place more weight on news pertaining to firm performance in downturns than to performance in upturns, regardless of whether the news is good or bad. As a result, prices react more strongly to fundamental news in downturns than in upturns.

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), the cross-sectional dispersion of returns increases in bad times. As a result, volatility is endogenously countercyclical. Further, a direct consequence of higher dispersion combined with lower average returns in downturns is that the unconditional return distribution is negatively skewed. This prediction of our model is consistent with a well-known set of empirical observations. What was not known previously is that these patterns can be generated by a Bayesian model with parameter uncertainty as the only friction.

Empirically, we measure the price response to unexpected earnings news with earnings-response coefficients (ERC). Using non-parametric techniques we first generate figures of the ERC-market state relationship. Consistent with the model's predictions, we find that ERCs depend on the state of the economy. ERCs are highest when market return is about -25% or when GDP growth is about -5%. These downturn-ERCs are up to 70% higher than ERCs in upturns of similar magnitude. The fact that ERCs *peak* at a negative market return (rather than decrease monotonically with market returns) helps distinguish our explanation from potential alternative theories that could also generate variation of ERCs across market states. Ordinary-least-squares (OLS) estimations formally confirm that ERCs tend to be higher in downturns and reject the null hypothesis of no differences in ERCs across market states. This result is robust to various alternative ways of measuring market states and to controlling for various potential confounders.

The insights from this paper contribute to the literature by establishing that imperfect knowledge of *cash-flow* risk loadings combined with a positive risk premium implies asymmetric price reactions to news, as well as negatively skewed returns. As such, we simplify the intuition for several empirically observed asymmetries over the market cycle.

2 Related Literature

This paper belongs to a literature on learning in financial markets; see Pastor and Veronesi (2009) for a review. The models of Banerjee and Green (2013) and Veronesi (1999) predict asymmetric reactions across good and bad news, whereas our model generates an asymmetry across upturns and downturns but not across good and bad news.[2] Veronesi and Ribeiro (2002) predict higher co-movement of stock returns in recessions, whereas we explain higher cross-sectional dispersion in recessions, which leads to negatively skewed returns.[3]

Several existing papers explain asymmetries across market states in asset pricing and the intermediation sector with a combination of (a subset of) Bayesian learning, limited channel capacity of the decision maker, costly effort, asymmetric information, 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 Veld-

[2]Also, the agents in our model are all identical. As a result, there is no asymmetric information, prices contain no more information than fundamentals, and hence agents cannot learn from prices. Also, there are no regime switches in our model. The online appendix provides detail on the distinction of our "revealing downturns" effect and the "bad news effect" in the literature.

[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 world is known, but firm parameters are uncertain. There is no contradiction between the established finding that correlations increase in downturns and our prediction that cross-sectional dispersion increases, as we show in the online appendix. Volatility, dispersion, and return correlations all increase in bad times.

kamp (2014, 2016). Whereas these papers address distinct phenomena from ours, another difference is that our model has only two key assumptions: a positive risk premium and parameter uncertainty.

Our model is based on a joint dissertation chapter (Schmalz, 2012; Zhuk, 2012), in which we explain asymmetries in involuntary CEO turnover over the business cycle. Franzoni and Schmalz (2017) use a special case of the multidimensional filtering problem developed there to help explain how mutual funds' flow-performance sensitivity depends on the state of the economy. Our contribution also complements Acharya, DeMarzo, and Kremer (2011), who study the endogenously clustered release of news over the market cycle; by contrast, we take the release of information as given but study how the strength of the reaction to a given piece of news varies over the market cycle.

The above discussion refers to our theoretical contribution. The empirical contribution is to the literature on stock price responses to information releases. In that realm, our paper is most closely related to Johnson (1999), who shows that the state of the business cycle explains time variation in ERCs of Value Line firms over the period January 1970–September 1987.[4] By contrast, we use 1984-2012 IBES data, and we do not normalize ERCs with market equity to avoid the potential concern of a mechanical relationship between ERCs and the state of the market cycle. We also contribute the first non-parametric estimates of the relationship between ERCs and market states.

3 Model

This section describes a model of Bayesian learning about the value of several assets by a mass of identical risk-averse agents. The assets' cash flows experience idiosyncratic shocks; in addition, they are subject to economy-wide shocks. The key ingredient of the model is that exposure to the economy-wide shock differs across assets and is not perfectly known by investors.

[4] Relatedly, Collins and Kothari (1989) and Mian and Sankaraguruswamy (2012) find that ERCs are negatively related to risk-free interest rates and investor sentiment, respectively.

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 need to be compensated for it in equilibrium. Under these assumptions, how much the agent learns from a piece of fundamental information about her utility from holding a particular asset depends on the state of the economy. As a result, 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. Asset prices therefore 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*, an asymmetry exists across states of the economy in the price response to fundamental news.

3.1 Economy

A large number of stocks $i = 1, 2, \ldots, N$ exists 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, ξ_t, that is identical for all assets. Then the reduced-form cash-flow process can we written as

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

In this equation, a^i and b^i represent firm-specific parameters capturing average cash flows and the cash flows' sensitivity to the aggregate shock, respectively. We refer to them as cash-flow alpha and cash-flow beta. Investors are uncertain about the precise value of both of them. Next,

[5]We focus on market risk for simplicity. A similar argument 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 generalize the model later to show robustness of the main predictions.

although the exact distribution of ξ_t including its mean is irrelevant for our main predictions, for concreteness, we assume the market shocks ξ_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 with known variance σ_ε^2 and are 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 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 values 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 $\Omega_0^i = \mathcal{N}\left(\mu_0^i, \Sigma_0\right)$ 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 $I_t = \{\{Y_1^i\}, \xi_1, \{Y_2^i\}, \xi_2 \ldots, \{Y_t^i\}, \xi_t\}$ the information set that becomes available at time t. Note specifically that the realization of ξ_t is known at the time the infer-

[7]We fix σ_ε^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 exogenously assumed. Empirically, we offer specifications that control for variance of earnings surprises to capture the possibility that variation in the parameter distributions over time drives the empirical findings. Similarly, the assumption that risk factor realizations, ξ_t, are *iid*, is a deliberate choice: our theoretical results might be viewed as less surprising if the fundamental distributions were asymmetric and shocks were allowed to be correlated in the time-series. 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 volatility is higher in bad times (i.e., σ_ε^2 is a decreasing function of ξ_t). In fact, the opposite prediction (i.e., a lower price reaction to news in downturns) would obtain.

ence is made; as a result, the conditional distribution of beliefs remains normal despite the multiplicative form of the cash-flow process.[8] We use the following notation for conditional posterior beliefs Ω_t about parameters $\psi^i = \begin{pmatrix} a^i \\ b^i \end{pmatrix}$ at the end of time t,

$$\psi^i | I_t = \Omega^i_t \sim \mathcal{N}(\mu^i_t, \Sigma_t), \tag{3.4}$$

where

$$\mu^i_t = \begin{pmatrix} a^i_t \\ b^i_t \end{pmatrix} \qquad \Sigma_t = \begin{pmatrix} \sigma^2_{a,t} & \sigma_{ab,t} \\ \sigma_{ab,t} & \sigma^2_{b,t} \end{pmatrix}. \tag{3.5}$$

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

We are interested in the speed at which investors update these parameters and hence their estimation of the value of the asset, at a given t, as a function of a given realization of the aggregate state ξ_t. To that end, the next subsection derives the equilibrium price of the asset. After that, we model the belief dynamics. The combination yields the final result.

3.3 Valuation

In our baseline model, we assume identical, risk-averse investors that live for two periods. In such an overlapping-generations (OLG) economy, a stochastic discount factor (*sdf*), m_t, prices the uncertain dividend stream $\{Y^i\}_t$, as follows:

$$p^i_t = E_t \left[m_{t+1}(p^i_{t+1} + Y^i_{t+1}) \right] \qquad E_t \left[m_{t+1} \right] = \frac{1}{R}. \tag{3.6}$$

[8] If ξ_t were not directly observable, it could be easily inferred from the aggregate dividend $Y_t = \sum Y^i_t = N(\bar{a} + \bar{b} \cdot \xi_t)$ 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 from several existing approaches, as discussed in the literature review. In our model, a positive cash-flow surprise means cash flows are higher than expected, *given the current state of the economy.* Merely below-average cash flows are not necessarily bad news for a firm's value, and vice versa. The following numerical example clarifies why. Suppose current beliefs about an asset's parameters are $a_t = 0,\ b_t = 1$, and the market shock ξ_t is $\xi_t = 4$ (recall ξ_t has mean zero.) A cash flow of $Y^i_t = 3$ is higher than the average cash flow the stock generates (which is 0), but the investor is nevertheless negatively surprised, because the expected cash flow in the current state of the economy is $E[Y^i_t] = a^i + b^i \cdot \xi_t = 0 + 1 \cdot 4 = 4$. As a result, the investor downward-adjusts her beliefs about both a^i and b^i, perhaps to -0.1 and $+0.75$, respectively. By contrast, when the cash-flow realization is higher than expected given current beliefs and given the state of the market, for example, $Y^i_t = 5$, the investor will adjust upward her beliefs about both a^i and b^i.

The OLG setup affords the convenient feature that the *sdf* depends only on the realization of the current aggregate dividend, and not on individual stock returns or current beliefs about the stocks' parameters.[9,10]

Lemma 1. *The stochastic discount factor, m_t, is a function of the aggregate dividend $Y_t = \sum_{i=1}^{N} Y_t^i$.*

Because N is large, no learning about the aggregate dividend occurs. Thus, both the aggregate dividend and the stochastic discount factor are *iid*. As a result, we can solve recursively for the price of asset i:

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

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

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

$$= \frac{R}{R-1} E_t\left[m_{t+1} \cdot Y_{t+1}^i\right], \tag{3.7}$$

where $E_t\left[m_{t+1}\right] = \frac{1}{R}$ is used for the third equality. Using the functional form (3.1) for the reduced-form cash-flow process, the price takes a simple form:

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

[9] Relatedly, investors cannot learn betas from (higher-frequency) returns, because stock prices contain no more information than fundamentals, and investors are identical. For prices to contain additional information, some other unmodeled agents would have to do the work of pricing in additional information.

[10] We discuss a generalization and contrast the model with the existing literature at the end of this section. In short, our baseline model microfounds a stochastic discount factor that depends on intra-period earnings Y_t^i, but not on past earnings Y_{t-1}^i. This feature affords a constant price of risk (called ϕ below) in the economy, which simplifies the algebra and intuition. However, we show later that this assumption, which is purely for analytical convenience, is not necessary to generate the key results. The only necessary assumption is that risk prices are positive.

$$= \frac{R}{R-1} \left(E_t \left[a^i \right] \cdot E_t \left[m_{t+1} \right] + E_t \left[b^i \right] \cdot E_t \left[m_{t+1} \xi_{t+1} \right] \right). \tag{3.8}$$

Note the stochastic discount factor is always positive, but covaries negatively with the aggregate state because of investors' risk aversion. 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 $\phi = -R \cdot E_t \left[m_{t+1} \xi_{t+1} \right] > 0$.

The lemma reflects that 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. The next lemma shows that, for CARA utility, we can explicitly solve for the utility cost of bearing economy-wide risk, ϕ. Specifically, it can be thought of as the product of the price of risk (γ) multiplied by the quantity of macro-economic risk ($N\bar{b} \cdot \sigma_\xi^2$). We give this result to help with the intuition of why ϕ is positive; however, CARA utility is not assumed for any other result in the paper.

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

3.4 Intuition of the Main Result

This subsection gives the intuition behind our main result that prices respond more strongly to news in downturns than in upturns. Formal proofs are developed in the following 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. Because 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 them 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. To make this intuition more formal, note that in an *iid* environment, we can approximate the conditional expectation in equation (3.7) 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 analogous to the decomposition $E_t \left[m_{t+1} \cdot Y_{t+1}^i \right] = E_t \left[m_{t+1} \right] E_t \left[Y_{t+1}^i \right] + Cov \left(m_{t+1}, Y_{t+1}^i \right)$:

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

This expression conveys: a higher observation of Y_τ^i always increases the first component of the price (the "average" term – notice that m is equal to $\frac{1}{R}$ on average). However, when a higher-than-average observation of Y_τ^i occurs when m_τ has a below-average realization (i.e., in good times), 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 an above-average observation of Y_τ^i occurs amid an above-average realization of m_τ (i.e., in bad times), the covariance term also increases, strengthening the value implication of the good news. Symmetrically, bad cash flow news in bad times has a negative effect on both the first and the second term, thus leading to a strong price reaction, whereas 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 nuance to the above intuition. In particular, we now clarify why the relationship between reaction to news and the state of the economy is not monotonic (as the above intuition may suggest). The nuance obtains from comparing in which state of the economy, ξ_t, the alignment between what the investor cares about and what she observes is greatest. From lemma 2, the quantity about which the investor is interested in learning is $a^i - \phi b^i$. The information used as a learning input is the reduced-form cash flow process (3.1): $Y_t^i = a^i + b^i \cdot \xi_t + \varepsilon_t^i$. The asset value conditional on observed cash flows is thus

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

Subtracting and adding ϕb^i, the conditioning information can be rewritten as

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

This expression conveys that 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 thus most aligned – when $\xi_t + \phi$ is close to zero, i.e. when ξ_t is close to $-\phi$. Of course, $-\phi$ is smaller than 0 because $\phi > 0$, because of risk aversion. Thus, the signal-to-noise ratio is maximized when ξ_t is a somewhat negative number. But when the market-wide shock is extremely negative, for example, $\xi_t \approx -2 \cdot \phi$, more "noise" is present in the observation than when $\xi_t \approx -\phi$. Thus, we have a non-monotonic relation between the price reaction to earnings news and the aggregate state, whereas the peak price reaction obtains for negative realizations of the aggregate factor. The following subsection proves these ideas formally.

3.5 Formal Results

3.5.1 Updating Beliefs

Each period, investors observe new realizations of dividends of each asset and use these observations to form posterior beliefs according to (3.4). For simplicity of exposition, we focus on the special case of uninformed priors ($\Sigma_0^{-1} = 0$) here; we consider the general case with informed priors in the online appendix and find that the results are qualitatively similar. (Given that an informed prior can be represented with additional initial observations, the similarity in results is not surprising.) In the case of uninformed priors, one can express the posterior beliefs about means recursively in terms of observables as

$$\mu_t^i = \left(\sum_{k=1}^{t} x_k x_k'\right)^{-1} \cdot \sum_{k=1}^{t} x_t Y_t^i = \mu_{t-1}^i + \left(\sum_{k=1}^{t} x_k x_k'\right)^{-1} x_t \left(Y_t^i - x_t' \mu_{t-1}^i\right), \tag{3.14}$$

where $x_t = (1 \quad \xi_t)'$. The posterior covariance, again in terms of observables, is

$$\Sigma_t = \sigma_\varepsilon^2 \left(\sum_{k=1}^{t} x_k x_k'\right)^{-1} = \frac{\sigma_\varepsilon^2 / t}{\overline{\xi_t^2} - (\overline{\xi_t})^2} \begin{pmatrix} \overline{\xi_t^2} & -\overline{\xi_t} \\ -\overline{\xi_t} & 1 \end{pmatrix}, \tag{3.15}$$

where $\overline{\xi_t} = \frac{1}{t}\sum_{k=1}^{t} \xi_k$, and $\overline{\xi_t^2} = \frac{1}{t}\sum_{k=1}^{t} \xi_k^2$ are summary statistics of the history of aggregate shocks.

Some of the mechanics of the results become apparent when one assumes for simplicity that $\Sigma_t / \sigma_\varepsilon^2$ is diagonal; this is approximately true for large t. The term

$$x_t \left(Y_t^i - x_t' \mu_{t-1}^i\right) = \begin{pmatrix} Y_t^i - x_t' \mu_{t-1}^i \\ \xi_t \left(Y_t^i - x_t' \mu_{t-1}^i\right) \end{pmatrix} \tag{3.16}$$

in equation (3.14) then reflects the intuition that good news in good times or bad news in bad times both yield a positive update about the asset's risk loading b^i.[11] Moreover, it is easy to see in these expressions that when parameters are constant, the updating magnitudes tend to decline as $t \to \infty$. Equation (3.15) also makes clear why some uncertainty in earnings quality ($\sigma_\varepsilon^2 > 0$) is needed to make the problem we study non-trivial: with $\sigma_\varepsilon = 0$, two observations of data would be sufficient to drive the posterior variance to zero.

3.5.2 The Price Response to News Depends on Aggregate States

We are now ready to present our main theoretical result.

[11] To be precise, the intuition holds if $\xi_t - \overline{\xi_t}$ has the same sign as ξ_t, because $b_t^i - b_{t-1}^i = \frac{\sigma_\varepsilon^2/t}{\overline{\xi_t^2} - (\overline{\xi_t})^2} \cdot (\xi_t - \overline{\xi_t}) \cdot \left(Y_t^i - x_t' \mu_{t-1}^i\right)$. Assuming a normally distributed ξ_t, the probability of this event occurring is 75% for $t = 2$; 92.8% for $t = 20$; and 96.8% when $t = 100$.

Lemma 4. *The price change of asset i from time $t-1$ to time t, when the realization of the market-wide shock is ξ_t, is*

$$p_t^i - p_{t-1}^i = \lambda(\xi_t) \cdot \frac{1}{R-1} \cdot \frac{Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]}{\sqrt{Var_{t-1,\xi_t}\left[Y_t^i\right]}}, \tag{3.17}$$

where

$$\lambda(\xi_t) = \sigma_\varepsilon \frac{\overline{\xi^2} + \phi\overline{\xi} - \left(\phi + \overline{\xi}\right)\xi_t}{\sqrt{(t-1)\left(\overline{\xi^2} - (\overline{\xi})^2\right)}\sqrt{\left(\overline{\xi} - \xi_t\right)^2 + t\left(\overline{\xi^2} - (\overline{\xi})^2\right)}}, \tag{3.18}$$

with $\overline{\xi} := \overline{\xi_{t-1}} = \frac{1}{t-1}\sum_{k=1}^{t-1}\xi_k$, *and* $\overline{\xi^2} := \overline{\xi_{t-1}^2} = \frac{1}{t-1}\sum_{k=1}^{t-1}\xi_k^2$.

The key insight of the lemma is that, as a result of uncertainty about exposure of cash flows to aggregate risk, the strength of the price response to a given earnings surprise depends on the state of the market: $\lambda = \lambda(\xi_t)$. We investigate the precise nature of this relationship below. Note moreover that λ depends on the averages of past realizations $\overline{\xi}$ and squared realizations $\overline{\xi^2}$ of the state of the economy. Lastly, note that given our choice to normalize the earnings surprise $Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]$ by its standard deviation, $\sqrt{Var_{t-1,\xi_t}\left[Y_t^i\right]}$, the variance of price changes of asset i from time $t-1$ to time t is entirely determined by the ERC $\lambda(\xi_t)$:

$$Var_{t-1,\xi_t}\left[p_t^i - p_{t-1}^i\right] = \frac{\lambda(\xi_t)^2}{(R-1)^2}. \tag{3.19}$$

We thus focus on the ERC λ as a measure of how strongly prices react to one additional cash-flow observation, for a given macro state ξ_t.[12]

3.5.3 Which Conditions Maximize the Price Response to News?

The expression for lambda in equation (3.18) is not point-symmetric. To see this most clearly, consider the case when $\overline{\xi} = 0$. (This case corresponds to the average earnings an-

[12]The definition we use is slightly different from ERCs used in the literature, which don't normalize by its variance. We ensure robustness of both our theoretical and empirical results to the more standard definition in the online appendix.

nouncement: since $\{\xi_k\}$ has 0 mean, $\overline{\xi}$ also has a 0 mean.) Then,

$$\lambda(\xi_t) = \frac{\overline{\xi^2} - \phi\xi_t}{\sqrt{(t-1)\overline{\xi^2}\left(\xi_t^2 + t\overline{\xi^2}\right)}}. \tag{3.20}$$

The denominator of (3.20) is symmetric around 0, and the numerator is a decreasing function of ξ_t. Thus, on average across histories, $\lambda(\xi_t)$ tends to be higher in market downturns. The following proposition formalizes the intuition for the general case of $\overline{\xi} \neq 0$.

Proposition 1. *The strongest price response to news occurs at*

$$\xi_{t,\lambda_{max}} = -t \cdot \phi - (t-1) \cdot \overline{\xi}. \tag{3.21}$$

The first insight is that a positive risk premium ϕ shifts the peak response point to the left. This effect is stronger when investors already know the firm's parameters quite precisely. In that situation, an earnings announcement will only reveal significant additional information if it gives information on firm performance in downturns.

The second insight from the proposition is that the recent history of aggregate shocks matters for the sign and precise location of $\xi_{t,\lambda_{max}}$. Specifically, the more positive the sum of the $t-1$ aggregate shocks, $\sum_{k=1}^{t-1} \xi_k := (t-1) \cdot \overline{\xi}$, the more negative the ξ_t for which the earnings response is maximized. In other words, the "Revealing Downturns" effect is magnified after a prolonged market upturn; vice versa, when the recent history of macro realizations has been sufficiently bleak, the effect is attenuated. If $\overline{\xi} < \frac{t}{t-1} \cdot \phi$, the effect may even be reversed. This happens because after many downturn observations, agents already know very well how the asset behaves in market downturns, and they would learn relatively more from an upturn-observation.

In the next proposition, we directly compare downturns and upturns of the same size and we show that for a majority of realizations of $\overline{\xi}$, the response to news in downturns is stronger than in upturns.

Proposition 2. *For any positive number x and realization of $\overline{\xi^2}$, there exists $\xi^* < 0$ such that*

$$|\lambda(\xi_t = -x)| > |\lambda(\xi_t = +x)| \text{ } for \text{ } \overline{\xi} > \xi^*,$$
$$|\lambda(\xi_t = -x)| < |\lambda(\xi_t = +x)| \text{ } for \text{ } \overline{\xi} < \xi^*.$$

The proposition says that unless $\bar{\xi}$ is lower than some negative cutoff ξ^* (which would be the case if investors have already observed many downturn-observations), prices react more strongly to news that pertains to performance in market downturns.

Figure 1 illustrates how the predicted earnings response nonlinearly depends on the aggregate shock ξ_t, and how this relationship depends on the history of aggregate shocks, $\overline{\xi}$. Most lines are downward-sloping over the domain $\xi_t \in [-1, 1]$, indicating that the earnings response is weaker when the factor realization is high. Importantly, this is true not only for all positive values of $\bar{\xi}$, but also for a "neutral" history with $\overline{\xi} = 0$. Earnings responses are stronger for larger values of ξ_t only for strongly negative values of $\overline{\xi}$. In sum, the figure reiterates the message that price responses to news are asymmetric with respect to zero. Moreover, on average, the responses in downturns appear to be higher than in upturns on average across histories, summarized by $\overline{\xi}$. We establish that result formally now.

3.5.4 Results about Average Price Responses

So far we have documented the asymmetry in the reaction to news only for specific realizations of past shocks. However, in the empirical tests, we can only measure asymmetries between upturns and downturns that arise *on average* (because arbitrary choices would have to be made to decide how long a history to condition on, at which frequency to collect the macro shocks, etc.). Therefore, we now make formal claims about the average reaction to news by deriving propositions for "average beliefs" resulting from learning in previous periods.

For any period t, the average price response to news over all possible realizations of beliefs that could arise from market shocks previous to t is

$$\overline{\lambda}(\xi_t) = E_{(\xi_1,\ldots,\xi_{t-1})}[\lambda(\xi_t)]. \quad (3.22)$$

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

Proposition 3. *Suppose the distribution of ξ_t is symmetric. Then for any positive number x,*

$$\overline{\lambda}\left(\xi_t = +x\right) < \overline{\lambda}\left(\xi_t = -x\right). \tag{3.23}$$

3.5.5 ERC in terms of beliefs

Above, we derived ERCs in terms of observables, which will help guide our empirical analysis. However, from a theoretical perspective, one may wonder whether the above results are robust to investors receiving information about parameters also from sources other than specific earnings announcements. Therefore, in this subsection, we present similar results expressed in terms of current beliefs, irrespective of how these beliefs were formed.

Lemma 5. *The ERC and variance of earnings surprise in terms of beliefs are, respectively,*

$$\lambda\left(\xi_t\right) = \frac{\sigma_{a_t}^2 - \phi\sigma_{ab} - \left(\phi\sigma_b^2 - \sigma_{ab}\right)\xi_t}{\sqrt{\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2}}, \tag{3.24}$$

and

$$Var_{t-1,\xi_t}\left[Y_t^i\right] = \sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2, \tag{3.25}$$

where σ_a^2, σ_b^2 and σ_{ab} refer to the elements of the matrix introduced in equation (3.5)

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

It is clear once more that the strength of the price reaction to news depends on the macro state ξ_t if and only if risk loadings are uncertain, $\sigma_b^2 > 0$. The next proposition shows that the ERC is more likely to be higher in market downturns.

Proposition 4. *The strongest stock price reaction to fundamental news occurs at*

$$\xi_{max}^{\lambda} = -\phi\left(1 + \frac{\sigma_\varepsilon^2\sigma_b^2}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2}\right) + \frac{\sigma_\varepsilon^2}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2}\sigma_{ab}. \tag{3.26}$$

The proposition shows that two terms affect the location of the maximum. The first reflects the intuition given previously and is always negative. The second term can be positive or negative depending on the sign of σ_{ab}, which in turn is determined by the sign of the average of the past observations $\overline{\xi}$ (equation (3.15)). $\sigma_{ab} > 0$ 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 $\left(a^i - b^i|\xi_t|\right)$, but know less about how the asset performs in upturns $\left(a^i + b^i|\xi_t|\right)$. As a result, prices may respond more strongly to news received in market upturns. By contrast, $\sigma_{ab} < 0$ means investors already know quite precisely the asset payoff in market upturns $\left(a^i + b^i|\xi_t|\right)$, whereas great uncertainty exists about the payoff in a downturn $\left(a^i - b^i|\xi_t|\right)$. In that case, the price response in downturns is stronger than in upturns – even more so than if $\sigma_{ab} = 0$. Because the distribution of σ_{ab} is centered around zero, on average, $\sigma_{ab} = 0$ and the price response in downturns is stronger than in upturns.

Note that the results in this subsection also hold if the variance of idiosyncratic noise, σ_ε^2 changes over time. The above discussion (but not the mathematic results) assumed implicitly that this variance is constant, and does not depend on the business cycle. If, however, volatility changes with the business cycle, our empirical results could be affected. Specifically, as we can see from equation (3.24), increased volatility in downturns would predict a *lower* ERC in downturns than in upturns (a prediction opposite to the one emphasized in the present paper). To alleviate that concern in the empirical results, we control for $Var_{t-1,\xi_t}\left[Y_t^i\right]$, which is increasing in σ_ε^2 and is ex-ante symmetric with respect to ξ_t. Introducing this control means, in the context of our model, that we keep the denominator of the ERC expression (3.24) fixed, whereas the numerator is clearly decreasing in ξ_t and does not depend on σ_ε^2.

3.5.6 Dispersion and Skewness

A direct consequence of the above predictions is that returns are more dispersed in downturns than in upturns; that is, volatility is higher in downturns than in upturns. The unconditional distribution of returns is therefore negatively skewed, even when the distributions of parameters and shocks are symmetric and shocks are *iid*.[13] To show this result formally,

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

consider the return between periods $t-1$ and t:

$$R_t^i = \frac{p_t^i + Y_t^i - p_{t-1}^i}{p_{t-1}^i}. \tag{3.27}$$

The following proposition shows that, for the majority of prior beliefs, returns are negatively skewed even if the underlying fundamental distribution is symmetric.

Proposition 5. *Suppose the distribution of* ξ_t *is symmetric. For any realization of* $\overline{\xi^2}$ *, a* $\xi^s < 0$ *exists such that*

$$E_{t-1}\left[\left(R_t^i - E_{t-1}\left[R_t^i\right]\right)^3\right] < 0 \tag{3.28}$$

for any $\overline{\xi} > \xi^s$.

This proposition shows that the only ingredients needed to generate unconditionally negatively skewed returns are positive risk premia and uncertainty about cash-flow risk loadings. Hence, in light of our model, negatively skewed returns are not a puzzling feature of asset prices, but can easily be explained with Bayesian learning about uncertain parameters.[14]

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. First, the model uses an overlapping-generations structure. This modeling choice is only for simplicity and tractability. The mechanism works very similarly for a general representative agent that maximizes expected utility in an infinite-horizon setup, as we show in the online appendix.

Relatedly, we focus only on cross-sectional learning. This focus is distinct from and largely orthogonal to a substantial part of the learning literature that focuses on learning about the stochastic discount factor (see Pastor and Veronesi, 2009). Including learning about the stochastic discount factor would not substantially change our results. The reason is that in our

[14] The theoretical assumption made here that fundamentals are not skewed is not meant to be a positive statement. Rather, we mean to convey that when the underlying parameters are already negatively skewed, the distribution of returns will be *even more* skewed. That is, uncertainty about fundamental risk loadings can work as a "skewness accelerator." The online appendix discusses this feature in detail.

setup, the parameters $\bar{a}$ and $\bar{b}$ represent beliefs of investors about the overall economy; those would depend on the realization of past shocks in a more complete model. However, $\bar{a}$ and $\bar{b}$ would only affect the sensitivity of an individual stock's earnings response through the risk premium, ϕ. It is easy to show that ϕ 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 including investor learning about the stochastic discount factor.

Another limitation is that our parameters a^i and b^i are time-fixed. 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 fundamental changes, for example changes in 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 δ 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) ERCs peak in downturns, and (2) ERCs are higher in downturns than in upturns, on average. Whereas prediction (2) is key for the "revealing downturns" intuition, prediction (1) of a non-monotonic relationship between ERCs and market state is a more distinct prediction of our model that is probably harder to obtain with alternative theories. We present our main results as figures obtained from non-parametric estimations, owing to the non-monotonic nature of the relationship between ERCs and market state. We also offer OLS regression results to be able to assess the statistical significance of an upturn/downturn difference in ERCs after controlling for potentially confounding covariates.

4.1 Empirical Methodology, Variable Definitions, and Data Sources

4.1.1 Empirical Methodology

Our goal is to measure how the strength of the stock price reaction to a given "earnings surprise" depends on the state of the economy. ERCs are a standard solution in the accounting literature to measure the strength of the reaction to a given piece of news while filtering out noise (see Ertimur, Livnat, and Martikainen (2003); Jegadeesh and Livnat (2006)). They have been used to similar ends in the finance literature (see, e.g., Pástor, Taylor, and Veronesi (2009)). The basic idea of an ERC is illustrated by the following regression:

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

In this regression, $CAR_{i,t}$ is the cumulative abnormal return of stock i around an announcement at time t, $ES_{i,t}$ is the earnings surprise, and λ is the ERC.[15] The statistical "null" hypothesis is that ERCs do not depend on the state of the economy. Note that equation (4.1) is the empirical analogue of equation (3.17) in the theory. The theoretical predictions derived in propositions 1 and 3 therefore translate into the following two alternative hypotheses:

1. The highest ERCs occur in downturns.

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

To test these alternative hypotheses against the null, our non-parametric analyses estimate a version of equation (4.1) that allows ERCs to vary with the state of the economy ξ_t:

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

We use local polynomial regressions of order zero with an Epanechnikov kernel. We thus calculate the best fit of $\lambda(\xi)$ without assuming a specific functional form.[16] The null hypothesis

[15] We follow Pástor, Taylor, and Veronesi (2009) (PTV) generally in the ERC estimation. However, one difference is that in our OLS analysis, we always estimate ERCs in a regression (rather than dividing returns by earnings surprises).

[16] The finance literature has used similar methods at least since Stanton (1997). To perform the estimation,

here is that the ERC, $\lambda(\xi_t)$, is positive but flat and does not depend on the state of the economy, $\lambda(\xi_t) = \lambda = const. > 0$, whereas the model predicts a positive ERC with a non-monotonic shape with the strongest reactions on average when negative aggregate states occur, $\xi_t < 0$.

We also offer OLS tests to examine the second key prediction, which is that ERCs on average are larger in downturns. We do so in two ways. First, we estimate the following regression across all firm-quarter observations:

$$CAR_{i,t} = \alpha + \beta_1 ES_{i,t} \times DT_{i,t} + \beta_2 ES_{i,t} + \beta_3 DT_{i,t} + \varepsilon_{i,t}, \tag{4.3}$$

where $DT_{i,t}$ is a downturn dummy that takes unity if the earnings period is a downturn, and zero otherwise. β_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 no difference in ERCs exists between upturns and downturns ($\beta_1 = 0$), whereas our model predicts the difference, namely, β_1, to be positive, in addition to a positive β_2. Graphically, this specification can be imagined as fitting one constant each for ERCs in downturns and upturns, respectively, and testing if that constant is different for the two states.

To account for time-changing volatility, including the empirically relevant case in which volatility is higher in downturn periods, we cluster the standard errors by the month of the announcement. We furthermore provide specifications that add various controls, namely 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 variation in earnings quality (measured, e.g., as the variance of idiosyncratic noise in earnings, as discussed in section 3.5.5) over states of the

we use smooth coefficient models (Hastie and Tibshirani, 1993; Li and Racine, 2007). Thus, $\lambda(\xi)$ is calculated according to,

$$\lambda(\xi) = \frac{\sum_{i,t} CAR_{i,t} \cdot ES_{i,t} K\left(\frac{\xi_t - \xi}{h}\right)}{\sum_{i,t} ES_{i,t}^2 \cdot K\left(\frac{\xi_t - \xi}{h}\right)}.$$

The expression is similar to how a coefficient is estimated in a linear regression, the only difference being each observation is weighted with an Epanechnikov kernel $K\left(\frac{\xi_t - \xi}{h}\right)$, which is decreasing in the distance between ξ and ξ_t (the realization of the aggregate shock corresponding to the observation). 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.

economy drives the variation in ERCs across these states, as observed in the non-parametric analysis. In addition, we want to assure robustness to potential model misspecification due to the fact that ERCs in general depend on the history of shocks. To do so, for the specifications in which downturns are defined based on market return or GDP growth, we complement regression (4.3) with averages of past aggregate shocks and squared past shocks, $\overline{\xi}$ and $\overline{\xi^2}$ as well as $\overline{\xi} \times ES$ and $\overline{\xi^2} \times ES$ as additional controls. To calculate these averages, for each earnings announcement we use the previous five years of quarterly observations.

As a second specification, we run

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

with similar variations in terms of controls as the first OLS specification. This second specification is best imagined as forcing a linear relationship between ERC and the aggregate state onto $\lambda(\xi_t)$ in equation (4.2). The null hypothesis is that ERCs do not depend on the aggregate state, and thus $\beta_1 = 0$. Alternative hypothesis 2 is that $\beta_1 < 0$.

4.1.2 Variable Definitions and Data Sources

We calculate cumulative abnormal announcement returns by computing raw cumulative earnings announcement returns net of Fama-French 49-industry returns. We measure these $CAR_{i,t}$s 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. The definition of earnings surprises is

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

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, and $st.dev.\left[EPS_{i,t}\right]$ is the standard deviation of expected earnings per share averaged across all analysts from the last pre-announcement set of forecasts for the given firm and fiscal quarter. We obtain these forecasts as well as the date of the earnings announcement from the IBES unadjusted detail files. We show in the online appendix that the empirical results are robust to alternative definitions as well.

The reference period pertaining to an earnings announcement at date t is the quarter during which the firm earned the earnings it reports at that date-t-announcement. The announcement date is typically a few weeks after the end of the reference period, and is available from IBES. Corresponding to the model's timeline, we measure the state of the economy, ξ_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.

For the non-linear tests, we measure the state of the economy, ξ_t, with market returns from CRSP in one specification and with GDP growth from the Bureau of Economic Analysis (BEA) 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 at least 1.5 months of the quarter coincide with 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.

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. We truncate the observations at 1% levels to remove outliers. After these filters, we end up with 195,924 observations.

4.1.3 Summary Statistics

Table 1 presents summary statistics. We report the mean standard deviation and several percentiles of both CAR and ES separately for the different downturn and upturn definitions.

Whereas the "market" and "GDP" definitions roughly split the sample in half, only about 15% of the earnings observations fall in an NBER downturn period. The table shows that cumulative abnormal announcement returns are slightly positive on average, both unconditionally and in the different market states. The mean earnings surprises are mildly positive across subsamples. An important observation is that earnings surprises in downturns are not consistently lower than earnings surprises in upturns; according to the GDP definition of a downturn, earnings surprises are actually 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. An implication for the interpretation of our results is that a stronger response to bad news than to good news is unlikely to drive a larger earnings response in downturns. We show direct evidence on the earnings response to good and bad news in the online appendix.

The summary statistics also reveal 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 the nearest hundredth. Observations with values of 0.01 for the standard deviation primarily drive that effect. To investigate the effect of this feature of the data, we analyze histograms of the sample, reported in the online appendix. Discarding observations with small standard deviations of earnings surprises can reduce such "discretization noise." We do so in a robustness check, reported in the online appendix. The empirical results tabulated there are qualitatively similar and consistent across the full and the restricted sample. If anything, slightly more significant results obtain with the restricted sample. This difference in results is consistent with less attenuation bias due to measurement noise in the restricted sample. For transparency, the results we report in the main paper are based on the full sample.

4.2 Empirical Results

4.2.1 Non-parametric Estimation Results

Figures 2 and 3 give non-parametric estimates of the ERC as a function of the economic state, where the market return and GDP growth are used as proxies for the state of the economy, respectively. The two figures are the empirical analogue to the simulations presented in Figure 1.

The ERCs are significantly positive throughout their domain. The point estimate of the ERC at -25% market return is about 0.0087, with a 95% confidence band of about 0.0005 in either direction, whereas the point estimate of ERCs at +20% market return is 0.0071, with 95% confidence bands tighter than 0.0003 in either direction. Similarly, ERCs at -5% GDP growth are 0.012, and 0.007 at 5% GDP growth, respectively. Thus, ERCs are about 25%-70% higher at their peak in downturns than at their low in upturns, depending on which measure of macroeconomic state we use.

More generally, the figures show, consistent with the model predictions, that the relationship between ERCs and state of the economy is not flat, not linear, and not monotonic, thus rejecting the null hypotheses. 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.

Note that these results not only provide strong support for the model predictions; they also distinguish the theory we propose from other potential explanations. For example, higher idiosyncratic volatility in downturns would lead to a monotonically *increasing* relationship between ERCs and market state, whereas the data show a non-monotonic relationship that is *decreasing* over much of its domain. Moreover, if changes in risk aversion across market states were the reason for higher ERCs in downturns than in upturns, the function should be monotonic. The fact that ERCs as a function of market state display a non-monotonic shape lends support to a unique prediction of our model (specifically, Proposition 1).

4.2.2 OLS Estimation Results

We now provide evidence from OLS regressions to re-examine the second hypothesis, namely whether the average ERCs in downturns (e.g., in the halves left of zero of Figures 2 and 3) are indeed significantly bigger than those in the halves right of zero, even after controlling for potential confounders. Note that in doing so, we force the ERC to jump at the midpoint, rather than using only more extreme upturn or downturn realizations from the tails of these functions. Thus, our OLS specification makes it more difficult to reject the null hypothesis that no difference exists in ERCs between upturns and downturns. For the same reason, the economic significance of the "revealing downturns" mechanism is best judged from the non-parametric estimation results rather than from the linear tests presented here.

Table 2 reports the results. The dependent variable in all specifications is the cumulative abnormal announcement return. Columns (1) to (3) report results using the NBER downturns definition. Columns (4) to (7) report results using the "market" return downturn definition. Columns (8) to (11) report results using the "GDP" downturn definition. The first specification of each of the three sets of results only has ES, DT, and their interaction as explanatory variables. The second specification also includes the variance of earnings surprises and its interaction with the earnings surprise. The third specification of each set 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 ERCs ensures that the effect we identify comes from a business cycle of shorter frequency and not from secular trends in earnings quality, or from other time trends that may affect ERCs and that might be correlated with macroeconomic states at the same time. The last specifications for each of the *market* and *GDP* downturn definitions, respectively, include also the averages of past ξ and ξ^2 as controls. These specifications test whether the asymmetry persists even when the history of shocks is controlled for.

In all specifications, we expect a positive ERC, that is, a significantly positive coefficient on the earnings surprise, ES. This result obtains, as reported in the second row of the table. For example, the first specification displays a positive and highly statistically significant coefficient of 0.00220 on the explanatory variable ES. That coefficient is the ERC in the baseline, that is, in upturns, when the downturn dummy DT takes the value zero.

The key coefficients are those on the interaction between ES and DT, reported in the first row. They indicate whether ERCs are significantly higher during downturns. The coefficient on the interaction term in the first specification is 0.00735. It indicates that ERCs in downturns are on average 30% higher than in the baseline. That increase in the ERCs in downturns relative to upturns is statistically significant at the 1% level. The second specification yields an ERC in upturns of 0.00435. It increases by 0.00174 or 40% in downturns. Again, the difference is highly statistically significant. A similar increase is reported in the most saturated specification (3).

The specifications using the market return downturn definition, reported in columns (4) to (7), report similar upturn-ERCs, ranging from 0.00366 to 0.00709, and statistically significant increases of the ERC in downturns of about 0.001. The specifications using the GDP definition of downturns in columns (8) to (11) show a similar pattern. Upturn-ERCs range from 0.00387 to 0.00691, and they increase by 0.000566 to 0.00143 points in downturns. The difference between downturn ERCs and upturn ERCs is quantitatively smaller in specifications (4) to (11) compared to specifications (1) to (3) because more earnings announcements refer to performance in downturns according to these definitions, compared to NBER recessions. Recall from the non-parametric plots in Figures 2 and 3 that the highest ERCs occur in quite strong downturns. As a result, splitting the sample in such a way that allows states of the economy to enter the "downturn" definition that also comprises weaker contractions will attenuate the measurement of differences between peak and trough of the ERC function.

Table 3 presents the results of OLS regressions that include the interaction between earnings surprise and the continuous market state variable, rather than a downturn dummy. Because only the market and GDP measures of aggregate state are available as a continuous variable, we cannot include the NBER specifications. Across all specifications, the sign of the interaction coefficient is negative and highly statistically significant. This finding corroborates the findings from the non-parametric regressions, which have the ERC-market state relationship declining over most of the domain, and also of the OLS results with downturn dummies, which indicate a higher ERC for lower realizations of ξ_t. We conclude that the data support the model's qualitative predictions.

4.3 Test of Quantitative Predictions

In this subsection we provide evidence that the theoretical explanation advanced above can quantitatively account for the observed variation in ERCs across market states. To make ERC levels comparable across firms of different sizes, we first calculate a normalized announcement return as[17]

$$R_t^i = \frac{p_t^i - p_{t-1}^i}{p_{t-1}^i} = \frac{\lambda(\xi_t)}{E[a^i - \phi b^i]} \cdot \frac{Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]}{\sqrt{Var_{t-1,\xi_t}\left[Y_t^i\right]}}. \tag{4.6}$$

The ERC then becomes

$$ERC = \frac{\lambda(\xi_t)}{E[a^i - \phi b^i]} = \tag{4.7}$$

$$\frac{1}{\frac{E[a^i]}{\sigma_\varepsilon}\left(1 - \phi\frac{E[b^i]}{E[a^i]}\right)} \cdot \frac{\overline{\xi^2} + \phi\overline{\xi} - \left(\phi + \overline{\xi}\right)\xi_t}{\sqrt{(t-1)\left(\overline{\xi^2} - \left(\overline{\xi}\right)^2\right)}\sqrt{\left(\overline{\xi} - \xi_t\right)^2 + t\left(\overline{\xi^2} - \left(\overline{\xi}\right)^2\right)}}. \tag{4.8}$$

This size-neutral ERC definition no longer depends on the absolute values of the parameters, but only on their relative values. For a quantitative evaluation, we need estimates of $E\left[a^i\right]$, $E\left[b^i\right]$ and σ_ε. To arrive at these estimates, for every earnings announcement, we regress earnings per share Y_t^i on realizations of the market return ξ_t during the reference period, using the previous five years of quarterly observations for each earnings announcement:

$$Y_t^i = a^i + b^i\xi_t + \varepsilon_t^i. \tag{4.9}$$

The online appendix provides more details. We use the estimated parameters to calculate $\frac{E\left[a^i\right]}{\sigma_\varepsilon}$, $\frac{E\left[b^i\right]}{E\left[a^i\right]}$, $\overline{\xi}$, and $\overline{\xi^2}$ and then calculate the average across all announcements in the sample for each of these terms. The parameter ϕ measures how strongly investors need to be compensated for taking risks. We assume 1.5% as the quarterly market risk premium. Finally, we need to ensure the correspondence between the empirical measure of the uncertainty of earnings

[17] A more standard return definition would include the current dividend, $R_t^i = \frac{p_t^i + Y_t^i - E\left[p_t^i + Y_t^i\right]}{E\left[p_t^i + Y_t^i\right]}$. We omit dividends here, because doing so yields significantly simpler expressions. We verified empirically that our return definition is quantitatively similar to the one we use.

surprises, which is the variance of analyst forecasts, and its theoretical analogue. The model's variance of earnings surprises is 1, whereas the standard deviation of earnings surprises is $st.dev\,[ES] = \sqrt{Var\,[ES]} \approx 2.784795$. This factor translates the normalized model-predicted ERCs as per equation 4.8 to yield functions that depict how ERCs depend on ξ_t.

Figure 4 shows the resulting model-predicted ERC as a function of the market state. The values are quantitatively similar to the empirically observed values, presented in Figure 2, and the differences between upturns and downturns are, if anything, larger in the simulation. These findings indicate that the model can quantitatively account for the empirically observed variation.

4.4 Robustness Test

We provide an additional test of the model predictions as follows. First, we linearize the expression (4.8) around zero,

$$ERC \approx Q_{0,t-1} + Q_{1,t-1} \cdot \xi_t, \tag{4.10}$$

where

$$Q_{0,t-1} = ERC|_{\xi_t=0} \qquad \text{and} \qquad Q_{1,t-1} = \left(\frac{dERC}{d\xi_t}\right)|_{\xi_t=0}. \tag{4.11}$$

(Wo omit stating the full expressions.) The main empirical work presented so far implicitly assumed that $Q_{0,t-1}$ and $Q_{1,t-1}$ are constants, thus testing only the first-order implication of the model that, on average across histories, ERCs are higher in downturns than in upturns. However, the model in fact predicts that the ERC's dependence on market states may depend on histories, as reflected by history-dependent coefficients $Q_{0,t-1}$ and $Q_{1,t-1}$, thus introducing the potential for model misspecification in our main results. To respond to this concern, we already included these quantities (which reflect summary statistics of histories of aggregate shocks) as additional controls in the previously presented results. Here, as an additional robustness test, we regress cumulative abnormal returns directly on $Q_{0,t-1}$ and $Q_{1,t-1} \cdot \xi_t$, as follows:

$$CAR_{i,t} = A \cdot Q_{0,t-1} \cdot ES_{i,t} + B \cdot Q_{1,t-1} \cdot \xi_t \cdot ES_{i,t} + \varepsilon_{i,t}. \quad (4.12)$$

Table 4's specification (1) presents the results. As predicted by the theory, all coefficients are significantly positive and highly statistically significant, indicating that our qualitative results are robust to the particular model misspecification concern. If $Q_{0,t-1}$ and $Q_{1,t-1}$ as well as the aggregate state ξ_t were precisely measured, both coefficients A and B should be equal to one in theory. In practice, however, our empirical measure of ξ_t is indeed only a proxy for the state of the economy, and $Q_{0,t-1}$ and $Q_{1,t-1}$ are measured with error.[18] One should thus expect attenuated coefficients, especially for the estimate of B which measures sensitivity of announcement returns to a quantity involving the proxy ξ_t.

To test whether attenuation due to measurement noise is indeed the most likely explanation, we offer a second specification (2) in which we smooth the variables with a bandwidth of 5 months and a third specification (3) with simple averages of $Q_{0,t-1}$ and $Q_{1,t-1}$ (corresponding to extreme smoothing to the time series average). Consistent with attenuation bias driving down the coefficients in specification (1), especially for the interaction of ES, $Q_{1,t-1}$, and ξ_t, the coefficients increase from specification (1) to (3), especially in row 2. We conclude that the particular concern about model misspecification related to the history-dependence of ERCs is unlikely to drive the main results. Instead, quite nuanced model predictions regarding the history-dependence of ERCs find support in the data.

5 Conclusion

This paper provides a new and simple rationale for asymmetries in investors' reaction to news over the market or business cycle. Specifically, a Bayesian learning model predicts that investors react more strongly to news in downturns than in upturns when they are uncertain

[18] An important reason why $Q_{0,t-1}$ and $Q_{1,t-1}$ are measured with noise is that our empirical measure of ξ is not the true ξ from the model. For example, a three-month negative market return during a secular up-trend would turn our empirical measure of ξ negative, although from an SDF perspective the economy is probably not in a downturn. An additional and maybe even more important reason is that $Q_{0,t-1}$ and $Q_{1,t-1}$ depend on our proxies about investors' beliefs about a and b, which necessarily depend on arbitrary assumptions such as how many periods are used for learning.

about individual assets' risk loadings. 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 70% more strongly to earnings news when the news pertains to firm performance in downturns than when the news pertains to performance in upturns. A direct consequence of this mechanism is that unless cash-flow risk loadings are measured with perfect accuracy, volatility is countercyclical, and stock returns are negatively skewed, even if fundamentals are not.

These results shed new light on how information gets impounded into stock prices. Specifically, the speed at which the cross-section of stock prices becomes reflective of fundamentals is faster in downturns than in upturns. Bayesian learning is sufficient to explain this pattern.

We conclude that the cleansing effect of recessions applies not only to real economic activity, but also to the price vector. Our results also suggest that "revelation risk" builds up during upturns and gets resolved once investors observe how firms performed "when the tide goes out." Implications for the dynamics of the aggregate stock market and macroeconomics are left for future research.

Appendix

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

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. Her expected utility is

$$U(x) = E_t \left[u \left(C_{t+1} + x \left(Z_{t+1} - Rp_z \right) \right) \right]. \tag{5.1}$$

In equilibrium, utility should be maximized when $x = 0$:

$$0 = U'(x)\,|_{x=0} = E_t \left[u' \left(C_{t+1} \right) \left(Z_{t+1} - Rp_z \right) \right]. \tag{5.2}$$

Therefore,

$$p_z = \frac{1}{R} E_t \left[\frac{u'(C_{t+1})}{E_t \left[u'(C_{t+1}) \right]} Z_{t+1} \right], \tag{5.3}$$

and the SDF is equal to

$$m_{t+1} = \frac{1}{R} \frac{u'(C_{t+1})}{E_t \left[u'(C_{t+1}) \right]}. \tag{5.4}$$

If W_0 is the initial wealth of the young generation in the OLG model, and p is the the price of the whole economy (it is a constant, because no learning about the aggregate state occurs), then the agents' consumption at $t+1$ is a function of Y_{t+1}

$$C_{t+1} = (W_0 - p) \cdot R + p + Y_{t+1}. \tag{5.5}$$

Proof of Lemma 3. (Valuation for CARA utility)

For normally distributed Z and a constant ρ,

$$E\left[e^{\rho Z} \right] = e^{\rho E[Z] + \frac{\rho^2}{2} Var[Z]}, \tag{5.6}$$

$$E\left[Z \cdot e^{\rho Z} \right] = \left(E[Z] + \rho Var[Z] \right) \cdot e^{\rho E[Z] + \frac{\rho^2}{2} Var[Z]} = \left(E[Z] + \rho Var[Z] \right) \cdot E\left[e^{\rho Z} \right]. \tag{5.7}$$

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

$$\phi = -E_t\left[m_{t+1}\xi_{t+1}\right] = -\frac{1}{E_t\left[e^{-\gamma Y_{t+1}}\right]} E_t\left[e^{-\gamma Y_{t+1}}\xi_{t+1}\right]. \tag{5.8}$$

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

$$E_t\left[e^{-\gamma Y_{t+1}}\xi_{t+1}\right] = E_t\left[e^{-\gamma N\left(\bar{a}+\bar{b}\cdot\xi_{t+1}\right)}\xi_{t+1}\right] = -\gamma N\bar{b}\sigma_\xi^2 \cdot E_t\left[e^{-\gamma Y_{t+1}}\right]. \tag{5.9}$$

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

Proof of Lemma 4.

We can rewrite the equation characterizing the value of the asset in vector notation, using $\Phi = (1 \quad -\phi)'$ and notation from (3.5), as follows:

$$p_t^i = \frac{1}{R-1} E_t\left[a^i - \phi b^i\right] = \frac{1}{R-1}\Phi'\cdot\mu_t^i. \tag{5.10}$$

Price changes are then

$$p_t^i - p_{t-1}^i = \frac{1}{R-1}\Phi'\left(\mu_t^i - \mu_{t-1}^i\right) =$$

$$\frac{1}{R-1}\frac{\Phi'\Sigma_t x_t}{\sigma_\varepsilon^2}\cdot\left(Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]\right), \tag{5.11}$$

whereas the second equality follows from equation (3.14) and replacing $\left(\sum_{k=1}^t x_k x_k'\right)^{-1} = \frac{\Sigma_t}{\sigma_\varepsilon^2}$ as per (3.15). We use expression (5.11) together with equation (3.17) to write λ as

$$\lambda = \frac{\Phi'\Sigma_t x_t}{\sigma_\varepsilon^2}\cdot\sqrt{Var_{t-1,\xi_t}\left[Y_t^i\right]}. \tag{5.12}$$

Note that

$$Var_{t-1,\xi_t}\left[Y_t^i\right] = Var_{t-1,\xi_t}\left[x_t'\begin{pmatrix} a^i \\ b^i \end{pmatrix} + \varepsilon_t^i\right] = x_t'\Sigma_{t-1}x_t + \sigma_\varepsilon^2 \tag{5.13}$$

and

$$\Sigma_t x_t \left(x_t' \Sigma_{t-1} x_t + \sigma_\varepsilon^2\right) = \sigma_\varepsilon^2 \Sigma_{t-1} x_t, \tag{5.14}$$

whereas the last expression obtains by replacing $x_t x_t' = \sigma_\varepsilon^2 \left(\Sigma_t^{-1} - \Sigma_{t-1}^{-1}\right)$, again using equation (3.15). We can now rewrite the above expression (5.12) for λ as

$$\lambda = \frac{\Phi' \Sigma_{t-1} x_t}{\sqrt{x_t' \Sigma_{t-1} x_t + \sigma_\varepsilon^2}}. \tag{5.15}$$

Finally, to obtain the expression for λ in terms of observables, we substitute Σ_{t-1} from equation (3.15).

Proof of Proposition 1.

Since, by lemma 4,

$$Var_{t-1,\xi_t}\left[\Phi'\left(\mu_t^i - \mu_{t-1}^i\right)\right] = Var_{t-1,\xi_t}\left[\lambda \cdot \frac{Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]}{\sqrt{Var_{t-1,\xi_t}\left[Y_t^i\right]}}\right] = \lambda^2, \tag{5.16}$$

we have

$$\lambda^2 = Var_{t-1,\xi_t}\left[\Phi'\left(\mu_t - \mu_{t-1}\right)\right] = \Phi' Var_{t-1,\xi_t}\left[\left(\mu_t - \mu_{t-1}\right)\right]\Phi =$$

$$\Phi'\left(\Sigma_{t-1} - \Sigma_t\right)\Phi = \Phi'\Sigma_{t-1}\Phi - \Phi'\Sigma_t\Phi. \tag{5.17}$$

Note that $\Phi'\Sigma_{t-1}\Phi$ does not depend on ξ_t. Hence, the maximum of λ^2 and hence of λ is attained when $\Phi'\Sigma_t\Phi$ is minimized. Given that

$$\Phi\Sigma_t\Phi = \frac{\sigma_\varepsilon^2/t}{\overline{\xi_t^2} - (\overline{\xi_t})^2}\begin{pmatrix} 1 & -\phi \end{pmatrix}\begin{pmatrix} \overline{\xi_t^2} & -\overline{\xi_t} \\ -\overline{\xi_t} & 1 \end{pmatrix}\begin{pmatrix} 1 \\ -\phi \end{pmatrix} =$$

$$\frac{\sigma_\varepsilon^2}{t} \cdot \frac{\overline{\xi_t^2} + 2\cdot\phi\cdot\overline{\xi_t} + \phi^2}{\overline{\xi_t^2} - (\overline{\xi_t})^2} = \frac{\sigma_\varepsilon^2}{t} \cdot \left(1 + \frac{\left(\overline{\xi_t} + \phi\right)^2}{\overline{\xi_t^2} - (\overline{\xi_t})^2}\right), \tag{5.18}$$

the minimum is attained when

$$\overline{\xi_t} = -\phi \tag{5.19}$$

or, equivalently, when $\xi_t = -t \cdot \phi - \sum_{k=1}^{t-1} \xi_k$.

Proof of Proposition 2.

As in proposition 1

$$\lambda^2 = \Phi' \Sigma_{t-1} \Phi - \frac{\sigma_\varepsilon^2}{t} \cdot \left(1 + \frac{\left(\overline{\xi_t} + \phi\right)^2}{\overline{\xi_t^2} - (\overline{\xi_t})^2} \right) \tag{5.20}$$

Consider

$$H = \frac{\left(\overline{\xi_t} + \phi\right)^2}{\overline{\xi_t^2} - (\overline{\xi_t})^2} = \frac{(y + \xi_t + t\phi)^2}{t^2 \overline{\xi_t^2} - (y + \xi_t)^2} = \frac{A + B\xi_t}{C - D\xi_t} \tag{5.21}$$

where $y = (t-1)\overline{\xi}$, and

$$A = (y + t\phi)^2 + \xi_t^2, \qquad B = 2\,(y + t\phi)\,,$$

$$C = t^2 \overline{\xi_t^2} - y^2 - \xi_t^2, \qquad D = 2y. \tag{5.22}$$

Then

$$\lambda^2_{\xi_t = -x} > \lambda^2_{\xi_t = +x} \qquad \Leftrightarrow$$

$$H_{\xi_t = +x} > H_{\xi_t = -x} \quad \Leftrightarrow \quad A \cdot D + B \cdot C > 0. \tag{5.23}$$

The last equation is equivalent to

$$f(y) = \left[(y + t\phi)^2 + x^2 \right] y + (y + t\phi) \left(t^2 \overline{\xi_t^2} - y^2 - x^2 \right) > 0, \tag{5.24}$$

whereas $f(y)$ is an increasing function of y. Moreover, $f(0) > 0$ and $f\left(-\sqrt{t^2 \overline{\xi_t^2} + x^2}\right) < 0$. Thus, a negative $y^* = (t-1) \cdot \xi^*$ exists such that

- $\lambda^2 \left[\xi_t = -x\right] > \lambda^2 \left[\xi_t = +x\right]$ for $\overline{\xi} > \xi^*$, and
- $\lambda^2 \left[\xi_t = -x\right] < \lambda^2 \left[\xi_t = +x\right]$ for $\overline{\xi} < \xi^*$.

Proof of Proposition 3.

Since the distributions of ξ_t and correspondingly of $\overline{\xi}$ are symmetric, to prove the proposition, it is sufficient to show that

$$\frac{1}{2}\lambda\left(\xi_t = -x, \overline{\xi} = +y\right) + \frac{1}{2}\lambda\left(\xi_t = -x, \overline{\xi} = -y\right) >$$

$$\frac{1}{2}\lambda\left(\xi_t = x, \overline{\xi} = +y\right) + \frac{1}{2}\lambda\left(\xi_t = x, \overline{\xi} = -y\right), \tag{5.25}$$

or equivalently,

$$X = \left(\lambda\left(\xi_t = +x, \overline{\xi} = +y\right) - \lambda\left(\xi_t = -x, \overline{\xi} = -y\right)\right) -$$

$$\left(\lambda\left(\xi_t = -x, \overline{\xi} = +y\right) - \lambda\left(\xi_t = x, \overline{\xi} = -y\right)\right) < 0. \tag{5.26}$$

From lemma 4

$$\lambda = \sigma_\varepsilon \frac{\overline{\xi^2} + \phi\overline{\xi} - \left(\phi + \overline{\xi}\right)\xi_t}{\sqrt{\left(t-1\right)V}\sqrt{\left(\overline{\xi} - \xi_t\right)^2 + tV}}, \tag{5.27}$$

where $V = \overline{\xi^2} - \left(\overline{\xi}\right)^2$. Thus,

$$X = 2\phi\sigma_\varepsilon \frac{y - x}{\sqrt{\left(t-1\right)V}\sqrt{\left(y-x\right)^2 + tV}} - 2\phi\sigma_\varepsilon \frac{y + x}{\sqrt{(t-1)V}\sqrt{\left(y+x\right)^2 + tV}} \tag{5.28}$$

As a result, $X < 0$ is equivalent to

$$\frac{y + x}{\sqrt{\left(y+x\right)^2 + tV}} > \frac{y - x}{\sqrt{\left(y-x\right)^2 + tV}}. \tag{5.29}$$

The last expression holds for positive x and y, which proves the proposition.

Proof of Lemma 5.

In the proof of lemma 4 we derived

$$var_{t-1,\xi_t}\left[Y_t^i\right] = x_t'\Sigma_{t-1}x_t + \sigma_\varepsilon^2, \tag{5.30}$$

$$\lambda = \frac{\Phi' \Sigma_{t-1} x_t}{\sqrt{x_t' \Sigma_{t-1} x_t + \sigma_\varepsilon^2}}. \tag{5.31}$$

Substituting

$$\Sigma_{t-1} = \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix} \tag{5.32}$$

into the above expressions yields the desired result.

Proof of Proposition 4.

The derivative of log of λ with respect to ξ_t is

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

$$= \frac{-M}{\left(\sigma_a^2 - \phi\sigma_{ab} - (\phi\sigma_b^2 - \sigma_{ab})\xi_t\right)\left(\sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2\right)}, \tag{5.33}$$

where

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

$$= \phi\left(\sigma_a^2\sigma_b^2 - \sigma_{ab}^2\right) + \sigma_\varepsilon^2\left(\phi\sigma_b^2 - \sigma_{ab}\right) + \xi_t\left(\sigma_a^2\sigma_b^2 - \sigma_{ab}^2\right). \tag{5.34}$$

The maximum is at the value for ξ_t at which M is equal to 0. Therefore,

$$\xi_{max}^\lambda = -\frac{\phi\left(\sigma_a^2\sigma_b^2 - \sigma_{ab}^2\right) + \sigma_\varepsilon^2\left(\phi\sigma_b^2 - \sigma_{ab}\right)}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2} = -\phi\left(1 + \frac{\sigma_\varepsilon^2\sigma_b^2}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2}\right) + \frac{\sigma_\varepsilon^2}{\sigma_a^2\sigma_b^2 - \sigma_{ab}^2}\sigma_{ab}. \tag{5.35}$$

Proof of Proposition 5

Because $E_{t-1}\left[R_t^i\right] = \frac{a_{t-1}^i}{p_{t-1}^i}$, the third moment is

$$E_{t-1}\left[\left(R_t^i - E_{t-1}\left[R_t^i\right]\right)^3\right] = \frac{1}{\left(p_{t-1}^i\right)^3} E_{t-1}\left[X^3\right], \tag{5.36}$$

where

$$X = \beta\left(Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]\right) + b_{t-1}^i\xi_t \tag{5.37}$$

$$\beta = \frac{1}{1-R}\frac{\lambda}{\sqrt{Var_{t-1,\xi_t}\left[Y_t^i\right]}} + 1. \tag{5.38}$$

We can then calculate $E_{t-1}\left[X^3\right]$ as

$$E_{t-1}\left[X^3\right] = \underbrace{E_{t-1}\left[\beta^3\left(Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]\right)^3\right]}_{=0} + 3\cdot E_{t-1}\left[\beta^2\left(Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]\right)^2 \cdot b_{t-1}^i\xi_t\right] +$$

$$+3\cdot \underbrace{E_{t-1}\left[\beta\left(Y_t^i - E_{t-1,\xi_t}\left[Y_t^i\right]\right)\cdot (b_{t-1}^i\xi_t)^2\right]}_{=0} + \underbrace{E_{t-1}\left[\left(b_{t-1}^i\xi_t\right)^3\right]}_{=0} =$$

$$3\cdot E_{t-1}\left[\beta^2 Var_{t-1,\xi_t}\left[Y_t^i\right]\cdot b_{t-1}^i\xi_t\right] = 3\cdot E_{t-1}\left[\left(\frac{\lambda}{1-R} + \sqrt{Var_{t-1,\xi_t}\left[Y_t^i\right]}\right)^2 \cdot b_{t-1}^i\xi_t\right]. \tag{5.39}$$

If $\bar{\xi} > 0$ then both λ and $Var_{t-1,\xi_t}\left[Y_t^i\right] = \sigma_a^2 + 2\sigma_{ab}\xi_t + \sigma_b^2\xi_t^2 + \sigma_\varepsilon^2$ are larger in a recession in comparison with a boom of equal magnitude (see proposition 2 and note that $\sigma_{ab} < 0$ for $\bar{\xi} > 0$). Thus, the above expectation is negative, which proves the proposition.

References

Acharya, V. V., P. DeMarzo, and I. Kremer (2011): "Endogenous information flows and the clustering of announcements," *The American Economic Review*, 101(7), 2955–2979.

Banerjee, S., and B. Green (2013): "Learning whether other Traders are Informed," *Available at SSRN 2139771.*

Bollerslev, T., R. F. Engle, and J. M. Wooldridge (1988): "A capital asset pricing model with time-varying covariances," *The Journal of Political Economy*, pp. 116–131.

Buffett, W. (2001): "Chairman's Letter," Discussion paper, Berkshire Hathaway.

Campbell, J. Y., and L. Hentschel (1992): "No news is good news: An asymmetric model of changing volatility in stock returns," *Journal of Financial Economics*, 31(3), 281–318.

Chen, J., H. Hong, and J. C. Stein (2001): "Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices," *Journal of Financial Economics*, 61(3), 345–381.

Collins, D. W., and S. Kothari (1989): "An analysis of intertemporal and cross-sectional determinants of earnings response coefficients," *Journal of Accounting and Economics*, 11(2), 143–181.

Ertimur, Y., J. Livnat, and M. Martikainen (2003): "Differential market reactions to revenue and expense surprises," *Review of Accounting Studies*, 8(2), 185–211.

Franzoni, F., and M. C. Schmalz (2017): "Fund Flows and Market States," *Review of Financial Studies*, 10.1093/rfs/hhx015.

Glode, V. (2011): "Why mutual funds "underperform"," *Journal of Financial Economics*, 99(3), 546–559.

Hastie, T., and R. Tibshirani (1993): "Varying-coefficient models," *Journal of the Royal Statistical Society. Series B (Methodological)*, pp. 757–796.

Jegadeesh, N., and J. Livnat (2006): "Revenue surprises and stock returns," *Journal of Accounting and Economics*, 41(1), 147–171.

Jenter, D., and F. Kanaan (2015): "CEO turnover and relative performance evaluation," *The Journal of Finance*, 70(5), 2155–2184.

Johnson, M. (1999): "Business cycles and the relation between security returns and earnings," *Review of Accounting Studies*, 4(2), 93–117.

Kacperczyk, M., S. van Nieuwerburgh, and L. Veldkamp (2014): "Time-varying fund manager skill," *The Journal of Finance*, 69(4), 1455–1484.

——— (2016): "A Rational Theory of Mutual Funds' Attention Allocation," *Econometrica*, 84, 571–626.

Kosowski, R. (2006): "Do mutual funds perform when it matters most to investors? US mutual fund performance and risk in recessions and expansions," *Manuscript, Imperial College, London*.

Li, Q., and J. S. Racine (2007): "Smooth varying-coefficient nonparametric models for qualitative and quantitative data," *Unpublished manuscript, Department of Economics, Texas A&M University*.

Merton, R. C. (1980): "On estimating the expected return on the market: An exploratory investigation," *Journal of Financial Economics*, 8(4), 323–361.

Mian, G. M., and S. Sankaraguruswamy (2012): "Investor Sentiment and Stock Market Response to Earnings News," *The Accounting Review*, 87(4), 1357–1384.

Moskowitz, T. (2000): "Discussion," *The Journal of Finance*, 55(4), 1695–1703.

Pástor, L., L. Taylor, and P. Veronesi (2009): "Entrepreneurial learning, the IPO decision, and the post-IPO drop in firm profitability," *Review of Financial Studies*, 22(8), 3005–3046.

Pastor, L., and P. Veronesi (2009): "Learning in financial markets," Discussion paper, National Bureau of Economic Research.

Schmalz, M. (2012): "Three Essays in Financial Economics," Ph.D. thesis, Princeton University.

Stanton, R. (1997): "A nonparametric model of term structure dynamics and the market price of interest rate risk," *The Journal of Finance*, 52(5), 1973–2002.

Sun, Z., A. Wang, and L. Zheng (2009): "Do Active Funds Perform Better in Down Markets? New Evidence from Cross-Sectional Study," *SSRN eLibrary*.

Van Nieuwerburgh, S., and L. Veldkamp (2006): "Learning Asymmetries in Real Business Cycles," *Journal of Monetary Economics*, 53(4), 753–772.

Veldkamp, L. L. (2005): "Slow Boom, Sudden Crash," *Journal of Economic Theory*, 124(2), 230–257.

Veronesi, P. (1999): "Stock market overreactions to bad news in good times: a rational expectations equilibrium model," *Review of Financial Studies*, 12(5), 975–1007.

Veronesi, P., and R. Ribeiro (2002): "The Excess Comovement of International Stock Markets in Bad Times," *Working Paper*.

Zhuk, S. (2012): "Three Essays in Financial Economics," Ph.D. thesis, Princeton University.

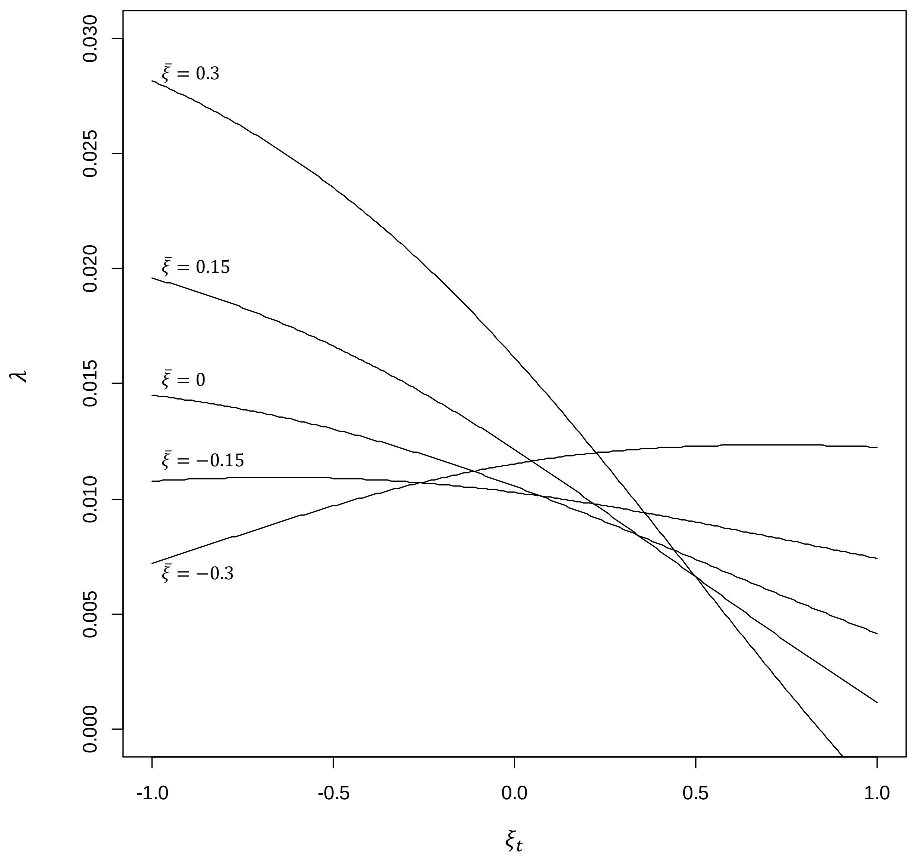

Figure 1: Illustration of how the market reaction to news depends on prior beliefs.

Simulation plot of the earnings response coefficient, $\lambda(\xi_t)$, over the realization of the market-wide shock, ξ_t, for different histories, i.e,. average of past shocks $\bar{\xi}$. Unless $\bar{\xi}$ is strongly negative, the part of the graph left of $\xi_t = 0$ tends to be higher than the part to the right of $\xi_t = 0$; that is, the earnings response is higher in downturns than in upturns; in other words, unless $\bar{\xi}$ is very low, the variance of price response to an observation is higher in downturns than in upturns. Simulation results for $\phi = 0.2$, $\overline{\xi^2} = 0.36$, $t = 10$, $\sigma_\varepsilon = 0.1$.

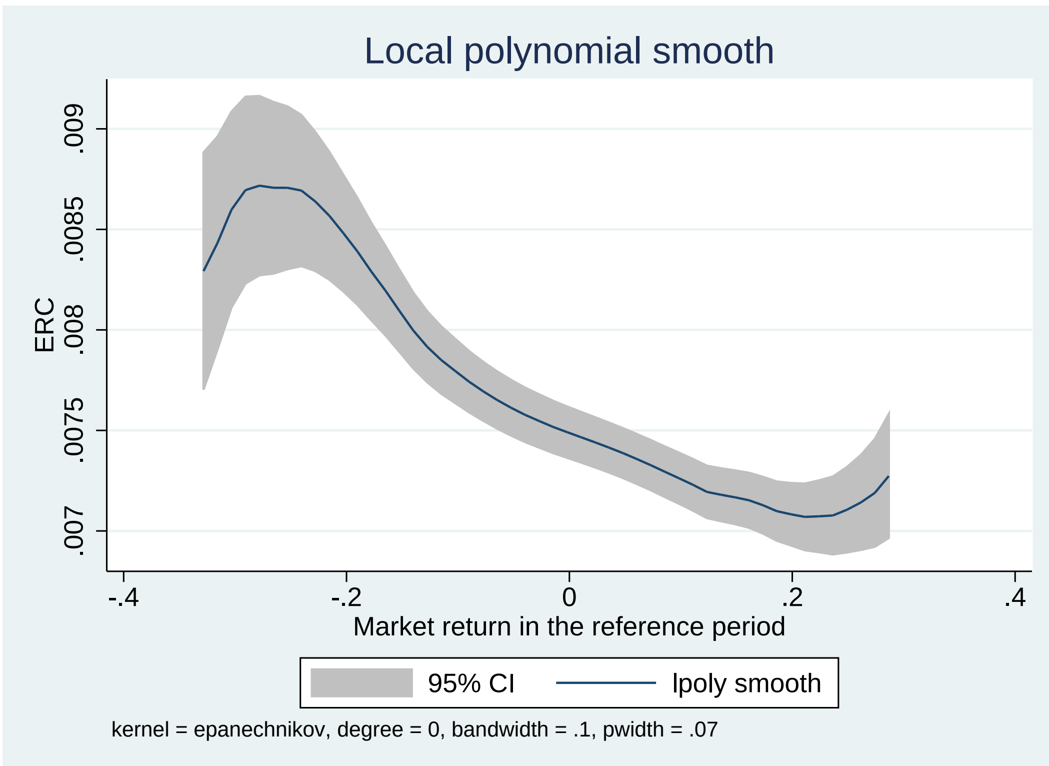

Figure 2: Non-parametric estimate of the earnings response coefficient as a function of the market return.

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 $ES = \frac{EPS-E[EPS]}{st.dev.[EPS]}$, where EPS is a stock's actual announced earnings per share; $E[EPS]$ is the expected earnings per share averaged across analysts from the IBES unadjusted detail files; $st.dev.[EPS]$ is the standard deviation of expected earnings per share across analysts from the IBES unadjusted detail files. The graph shows how the ERC λ depends on the state of the economy ξ_t, which is represented by the market return in the reference period (i.e., the period during which earnings are earned).

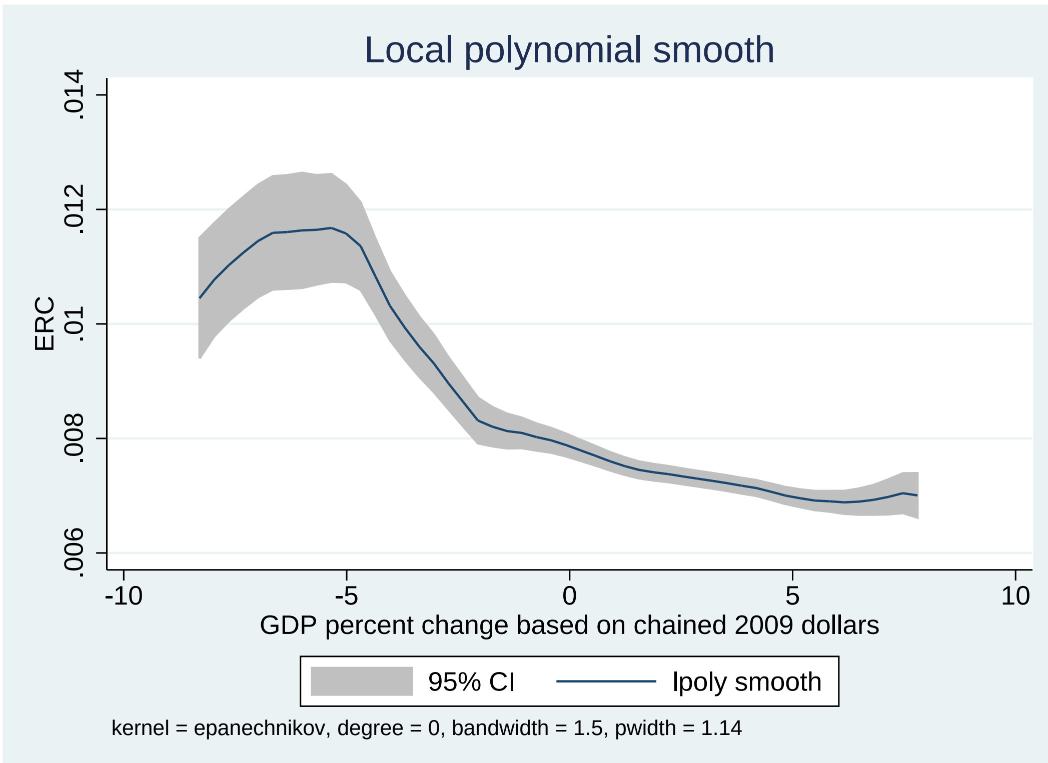

Figure 3: Non-parametric estimate of the earnings response coefficient as a function of GDP growth.

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 $ES = \frac{EPS - E[EPS]}{st.dev.[EPS]}$, where EPS is a stock's actual announced earnings per share; $E[EPS]$ is the expected earnings per share averaged across analysts from the IBES unadjusted detail files; $st.dev.[EPS]$ is the standard deviation of expected earnings per share across analysts from the IBES unadjusted detail files. The graph shows how the ERCλ depends on the state of the economy ξ_t, which is represented by the real US GDP growth rate in the quarter with the largest intersection with the reference period (i.e., the period during which earnings are earned).

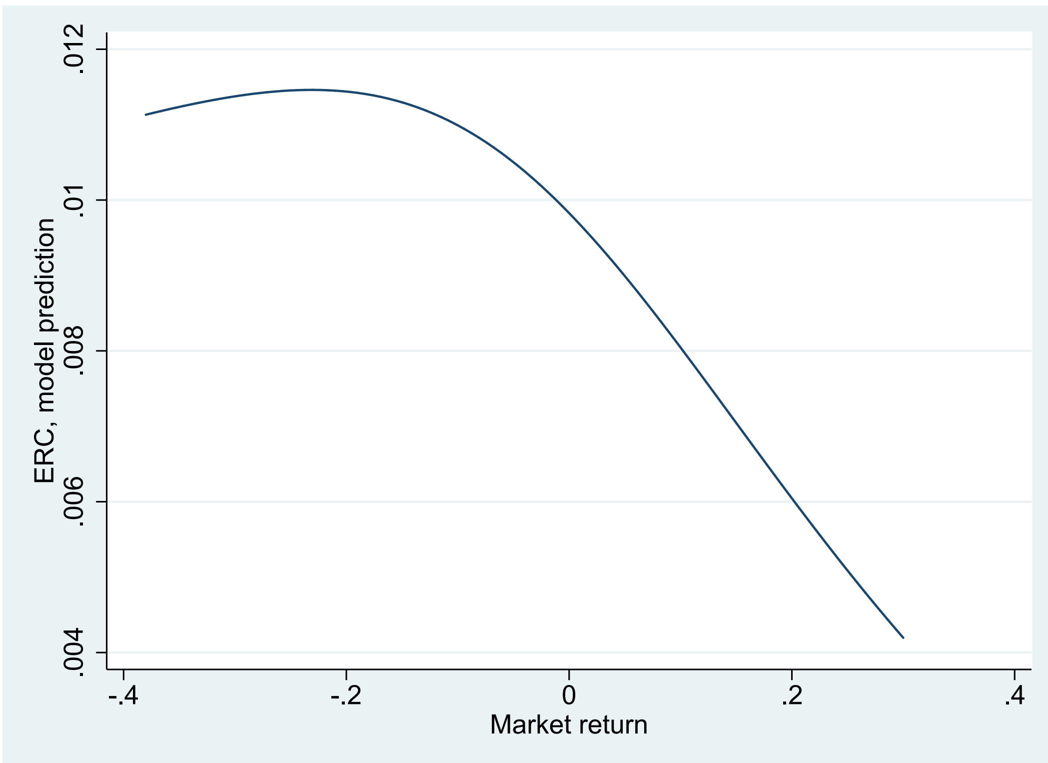

Figure 4: Predicted earnings response coefficients for a given aggregate shock.

For each announcement, we estimate the investors' pre-announcement beliefs $\begin{pmatrix} E\left[a^i\right] \\ E\left[b^i\right] \end{pmatrix}$ and calculate $\bar{\xi}$ and $\overline{\xi^2}$ from the regression $Y_t^i = a^i + b^i \xi_t + \varepsilon_t^i$ using the the previous five years of quarterly observations. Then we calculate the averages of $\frac{E\left[a^i\right]}{\sigma_\varepsilon}$, $\frac{E\left[b^i\right]}{E\left[a^i\right]}$, $\bar{\xi}$, and $\overline{\xi^2}$ over all announcements. From these average values, we predict how ERCs depend on ξ_t according to equation (4.8).

Table 1: Summary statistics.

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

Full sample						
	N	Mean	St.Dev.	p25	p50	p75
CAR	195924	0.00077	0.08374	-0.03346	0.00027	0.03514
CAR, NBER, DT = 1	25172	0.00278	0.11042	-0.04607	0.00104	0.05004
CAR, NBER, DT = 0	170752	0.00047	0.07905	-0.03194	0.00020	0.03347
CAR, Market, DT = 1	99142	0.00024	0.09125	-0.03618	0.00029	0.03749
CAR, Market, DT = 0	96782	0.00131	0.07528	-0.03086	0.00025	0.03296
CAR, GDP, DT = 1	97605	0.00074	0.09099	-0.03671	0.00016	0.03822
CAR, GDP, DT = 0	98319	0.00079	0.07586	-0.03055	0.00034	0.03228
ES	195924	0.39900	2.78480	-0.75000	0.33333	1.66667
ES, NBER, DT = 1	25172	0.28031	2.95922	-1.00000	0.26158	1.66667
ES, NBER, DT = 0	170752	0.41650	2.75773	-0.75000	0.33500	1.66667
ES, Market, DT = 1	99142	0.36513	2.81177	-0.80000	0.33333	1.66667
ES, Market, DT = 0	96782	0.43370	2.75647	-0.73684	0.37500	1.67000
ES, GDP, DT = 1	97605	0.43329	2.86385	-0.80000	0.40000	1.83333
ES, GDP, DT = 0	98319	0.36496	2.70362	-0.75000	0.33333	1.50000

Table 2: Earnings response coefficients as a function of the macroeconomic state (dummy).

ERC is the coefficient β_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. 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 to 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) NBER	(2) NBER	(3) NBER	(4) Market	(5) Market	(6) Market	(7) Market	(8) GDP	(9) GDP	(10) GDP	(11) GDP
ES x DT	0.00220***	0.00174***	0.00156***	0.00118***	0.00103***	0.000955***	0.000772***	0.00143***	0.00109***	0.000602**	0.000566**
	(3.95)	(3.32)	(3.20)	(3.87)	(3.63)	(3.88)	(3.32)	(4.60)	(3.61)	(2.34)	(2.34)
ES	0.00735***	0.00435***	0.00453***	0.00709***	0.00366***	0.00389***	0.00527***	0.00691***	0.00404***	0.00422***	0.00387***
	(48.31)	(6.98)	(8.07)	(45.83)	(5.85)	(7.04)	(7.52)	(34.49)	(6.30)	(7.34)	(4.68)
DT	0.00270	0.00382*	0.00421**	-0.00133	-0.000966	-0.000715	-0.000787	-0.00114	-0.000352	0.000560	0.000664
	(1.32)	(1.90)	(2.09)	(-1.27)	(-0.95)	(-0.76)	(-0.81)	(-1.10)	(-0.34)	(0.59)	(0.70)
ES x Var[ES]		0.000372***	-0.000156*		0.000425***	-0.000113	-0.000145*		0.000370***	-0.000120	-0.0000729
		(4.82)	(-1.86)		(5.59)	(-1.39)	(-1.90)		(4.61)	(-1.40)	(-0.88)
Var[ES]		-0.000972***	0.000194		-0.000788***	0.000359	0.000345		-0.000818***	0.000295	0.000353
		(-3.53)	(0.60)		(-2.81)	(1.10)	(1.02)		(-2.83)	(0.91)	(1.03)
ES x Time			0.000000631***			0.000000635***	0.000000727***			0.000000617***	0.000000628***
			(13.36)			(13.17)	(15.95)			(12.37)	(10.18)
Time			-0.00000133***			-0.00000130***	-0.00000116***			-0.00000133***	-0.00000149***
			(-7.54)			(-7.07)	(-6.96)			(-7.31)	(-6.92)
ES x $\overline{\xi}$							0.00189				0.000671***
							(0.16)				(4.39)
$\overline{\xi}$							-0.0192				0.000293
							(-0.40)				(0.48)
ES x $\overline{\xi^2}$							-0.227***				-0.000132***
							(-5.08)				(-4.96)
$\overline{\xi^2}$							-0.394*				-0.000231***
							(-1.96)				(-2.63)
Intercept	-0.00259***	0.00493**	0.00393**	-0.00164***	0.00440**	0.00328	0.00572**	-0.00173***	0.00433**	0.00335*	0.00642**
	(-5.08)	(2.34)	(2.01)	(-3.09)	(2.06)	(1.64)	(2.06)	(-2.64)	(2.04)	(1.69)	(2.05)
N	195924	195924	195924	195924	195924	195924	195924	195924	195924	195924	195924

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Earnings response coefficients as a function of the macroeconomic state (linear-continuous).

ERC is the coefficient β_2 in a regression of cumulative abnormal earnings announcement returns (CAR) on earnings surprises ($ES = \frac{EPS-E[EPS]}{st.dev.[EPS]}$) $CAR_{i,t} = \alpha + \beta_1 \cdot ES_{i,t} \times \xi_t + \beta_2 \cdot ES_{i,t} + \beta_3 \cdot \xi_t + \varepsilon_{i,t}$. The regression specifications allow for a higher coefficient in some states ξ_t than in others. The null hypothesis is that $\beta_1 = 0$. Our theory predicts that $\beta_1 < 0$. The two sets of columns differ in what we use to proxy for ξ: (i) market return net of risk-free rate, or(ii) real GDP growth. 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 to 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.

	(1) Market	(2) Market	(3) Market	(4) Market	(5) GDP	(6) GDP	(7) GDP	(8) GDP
ES x ξ	-0.00566***	-0.00436***	-0.00469***	-0.00359**	-0.000295***	-0.000221***	-0.000153***	-0.000132**
	(-3.33)	(-2.79)	(-2.98)	(-2.29)	(-4.91)	(-3.41)	(-2.62)	(-2.21)
ES	0.00774***	0.00423***	0.00447***	0.00571***	0.00836***	0.00548***	0.00523***	0.00460***
	(45.28)	(6.66)	(7.86)	(7.66)	(37.02)	(6.98)	(7.53)	(5.17)
ξ	-0.000294	-0.00332	-0.00303	-0.00331	-0.000209	-0.000456*	-0.000602**	-0.000591**
	(-0.04)	(-0.52)	(-0.47)	(-0.49)	(-0.81)	(-1.69)	(-2.24)	(-2.16)
ES x Var[ES]		0.000425***	-0.000127	-0.000153*		0.000329***	-0.000154*	-0.000102
		(5.43)	(-1.51)	(-1.94)		(3.80)	(-1.76)	(-1.16)
Var[ES]		-0.000831***	0.000333	0.000303		-0.00106***	0.000103	0.000156
		(-2.95)	(1.01)	(0.87)		(-3.53)	(0.30)	(0.43)
ES x Time			0.000000645***	0.000000734***			0.000000613***	0.000000634***
			(12.83)	(15.67)			(12.69)	(10.23)
Time			-0.00000131***	-0.00000119***			-0.00000140***	-0.00000152***
			(-6.92)	(-6.94)			(-8.24)	(-7.48)
ES x $\overline{\xi}$				0.00237				0.000661***
				(0.21)				(4.39)
$\overline{\xi}i$				-0.0314				0.000237
				(-0.63)				(0.39)
ES x $\overline{\xi^2}$				-0.228***				-0.000124***
				(-5.02)				(-4.45)
$\overline{\xi^2}$				-0.398**				-0.000197**
				(-1.97)				(-2.28)
Intercept	-0.00224***	0.00436**	0.00325	0.00617**	-0.00171*	0.00728***	0.00717***	0.00975***
	(-3.87)	(2.01)	(1.59)	(1.97)	(-1.82)	(2.73)	(2.85)	(2.75)
N	195924	195924	195924	195924	195924	195924	195924	195924

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regression of CAR on $Q_{0,t-1} \cdot ES_t$ and $Q_{1,t-1} \cdot \xi_t \cdot ES_t$ as regressors.

In this table we regress the cumulative abnormal announcement return (CAR) on the product of $Q_{0,t-1}$ and $Q_{1,t-1} \cdot \xi_t$ with earnings surprises (ES), where $Q_{0,t-1}$ and $Q_{1,t-1}$ are the parameters of the linearization of Earning Response Coefficient (ERC), predicted by the theory: $ERC \approx Q_{0,t-1} + Q_{1,t-1} \cdot \xi_t$. In specification (1) the actual values for $Q_{0,t-1}$ and $Q_{1,t-1}$ are used. In specification (2) we smooth the variables with a bandwidth of 5 months. In specification (3) we use simple averages of $Q_{0,t-1}$ and $Q_{1,t-1}$ corresponding to extreme smoothing to the time series average.

	(1) Actual	(2) Smoothed	(3) Average
ES x Q0	0.757^{***}	0.761^{***}	0.772^{***}
	(46.72)	(47.67)	(49.51)
ES x Q1 x ξ	0.0711^{**}	0.104^{***}	0.210^{***}
	(2.21)	(2.94)	(3.50)
N	195924	195924	195924

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$