Yale ICF Working Paper No. 09-20

First version: August 2009

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This Draft: August, 2009

* We thank Viral Acharya, Nick Barberis, Suleyman Basak, Ian Cooper, David Menagarishvili, Stefan Nagel, Jose Scheinkman, Shyam Sunder, Jake Thomas, Raman Uppal, Haiying Wang and Frank Zhang for helpful comments. We are responsible for any errors. The latest version is available at http://www.som.yale.edu/faculty/hy92/.

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ABSTRACT

This paper analyzes a dynamic general equilibrium model to study the impact of earnings surprises on contemporaneous stock returns. The model shows that earnings surprises can affect stock returns through two channels. On the one hand, earnings surprises affect the expected future earnings of the stock and so induce a positive earnings-returns correlation (*cash flow effect*). On the other hand, earnings surprises affect discount rates and so induce a negative earnings-returns correlation (*discount rate effect*). We show that the first channel is likely to dominate for most individual stocks, while the second channel can dominate for the aggregate stock market. Our model provides a theoretical foundation for the empirical findings in Kothari, Lewellen and Warner (2006) and generates two main implications: i) aggregate earnings surprises are positively related to interest rate changes, and ii) a stock's return is less sensitive to earnings news if the stock's earnings growth is more pro-cyclical. Our empirical evidence is consistent with both implications. More generally, our analysis illustrates that, due to the discount rate effect, firm-level phenomena may fail to extend to the aggregate stock market.

JEL classification: G12.

Keywords: Earnings surprises, aggregate, cyclicality, earnings response coefficient.

I. Introduction

Beginning with Ball and Brown (1968) a long line of research provides strong and robust evidence of a positive relation between earnings surprises and contemporaneous stock returns at the firm level. Recently, however, Kothari, Lewellen and Warner (2006) find that this relation is reversed at the stock market level: aggregate earnings surprises and contemporaneous aggregate stock returns are negatively related. An evolving literature explores possible explanations for this surprising result. Kothari, Lewellen and Warner (2006) conjecture that aggregate earnings surprises are positively related to discount rates changes, while Sadka and Sadka (2009) explore the possibility that the negative contemporaneous aggregate earnings-returns correlation is driven by the negative relation between expected returns and expected earnings growth. More recently, Hirshleifer, Hou and Teoh (2009) document that the negative correlation between aggregate earnings surprises and aggregate stock returns is driven by the accruals component of earnings and argue that innovations in aggregate accruals contain information for discount rates.

Even though these studies have furthered our understanding of the impact of earnings news on stock prices, both at the individual stock level and the aggregate stock market level, a theoretical foundation is yet to be developed. The goal of our paper is to fill this gap by providing a theoretical model for earnings surprises and stock returns, as well as empirically testing its further implications. In particular, we provide a simple dynamic general equilibrium model which accounts for the positive earnings-returns correlation at the individual stock level and the negative correlation at the aggregate market level.

The idea behind our model is quite simple. Earnings surprises affect stock prices through two channels. The first one is the *cash flow effect*. The arrival of a positive earnings surprise increases the expected future earnings from the stock and, hence, increases the stock price. That is, the cash flow effect induces a positive earnings-return relation. The second one is the *discount rate effect*. The earnings surprise from the stock may have implications for the growth rate of the overall economy, which determines the discount rate and therefore affects the stock price. It is this discount rate effect that makes the earnings-returns correlation at the aggregate level different from that at the individual stock level. This is because, for a typical stock, an earnings surprise has little impact on the expectation of the overall economy growth. Hence, the cash flow effect dominates and the earnings-returns correlation at the individual stock level is positive. For the aggregate stock market, however, its earnings surprise may have a significant impact on the expectation of the economy's growth and the discount rate in the economy. A positive earnings surprise for the aggregate stock market increases investors' expected economy growth rate. This reduces investors' saving motive and in equilibrium causes interest rates to rise and stock prices to drop.[1] The discount rate effect counter-balances the cash flow effect and makes the earnings-returns correlation weaker or even negative. Although the discount rate effect may be small for the average individual stock, our model implies the existence of considerable variation across stocks with different cyclicality. For a more pro-cyclical stock, its earnings surprises commove more closely with the expectations of the economy's growth and thus the discount rate effect is deemed to be stronger. This, in turn, implies a weaker earnings-returns correlation for more pro-cyclical stocks.

We formalize the above idea in a Lucas (1978) exchange economy. The investors in the economy cannot observe the mean earnings growth rates and form their expectations based on the realized earnings. The cyclicality of a stock is captured by a parameter that measures the correlation between the stock's earnings growth and the overall economy growth. Upon the arrival of earnings surprises, investors follow Bayes' rule to update their expectations of the stock's and the market's earnings growth rates. Based on their expectations, investors make their optimal consumption and investment decision. The equilibrium is determined by market clearing conditions. We obtain the equilibrium in a closed form, which makes the above intuition transparent.

Our model provides a general equilibrium foundation for the findings in Kothari, Lewellen and Warner (2006) by demonstrating that the correlation between earnings surprises and contemporaneous returns is, on average, positive at the individual stock level, but weaker or negative at the aggregate stock market level. Our model further leads to two key implications: i) aggregate earnings surprises are positively related to interest

[1] Although this intuition is based on a standard mechanism in consumption-based asset pricing models, alternative mechanisms may have similar effects. For example, a higher expected economy growth may prompt the Federal Reserve to increase the short-term interest rate. This will have a similar impact on the stock prices as the discount rate effect in our model.

rate changes, and ii) a stock's return is less sensitive to earnings news if the stock's earnings growth is more pro-cyclical.

We test these implications using COMPUSTAT and CRSP data on U.S. stocks over the period 1965 to 2006. Consistent with the first implication, we document that changes in interest rates are significantly positively associated with aggregate earnings surprises (correlation coefficients in excess of +0.55). Given that the driving force in our model is the impact of aggregate earnings surprises on the discount rate, this finding supports our explanation for the negative contemporaneous association between earnings surprises and stock returns at the stock market level.

The main part of our empirical analysis focuses on the second implication of our model. For a sample of 1,911 firms with at least 15 years of annual data we measure the correlation of each firm's earnings growth rate with the aggregate earnings growth rate. These firm-level correlations constitute our cyclicality measure. Similarly, each firm's earnings response coefficient − henceforth ERC − is obtained by running a time-series regression of the firm's annual returns on the firm's earnings surprises. We measure earnings surprises as the annual change in earnings scaled by either the beginning of year book value of equity or the beginning of year market value of equity.[2]

In the first set of results, we associate the firm-level estimates of cyclicality with the firm-level ERCs using portfolio and regression analysis. Our main finding is consistent across methodologies and in support of our model's prediction: a stock's return is less sensitive to its earnings surprises if the stock is more pro-cyclical. To illustrate, defining earnings surprises as the annual change in earnings scaled by the beginning of year book value of equity, we find that the ERC of firms in the lowest percentile of the cross-sectional distribution of cyclicality is +1.86 while the ERC of firms in the highest percentile is +0.69. Stated otherwise, the ERC of the least cyclical firms tends to be more than 2.5 times larger than the ERC of the most cyclical firms and that difference is significant at below the 1% level. Portfolio sorts demonstrate that the negative association between cyclicality and ERCs is pervasive in the cross-section of our firm-level cyclicality estimates. Regressions of firm-level ERCs on firm-level estimates of

[2] In additional robustness checks we define earnings news relatively to analysts' earnings expectations. As a practical matter, our results are consistent for the different measures of earnings surprises considered.

cyclicality reveal large and significantly negative coefficients with t-statistics (based on clustered standard errors by industry) between -6.88 and -9.90.

In order to alleviate concerns of measurement error in firm-level estimates of cyclicality and provide further insights, we group firms into industries and investigate the association between cyclicality and ERCs at the industry-level. Specifically, for each industry we measure cyclicality as the average of the firm-level estimates of cyclicality across firms classified in that industry. In a similar fashion, we obtain industry-level ERCs. Regression and portfolio analyses deliver a consistent message: ERCs tend to be lower in the more pro-cyclical industries. For example, defining earnings surprises as the annual change in earnings scaled by the beginning of year book value of equity, we find that, on average, the industry-level ERC is +1.68 for the ten least cyclical industries and +0.88 for the ten most cyclical industries. In additional analysis we estimate ERCs using annual cross-sectional earnings-returns regressions. The cross-sectional regression analysis demonstrates a negative and significant interaction effect between earnings surprises and our industry-level measure of cyclicality in the earnings-returns relation.

Collectively, our empirical analysis reveals that a stock's return is less sensitive to its earnings surprises if the stock is more pro-cyclical and thus provides support for the second implication of our model. Further analysis reveals that our findings remain robust to i) alternative measures of cyclicality, ii) alternative proxies of earnings surprises, iii) measurement error in our firm-level estimates of ERCs and cyclicality, iv) the impact of loss firms and v) period-specific effects.

Our paper contributes to the literature on the impact of earnings surprises on asset prices − one of the key issues in accounting and finance. In particular, the paper offers a theoretical foundation and new empirical evidence reconciling the conflicting findings at the firm level and at the aggregate stock market level. Perhaps more importantly, our analysis formalizes the general idea that one should not take for granted that firm-level phenomena necessarily extend to the aggregate stock market: Shocks at the individual level usually have little impact on the prospects of the aggregate economy. Shocks at the aggregate stock market, however, may have a significant impact on the prospects of the economy and, hence, a large impact on the pricing kernel. It is this impact through the pricing kernel that makes aggregate stock prices react to shocks differently from the way individual stock prices do. Recently, Hirshleifer, Hou and Teoh (2009) offer yet another example where a firm-level phenomenon fails to extend to the stock market level: the well-known accruals anomaly, first documented at the individual stock level by Sloan (1996), is reversed at the aggregate stock market level. Maybe it is not a pure speculation to expect that future research will uncover more firm-level phenomena that fail to extend to the aggregate stock market level.

The rest of the paper is organized as follows. Section II presents the model, Section III reports the empirical results and Section IV concludes. All proofs are provided in the Appendix.

II. Model

In this section, we present a dynamic general equilibrium model. Section II.A describes the economic environment and derives the impact of earnings surprises on expectations for future earnings. Section II.B derives the equilibrium and analyzes the impact of earnings surprises on interest rates and on individual and aggregate stock prices.

A. The economy

We consider an endowment economy with three periods (*t=0,1,2*).[3] For t=0,1,2, the aggregate endowment at time t is denoted by $Y_t > 0$. We focus our analysis on a "stock", which is a claim to a dividend stream D_t. We use lower case letters to denote logarithmic quantities: $y_t = \log(Y_t)$ and $d_t = \log(D_t)$. The aggregate endowment and the dividend processes are given by

$$y_{t+1} - y_t = g^y + \varepsilon_t^y, \tag{1}$$

$$d_{t+1} - d_t = g^d + \varepsilon_t^d, \tag{2}$$

for t=0,1, where g^y is the expected endowment growth rate and g^d is the expected dividend growth rate. We sometimes refer to g^y as the "expected economy growth rate" or the "expected aggregate earnings growth rate". ε_t^y and ε_t^d are normally distributed and

[3] This simple structure is chosen to make our intuition transparent. We have also solved a more elaborate continuous-time model with an infinite horizon, which leads to similar insights. This extra analysis is available upon request.

$E[\varepsilon_t^y] = E[\varepsilon_t^y] = 0$. To simplify the calculations, we assume ε_t^y and ε_t^d are independent from each other and across time and $Var[\varepsilon_t^y] = Var[\varepsilon_t^y] = \sigma^2$. These assumptions greatly simply the analysis and are not essential to our implications.

To model the stock's cyclicality, we assume that the endowment growth rate g^y and the dividend growth rate g^d are drawn from the following joint normal distribution:

$$N\left(\begin{pmatrix} \bar{g}^y \\ \bar{g}^d \end{pmatrix}, \sigma^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right), \tag{3}$$

where $\bar{g}^y$, $\bar{g}^d$ and ρ are constants with $-1 < \rho < 1$. $\bar{g}^y$ and $\bar{g}^d$ are the average growth rates of the endowment and the dividend. ρ measures the cyclicality of the stock: $\rho > 0$ implies that the dividend growth rate of the stock tends to be higher when the aggregate economy grows faster and so the stock is pro-cyclical. Similarly, $\rho < 0$ implies that the dividend growth rate of the stock tends to be lower when the aggregate economy grows faster and so the stock is counter-cyclical. Finally, the assumption that the variance of $\tilde{g}^y$ and $\tilde{g}^d$ are also σ^2 is made only to simplify notations, and it is straightforward to relax this simplification.

The growth rates g^y and g^d are realized at t=0 and remain constant, but investors cannot observe them directly and need to form their estimates over time. We assume investors' prior beliefs about the growth rates are consistent with (3):

$$\begin{pmatrix} g^y \\ g^d \end{pmatrix} \sim N\left(\begin{pmatrix} \bar{g}^y \\ \bar{g}^d \end{pmatrix}, \sigma^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right). \tag{4}$$

At t=1, endowment and dividend (Y_1 and D_1) are realized. We denote the unexpected endowment and dividend as

$$\tilde{\varepsilon}_1^y \equiv y_1 - y_0 - \bar{g}^y, \tag{5}$$

$$\tilde{\varepsilon}_1^d \equiv d_1 - d_0 - \bar{g}^d. \tag{6}$$

We will refer to $\tilde{\varepsilon}_1^y$ as the "aggregate earnings surprise" and $\tilde{\varepsilon}_1^d$ as the "earnings surprises" of the stock at *t*=1. Observing the realized endowment and dividend, investors revise their beliefs following Bayes' rule, and their posterior belief is given by the following lemma.

Lemma 1. *After the realization of the endowment and dividend at t=1, investors' posterior beliefs of* g^y *and* g^d *are normally distributed, with the mean given by*

$$E_1\left[g^y\right] = \bar{g}^y + \frac{2-\rho^2}{4-\rho^2}\tilde{\varepsilon}_1^y + \frac{\rho}{4-\rho^2}\tilde{\varepsilon}_1^d, \tag{7}$$

$$E_1\left[g^d\right] = \bar{g}^d + \frac{2-\rho^2}{4-\rho^2}\tilde{\varepsilon}_1^d + \frac{\rho}{4-\rho^2}\tilde{\varepsilon}_1^y, \tag{8}$$

and the variance-covariance matrix given by

$$\frac{\sigma^2}{4-\rho^2}\begin{pmatrix} 2-\rho^2 & \rho \\ \rho & 2-\rho^2 \end{pmatrix}. \tag{9}$$

The above lemma summarizes how investors' belief responds to earnings surprises. As shown in (7), for example, investors' expectation of the aggregate earnings growth rate responds to both the aggregate earnings surprise $\tilde{\varepsilon}_1^y$ and the earnings surprise of the stock $\tilde{\varepsilon}_1^d$. When realized aggregate earnings are higher than expected $(\tilde{\varepsilon}_1^y > 0)$, investors upgrade their expectation of the aggregate earnings growth rate in the future. More interestingly, the impact of the stock's earnings surprise on the belief about the aggregate earnings growth depends on the cyclicality of the stock. If the stock is pro-cyclical $(\rho > 0)$, a positive earnings surprise increases the expected aggregate earnings growth rate. If the stock is counter-cyclical ($\rho < 0$), however, a positive earnings surprise of the stock actually decreases the expected aggregate earnings growth rate. This is quite intuitive. A positive earnings surprise indicates that the expected earnings growth rate of the stock is higher. If the stock is pro-cyclical, this is good news for the aggregate earnings growth rate since these two growth rates tend to move together. If the stock is counter-cyclical, however, a higher growth rate of the stock is bad news for the aggregate earnings growth rate since these two growth rates tend to move to opposite directions. This insight is the basis for our later theoretical and empirical analysis.

Investors' expected earnings growth rate for the stock is given by (8), and the intuition behind this result is similar. A positive earnings surprise from the stock increases the expected earnings growth rate of the stock. But the impact of the aggregate earnings surprise depends on the cyclicality of the stock. A positive aggregate earnings surprise increases the expected earnings growth rate of a pro-cyclical stock but decreases the expected earnings growth rate of a counter-cyclical stock. Finally, the variance-covariance matrix of the expected growth rates is given by (9).

B. Equilibrium

Investors can trade a riskless bond which is in zero net supply, the aggregate market portfolio which is a claim to the aggregate endowment, and the stock which is a claim to the dividend stream. Both the market portfolio and the stock have a net supply of one share. We assume all investors are identical, so we can construct a representative investor. The representative investor has a constant relative risk aversion (CRRA) utility function:

$$u(c_t) = \frac{c_t^{1-\phi}}{1-\phi}, \qquad \text{with } \phi > 0, \tag{10}$$

where ϕ is the relative risk aversion coefficient and the case of $\phi = 1$ corresponds to the case of logarithmic utility function $u(c_t) = \log(c_t)$. The representative investor's optimization problem is to choose a consumption and investment plan to maximize his expected life time utility

$$\max \sum_{t=0}^{2} u(c_t), \tag{11}$$

subject to his budget constraint. We follow the standard competitive equilibrium definition: in equilibrium, the investor chooses his consumption and investment plan to maximize his objective function (11), and all markets clear. In equilibrium, as has been well known since Lucas (1978), the representative investor consumes the whole endowment, which then determines the representative investor's marginal rate of substitution and so the prices in the economy.

Proposition 1. *For the economy defined above, the equilibrium one period riskless (continuously compounded) interest rate at time t, r_t, is given by*

$$r_0 = \phi E_0\left[g^y\right] - \phi^2\sigma^2, \tag{12}$$

$$r_1 = \phi E_1\left[g^y\right] - \frac{3-\rho^2}{4-\rho^2}\phi^2\sigma^2. \tag{13}$$

As shown in the above proposition, the riskless interest rate is positively related to the expected economy growth rate g^y. This is intuitive: investors have less incentive to save when the economy grows faster and so the interest rate has to increase to counterbalance this lack of saving motive. The last term in equation (12) and the last term in equation (13) capture the precautionary saving motive. When the economy is more uncertain, investors have a stronger incentive to save, and this pushes down the interest rate.

It is important to note that equation (13) also shows how the interest rate is related to earnings surprises. We can see this clearly by substituting (7) into (13):

$$r_1 = \phi\left(\bar{g}^y + \frac{2-\rho^2}{4-\rho^2}\tilde{\varepsilon}_1^y + \frac{\rho}{4-\rho^2}\tilde{\varepsilon}_1^d\right) - \frac{3-\rho^2}{4-\rho^2}\phi^2\sigma^2. \tag{14}$$

The above equation shows that the interest rate is positively related to the aggregate earnings surprise $\tilde{\varepsilon}_1^y$. Intuitively, a positive aggregate earnings surprise implies that the economy growth rate $E_1\left[g^y\right]$ is going to be higher, which decreases the saving motive and so increases the equilibrium interest rate. The impact of $\tilde{\varepsilon}_1^d$, the earnings surprise of the stock, depends on the cyclicality of the stock. If the stock is pro-cyclical ($\rho > 0$) its earnings surprise is positively related to the interest rate however, if the stock is counter-cyclical ($\rho < 0$) its earnings surprise and the interest rate are negatively related. The intuition also directly follows from that in Lemma 1: for a pro-cyclical stock a positive earnings surprise implies a higher earnings growth rate not only for the individual stock but also for the aggregate economy and, in turn, a higher interest rate. Similar intuition follows for the case of a counter-cyclical stock.

Given the representative investor's consumption plan, we can obtain asset prices in this economy. Since our later discussions will be focused on the stock price responses to earnings surprises at *t*=1, we report the equilibrium stock prices t =1 in the following proposition and leave the derivation of the rest of the equilibrium to the Appendix.

Proposition 2. *The price of the aggregate stock market at t=1 is given by*

$$S_1^A = Y_1 \exp\left((1-\phi) E_1\left[g^y \right] + (1-\phi)^2 \frac{3-\rho^2}{4-\rho^2} \sigma^2 \right), \tag{15}$$

and the price of the stock is given by

$$S_1 = D_1 \exp\left(-\phi E_1\left[g^y \right] + E_1\left[g^d \right] + (\phi^2+1)\sigma^2 \frac{3-\rho^2}{4-\rho^2} \right). \tag{16}$$

The above proposition demonstrates how stock prices respond to earnings expectations. In particular, equation (15) shows that an increase in the expected aggregate earnings growth rate actually decreases the price of the market portfolio if $\phi > 1$. Therefore, an increase in aggregate earnings surprise $\tilde{\varepsilon}_1^y$ increases the expected aggregate earnings growth $E_1\left[g^y \right]$ and, hence, *decreases* the aggregate stock price S_1^A. As a result, the correlation between aggregate earnings surprises and aggregate returns is negative for the case of $\phi > 1$.

The intuition behind this surprising result has been made clear in Lemma 1 and Proposition 1. Suppose there is a positive earnings surprise for the aggregate stock market $\tilde{\varepsilon}_1^y$. This has two effects. The first one is the cash flow effect. A positive surprise $\tilde{\varepsilon}_1^y$ implies that, as shown in Lemma 1, the expected growth rate of the economy $E_1\left[g^y \right]$ is higher. This means that the aggregate cash flow will be higher, leading to a higher stock price. The second effect is the discount rate effect: A positive aggregate earnings surprise increases the expected growth rate of the economy, and therefore increases the interest rate (as shown in Proposition 1). A higher discount rate naturally leads to a lower stock price. That is, the cash flow effect induces a positive relation between earnings surprises and contemporaneous returns while the discount rate effect induces a negative relation. The total impact of the aggregate earnings surprise is therefore the combination of these two effects.[4] For an average stock, the discount rate effect is very small while the cash flow effect is the dominant force leading to a positive earnings-returns correlation. For the aggregate stock market, however, the discount rate effect plays a bigger role. Note

[4] This decomposition is well-known in the literature (see, e.g., Cecchetti, Lam and Mark (1990), Veronesi (2000) and Yan (2007)). The contribution of our paper is to analyse the impacts from the changes of the relative strength of these two effects.

that, from Proposition 1, the discount rate effect increases with ϕ. In fact, for the case of $\phi > 1$, the discount rate effect dominates and induces a negative relation between aggregate earnings surprises and contemporaneous stock market returns.[5]

This result offers a general equilibrium explanation of the empirical finding in Kothari, Lewellen and Warner (2006) that, in sharp contrast to the individual stock level evidence, aggregate earnings surprises and contemporaneous aggregate stock returns are negatively related.

Importantly, while the cash flow effect dominates the discount rate effect for an average stock, the relative strength of these two effects varies across stocks. The stock valuation formula (16) shows that the price of the stock increases in $E_1\left[g^d\right]$ but decreases in $E_1\left[g^y\right]$. A higher $E_1\left[g^d\right]$ implies higher earnings from this stock and so increases its value, while a higher $E_1\left[g^y\right]$ leads to a higher discount rate, as shown in (13), and so decreases the stock price.

This result also illustrates how the stock's price responds to its earnings surprise. As shown in Lemma 1, the stock's earning surprise $\tilde{\varepsilon}_1^d$ affects both its expected earnings growth $E_1\left[g^d\right]$ and the expected aggregate earnings growth $E_1\left[g^y\right]$. That is, similar to the intuition for the aggregate stock market case, an earnings surprise $\tilde{\varepsilon}_1^d$ affects the stock price through both the cash flow effect and the discount rate effect. First, a positive earnings surprise increases the expected future cash flow from the stock, as shown in equation (8), and hence increases the stock price. So the cash flow effect induces a positive correlation between earnings surprises and stock returns. Second, for a pro-cyclical stock ($\rho > 0$), as shown in equation (7), a positive earnings surprise increases the expected aggregate earnings growth and, hence, increases the discount rate, which, in turn, decreases the stock price. Therefore, for a pro-cyclical stock, the discount rate effect induces a negative relation between earnings surprises and stock returns. Similarly, for a counter-cyclical stock, a positive earnings surprise decreases the expected aggregate

[5] The case of $\phi > 1$ is generally considered to be empirically more plausible. See Chetty (2006) for a recent estimate of risk aversion.

earnings growth and, hence, decreases the discount rate, which further increases the stock price.

Note that the strength of the discount rate effect depends on the stock's cyclicality. Hence, the cross-sectional variation in cyclicality naturally leads to cross-sectional variation in the sensitivity of stock prices to earnings surprises. This result is formally stated in the following corollary.

Corollary 1. *The sensitivity of the stock price to the earnings surprise is given by*

$$\frac{\partial \ln S_1}{\partial \tilde{\varepsilon}_1^d} = \frac{1}{2}\left(1 - \phi\rho\right). \tag{17}$$

$\partial \ln S_1 / \partial \tilde{\varepsilon}_1^d$ measures the overall price impact of an earnings surprise and thus corresponds to the stock's ERC. Clearly, the stock's ERC is determined by the balance between the cash flow effect and the discount rate effect. While the former effect induces a positive relation, the latter depends on the stock's cyclicality ρ. Higher values of ρ lead to a stronger discount rate effect, which counter-balances the cash flow effect. This naturally leads to the result in the corollary that a stock's ERC decreases in its cyclicality ρ.

To simplify our analysis, we explicitly model the aggregate market and one individual stock. Alternatively, one can explicitly model the dividend process of each individual stock then, the aggregate endowment is the sum of the dividends from all the individual stocks. While this formulation is more intuitive, the learning in this alternative model will be similar to that in Lemma 1. Hence, the main insights will remain the same as the current model. On the other hand, the analysis of this alternative model will be substantially more complicated mathematically.

It is also worth pointing out that our model can readily be extended to incorporate inflation to derive implications on nominal quantities. One can see that the main insights in this alternative model remain the same: The discount rate effect is more prominent for the shocks from aggregate earnings surprises. While the nominal earnings surprises from an individual stock have few implications for the inflation expectation, the surprises from the aggregate stock market can significantly affect the expectation on future inflation. Hence, we can carry out our empirical analysis on nominal quantities directly. Just for clarity in our theoretical analysis, we choose our current set-up over this alternative model with inflation.

III. Empirical analysis

In this section, we empirically test our model's predictions. In particular, we focus on the implication in Proposition 1 that aggregate earnings surprises are positively related with interest rate changes and the implication in Corollary 1 that a stock's ERC decreases with its cyclicality.

A. Sample and variables

We collect our sample from the intersection of COMPUSTAT annual files and the CRSP monthly returns file. We scan the COMPUSTAT files for firm-years with December fiscal year-end that have non-missing values in the current and prior year for earnings before extraordinary items (X_{it}), book value of equity (BV_{it}), market value of equity (MV_{it}) and fiscal year-end stock price (P_{it}) from 1965 to 2006.[6] The December fiscal year-end requirement mitigates temporal misspecifications due to different reporting periods of annual earnings. In each period we exclude observations with beginning of year price below $1 so as to ensure that the results are not driven by a subset of penny stocks.

Next, we match these observations to compounded inter-announcement buy-and-hold stock returns. We require non-missing returns (including distributions) on the CRSP monthly returns file for the 12 months spanning the time frame from 9 months before the fiscal year-end to three months after the fiscal year-end. Compounding these monthly returns generates a buy-and-hold return (R_{it}) that proxies for the return from holding the stock between last year's earnings announcement and this year's announcement. To mitigate survivorship bias, if a security delists during a particular year then the CRSP delisting return is included in the buy-and-hold return.

We construct two proxies of earnings surprises, one measured as the earnings change between t and t-1 scaled by the beginning of year market value of equity ($\frac{\Delta X_{it}}{MV_{it-1}}$) and the other measured as the earnings change between t and t-1 scaled by the beginning

[6] Our results are not sensitive if we measure earnings as operating income after depreciation.

of year book value of equity ($\frac{\Delta X_{it}}{BV_{it-1}}$).[7] To construct our cyclicality measure, we need to measure each stock's earnings growth. We calculate earnings growth as the earnings change between t-1 and t scaled by earnings in t-1 ($\frac{\Delta X_{it}}{X_{it-1}}$).

To reduce the impact of outliers we exclude firm-years falling in the top or bottom 1% of the annual cross-sections of any of the following variables: $\frac{\Delta X_{it}}{MV_{it-1}}$, $\frac{\Delta X_{it}}{BV_{it-1}}$, $\frac{\Delta X_{it}}{X_{it-1}}$. The resulting sample contains 100,218 firm-year observations from 1967 to 2006. Firm-years observations are assigned into 50 industries according to Kenneth French's classification scheme and organized based on the calendar year of the fiscal year-end.[8]

We construct aggregate-level time-series of earnings growth, earnings surprises and returns using value-weighted cross-sectional averages of individual firm earnings growth, earnings surprises and returns. Value weights are calculated as the beginning of year market capitalization. Panel A of Figure 1 reveals that the aggregate growth rate in annual earnings ($\frac{\Delta X_t}{X_{t-1}}$) exhibits substantial variability over time. Earnings are volatile with growth rates often in excess of +/-20%, consistent with Kothari, Lewellen and Warner (2006). Intuitively, our measure of aggregate stock market earnings growth is closely tied to macroeconomic growth. Using data from the Federal Reserve System and the Bureau of Economic Analysis we find that $\frac{\Delta X_t}{X_{t-1}}$ commoves with industrial production growth (correlation coefficient of +0.45 significant at <1% level) and GDP growth (correlation coefficient of +0.37 significant at 2% level). Panel B of Figure 1 provides the time-series of aggregate earnings surprises. The two measures of aggregate earnings surprises are highly correlated with each other (+0.89) and with aggregate earnings growth. The correlation is +0.67 between $\frac{\Delta X_t}{X_{t-1}}$ and $\frac{\Delta X_t}{MV_{t-1}}$ and +0.71 between $\frac{\Delta X_t}{X_{t-1}}$ and $\frac{\Delta X_t}{BV_{t-1}}$.

[7] As a robustness check, we repeat our analysis for a subsample of firm-years with available analysts' earnings forecasts from the IBES database and for these observations we measure earnings surprises as the difference between realized earnings per share in t and analysts' mean consensus one-year-out forecast of earnings per share as of the beginning of the period scaled by either the beginning of year price per share or the beginning of year (per share) book value of equity. Our inferences remain robust to this alternative proxy of earnings surprises. See Section III.E for more details.

[8] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/changes_ind.html. We extend this scheme to include "Miscellaneous Manufacturing" (firms with 4-digit SIC codes between 3900 and 3999).

Proposition 1 suggests that aggregate earnings surprises are positively related to the riskless interest rate. In order to test this prediction, in Panel C of Figure 1 we plot the time-series of year-by-year changes in the one-year T-bill rate ($\Delta TBILL$).[9] Consistent with results reported in Kothari, Lewellen and Warner (2006), we find that changes in the T-bill rate are significantly positively correlated with aggregate earnings surprises. The correlations are +0.55 between $\Delta TBILL$ and $\frac{\Delta X_t}{MV_{t-1}}$ and +0.56 between $\Delta TBILL$ and $\frac{\Delta X_t}{BV_{t-1}}$, both significant at <1% level. Given that the driving force in our model is the impact of aggregate earnings surprises on the discount rate, this finding provides credence to our explanation for the negative contemporaneous association between earnings surprises and stock returns at the stock market level.

In order to test our prediction that a stock's return is less (more) sensitive to its earnings surprises if the stock is more (less) pro-cyclical, we search for a measure that captures the extent to which the stock's growth rate commoves with the economy growth rate. To this end, for a subsample of 1,911 firms with at least 15 years of annual data we calculate the time-series correlation of individual-firm earnings growth with the aggregate earnings growth:

$$CYCL_i = corr(\frac{\Delta X_{it}}{X_{it-1}}, \frac{\Delta X_t}{X_{t-1}}). \tag{18}$$

The main appealing feature of our empirical measure of cyclicality is that it hews closely to our theoretical construct of cyclicality. However, the measure's main drawback is that it is not well-defined when $X_{it-1} \leq 0$. This drawback may be especially problematic in the later part of our sample period due to the increasing frequency of loss firms in the COMPUSTAT universe (see, for example, Givoly and Hayn (2000), Klein and Marquardt (2003), Joos and Plesko (2005) and Patatoukas and Thomas (2009)). As a robustness check we repeat the entire analysis for the subsample of firms with $X_{it-1} > 0$ and find that all our results are qualitatively unaltered. In additional robustness checks we also adopt alternative measures that are not subject to this non-positive denominator problem, and find that that our results remain similar. See Section III.E for more details.

[9] We obtain annual data on one-year T-bill rates from the Federal Reserve System.

Figure 2 reveals that the distribution of the firm-level estimates of $CYCL_i$ − our measure of how cyclical a firm's earnings growth is − is symmetric with mean and median of +0.13.[10] Firm-level cyclicality estimates range widely from -0.72 to +0.82. Also note that even though on average firms are pro-cyclical, 29.5% of the firms are counter-cyclical.

Next, for the same sample of 1,911 firms, we estimate firm-level ERCs using time-series regressions of individual stock returns on individual stock earnings surprises:

$$R_{it} = a_{1i} + \beta_{1i} \frac{\Delta X_{it}}{MV_{it-1}} + e_{it}, \tag{19}$$

$$R_{it} = a_{2i} + \beta_{2i} \frac{\Delta X_{it}}{BV_{it-1}} + e_{it}. \tag{20}$$

Table 1, Panel A reports summary statistics for the pooled distribution of the firm-level estimates of ERCs revealing that these estimates vary widely across firms. Consistent with the well-documented positive contemporaneous association between earnings and returns at the firm-level, we find that for $\frac{\Delta X_{it}}{MV_{it-1}}$ the mean (median) ERC is +2.09 (+1.24) and for $\frac{\Delta X_{it}}{BV_{it-1}}$ the mean (median) ERC is +1.28 (+0.90).[11] Further scrutiny of the cross-section of ERCs reveals that β_{1i} (β_{2i}) is negative for 16.7% (18.2%) of the firms. Panel B of Table 1 shows that β_{1i} and β_{2i} are highly positively correlated with each other. More relevant to our investigation is the correlation between ERCs and cyclicality. The large and significant (at <1% level) negative correlation between ERCs and cyclicality provides preliminary evidence consistent with the implication of Corollary 1 that a stock's return is less sensitive to its earnings surprises if the stock is more pro-cyclical. Next, we probe deeper into this association.

Before we move to the main analysis, we revisit the contemporaneous association between aggregate earnings surprises and aggregate stock returns. Table 2 reports the

[10] Note that the mean (median) number of annual observations per firm used in the calculation of the firm-level time-series estimates of cyclicality and ERCs is 24.4 (22).

[11] See for example Easton and Zmijewski (1989), Teets (1992), Pownall, Wasley and Waymire (1993), Teets and Wasley (1996) and Sadka and Sadka (2009) for similar applications and results on firm-specific ERC estimates.

results of estimating the earnings-returns relation for the aggregate stock market. Specifically, we estimate time-series regressions of the following form:

$$R_t = a_1 + \beta_1 \frac{\Delta X_t}{MV_{t-1}} + e_t, \tag{21}$$

$$R_t = a_2 + \beta_2 \frac{\Delta X_t}{BV_{t-1}} + e_t, \tag{22}$$

where R_t is the CRSP value-weighted market return, while $\frac{\Delta X_t}{MV_{t-1}}$ and $\frac{\Delta X_t}{BV_{t-1}}$ are our two measures of aggregate earnings surprises.[12]

A comparison of Table 1 and Table 2 highlights the disparity between firm-level and aggregate-level time-series estimates of the earnings-returns relation. Panel A of Table 2 reveals that for the entire sample period, i.e., from 1967 to 2006, the ERC for the aggregate market is negative, albeit statistically insignificant. Interestingly, changes in the discount rate eliminate the negative market reaction to aggregate earnings news: the ERC for the aggregate stock market flips sign from negative to positive when we control for year-by-year changes in the one year T-bill. Even though this finding is consistent with the hypothesis that the negative ERC for the aggregate market is driven by the discount rate channel, it contradicts Kothari, Lewellen and Warner (2006) who find that over the period 1970-2000 changes in the discount rate reduce but do not eliminate the market's negative reaction to aggregate earnings news. However, additional analysis, reported in Panel B of Table 2, shows that these seemingly inconsistent results are due to differences in the sample periods examined. In fact, for the period 1970-2000, our results hew closely to Kothari, Lewellen and Warner (2006) since i) the estimated ERC for the aggregate market is between -3.96 and -5.50 (significant at the 5% level) and ii) changes in the discount rate reduce but do not eliminate the market's negative reaction to aggregate earnings news.

[12] We obtain similar results when we use the in-sample aggregate returns. This is not surprising given that the in-sample aggregate return series closely tracks the CRSP value-weighted market returns (correlation of +0.98).

Overall, our results are consistent with the existing evidence that although ERCs at the individual stock level are mostly positive, the ERC for the aggregate stock market is much weaker or even negative.

B. Firm-level analysis

We first sort the sample of 1,911 firms for which we have estimated cyclicality and ERCs into percentiles based on the cross-sectional distribution of $CYCL_i$ and then in Figure 3 we plot the mean values of ERCs for each cyclicality-based percentile rank. To ease the interpretation of regression results we scale the percentile ranks to lie between 0 (lowest percentile) and 1 (highest percentile).

A visual inspection of Panels A and B of Figure 3 reveals that ERCs tend to be higher (lower) among less (more) cyclical stocks. In order to formally test whether the difference in the ERCs of more and less cyclical stocks is statistically different, we fit regressions of the following form:

$$\beta_i = \gamma + \delta CYCL_i + e_i. \tag{23}$$

Table 3 reports the regression results using both the scaled ordinal ranks and the raw values of cyclicality. We calculate t-statistics using clustered standard errors by industry so as to correct for correlation across firms in the same industry.

The estimates reported in Panel A of Table 3 are based on the scaled ordinal ranks of our cyclicality measure.[13] These estimates are +2.98 (t-statistic=14.00) for γ and -1.79 (t-statistic=-6.88) for δ when ERCs are calculated relative to earnings changes scaled by beginning of year market value of equity. The results are consistent when ERCs are calculated relatively to earnings changes scaled by beginning of year book value of equity: our estimates are +1.86 (t-statistic=17.37) for γ and -1.17 (t-statistic=-9.53) for δ. The results documented in Panel A of Table 3 imply that the mean value of β_{1i} (β_{2i}) is +2.98 (+1.86) among firms in the lowest percentile of cyclicality while the mean value of β_{1i} (β_{2i}) is +1.19 (+0.69) among firms in the highest percentile of cyclicality. Stated otherwise, the ERC of the least cyclical firms (i.e., firms in the lowest percentile of the cross-section of $CYCL_i$) tends to be more than 2.5 times larger than the ERC of the most cyclical firms (i.e., firms in the highest percentile of the cross-section of $CYCL_i$.). Panel B

[13] Note that these estimates correspond to the fitted lines plotted in Panels A and B of Figure 3.

of Table 3 shows that our finding holds whether we use the percentile rank values or the raw values of cyclicality.

In sum, the main finding of the firm-level analysis aligns with the preliminary evidence reported in Panel B of Table 1: a stock's return is less sensitive to its earnings surprises if the stock is more pro-cyclical.

C. Industry-level analysis

In order to alleviate concerns of measurement error in firm-level estimates of cyclicality and to provide further insights, we group firms into industries and investigate the association between cyclicality and ERCs at the industry-level. Specifically, for each industry j we measure cyclicality ($CYCL_j$) as the average of the firm-level estimates of cyclicality across firms classified in industry j.[14] We also calculate for each industry the average values of the firm-level ERCs denoted as β_j. Consistent with our main hypothesis we expect industry-level ERCs to decrease in the cyclicality of the industry. That is, we expect a negative association between β_j and $CYCL_j$. We test this prediction using regressions of the following form:

$$\beta_j = \lambda + \mu CYCL_j + e_j. \tag{24}$$

Note that even though all industries are represented in our sample of 1,911 firms, the sample is not evenly distributed across industries. The mean (median) number of firms per industry is 38 (26) and the min (max) number of firms per industry is 2 (189). To make sure that few sparsely populated industries are not driving our results we estimate the above equation using weighted least squares regression where the weights are set equal to the frequency of firms in each industry.[15]

The regression results are reported in Table 4. In Panel A the industry-level measure of cyclicality is based on the scaled percentile ranks of the firm-level cyclicality estimates and in Panel B the industry-level measure is based on the raw values of these

[14] Our grouping of sectors into more and less cyclical is consistent with conventional wisdom and findings reported in Boudoukh, Richardson and Whitelaw (1994) based on alternative measures of industry-level cyclicality. To illustrate, the five least cyclical sectors based on our measure of industry–level cyclicality are: "Healthcare", "Tobacco Products", "Restaurants, Hotels and Motels", "Beer & Liquor" and "Food Products". Accordingly the five most cyclical sectors are: "Chemicals", "Personal Services", "Aircraft", "Petroleum & Natural Gas" and "Non-Metallic & Industrial Metal Mining".

[15] Our results are qualitatively unchanged if we estimate the model using ordinary least squares regression.

estimates. Consistent with our model's prediction that ERCs should be lower among more pro-cyclical industries, we find that estimates of μ are negative and significant at below the 1% level across all specifications considered with t-statistics ranging between -3.88 and -5.02.[16]

To provide a simple visualization of the regression results, we sort the 50 industries into five equal-sized bins based on the cross-industry distribution of $CYCL_j$ and then for each bin we plot in Figure 4 the frequency-weighted mean values of ERCs. By construction the first bin includes the ten least cyclical industries and the fifth bin includes the ten most cyclical industries. The figure clearly illustrates that industry-level ERCs tend to be lower among more pro-cyclical industries. Among the most cyclical industries the mean value of β_{1j} (β_{2j}) is +2.74 (+1.68) whereas among the least cyclical industries the mean value of β_{1j} (β_{2j}) is +1.19 (+0.88).

To recap, the message is consistent across the industry-level analysis and the firm-level analysis and in support of the implication of Corollary 1. A stock's return sensitivity to its earnings news is negatively associated to the extent to which the stock's earnings growth commoves with the aggregate earnings growth.

D. Cross-sectional estimates of ERC

An alternative to the firm-specific approach employed so far is to estimate ERCs cross-sectionally. The cross-sectional regression method ignores ERC variation across firms and estimates a single response coefficient for the cross-section of firms. Teets and Wasley (1996) argue that the implicit assumption of coefficient equality across firms under the cross-sectional method contrasts with evidence in the accounting literature that ERCs vary across firms due to firm-specific factors such as earnings persistence, growth prospects, risk and earnings predictability (see, for example, Kormendi and Lipe (1987), Collins and Kothari (1989), Easton and Zmijewski (1989), Lipe (1990), Hayn (1995) and Basu (1997)).

[16] As a robustness check, we use industry-level regressions to estimate ERCs and cyclicality. We obtain similar results based on this alternative method; industry-level ERCs tend to be significantly lower among more cyclical industries.

Nevertheless, we complement our firm-level and industry-level analyses of the association between ERCs and cyclical earnings growth by estimating annual cross-sectional earnings-returns regressions of the following form:

$$R_{ijt} = a_{1t} + \zeta_{1t} CYCL_j + \beta_{1t} \frac{\Delta X_{ijt}}{MV_{ijt-1}} + \gamma_{1t} CYCL_j \times \frac{\Delta X_{ijt}}{MV_{ijt-1}} + e_{ijt}, \tag{25}$$

$$R_{ijt} = a_{2t} + \zeta_{2t} CYCL_j + \beta_{2t} \frac{\Delta X_{ijt}}{BV_{ijt-1}} + \gamma_{2t} CYCL_j \times \frac{\Delta X_{ijt}}{BV_{ijt-1}} + e_{ijt}. \tag{26}$$

The coefficients of interest are γ_{1t} and γ_{2t}, the coefficients on the interaction between our industry-level measure of cyclicality $CYCL_j$ and earnings surprises. Similarly to the analysis reported in Section III.C, $CYCL_j$ is measured as the average of the firm-level estimates of cyclicality across all firms classified in industry *j*. Using the industry-level measure of pro-cyclicality not only allays the impact of measurement error in the firm-specific estimates of cyclicality but also enables us to estimate equations (25) and (26) using our extensive sample of 100,218 firm–year observations (or 11,912 firms) from 1967 to 2006. To make sure that small stocks are not driving our results, we estimate equations (25) and (26) using weighted least squares annual cross-sectional regressions, where the weights are the market capitalization of a firm at the beginning of each year.

Table 5 reports the time-series means of the estimated coefficients along with Fama-MacBeth (1973) t-statistics based on the time-series standard errors of the estimated coefficients with a Newey-West adjustment with three lags. In Panel A our industry-level measure of cyclicality is based on the scaled percentile ranks of the firm-level cyclicality estimates and in Panel B the industry-level measure is based on the raw values of these estimates. The results support our hypothesis across the specifications considered. Consistent with prior literature the coefficient on the earnings surprise is positive and significant, ranging between +1.28 and +2.43. Importantly, the coefficient on the interaction term is negative and significant across all specifications ranging between -1.87 and -2.60 with t-statistics between -2.36 and -3.39.

E. Relation to other studies

Prior accounting literature hypothesizes and finds a negative association between measures of systematic risk and ERCs.[17] In light of this evidence, if more cyclical stocks tend to have higher systematic risk then it would imply a negative correlation between our measure of cyclicality and ERCs. To address this concern, we first calculate firm-level estimates of systematic risk ($RISK_i$) based on time-series regressions of annual stock returns on annual market returns. Next, we run regressions of ERCs on $CYCL_i$ while controlling for $RISK_i$. Our main finding is that the negative association between cyclicality and ERCs remains large, negative and significant (at the 1% level) even after controlling for systematic risk.

In a related study, Sadka and Sadka (2009) hypothesize that the positive contemporaneous relation between earnings changes and stock returns declines as earnings changes become more predictable. Consistent with this hypothesis, the authors find that the contemporaneous earnings-returns relation declines as they aggregate firms into larger portfolios while the portfolio earnings changes become more predictable. Accordingly, if the earnings changes of more cyclical stocks are more predictable then the negative association between cyclicality and ERCs will be confounded by cross-sectional variability in predictability. In order to control for the predictable portion of earnings changes, we follow Sadka and Sadka (2009) and extend our firm-level ERC regression model to include lagged returns (R_{it-1}) as an additional regressor. Effectively, R_{it-1} controls for the predictable portion of (scaled) earnings changes as of the beginning of the year. We then estimate firm-level ERCs based on the extended model and associate these estimates to our firm-level measure of cyclicality. In unreported analysis, we find that the negative association between cyclicality and ERCs remains large, negative and significant (at the 1% level) even after controlling for the predictable portion of earnings changes. In other words, our findings are not driven by the cross-sectional variation in earnings predictability.

According to our explanation of the negative earnings-returns relation at the market level, a positive (negative) earnings surprise increases (decreases) the discount rate, and

[17] For example, Easton and Zmijewski (1989) document at the firm-level a negative correlation between ERCs and market model betas.

so implies higher (lower) future expected returns. Kothari, Lewellen and Warner (2006) find that future returns are unrelated to past earnings surprises over the period 1970-2000. We replicate this finding for our sample period (1967-2006) and find a positive, albeit insignificant, association between one-year-ahead returns and earnings surprises. As an alternative proxy of expected returns, we construct implied cost of capital estimates based on accounting data and analysts' earnings forecasts using the approach of Claus and Thomas (2001). Again, we find a positive, albeit insignificant, association between implied cost-of-capital estimates and earnings surprises at the aggregate level. Although the evidence does not strongly support the positive relation between the aggregate earnings surprise and higher expected future stock returns, it may well be driven by the lack of statistical power in the tests due to measurement errors in expected returns.

F. Robustness

As a robustness check we repeat our analysis for two other measures of cyclicality. For the sample of 1,911 firms we calculate the time-series correlation of individual-firm earnings surprises with the aggregate earnings surprises using our two alternative definitions of annual earnings surprises: $CYCL'_i = corr(\frac{\Delta Xi_t}{MV_{it-1}}, \frac{\Delta X_t}{MV_{t-1}})$ and $CYCL''_i = corr(\frac{\Delta Xi_t}{BV_{it-1}}, \frac{\Delta X_t}{BV_{t-1}})$. The advantage of these two alternative cyclicality measures is that they are less prone to the non-positive denominator problem that inhibits firm-level earnings growth rates, while their disadvantage is that they do not capture as closely our theoretical construct of cyclicality. We find that the firm-level estimates of cyclicality based on these two alternative measures are highly correlated with each other and with the firm-level estimates based on our primary measure of cyclicality. Accordingly, we find that all results are not sensitive to the choice of cyclicality measure.

To address the concern that our primary measure of cyclicality is inhibited by measurement error introduced due to loss firms we repeat the entire analysis after eliminating firm-years with negative or zero reported earnings in t and t-1. All our results remain qualitatively unchanged. In fact, some of the regression results become even stronger − a finding that suggests that measurement error in our primary measure of cyclicality due to negative reported earnings biases our analysis against finding any relationship between ERCs and cyclicality.

To increase the power of our tests, we repeat the analysis by requiring at least 20 years of data when we calculate firm-level estimates of ERCs and cyclicality. Even though this stricter requirement reduces our sample of 1,911 firms to 1,174 firms, our results remain qualitatively unchanged. Finally, to align our results with prior studies (e.g., Kothari, Lewellen and Warner (2006); Sadka and Sadka (2009)) we repeat the entire analysis for the pre-2000 period and find that all results are similar to those reported above.

We also extend our analysis using analysts' earnings forecasts from the IBES database. Specifically, we measure earnings surprises as the difference between realized earnings per share in t and analysts' mean consensus one-year-out forecast of earnings per share as of the beginning of the period, scaled by either the beginning of year price per share or the beginning of year per share book value of equity. We also measure cyclicality as the time-series correlation of firm i's mean consensus analysts' expectation of long-term earnings growth (LTG_{it}) with the aggregate expectation of long-term earnings growth (LTG_t) or $CYCL'''_i = corr(LTG_{it}, LTG_t)$.[18] Results using analysts' forecasts are consistent with the model prediction that a stock's ERC decreases in its cyclicality but they should be interpreted with caution for at least two reasons. First, it is well understood that analysts may have incentives to predict future earnings less than accurately.[19] Second, broad analyst coverage starts after the mid-80s and analysts' earnings and long-term growth forecasts are available only for a subset of typically large firms.

[18] LTG_t is calculated as the value-weighted average of the individual firms' growth forecasts at each point in time.

[19] Biases in analysts' earnings forecasts are widely documented in the accounting and finance literature. Early research finds that analysts' forecasts are optimistically biased (e.g., Brown, Foster, and Noreen, 1985). A number of subsequent studies focus on possible explanations for analysts' forecast optimism. For example, Francis and Philbrick (1997) and Lim (2001) argue that analysts issue optimistic forecasts to improve their access to management, while McNichols and O'Brien (1997) propose as an explanation the self-selection bias that results when analysts stop covering firms on which they have negative views. Other studies point to possible conflicts of interest associated with underwriting relationships or brokerage trading business.

IV. Conclusion

We have analyzed a dynamic general equilibrium model to study the impact of earnings surprises on stock returns. The model shows that earnings surprises can affect contemporaneous stock returns through two channels. The first one is the cash flow effect. Earnings surprises affect the expected future earnings of the stock and so induce a positive earnings-returns correlation. The second one is the discount rate effect. Earnings surprises affect the discount rate in the economy, and this induces a negative earnings-returns correlation. We show that the first channel is likely to dominate for most individual stocks but the second channel can dominate for the aggregate stock market. This offers a general equilibrium explanation of the findings in Kothari, Lewellen and Warner (2006) that, in contrast to well-documented firm-level evidence, the contemporaneous association between earnings surprises and stock returns is weak or even negative at the aggregate stock market level. Our model also predicts that aggregate earnings surprises are positively related to interest rate changes and that a stock's earnings response coefficient decreases in its cyclicality (i.e., the extent to which the stock's earnings growth commoves with the aggregate earnings growth). Our empirical evidence is consistent with both of these predictions.

Despite the encouraging evidence, we note that our model may not completely explain the negative earnings-returns relation documented at the aggregate level. For example, Hirshleifer, Hou and Teoh (2009) find that this negative relation is mostly driven by the accruals component of aggregate earnings surprises, rather than by the surprises in cash flows. Moreover, Sadka and Sadka (2009) find that the negative earnings-returns relation could be driven by a negative association between risk premium and earnings growth. These findings provide valuable clues for improving our understanding of the relation between earnings and stock returns. These findings also demand a more elaborate model of accruals, cash flows and time-varying risk premium. It is important to note, however, that a necessary key component of this "to-be-developed" model is exactly the general idea advocated in our paper. Shocks at the individual firm-level usually have little impact on the prospects of the aggregate economy. Shocks at the aggregate stock market level, however, may have a significant impact on the prospects of the entire economy and a large impact on the pricing kernel. It is this impact through the pricing kernel that makes aggregate stock market prices react to earnings shocks differently from individual firm stock prices.

At a conceptual level we point out that one should not take for granted that firm-level phenomena necessarily extend to the aggregate stock market. In fact, well-established phenomena documented at the firm-level may not extend or completely reverse at the aggregate level. The earnings-return relation in Kothari, Lewellen and Warner (2006) is one such example. Hirshleifer, Hou and Teoh (2009) offer yet another example. They examine whether the firm-level accruals and cash flow effects extend to the aggregate stock market. Contrary to previous firm-level findings (e.g., Sloan (1996) and Desai, Rajgopal and Venkatachalam (2004)), aggregate accruals is a strong positive time-series predictor of aggregate stock returns whereas cash flows is a negative predictor. It perhaps is not a pure speculation to expect that future research will uncover more firm-level phenomena that fail to extend to the aggregate stock market level.

APPENDIX

A. Proof of Lemma 1

We first write down the following joint distribution

$$\begin{pmatrix} g^y \\ g^d \\ y_1 - y_0 \\ d_1 - d_0 \end{pmatrix} \sim N\left(\begin{pmatrix} \bar{g}^y \\ \bar{g}^d \\ \bar{g}^y \\ \bar{g}^d \end{pmatrix}, \sigma^2 \begin{pmatrix} 1 & \rho & 1 & \rho \\ \rho & 1 & \rho & 1 \\ 1 & \rho & 2 & \rho \\ \rho & 1 & \rho & 2 \end{pmatrix}\right).$$

Then, by Projection Theorem, the conditional distribution of the growth rates is given by

$$\begin{pmatrix} g^y \\ g^d \end{pmatrix}\Bigg| \begin{matrix} y_1 \\ d_1 \end{matrix} \sim N\left(\begin{pmatrix} \bar{g}^y \\ \bar{g}^d \end{pmatrix} + \frac{1}{4-\rho^2}\begin{pmatrix} 2-\rho^2 & \rho \\ \rho & 2-\rho^2 \end{pmatrix}\begin{pmatrix} y_1 - y_0 - \bar{g}^y \\ d_1 - d_0 - \bar{g}^d \end{pmatrix}, \frac{\sigma^2}{4-\rho^2}\begin{pmatrix} 2-\rho^2 & \rho \\ \rho & 2-\rho^2 \end{pmatrix}\right).$$

This leads to the results in (7)-(9).

B. Proof of Proposition 1

In the equilibrium, the representative investor consumes the whole endowment:

$$C_t = Y_t.$$

for t=0,1,2. The pricing kernel is given by the marginal rate of substitution of the representative investor. At t=0, one unit of consumption at t=1 is worth

$$B_0 = E_0\left[\frac{C_1^{-\phi}}{C_0^{-\phi}}\right] = E_0\left[\frac{Y_1^{-\phi}}{Y_0^{-\phi}}\right].$$

Substituting (1) into the above expression, after some algebra, we obtain

$$B_0 = e^{-\phi\bar{g}^y + \phi^2\sigma^2}.$$

Hence, $r_0 = -\log(B_0)$, which leads to (12).

Similarly, at t=1, one unit of consumption at t=2 is worth

$$B_1 = E_1\left[\frac{Y_2^{-\phi}}{Y_1^{-\phi}}\right].$$

Substituting (1) into the above expression, after some algebra, we obtain

$$B_1 = e^{-\phi\bar{g}^y + \phi^2\sigma^2}.$$

Hence, $r_1 = -\log(B_1)$, which leads to (13).

C. Proof of Proposition 2

The price of the aggregate stock market at t=1 is given by

$$S_1^A = E_1\left[\frac{Y_2^{-\phi}}{Y_1^{-\phi}} Y_2\right].$$

Substituting (1) into the above expression, after some algebra, we obtain (15). Similarly, the price of the stock market at t=1 is given by

$$S_1 = E_1\left[\frac{Y_2^{-\phi}}{Y_1^{-\phi}} D_2\right].$$

Substituting (1) and (2) into the above expression, after some algebra, we obtain (16). The derivations for the stock prices at t=0 are similar. The prices at t=0 are given by

$$S_0^A = E_0\left[\frac{Y_1^{-\phi}}{Y_0^{-\phi}} Y_1 + \frac{Y_2^{-\phi}}{Y_0^{-\phi}} Y_2\right],$$

$$S_0 = E_0\left[\frac{Y_1^{-\phi}}{Y_0^{-\phi}} D_1 + \frac{Y_2^{-\phi}}{Y_0^{-\phi}} D_2\right].$$

The above equations directly lead to

$$S_0^A = Y_0\left(e^{(1-\phi)\bar{g}^y + (1-\phi)^2\sigma^2} + e^{2(1-\phi)\bar{g}^y + 3(1-\phi)^2\sigma^2}\right)$$

$$S_0 = D_0\left(e^{-\phi\bar{g}^y + \bar{g}^d + \sigma^2(\phi^2+1)} + e^{-2\phi\bar{g}^y + 2\bar{g}^d + 3\sigma^2(\phi^2+1)}\right).$$

D. Proof of Corollary 1

Note that the correlation between $\tilde{\varepsilon}_1^y$ and $\tilde{\varepsilon}_1^d$ is $\frac{\rho}{2}$. Hence, we can decompose $\tilde{\varepsilon}_1^y$ into

$$\tilde{\varepsilon}_1^y = \frac{\rho}{2}\tilde{\varepsilon}_1^d + \sqrt{1-\left(\frac{\rho}{2}\right)^2}\,\xi$$

where ξ is independent of $\tilde{\varepsilon}_1^d$. Substituting the above expression and equations (7) and (8) into (16), after some algebra, we obtain (17).

Table 1: Firm-level time-series estimates of earnings response coefficients and cyclicality

This table reports summary statistics of the cross-section of the slope coefficients (earnings response coefficients) for the following firm-level time-series regressions:

1) $R_{it} = a_{1i} + \beta_{1i} \frac{\Delta X_{it}}{MV_{it-1}} + e_{it}$

2) $R_{it} = a_{2i} + \beta_{2i} \frac{\Delta X_{it}}{BV_{it-1}} + e_{it}$.

R_{it} is the annual buy-and-hold inter-announcement return of firm i in year t, $\frac{\Delta X_{it}}{MV_{it-1}}$ is the earnings change between t and t-1 scaled by beginning of year market value of equity and $\frac{\Delta X_{it}}{BV_{it-1}}$ is the earnings change between t and t-1 scaled by beginning of year book value of equity. The table also reports descriptive statistics for the firm-level time-series estimates of cyclicality ($CYCL_i$) measured as the time-series correlation of individual-firm earnings growth with the aggregate earnings growth. $CYCL_i = corr(\frac{\Delta X_{it}}{X_{it-1}}, \frac{\Delta X_t}{X_{t-1}})$, where $\frac{\Delta X_t}{X_{t-1}}$ is the value-weighted annual cross-sectional average of the individual-firm earnings growth rates. The sample includes 1,911 firms with at least 15 years of annual data for the period 1967-2006.

Panel A: Descriptive statistics

	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
β_{1i}	2.09	3.75	-28.37	0.36	1.24	2.86	64.23
β_{2i}	1.28	2.04	-7.96	0.20	0.90	2.00	34.96
$CYCL_i$	0.13	0.24	-0.72	-0.04	0.13	0.30	0.82
# Obs. (per firm)	24.4	8.0	15.0	18.0	22.0	31.0	40.0

Panel B: Pearson (Spearman) pair-wise correlations above (below) the main diagonal (all correlations are significant at <1%)

	β_{1i}	β_{2i}	$CYCL_i$
β_{1i}		0.59	-0.15
β_{2i}	0.79		-0.17
$CYCL_i$	-0.18	-0.19	

Table 2: Aggregate-level time-series estimates of earnings response coefficients

This table reports time-series regression results at the aggregate-level. The regression models considered are the following:

1) $R_t = a_1 + \beta_1 \frac{\Delta X_t}{MV_{t-1}} + \theta_1 \Delta TBILL_t + e_t$

2) $R_t = a_2 + \beta_2 \frac{\Delta X_t}{BV_{t-1}} + \theta_2 \Delta TBILL_t + e_t$

R_t is the CRSP value-weighted market return including distributions, $\frac{\Delta X_t}{MV_{t-1}}$ is the value-weighted annual cross-sectional average of the individual-firm earnings change between t and t-1 scaled by beginning of year market value of equity, $\frac{\Delta X_t}{BV_{t-1}}$ is the value-weighted annual cross-sectional average of the individual-firm earnings change between t and t-1 scaled by beginning of year book value of equity and $\Delta TBILL$ is the year-by-year changes in the one year T-bill rate. The models are estimated using ordinary least squares regressions. In Panel A (Panel B) the regressions are based on 100,218 (75,898) firm-years over the period 1967-2006 (1970-2000).

Panel A: Full sample period (1967-2006)

Model		**Estimate**	***t-statistic***	***p-value***	**Adj. R^2**
1	$\boldsymbol{a_1}$	0.13	*4.18*	*0.00*	-0.01
	$\boldsymbol{\beta_1}$	-1.61	*-0.72*	*0.48*	
2	$\boldsymbol{a_1}$	0.12	*3.71*	*0.00*	0.00
	$\boldsymbol{\beta_1}$	0.29	*0.11*	*0.91*	
	$\boldsymbol{\theta_1}$	-2.82	*-1.28*	*0.21*	
3	$\boldsymbol{a_2}$	0.13	*3.58*	*0.00*	-0.02
	$\boldsymbol{\beta_2}$	-0.41	*-0.31*	*0.76*	
4	$\boldsymbol{a_2}$	0.10	*2.77*	*0.01*	0.01
	$\boldsymbol{\beta_2}$	1.00	*0.62*	*0.54*	
	$\boldsymbol{\theta_2}$	-3.45	*-1.57*	*0.13*	

Panel B: Sub-sample period (1970-2000)

Model		**Estimate**	***t-statistic***	***p-value***	**Adj. R^2**
1	$\boldsymbol{a_1}$	0.16	*5.00*	*0.00*	0.12
	$\boldsymbol{\beta_1}$	-5.50	*-2.24*	*0.03*	
2	$\boldsymbol{a_1}$	0.16	*4.47*	*0.00*	0.11
	$\boldsymbol{\beta_1}$	-4.06	*-1.35*	*0.19*	
	$\boldsymbol{\theta_1}$	-1.95	*-0.83*	*0.41*	
3	$\boldsymbol{a_2}$	0.19	*4.60*	*0.00*	0.10
	$\boldsymbol{\beta_2}$	-3.96	*-2.07*	*0.05*	
4	$\boldsymbol{a_2}$	0.17	*3.60*	*0.00*	0.09
	$\boldsymbol{\beta_2}$	-2.70	*-1.13*	*0.27*	
	$\boldsymbol{\theta_2}$	-2.13	*-0.88*	*0.39*	

Table 3: Firm-level analysis

This table reports results of regressions of firm-level time-series estimates of earnings response coefficients on firm-level time-series estimates of cyclicality:

$$1)\quad \beta_{1i} = \gamma_1 + \delta_1 CYCL_i + e_i$$

$$2)\quad \beta_{2i} = \gamma_2 + \delta_2 CYCL_i + e_i$$

The models are estimated using ordinary least squares regressions. We calculate t-statistics using clustered standard errors by industry. Panel A reports results using the raw values of the firm-level estimates of cyclicality and Panel B reports results using the scaled (between 0 and 1) percentile ranks of these estimates. The sample includes 1,911 firms with at least 15 years of annual data for the period 1967-2006.

Panel A: Scaled percentile ranks of $CYCL_i$

Model		Estimate	*t-statistic*	*p-value*	N	Adj. R^2
1	$\boldsymbol{\gamma_1}$	2.98	*14.00*	*0.00*	1,911	0.02
	$\boldsymbol{\delta_1}$	-1.79	*-6.88*	*0.00*		
2	$\boldsymbol{\gamma_2}$	1.86	*17.37*	*0.00*	1,911	0.03
	$\boldsymbol{\delta_2}$	-1.17	*-9.53*	*0.00*		

Panel B: Raw values of $CYCL_i$

Model		Estimate	*t-statistic*	*p-value*	N	Adj. R^2
1	$\boldsymbol{\gamma_1}$	2.39	*15.74*	*0.00*	1,911	0.02
	$\boldsymbol{\delta_1}$	-2.28	*-7.39*	*0.00*		
2	$\boldsymbol{\gamma_2}$	1.47	*17.59*	*0.00*	1,911	0.03
	$\boldsymbol{\delta_2}$	-1.46	*-9.90*	*0.00*		

Table 4: Industry-level analysis

This table reports results of regressions of industry-level time-series estimates of earnings response coefficients on industry-level time-series estimates of cyclicality:

1) $\beta_{1j} = \lambda_1 + \mu_1 CYCL_j + e_j$

2) $\beta_{2j} = \lambda_2 + \mu_2 CYCL_j + e_j$

For industry j we measure cyclicality $CYCL_j$ as the average of the firm-level estimates of cyclicality across all firms classified in industry j. We also calculate for each industry the average values of the firm-level earnings response coefficients denoted as β_{1j} and β_{2j}. The models are estimated using weighted least squares regressions where the weights are set equal to the frequency of firms in each industry. In Panel A our industry-level measure of cyclicality is based on the scaled (between 0 and 1) percentile ranks of the firm-level cyclicality estimates and in Panel B the industry-level measure is based on the raw values of these estimates. The sample includes 1,911 firms with at least 15 years of annual data for the period 1967-2006, classified in 50 industries based on the classification scheme of Professor Kenneth French.

Panel A: Scaled percentile ranks of $CYCL_i$

Model		**Estimate**	***t-statistic***	***p-value***	**N**	**Adj. R^2**
1	$\boldsymbol{\lambda_1}$	4.64	*8.38*	*0.00*	50	0.30
	$\boldsymbol{\mu_1}$	-5.11	*-4.72*	*0.00*		
2	$\boldsymbol{\lambda_2}$	2.46	*7.87*	*0.00*	50	0.22
	$\boldsymbol{\mu_2}$	-2.37	*-3.88*	*0.00*		

Panel B: Raw values of $CYCL_i$

Model		**Estimate**	***t-statistic***	***p-value***	**N**	**Adj. R^2**
1	$\boldsymbol{\lambda_1}$	2.92	*14.37*	*0.00*	50	0.33
	$\boldsymbol{\mu_1}$	-6.39	*-5.02*	*0.00*		
2	$\boldsymbol{\lambda_2}$	1.66	*14.39*	*0.00*	50	0.24
	$\boldsymbol{\mu_2}$	-2.95	*-4.08*	*0.00*		

Table 5: Additional analysis

This table reports results of annual cross-sectional regressions of firm-specific stock returns on firm-specific earnings surprises and cyclicality:

$$1)\quad R_{it} = a_{1t} + \zeta_{1t} CYCL_j + \beta_{1t} \frac{\Delta X_{it}}{MV_{it-1}} + \gamma_{1t} CYCL_j * \frac{\Delta X_{it}}{MV_{it-1}} + e_{it}$$

$$2)\quad R_{it} = a_{2t} + \zeta_{2t} CYCL_j + \beta_{2t} \frac{\Delta X_{it}}{BV_{it-1}} + \gamma_{2t} CYCL_j * \frac{\Delta X_{it}}{BV_{it-1}} + e_{it}$$

Specifically, the table reports the time-series means of the annually estimated coefficients along with t-statistics based on the time-series standard errors of the estimated coefficients with a Newey-West adjustment with three lags. The models are estimated using weighted least squares regressions for each year, where the weights are the market capitalization of a firm at the beginning of each year. R_{it} is the annual buy-and-hold inter-announcement return of firm *i* in year t, $\frac{\Delta X_{it}}{MV_{it-1}}$ is the earnings change between t and t-1 scaled by beginning of year market value of equity and $\frac{\Delta X_{it}}{BV_{it-1}}$ is the earnings change between t and t-1 scaled by beginning of year book value of equity. $CYCL_j$ is the average of the firm-level estimates of cyclicality across all firms classified in industry *j*. In Panel A our industry-level measure of cyclicality is based on the scaled (between 0 and 1) percentile ranks of the firm-level cyclicality estimates and in Panel B the industry-level measure is based on the raw values of these estimates. The sample includes 100,218 firm-years over the period 1967-2006, classified in 50 industries based on the classification scheme of Professor Kenneth French.

Panel A: Industry level cyclicality based on the scaled percentile ranks of $CYCL_i$

Model		**Estimate**	***t-statistic***	***p-value***	**Years**	**N**	**Adj. R^2**
1	a_{1t}	0.10	*2.03*	*0.05*	40	100,218	0.11
	ζ_{1t}	0.02	*0.37*	*0.71*			
	β_{1t}	2.43	*5.63*	*0.00*			
	γ_{1t}	-1.87	*-2.55*	*0.01*			
2	a_{2t}	0.08	*1.47*	*0.15*	40	100,218	0.11
	ζ_{2t}	0.06	*0.90*	*0.37*			
	β_{2t}	2.10	*3.93*	*0.00*			
	γ_{2t}	-2.30	*-3.39*	*0.00*			

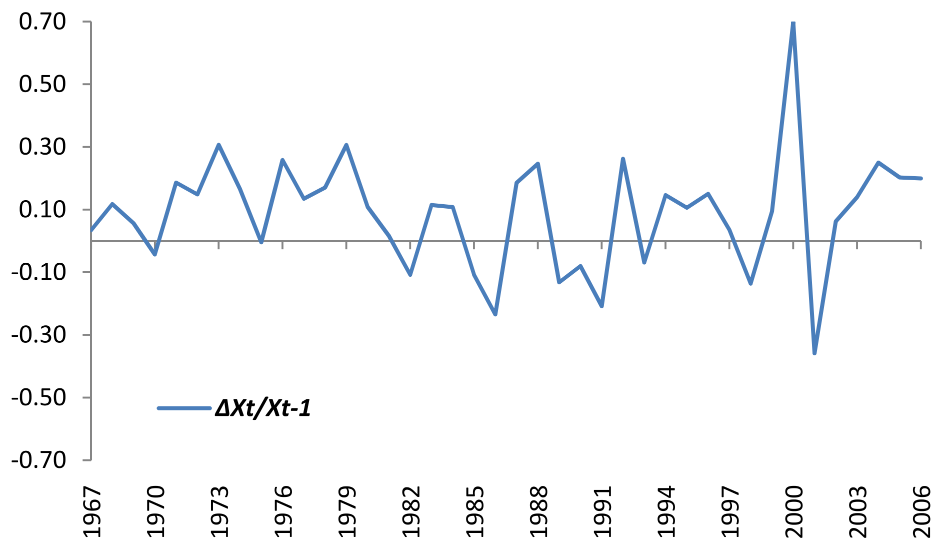
Panel B: Industry level cyclicality based on the raw values of $CYCL_i$

Model		**Estimate**	***t-statistic***	***p-value***	**Years**	**N**	**Adj. R^2**
1	$\boldsymbol{a_{1t}}$	0.11	*3.40*	*0.00*	40	100,218	0.11
	$\boldsymbol{\zeta_{1t}}$	0.03	*0.38*	*0.71*			
	$\boldsymbol{\beta_{1t}}$	1.75	*6.47*	*0.00*			
	$\boldsymbol{\gamma_{1t}}$	-2.06	*-2.36*	*0.02*			
2	$\boldsymbol{a_{2t}}$	0.10	*2.87*	*0.01*	40	100,218	0.11
	$\boldsymbol{\zeta_{2t}}$	0.07	*0.90*	*0.38*			
	$\boldsymbol{\beta_{2t}}$	1.28	*4.23*	*0.00*			
	$\boldsymbol{\gamma_{2t}}$	-2.60	*-3.37*	*0.00*			

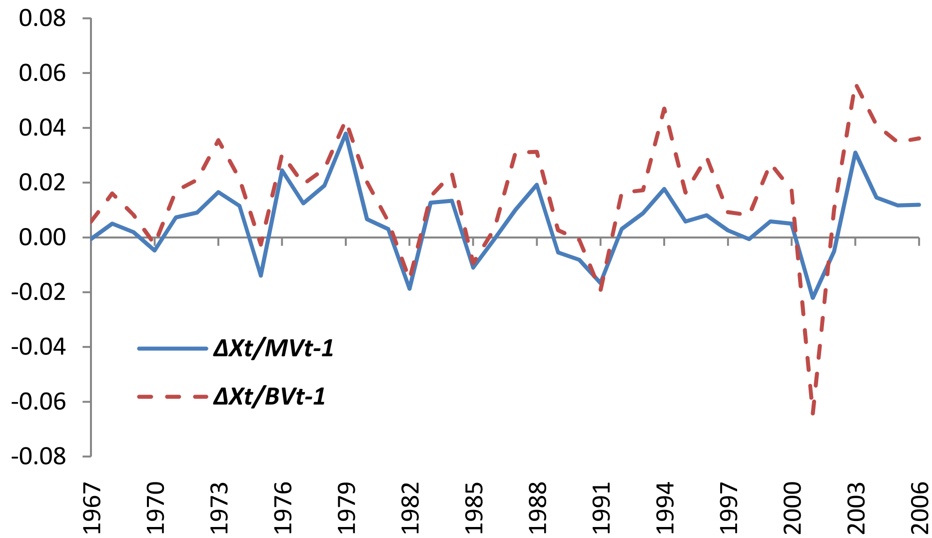
Figure 1: Aggregate-level time-series plots

This figure plots, in Panels A and B, the aggregate-level time-series values for the following variables: $\frac{\Delta X_t}{X_{t-1}}$ measured as the value-weighted annual cross-sectional average of individual-firm earnings change between t and t-1 scaled by earnings in t-1, $\frac{\Delta X_t}{MV_{t-1}}$ measured as the value-weighted annual cross-sectional average of the individual-firm earnings change between t and t-1 scaled by beginning of year market value of equity and $\frac{\Delta X_t}{BV_{t-1}}$ measured as the value-weighted annual cross-sectional average of the individual-firm earnings change between t and t-1 scaled by beginning of year book value of equity. The aggregated time-series are based on 100,218 firm-years over the period 1967-2006. In Panel C we plot the time series of year-by-year changes in the one year T-bill rate ($\Delta TBILL$).

Panel A: Aggregate-level time-series of earnings growth



Panel B: Aggregate-level time-series of earnings surprises



Panel C: Year-by-year changes in the one-year T-bill rate

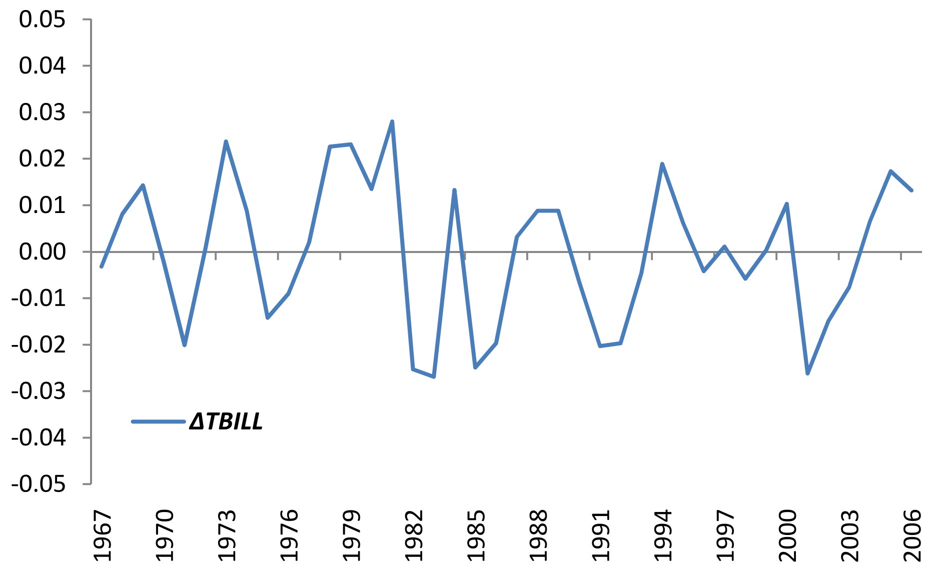


Figure 2: Histogram of firm-level time-series estimates of cyclicality

This figure plots the histogram of the firm-level estimates of cyclicality ($CYCL_i$). Firm-level estimates of cyclicality are measured as the time-series correlation of individual-firm earnings growth with the aggregate earnings growth. $CYCL_i = corr(\frac{\Delta X_{it}}{X_{it-1}}, \frac{\Delta X_t}{X_{t-1}})$; where $\frac{\Delta X_{it}}{X_{it-1}}$ is firm i's earnings change between t and t-1 scaled by earnings in t-1 and $\frac{\Delta X_t}{X_{t-1}}$ is the value-weighted annual cross-sectional average of the individual-firm earnings growth rates. The sample includes 1,911 firms with at least 15 years of annual data for the period 1967-2006.

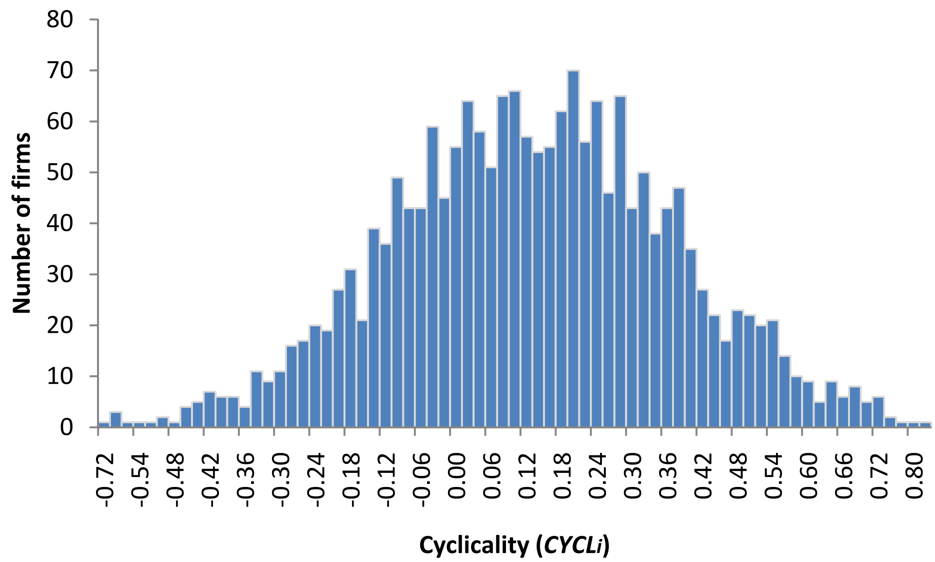
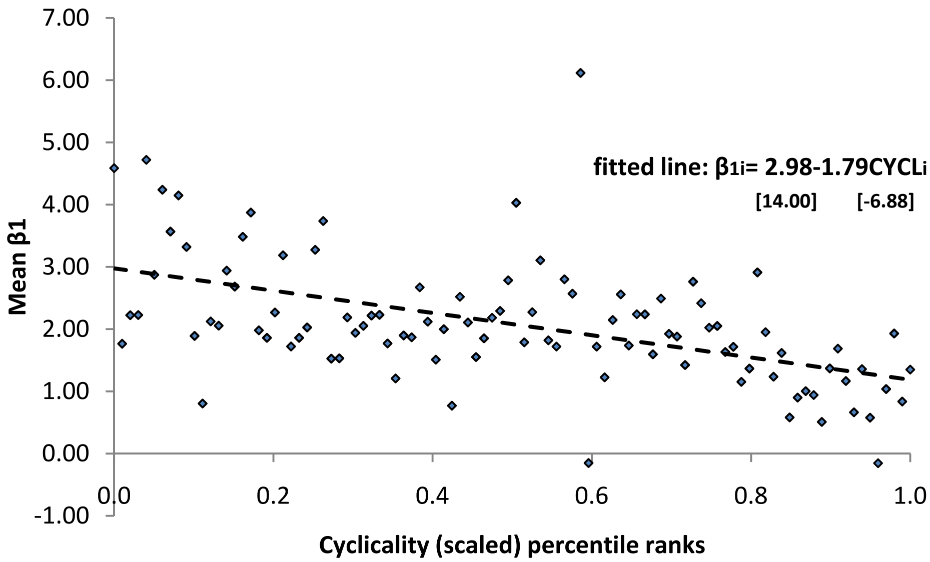


Figure 3: Firm-level analysis

This figure plots firm-level time-series mean estimates of earnings response coefficients for each scaled percentile rank of the cross-section of firm-level time-series estimates of cyclicality. Cyclicality-based percentile ranks are scaled to lie between 0 (lowest) and 1 (highest). The sample includes 1,911 firms with at least 15 years of annual data for the period 1967-2006.

Panel A: Mean values of β_1 for each cyclicality-based percentile rank



Panel B: Mean values of β_2 for each cyclicality-based percentile rank

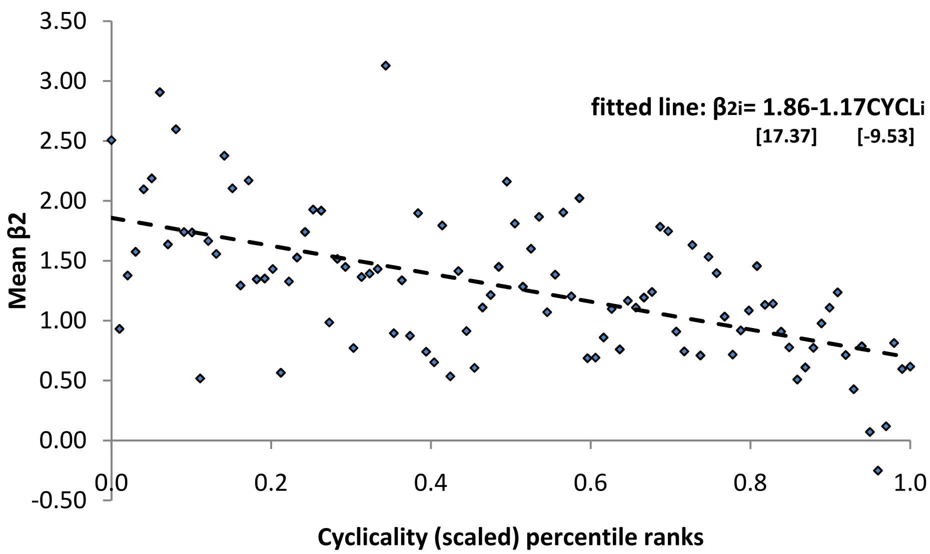
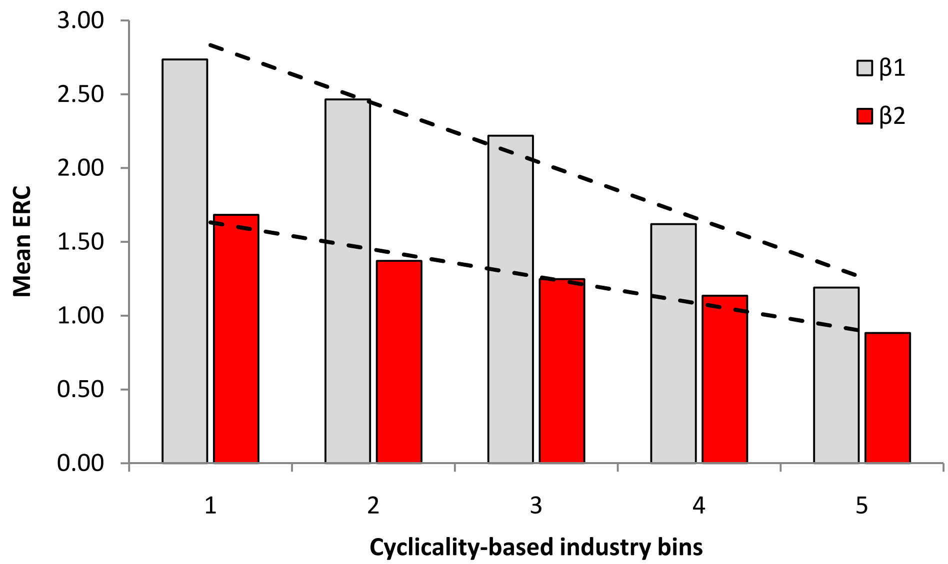


Figure 4: Industry-level analysis

This figure plots mean values of earnings response coefficients for five groups of industries based on our industry-level measure of cyclicality. Specifically, we classify our sample of 1,911 firms with at least 15 years of annual data for the period 1967-2006 into 50 industries using the classification scheme of Professor Kenneth French. For industry j we measure cyclicality $CYCL_j$ as the average of the firm-level estimates of cyclicality across all firms classified in industry j. We also calculate for each industry j the average values of the firm-level earnings response coefficients denoted as β_{1j} and β_{2j}. Next, we sort the 50 industries into five equal-sized bins based on the cross-industry distribution of $CYCL_j$ and then for each bin we plot the weighted mean values of earnings response coefficients. Weights are based on the number of firms classified in each industry.



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