# What Drives Stock Price Movement?

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First version: May 2007
This version: August 2010[‡]

**Abstract**

A central issue in asset pricing is whether stock prices move due to the revisions of expected future cash flows or/and revisions of expected discount rates, and by how much of each. Using direct cash flow forecasts, we show that there is a significant component of cash flow news in stock returns, whose importance relative to the discount rate news increases with investment horizons. For horizons over two years, the importance of cash flow news far exceeds that of discount rate news. These conclusions hold at both the firm and aggregate levels, and diversification only plays a secondary role in affecting the relative importance of cash flow/discount rate news. The conventional wisdom that cash flow news dominates at the firm level but discount rate news dominates at the aggregate level is driven by applying the predictive regression method inconsistently.

JEL Classification: G12, E44
Key Words: Expected return, discount rate news, cash flow news, predictability, analyst forecast

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[‡]We thank Bo Becker, George Benston, Michael Boldin, Jeff Callen, John Campbell, John Cochrane, Ilan Cooper, Pengjie Gao, Narasimhan Jegadeesh, Timothy Johnson, Raymond Kan, Andrew Karolyi, Jun Liu, George Pennacchi, Richard Priestley, Jesper Rangvid, Dan Segal, Jay Shanken, Rene Stulz, Michael Weisbach, Avi Wohl, and seminar participants at Beijing University, the Central Bank of Denmark, Copenhagen Business School, Hebrew University of Jerusalem, Hong Kong University of Science and Technology, McGill University, Norwegian School of Management (BI), Ohio State University, Tel Aviv University, Tsinghua University, University of Emory, University of Hong Kong, University of Illinois in Urbana Champaign, University of Toronto, Villanova University, Washington University in St. Louis, and 2008 WFA annual meeting for their helpful comments. The usual disclaimer applies. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Office of the Comptroller of the Currency or the U.S. Department of the Treasury.

# 1 Introduction

As shown in Figure 1, during the heat of the financial crisis, when investors, policymakers, and economists were debating the prospect of another great depression, the financial market revised downward the forecast of five-year-ahead aggregate earnings over consecutive quarters. This pattern is robust: the correlation between the revision of five-year earnings forecast and a recession dummy is -78%. Based on the evidence, it seems natural to conclude that a significant portion of stock price movement is due to the fact that investors revise their expectations on future cash flows when evaluating stocks.

But this is not what could be concluded from the bulk of asset pricing literature. The question of what causes stock price movement is central for asset valuation. Conceptually, stock prices can move because investors revise expectations on future cash flows (CF news) or on discount rates (DR news). Since neither expected CFs nor DRs are observable, the traditional approach is to predict them, and calculate CF news and DR news as functions of the predictive variables. It has been widely documented that returns are much easier to predict than dividends in the postwar period. The subsequent conclusion is that almost all aggregate stock variation is driven by DR news; almost none by CF news. Following this logic, almost all of the aggregate price swings during the financial crisis are related to DRs. The prospect of another great depression, though intensely discussed, never affected price movement.

Economists are not comfortable with this conclusion. As Cochrane (2006) notes, "Our lives would be so much easier if we could trace price movements back to visible news about dividends or cashflows...But that is where the data have forced us, and they still do so."

The data have "forced us" because predictive regressions require a long sample. Their conclusions are sensitive to the sample period (Chen (2009)), to the choice of predictive variables (Goyal and Welch (2008) and Chen and Zhao (2009)), and, as we show below, to the difference between time series and cross-sectional predictability. Varying among these dimensions, the role of CF news could vary from "being dominant" to "non-existent."

The above discussion suggests that it might be fruitful to explore some alternative methods that do not rely on predictability. We propose such a new method by using direct expected cash flow measures. Specifically, given stock prices, we use the market prevailing forecasts for future cash flows (from I/B/E/S), for each firm and at each point of time, to back out the firm-specific implied cost of equity (e.g., Pastor, Sinha, and Swaminathan (2008)). Consequently, a price change can be decomposed into two pieces: the CF news, defined as the price change holding implied cost of equity (ICC) constant, and the DR news, defined as the price change holding CF constant; this decomposition holds by definition without resorting to predictability. We can then study the relation between proportional price change (i.e., capital gain return), CF news, and DR news at the firm and aggregate levels, and at short to long horizons.

Such a method leads to fresh insights. We discuss our findings in detail below.

**What drives aggregate stock returns?** Using the ICC method, at the aggregate level, the portion of return variance attributed to CF news is a significant 37% at the annual horizon, 54% at the two-year horizon, and 89% at the seven-year horizon. Therefore, a significant portion of stock price variations is related to CF news, and increasingly more so as investment horizon expands. For horizons beyond two years, CF news outweighs DR news.

The finding that the relative importance of CF/DR news changes with time horizon is intuitive. By definition, negative DR news in the current period (because DR goes up) will be offset by higher returns in the future. Therefore, the impact of DR news is temporary and attenuates with time. In the long-run limit, almost all stock return news must be CF news (e.g., Campbell and Vuolteenaho (2004), Bansal, Dittmar, and Kiku (2009), and Hansen, Heaton, and Li (2008)). This is a fundamental property that holds irrespective of economic models.

The results using the predictive regression method vary, in a dramatic fashion, depending on the sample period. For example, using dividend yield as the predictor for 1926-2009, the portion of return variance driven by CF news is 56% at the annual horizon and 76% at the seven-year horizon. In stark contrast, for 1946-2009, the portion of return variance driven by CF news is -12% at the annual horizon and -6% at the seven-year horizon. If one takes the view that time series predictability is more reliable using a longer sample, then the predictive regression approach, consistent with the ICC approach, suggests that aggregate CF news is important for price movement.

Therefore, the ICC method indicates a role of CF news much more important than suggested by the predictive regression method for the postwar period. This finding has at least two implications. First, the previous conclusion that there is little CF news, albeit disconcerting, has provided an important empirical basis for theoretic modeling (e.g., Campbell and Cochrane (1999) versus Bansal and Yaron (2004)). Our finding that there is significant CF news at reasonable horizons suggests that CF news deserves a bigger role in theoretical considerations.

Second, in his seminal paper, Shiller (1981) argues that aggregate returns are too volatile to be explained by future dividend growth. Our finding suggests that this argument is incomplete because it should only hold at certain investment horizons. In particular, beyond two years CF news starts to exceed and dominate DR news. Aggregate returns beyond the two-year horizon are not "too volatile" anymore. As Cochrane (2001) points out, the "disconcerting" excess volatility puzzle stems from the excess (lack of) predictability for returns (dividend growth). We largely mitigate this puzzle by avoiding predictive regressions and thus some limitations data could force.

**What drives firm-level stock returns?** Using the ICC method, at the firm level, on average, the portion of stock returns attributed to CF news is 50% at the annual horizon, 69% at the two-year horizon, and 74% at the seven-year horizon. These numbers are slightly higher than those for the aggregate portfolio at shorter horizons, suggesting that CF news is diversified away relatively more than the DR news. However, this diversification effect is secondary in the sense that, starting from the two-year horizon, CF news is at least as important as DR news at both firm and aggregate levels.

The finding that there is only a limited *relative* CF/DR diversification effect when moving from individual firms to the aggregate portfolio provides a stark contrast to the prevailing view that, because of diversification, CF news dominates at the firm level but DR news dominates at the aggregate level. This prevailing view, from Vuolteenaho (2002), is achieved by running predictive panel regressions without controlling for firm fixed effect.

In panel regressions, there is a critical difference between cross-sectional and time series predictability, an issue that has been largely ignored in the current literature. Basically, the cross-sectional heterogeneity of CFs is persistent (e.g., Lakonishok, Shleifer, and Vishny (1994) and Fama and French (1995)) and predictable; it is thus easy to find that CF news dominates whenever a panel data (without firm fixed-effect control) is studied. However, in the time series dimension, CFs are less predictable than DRs, and DR news is usually found to be more important in pure time series regressions – common for the aggregate portfolio analysis. The prevailing conclusion is thus reached by mixing the strong cross-sectional CF predictability with the weak time series CF predictability. Such a conclusion is unreliable because it compares apples with oranges.

Panel analysis without firm fixed effect assumes that all firms are homogeneous in the long run. If one takes such a view, to understand the role of diversification, she can compare the case of firm-level panel regression without firm fixed effect with the case of "aggregate market" by grouping all firms into two portfolios. A panel of two-portfolio aggregate market has the advantage that it preserves the cross-sectional predictability and each portfolio is about as diversified as the market. In this case, we find that at the firm level 11% (56%) of return variance is driven by DR (CF) news; at the two-portfolio level, 4% (74%) of return variance is driven by DR (CF) news.[1] Therefore, the predictive regression method without firm fixed effect (as in Vuolteenaho (2002)) leads to two conclusions: (i) CF news dominates DR news at both firm and aggregate levels, and (ii) diversification plays no role. The first conclusion overturns the prevailing one for the aggregate market; the second overturns Vuolteenaho (2002).

Alternatively, if one relies solely on time series predictability, he can compare the results using panel regressions with firm fixed effect (or firm-by-firm time series analysis) with the results for the market portfolio. In this case, we find that DR news seems more important than CF news even at the firm level, and there is no flip of the relative importance of CF/DR news from the firm to the aggregate levels.

We can draw two conclusions using the predictive regression method. First, regardless of the source of predictability, so long as one conducts consistent analysis, there is no flip of the relative importance of CF/DR news and diversification plays a relatively secondary role. This conclusion overthrows that in the current literature. Second, if one considers both time series and cross-sectional predictability, then CF news plays an important role at both firm and aggregate levels at annual horizon. This conclusion challenges a major conclusion in the current literature regarding the aggregate market. Both conclusions are consistent with what we have found using the ICC method.

**Summary** The issue of what drives stock price movement is crucial for asset pricing because it reveals how investors evaluate securities. Long overdue is a consistent understanding on the relative importance of CF versus DR news, at both the aggregate and firm levels, and at different horizons. In this regard, this paper makes two contributions.

First, methodologically, we provide a new method to decompose returns that does not rely on predictability. It is forward-looking and thus is little affected by past data, the choice of predictive variables, or the sources of predictability. The method can be easily applied at firm, portfolio, and market levels, and from short to long horizons. Importantly, cash flow forecasts are taken from

[1] Due to various misalignments, the directly estimated DR news and CF news do not sum up to the total unexpected return. Vuolteenaho (2002) does not estimate CF news directly but backs it out as the residual. He would have concluded that 89% (rather than 56%) of return variance is driven by CF news at the firm level. Therefore most of his estimates on CF news are severely biased.

practitioners and are consistent with industry practice in security valuation.

A key assumption of the ICC approach is that analyst earnings forecasts timely reflect marginal investors' belief regarding future CFs. Any deviation from this assumption, such as stale or too optimistic analyst forecasts, is likely to prevent us from finding a strong role of CF news in driving stock returns.[2] In this sense, our estimates on the importance of CF news in the short run can be regarded as a lower bound, and we provide extensive robustness checks in the paper.

Second, in companion with the ICC approach, we provide the first study to *consistently* apply the predictive regression approach to both firm and aggregate levels, and at different horizons. We show that the prevailing conclusion on the relation between CF news and diversification is overturned once one uses the estimation method consistently. In addition, if one considers cross-sectional predictability, she can conclude that there is a lot of CF news at both firm and aggregate levels. While these two messages are new and are independent of the ICC approach, they are consistent with the conclusions from the ICC approach.

Combining the two approaches, our takeaway message is that, contrary to some prevailing views, the evidence can be consistent with the presence of significant CF news at both firm and aggregate levels, and diversification plays a secondary role in the relative importance of CF/DR news.

**Link to literature** Our paper is the first to use the ICC approach to study return decomposition. Our contribution is related to, but distinctly different from the literature that uses the ICC approach to study asset valuation and risk-return tradeoff, including, among others, Kaplan and Ruback (1995), Botosan (1997), Liu and Thomas (2000), Claus and Thomas (2001), Gebhardt, Lee, and Swaminathan (2001), Jagannathan and Silva (2002), Brav, Lehavy, and Michaely (2005), Lee, Ng, and Swaminathan (2003), Hail and Leuz (2006), Botosan and Plumlee (2005), Easton, Taylor, Shroff, and Sougiannis (2002), Easton (2004), Olson and Juettner-Nauroth (2005), Pastor, Sinha, and Swaminathan (2006), and Chen and Zhang (2007). This approach is in the same spirit of Graham and Harvey (2005) who use surveys among CFOs to measure the expected equity premium. Our results suggest that such an approach can shed fresh lights on several fundamental issues in asset valuation.

Our findings complement the literature that studies the relative return/cash flow predictability by the dividend yield (e.g., Campbell and Shiller (1988, 1998), Cochrane (1992, 2001, 2006), Ang

[2]There is a literature documenting that stock prices respond to revisions of analyst forecasts. This literature includes, among others, Griffin (1976), Givoly and Lakonishok (1979), Imhoff and Lobo (1984), Elton, Martin, and Gultekin (1981), Lys and Sohn (1990), Francis and Soffer (1997), and Park and Stice (2000).

(2002), Goyal and Welch (2003), Lettau and Ludvigson (2005), Lettau and Nieuwerburgh (2006), Ang and Bekaert (2007), Larrain and Yogo (2008), Binsbergen and Koijen (2009) and Chen (2009)). This literature provides important evidence on predictability and on the informational content of the dividend yield; we study price volatility without resorting to predictability.

The rest of the paper proceeds as follows. In Section 2 we describe the method to construct CF news and DR news, and report the sample summary. In Sections 3 and 4 we report the evidence at aggregate and firm levels respectively. In Section 5 we conduct robustness checks. A brief conclusion is provided in Section 6.

# 2 The model and the sample

## 2.1 The model

We back out the discount rate for each firm quarter following Pastor, Sinha, and Swaminathan (2008). The equity value is the present value of future "dividends" and a terminal value:

$$P_t = \sum_{k=1}^{T} \frac{FE_{t+k}\left(1-b_{t+k}\right)}{\left(1+q_t\right)^k} + \frac{FE_{t+T+1}}{q_t\left(1+q_t\right)^T}, \tag{1}$$

where $P_t$ is stock price, $FE_{t+k}$ is earnings forecast $k$ years ahead, $b_{t+k}$ is the plowback rate (i.e., $1-b_{t+k}$ is the payout ratio), and $q_t$ is the cost of equity. $T$ is set to 15 years.

For each firm, the earnings forecasts for $t+1$, $t+2$ , $t+3$ are the consensus analyst forecasts for the first three years respectively, and are obtained from the I/B/E/S database. For year $t+4$ to $t+T+1$, the earnings growth rate and the earnings forecasts are

$$g_{t+k} = g_{t+k-1} \times \exp\left[\log\left(g/g_{t+3}\right)/\left(T-1\right)\right] \tag{2}$$

$$FE_{t+k} = FE_{t+k+1} \times \left(1+g_{t+k}\right) \tag{3}$$

Here $g_{t+3}$ is the firm-specific consensus long-term earnings growth forecast; $g$ is the mean long-term industry growth forecast by analysts. The above formulas suggest that the earnings growth rate for each firm mean reverts to the long-term industry growth by year $t+T+2$.

For the first two years, the plowback rate is calculated from the most recent net payout ratio for each firm. The net payout ratio is the ratio of common dividends (item DVC in COMPUSTAT) to net income (item IBCOM). If net income is negative, we replace it by 6% of assets. The plowback rate then reverts between year $t+3$ and $t+T+1$ to a steady-state rate. This is based on the assumption that, in a steady state, the product of the return on investment, ROI, and the plowback rate, b, is equal to the growth rate in earnings: $g = ROI \times b$. Under the assumption that the return on investment is equal to the cost of equity, the steady-state plowback rate is $b = g/q$, that is,the ratio of industry growth to cost of equity. Therefore, the plow back rates from $t+3$ to $t+T$ are

$$b_{t+k} = b_{t+k-1} - \frac{b_{t+2} - b}{T-1}. \tag{4}$$

With the forecasted earnings and plowback rates, the cost of equity is then backed out based on equation (1) for each firm at each point of time. We examine alternative models in Section 5.

**CF news and DR news** We can rewrite equation (1) as

$$\begin{aligned} P_t &= \sum_{k=1}^{T} \frac{FE_{t+k}\left(1-b_{t+k}\right)}{\left(1+q_t\right)^k} + \frac{FE_{t+T+1}}{q_t\left(1+q_t\right)^T} \\ &= f\left(c^t, q_t\right). \end{aligned} \tag{5}$$

By construction, stock price $P_t$ is a function of the vector of cash flow forecast variables available at time $t$ (with superscript $t$), $c^t$, and the discount rate $q_t$. The proportional price difference between $t+j$ and $t$ is then (subscript changed from t to j.)

$$\begin{aligned} r_j &= \frac{P_{t+j} - P_t}{P_t} && (6) \\ &= \frac{f\left(c^{t+j}, q_{t+j}\right) - f\left(c^t, q_t\right)}{P_t} && (7) \\ &= \frac{\left(f\left(c^{t+j}, q_{t+j}\right) - f\left(c^t, q_{t+j}\right)\right)}{P_t} + \frac{\left(f\left(c^t, q_{t+j}\right) - f\left(c^t, q_t\right)\right)}{P_t} && (8) \\ &= CF_j + DR_j, && (9) \end{aligned}$$

where

$$CF_j = \frac{\left(f\left(c^{t+j}, q_{t+j}\right) - f\left(c^t, q_{t+j}\right)\right)}{P_t} \tag{10}$$

is the CF news; it is so because the numerator is calculated by holding the discount rate constant at $t+j$ and the difference is driven by the CF difference between $t$ and $t+j$. Similarly,

$$DR_j = \frac{\left(f\left(c^t, q_{t+j}\right) - f\left(c^t, q_t\right)\right)}{P_t} \tag{11}$$

is the DR news; it is so because CFs do not change in the numerator, and the difference is driven by the variation of discount rates in the period. Note that DR news and DR go in opposite directions.

We can then study the variance of the capital gain return through CF news and DR news:

$$VAR(r_t) = COV(CF_t, r_t) + COV(DR_t, r_t) \tag{12}$$
$$1 = \frac{COV(CF_t, r_t)}{VAR(r_t)} + \frac{COV(DR_t, r_t)}{VAR(r_t)}, \tag{13}$$

where $VAR$ and $COV$ are variance and covariance operators. $\frac{COV(CF_t,t_t)}{VAR(t_t)}$ is the slope coefficient of regressing $CF_t$ on $r_t$; $\frac{COV(DR_t,r_t)}{VAR(r_t)}$ is the slope coefficient of regressing $DR_t$ on $r_t$. In other words, to understand the portion of return variance that is driven by CF news and DR news, one only needs to regress CF news and DR news on the capital gain returns respectively to draw inferences based on the slope coefficients.

## 2.2 Model properties and comparison with the current literature

**Expected return versus implied cost of equity** The discount rate in our model is the implied cost of equity (ICC). Hughes, Liu, and Liu (2009) show that ICC, the single discount rate that applies to all horizons, might deviate from the expected next-period return. This is not a concern for us because our goal is not to estimate the expected return for the next period, but to capture price variations due to changes of expected returns for all future horizons, in which case ICC is the proper measure to use. To see this point, consider the present value formula

$$P_t = \sum_{n=0}^{\infty} E_t \left( \exp\left( - \sum_{s=t}^{t+n} \mu_s \right) c_{t+n+1} \right) \tag{14}$$
$$= \sum_{n=0}^{\infty} E_t \left( \exp\left( -(n+1) \times \pi_t \right) c_{t+n+1} \right), \tag{15}$$

where $E_t$ is the expectation taken at time $t$, $\mu_s$ is the expected return for period $s$, $c_{t+n+1}$ is cash payout, and $\pi_t$ is ICC. Equations (14) and (15) are alternative but equivalent forms of the present value formula. DR news is caused by revisions of expected returns for all future periods ($\mu$), whose impact can be summarized by the revision of ICC ($\pi$). Nothing is lost in this equivalence since it is by definition.

An analog is the relation between the term structure of interest rates and bond yield. Bond yield tells nothing about the term structure. Bond price changes, however, can be completely captured by yield changes by definition.

Importantly, the use of ICC does not mean that the discount rate remains constant through time. In fact, since the approach backs out ICC at each point of time, the discount rate is time varying.

**ICC versus predictive regression** The challenge of interpreting asset price variation is that usually neither expected CFs nor DRs are observable. The common practice in the current literature is to predict cash flows and returns. Price variations, in turn, are interpreted by the variation of the predictors through their predictive powers.

The predictive regression method requires a long sample, or, put differently, is sensitive to the choice of sample period. For example, if one uses dividend yield as the predictor, depending on whether he studies a sample during 1870-2009, 1926-2009, or 1946-2009, the conclusion ranges from "the majority of aggregate price variation is driven by CF news" to "almost no variation of price variation is driven by CF news" (see Chen (2009)). Which version should one trust?

This problem becomes worse with firm-level data due to the lack of long time series. To overcome the problem, the current approach is to run panel OLS predictive regressions (Vuolteenaho (2002)) with the implicit assumption that firms are homogeneous. As we show below, the results using this approach at the firm level are incompatible with the results using aggregate data because the former mixes cross-sectional with time series predictability. Once corrected, almost all major firm-level conclusions in the current literature are reversed.

The predictive regression method is also sensitive to the choice of predictive variables. Intuitively, if price variations are interpreted through the variation of state variables, it matters which variables are used. Chen and Zhao (2009) show that different choices of state variables, with seemingly minor alterations, can lead to dramatically different conclusions.

In contrast, since our approach uses forward-looking information and thus does not run predictive regressions, it does not require long time series data. Rather than relying on coefficient stability using long past data, it can use current information to interpret current events. Importantly, it is consistent with industry practice where analyst cash flow forecasts are used to evaluate securities. Since our goal is to interpret price variation from the point of view of practitioners, it is comforting that at least the methods are consistent. In addition, the choice of predictive variables is a non-issue in our approach.

**Linearization** The predictive regression method, following Campbell and Shiller (1988), interprets price variations through log-linearization of the present value formula. In comparison, our approach does not linearize the pricing model. The impact of nonlinearity will be considered in our model.

**Model assumptions and limitations** Since our approach is based on the present value formula, the main potential limitation centers on the quality and richness of analyst forecasts.

First, the model uses analyst forecasts and stock prices to back out the DRs. This means that the DR news captures the residual news. For example, if the updates on analyst forecasts are purely noises, then the burden of explaining returns falls completely on the DR news. In other words, it would not be surprising to see a strong role of the DR news; the success of the model depends on how well we can capture the CF news since the DR news will pick up the rest.

Second, the model assumes that analyst forecasts timely capture the marginal investors' revisions on expected future CFs. In real life some analyst forecasts could be stale. In addition to sluggishness, analyst forecasts could be biased due to over-optimism or (investment banking-related) conflict of interest (see also Ljungqvist, Malloy, and Marston (2007)). We provide extensive robustness checks in Section 5.

In general, limitations of analyst forecasts tend to prevent us from finding strong CF effects – better proxies of expected CFs are likely to yield stronger results. In this sense, our estimates of the CF effects can be regarded as a lower bound for the actual CF effects. In addition, analyst sluggishness can be mitigated at longer horizons. This suggests that the model might explain price variation better at longer horizons (e.g., one year or two years rather than one quarter).

Finally, we do not assume that analyst forecasts are more informative than, or lead, the stock prices. The job of the analysts is to forecast future cash flows based on all information (including prices). So long as the forecasts revisions are largely consistent with the investors' views, our story is likely to go through.

**Summary and plan** The predictive regression approach is sensitive to the sample length and the choice of predictive variables; historically, these limitations also have made it difficult to consistently apply the approach at firm and aggregate levels. Since these are essentially non-issues for the ICC approach, one can easily apply the ICC approach consistently at firm and aggregate levels, and at different horizons. The ICC approach is limited by the timeliness of analyst forecasts. This limitation can be partly mitigated by emphasizing results at longer horizons; the results, in general, can be regarded as a lower bound for the role of CF news.

The goal of the paper is to understand price movement (rather than merely advocating for the ICC approach). As such, we will present results using both approaches at firm and aggregate levels, and at different horizons, based on which we search for the best interpretation.

### 2.3 The sample

Our main results are based on quarterly data. I/B/E/S reports consensus analyst forecasts on earnings as of the middle of each month. We collect earnings forecast data as of March, June, September, and December of each year for all firms. The accounting data is from COMPUSTAT. We match analyst forecasts with the accounting information that has been publicly released.

Besides earnings forecasts, we also collect from I/B/E/S share prices and the number of shares outstanding. To be included in the sample, we require non-missing data for one-year ahead earnings forecasts. If a firm has missing forecasts for year two, we follow the existing literature and project earnings in the second year using the long-term growth rate and the prior year's earnings forecast: $FE_{t+2} = FE_{t+1} \times (1 + g_{t+3})$. We also require that the firm has prior year's dividends in COMPUSTAT. We restrict our sample to the 1985-2009 period because I/B/E/S covers too few firms before 1985.

Table 1 provides the year-by-year quarterly statistics for the final sample. The number of firms ranges from 1011 to 2803, and the average payout ratio varies from 43% to 64%. Overall, our sample represents more than 78 percent of the total market capitalization. There is a general downward trend of cost of equity during the sample period before 2008, which makes sense because there is also a similar downward trend in the riskfree rate for the same period.

## 3 What drives aggregate stock price volatility?

We winsorize all firm-specific variables in the final sample at the 1% and 99% breakpoints. We then collapse the sample into a value-weighted aggregate time series covering 1985-2009. The purpose is to study the relation among returns, CF news, and DR news for the market portfolio.

We note that returns, as defined in equation (6), do not include dividends since our primary goal is to study price volatility. In addition, dividends play a minor role in the total return volatility anyway.[3]

Following Equation (13), we regress CF news and DR news, respectively, on cumulative capital gain returns, ranging from one to 28 quarters. The slope coefficients represent the portion of stock return variance that is driven by each component. At the annual horizon, a significant 37% of the

[3]For example, during 1926-2008 the average quarterly total return for the CRSP value-weighted portfolio is 2.83% with a standard deviation of 11.31%; the average quarterly return excluding dividends is 1.85% with a standard deviation of 11.24%. During 1985-2008 the average total return is 2.70% with a standard deviation of 8.67%; the average return excluding dividends is 2.09% with a standard deviation of 8.61%. Therefore, dividend payout only affects the level of returns; its impact on return volatility is negligible.

return variation of the market portfolio is explained by CF news. This percentage increases to 54% at the two-year horizon, 67% at the three-year horizon, and 89% at the seven-year horizon.[4]

Most coefficients are significant at 1% according to the Newey-West t-statistics. Note that the regressions with horizons over one quarter use overlapping data. However, unlike the usual long-horizon predictive regressions with overlapping data, the coefficients and t-statistics (e.g., those for DR news) here do not mechanically increase with horizon (see Boudoukh, Richardson, and Whitelaw (2008)). This is because we do not run predictive regressions. In untabulated simulations, we find that the use of overlapping data within our context does not lead to biased coefficients or t-statistics that vary systematically with investment horizon.

Therefore, for the market portfolio, there is a significant component of CF news in returns, which increases with investment horizons. For horizons beyond two years, CF news outweighs DR news.

**The predictive regression approach**

To understand our results, it is useful to compare them with the results using the predictive regression method. Consider a first order VAR with return, dividend growth, dividend yield, and additional variables, $Z_t = [r_t \bigtriangleup d_t \; dp_t \; x_t']'$, with

$$Z_t = \Gamma Z_{t-1} + \varepsilon_t, \tag{16}$$

where $r_t$ is return, $\bigtriangleup d_t$ is dividend growth, $dp_t$ is dividend yield, and $x_t$ is a vector of additional predictive variables. As we show in Appendix A, the one-period unexpected return, $\varepsilon_{r,t}$, can be decomposed into DR news ($e_{DR,t}$) and CF news ($e_{CF,t}$):

$$\varepsilon_{r,t} = e_{DR,t} + e_{CF,t}, \tag{17}$$

$$e_{DR,t} = -e1'\lambda\varepsilon_t, \tag{18}$$

$$e_{CF,t} = e2'\left(I + \lambda\right)\varepsilon_t, \tag{19}$$

where $\lambda = \rho\Gamma\left(I - \rho\Gamma\right)^{-1}$, $e1$ is a vector whose first element is equal to one and zero otherwise, and $e2$ is a vector whose second element is equal to one and zero otherwise. Intuitively, returns and dividend growth are projected onto predictive variables. DR news and CF news are then functions of shocks to the predictive variables ($\varepsilon_t$) multiplied by the predictive coefficients ($\lambda$).

[4] CF news is small and insignificant at quarterly horizon. However, due to the sluggishness of analyst forecasts (e.g., Chan, Jegadeesh and Lakonishok (1996)), the results are more reliable at longer horizons. In addition, standard studies in the literature use annual horizon.

As shown in Appendix A, the impact of one-period CF news on n-period CF news is simply the one-period CF news. In contrast, the impact of one-period DR news on n-period DR news is

$$\begin{aligned} & e1' \times (\rho\Gamma)^n \times (I - \rho\Gamma)^{-1} \varepsilon_t \\ \simeq \; & 0 \text{ if n is large.} \end{aligned}$$

Intuitively, if stock price goes down because DR goes up, the current period negative return will be offset by higher future returns if one holds the stock for multiple periods. In the long run, DR news is temporary; all return news is CF news. By definition then, the importance of CF (DR) news is an increasing (decreasing) function of time horizon. The issue of the relative importance of CF/DR news is only relevant at relatively shorter horizons.

Panel A of Table 3 reports the results of return decomposition by using dividend yield as the only predictive variable for 1926-2009.[5] At one-year horizon, 56% (44%) of return variance is driven by CF (DR) news. CF news explains 75% of return variance at the 5-year horizon, and 80% at the 15-year horizon. Therefore, consistent with the ICC approach, there is significant CF news for the market portfolio, whose importance increases with horizon.

Panel B repeats the exercise for 1946-2009. Dividend yield predicts return with a significant coefficient of 0.12, but predicts dividend growth with the wrong sign (0.02). Consequently, 110% (-12%) of the annual return variance is driven by DR news. This is the well-known conclusion that almost all of the aggregate return variation is driven by DR news, almost none by CF news. Even at the seven-year horizon, CF news still explains none of the return variance. The results in Panels A and B change to some degree if we include additional predictive variables such as the Baa over Aaa spread or the consumption surplus ratio $CAY$ (Lettau and Ludvigson (2001)), but the basic conclusions remain.

Therefore, the conclusions using the predictive regression approach vary dramatically depending on the sample length and the choice of predictive variables. The question is which conclusion should one adopt. We believe that the long sample results are more reliable for the following reasons.

First, due to the persistence of the predictive variables, it is preferable to use a longer sample, when possible, in time series analysis. For example, Cochrane (1992, 2008) uses the long CRSP sample.[6] Campbell and Vuolteenaho (2004) use data covering 1929-2001 to obtain coefficients even

[5]Dividend yield has been the focus of a large literature on return and dividend growth predictability. See, among others, Campbell and Shiller (1988, 1998), Cochrane (1992, 2001, 2006), Ang (2002), Goyal and Welch (2003), Lettau and Nieuwerburgh (2006), Ang and Bekaert (2007), Chen (2009), and Binsbergen and Koijen (2009).

[6]Even though using a long sample, Cochrane (1992, 2008) concludes that there is little CF news in aggregate

though their main intention is to explain the cross-sectional returns during 1963-2001.

Second, as Cochrane (2008) points out, "our lives would be so much easier if we could trace price movements back to visible news about dividends or cashflows." Confirming basic intuition, the long sample results suggest that there is indeed a large portion of CF news in aggregate returns. In addition, if one believes in the postwar result, then she needs to explain why the world has switched from time-varying expected dividend growth (and relatively stable DRs) to time-varying DRs (and constant expected dividend growth).

Third, Chen, Da, and Priestley (2010) show that dividends are much more smoothed in the postwar period, which buries dividend growth predictability. This means that dividends, as a result of corporate policy, do not represent well the prospect of future cash flows.

Fourth, if one believes that there is no CF news in the aggregate returns, she must conclude that the large swing of returns is mostly a DR phenomenon and investors never priced the possibility of another great depression. Such a conclusion is contrary to the consecutive downward revision of five-year ahead aggregate analyst forecasts as shown in Figure 1.

During the financial crisis, the quarters experiencing the most negative annual returns (compared to four quarters ago) are the fourth quarters (-38%) of 2008 and the first (-36%) and second (-31%) quarters of 2009. The predictive regression approach would have attributed these to DR news. To the contrary, using the ICC approach, the corresponding CF news are, respectively, -23%, -31%, and -46%. Large negative swings of the aggregate market are accompanied by large downward revisions of future cash flows, consistent with the view that the prospect of a potential great depression (i.e., CF news) dragged the market down. This view seems to be shared by policy makers, practitioners, and academicians at that time, and provides a sharp contrast to the view that there is little CF news in aggregate price variation.

**Shiller's volatility puzzle**

Shiller (1981) argues that aggregate return volatility is too volatile to be explained by the movement of future dividend growth. Our finding suggests that this argument is incomplete because it should only hold at certain investment horizons.

Figure 2 plots returns at one-year horizons and the corresponding CF news (ICC approach). That is, we show how returns are related to CF news by holding DR constant during the period.

returns. As shown by Chen (2009), this conclusion is reached because Cochrane assumes that monthly dividends are reinvested in the equity market; the annual dividend growth rate is thus strongly correlated with returns. This assumption, while reasonable, makes it difficult to detect dividend growth predictability. The dividend growth rate without reinvestment in the equity market is actually strongly predictable in the long sample.

This is in spirit similar to Shiller (1981) who compare actual prices with prices calculated using realized future cash flows. Except for the first year 1985, in which case there are fewest firms, CF news tracks actual return very well in most years at the annual horizon. Figure 3 shows that returns at two-year horizons and the corresponding CF news are even more closely related. Indeed, our results indicate that aggregate returns beyond the two-year horizon are not "too volatile" anymore.

As Cochrane (2005) points out, excess return volatility means excess return forecastability. The lack of dividend growth predictability has motivated important theoretical models in which CF news assumes a minor role (e.g., Campbell and Cochrane (1999)). Our finding mitigates the excess volatility puzzle and the concern by Cochrane. We reach the conclusion without running predictive regressions and thus get around the data that could have "forced us" to make "uncomfortable' conclusions.

## 4 Firm level evidence

How are returns, CF news, and DR news related at the firm level? If returns are driven by both CF news and DR news at the firm level, which component is relatively more diversified away when an increasingly more diversified portfolio is held? These are important issues that help us understand the nature of the financial market and portfolio management.

To examine these issues, we conduct the same time series analysis, as we have done for the aggregate portfolio, for each firm separately. To do so, we require that each firm should have at least 16 quarters of data. We then report the cross-sectional average of firm-specific results in Table 4.

At the annual horizon, a significant 50% of firm stock returns is related to CF news; this number increases to 69% at the two-year horizon and 74% at the seven-year horizon. Therefore, similar to what we have observed at the aggregate level, there is a significant portion of CF news in stock returns at the firm level, and increasingly more so at longer horizons.

CF news is more important at the firm level than at the aggregate level for shorter horizons. This suggests that, as investors hold more stocks, CF news is relatively more diversified away than DR news. However, this diversification effect is mild in the following sense. First, at both firm and aggregate levels CF news is important. Second, CF news is slightly more important at the firm level only up to the three-year horizon; at longer horizons CF news appears to be even more important at the aggregate level.

The bottom line is that we observe very similar patterns at the firm and aggregate levels. CF news outweighs DR news at horizons beyond two years. There exists some diversification effect of CF news from the firm to the aggregate level, but this effect is only secondary in the sense that it does not change the overall patterns.

## 4.1 Link to the literature

The widely cited view, based on the literature on return volatility at firm and portfolio levels (e.g., Vuolteenaho (2002), Cohen, Polk, and Vuolteenaho (2003), Callen and Segal (2004), Callen, Hope and Segal (2005), and Callen, Livnat and Segal (2006)), and the literature on the aggregate portfolio, is that CF news dominates at firm level, but most of it can be diversified away, leading to the dominance of DR news at the aggregate level. This finding seems to suggest that CF news is more related to firm-specific risk, but DR news is more related to systematic risk.[7] Because of diversification, there is a complete flip of the relative importance of CF news and DR news .

Since our finding suggests that such a flip does not exist, we proceed to reconcile our results with the current literature. The prevailing approach, following Vuolteenaho (2002) as an extension on Campbell (1991), is to apply a panel VAR analysis using Equation (16), calculate unexpected return and DR news using Equations (17) and (18), and finally back out the CF news as the difference between unexpected return and DR news. Let's call this the residual-based predictive regression approach.

**Predictive regression approach** Following Vuolteenaho (2002) and Cohen, Polk, and Vuolteenaho (2003), we combine the COMPUSTAT annual tape with CRSP data. We consider the vector $Z_t = [r_t \ roe_t \ bm_t]'$, where $r_t$ is log annual return, $roe_t$ is the log return on book equity (ROE), and $bm_t$ is log book-to-market ratio.[8] The annual return $r_t$ covers June of year $t$ to May of year $t+1$.

The results are reported in Table 5. We first apply the panel VAR controlling for year fixed effect, which is **similar** to Vuolteenaho (2002) who demeans all variables cross-sectionally year by

[7] When summarizing the results in Vuolteenaho (2002), Cochrane (2005) points out, "Much of the expected cashflow variation is idiosyncratic, while the expected return variation is common, which is why variation in the index book/market ratio, like variation in the index dividend/price ratio, is almost all due to varying expected excess returns."

[8] Return on equity is defined as $roe_t = ln((1+E_t)/B_t)$, where $E_t$ is earnings and $B_{t-1}$ is book equity. Earnings is defined as net income (Compustat item NI); if net income is unavailable we replace it by $NI_t = (1+retx_t) \times \frac{M_{t-1}}{M_t} \times B_t - B_{t-1} + D_t$, where $retx_t$ is capital gain return from CRSP, $M_t$ is market cap, and $D_t$ is dividend (from CRSP). The equation is based on the clean-surplus formula adjusted for net equity issuance (see Cohen, Polk, and Vuolteenaho (2003)). To calculate book equity, we start with common book equity (CEQ, replaced by CEQL if not available); if common book equity is still not available we replace it by the lagged common book equity plus current period net income (NI) minus dividend payout (DVC). Book equity is then defined as common book equity plus deferred taxes and investment tax credit (TXDITC if available) plus income taxes payable (TXP if available). We delete firms with negative book equity.

year. The predictive coefficient for return (return on equity) on the lagged book-to-market is 0.04 (-0.03).[9] We report the coefficient of regressing DR news, direct CF news (using Equations (19), and residual-based CF news (following Vuolteenaho) on unexpected return. DR news explains 11% of return variance. Direct CF news explains 56% of return variance; the residual-based CF news explains 89% of return variance.

While the evidence thus far supports the conclusion in Vuolteenaho (2002) that CF news dominates DR news at the firm level, there is a large discrepancy between direct and residual-based CF news. As shown by Chen and Zhao (2009) and Chen (2010), the residual-based approach can lead to severely biased estimates on CF news.[10]

We then repeat the panel VAR controlling for firm fixed effect, which is similar to demeaning all variables time series wise. In this case DR news explains 30% of return variance and direct (residual-based) CF news explains 32% (70%) of return variance. The residual-based approach cannot be trusted since it is biased. The conclusion is that, after controlling for firm-fixed effect, DR news and CF news explain about equal amount of return variance.

We note that the annual return (from June to next May) is delayed relative to return on equity (from January to December), which might affect the importance of DR news (because return becomes harder to predict with the additional time lag). To compare CF news and DR news on equal footing, we repeat the panel VAR with firm fixed effect and with return from January to December (i.e., without the additional time lag). In this case DR news explains 44% of return variance and direct CF news explains 36%. Therefore, the combined evidence suggests that, when using the predictive regression method with firm fixed effect, DR news is likely to be more important than CF news even at the firm level. There is no flip of the relative importance from the firm to the aggregate level.

The predictability in the regression method can come from the time series or/and cross section. The cross-sectional heterogeneity in earnings is persistent, a fact widely documented with respect to value versus growth stocks (e.g., Lakonishok, Shleifer, and Vishny (1994), Fama and French

[9] The corresponding number in Vuolteenaho (2002) is 0.0477 (-0.0264) in Table II.

[10] The variables in the vector, $[r_t \ roe_t \ bm_t]'$, are related to each other by definition. Therefore, if one strictly follows the present value formula to log linearize their relations, it makes no difference whether one directly estimates CF news or backs it out as the residual. In practice, return covers June of year $t$ to May of $t+1$ to accommodate the fact that accounting data might not be available at the beginning of the year. This misalignment breaks the definitional relation among variables; as a result the direct and backed-out news are different. In addition, the definitional relation requires that earnings and book equity must satisfy the clean-surplus formula, which might not be the case when measures of earnings and book equity from Compustat are used. The bottom line is that the adjustments, while sometimes necessary, make direct CF news different from the backed-out CF news, with the latter containing all measurement errors due to the adjustments.

(1995), and Cohen, Polk, and Vuolteenaho (2003)). It is thus relatively easier to predict CF growth cross-sectionally – growth firms tend to have higher CF growth in the following period, leading to the finding that CF news is more important at firm or portfolios levels. In contrast, the literature on the aggregate portfolio can only rely on time-series predictability; this literature has shown that return is much easier to predict than CF in the postwar period, leading to the conclusion that DR news is more important at the aggregate level.

What this says is that the results at firm level are not compatible with those at the aggregate level since the predictability comes from completely different sources. To further verify this point, we conduct time series VAR for each firm separately and report the average coefficients and t-statistics in Panel D of Table 5 (we require at least 16 years of data for each year).[11] On average, when using returns from June to next May, DR news explains 36% of return variance and direct CF news explains 33%. When using return from January to December, DR (direct CF) news explains 57% (34%) of return variance. Therefore, when pure time series regressions are conducted, DR news is more important than CF news even at the firm level.

**Cross-sectional versus time series predictability: How to draw conclusions?**

Therefore, the conclusions in the predictive regression approach vary dramatically depending on whether one relies on the combination of time series and cross-sectional predictability or on time series predictability alone.

If one relies on the combination of time series and cross-sectional predictability (as in Vuolteenaho (2002)), the implicit assumption is that all firms are homogeneous in the long run. With such a view, running a panel VAR without the fixed-effect control is reasonable. The effect of diversification can be detected by comparing the case of firm-level panel regression with the case of "aggregate market" by grouping all firms into two portfolios. A panel of two-portfolio aggregate market has the advantage that it preserves the cross-sectional predictability and each portfolio, containing thousands of firms, is about as diversified as the market.

We sort all stocks into two book-to-market portfolios and repeat the return decomposition for this two-portfolio "aggregate market" in Panel A of Table 6. With year fixed effect, 4% (74%) of return variance is explained by DR (directly CF) news, and 97% of return variance is "explained"

[11] The discounting parameter $\rho = \frac{P/D}{1+P/D} = \frac{1}{1+D/P}$, where $P$ is price and $D$ is dividend. When using the full panel, following Vuolteenaho (2002), we set $\rho$ at 0.96. When using individual firms, we use the discounting parameter for the industry to which the firm belongs. We have also used the discounting parameter for each firm separately and find the same conclusions hold.

by the residual-based CF news. The corresponding numbers at the firm level are 11% (56%) and 89% respectively. One would draw the conclusion that CF news plays a more important role at the aggregate level than at the firm level.

We have thus shown that the conclusion in the current literature is reached based on the estimation method at the firm level that is incompatible with that at the aggregate level. If we consistently consider cross-sectional and time series predictability at both firm and aggregate levels, then two conclusions can be reached. The first is that diversification plays little role in affecting the relative importance of CF/DR news; this conclusion completely reverses the one in Vuolteenaho (2002). The second is that CF news plays an important role at both firm and aggregate levels; this conclusion challenges the prevailing conclusion regarding the aggregate market. Both conclusions are overall consistent with what we have found using the ICC approach.

Alternatively, one can draw conclusions based on time series predictability alone. In Panel A3 of Table 6, the case of panel regression with portfolio fixed-effect control (and without additional lag on returns), DR news (direct CF news) explains 82% (12%) of return variance. The corresponding numbers are 44% (36%) at the firm level in Table 5. The corresponding numbers for the single market portfolio are 92% and 9% in Panel B of Table 6. Therefore, if one stick to time series predictability, the conclusion is that DR news seems more important than CF news even at the firm level, and diversification plays a secondary role. This conclusion overturns the one from Vuolteenaho (2002).[12]

The case of pure time series predictability using postwar data is similar to the case for the aggregate portfolio in Section 3. As we have explained earlier, the results might not be reliable since they are so different from those using a longer sample. On top of that, relying on time series predictability alone would lead to the conclusion that DR news is more important than CF news even at the firm level, contrary to what is commonly believed. If our lives have not been "easy" interpreting the aggregate market, they get even tougher given the new evidence we present at the firm level. This is thus another reason why the evidence based on time series predictability using the postwar data might not be reliable.

In summary, applying the predictive regression approach to the firm level requires careful treat-

[12]We do not take a strong stand on the sources of predictability. We merely point out that the conclusions should be drawn based on predictability consistently at both the firm and aggregate levels. Otherwise one would confuse the effect of estimation method with the effect of diversification. The fact that the panel regression with firm fixed effect leads to conclusions very differently from the one without fixed effect suggests that cross-sectional heterogeneity is present. Indeed, a Hausman specification test rejects an OLS panel regression with a chi-square value at 15739.81 (3 degrees of freedom). Nevertheless, one can still present results based on the assumption that firms are homogeneous in the very long run.

ment since it combines time series predictability with cross-sectional predictability. Based on both sources of predictability, one can conclude that (i) CF news is important at both firm and aggregate levels, and (ii) diversification plays a secondary role in affecting the relative importance of CF/DR news. Both conclusions are consistent with those using the ICC approach. Based on time series predictability alone, one can also conclude that diversification plays a secondary role and there is no flip of the relative importance of CF/DR news. Therefore, the prevailing conclusion regarding return decomposition, namely that there is a flip of the relative importance of CF/DR news from firm to the aggregate level due to diversification, seems overturned based on both the predictive regression approach and the ICC approach. In addition, the new evidence at the firm level also challenges the prevailing conclusion at the aggregate level.

# 5 Robustness checks

## 5.1 ICC method

**Decomposition of CF news** Equation (1) suggests that CF news can be decomposed into four parts: the revisions of CF forecasts for one year ahead, two years ahead, three years ahead (if not available, is calculated based on the long-term growth rate), and for the rest of the years (which uses the long-term earnings growth rate and the industry forecasts for growth rate). We naturally ask whether the updates on these forecasts are consistent, and whether they all contributes to the positive relation between stock returns and CF news.

Table 7 reports the correlation between the aggregate return and the four CF news components, from one to 28 quarters. All correlations are positive and mostly significant. For example, the correlation between aggregate returns and the CF news for two-year ahead is 0.18 at the quarterly horizon. This correlation increases to 0.33 at the one-year horizon, and 0.53 at the seven-year horizon. This pattern is fairly consistent for all four CF news components.

We also report the correlation between aggregate returns and simple changes of earnings per share forecasts scaled by the lagged price. These simple changes do not go through the present value calculations and thus can provide us a good sense of the robustness of our results. Again, the correlation between the aggregate returns and the simple forecast changes are mostly significant and positive, and increases with investment horizon. For example, the correlation for simple changes of two-year ahead earnings is 0.17 at the quarterly horizon, and increases to 0.85 at the seven-year horizon.

Overall, the evidence suggests that the importance of the CF news stems from consistent revisions of cash flow forecasts across all horizons.

**Alternative method to calculate news items** We have used future DRs in Equation (10) and current expected CFs in Equation (11). Alternatively, we can calculate CF news as

$$CF_j = \frac{\left(f\left(c^{t+j}, q_t\right) - f\left(c^t, q_t\right)\right)}{P_t}, \tag{20}$$

and DR news as[13]

$$DR_j = \frac{\left(f\left(c^{t+j}, q_{t+j}\right) - f\left(c^{t+j}, q_t\right)\right)}{P_t}. \tag{21}$$

A more balanced way is

$$CF_j = \left(\frac{\left(f\left(c^{t+j}, q_{t+j}\right) - f\left(c^t, q_{t+j}\right)\right)}{P_t} + \frac{\left(f\left(c^{t+j}, q_t\right) - f\left(c^t, q_t\right)\right)}{P_t}\right)/2, \tag{22}$$

and

$$DR_j = \left(\frac{\left(f\left(c^t, q_{t+j}\right) - f\left(c^t, q_t\right)\right)}{P_t} + \frac{\left(f\left(c^{t+j}, q_{t+j}\right) - f\left(c^{t+j}, q_t\right)\right)}{P_t}\right)/2. \tag{23}$$

We report the results using Equations (22) and (23) in Table 8. In Panel A for the market portfolio, CF news explains a significant 32% of return variance at the annual horizon and 65% at the seven-year horizon. The corresponding numbers at the firm level in Panel B are 48% and 61% respectively. Therefore, CF news plays a significant role at both the firm and aggregate levels, whose importance increases with investment horizon. These are the same conclusions we have drawn earlier.

**Analyst forecast bias** There is ample evidence indicating that analyst forecasts could be biased (e.g., Ljungqvist, Malloy, and Marston (2007)). As noted earlier, what we care is not the levels, but the revisions in these variables. Presumably the biases can be mitigated in the revisions. Still, it is possible that the forecast biases may affect the revisions.

To mitigate this concern, we construct two measures of analyst forecasts that can help address the bias issue. These two measures have also been used by Chava and Purnanandam (2009).

1. Forecast according to optimism: Rather than using the consensus analyst forecasts, we can

[13] We prefer formulas (10) and (11) to formulas (20) and (21) for the reason that discount rates are stationary but cash flows are not. When calculating CF news, whether one uses current or future DRs in principle should not make a big difference because there is no necessary reason of why future DRs are higher or lower than current ones. It makes a difference, however, if one uses future cash flows to calculate DR news. This is because all news items are scaled by the current price. Future cash flows usually increase with horizon. The calculated DR news is likely to be amplified if one uses CF forecasts in the future. Since our goal is to calculate DR news by holding current CF forecasts constant, it makes sense to use formulas (10) and (11).

use the lowest (most pessimistic) forecasts or the highest (most optimistic) forecasts. In this way, even if there is a bias when the consensus forecasts are used, this bias might not be as strong if the lowest or the highest forecasts are alternatively used.

2. Forecast adjusted by external financing: It has been documented that analyst forecasts can be overly optimistic for firms with large investment banking demand (e.g., Rajan and Servaes (1997), and Bradshaw, Richardson, and Sloan (2006)). Bradshaw, Richardson, and Sloan (2006) measure investment banking business as the amount of cash raised through external financing. We thus rank all firms, year by year, according to the amount of net external financing (equity and debt issuance) and calculate the percentile ranking, $Rank_i$, for each firm $i$. The external-financing-adjusted forecast is calculated as

$$EPS_i = Rank_i \times LOW\ EPS_i + (1 - Rank_i) \times HIGH\ EPS_i, \tag{24}$$

where $LOW\ EPS_i$ is the lowest forecast and $HIGH\ EPS_i$ is the highest forecast. The idea is to rely more on the pessimistic estimate if a firm has more investment banking business in a particular year, in an effort to correct for the potential bias.

Table 9 reports the main results using the lowest and highest analyst forecasts. The results are remarkably stable. For the aggregate portfolio, CF news explains 38% of return variance at the annual frequency; this number increases to 51% at the two-year horizon. The corresponding numbers are 51% and 69% respectively at the firm level.

Table 10 reports the main results after correcting for the potential bias related to external financing. For the aggregate portfolio, CF news explains 47% of return variance at the annual frequency; this number increases to 60% at the two-year horizon. The corresponding numbers are 40% and 58% respectively at the firm level. Again, CF news plays an important role at both the firm and aggregate levels, and diversification only plays a secondary role.

We conclude that analyst forecast biases are unlikely to be the main driver of our results.

## 5.2 Predictive regression method

The predictive regression method could be sensitive to the choice of predictive variables. To examine this issue, we consider the vector, $Z_t = [r_t\ roe_t\ bm_t\ \beta_t\ \sigma_t]'$, where $\beta_t$ is firm beta estimated using monthly return in the past 60 months, and $\sigma_t$ is daily return volatility in the past three months. The two new factors are meant to capture systematic risk and idiosyncratic risk. Table 11 reports the results. In the firm-by-firm analysis, on average 46% (28%) of return variance is driven by DR (CF) news; the corresponding number in Table 5 is 36% (33%). Therefore, the new VAR makes DR news more important at the firm level. Nevertheless, the two main conclusions remain. First, there is no flip of the relative importance of CF/DR news from firm to aggregate levels; diversification plays a secondary role. Second, if one takes the view that firms are homogeneous in the long run, then CF news plays an important role at annual horizon even for the aggregate market.

In the online appendix of this paper, we report two more scenarios. First, we subtract each variable by the corresponding number for the aggregate market, as in Vuolteenaho (2002). Second, similar to Vuolteenaho (2002), we consider a long VAR consisting four lags of return, one lag of return on equity, one lag of log book-to-market, two lags of leverage, and one lag of firm size. We find that the main conclusions are not affected by these alterations.

# 6 Conclusion

A central issue in asset pricing is whether stock prices move due to the revisions of expected future cash flows or/and of expected discount rates, and by how much. Since neither expectation item is observable, the current literature usually calculate cash flow and discount rate news from predictive regressions. The conclusions based on this predictive regression approach could be sensitive to the sample period (Chen (2009)), to the choice of predictive variables (Goyal and Welch (2008) and Chen and Zhao (2009)), and to the difference between time series and cross-sectional predictability. Varying among these dimensions, the role of cash flow news could vary from "being dominant" to "non-existent." It is thus difficult to interpret price movement in a reliable way.

This paper makes two contributions. First, we provide a new method to decompose returns that does not rely on predictability. In particular, we use firm-specific market consensus forecasts, coupled with prices, to back out the discount rates; in this way the cash flow news and discount rate news can be identified by construction without resorting to predictability. This method is forward-looking and thus is little affected by the major drawbacks of the predictive regression approach. The method can be easily applied at firm, portfolio, and market levels, and from short to long horizons. Crucially, the cash flow forecasts are taken from practitioners and are consistent with industry practice in security valuation.

We find that there is a significant component of cash flow news in stock returns, whose importance increases with investment horizon. At horizons beyond two years, cash flow news far exceeds discount rate news in driving stock returns. This conclusion holds at both firm and aggregate levels. Accordingly, diversification plays a secondary role in affecting the relative importance of cash flow/discount rate news in driving stock returns.

Second, in comparison with our approach, we provide the first study to *consistently* apply the traditional predictive regression approach to both firm and aggregate levels, and at different horizons. A prevailing conclusion in the current literature is that cash flow news dominates at the firm level but discount rate news dominates at the aggregate level due to diversification of cash flow news. We show that this conclusion is overturned once one uses the estimation method consistently. Overall the interpretation of price movement can be quite consistent using both our approach and the predictive regression approach.

## Appendix

Campbell and Shiller (1988) show

$$dp_{t-1} = E_{t-1}\sum_{j=0}^{\infty}\rho^j r_{t+j} - E_t\sum_{j=0}^{\infty}\rho^j \triangle d_{t+j}. \tag{A1}$$

A higher dividend yield ($dp_t$) means that either the expected returns ($r_{t+j}$) are higher, or the expected dividend growth ($\triangle d_{t+j}$) is lower. Define $\varepsilon_{r,t} = r_t - E_{t-1}[r_t]$ as the unexpected return and $\varepsilon_{d,t} = \triangle d_t - E_{t-1}[\triangle d_t]$ as the unexpected dividend growth. Then Equation (A1) leads to the decomposition of unexpected return:

$$\begin{aligned}\varepsilon_{r,t} &= (E_t - E_{t-1})\sum_{j=0}^{\infty}\rho^j \triangle d_{t+j} - (E_t - E_{t-1})\sum_{j=1}^{\infty}\rho^j r_{t+j} && \text{(A2)}\\ &= e_{CF,t} + e_{DR,t}, && \text{(A3)}\end{aligned}$$

where

$$\begin{aligned}e_{CF,t} &= (E_t - E_{t-1})\sum_{j=0}^{\infty}\rho^j \triangle d_{t+j} && \text{(A4)}\\ &= \varepsilon_{d,t} + (E_t - E_{t-1})\sum_{j=1}^{\infty}\rho^j \triangle d_{t+j} && \text{(A5)}\end{aligned}$$

is cash flow news. It contains a current dividend shock and revisions to expectations of future dividends. The term,

$$e_{DR,t} = -(E_t - E_{t-1})\sum_{j=1}^{\infty}\rho^j r_{t+j} \tag{A6}$$

is discount rate news, i.e., the news that future discount rates will become lower. To calculate these terms, consider a first order VAR with return, dividend growth, dividend yield, and additional variables, $Z_t = [r_t \triangle d_t \; dp_t \; x_t']'$, with

$$Z_t = \Gamma Z_{t-1} + \varepsilon_{t+1}, \tag{A7}$$

where $r_t$ is return, $\triangle d_t$ is dividend growth, $dp_t$ is dividend yield, and $x_t$ is a vector of additional state variables. It can be shown that

$$\begin{aligned}e_{DR,t} &= -e1'\lambda\varepsilon_t, && \text{(A8)}\\ e_{CF,t} &= e2'(I+\lambda)\varepsilon_t, && \text{(A9)}\end{aligned}$$

where $\lambda = \rho\Gamma\left(I - \rho\Gamma\right)^{-1}$, $e1$ is a vector whose first element is equal to one and zero otherwise, and $e2$ is a vector whose second element is equal to one and zero otherwise.

To decompose multiperiod return, take expectation at time $t + n - 1$ on Equation (A1) and then subtract it by Equation (A1). We obtain

$$\begin{aligned} \varepsilon_{r,t}^{n} &= \sum_{j=0}^{n-1} \rho^{j}\left(r_{t+j} - E_{t-1}\left(r_{t+j}\right)\right) && \text{(A10)} \\ &= \left(E_{t+n-1} - E_{t-1}\right)\sum_{j=0}^{\infty} \rho^{j}\left(\triangle d_{t+j}\right) - \left(E_{t+n-1} - E_{t-1}\right)\sum_{j=n}^{\infty} \rho^{j}\left(r_{t+j}\right) && \text{(A11)} \\ &= e_{CF,t}^{n} + e_{DR,t}^{n}. && \text{(A12)} \end{aligned}$$

It can be shown that the unexpected n-period cumulative return, $\varepsilon_{r,t}^{n}$, can be written as

$$\begin{aligned} \varepsilon_{r,t}^{n} &= \sum_{j=0}^{n-1} \rho^{j}\left(\varepsilon_{r,t}\right) + \sum_{j=0}^{n-1} \rho^{j} e1' \times \left(\rho\Gamma - (\rho\Gamma)^{n-j}\right) \times \left(I - \rho\Gamma\right)^{-1} \varepsilon_{t+j} && \text{(A13)} \\ e_{CF,t}^{n} &= \sum_{j=0}^{n-1} \rho^{j} e_{CF,t} && \text{(A14)} \\ e_{DR,t}^{n} &= \sum_{j=0}^{n-1} \rho^{j} e_{DR,t} - \sum_{j=0}^{n-1} \rho^{j} e1' \times \left(\rho\Gamma - (\rho\Gamma)^{n-j}\right) \times \left(I - \rho\Gamma\right)^{-1} \varepsilon_{t+j}. && \text{(A15)} \end{aligned}$$

While n-period CF news is simply the summation of one-period CF news, n-period DR news is equal to the summation of one-period DR news adjusting for the fact that a positive shock to DR right now, which reduces prices, causes higher future returns. For example, the impact of one-period DR news at time t on n-period DR news is

$$e_{DR,t} - e1' \times \left(\rho\Gamma - (\rho\Gamma)^{n}\right) \times \left(I - \rho\Gamma\right)^{-1} \varepsilon_{t}. \tag{A16}$$

If n is large, the above equation becomes

$$e_{DR,t} - e1' \times \rho\Gamma \times \left(I - \rho\Gamma\right)^{-1} \varepsilon_{t} = 0. \tag{A17}$$

In other words, the impact of DR news is temporary. In comparison, the impact of CF news is permanent: a positive current CF news does not automatically lead to lower CF news in the future. Since DR news is temporary, as the horizon n increases, the cumulative returns must increasingly represent CF news.

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**Table 1 : Sample Summary by Year**

The sample consists of firms, at quarterly frequency from 1985:Q1 to 2009:Q4, on the I/B/E/S Summary files with earnings forecasts for one-year ahead, two-year ahead, and a long-run earnings growth rate estimate. All per share numbers are multiplied by the number of shares outstanding (from I/B/E/S) to obtain amounts at the firm level. This table reports the aggregate amount at the market level for each year. Cost of equity is estimated using the present value model similar to Pastor, Sinha, and Swaminathan (2006). All amounts, except for the net payout ratio and cost of equity, are in millions of dollars.

| Year | Number of Firms | Quarterly Earnings | Net Payout(%) | Market Capitalization | Cost of Equity(%) |
|---|---|---|---|---|---|
| 1985 | 1,011 | 22,390 | 46 | 1,101,047 | 13.92 |
| 1986 | 1,126 | 22,236 | 46 | 1,398,920 | 11.84 |
| 1987 | 1,096 | 26,175 | 47 | 1,647,224 | 12.43 |
| 1988 | 1,152 | 33,960 | 48 | 1,503,152 | 13.34 |
| 1989 | 1,196 | 31,863 | 46 | 1,798,853 | 12.81 |
| 1990 | 1,261 | 30,981 | 46 | 1,855,319 | 13.65 |
| 1991 | 1,358 | 26,601 | 50 | 2,238,158 | 12.12 |
| 1992 | 1,548 | 28,526 | 47 | 2,597,002 | 11.52 |
| 1993 | 1,834 | 42,119 | 46 | 3,022,032 | 11.18 |
| 1994 | 1,983 | 56,248 | 44 | 3,384,655 | 11.70 |
| 1995 | 2,230 | 64,970 | 43 | 4,064,803 | 11.45 |
| 1996 | 2,533 | 75,835 | 44 | 5,265,117 | 11.20 |
| 1997 | 2,783 | 78,856 | 46 | 6,926,230 | 11.08 |
| 1998 | 2,803 | 83,060 | 48 | 8,184,202 | 11.60 |
| 1999 | 2,516 | 95,350 | 50 | 9,410,787 | 12.17 |
| 2000 | 2,216 | 102,869 | 53 | 12,035,070 | 12.69 |
| 2001 | 2,091 | 38,284 | 50 | 10,896,470 | 11.28 |
| 2002 | 2,252 | 97,817 | 47 | 10,359,020 | 10.60 |
| 2003 | 2,273 | 139,254 | 47 | 11,224,420 | 9.59 |
| 2004 | 2,417 | 183,315 | 46 | 13,402,920 | 9.19 |
| 2005 | 2,490 | 222,030 | 51 | 15,088,850 | 9.36 |
| 2006 | 2,544 | 268,667 | 55 | 17,056,200 | 9.73 |
| 2007 | 2,592 | 273,462 | 59 | 20,619,200 | 9.93 |
| 2008 | 2,500 | 91,455 | 64 | 15,618,510 | 12.06 |

**Table 2 : Cash Flow News and Discount Rate News at Aggregate Level**

Panel A reports, for the value-weighted market portfolio, the mean of cumulative capital gain return (CG), cash flow (CF) news, discount rate (DR) news, from one quarter up to 28 quarters. Panel B reports the variances of these three components. The means and variances are in percentage. Panel C reports the slope coefficients of regressing CF news or DR news on the aggregate return; the rows beneath the coefficients report the Newey-West t-statistics. The sample is quarterly from 1985:Q1 to 2009:Q4.

| | Horizons (Quarters) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 4 | 8 | 12 | 16 | 20 | 24 | 28 |
| Panel A: Means of aggregate return and components (%) | | | | | | | | | |
| CG return | 2.49 | 5.23 | 10.25 | 21.60 | 35.86 | 51.41 | 68.84 | 85.12 | 106.03 |
| CF news | -0.71 | -1.31 | -2.32 | -0.98 | 2.58 | 12.56 | 26.94 | 41.51 | 54.31 |
| DR news | 3.21 | 6.61 | 12.68 | 22.76 | 33.60 | 39.39 | 42.28 | 44.10 | 52.22 |
| Panel B: Variance of aggregate return components | | | | | | | | | |
| Var(CG) | 0.65 | 1.45 | 2.76 | 5.55 | 10.03 | 15.33 | 23.32 | 28.86 | 40.76 |
| Var(CF) | 0.46 | 1.23 | 3.49 | 9.20 | 20.31 | 29.65 | 32.17 | 35.53 | 49.40 |
| Var(DR) | 0.97 | 2.01 | 4.22 | 8.71 | 17.34 | 23.11 | 21.87 | 12.54 | 19.82 |
| Panel C: Slope coefficients | | | | | | | | | |
| CF news | 0.11 | 0.23 | 0.37 | 0.54 | 0.67 | 0.76 | 0.75 | 0.91 | 0.89 |
| T-stat | (1.38) | (2.75) | (3.60) | (4.72) | (5.28) | (6.36) | (7.89) | (13.57) | (12.24) |
| DR news | 0.88 | 0.76 | 0.63 | 0.45 | 0.33 | 0.25 | 0.26 | 0.08 | 0.11 |
| T-stat | (11.01) | (8.90) | (6.07) | (3.95) | (2.60) | (2.04) | (2.66) | (1.18) | (1.49) |

**Table 3 : Return Decomposition Using Predictive Regressions**

In each panel VAR coefficients are first reported and then unexpected return is decomposed into cash flow (CF) news and discount rate (DR) news. T-statistics controlling for heteroskedasticity and autocorrelation are reported in parentheses. Panels A and B use log dividend yield (LnDP) as the only state variable. Panel C uses LnDP and the Baa over Aaa yield spread as two state variables. Panel D uses LnDP and CAY (Lettau and Ludvigson (2001)) as state variables. For example, in Panel A, LnDP predicts return (dividend growth) for 1926-2009 with a coefficient of 0.07 (-0.08). At one-year horizon, 56% of return variance is driven by CF news, 44% by DR news; at 10-year horizon, 76% of return variance is driven by CF news, 24% by DR news.

Panel A: LnDP–26-09

Panel A1: VAR coefficients

| | $r_t$ | $\triangle d_t$ | $dp_t$ |
|---|---|---|---|
| $dp_{t-1}$ | 0.07 | -0.08 | 0.88 |
| t-stat | (1.26) | (-1.46) | (14.56) |
| $R^2$ | 0.02 | 0.07 | 0.76 |

Panel A2: Return Decomposition

| Year | 1 | 3 | 5 | 7 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|---|
| CF news | 0.56 | 0.70 | 0.75 | 0.76 | 0.76 | 0.80 | 0.80 |
| t-stat | (13.48) | (11.46) | (9.23) | (7.95) | (10.15) | (12.25) | (14.61) |
| DR news | 0.44 | 0.30 | 0.25 | 0.24 | 0.24 | 0.21 | 0.20 |
| t-stat | (11.64) | (5.46) | (3.40) | (2.73) | (3.57) | (3.76) | (4.67) |

Panel B: LnDP–46-09

Panel B1: VAR coefficients

| | $r_t$ | $\triangle d_t$ | $dp_t$ |
|---|---|---|---|
| $dp_{t-1}$ | 0.13 | 0.02 | 0.92 |
| t-stat | (2.44) | (0.67) | (18.22) |
| $R^2$ | 0.09 | 0.00 | 0.83 |

Panel B2: Return Decomposition

| Year | 1 | 3 | 5 | 7 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|---|
| CF news | -0.12 | 0.01 | 0.02 | -0.06 | -0.07 | 0.06 | 0.22 |
| t-stat | (-2.28) | (0.14) | (0.13) | (-0.36) | (-0.43) | (0.32) | (1.48) |
| DR news | 1.10 | 0.97 | 0.96 | 1.02 | 1.03 | 0.90 | 0.75 |
| t-stat | (21.00) | (9.79) | (7.04) | (6.47) | (5.95) | (4.99) | (5.23) |

Panel C: LnDP and x (Baa_Aaa)–26-09

Panel C1: VAR coefficients

| | $r_t$ | $\triangle d_t$ | $dp_t$ | $x_t$ |
|---|---|---|---|---|
| $dp_{t-1}$ | 0.08 | -0.03 | 0.92 | 0.00 |
| t-stat | (1.45) | (-0.94) | (16.82) | (0.44) |
| $x_{t-1}$ | -0.64 | -6.68 | -6.16 | 0.70 |
| t-stat | (-0.23) | (-2.34) | (-2.16) | (8.04) |
| $R^2$ | 0.00 | 0.22 | 0.76 | 0.50 |

Panel C2: Return Decomposition

| Year | 1 | 3 | 5 | 7 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|---|
| CF news | 0.69 | 0.84 | 0.86 | 0.79 | 0.77 | 0.79 | 0.79 |
| t-stat | (7.12) | (7.40) | (6.07) | (5.36) | (7.34) | (11.33) | (13.92) |
| DR news | 0.31 | 0.17 | 0.15 | 0.21 | 0.22 | 0.21 | 0.21 |
| t-stat | (3.46) | (1.61) | (1.15) | (1.53) | (2.35) | (3.49) | (4.20) |

Panel D: LnDP and x (CAY)–53-08

Panel D1: VAR coefficients

| | $r_t$ | $\triangle d_t$ | $dp_t$ | $x_t$ |
|---|---|---|---|---|
| $dp_{t-1}$ | 0.12 | 0.01 | 0.92 | 0.00 |
| t-stat | (1.92) | (0.46) | (16.68) | (0.59) |
| $x_{t-1}$ | 4.31 | -0.90 | -5.38 | 0.66 |
| t-stat | (2.76) | (-2.06) | (-3.85) | (5.84) |
| $R^2$ | 0.22 | 0.03 | 0.85 | 0.42 |

Panel D2: Return Decomposition

| Year | 1 | 3 | 5 | 7 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|---|
| CF news | 0.21 | 0.32 | 0.33 | 0.19 | 0.13 | 0.13 | 0.21 |
| t-stat | (3.71) | (2.91) | (2.36) | (1.33) | (0.83) | (0.96) | (2.06) |
| DR news | 0.78 | 0.67 | 0.65 | 0.78 | 0.83 | 0.83 | 0.75 |
| t-stat | (14.08) | (6.40) | (4.82) | (5.63) | (5.22) | (5.79) | (7.32) |

**Table 4 : Cash Flow News and Discount Rate News at Firm Level**

Panel A reports the average firm-specific variances of return (CG), cash flow (CF) news, discount rate (DR) news, from one quarter up to 28 quarters. The variances are in percentages. Panel B reports the slope coefficients of regressing CF news and DR news on return respectively. The rows beneath the slope coefficients report the Newey-West t-statistics. The sample is quarterly from 1985:Q1 to 2009:Q4.

| | Horizons (Quarters) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 4 | 8 | 12 | 16 | 20 | 24 | 28 |
| Panel A: Variances of firm return components (%) | | | | | | | | | |
| Var(CG) | 5.29 | 10.66 | 22.20 | 48.52 | 84.81 | 128.86 | 191.03 | 250.34 | 363.65 |
| Var(CF) | 11.92 | 25.26 | 54.88 | 102.21 | 156.28 | 197.69 | 260.16 | 316.94 | 428.56 |
| Var(DR) | 15.49 | 29.23 | 52.60 | 75.09 | 96.92 | 101.17 | 113.97 | 109.56 | 116.65 |
| Panel B: Slope coefficients | | | | | | | | | |
| CF news | 0.18 | 0.31 | 0.50 | 0.69 | 0.72 | 0.74 | 0.72 | 0.77 | 0.74 |
| T-stat | (0.75) | (1.43) | (2.56) | (4.49) | (5.94) | (7.42) | (8.72) | (10.51) | (11.94) |
| DR news | 0.82 | 0.68 | 0.49 | 0.31 | 0.27 | 0.25 | 0.27 | 0.23 | 0.25 |
| T-stat | (4.25) | (3.69) | (3.05) | (2.52) | (2.45) | (2.32) | (2.39) | (2.23) | (2.39) |

**Table 5 : Firm-Level Analysis Using Predictive Regression Method**

Consider a vector $Z_t = [r_t \; roe_t \; bm_t]'$, where $r_t$ is log annual return, $roe_t$ is log return on book equity (ROE), and $bm_t$ is log book-to-market ratio. Assume that the vector follows a first order VAR:

$$z_{t+1} = \Gamma z_t + u_{t+1}.$$

Then both cash flow news and discount rate news can be estimated. We report the VAR coefficient of return ($Coe(r)$) and return on equity ($Coe(roe)$) on the lagged book-to-market and their standard errors respectively. We then report the regression coefficient of DR news on unexpected return ($Coe(DR)$), of directly estimated CF news on unexpected return ($Coe(DCF)$), and of residual-implied CF news on unexpected return ($Coe(ICF)$). The standard errors of the coefficients (in parentheses) are obtained controlling for clustering, heteroscedasticity, and/or autocorrelation. Panels A-C report the panel regression results. Panels D-E report the average coefficients and standard errors of firm-by-firm time series regressions. The sample is annual from 1952-2008.

| bm coefficent | | | | News coefficient | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Coe(r) | se(r) | Coe(roe) | se(roe) | Coe(DR) | se(DR) | Coe(DCF) | se(DCF) | Coe(ICF) | se(ICF) |
| Panel A: Panel with year fixed effect | | | | | | | | | |
| 0.04 | (0.01) | -0.03 | (0.00) | 0.11 | (0.00) | 0.56 | (0.00) | 0.89 | (0.00) |
| Panel B: Panel with firm fixed effect | | | | | | | | | |
| 0.14 | (0.00) | -0.08 | (0.00) | 0.30 | (0.00) | 0.32 | (0.00) | 0.70 | (0.00) |
| Panel C: Panel with firm fixed effect and no additional return lag | | | | | | | | | |
| 0.19 | (0.01) | -0.08 | (0.00) | 0.44 | (0.00) | 0.36 | (0.00) | 0.56 | (0.00) |
| Panel D: Firm-by-firm times series | | | | | | | | | |
| 0.20 | (0.15) | -0.06 | (0.04) | 0.36 | (0.12) | 0.33 | (0.11) | 0.64 | (0.12) |
| Panel E: Firm-by-firm times series without additional return lag | | | | | | | | | |
| 0.28 | (0.18) | -0.05 | (0.05) | 0.57 | (0.11) | 0.34 | (0.09) | 0.44 | (0.11) |

**Table 6 : Aggregate-Level Analysis Using Predictive Regression Method**

Consider a vector $Z_t = [r_t \; roe_t \; bm_t]'$, where $r_t$ is log annual return, $roe_t$ is log return on book equity (ROE), and $bm_t$ is log book-to-market ratio. Assume that the vector follows a first order VAR:

$$z_{t+1} = \Gamma z_t + u_{t+1}.$$

Then both cash flow news and discount rate news can be estimated. We report the VAR coefficient of return ($Coe(r)$) and return on equity ($Coe(roe)$) on the lagged book-to-market and their standard errors respectively. We then report the regression coefficient of DR news on unexpected return ($Coe(DR)$), of directly estimated CF news on unexpected return ($Coe(DCF)$), and of residual-implied CF news on unexpected return ($Coe(ICF)$). The standard errors of the coefficients (in parentheses) are obtained controlling for clustering, heteroscedasticity, and/or autocorrelation. Panel A reports the results for the aggregate market consisting of two book-to-market portfolios. Panel B reports the results for the aggregate market consisting of a single market portfolio. The sample is annual from 1952-2008.

| | bm coefficent | | | | News coefficient | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coe(r) | se(r) | Coe(roe) | se(roe) | Coe(DR) | se(DR) | Coe(DCF) | se(DCF) | Coe(ICF) | se(ICF) |
| Panel A: Two book-to-market portfolios | | | | | | | | | | |
| Panel A1: Panel with year fixed effect | | | | | | | | | | |
| | 0.06 | (0.05) | -0.02 | (0.01) | 0.04 | (0.03) | 0.74 | (0.06) | 0.97 | (0.03) |
| Panel A2: Panel with portfolio fixed effect | | | | | | | | | | |
| | 0.13 | (0.02) | -0.01 | (0.00) | 0.52 | (0.04) | 0.15 | (0.02) | 0.48 | (0.04) |
| Panel A3: Panel with portfolio fixed effect and no additional return lag | | | | | | | | | | |
| | 0.15 | (0.01) | -0.01 | (0.01) | 0.82 | (0.04) | 0.12 | (0.02) | 0.18 | (0.04) |
| Panel A4: Portfolio-by-portfolio times series | | | | | | | | | | |
| 1 | 0.15 | (0.07) | -0.01 | (0.01) | 0.65 | (0.07) | 0.14 | (0.03) | 0.35 | (0.07) |
| 2 | 0.11 | (0.08) | -0.01 | (0.01) | 0.43 | (0.03) | 0.15 | (0.03) | 0.57 | (0.03) |
| Panel B: Market portfolio | | | | | | | | | | |
| Panel B1: Times series | | | | | | | | | | |
| | 0.13 | (0.05) | -0.01 | (0.01) | 0.66 | (0.06) | 0.13 | (0.03) | 0.34 | (0.06) |
| Panel B2: Time series with no additional return lag | | | | | | | | | | |
| | 0.14 | (0.06) | -0.00 | (0.01) | 0.92 | (0.06) | 0.09 | (0.04) | 0.08 | (0.06) |

**Table 7 : Correlations between Returns and Cash Flow Components**

We decompose the CF news into four parts: the revisions of cash flow forecasts for one year ahead, two years ahead, three years ahead, and for the rest of the years. We then report the correlation between the aggregate return and the four CF news components, from one quarter to 28 quarters. We also report the correlation between aggregate return and simple changes of earnings per share forecasts for one year ahead, two years ahead, and simple changes of the long-term growth rate. The sample is quarterly from 1985:Q1 to 2009:Q4.

| | Horizons (Quarters) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 4 | 8 | 12 | 16 | 20 | 24 | 28 |
| 1-year CF news | 0.18 | 0.27 | 0.21 | 0.23 | 0.23 | 0.33 | 0.39 | 0.31 | 0.41 |
| P-value | (0.06) | (0.00) | (0.03) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| 2-year CF news | 0.18 | 0.32 | 0.33 | 0.26 | 0.27 | 0.34 | 0.44 | 0.40 | 0.53 |
| P-value | (0.06) | (0.00) | (0.00) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| 3-year CF news | 0.10 | 0.27 | 0.27 | 0.20 | 0.22 | 0.32 | 0.45 | 0.45 | 0.57 |
| P-value | (0.28) | (0.00) | (0.00) | (0.04) | (0.03) | (0.00) | (0.00) | (0.00) | (0.00) |
| Rest of CF news | 0.12 | 0.23 | 0.31 | 0.42 | 0.47 | 0.55 | 0.63 | 0.81 | 0.79 |
| P-value | (0.22) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Chg. in 1-year CF forecast | 0.15 | 0.26 | 0.29 | 0.32 | 0.36 | 0.43 | 0.53 | 0.60 | 0.64 |
| P-value | (0.10) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Chg. in 2-year CF forecast | 0.17 | 0.31 | 0.29 | 0.43 | 0.40 | 0.49 | 0.60 | 0.75 | 0.85 |
| P-value | (0.07) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Chg. in LT CF forecast | 0.09 | 0.23 | 0.41 | 0.51 | 0.54 | 0.70 | 0.67 | 0.75 | 0.75 |
| P-value | (0.35) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |

**Table 8 : Alternative Measure of CF and DR News (average approach)**

We first calculate CF news and DR news according to the formulas in Section 5.1. Panel A reports, for the value-weighted market portfolio, the slope coefficients of regressing cash flow (CF) news and discount rate (DR) news on return respectively. Panel B reports the average firm-level slope coefficients and t-statistics of regressing CF news and DR news on returns respectively. The rows beneath the slope coefficients report the Newey-West t-statistics. The sample is quarterly from 1985:Q1 to 2009:Q4.

| | Horizons (Quarters) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 4 | 8 | 12 | 16 | 20 | 24 | 28 |
| Panel A: Slope coefficients for the value-weighted market portfolio | | | | | | | | | |
| CF news | 0.10 | 0.21 | 0.32 | 0.43 | 0.49 | 0.59 | 0.58 | 0.68 | 0.65 |
| T-stat | (0.88) | (1.69) | (2.23) | (2.72) | (3.80) | (6.58) | (6.04) | (9.52) | (7.73) |
| DR news | 0.90 | 0.78 | 0.68 | 0.57 | 0.51 | 0.43 | 0.44 | 0.33 | 0.36 |
| T-stat | (7.83) | (6.28) | (4.77) | (3.63) | (3.97) | (4.71) | (4.70) | (5.47) | (4.51) |
| Panel B: Slope coefficients for an average firm | | | | | | | | | |
| CF news | 0.19 | 0.32 | 0.48 | 0.64 | 0.66 | 0.67 | 0.63 | 0.65 | 0.61 |
| T-stat | (0.85) | (1.58) | (2.69) | (4.25) | (5.06) | (5.69) | (6.03) | (6.62) | (6.73) |
| DR news | 0.81 | 0.67 | 0.52 | 0.37 | 0.34 | 0.33 | 0.37 | 0.35 | 0.39 |
| T-stat | ( 4.48) | (4.04) | (3.58) | (3.21) | (3.32) | (3.40) | (3.83) | (3.98) | (4.57) |

**Table 9 : Robustness Check Using The Lowest and Highest Analyst Forecast**

We use two analyst forecast measures to calculate the cost of equity. The first measure is the lowest forecast, rather than the consensus forecast, from analysts as the measure of earnings forecast. The second measure is the highest forecast. See Section 5.1 for more details. In each panel, we first report, for the value-weighted market portfolio, the slope coefficients of regressing cash flow (CF) news and discount rate (DR) news on returns respectively. We then report the average firm-level slope coefficients of regressing CF news and DR news on returns respectively. The rows beneath the slope coefficients report the Newey-West t-statistics. The sample is quarterly from 1985:Q1 to 2009:Q4.

| | Horizons (Quarters) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 4 | 8 | 12 | 16 | 20 | 24 | 28 |
| Panel A: Results using the lowest analyst forecast | | | | | | | | | |
| Panel A1: Slope coefficients for the value-weighted market portfolio | | | | | | | | | |
| CF news | 0.12 | 0.23 | 0.38 | 0.51 | 0.65 | 0.78 | 0.80 | 0.85 | 0.83 |
| T-stat | (1.16) | (2.42) | (3.31) | (4.79) | (6.08) | (9.88) | (13.05) | (19.57) | (16.67) |
| DR news | 0.87 | 0.76 | 0.61 | 0.49 | 0.35 | 0.23 | 0.21 | 0.15 | 0.17 |
| T-stat | (9.05) | (7.95) | (5.36) | (4.68) | (3.26) | (2.89) | (3.37) | (3.52) | (3.37) |
| Panel A2: Slope coefficients for an average firm | | | | | | | | | |
| CF news | 0.19 | 0.32 | 0.51 | 0.69 | 0.73 | 0.75 | 0.75 | 0.77 | 0.74 |
| T-stat | (0.67) | (1.25) | (2.28) | (3.98) | (5.31) | (6.55) | (7.73) | (8.91) | (10.12) |
| DR news | 0.80 | 0.67 | 0.49 | 0.31 | 0.26 | 0.25 | 0.24 | 0.23 | 0.25 |
| T-stat | (3.32) | (3.01) | (2.59) | (2.22) | (2.08) | (1.97) | (1.95) | (1.82) | (2.04) |
| Panel B: Results using the highest analyst forecast | | | | | | | | | |
| Panel B1: Slope coefficients for the value-weighted market portfolio | | | | | | | | | |
| CF news | 0.13 | 0.31 | 0.43 | 0.66 | 0.72 | 0.75 | 0.79 | 1.06 | 1.03 |
| T-stat | (1.51) | (3.56) | (3.84) | (4.82) | (4.06) | (4.51) | (5.77) | (9.14) | (8.45) |
| DR news | 0.87 | 0.68 | 0.57 | 0.33 | 0.28 | 0.26 | 0.20 | -0.07 | -0.04 |
| T-stat | (9.76) | (7.67) | (5.14) | (2.43) | (1.55) | (1.48) | (1.39) | (-0.59) | (-0.34) |
| Panel B2: Slope coefficients for an average firm | | | | | | | | | |
| CF news | 0.15 | 0.28 | 0.44 | 0.64 | 0.68 | 0.70 | 0.68 | 0.72 | 0.71 |
| T-stat | (0.52) | (1.06) | (1.92) | (3.49) | (4.73) | (5.81) | (6.82) | (8.25) | (9.66) |
| DR news | 0.85 | 0.72 | 0.55 | 0.36 | 0.31 | 0.29 | 0.31 | 0.27 | 0.28 |
| T-stat | ( 3.39) | (3.04) | (2.64) | (2.17) | (2.09) | (2.00) | (2.02) | (1.85) | (1.98) |

**Table 10 : Robustness Check Taking into Consideration External Financing**

Rajan and Servaes (1997) and Bradshaw, Richardson, and Sloan (2006) find that analyst forecasts are more optimistic for firms with more investment banking business. This tables uses earnings forecasts that account for this bias. Panel A reports, for the value-weighted market portfolio, the slope coefficients of regressing cash flow (CF) news and discount rate (DR) news on returns respectively. Panel B reports the average firm-level slope coefficients of regressing CF news and DR news on returns respectively. The rows beneath the slope coefficients report the Newey-West t-statistics. The sample is quarterly from 1985:Q1 to 2008:Q4.

| | Horizons (Quarters) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 4 | 8 | 12 | 16 | 20 | 24 | 28 |
| Panel A: Slope coefficients for the value-weighted market portfolio | | | | | | | | | |
| CF news | 0.15 | 0.38 | 0.47 | 0.60 | 0.72 | 0.74 | 0.82 | 0.90 | 0.87 |
| T-stat | (1.45) | (3.71) | (4.06) | (4.86) | (6.02) | (7.25) | (9.86) | (11.62) | (12.24) |
| DR news | 0.84 | 0.61 | 0.52 | 0.38 | 0.27 | 0.26 | 0.18 | 0.09 | 0.12 |
| T-stat | (8.21) | (5.94) | (4.53) | (2.95) | (2.06) | (2.36) | (1.99) | (1.05) | (1.58) |
| Panel B: Slope coefficients for an average firm | | | | | | | | | |
| CF news | 0.16 | 0.28 | 0.40 | 0.58 | 0.65 | 0.66 | 0.67 | 0.72 | 0.71 |
| T-stat | (0.54) | (1.00) | (1.71) | (3.15) | (4.41) | (5.48) | (6.44) | (7.91) | (9.42) |
| DR news | 0.84 | 0.72 | 0.59 | 0.41 | 0.34 | 0.33 | 0.32 | 0.28 | 0.29 |
| T-stat | ( 3.25) | (2.87) | (2.62) | (2.29) | (2.18) | (2.06) | (2.06) | (1.83) | (2.03) |

**Table 11 : VAR with Additional Predictive Variables**

Consider a vector $Z_t = [r_t \; roe_t \; bm_t \; \beta_t \; \sigma_t]'$, where $r_t$ is log annual return, $roe_t$ is log return on book equity (ROE), $bm_t$ is log book-to-market ratio, $\beta_t$ is firm beta estimated using monthly return in the past 60 months, and $\sigma_t$ is daily return volatility in the past three months. Assume that the vector follows a first order VAR:

$$z_{t+1} = \Gamma z_t + u_{t+1}.$$

Then both cash flow news and discount rate news can be estimated. We report the VAR coefficient of return ($Coe(r)$) and return on equity ($Coe(roe)$) on the lagged book-to-market and their standard errors respectively. We then report the regression coefficient of DR news on unexpected return ($Coe(DR)$), of directly estimated CF news on unexpected return ($Coe(DCF)$), and of residual-implied CF news on unexpected return ($Coe(ICF)$). The standard errors of the coefficients are obtained controlling for clustering, heteroscedasticity, and/or autocorrelation.The sample is annual from 1952-2008.

| | bm coefficent | | | | News coefficient | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coe(r) | se(r) | Coe(roe) | se(roe) | Coe(DR) | se(DR) | Coe(DCF) | se(DCF) | Coe(ICF) | se(ICF) |
| Panel A: Firm level analysis | | | | | | | | | | |
| Panel A1: Panel with year fixed effect | | | | | | | | | | |
| | 0.03 | (0.01) | -0.04 | (0.00) | 0.10 | (0.00) | 0.58 | (0.00) | 0.90 | (0.00) |
| Panel A2: Panel with firm fixed effect | | | | | | | | | | |
| | 0.14 | (0.00) | -0.08 | (0.00) | 0.30 | (0.00) | 0.32 | (0.00) | 0.70 | (0.00) |
| Panel A3: Panel with firm fixed effect and no additional return lag | | | | | | | | | | |
| | 0.19 | (0.00) | -0.08 | (0.00) | 0.45 | (0.00) | 0.36 | (0.00) | 0.55 | (0.00) |
| Panel A4: Firm-by-firm times series | | | | | | | | | | |
| | 0.22 | (0.18) | -0.06 | (0.05) | 0.46 | (0.18) | 0.28 | (0.14) | 0.54 | (0.18) |
| Panel A5: Firm-by-firm times series without additional return lag | | | | | | | | | | |
| | 0.31 | (0.21) | -0.06 | (0.06) | 0.63 | (0.16) | 0.30 | (0.13) | 0.37 | (0.16) |
| Panel B: Two book-to-market portfolios | | | | | | | | | | |
| Panel B1: Panel with year fixed effect | | | | | | | | | | |
| | 0.05 | (0.05) | -0.02 | (0.01) | 0.04 | (0.03) | 0.72 | (0.06) | 0.96 | (0.03) |
| Panel B2: Panel with portfolio fixed effect | | | | | | | | | | |
| | 0.14 | (0.03) | -0.01 | (0.00) | 0.58 | (0.08) | 0.14 | (0.03) | 0.42 | (0.08) |
| Panel B3: Panel with portfolio fixed effect and no additional return lag | | | | | | | | | | |
| | 0.16 | (0.04) | -0.01 | (0.00) | 0.84 | (0.05) | 0.11 | (0.03) | 0.16 | (0.05) |
| Panel B4: Portfolio-by-portfolio times series | | | | | | | | | | |
| 1 | 0.13 | (0.07) | -0.00 | (0.01) | 0.68 | (0.06) | 0.14 | (0.03) | 0.32 | (0.06) |
| 2 | 0.26 | (0.11) | -0.00 | (0.01) | 0.34 | (0.18) | 0.17 | (0.07) | 0.66 | (0.18) |

**Figure 1 : Analyst Forecast Revisions for Five-Year Ahead Earnings**

The figure plots the change of aggregate earnings forecasts scaled by last year's aggregate book equity. The data are aggregated from the firm level. The earnings focast data are from I/B/E/S; the book equity data are from COMPUSTAT. The recession dummy is equal to one during recessions and zero otherwise. The data cover 1985-2009.

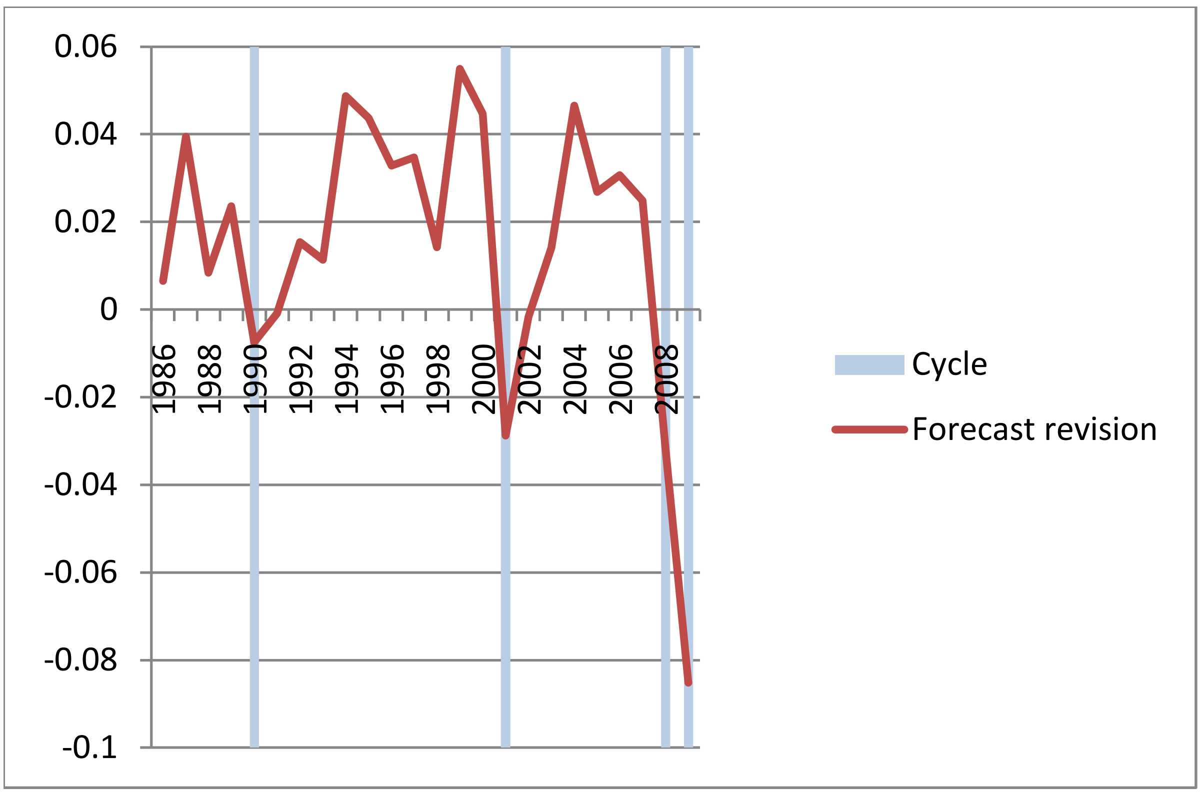

**Figure 2 : One-Year Returns and CF News**

The figure show how the one-year returns and the corresponding CF news are related. The data are at quarterly frequency and cover 1985:Q1-2009:Q4.

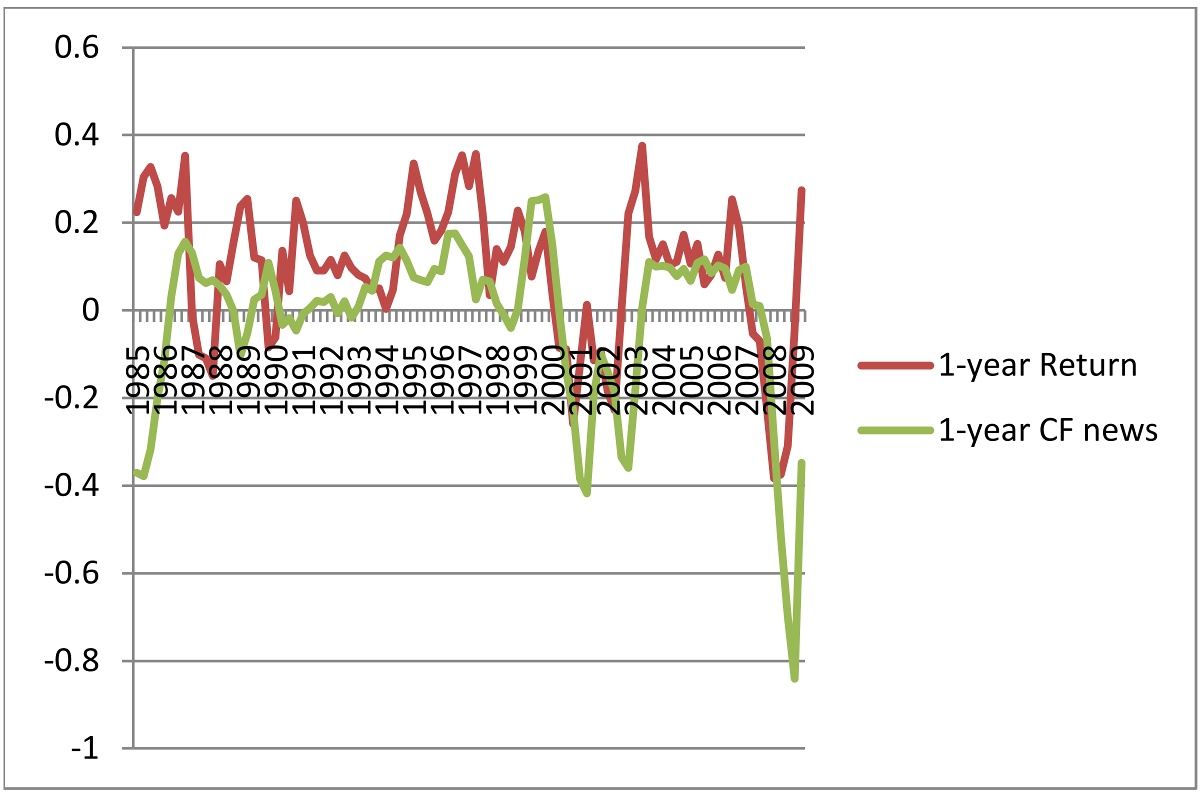

**Figure 3 : Two-Year Returns and CF News**

The figure show how the two-year returns and the corresponding CF news are related. The data are at quarterly frequency and cover 1985:Q1-2009:Q4.