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What Drives Stock Price Movements?

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A central issue in finance is whether stock prices move because of revisions in expected cash flows or discount rates, and by how much of each. Using direct cash flow forecasts, we show that stock returns have a significant cash flow news component whose importance increases with the investment horizon. For horizons over two years, cash flow news is more important. These conclusions hold at both the firm and aggregate levels, and diversification plays a secondary role in affecting the relative importance of cash flow and discount rate news. Our findings highlight the importance of cash flows in asset pricing. (*JEL* G12, E44)

As investors, policymakers, and economists during the recent financial crisis were debating the likelihood of another great depression in 2008, accompanying the stock market plunge, the financial market revised downward its forecasts of five-years-ahead aggregate earnings. This is a consistent pattern over the period 1986–2010: The correlation between the revision of the five-year earnings forecasts and a recession dummy is -71% (Figure 1). It seems natural to conclude that a significant portion of stock price movement occurs because, when evaluating stocks, investors revise their expectations of future cash flows.

Yet this is not what one would conclude from the bulk of the asset pricing literature that examines the drivers of stock price movement. Conceptually, stock prices can move unexpectedly because investors update expectations

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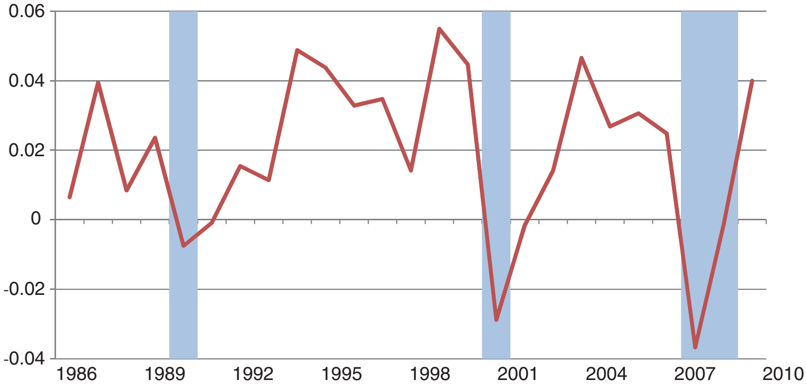

Figure 1
Analyst forecast revisions for five-year ahead earnings
The figure plots the change of aggregate earnings forecasts scaled by last year's aggregate book equity. The data are aggregated from the firm level. The earnings forecast data are from IBES; the book equity data are from Computstat. The shaded bars represent NBER recessions. The data cover 1986–2010.

of future cash flows or discount rates. Since neither expected cash flows nor discount rates are observable, the traditional approach is to predict them, and calculate cash flow news and discount rate news as functions of the predictive variables. Because returns have been much easier to predict than dividends post-World War II, the prevailing view is that almost all aggregate stock return innovation is driven by discount rate news, and almost none by cash flow news.[1]

Several studies (e.g., Goyal and Welch 2008 and Chen and Zhao 2009) cast doubt on this prevailing view with the evidence that the traditional approach based on predictive regressions is sensitive to the choice of sample periods or predictive variables. A growing literature shows that, with different sample periods or cash flow measures, cash flow news can be more important than what is normally perceived (e.g., Ang and Bekaert 2007; Larrain and Yogo 2008; Chen 2009; Binsbergen and Koijen 2010; Chen, Da, and Priestley 2012).[2]

The relative importance of cash flow and discount rate news has an important bearing on the theoretical modeling of asset prices. For example, Campbell and Cochrane (1999) focus on time-varying discount rates with changing risk aversion, while the long-run risk literature highlights the role of cash flow risk (Bansal and Yaron 2004).

[1] Cochrane (2011) summarizes the literature over the last 40 years by saying, "Previously, we thought returns were unpredictable, with variation in price-dividend ratios due to variation in expected cashflows. Now it seems all price-dividend variation corresponds to discount-rate variation (page 1047)."

[2] Koijen and Van Nieuwerburgh (2011) in a survey of the recent literature on the predictability of returns and cash flows concluded that dividend growth is more predictable than commonly believed. Recently, Golez (2012) demonstrates that information from the derivatives market also helps to predict future dividend growth for the S&P 500 Index.

Given the importance of the subject and the sensitivity of the regression-based approach, it is therefore useful to explore some alternative methods that do not rely on predictability. The alternative method we propose here uses direct expected cash flow measures. Given stock prices, we use the market prevailing forecasts for future cash flows (from IBES), for each firm and at each point of time, to back out the firm-specific implied cost of equity capital [see Pastor, Sinha, and Swaminathan (2008), among others]. Consequently, a price change can be decomposed into two pieces: (1) "CF news," defined as the price change holding the implied cost of capital (ICC) constant, and (2) "DR news," defined as the price change holding the cash flow forecasts constant. This decomposition holds by definition without resorting to predictability.

We emphasize that our CF and DR news are different from the traditional cash flow and discount rate news in the existing literature and our ICC is different from the more commonly studied one-period expected return. However, as demonstrated in Appendix A and consistent with the analysis in Pastor, Sinha, and Swaminathan (2008), ICC does convey information similar to the discount rate component of Campbell and Shiller's (1998) return decomposition. Consequently, our CF news and DR news also contain similar information as the cash flow news and discount rate news in the more traditional return decomposition framework.

A key assumption of the ICC approach is that analyst earnings forecasts are timely reflections of the marginal investors' belief regarding future cash flows. Any deviation from this assumption, such as stale or biased analyst forecasts could result in biased CF news estimates.[3] We address these issues in a battery of empirical checks and find our conclusions from the ICC approach to be robust to biases in analyst forecasts and different assumptions governing the steady-state cash flows.

The ICC method provides new insights. During the sample period of 1985–2010 when the earnings forecast data are available, we find that CF news contributes significantly to stock price variation. For example, at the one-year horizon, CF news accounts for 36% of the stock price variation at the aggregate level and 48% of the price variance at the firm level.

The extent of stock price variation explained by CF news increases with the investment horizon, and for horizons beyond two years, CF news outweighs DR news. At the aggregate level, the CF news portion is 53% at the two-year horizon, and 60% at the three-year horizon. At the firm level, the CF news portion is 63% at the two-year horizon, and 68% at the three-year horizon. CF news is more important at the firm level than at the aggregate level, suggesting that CF news is diversified away relatively more than DR news.

[3] 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), Elton, Gruber, and Gultekin (1981), Imhoff and Lobo (1984), Lys and Sohn (1990), Francis and Soffer (1997), and Park and Stice (2000).

This diversification effect is secondary, however, in the sense that, at longer horizons, CF news is only slightly more important at the firm level.

The finding that the relative importance of cash flow/discount rate news changes with time horizon is intuitive. As long as discount rates are stationary, negative discount rate news in the current period (because discount rate goes up) will be offset by higher returns in the future. Therefore, the impact of discount rate news is temporary and attenuated with time. In the long-run limit, all stock return news must be cash flow news (e.g., Campbell and Vuolteenaho 2004; Hansen, Heaton, and Li 2008; Bansal, Dittmar, and Kiku 2009). This is a fundamental property that holds irrespective of economic models.

The finding that there is only a limited relative cash flow/discount rate diversification effect when moving from individual firms to the aggregate portfolio provides a stark contrast to the prevailing view (Vuolteenaho 2002) that, because of diversification, cash flow news dominates at the firm level but discount rate news dominates at the aggregate level.

We argue, however, that the cash flow diversification effect is likely overstated because the panel regressions in Vuolteenaho (2002) do not control for the firm-fixed effects. In panel regressions, there is a critical difference between cross-sectional and time-series predictability, an issue that has been largely overlooked in the current literature. The cross-sectional heterogeneity of cash flows is persistent and predictable (e.g., Lakonishok, Shleifer, and Vishny 1994; Fama and French 1995); it is thus easy to find that cash flow news dominates whenever panel data (without firm fixed-effects controls) are studied. In the time-series dimension, however, cash flows are less predictable than discount rates, and discount rate news is usually found to be more important in the pure time-series regressions that are common for aggregate portfolio analysis. The prevailing conclusion is thus the result of mixing the strong cross-sectional cash flow predictability with the weak time-series cash flow predictability. Such a conclusion is unreliable, as it compares apples with oranges. In an apples-to-apples comparison, we run time-series predictive regressions firm-by-firm. For the period of 1985–2010, cash flow news explains 48% of stock return at the firm level over the one-year horizon, a result very comparable to that using the ICC method.

To summarize, while the issue of what drives stock price movement is crucial for asset pricing because it reveals how investors evaluate securities, long overdue is a comprehensive investigation of the relative importance of cash flow versus discount rate news, at both the aggregate and firm levels, using different methods, and at different horizons.

Our paper attempts to fill in the void. Our main message is that, contrary to prevailing views, cash flow news is important in driving stock price movement at both the firm and aggregate levels. The previous conclusion that there is little cash flow 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 cash flow news at reasonable horizons suggests that cash flow news deserves a greater role in theoretical considerations.

We believe we are the first to use the ICC approach to study return decomposition. Our contribution is related to but distinct from the literature that uses the ICC approach to study asset valuation and risk-return trade-off, including, among others, Kaplan and Ruback (1995), Liu and Thomas (2000), Claus and Thomas (2001), Gebhardt, Lee, and Swaminathan (2001), Jagannathan and Silva (2002), Easton and Monahan (2005), Pastor, Sinha, and Swaminathan (2008), and Da and Warachka (2009). Our approach is in the spirit of Graham and Harvey (2005), who use surveys of CFOs to measure the expected equity premium. Our results suggest that such an approach can shed fresh light on several fundamental issues in asset valuation.

Our findings complement the literature that studies relative return/cash flow predictability by the dividend yield (e.g., Campbell and Shiller 1988, 1998; Cochrane 1992, 2001, 2008; Goyal and Welch 2003; Lettau and Ludvigson 2005; Ang and Bekaert 2007; Larrain and Yogo 2008; Lettau and Van Nieuwerburgh 2008; Chen 2009; Binsbergen and Koijen 2010; Koijen and Van Nieuwerburgh 2011). This literature provides important evidence on predictability and on the information content of the dividend yield; we study price volatility without resorting to predictability.

The rest of the paper proceeds as follows. In Section 1, we describe the method we use to construct the ICC, the CF news, and the DR news. In Sections 2 and 3, we report the evidence at the aggregate and firm levels using the ICC method and the more traditional predictive regression, respectively. A brief conclusion is provided in Section 4. Appendix A compares our ICC-based decomposition to the more standard Campbell and Shiller (1988) loglinear return decomposition; examines the discount rate news over the long run; and studies the impact of a persistent cash flow forecast error. Appendix B provides details on computing the ICC.

1. The Implied Cost of Equity Capital Model

We back out the ICC for each firm quarter following Pastor, Sinha, and Swaminathan (2008). Appendix B provides the details on the sample selection and the calculation of ICC.

The equity value is the present value of future dividends and a terminal value:

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

$$= f\left(c^t, q_t\right), \quad (2)$$

where P_t is the stock price, FE_{t+k} is the 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 ICC. T is set to 15 years. In short, the stock price P_t is a function of the vector of cash flow forecasts c^t (available at time t) and the discount rate q_t. As detailed in Appendix B, FE_{t+k} are calculated from at least three analyst forecasts from IBES: the earnings forecasts for the current fiscal year (FE_{t+1}), the next fiscal year (FE_{t+2}), and the long-term growth forecast (g_{t+3}). While this calculation also depends on the assumptions of steady-state earnings growth rates and plowback rates, our decomposition results should not be materially affected by these assumptions for two reasons. First, since our decomposition focuses on price changes over time, as long as the assumed steady-state growth rates and plowback rates are slow-moving, they should not have a large impact on our decomposition results. Second, long-term cash flows are more heavily discounted relative to those in the nearer term (determined directly by IBES forecasts) in Equation (1).

1.1 CF and DR news

The proportional price difference or capital gain return ($Retx$) between $t+j$ and t is then (subscript changed from t to $t+j$):

$$
\begin{aligned}
Retx_j &= \frac{P_{t+j} - P_t}{P_t} \\
&= \frac{f\left(c^{t+j}, q_{t+j}\right) - f\left(c^t, q_t\right)}{P_t} \\
&= CF_j + DR_j, \qquad (3)
\end{aligned}
$$

where:

$$CF_j = \left(\frac{f(c^{t+j}, q_{t+j}) - f(c^t, q_{t+j})}{P_t} + \frac{f(c^{t+j}, q_t) - f(c^t, q_t)}{P_t} \right) / 2 \qquad (4)$$

$$DR_j = \left(\frac{f(c^t, q_{t+j}) - f(c^t, q_t)}{P_t} + \frac{f(c^{t+j}, q_{t+j}) - f(c^{t+j}, q_t)}{P_t} \right) / 2. \qquad (5)$$

Take CF_j as an example. It is labeled as CF news because the numerator is calculated by holding the discount rate constant, and CF_j captures the price change driven primarily by the changing CF expectations from t to $t+j$. Note that for both CF_j and DR_j, the differences are computed at t and $t+j$. This is a balanced approach as CF and DR changes are defined symmetrically, neither given a higher weight in the definition.

It is important to note that our decomposition in (3) is different from the more standard loglinear return decomposition in Campbell and Shiller (1988) in at least three respects. First, we work with capital gain returns, which do not include dividends. However, exclusion of dividends should not have a material impact on our conclusions as dividends play a minor role in the total return volatility. For example, during 1926–2010, the average quarterly total return for the CRSP value-weighted portfolio is 2.91% (std. dev. = 11.32%); the average quarterly return excluding dividends is 1.94% (std. dev. = 11.25%).

During 1985–2010, the average total return is 2.96% (std. dev. = 8.86%); the average return excluding dividends is 2.36% (std. dev. = 8.80%). Therefore, dividend payout affects only the level of returns; its impact on return volatility is negligible. Second, while Campbell and Shiller (1988) interpret return variations through a log-linearization approximation of the present value formula, our approach does not linearize the formula, and nonlinearity is implicit in the ICC method.

Third, while the cash flow and discount rate news in Campbell and Shiller (1988) sum up to the *unexpected* return (realized return minus expected return), our CF and DR news add up to the *realized* price change. However, the variation in expected returns is typically small relative to the variation in realized returns for stocks.

To understand the differences more directly, Appendix A compares these two decomposition methods empirically using the annual stock market data for the S&P 500 Index during the sample period of 1871–2009. We find that *unexpected* returns and *realized* price changes are highly correlated. Further, the cash flow (or discount rate) news components computed using the two decompositions are also highly correlated. The high correlations suggest that, as long as similar forecasts for future cash flows are used, our ICC-based decomposition and the more standard Campbell and Shiller (1988) decomposition, though implemented differently, produce very similar inferences.

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

$$VAR(Retx_t) = COV(CF_t, Retx_t) + COV(DR_t, Retx_t) \tag{6}$$

$$1 = \frac{COV(CF_t, Retx_t)}{VAR(Retx_t)} + \frac{COV(DR_t, Retx_t)}{VAR(Retx_t)}, \tag{7}$$

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

1.2 Expected return, discount rate component, and implied cost of equity capital

The discount rate in our model is the 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 the changes in expected returns for all future horizons, or changes in the discount rate component of the Campbell and Shiller (1988) decomposition (DR^{CS}):

$$DR_t^{CS}=\sum_{j=1}^{\infty}\rho^{j-1}E_t(r_{t+j})\approx\frac{k}{1-\rho}-(p_t-d_t)+\sum_{j=1}^{\infty}\rho^{j-1}E_t(\Delta d_{t+j}), \tag{8}$$

where ρ and κ are the loglinear constants; p, d, and Δd are the log price, log dividend, and log dividend growth, respectively.

Similarly, the ICC solves:

$$P_t=\sum_{j=1}^{\infty}\frac{E_t(D_{t+j})}{(1+ICC_t)^j} \tag{9}$$

where D_{t+j} is the dividend in time $t+j$.

Following Jagannathan, McGrattan, and Scherbina (2000), a linearized version of Equation (9) yields:

$$ICC_t\approx\left(\frac{y-g}{1+g}\right)\left[2+g-(y-g)\frac{P_t}{D_t}+\sum_{j=1}^{\infty}\omega_j E_t\left(\Delta D_{t+j}\right)\right] \tag{10}$$

$$\Delta D_{t+j}=\frac{D_{t+j}}{D_{t+j-1}}-1$$

$$\omega_j=\left(\frac{1+g}{1+y}\right)^{j-1},$$

where g is the mean expected dividend growth rates, and y is the mean ICC. Appendix A provides detailed derivations of Equation (10) and a direct comparison between DR^{CS} and ICC.

Comparing the ICC in (10) to the DR^{CS} in (8), we find them to contain similar information. Subject to the difference in linear and loglinear approximations, both are linear combinations of the current price-to-dividend ratio and the weighted average of future expected dividend growth rates. Appendix A, using the S&P annual stock market data of 1871–2009, shows a correlation exceeding 0.98. For this reason, Pastor, Sinha, and Swaminathan (2008) in their Equation (3) go so far as to define ICC as a scaled version of DR^{CS}. As a result, return decompositions using ICC, like those in the Campbell and Shiller (1988), should also shed light on the fundamental question of whether cash flow or discount rate news is the main drivers of stock price movement.

1.3 ICC vs. predictive regression

Return innovations can be decomposed into cash flow news and discount rate news. Since usually neither expected cash flows nor discount rates are observable, the common practice in the current literature is to predict cash flows and returns, and cash flow and discount rate news are then computed as functions of the predictive variables.

The predictive regression method is sensitive to the choice of sample period. For example, if we use dividend yield as the predictor, depending on whether we study a sample period of 1870–2010, 1926–2010, or 1946–2010, the conclusion ranges from "the majority of aggregate price variation is driven by cash flow news" to "almost no variation of price variation is driven by cash flow news" (Chen 2009). Which version should one trust?

The predictive regression method is also sensitive to the choice of predictive variables and measures of cash flows (Goyal and Welch 2008). Chen and Zhao (2009) show that different combinations of state variables, with seemingly minor alterations, can lead to dramatically different conclusions.

In contrast, since the ICC approach uses forward-looking information and thus does not involve predictive regressions, it does not require long time-series data. Rather than relying on coefficient stability and historical data, it uses current information to explain current price changes. It is also consistent with industry practice, in which case analyst forecasts are used to evaluate securities. In addition, the choice of predictive variables is a non-issue in the ICC approach.

1.4 Model assumptions and limitations

Since the ICC approach is based on the present value formula, few assumptions are made. The main potential limitation is the quality of analyst forecasts.

First, the model uses analyst forecasts and stock prices to back out the ICCs. This means that the DR news captures the residual news. In other words, if updates on analyst forecasts are random noises, then the burden of explaining returns falls completely on the DR news. Therefore, the success of the model depends on how accurately we can capture the CF news, as the DR news will pick up the rest.

Second, the model assumes that analyst forecasts capture the marginal investors' expectation of future cash flows in a timely fashion. In real life, some analyst forecasts could be stale. Analyst forecasts could also be biased due to over-optimism or (investment banking-related) conflicts of interest (Ljungqvist, Malloy, and Marston 2009). We are interested in explaining price changes with changing cash flow expectations. Even if the levels of earnings forecasts are subject to positive biases, as long as such biases are slow-moving [as documented by Mendenhall (1991) and Abarbanell and Bernard (1992), among others], the forecast revisions should mostly capture "true" cash flow news. In addition, using simulations, Appendix A shows that forecast errors do not have a material impact on our ICC-based decomposition.

Third, our approach depends on the assumptions of the steady-state earnings growth rates and plowback rates that could be firm-specific. Following similar logic as before, as long as these steady-state rates are slow-moving, our decomposition results should not be very sensitive to these assumptions.

We provide extensive robustness checks to ensure that our main conclusions based on ICC are not driven by the issues mentioned above. In general, the limitations of analyst forecasts tend to prevent us from finding strong cash flow effects—better proxies for expected cash flows would likely yield greater importance from CF news. In addition, analyst sluggishness can be mitigated at longer horizons. This suggests that the model might explain price variations better at longer horizons (e.g., one year or two years rather than one quarter).

2. Empirical Results: ICC Method

2.1 Summary statistics

Table 1 provides summary statistics for our sample. Panel A provides year-by-year average quarterly statistics for the final sample. The number of firms starts at 1,645 in 1985, peaks at 3,494 in 1998, and drops to around 2,221 in 2010. Overall, our sample represents about 80% of the total market capitalization in the United States. The average steady-state plowback ratio varies from 47.3% to 62.6%, and the average quarterly earnings-to-price ratio ranges from 1.05% to 1.88%.

There is a general downward trend in the median ICC during the sample period before 2008, consistent with a similar downward trend in the risk-free rate for the period. The level of median ICC is probably higher than what is generally believed. We show later that this is in part driven by the optimistic biases in the analyst forecasts, the long-term growth forecasts in particular. The cross-sectional distribution of the ICC is reasonably tight judging from the first and third quartiles. The average cross-sectional standard deviation is about 4.3%.

Panel B in Table 1 reports forecast errors (actual minus forecast) in annual earnings forecasts (scaled by the beginning-of-period price) for the first to the fifth years ($EPS1$ to $EPS5$) and for the long-term growth forecast (LTG, or g_{t+3}). As direct earnings forecasts are often not available beyond year 2, $EPS3$ to $EPS5$ are computed by growing the earnings forecasts for the prior years at LTG. The first row in Panel B reports the average forecast errors. Consistent with the findings in the analyst literature, the average analyst forecast errors are negative, reflecting an optimism bias, especially for longer forecasting maturities. The average forecast errors range from -0.09% at year one to -3.56% at year five. The LTG forecast shows a strong optimism bias. It is 6.01% too high on average. The positive bias in analyst forecasts explains the high level of ICCs. The second row in Panel B reports the mean absolute forecast errors. We find that analysts are doing a reasonably good job in providing informative cash flow forecasts at short- to medium-term horizons. The average absolute error increases from 0.53% for next-year earnings to 5.11% for earnings in year five. The average absolute error in LTG, in contrast, is higher at 19.64%, in part because of higher volatility associated with earnings growth rates relative to the level of earnings.

2.2 Aggregate evidence

We collapse our firm/quarter panel into a value-weighted aggregate time-series covering 1985–2010. The purpose is to study the relation among capital gain

Table 1
Summary statistics

Panel A: Sample summary by year

Year	Number of Firms	Market Cap	Qtrly E/P (%)	Steady -state Plowback (%)	ICC Q1 (%)	ICC Median (%)	ICC Q3 (%)	ICC Std Dev (%)
1985	1645	237.7	1.82	50.1	14.0	15.8	18.1	3.8
1986	1686	261.1	1.49	57.0	11.9	13.8	16.0	3.5
1987	1725	257.2	1.53	55.8	12.0	14.0	16.3	3.6
1988	1726	231.8	1.88	52.8	12.7	14.7	17.1	3.7
1989	1750	255.2	1.79	56.2	12.0	13.8	16.1	3.7
1990	1749	239.1	1.84	52.4	12.6	14.8	17.5	4.3
1991	1736	303.9	1.42	56.9	11.6	13.5	15.7	3.7
1992	1914	320.9	1.35	56.5	11.5	13.4	15.8	3.7
1993	2233	336.4	1.31	57.1	11.3	13.2	15.8	3.8
1994	2543	310.9	1.47	53.5	12.1	14.0	16.5	4.0
1995	2733	346.0	1.47	53.0	12.1	14.1	16.3	3.9
1996	3023	370.6	1.32	53.1	11.8	14.0	16.6	4.2
1997	3427	408.4	1.24	51.6	11.6	14.3	17.6	4.8
1998	3494	404.9	1.23	49.6	11.7	14.9	18.4	5.5
1999	3216	419.2	1.30	49.7	11.9	14.8	18.4	5.6
2000	2930	571.8	1.31	47.3	12.6	15.5	19.1	6.2
2001	2525	629.6	1.05	51.2	11.7	14.3	18.1	7.2
2002	2446	647.9	1.08	54.7	11.2	13.2	15.9	5.1
2003	2543	783.5	1.18	60.9	10.0	11.8	13.8	3.7
2004	2597	993.3	1.16	62.6	9.7	11.4	13.2	3.5
2005	2631	1094.5	1.18	62.1	9.8	11.4	13.2	3.4
2006	2614	1197.5	1.24	61.3	9.9	11.6	13.5	3.6
2007	2577	1293.5	1.19	60.3	10.1	11.7	13.6	3.3
2008	2481	962.1	1.42	53.2	11.1	13.2	15.8	4.8
2009	2153	999.5	1.19	60.4	9.5	11.5	13.7	4.6
2010	2221	1343.3	1.29	58.8	9.6	11.5	13.6	4.3

Panel B: Forecast errors

	EPS1 (%)	EPS2 (%)	EPS3 (%)	EPS4 (%)	EPS5 (%)	LTG (%)
mean error	−0.09	−0.72	−1.43	−2.32	−3.56	−6.01
mean abs error	0.53	1.64	2.68	3.76	5.11	19.64

The sample consists of firms, at quarterly frequency from 1985:Q1 to 2010:Q4, in the IBES Summary files with earnings forecasts for the current fiscal year and the next fiscal year and a long-run earnings growth rate estimate. All per share numbers are multiplied by numbers of shares outstanding (from IBES) to obtain amounts at the firm level. Panel A reports the sample summary statistics year by year. The market capitalizations (Market Cap) are in millions of dollars. Quarterly earnings-to-price ratios (E/P) are scaled by the market price at the beginning of the month. The steady-state plowback rate is computed as the ratio of average GDP growth rate to ICC. ICC is estimated using a present value model similar to Pastor, Sinha, and Swaminathan (2008). We report the first quartile (Q1), median, and third quartile (Q3) of its cross-sectional distribution. Panel B reports forecast errors (actual minus forecast) in annual earnings forecasts (scaled by the beginning-of-month price) for the first to the fifth year (EPS1 to EPS5) and in the long-term growth forecast (LTG).

returns, CF news, and DR news for the market portfolio. Panel A of Table 2 reports the means and variances of capital gain returns, CF news, and DR news. In general, as the investment horizon lengthens, the variance of CF news increases more than the variance of capital gain returns.

Following Equation (7), we regress CF news and DR news, respectively, on 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. Results are also reported in Panel A of Table 2. At the annual horizon, a significant 36% of the return variation of the market portfolio is explained

Table 2
Return decomposition using ICC approach

	Horizons (Quarters)								
	1	2	4	8	12	16	20	24	28
Panel A: Aggregate									
	Summary stats								
Mean(Retx)	2.37%	4.79%	9.72%	19.84%	29.25%	43.51%	58.34%	73.18%	91.11%
Mean(CF)	2.06%	4.04%	7.37%	13.95%	22.26%	32.62%	43.34%	53.96%	65.23%
Mean(DR)	0.36%	0.90%	2.58%	6.14%	7.99%	12.30%	16.71%	21.49%	28.64%
Var(Retx)	0.63%	1.36%	2.69%	6.07%	10.37%	16.62%	23.32%	28.63%	38.72%
Var(CF)	0.43%	1.09%	2.73%	5.01%	7.58%	10.55%	13.17%	14.67%	19.45%
Var(DR)	0.86%	1.69%	3.48%	4.63%	5.52%	6.89%	7.70%	6.77%	11.39%
	Decomposition								
CF	0.16	0.27	0.36	0.53	0.60	0.61	0.61	0.63	0.59
5%	−0.04	−0.01	0.06	0.24	0.43	0.43	0.46	0.48	0.47
95%	0.36	0.54	0.65	0.81	0.76	0.78	0.77	0.78	0.71
DR	0.84	0.73	0.64	0.47	0.40	0.39	0.39	0.37	0.41
5%	0.63	0.46	0.34	0.18	0.23	0.23	0.25	0.24	0.29
95%	1.04	1.00	0.94	0.75	0.56	0.56	0.53	0.50	0.52
Panel B: Firm-level									
	Summary stats								
Var(Retx)	5.60%	11.42%	25.08%	57.19%	94.38%	145.12%	207.55%	279.37%	390.28%
Var(CF)	9.85%	19.54%	39.28%	81.57%	125.42%	174.03%	216.67%	281.25%	365.49%
Var(DR)	13.10%	22.77%	37.28%	57.12%	74.82%	92.55%	113.66%	131.07%	163.80%
	Decomposition								
CF	0.19	0.32	0.48	0.63	0.68	0.68	0.67	0.66	0.62
5%	0.16	0.26	0.41	0.58	0.61	0.63	0.59	0.58	0.55
95%	0.22	0.36	0.51	0.68	0.70	0.73	0.69	0.71	0.67
DR	0.81	0.68	0.52	0.37	0.32	0.32	0.33	0.34	0.38
5%	0.78	0.64	0.48	0.32	0.30	0.27	0.31	0.29	0.33
95%	0.84	0.74	0.59	0.42	0.39	0.38	0.42	0.43	0.46
Panel C: Aggregate minus firm-level									
	Decomposition								
CF	−0.04	−0.06	−0.13	−0.11	−0.08	−0.08	−0.05	−0.03	−0.02
p-value	0.01	0.00	0.00	0.00	0.00	0.01	0.09	0.24	0.34
DR	0.04	0.05	0.13	0.10	0.07	0.07	0.06	0.03	0.02
p-value	0.03	0.00	0.00	0.00	0.01	0.01	0.05	0.23	0.29

Panel A reports, for the value-weighted market portfolio, the mean and variance of cumulative capital gain return (Retx), cash flow (CF) news, discount rate (DR) news, from one quarter up to 28 quarters. It also reports the fractions of variation in Retx attributable to the CF news and the DR news (slope coefficients of regressing CF news or DR news on the aggregate Retx). The rows beneath the coefficients report the 5% and 95% confidence bands associated with the coefficients computed using the Hansen-Hodrick (1980) standard errors to account for the overlapping observations. Panel B reports the average firm-level variance of items. It also reports the fractions of variation in Retx attributable to the CF news and the DR news. The rows beneath the coefficients report the 5% and 95% confidence bands associated with the coefficients computed using bootstraps. Specifically, we form 1,000 bootstrapped firm/quarter panels by randomly sampling firms with replacement. In the time-series dimension, we block-bootstrap with replacement using a block length of 20 quarters to preserve the autocorrelation structure in the error terms. Panel C tests for the difference between the aggregate and firm-level decomposition coefficients. The *p*-values are again based on the empirical distribution implied by the 1,000 bootstrapped firm/year panels. The sample is quarterly from 1985:Q1 to 2010:Q4.

by CF news. This percentage increases to 53% at the two-year horizon, 60% at the three-year horizon, and 59% at the seven-year horizon.[4]

We report the 5% and 95% confidence bands below the point estimates in Table 2. These confidence bands are computed using Hansen-Hodrick (1980) standard errors since the regressions with horizons over one quarter use overlapping data. However, unlike the usual long-horizon predictive regressions with overlapping data (Boudoukh, Richardson, and Whitelaw 2008), the statistical significance of coefficient estimates does not increase mechanically with horizon. 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 standard errors that vary systematically with investment horizon.

The confidence bands suggest that the CF news contribution is significantly greater than zero beyond one quarter. At the three-year horizon and beyond, it is reliably higher than 40%. Therefore, for the market portfolio, there is a significant component of CF news in returns, and it increases with the investment horizon. 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, and we discuss the intuition in detail within the predictive regression framework in Appendix A. By definition, the impact of one-period cash flow news on n-period cash flow news is simply the one-period cash flow news. In contrast, negative discount rate news in the current period (because the discount rate rises) will be offset by higher expected returns in the future. Intuitively, if stock price goes down because the discount rate goes up, the current-period negative return will be offset by higher future returns if one holds the stock for multiple periods. As a result, the relative importance of discount rate news is a declining function of the time horizon.[5]

Figure 2 plots returns at the one-year and two-year horizons and the corresponding CF news (from the ICC approach). That is, we show how returns are related to CF news by holding DR constant during the period. CF news tracks actual returns very well in most years at the annual horizon. At the two-year horizon, returns 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" any more.

[4] The CF news contribution is small and insignificantly different from zero at the quarterly horizon. However, due to 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 horizons.

[5] We note that the portion of CF news declined at the seven-year horizon. Over such a long horizon, expected steady-state growth rates are more likely to change and have a large impact on stock prices. As we have seen in Table 1, the forecasts for long-run growth rates are associated with large errors, and such errors could dampen the importance of CF news.

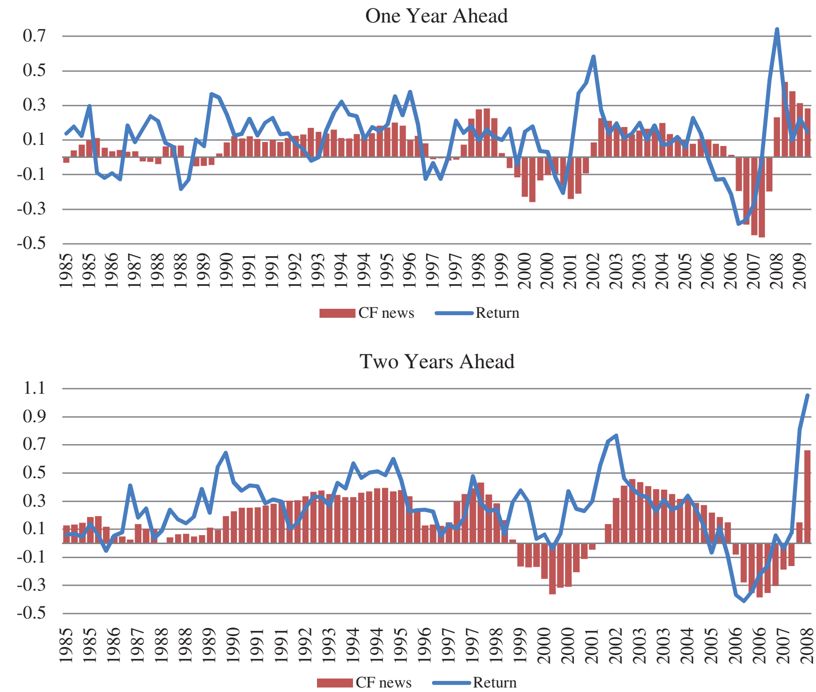

Figure 2
Returns and CF news—ICC method
The figure shows how the one-year (top) and two-year (bottom) return news and the corresponding CF news are related. The numbers are computed using the implied cost of equity capital (ICC) method at the firm level and then aggregated at the market level. The data are at quarterly frequency and cover 1985:Q1-2010:Q4.

2.3 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 more diversified away in a large portfolio? To examine these issues, we conduct the same time-series analysis as for the aggregate portfolio and for each firm separately. We require each firm to have at least 16 quarters of data. We then report the cross-sectional average of firm-specific results in Panel B of Table 2. The confidence bands associated with the decomposition coefficients at the firm level are computed using the bootstrap method. We form 1,000 bootstrapped firm/quarter panels by randomly sampling firms with replacement. In the time-series dimension, we block-bootstrap with replacement using a block length of 20 quarters to preserve the autocorrelation structure in the error terms. We calculate the decomposition coefficients in each bootstrapped panel, which allows us to build up the empirical distribution of these coefficients.

At the annual horizon, 48% of firm stock returns is due to CF news; this number increases to 63% at the two-year horizon and 62% at the seven-year horizon. Therefore, much like 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 at longer horizons. The proportion is significantly *higher* than 50% at two years and beyond.

Comparing the results in Panel A in Table 2 with those in Panel B, we find CF news to be slightly more important at the firm level than at the aggregate level. In Panel C, we use the bootstrap method to show that CF news is statistically more important at the firm level, especially at horizons shorter than five years. This evidence suggests that, as investors hold more stocks, CF news is relatively more diversified away than DR news. Still, this diversification effect is mild. At both the firm and aggregate levels, CF news is important.

The bottom line is that we observe very similar patterns at the firm and aggregate levels using the ICC method. CF news is always important, and it outweighs DR news at the horizons of two years and beyond. There is some diversification effect of CF news from the firm to the aggregate level, but this effect is only secondary.

2.4 Assumptions for the steady-state

We acknowledge that the assumptions on steady-state earnings growth rate and plowback rate are crucial to the ICC computation. We argue that as long as these steady-state rates are slow-moving, our decomposition results should not be very sensitive to these assumptions. Nevertheless, we now allow both parameters to be functions of firm characteristics and estimate them using historical data.

Starting from 1952, within each of the 12 Fama-French industries, we classify stocks into eight portfolios by an independent triple-sort according to their sizes, book-to-market ratios, and ages. We compute the average earnings growth rates and plowback rates 15 years later for each of the 96 ($=12\times 8$) portfolios. We repeat the calculations through 1969. We then average these long-run growth rates and plowback rates over 1952–1969. We use these portfolio averages as our forecasted steady-state earnings growth rates and plowback rates in year 1985 for individual stocks with similar industry, size, book-to-market, and age characteristics. Likewise, we average the long-run rates across portfolios constructed for the 1953–1970 period to obtain forecasts for year 1986. Our forecasts are always computed using a backward-rolling window of 18 years, and we always use information available at the time of forecasts.

Panel A of Table 3 reports the decomposition results when we use these alternative forecasts for the steady-state rates. Overall, the results are very similar to those in the benchmark case in Table 2.

2.5 Analyst forecast bias

There is ample evidence indicating that analyst forecasts could be biased (e.g., Ljungqvist, Malloy, and Marston 2009). As noted earlier, what we are interested in is not the levels, but the revisions in these variables. Still, it is possible that forecast biases may affect the revisions.

Table 3
ICC approach—robustness

		Aggregate							Firm Level						
		1	4	8	12	16	20	24	1	4	8	12	16	20	24
Panel A: Using predicted payout and earnings growth															
CF	coeff	0.24	0.41	0.56	0.58	0.58	0.57	0.55	0.29	0.53	0.66	0.69	0.69	0.67	0.67
	5%	0.06	0.18	0.35	0.45	0.40	0.40	0.37	0.26	0.48	0.61	0.62	0.64	0.59	0.60
	95%	0.42	0.64	0.78	0.71	0.75	0.73	0.72	0.31	0.57	0.70	0.71	0.73	0.69	0.72
DR	coeff	0.75	0.59	0.43	0.41	0.42	0.43	0.45	0.71	0.47	0.34	0.31	0.31	0.33	0.33
	5%	0.57	0.36	0.22	0.29	0.26	0.28	0.29	0.69	0.43	0.29	0.29	0.27	0.31	0.28
	95%	0.93	0.82	0.65	0.54	0.58	0.59	0.61	0.74	0.52	0.39	0.38	0.37	0.41	0.42
Panel B: Using low forecast															
CF	coeff	0.14	0.33	0.49	0.52	0.51	0.51	0.51	0.17	0.44	0.58	0.63	0.64	0.63	0.61
	5%	−0.04	0.03	0.16	0.27	0.29	0.33	0.33	0.13	0.37	0.53	0.57	0.59	0.54	0.53
	95%	0.33	0.64	0.81	0.76	0.72	0.68	0.69	0.20	0.48	0.63	0.65	0.70	0.65	0.66
DR	coeff	0.85	0.66	0.51	0.47	0.48	0.48	0.48	0.83	0.56	0.41	0.37	0.36	0.37	0.39
	5%	0.66	0.35	0.18	0.23	0.27	0.33	0.32	0.80	0.52	0.36	0.34	0.30	0.35	0.34
	95%	1.03	0.97	0.83	0.71	0.69	0.64	0.64	0.87	0.63	0.47	0.43	0.41	0.47	0.49
Panel C: Using high forecast															
CF	coeff	0.17	0.39	0.61	0.71	0.75	0.78	0.85	0.22	0.53	0.72	0.77	0.75	0.72	0.73
	5%	−0.04	0.10	0.36	0.65	0.62	0.62	0.71	0.17	0.45	0.65	0.68	0.68	0.62	0.64
	95%	0.38	0.68	0.86	0.76	0.89	0.95	0.99	0.25	0.59	0.79	0.80	0.81	0.75	0.80
DR	coeff	0.82	0.60	0.39	0.29	0.25	0.23	0.17	0.78	0.47	0.29	0.24	0.26	0.29	0.27
	5%	0.61	0.31	0.14	0.22	0.13	0.07	0.03	0.75	0.42	0.22	0.21	0.19	0.25	0.20
	95%	1.04	0.89	0.64	0.36	0.38	0.38	0.31	0.83	0.55	0.36	0.33	0.33	0.42	0.38
Panel D: Using EF rank															
CF	coeff	0.18	0.42	0.56	0.56	0.63	0.61	0.65	0.18	0.43	0.60	0.63	0.64	0.62	0.63
	5%	−0.05	0.14	0.39	0.42	0.56	0.50	0.50	0.13	0.34	0.52	0.54	0.56	0.50	0.53
	95%	0.40	0.70	0.73	0.70	0.71	0.71	0.81	0.22	0.49	0.67	0.67	0.70	0.65	0.70
DR	coeff	0.80	0.56	0.43	0.41	0.35	0.36	0.32	0.82	0.57	0.41	0.37	0.37	0.39	0.37
	5%	0.57	0.27	0.25	0.28	0.27	0.30	0.19	0.78	0.52	0.34	0.34	0.30	0.35	0.30
	95%	1.04	0.85	0.60	0.54	0.42	0.42	0.46	0.87	0.66	0.49	0.47	0.45	0.52	0.50
Panel E: Using FE rank															
CF	coeff	0.15	0.37	0.55	0.62	0.64	0.68	0.72	0.20	0.48	0.63	0.65	0.65	0.63	0.64
	5%	−0.05	0.09	0.31	0.49	0.49	0.54	0.58	0.15	0.41	0.57	0.59	0.60	0.54	0.56
	95%	0.35	0.66	0.79	0.75	0.79	0.81	0.86	0.23	0.53	0.68	0.68	0.70	0.65	0.70
DR	coeff	0.84	0.61	0.44	0.37	0.36	0.33	0.28	0.80	0.52	0.37	0.35	0.35	0.37	0.35
	5%	0.64	0.33	0.20	0.25	0.22	0.21	0.16	0.77	0.47	0.32	0.32	0.30	0.35	0.30
	95%	1.04	0.90	0.68	0.50	0.49	0.45	0.40	0.85	0.59	0.43	0.41	0.41	0.47	0.45

This table reports results from various robustness checks for the ICC approach. In Panel A, we use alternative methods to compute the steady-state earnings growth and plowback rates. We allow both parameters to be functions of firm characteristics such as size, book-to-market ratio, and ages. We estimate them using a backward-rolling window of 18 years to ensure that we always use information available at the time of estimation. In Panel B, we use the lowest forecast, rather than the consensus forecast, from analysts as the measure of earnings forecast. In Panel C, we use the highest forecast. In Panel D, we use external-financing-adjusted earnings forecasts to account for the optimism bias associated with investment banking business. In Panel E, we use recent-forecast-error-adjusted earnings forecasts to alleviate forecast bias that tends to persist. The current earnings forecasts will be adjusted downward for a firm that has been associated with optimistic forecasts recently. Details on these robustness checks are provided in Sections 2.4 and 2.5.

In each panel, we report the decomposition coefficients at both the aggregate- and the firm-level. The 5% and 95% confidence bands associated with the decomposition coefficients are computed using Hansen-Hodrick (1980) standard errors at the aggregate-level and using bootstraps at the firm-level. We form 1,000 bootstrapped firm/quarter panels by randomly sampling firms with replacement. In the time-series dimension, we block-bootstrap with replacement using a block length of 20 quarters to preserve the autocorrelation structure in the error terms. The sample is quarterly from 1985:Q1 to 2010:Q4.

To mitigate this concern, we construct three measures of analyst forecasts that can help address the bias issue. These three measures are similar to those used by Chava and Purnanandam (2010).

1. Forecasts according to optimism: Rather than using the consensus analyst forecasts, we can 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, the bias might not be as strong if the lowest or the highest forecasts are alternatively used.
2. Forecasts adjusted by external financing: It has been documented that analyst forecasts can be overly optimistic for firms for which there is large investment banking demand (Rajan and Servaes 1997; 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, $Rank_i^{EF}$, for each firm i. The external-financing-adjusted forecast is calculated as:

$$EPS_i = Rank_i^{EF} \times LOW\ EPS_i + \left(1 - Rank_i^{EF}\right) \times HIGH\ EPS_i, \qquad (11)$$

   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.
3. Forecasts adjusted by recent forecast error: Analyst forecast errors tend to be persistent (Mendenhall 1991; Abarbanell and Bernard 1992). Therefore, current earnings forecasts are more likely to be optimistic (or pessimistic) if they were optimistic (pessimistic) during the recent past. We thus rank all firms, year by year, according to the consensus earnings forecast errors (FE) during the most recent fiscal year and calculate the percentile ranking, $Rank_i^{FE}$, for each firm i. The forecast error (FE) is defined as forecast minus the actual scaled by the price at the beginning of the fiscal year. The recent-forecast-error-adjusted forecast is calculated as:

$$EPS_i = Rank_i^{FE} \times LOW\ EPS_i + \left(1 - Rank_i^{FE}\right) \times HIGH\ EPS_i, \qquad (12)$$

   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 been associated with optimistic earnings forecasts in the recent past.

Panels B and C of Table 3 report the main results using the lowest and highest analyst forecasts. The results are fairly stable. Using the lowest forecasts, CF news explains 33% of return variance at the annual frequency for the aggregate portfolio and 49% at two years. The corresponding numbers are 44% and

58%, respectively, at the firm level. Using the highest forecasts, the portion of CF news increases. For the aggregate portfolio, CF news explains 39% of return variance at the annual frequency and 61% at the two-year horizon. The corresponding numbers are 53% and 72%, respectively, at the firm level. Note that these decomposition coefficients are reflecting extreme views from the cross-section of analysts, the “true" decomposition coefficients will be less extreme.

Panel D of Table 3 reports the main results after correcting for the potential bias related to external financing (EF). For the aggregate portfolio, CF news explains 42% of return variance at the annual frequency, increasing to 56% at the two-year horizon. The corresponding numbers are 43% and 60%, respectively, at the firm level.

Panel E of Table 3 reports the main results after correcting for the potential bias using the recent forecast errors (FE). For the aggregate portfolio, CF news explains 37% of return variance at the annual frequency, increasing to 55% at the two-year horizon. The corresponding numbers are 48% and 63%, respectively, at the firm level. Again, CF news plays an important role at both the firm and aggregate levels, while diversification plays only a secondary role.

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

3. Empirical Results: Predictive Regression Approach

The traditional approach to understand the relative importance of cash flow and discount rate news is to conduct predictive regressions.

3.1 Aggregate evidence

The traditional predictive regression approach is based on the Campbell-Shiller (1988) return loglinearization. Consider the following VAR:

$$Z_t = \Gamma Z_{t-1} + \varepsilon_t. \tag{13}$$

The vector $Z_t = \left[r_t \, \triangle d_t \; dp_t \; x_t'\right]'$, where r_t is log return, $\triangle d_t$ is log dividend growth, dp_t is log dividend yield, and x_t is the additional predictive variable. The one-period unexpected return, $\varepsilon_{r,t}$, can be decomposed into discount rate news ($e_{DR,t}$) and cash flow news ($e_{CF,t}$):

$$e_{DR,t} = -e1'\lambda\varepsilon_t \tag{14}$$

$$e_{CF,t} = e2'(I+\lambda)\varepsilon_t \tag{15}$$

where $\lambda = \rho\Gamma(I-\rho\Gamma)^{-1}$, $e1$ is a vector whose first element is equal to one and zero otherwise, $e2$ is a vector whose second element is equal to one and zero otherwise, and ρ is set to 0.96. Intuitively, returns and dividend growth are projected onto predictive variables. Discount rate news and cash flow news are then functions of shocks to the predictive variables (ε_t) multiplied by the predictive coefficients (λ).[6]

For the predictive variable x_t, we examine a comprehensive list of them from Goyal and Welch (2008) and find them to produce similar results qualitatively. To save space, we only report results using $x = eqis$ (percent equity issuing, or the ratio of equity issuing activity as a fraction of total issuing activity). Goyal and Welch (2008) conclude that *eqis* is the only variable with good return predictive power both in-sample and out-of-sample.

Panel A of Table 4 reports the results of return decomposition using this approach. During the long sample period of 1927–2010, at the one-year horizon, 51% (49%) of return variance is driven by cash flow (discount rate) news. Cash flow news explains 74% of return variance at the five-year horizon, and 80% at the 15-year horizon. Therefore, consistent with the ICC approach, cash flow news is significant for the market portfolio, and its importance increases with the horizon.

When we examine the shorter postwar sample period of 1946–2010, 113% (−14%) of the annual return variance is driven by discount rate news (cash flow news). This is the well-known conclusion that almost all of the aggregate return variation is driven by discount rate news, and almost none by cash flow news. Even at the seven-year horizon, cash flow news still explains none of the return variance. Overall, confirming the results in the existing literature (Chen 2009), we find the conclusion from the predictive regression approach to be sensitive to the sample period.

Traditional predictive regressions measure cash flows using dividends. Chen, Da, and Priestley (2012) show that dividends are much more smoothed in the post-World War II period, which masks dividend growth predictability. This means that dividends, as a result of corporate policy, are not good at representing the prospect of future cash flows in the more recent sample (e.g., Boudoukh et al. 2007; Larrain and Yogo 2008; Pontiff and Woodgate 2008). To address this issue, we consider two alternative measures of cash flow. Each results in a new predictive variable and a new vector for the VAR.

The first measure is the net equity payout (dividend plus repurchase minus issuance), following Larrain and Yogo (2008, see Section 5 and the appendix of their paper). Since net equity payout can be negative, the authors consider a loglinear approximation and define the net payout yield as: $v_t = \theta d_t - (\theta - 1)e_t - a_t$, where d, e, and a denote the log of the dividend plus repurchase, the log of equity issuance, and the log of market value of equity, respectively. θ is a loglinear constant chosen to be 2.5. Return, cash flow, and net payout yield

[6] The dividend yield is the focus of a large literature on return and dividend growth predictability. See, among others, Campbell and Shiller (1988, 1998), Cochrane (1992, 2001, 2008), Goyal and Welch (2003), Ang and Bekaert (2007), Lettau and Van Nieuwerburgh (2008), Chen (2009), and Binsbergen and Koijen (2010).

Table 4
Return decomposition using predictive regressions—aggregate evidence

Panel A: Using the dividend yield and *eqis*

	A1: 1927–2010							A2: 1946–2010						
Year	1	3	5	7	10	15	20	1	3	5	7	10	15	20
Cash flow	0.51	0.68	0.74	0.73	0.76	0.80	0.79	−0.14	0.04	0.08	0.02	0.00	0.09	0.23
5%	0.44	0.56	0.59	0.59	0.66	0.70	0.72	−0.23	−0.12	−0.18	−0.26	−0.28	−0.20	−0.02
95%	0.58	0.80	0.89	0.86	0.86	0.90	0.87	−0.06	0.21	0.33	0.29	0.28	0.38	0.48
Discount rate	0.49	0.32	0.27	0.28	0.24	0.21	0.21	1.13	0.94	0.90	0.95	0.96	0.87	0.73
5%	0.42	0.21	0.13	0.15	0.15	0.12	0.15	1.04	0.78	0.65	0.68	0.68	0.57	0.49
95%	0.55	0.39	0.33	0.35	0.30	0.26	0.25	1.21	1.07	1.08	1.14	1.16	1.06	0.89

Panel B: Using the net payout yield as in Larrain and Yogo (2008)

	B1: 1927–2010							B2: 1946–2010						
Year	1	3	5	7	10	15	20	1	3	5	7	10	15	20
Cash flow	0.58	0.60	0.66	0.69	0.75	0.84	0.87	0.60	0.71	0.74	0.73	0.80	0.79	0.78
5%	0.49	0.51	0.57	0.57	0.62	0.78	0.83	0.45	0.51	0.56	0.55	0.66	0.70	0.71
95%	0.67	0.69	0.75	0.81	0.87	0.91	0.90	0.76	0.90	0.92	0.90	0.94	0.88	0.84
Discount rate	0.42	0.40	0.34	0.31	0.25	0.16	0.13	0.40	0.29	0.26	0.27	0.20	0.21	0.22
5%	0.33	0.31	0.25	0.19	0.13	0.09	0.10	0.24	0.10	0.08	0.10	0.06	0.12	0.16
95%	0.51	0.49	0.43	0.43	0.38	0.22	0.17	0.55	0.49	0.44	0.45	0.34	0.30	0.29

Panel C: Using book-to-market ratio, 1952–2010

	Cash flow	Discount rate
coeff	0.34	0.66
5%	0.24	0.57
95%	0.43	0.76

We implement the return decomposition at the aggregate level using a first-order VAR:

$$Z_{t+1} = \Gamma Z_t + \varepsilon_{t+1}.$$

In Panel A, $Z_t = \left[r_t \, \Delta d_t \; dp_t \; eqis_t\right]'$, where r_t is log annual return, Δd_t is log dividend growth rate, and dp_t is log dividend yield, and $eqis_t$ is the ratio of equity issuing activity as a fraction of total issuing activity. Panel A1 reports the decomposition results for the long sample period of 1927–2010 and Panel A2 reports the results for the shorter sample period of 1946–2010. In Panel B, we implement the return decomposition following Larrain and Yogo (2008) closely. The net payout yield is defined as: $v_t = \theta d_t - (\theta - 1)e_t - a_t$ where d, e, and a denote log of dividend plus repurchase, log of equity issuance and log of market value of equity, respectively. θ is a loglinear constant chosen to be 2.5. We then consider the vector $Z_t = [r_t \;\; \Delta d_t \;\; \Delta e_t \;\; v_t]'$. Panel B1 reports the decomposition results for the long sample period of 1927–2010 and Panel B2 reports the results for the shorter sample period of 1946–2010. In Panel C, we use the log book-to-market ratio as the main predictor of future accounting return, or $Z_t = [r_t \;\; roe_t \;\; bm_t]'$, 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. We report the regression coefficient of discount rate news on unexpected return ($Coe(DR)$), and of residual-implied cash flow news on unexpected return ($Coe(CF)$). The sample period is 1952–2010. For Panels A to B, the 5% and 95% confidence bands associated with decomposition coefficients are based on standard errors controlling for heteroscedasticity and autocorrelation. For Panel C, the 5% and 95% confidence bands associated with the decomposition coefficients are computed using bootstraps. Specifically, we simulate 1,000 bootstrap firm/year panels by re-sampling firms with replacements. All data are in annual frequency.

are related to each other by a present value relation:

$$v_t = r_{t+1} - \theta \Delta d_{t+1} + (\theta - 1)\Delta e_{t+1} + \phi v_{t+1}, \tag{16}$$

which motivates a new VAR vector: $Z_t = [r_t \;\; \Delta d_t \;\; \Delta e_t \;\; v_t]'$.

Panel B of Table 4 reports the results of return decomposition using the net payout yield as the predictor. Three interesting patterns emerge. First, cash flow news explains 58% of return variance even at the annual horizon during the long sample period of 1927–2010. Second, as before, the importance of cash flow news increases with the horizon. Third, the results are very similar in the shorter postwar sample period of 1946–2010. There is no reversal in the importance of cash flow news as we saw in the comparison of Panels A1 and A2, suggesting that a more comprehensive measure of cash flow alleviates the problems arising from dividend smoothing and provides strong support for the importance of cash flow news.

The second alternative cash flow measure is corporate earnings. We run predictive regressions using the book-to-market ratio to predict the accounting return on equity (ROE). Vuolteenaho (2000) justifies this approach by loglinearizing the accounting clean-surplus identity.

Following Vuolteenaho (2002) and Cohen, Polk, and Vuolteenaho (2003), we combine the Compustat annual tape with the CRSP data. We consider the vector $Z_t = [r_t \; roe_t \; bm_t]'$, where r_t is the log annual return, roe_t is the log return on book equity (ROE), and bm_t is the log book-to-market ratio.

The return on equity is defined as $roe_t = ln((1+E_t)/B_t)$, where E_t is the earnings and B_t is the 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 the capital gain return from CRSP, M_t is the market cap, and D_t is the dividend (from CRSP). The equation is based on the clean-surplus formula adjusted for net equity issuance (Cohen, Polk, and Vuolteenaho 2003).[7] The corresponding decomposition results are reported in Panel C of Table 4.

When we use ROE as the cash flow measure, cash flow news becomes more important and explains 34% of annual return variance, very close to the result using the ICC approach, where the corresponding number is 36% (Panel A in Table 2).

Overall, we confirm the evidence from a growing literature that, predictive regressions may also conclude cash flow news to be important in driving stock returns even at the aggregate level. This conclusion is reached when we use dividends as a measure of cash flow over a longer sample from 1927 to 2010 or use alternative measures of cash flows.

3.2 Firm-level evidence

Since many firms do not pay dividends, we need to run predictive regressions at the firm level using ROE and the book-to-market ratio. Applying such

[7] 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. The annual return r_t covers June of year t to May of year $t+1$ to ensure that the accounting information is fully incorporated into prices. We collapse the vector Z into value-weighted aggregate annual time-series covering 1952–2010.

predictive regressions at the firm and portfolio levels during the post-World War II sample period, Vuolteenaho (2002), Cohen, Polk, and Vuolteenaho (2003), Callen and Segal (2004), Callen, Hope, and Segal (2005), and Callen, Livnat, and Segal (2006) conclude that cash flow news dominates at the firm level, but most of it can be diversified away, making discount rate news dominant at the aggregate level. This finding seems to suggest that cash flow news is more related to firm-specific risk, while discount rate news is more related to systematic risk.[8] Because of diversification, there is a complete reversal of the relative importance of cash flow news and discount rate news.

The prevailing approach, following Vuolteenaho (2002) as an extension of Campbell (1991), is to apply a panel VAR analysis using Equation (13), calculate the unexpected return and discount rate news, and finally back out the residual cash flow news as the difference between the unexpected return and discount rate news.

We report the firm-level predictive regression results in Panel A of Table 5. All the confidence bands associated with the decomposition coefficients are again constructed by the bootstrap method where we form 1,000 bootstrap firm/year panels by randomly resampling firms with replacement. We first apply the panel VAR controlling for the year fixed effect, which is *similar* to Vuolteenaho (2002) who de-means all variables cross-sectionally year by year. The predictive coefficient for return (return on equity) on the lagged book-to-market ratio is 0.03 (−0.02).[9]

In the panel "decomposition coefficients," we report the coefficients of regressing discount rate news and residual-based cash flow news [following Vuolteenaho (2002)] on unexpected return. Discount rate news explains 10% of return variance, and cash flow news explains 90% of return variance, confirming the conclusion in Vuolteenaho (2002) that cash flow news dominates discount rate news at the firm level.

We then repeat the panel VAR controlling for the firm fixed effects, which is similar to de-meaning all variables time-series wise. In this case, discount rate news explains 28% of return variance and cash flow news explains 72% of return variance. In other words, after controlling for the firm fixed effects, cash flow news becomes less important.[10]

Predictability in the regression method can come from the time-series or the cross-section. The cross-sectional heterogeneity in earnings is persistent,

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8 Summarizing the results in Vuolteenaho (2002), Cochrane (2008) 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."

9 The corresponding number in Vuolteenaho (2002) is 0.0477 (−0.0264) in Table II.

10 Note that the annual return (from June to the following May) is delayed relative to the return on equity (from January to December), which might affect the importance of the discount rate news (because return becomes harder to predict with the additional time lag). We also repeat the panel VAR with firm fixed effects and with returns from January through December (i.e., without the additional time lag). In this case, discount rate news becomes even more important and explains 41% of return variance.

Table 5
Return decomposition using predictive regressions—firm- and portfolio-level evidence

Panel A: Firm-level

VAR Coeffs	r	roe	Decomposition Coeffs	Cash flow	Discount rate
			A1: Panel with year fixed effect		
coeff	0.03	−0.02	coeff	0.90	0.10
robust se	0.01	0.00	5%	0.89	0.09
			95%	0.91	0.11
			A2: Panel with firm fixed effect		
coeff	0.14	−0.08	coeff	0.72	0.28
robust se	0.00	0.00	5%	0.72	0.27
			95%	0.73	0.28
			A3: Firm-by-firm time-series		
coeff	0.20	−0.06	coeff	0.63	0.37
boot se	0.00	0.00	5%	0.55	0.30
			95%	0.70	0.45

Panel B: Two book-to-market portfolios

VAR Coeff		r	roe	Decomposition Coeff	Cash flow	Discount rate
				B1: Panel with year fixed effect		
coeff		0.06	−0.02	coeff	0.95	0.05
robust se		0.04	0.01	5%	0.90	0.01
				95%	0.99	0.10
				B2: Panel with portfolio fixed effect		
coeff		0.13	−0.01	coeff	0.48	0.52
robust se		0.03	0.00	5%	0.42	0.47
				95%	0.53	0.58
				B3: Portfolio-by-portfolio time-series		
coeff	growth	0.15	−0.01	coeff	0.36	0.64
robust se		0.07	0.01	5%	0.24	0.53
				95%	0.47	0.76
coeff	value	0.09	−0.01	coeff	0.57	0.43
robust se		0.08	0.01	5%	0.53	0.38
				95%	0.62	0.47

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:

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

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 discount rate news on unexpected return ($Coe(DR)$), and of residual-implied cash flow news on unexpected return ($Coe(CF)$). The robust standard errors (se) associated with the VAR coefficients are obtained controlling for clustering, heteroscedasticity, and/or autocorrelation. The 5% and 95% confidence bands associated with the decomposition coefficients are computed using bootstraps. Specifically, we simulate 1,000 bootstrap firm/year panels by re-sampling firms with replacements. Panel A reports the results at individual firm-level. Panel B reports the results for the aggregate market consisting of two book-to-market portfolios. The sample is annual from 1952 to 2010.

a fact widely documented with respect to value versus growth stocks (e.g., Lakonishok, Shleifer, and Vishny 1994; Fama and French 1995; Cohen, Polk, and Vuolteenaho 2003). It is thus relatively easier to predict cash flow growth cross-sectionally—growth firms tend to have higher cash flow growth in the next period, meaning that cash flow news is more important at the firm or portfolio levels. The literature on the aggregate market portfolio, which can only rely on time-series predictability, shows that returns are much easier to predict than cash flows in the postwar period, thus leading to the conclusion that discount rate news is more important at the aggregate level.

Consequently, the results at the firm level are not compatible with those at the aggregate level because the predictability comes from different sources. To further demonstrate this point, we run a VAR for each firm separately and report the average coefficients and bootstrapped the confidence bands (we require at least 16 years of data for each firm).[11] On average, discount rate news explains 37% of return variance, and cash flow news explains 63%.

Therefore, the conclusions at the firm-level based on the predictive regression approach vary dramatically depending on whether one relies on a combination of time-series and cross-sectional predictability or on time-series predictability alone. Which of the two approaches is more reasonable? We address this question below with additional analysis.

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 firm fixed-effect control is reasonable. However, the validity of such a view is questionable, and we argue that the effect of diversification can be better detected by comparing the firm-level panel regressions with the “aggregate market” where we group all firms into two portfolios. A two-portfolio aggregate market panel has the advantage that it preserves cross-sectional predictability, and each portfolio, including 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 B of Table 5. With the year fixed effect, 95% of return variance is explained by cash flow news, and 5% of return variance is explained by discount rate news. The corresponding numbers at the firm level following the approach in Vuolteenaho (2002) are 90% and 10% respectively (Panel A). The fact that cash flow news is dominant for both diversified portfolios and individual firms implies that such cash flow dominance does not come from a lack of diversification but rather from cross-sectional predictability.

We then examine the time-series predictability alone for the two book-to-market sorted portfolios in Panel B of Table 5. In the panel regression with portfolio fixed effects, cash flow news explains 48% of return variance. If we run time-series regressions for the two portfolios separately, we find that cash

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

flow news explains 36% and 57% of return variance for the growth and value portfolios, respectively.

Finally, recall from Panel C of Table 4 that cash flow news explains 34% of return variance at the market level. Overall, as we move gradually from the firm level to the aggregate level but focus our attention on time-series predictability consistently, we find cash flow news to become less and less important, indeed suggesting that cash flow news can be diversified to some extent. However, such diversification plays only a secondary role: discount rate news does not dominate at the aggregate level, while cash flow news does not dominate at the firm level.

In summary, the firm-level predictive regression requires careful treatment since it combines time-series predictability with cross-sectional predictability. If we focus on time-series predictability, we find that cash flow news is important but not dominant at the firm level; as a result, the cash flow diversification effect is only secondary.

3.3 ICC vs. predictive regression: 1985–2010

Because of data availability, we examined the ICC method for a short sample period, 1985–2010, while most of the predictive regressions are conducted for a longer period from 1926 or from 1952. To remove the impact of different sample periods, we now directly compare the ICC method and the predictive regression at the annual frequency in the same sample period from 1985 through 2010.

During the financial crisis, the quarters experiencing the most negative annual returns (compared to four quarters before) are the fourth quarters (−39%) of 2008 and the first (−36%) and second (−27%) quarters of 2009. Using the ICC approach, the corresponding CF news are, respectively, −19%, −39%, and −45%. 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 academics at that time.

In sharp contrast, the predictive regression approach based on dividend yield attributes the market crash in 2008 mainly to discount rate news. For example, in Figure 3, we plot the annual return news and the corresponding cash flow news using the predictive regression approach estimated over the same 1985–2010 period. We find that the annual cash flow news in the three quarters starting from the last quarter of 2008 is −9.5%, −13.7%, and −16.9%, which is only a small fraction of return news (return news being −55.6%, −57.5%, and −41.0% respectively).[12]

12 Return news, which is defined as the unexpected return (after running a VAR), can be different from the raw return.

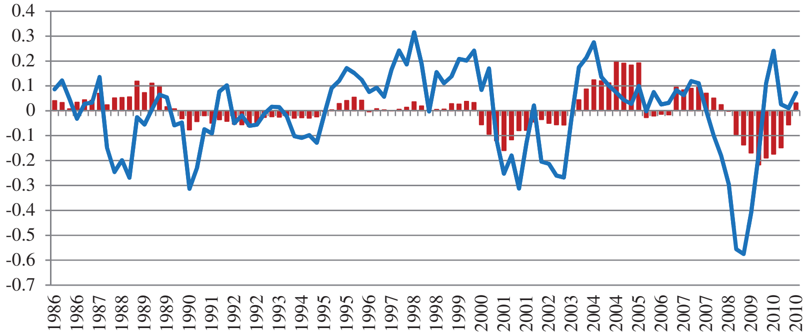

Figure 3
Returns and CF news—predictive regression method
The figure shows how annual return news and the corresponding CF news (at quarterly frequency) are related. The numbers are computed using the predictive regression method with the log dividend yield as the predictor. We run four separate regressions using data at annual frequency, with each year ending at different quarters (1 to 4). We then append the CF news and DR news from the four regressions together. The purpose is to obtain annual news items at quarterly frequency. The resulting news items cover 1986:Q1-2010:Q4.

Table 6
Decomposition results—ICC vs. predictive regression method

	CF			DR		
	1	2	3	1	2	3
			Aggregate			
ICC	0.22	0.53	0.58	0.78	0.46	0.41
BM_VAR	0.31	0.35	0.34	0.69	0.65	0.66
ICC-BM_VAR	−0.09	0.19	0.24	0.09	−0.19	−0.25
p-value	0.16	0.33	0.02	0.15	0.34	0.02
			Firm-level			
ICC	0.46	0.62	0.69	0.54	0.38	0.31
BM_VAR	0.48	0.52	0.61	0.52	0.48	0.39
ICC-BM_VAR	−0.02	0.10	0.09	0.02	−0.10	−0.09
p-value	0.12	0.52	0.59	0.12	0.52	0.59

This table directly compares the ICC method against the predictive regression methods in the same sample period from 1985 to 2010. ICC refers to the implied cost of equity capital method. BM_VAR refers to the predictive regression method where we use book-to-market ratio to predict return and ROE. To reduce estimation error, the predictive regressions are estimated using the full samples and the estimated coefficients are applied to the shorter sample period 1985–2010. We consider calendar-year returns consistently across the two methods. In other words, we do not use overlapping quarterly observations for the ICC method as in Table 1. In addition, for the firm-level predictive regressions, we run time-series regressions firm by firm as what we do for the ICC method. The *p*-values are based on the empirical distribution implied by the 1,000 bootstrapped firm/year panels.

We use the book-to-market ratio to predict the ROE (BM_VAR). To reduce estimation error, the predictive regressions are estimated using the full samples and the estimated coefficients are applied to the shorter sample period, 1985–2010. The results are reported in Table 6 for the one-, two-, and three-year horizons. We consider calendar-year returns consistently across the two methods. In addition, for the firm-level predictive regressions, we run time-series regressions firm by firm, similar to what we do for the ICC method.

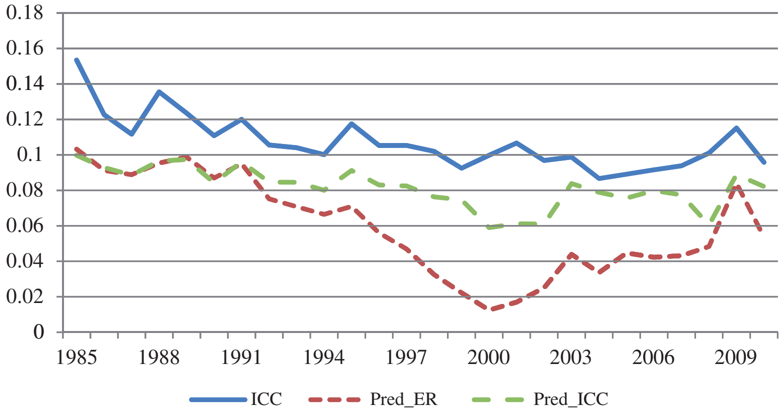

Figure 4
ICC and expected returns
The figure plots the implied cost of equity capital (ICC) against expected return forecasts for the next year (Pred_ER) and for the long-run (Pred_ICC). Both expected return forecasts are computed from a VAR consist of return, dividend growth, and dividend yield. The data are at annual frequency and cover 1985–2010.

Overall, the results in Table 6 suggest that the decomposition results are fairly consistent across the two methods, but cash flow news is slightly more important under the ICC method. At the aggregate level, the differences are significant beyond two years in the case of BM_VAR. At the firm level, however, the differences are never statistically significant at the 10% level.

We apply both approaches in the same sample period to provide a visual comparison of different discount rate forecasts. Figure 4 plots the *ICC*, the next-year expected return forecast from the predictive regression (*Pred_ER*), and the long-run discount rate from the predictive regression (*Pred_ICC*) at the end of each year from 1985 through 2010. The predictive regression is run using the traditional approach, where the vector $Z_t = [r_t, \triangle d_t, dp_t]$. The long-run discount rate (*Pred_ICC*), following Pastor, Sinha, and Swaminathan (2008), is defined as:

$$Pred\_ICC_t = (1-\rho)\sum_{j=1}^{\infty}\rho^{j-1}E_t(r_{t+j}), \tag{17}$$

which is more comparable to the *ICC*.

Figure 4 shows that the *ICC* is highly correlated with the other two proxies of expected returns. Its correlation with *Pred_ER* is 0.77, while its correlation with *Pred_ICC* is 0.68. In terms of level, we notice that the dot-com bubble in 2000 results in a very low next-year expected return forecast, *Pred_ER*. *ICC* and *Pred_ICC*, both capturing long-run expected returns, are less affected by this transitory bubble. *ICC* is also always higher than the other two expected return proxies, reflecting the optimism biases in the analyst earnings forecasts. Since we are interested in changes in stock prices, these biases, as long as they are slow-moving, should not have a strong impact on our results. Indeed, the changes in *ICC* are still highly correlated with changes in *Pred_ER* and *Pred_ICC* (63% and 46%, respectively). Overall, Figure 4 confirms that the *ICC* is a reasonable proxy for the discount rate.

4. Conclusion

A central issue in asset pricing is whether stock prices move because of the revisions of expected future cash flows or of expected returns, and by how much. Since neither expectation is observable, researchers usually calculate cash flow and discount rate news from predictive regressions. Conclusions based on this predictive regression approach could be sensitive to sample period, to the choice of predictive variables, to the choice of cash flow measures, and to the difference between time-series and cross-sectional predictability. For these reasons, the role of cash flow news could vary from dominant to non-existent. It is thus difficult to interpret price movements in a reliable way.

Our article makes two contributions. First, we provide a new method to decompose returns that does not rely on predictability. We use firm-specific market consensus earnings forecasts, coupled with prices, to back out the discount rate. In this way, we can identify cash flow news and discount rate news 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 the firm, portfolio, and market levels, and over short to long horizons. Also, the cash flow forecasts are taken from practitioners and are consistent with industry practice in security valuation.

Second, we provide the first attempt of consistent application of the predictive regression approach to both firm and aggregate levels, using different cash flow measures, and at different horizons. We find that there is a significant component of cash flow news in stock returns, and that its importance increases with the investment horizon. At horizons beyond two years, cash flow news is a more important share of stock returns than is discount rate news. This conclusion holds at both the firm and aggregate levels. Diversification plays a secondary role in affecting the relative importance of cash flow or discount rate news in driving stock returns.

Appendix A: Cash Flow, Discount Rate and the Implied Cost of Equity Capital

We first compare ICC, CF news, and DR news from our ICC-based decomposition to their counterparts in the more standard Campbell and Shiller (1988, CS hereafter) loglinear return decomposition. We then examine the discount rate news over the long run. Finally, we study the impact of a persistent cash flow forecast error. All empirical analysis is conducted using the annual stock market data for the S&P Index for the period 1871–2009. The data are obtained from the website of Robert Shiller.

A.1 ICC vs. discount rate component in CS

We start with the definition of ICC in Equation (9):

$$P_t = \sum_{j=1}^{\infty} \frac{E_t(D_{t+j})}{(1+ICC_t)^j} \text{ or}$$

$$\frac{P_t}{D_t} = \sum_{j=1}^{\infty}(1+ICC_t)^{-j} E_t\left[\prod_{i=1}^{j}(1+\Delta D_{t+i})\right], \text{ where} \tag{A1}$$

$$\Delta D_{t+i} = \frac{D_{t+i}}{D_{t+i-1}} - 1.$$

Linearize ICC_t and ΔD_{t+i} around mean ICC y and mean log dividend growth rate g:

$$(1+ICC_t)^{-j} \approx (1+y)^{-j} - j(1+y)^{-j-1}(ICC_t - y) \tag{A2}$$

$$\prod_{i=1}^{j}(1+\Delta D_{t+i}) \approx (1+g)^j + (1+g)^{j-1}\sum_{i=1}^{j}(\Delta D_{t+i} - g). \tag{A3}$$

Plugging (A2) and (A3) into (A1), we have:

$$\frac{P_t}{D_t} \approx \sum_{j=1}^{\infty}\left\{\begin{array}{c} (1+y)^{-j}(1+g)^j \\ -j(1+y)^{-j-1}(1+g)^j(ICC_t - y) \\ +(1+y)^{-j}(1+g)^{j-1}E_t\left[\sum_{i=1}^{j}(\Delta D_{t+i} - g)\right] \end{array}\right\}.$$

Simplifying the algebra, we have:

$$\frac{P_t}{D_t} \approx \frac{2+g}{y-g} - \frac{1+g}{(y-g)^2}ICC_t + \frac{1}{y-g}\sum_{j=1}^{\infty}\left(\frac{1+g}{1+y}\right)^{j-1}E_t\left(\Delta D_{t+j}\right).$$

Rearranging the equation, we have:

$$ICC_t \approx \left(\frac{y-g}{1+g}\right)\left[2+g-(y-g)\frac{P_t}{D_t} + \sum_{j=1}^{\infty}\omega_j E_t\left(\Delta D_{t+j}\right)\right]$$

$$\omega_j = \left(\frac{1+g}{1+y}\right)^{j-1}.$$

Intuitively, DR^{CS} and ICC should be highly correlated since they share almost identical time-varying components. To gauge their empirical correlation, we need a model to compute expectations and we choose the popular approach based on VAR. As such, we inherit the log-normality and homoskedasticity assumptions underlying the VAR.

Specifically, we consider a vector $Z_t = \left[r_t \, \triangle d_t \, dp_t\right]'$, where r_t is log return, $\triangle d_t$ is log dividend growth, and dp_t is log dividend yield. We estimate a first-order VAR ($Z_t = \Gamma Z_{t-1} + \varepsilon_t$) using the annual stock market data for the S&P 500 Index for the period from 1871 to 2009. The estimated VAR coefficients, variance of VAR innovations, and Z_t allow us to compute $E_t(\triangle d_{t+j})$ and $E_t(D_{t+j})$, from which we obtain the entire time-series of DR^{CS} (using Equation (8)) and ICC (using Equation (9)). We set $\rho = 0.96$, which implies $\kappa = 0.1679$. Following Pastor, Sinha, and Swaminathan (2008), we scale DR^{CS} by $1-\rho$, which is more comparable to ICC.

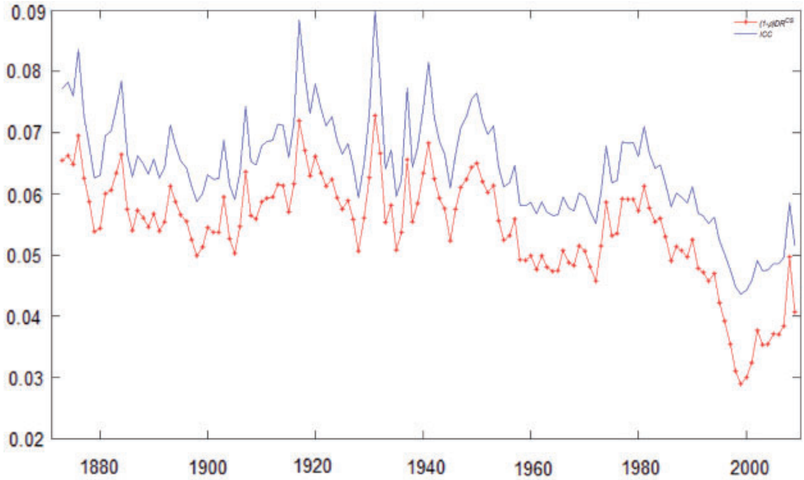

Figure A1
DR^{CS}* vs. *ICC
The figure shows how ICC and Campbell-Shiller discount rate news are related. The numbers are computed using the predictive regression method with the log dividend yield as the predictor. The annual data cover 1871–2009.

We plot both $(1-\rho)DR^{CS}$ and ICC in Figure A1. Indeed, the two time-series are highly correlated with a correlation coefficient of 0.983. ICC is higher than $(1-\rho)DR^{CS}$ due to Jensen's convexity adjustment.

A.2 Cash flow news and discount rate news—ICC vs. CS

In the standard CS framework, return innovations ($\varepsilon_{r,t}$) can be decomposed into cash flow news ($e_{CF,t}$) and discount rate news ($e_{DR,t}$) using the estimated VAR coefficients (Γ) and innovations (ε_t) as follows:

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

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

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

where $\lambda = \rho\Gamma(I-\rho\Gamma)^{-1}$, $e1$ 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.

In contrast, our ICC-based method decomposes the capital gain return in Equation (3) into CF news and DR news, as in Equations (4) and (5). After computing future expected dividends and the associated ICCs from the VAR, we can implement our ICC-based decomposition. In other words, using the same stock market data (S&P 500 Index) and the same model for computing expectations (the VAR), we can empirically compare CF/DR news from our ICC method against the cash flow/discount rate news from the CS decomposition. Figure A2 plots the return innovations, cash flow news and discount rate news from the CS decomposition against capital gain returns, CF news, and DR news accordingly from our ICC-based decomposition. The figures suggest that the two decomposition components produce strikingly similar results. The correlation between return innovations and capital gain returns is 0.979. The correlation between the cash flow news is 0.989 and the correlation between the two discount rate news is 0.932.

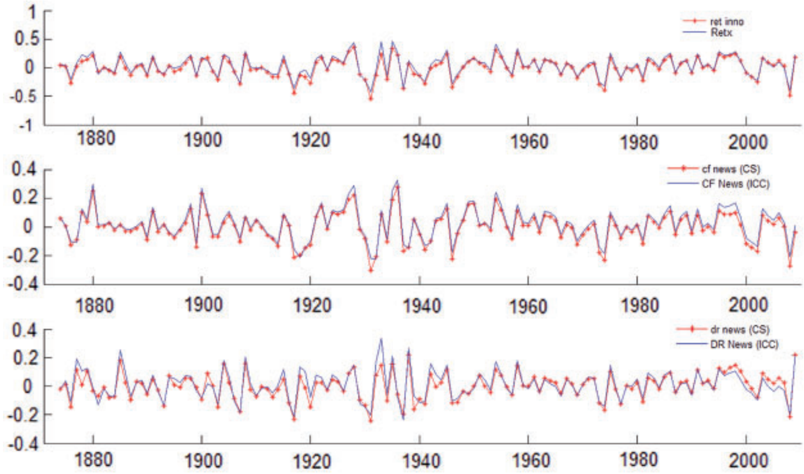

Figure A2
Decomposition: *CS* vs. *ICC*
The figure shows how return innovations, cash flow news, and discount rate news from the CS decomposition are related to capital gain returns, CF news, and DR news accordingly from our ICC-based decomposition. The numbers are computed using the predictive regression method with the log dividend yield as the predictor. The annual data cover 1871–2009.

A.3 Discount rate news in the long run

Under the CS decomposition, it can be shown that the unexpected n-period cumulative return, $\varepsilon^n_{r,t}$, can be written as:

$$\varepsilon^n_{r,t} = \sum_{j=0}^{n-1} \rho^j \left(\varepsilon_{r,t}\right) + \sum_{j=0}^{n-1} \rho^j e1' \times \left(\rho\Gamma - (\rho\Gamma)^{n-j}\right) \times (I - \rho\Gamma)^{-1} \varepsilon_{t+j}$$

$$e^n_{CF,t} = \sum_{j=0}^{n-1} \rho^j e_{CF,t}$$

$$e^n_{DR,t} = \sum_{j=0}^{n-1} \rho^j e_{DR,t} - \sum_{j=0}^{n-1} \rho^j e1' \times \left(\rho\Gamma - (\rho\Gamma)^{n-j}\right) \times (I - \rho\Gamma)^{-1} \varepsilon_{t+j}.$$

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

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

If n is large, the equation becomes:

$$e_{DR,t} - e1' \times \rho\Gamma \times (I - \rho\Gamma)^{-1} \varepsilon_t = 0.$$

In other words, the impact of discount rate news is temporary. In comparison, the impact of cash flow news is permanent: positive current cash flow news does not automatically lead to lower cash flow news in the future. Since discount rate news should be, in theory, stationary and mean-reverting, as the horizon n lengthens, the cumulative returns must increasingly represent cash flow news.

Table A1
ICC-based decomposition results

	1	3	5	7	10
			No forecast error		
CF	0.52	0.64	0.66	0.68	0.70
t-value	19.30	25.28	19.85	17.70	19.38
DR	0.48	0.36	0.34	0.32	0.30
t-value	17.55	14.46	10.36	8.15	8.40
			With forecast error		
CF	0.53	0.63	0.65	0.67	0.69
std dev	0.035	0.041	0.044	0.046	0.046
DR	0.47	0.37	0.35	0.33	0.31
std dev	0.035	0.041	0.044	0.046	0.046

This table reports the decomposition results using our ICC-based approach. The top panel uses the raw Shiller's data and the t-values are reported below the decomposition coefficients and are computed using Hansen-Hodrick standard errors. The bottom panel uses the augmented Shiller's data that incorporate simulated persistent forecast errors. We simulate 1,000 time-series of forecast errors and report the means and standard deviations of the resulting decomposition coefficients. The annual data cover 1871–2009.

A.4 The impact of forecast errors on the ICC-based decomposition

We implement our ICC-based decomposition using analyst earnings forecasts. While analyst earnings forecasts provide direct measures of expected future CF without resorting to predictive regressions, they are well-known to be biased. To gauge the impact of analyst forecast errors on our ICC-based decomposition, we add a layer of simulated forecast errors to the S&P stock market data. Using our IBES sample, we compute forecast error (defined as ln(forecast/actual)) for the current fiscal year at the aggregate level. We then fit an AR(1) process to the time-series of annual forecast errors. The forecast error has a mean of 0.05, an AR(1) coefficient of 0.7 and its innovation has a standard deviation of 0.03. These parameters confirm that analyst forecasts are overly optimistic on average and the forecast errors are quite persistent over time. Based on these parameters, we simulate annual forecast errors for the sample period of 1871–2009 and apply these forecast errors to the actual log dividend growth rates. We then implement our ICC-based decompositions for horizons equal to 1, 3, 5, 7, and 10 years, with the actual dividend data and with the forecast-error-augmented dividend data. The results are reported in Table A1.

We find that the results with and without forecast errors are qualitatively similar. Using the actual data, we find CF news to explain 52% of capital gain return variations at the one-year horizon. Using the forecast-error augmented data, CF news on average explains 53% of capital gain return variations in the one-year horizon. As horizon increases, CF news becomes more important while DR news becomes less important. Therefore, analyst forecast errors do not seem to drive our decomposition results. Note that CS decomposition gives almost identical results given the high correlations displayed in Figure A2.

Appendix B: Details on Computing the Implied Cost of Equity Capital

Our sample of the implied cost of equity capital (ICC) is based on quarterly data. IBES reports consensus analyst forecasts on earnings each month. We collect earnings forecast data as of March, June, September, and December of each year for all firms. The accounting data are from Compustat. We match analyst forecasts with accounting information that has been publicly released. We also collect from IBES share prices and numbers of shares outstanding. Earnings forecasts and share prices are both split-adjusted.

Recall that ICC is computed from the equation:

$$P_t = \sum_{k=1}^{15} \frac{FE_{t+k}(1-b_{t+k})}{(1+q_t)^k} + \frac{FE_{t+16}}{q_t(1+q_t)^{15}},$$

where P_t is the stock price, FE_{t+k} is the 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 ICC.

To be included in the sample, we require non-missing data for earnings forecasts for the current fiscal year (FE_{t+1}), the next fiscal year (FE_{t+2}), and the long-term growth forecast (g_{t+3}). If a firm has missing forecasts for the third fiscal year, we follow common practice and project earnings using the long-term growth forecast and the prior year's earnings forecast: $FE_{t+3}=FE_{t+2}\times(1+g_{t+3})$. We also require that prior year's dividends be available from Compustat. We restrict our sample to the 1985–2010 period because IBES covers too few firms before 1985.

To obtain earnings forecasts for years $t+4$ to $t+16$, we assume that the earnings growth rate reverts from g_{t+3} to the mean long-term analyst industry growth forecast g_{t+3}^{ind} by year $t+16$. As a result, for years $t+4$ to $t+16$, the earnings growth rates and the earnings forecasts are:

$$g_{t+k}=g_{t+k-1}\times\exp\left[\log\left(g_{t+3}^{ind}/g_{t+3}\right)/(13)\right]$$

$$FE_{t+k}=FE_{t+k-1}\times(1+g_{t+k})$$

$$\forall \quad 4\leq k\leq 16.$$

Beyond year $t+16$, earnings growth rates for all firms are assumed to be equal to a steady-state rate g_t^{ss}, namely the average historical GDP growth rate estimated using an expanding rolling window starting in 1947.

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 years $t+3$ and $t+16$ to a steady-state rate. The assumption is that, in a steady state, the product of return on investment, ROI, and the plowback rate, b_t^{ss}, is equal to the growth rate in earnings: $g_t^{ss}=ROI_t\times b_t^{ss}$. Assuming that the ROI is equal to the ICC, the steady-state plowback rate is $b_t^{ss}=g_t^{ss}/q_t$, that is, the ratio of average GDP growth rate to ICC. Therefore, the plowback rates from $t+3$ to $t+16$ are:

$$b_{t+k}=b_{t+k-1}-\frac{b_{t+2}-b_t^{ss}}{15}, \quad \forall 3\leq k\leq 16.$$

With the forecasted earnings and plowback rates, the ICC is then backed out numerically. When there are multiple roots, we choose the root that is closest to the risk-free rate. We exclude penny stocks with prices below $1. Finally, we winsorize all firm-specific variables in the final sample at the 1% and 99% breakpoints.

References

Abarbanell, J. S., and V. L. Bernard. 1992. Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior. *Journal of Finance* 47:1181–207.

Ang, A., and G. Bekaert. 2007. Stock return predictability: Is it there? *Review of Financial Studies* 20:651–707.

Bansal, R., R. Dittmar, and D. Kiku. 2009. Cointegration and consumption risks in asset returns. *Review of Financial Studies* 22:1343–75.

Bansal, R., and A. Yaron. 2004. Risks for the long run: A potential resolution of asset pricing puzzles. *Journal of Finance* 59:1481–509.

Binsbergen, J. V., and R. Koijen. 2010. Predictive regressions: A present-value approach. *Journal of Finance* 65:1439–71.

Boudoukh, J., R. Michaely, M. Richardson, and M. Roberts. 2007. On the importance of measuring payout yield: Implications for empirical asset pricing. *Journal of Finance* 62:877–915.

Boudoukh, J., M. Richardson, and R. F. Whitelaw. 2008. The myth of long-horizon predictability. *Review of Financial Studies* 24:1577–605.

Bradshaw, M. T., S. A. Richardson, and R. G. Sloan. 2006. The relation between corporate financing activities, analyst forecasts and stock returns. *Journal of Accounting and Economics* 42:53–85.

Callen, J., O. Hope, and D. Segal. 2005. Domestic and foreign earnings, stock return variability, and the impact of investor sophistication. *Journal of Accounting Research* 43:377–412.

Callen, J., J. Livnat, and D. Segal. 2006. The information content and information environment of SEC filings: A variance decomposition analysis. *Accounting Review* 81:1017–43.

Callen, J., and D. Segal. 2004. Do accruals drive firm-level stock returns? A variance decomposition analysis. *Journal of Accounting Research* 42:527–60.

Campbell, J. 1991. A variance decomposition for stock returns. *The Economic Journal* 101:157–79.

Campbell, J., and J. Cochrane. 1999. By force of habit: A consumption-based explanation of stock market behavior. *Journal of Political Economy* 107:205–51.

Campbell, J., and R. Shiller. 1988. The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies* 1:195–228.

———. 1998. Valuation ratios and the long-run stock market outlook: An update. Working paper, Harvard University.

Campbell, J., and T. Vuolteenaho. 2004. Bad beta, good beta. *American Economic Review* 94:1249–275.

Chan, L. K. C., N. Jegadeesh, and J. Lakonishok. 1996. Momentum strategies. *Journal of Finance* 51:1681–713.

Chava, S., and A. Purnanandam. 2010. Is default-risk negatively related to stock returns? *Review of Financial Studies* 23:2523–59.

Chen, L. 2009. On the reversal of return and dividend growth predictability: A tale of two periods.*Journal of Financial Economics* 92:128–51.

Chen, L., and X. Zhao. 2009. Return decomposition. *Review of Financial Studies* 22:5213–49.

Chen, L., Z. Da, and R. Priestley. 2012. Dividend smoothing and predictability. *Management Science* 58:1834–53.

Claus, J., and J. Thomas. 2001. Equity premia as low as three percent? Evidence from analysts' earnings forecasts for domestic and international stock markets. *Journal of Finance* 56:1629–66.

Cochrane, J. H. 1992. Explaining the variance of price-dividend ratio. *Review of Financial Studies* 5:243–80.

———. 2001. *Asset Pricing*. Princeton University Press, New Jersey.

———. 2008. The dog that did not bark: A defense of return predictability. *Review of Financial Studies* 21: 1533–75.

———. 2011. Discount rates. *Journal of Finance* 66:1047–108.

Cohen, R. B., C. Polk, and T. Vuolteenaho. 2003. The value spread. *Journal of Finance* 58:609–41.

Da, Z., and M. Warachka. 2009. Cashflow risk, systematic earnings revisions, and the cross-section of stock returns. *Journal of Financial Economics* 94:448–68.

Easton, P., and S. Monahan. 2005. An evaluation of accounting-based measures of expected returns. *Accounting Review* 80:501–38.

Elton, E. J., M. J. Gruber, and M. Gultekin. 1981. Expectations and share prices. *Management Science* 27:975–87.

Fama, E., and K. French. 1995. Size and book-to-market factors in earnings and returns. *Journal of Finance* 50:131–55.

Francis, J., and L. Soffer. 1997. The relative informativeness of analysts' stock recommendations and earnings forecast revisions. *Journal of Accounting Research* 21:193–211.

Gebhardt, W., C. M. C. Lee, and B. Swaminathan. 2001. Toward an implied cost of capital. *Journal of Accounting Research* 39:135–76.

Givoly, D., and J. Lakonishok. 1979. The information content of financial analysts' forecast of earnings. *Journal of Accounting and Economics* 2:165–85.

Golez, B. 2012. Expected returns and dividend growth rates implied in derivative markets. Working Paper, University of Notre Dame.

Goyal, A., and I. Welch. 2003. Predicting the equity premium with dividend ratios. *Management Science* 49: 639–54.

———. 2008. A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies* 21:1455–508.

Graham, J. R., and C. Harvey. 2005. The long-run equity risk premium. *Finance Research Letters* 2:185–94.

Griffin, P. 1976. Competitive information in the stock market: An empirical study of earnings, dividends, and analysts' forecasts. *Journal of Finance* 31:631–50.

Hansen, L. P., J. Heaton, and N. Li. 2008. Consumption strikes back?: Measuring long-run risk. *Journal of Political Economy* 116:260–302.

Hansen, L. P., and R. J. Hodrick. 1980. Forward exchange rates as optimal predictors of future spot rates: An econometric analysis. *Journal of Political Economy* 88:829–53.

Hughes, J., J. Liu, and J. Liu. 2009. On the relation between expected returns and implied cost of capital. *Review of Accounting Studies* 14:246–59.

Imhoff, E., and G. Lobo. 1984. Information content of analysts' composite forecast revisions. *Journal of Accounting Research* 22:541–54.

Jagannathan, R., E. R. McGrattan, and A. Scherbina. 2000. The declining U.S. equity premium. *Quarterly Review, Federal Reserve Bank of Minneapolis* 24:3–19.

Jagannathan, R., and A. B. Silva. 2002. Stock yields and the decomposition of actual returns on benchmark stock index portfolios. Working paper, Northwestern University.

Kaplan, S. N., and R. S. Ruback. 1995. The valuation of cash flow forecasts: An empirical analysis. *Journal of Finance* 50:1059–93.

Koijen, R., and S. Van Nieuwerburgh. 2011. Predictability of returns and cash flows. *Annual Review of Financial Economics* 3:467–91.

Lakonishok, J., A. Shleifer, and R. Vishny. 1994. Contrarian investment, extrapolation, and risk. *Journal of Finance* 49:1541–78.

Larrain, B., and M. Yogo. 2008. Does firm value move too much to be justified by subsequent changes in cash flow? *Journal of Financial Economics* 87:200–26.

Lettau, M., and S. C. Ludvigson. 2005. Expected returns and expected dividend growth. *Journal of Financial Economics* 76:583–626.

Lettau, M., and S. Van Nieuwerburgh. 2008. Reconciling the return predictability evidence. *Review of Financial Studies* 21:1607–52.

Liu, J., and J. Thomas. 2000. Stock returns and accounting earnings. *Journal of Accounting Research* 38: 71–101.

Ljungqvist, A., C. Malloy, and F. Marston. 2009. Rewriting history. *Journal of Finance* 64:1935–60.

Lys, T., and S. Sohn. 1990. The association between revisions of financial analyst's earnings forecasts and security-price changes. *Journal of Accounting and Economics* 13:341–63.

Mendenhall, R. 1991. Evidence on the possible underweighting of earnings-related information. *Journal of Accounting Research* 29:170–9.

Park, C. W., and E. K. Stice. 2000. Analyst forecasting ability and the stock price reaction to forecast revisions. *Review of Accounting Studies* 5:259–72.

Pastor, L., M. Sinha, and B. Swaminathan. 2008. Estimating the intertemporal risk-return tradeoff using the implied cost of capital. *Journal of Finance* 63:2859–97.

Pontiff, J., and A. Woodgate. 2008. Share issuance and cross-sectional returns. *Journal of Finance* 63:921–45.

Rajan, R., and H. Servaes. 1997. Analyst following of initial public offering. *Journal of Finance* 52:507–29.

Vuolteenaho, T. 2000. Understanding the aggregate book-to-market ratio and its implication to current equity-premium expectations. Working paper, Harvard University.

———. 2002. What drives firm-level stock returns? *Journal of Finance* 42:233–64.