

Unifying Underreaction Anomalies

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Abstract

This paper asks whether momentum and post-event drift are manifestations of the same underlying mechanism or whether they are separate phenomena. We find that both effects can be attributed to persistence in returns following news which affects expected earnings or earnings growth. Holding these quantities fixed, there is no momentum effect, nor is there post-event drift for our sample of events.

1 Introduction

Two of the most convincingly documented stock market anomalies are momentum and post-event drift. Momentum refers to the persistent excess returns of winner portfolios over loser portfolios, where winners and losers are judged over a backward-looking horizon of six months to a year.¹ Post-event drift, by contrast, is the tendency of individual stocks' performances following major corporate news events to persist for long periods in the same direction as the return over a short window – usually one to three days – encompassing the news announcement itself.² While the details

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¹The original momentum findings are in Jegadeesh and Titman (1993).

²See Fama (1998) for a critical summary of the literature.

of these two types of behavior (as well as the statistical issues surrounding their measurement) definitely differ, they share a common intuitive interpretation: markets appear to underreact. Periods of good news are followed by periods of unusually high returns relative to natural benchmarks, with the reverse for bad news. This paper addresses the question of whether, indeed, the two types of anomalies are the same phenomenon, just measured in different ways. That is, we would like to know whether there are two puzzles here, or only one.

The answer is not obvious. Momentum itself does not explain post-event drift. For example, firms undertaking share repurchases have usually had negative recent performance (even including the positive announcement return), and yet subsequently outperform. Conversely, corporate news events do not happen all that often, whereas momentum effects seem to be present in stocks generally in all time periods. But perhaps our understanding of what constitutes an “event” is too narrow. Certainly researchers have focussed on those that are most conspicuous and easy to isolate. It could be that drift happens after small and hard-to-observe events as well.

In other words, the hypothesis we wish to test is that momentum is the aggregate effect of post-event drift across all classes of event. If, in fact, future returns are high following any type of good news generally, then presumably, a portfolio of the best performing stocks over the last six months – which ought to contain the firms with the most good news – will also include the best subsequent performers. Mechanically, that seems likely enough. But it would not be sufficient. We would also need to be convinced that these event firms were responsible for all the ensuing outperformance. Or, equivalently, we would need to show that, controlling for the occurrence of news events of known impact, there is no residual momentum effect.

The goal of the paper, then, is somewhat prosaic. We are not attempting to explain either of the two anomalies, nor to take a stand on the rationality of the observed patterns. Moreover, while there are still econometric grounds to dispute the patterns themselves, we take both as established fact. Our aim is just to contribute something to the organizational side of the seemingly ever-broadening literature on return anomalies.

Indeed, the most straightforward way, conceptually, to carry out our investigation would be to undertake a giant book-keeping exercise. If we had an exhaustive list of the occurrences of all types of news events, along with estimates of the return drift associated with each, it would be a simple matter to determine if there were an independent momentum effect. Recently, Chan (2001) has done something like this for a sample of 1557 stocks. He identifies all news events for each over the period 1980-1999, and demonstrates both that there is a generic post-event drift – irrespective of news type – and that, among stocks without any news, there is no momentum effect in the sense that, within this group, winners no longer outperform losers in the post-formation period.³ These results strongly suggest the conjecture of a single underlying effect may be correct. The remaining step is to actually show the connection between the news events (or their absence) and the subsequent return dynamics for each stock.

Broadly, that is our goal here. Our aim is to be able to write down a tractable specification of the the cross-section in terms of some observable indicators of the occurrence of important news. The hope is that, rather than having to describe each firm’s expected returns by reference to some omnibus event table, we may be able to find instrumental variables that signal the occurrence of whatever type of news has persistent effects on returns. If a candidate (or set of them) can both explain momentum (in the sense of knocking past returns out of cross-sectional regressions of current returns) and also account for diverse post-event returns, then there are legitimate grounds for viewing the instruments as identifying a common channel through which both effects operate.

We claim to be reasonably successful in this pursuit. We do, in fact, isolate such explanatory variables. Moreover, in doing so, we move beyond our initial objective of drawing a mechanical connection between the two underreaction puzzles. The variables that explain them both are directly related to changes in expected earnings.

To summarize, our findings are that both momentum and the drift observed after

³Pritamani and Singal (2001) also find return continuation (at a 20 day horizon) for news events generically classified as positive or negative.

the occurrence of several previously-studied event types are coincident with changes in either expected earnings or expected earnings growth, and that changes in the latter two quantities account for all the subsequently observed abnormal performance. Holding these quantities fixed, there is no momentum effect, nor is there post-event drift for our sample of corporate actions.

Methodologically, the key step in our analysis is coming up with clean proxies for these changes in expectations. We start from analyst forecast revisions, and then explicitly model and correct for their predictable component. In doing so, we also document a consistent pattern of analyst underreaction both to price changes (which is well-known) and to corporate events (which is less so).

The correspondence between patterns of analyst underreaction and price underreaction is highly suggestive of a behavioral explanation for return persistence. However, rational stories based on contemporaneous shocks to cash-flow risk may also be consistent with these patterns.

In short, we do not yet know why news that affects earnings expectations has persistent effects on returns. But we do think that identifying this association considerably sharpens the focus of the theoretical effort to understand what is going on.

Our work is closely related to two other important recent papers. Chan, Jegadeesh, and Lakonishok (1996) sought to clarify the relationship between momentum and post-earnings-announcement drift. Their goals were similar to ours, and, indeed, some of our techniques and variable definitions are directly attributable to them. Ultimately they conclude that momentum is not fully explainable by changes in earnings expectations or earnings surprises (although these do account for a significant fraction of the effect). Nor does momentum explain the drift following these surprises. Building on their results, we employ what we think are improved measures of expectations, and claim that these can finish the job.⁴ In a similar vein, Vuolteenaho (2002) runs panel vector autoregressions of changes in earnings and returns, thereby

⁴We examine post earnings announcements drift in subsequent work (in progress), but do not do so here.

controlling for contemporaneous and lagged earnings effects as well as momentum in explaining returns. He, too, finds a residual influence for momentum. Our innovation with respect to his set-up, is to control for, not contemporaneous earnings changes, but contemporaneous changes in expected earnings. While we must sacrifice the elegance of the VAR framework, our specification may be viewed as an extension of his.

The outline of the paper is as follows. The next section introduces the instrumental variables we employ and the specification that relates them to returns and other predictors. Section 3 fits the basic model and demonstrates that it explains momentum. In Section 4 we examine three samples of corporate events that have been widely used in the long-horizon event-study literature. An expanded version of our original model is then shown to explain the abnormal returns subsequent to those. Section 5 contains some concluding remarks on the interpretation of our findings.

2 The Model

To investigate the hypothesis that underreaction anomalies can be traced to changes in fundamental expectations, one would like to simply run regressions of returns on proxies for those expectations alongside other explanatory variables known to be associated with return persistence. Things become less straightforward, however, when the available expectational proxies are poor. In this study, we use changes in consensus earnings forecasts (and growth forecasts) from IBES, which turn out to be both autocorrelated and forecastable from other predictors, including momentum. In this section we derive the return specification that ensues from cleaning up these “expectations.”

Before launching into the equations, let us describe what needs to be done. The defining property of true conditional expectations is their non-forecastability. So the first step in cleaning up our proxies is to remove their predictable component. But

there is a second step as well. Even if there is no innovation in the proxy at time t , if there are contemporaneous changes in other variables that imply future changes in the proxy, then the true conditional expectations at t must be updated to reflect this. To make this concrete, if we know that the analysts polled by IBES do not weigh current returns sufficiently in changing their growth estimates, then even when these estimates are unchanged today, if observed stock returns cue us to the updates they will subsequently have to make, then we will impound those updates in our true expectations at the time of the return observation. We need our cleaned-up expectations to correctly reflect future predictable revisions immediately.

Mathematically, suppose i^* is a vector of parameters that affects a firm's value, and that $\{i_t\}$ is any (noisy) series that eventually converges to i^* . Then, $E_t[i^*] = i_t + E_t[\sum_{k=0}^{\infty} \Delta i_{t+k}] = i_t + \sum_{k=0}^{\infty} E_t[\Delta i_{t+k}]$, (assuming the latter is finite). The correct measure of the amount of news about i^* that arrives at time t then is

$$(1) \quad \xi_t \equiv E_t[i^*] - E_{t-1}[i^*] = \sum_{k=0}^{\infty} [E_t[\Delta i_{t+k}] - E_{t-1}[\Delta i_{t+k}]].$$

Equation (1) is quite general: it does not actually require the true parameter to be constant through time. Moreover, it gives the correct expression for the change in conditional expectations even if the estimates never do, in fact, converge to the true value, as long as any bias component is stationary. In our setting, we interpret the observed IBES estimates as the noisy series $\{i_t\}$, with Δi_t being the time- t revisions of those numbers.

To construct the true forecast innovation series, then, we require a model of the evolution of Δi_t . We return to this in a moment. But first let us write down our basic hypothesis using the current notation. If r_t is the excess return at time t (for a given asset), then our model simply says

$$(2) \quad r_t = \alpha_0 + \alpha_1' \xi_{t-1} + \epsilon_t^{(1)}.$$

That is, innovations in our fundamental variables cause changes in expected returns,

and other things do not.⁵ The basic model (2) envisions only one-period-ahead effects (so $E_t[r_{t+2}]$ is a constant), which of course is not essential. We have also fit two-lag and geometric lag models. And the best specification will, in general, depend on the time interval Δt . While we intend to report refinements based on these variations in future work, we do not want to obscure the fact that the economic content of what we are doing boils down to this one restriction.

Econometrically, (2) complicates matters because it turns out that returns also predict changes in Δi . At this stage, let us suppose for simplicity, that they are the only quantity – besides lags of Δi – that does so. This implies a specification like

$$(3) \quad \Delta i_t = \mu + A(L)\Delta i_{t-1} + a(L)r_{t-1} + \epsilon_t^{(2)}$$

where μ is a constant and A and a are polynomials (of appropriate dimension) in the lag operator L .

We can then combine (3) with (2) and (1) to derive the following equation for the true change in conditional expectations

$$(4) \quad \xi_t = (I + EL)^{-1} F \lambda_t$$

where

$$(5) \quad F = [I - A(1) - a(1)\alpha'_1]^{-1}$$

$$(6) \quad E = F a(1) \alpha'_1$$

$$(7) \quad \lambda_t = (\epsilon_t^{(2)} + a(1)r_t).$$

(The derivation appears in the appendix.) Combining (4) with (2), our return model becomes

$$(8) \quad r_t = \alpha_0 + \alpha'_1(I + EL)^{-1} F \lambda_{t-1} + \epsilon_t^{(1)}.$$

Intuitively, equation (8) is just a regression of returns on a filtered version of the

⁵We might add the hypothesis that $\alpha_1 > 0$, when positive changes in ξ denote good news, to describe the effect as persistence and not reversal.

series $\{\lambda_t\}$. That series is the augmentation described above of the current unexpected change in the observed forecast by the cumulative future revision predicted by current returns. There is a further filtering step required (implemented by the operator $(I + EL)^{-1}$) only because of the added complication that the return part of λ_t is itself partially predictable according to (2). With typical parameter values, eigenvalues of E are small, and the contribution of the lagged terms is of secondary importance.

It is also worth noting that past returns appear implicitly now in our model via (7). The important point, however, is that their weighting is not a free parameter in fitting returns. Instead, this weight is determined by the analyst forecast model equation (3). To emphasize this, at the testing stage we will explicitly give the data the chance to un-do this constraint.

While (8) may be understood as just a linear regression on the corrected innovations, estimation is rendered harder by the fact that the regression coefficient α_1 (which gives the return premium associated with the innovation ξ) is also involved in the matrices E and F which define ξ . So, even though we have a straightforward linear time-series model for Δi , this ends up producing a non-linear model for returns. This means that we will not ultimately be able to gauge our model by the familiar method of running OLS regressions of returns on some new candidate variables alongside established competitors. Instead, we fit our model (via non-linear least squares), and then test it by regressing its residuals (the unexplained component) on the competing predictors.

The next section introduces the data series we employ, and describes how we carry out the estimation and testing steps. Results are presented for the basic model described by equations (2) and (3). From these we are able to conclude that our corrected informational variables do, in fact, account for momentum effects. After that, we turn to the connection to post-event drift in Section 4.

3 Initial Results

As discussed at the start of the preceding section, the initial expectational variables employed in this study are based on IBES consensus earnings forecasts. Our working hypothesis is that good news generates persistent positive abnormal returns if and only if the IBES forecasts – corrected as described above – concurrently increase, with negative abnormal returns likewise when they decrease. For each stock tracked by IBES, the monthly data records include average forecasts (by varying numbers of analysts) for a number of fiscal horizons, as well as a separate consensus forecast for five-year growth. One could imagine different types of news affecting earnings at different horizons independently, and hence an informational role for changes in each horizon’s forecast. For parsimony, we employ only revisions to the nearest fiscal year’s estimate and to the five-year growth number. The latter is included to capture news about long-term cash-flow prospects, and is at least partially motivated by models such as that in Johnson (2002), which suggests an independent role for growth-rate risk.

The basic time unit of the study will be six month intervals. Thus our fundamental variable Δi_t consists of two components for each stock (which we call DFY1 and DLTG in the tables), defined to be (respectively) the change over the preceding six months in the mean forecast for the next fiscal year⁶, and the change in the mean long-term growth forecast over the same period. Although the long-term forecasts do not go back in time as far as the annual ones, we still have observations for both series for several thousand stocks for each month from the beginning of 1983 through the end of 1999. Following Chan, Jegadeesh, and Lakonishok (1996), we further transform each variable into its percentile rank in each month. Table 1 summarizes some aggregate properties of the sample.

The first step in our estimation is to fit the prediction equation (3) for our bivariate process Δi in order to extract its innovation component. Table 2 shows estimates of a specification which incorporates one lag of Δi itself and two lags of re-

⁶A complete description of all data fields and variables is given in Appendix 5.

Table 1: *Stocks With IBES Data*

Year:	Number of Firms	Average size decile:		Stocks by Exchange:		
		mean	median	NYSE	AMEX	NASDAQ
1983	1546	4.1	3.0	1140	107	299
1984	1715	3.4	2.0	1140	119	456
1985	1945	3.3	1.0	1141	137	666
1986	1963	3.3	2.0	1139	135	688
1987	2007	3.2	2.0	1113	144	749
1988	1982	2.7	1.0	1005	139	838
1989	1979	2.8	1.0	1026	142	811
1990	2058	2.8	1.0	1020	157	881
1991	2027	2.9	2.0	1009	133	885
1992	2050	3.2	2.0	1070	120	859
1993	2181	3.4	2.0	1136	114	930
1994	2452	3.6	2.0	1227	97	1126
1995	2638	3.8	3.0	1278	82	1275
1996	2791	4.0	3.0	1362	74	1353
1997	3069	4.0	3.0	1456	80	1531
1998	3355	4.2	3.0	1568	89	1697
1999	3435	4.6	4.0	1621	101	1712

The table describes the stocks for which there are IBES forecasts for both next fiscal year's earnings and long-term (five year) growth. For a firm to be included in a given month it must have forecasts for at least the previous six months, and have stock prices on CRSP for the previous twelve months and the following six months. Size deciles are computed using month-end NYSE breakpoints.

turns.⁷ The estimates shown are time-series averages of the coefficients from monthly cross-sectional regressions (a la Fama and Macbeth (1973)), with standard errors corrected for the induced six-lag autocorrelation.

The most notable finding here is the extreme predictability of the changes in annual forecasts. It is well known in the accounting literature that analysts tend to smooth their revisions over time, and thus the significance of lagged revisions is not surprising. The degree with which they appear to underreact to stock returns at lags up to one year is perhaps less well appreciated. The same is true of revisions

⁷Including longer lags has no significant effects on the results below.

Table 2: *Forecasting Forecast Revisions*

	μ	DFY1 _{<i>t</i>-1}	DLTG _{<i>t</i>-1}	R6	LR6
DFY1 _{<i>t</i>}	.0021 (1.60)	.2718 (38.03)	-.0012 (0.43)	.3219 (20.51)	.0924 (9.95)
DLTG _{<i>t</i>}	.0006 (0.60)	-.0071 (1.21)	-.0573 (11.07)	.2052 (23.02)	.0744 (9.45)

The table shows estimates for the semi-annual specification: $\Delta i_t = \mu + A\Delta i_{t-1} + a_1 r_{t-1} + a_2 r_{t-2} + \epsilon_t^{(2)}$ where Δi is the bi-variate process of IBES forecast revisions whose components are DFY1 and DLTG, the percentile rank changes in next-fiscal-year and long-term growth respectively. R6 and LR6 are the stock returns over months $t - 5$ to t and $t - 11$ to $t - 6$ respectively. Coefficients are estimated by Fama-Macbeth regressions for each component. The data are monthly observations from 1983 through 1999. Standard errors are adjusted for induced six-month autocorrelation. The resulting t statistics are in parentheses.

to long-run growth forecasts. Accounting for the momentum dependency, analysts actually over adjust this number in the sense that there is a significant tendency to reverse the direction of time- t changes at $t + 1$. This overreaction has been previously documented by LaPorta (1996).

The next stage in our program involves estimating the parameters of the return equation. This requires as inputs the coefficients of the Δi evolution equation, for which we use the point estimates in Table 2.⁸ Given these values for A and a , and the fitted Δi residuals $\hat{\epsilon}^{(2)}$, the only unknowns in equation (8) are the α s. We fit these by non-linear least squares with a time-varying intercept. The resulting pair of return premia, the two components of α_1 , is shown in Table 3.⁹

Innovations to near-term expected earnings have about three times the effect that innovations to long-run growth do upon expected returns. For reference, the

⁸By not accounting for the estimation uncertainty in these, we overstate the accuracy of our estimate of the return parameter α_1 below. On the other hand, when we test our return residuals for remaining underreaction effects, the t -statistics overstate significance levels, i.e. we bias the tests in the direction of rejecting our model.

⁹Standard errors are computed from the asymptotic covariance matrix $T^{-1} A^{-1} B A^{-1}$ where B is the estimated covariance of the normalized scores of the NLLS criterion function, Q , and A is Q 's numerical second derivative. See Amemiya (1985) Theorem 4.1.3.

Table 3: *News Premia Estimates*

	α_1	(s.e.)	avg std dev:		autocorr:
			CS	TS	lag=6mo
ξ_1	.0514	(3.03)	.351	.377	-.217
ξ_2	.0159	(2.15)	.237	.246	-.166

The first column of the table gives return premium estimates, α_1 , in the return model $r_t = \alpha_0 + \alpha_1' \xi_{t-1} + \epsilon_t^{(1)}$, where ξ is the corrected news process defined by equations (4) - (8). The parameters are estimated by non-linear least squares, with asymptotic t -statistics shown in parentheses (see footnote 9). Estimates of the ξ process, which depend on α_1 , are then computed for each stock in our sample. The two middle columns report the average cross-sectional (CS) and time-series (TS) standard deviations of these imputed series. The right-most column shows the average autocorrelation of each component.

table also shows the average cross-sectional and time-series variability¹⁰ of the two components of the innovation series. Combined with the α estimates, these indicate that the magnitude of the fitted model's effects are of the order of plus and minus 250 basis points of return differential (in expected six-month returns), with, again, the earnings revisions accounting for a larger share than the growth rate revisions. Both components of the transformed series have negative first-order autocorrelation (last column) which will, if anything, handicap their ability to explain persistence in returns.¹¹

Table 4 shows results from ordinary Fama-Macbeth regressions using momentum (trailing six-month returns) as a predictor. The first panel shows results when the raw returns themselves (over the next six months) are the dependent variable. The second panel uses instead the residual part of these returns in excess of that fitted by our model. The message is clear. Regardless of what other controls are in the regression, the momentum anomaly is strongly present in our sample of returns, but has been almost entirely erased by our model.

¹⁰These are arithmetic averages of standard deviations. Root mean squares were similar. The average time-series correlation between the two components is 0.35.

¹¹There is no problem here for our interpretation of ξ as a martingale difference sequence. The negative autocorrelations are highly variable across stocks, (most of whom have only about five years of history) and are not statistically significant. Formally, lags of ξ do not predict ξ .

Table 4: *Return Regressions*

R6	DFY1	DLTG	E/P	SIZE
DEPENDENT VARIABLE=6-MONTH RETURNS				
.0577				
(5.36)				
.0600	.0606	.0135		
(3.96)	(5.26)	(3.75)		
.0624	.0529	.0147	.0238	.0096
(5.03)	(5.87)	(4.21)	(1.03)	(0.61)
DEPENDENT VARIABLE=MODEL RESIDUALS				
.0178				
(1.07)				
.0127	.0088	.0007		
(0.80)	(0.75)	(0.18)		
.0155	-.0029	.0019	.0264	.0148
(1.20)	(0.14)	(0.51)	(1.16)	(0.91)

The table shows results from Fama-Macbeth regressions for monthly stock returns (top panel) and estimated model return residuals (bottom panel), for different specifications of independent variables. R6, DFY1, and DLTG are the six-month trailing returns, and IBES forecast series defined in the text. E/P is the percentile rank of earnings to price, where the numerator is the consensus forecast for the next fiscal year. SIZE is the percentile rank of market capitalization. The data are monthly observations from 1983 through 1999. Standard errors are adjusted for induced six-month autocorrelation. The resulting t statistics are in parentheses.

It is important to point out that, although past returns are indeed incorporated in our innovation variable λ , our model was not free to adjust their weight which was determined solely by the Δi equation. In this regard, the specification in Table 4 which also includes the unadjusted IBES variables is especially important. If all our model was doing was picking up the momentum component of λ , the story would come out here. The data would then take the opportunity to undo the spurious inclusion of the IBES variables by negatively weighting them here, while simultaneously according momentum its “true” weight. This is not what happens. Instead, all the predictors in the residual regression are insignificant. This clearly indicates that the model has not simply included momentum by the backdoor. Instead, the results shows that momentum matters by exactly the amount that it matters to purge analysts forecasts of their underreaction.

In the next section we extend these results to encompass the return persistence that follows corporate news events. Our basic framework for estimation and testing will be the same as that used in this section. But we will have to extend the econometric specification of Section 2 slightly.

4 Post-Event Drift

Our inferential approach to post-event return persistence is based on simple calendar-time regressions, and thus departs somewhat from the usual methodology of the long-horizon event study literature. Specifically, the procedure is as follows. For a given type of corporate event, we include a dummy variable in our Fama-Macbeth regressions which is one for firm i at time t if the announcement date of such an event occurred for firm i in the six months prior to (and including) t . If the dependent variable in the regression is the return in the following six months, then we are implicitly examining the average post-event drifts for months +1 to +12 in event-time. This set-up allows us to employ the same methodology used in the last section, as well as to include whatever controls may be of interest in determining the appropriate benchmark.

To find out if our corrected earnings expectation variables can explain post-event drift, we collect samples for three types of event that have been examined extensively: secondary equity offerings (SEOs), share repurchases, and stock-financed mergers.¹² We collect announcement dates on all three from SDC for the years for which we have constructed our expectation variables.¹³ Table 5 summarizes the events by year for those that also intersect with our IBES sample.

The table confirms that the pattern of underreaction documented by previous studies is present in our data. For SEOs and share repurchases the sign of the average excess three-day announcement returns is the same as that of returns for the following 12 months (starting with the first post-announcement month). For stock financed mergers, the initial news is ambiguous. The mean announcement return is small and positive and the median is negative, which probably indicates that we haven't identified the real event-date correctly in a lot of cases.¹⁴ In any case, the one year returns are reliably negative. When we perform the return regressions described above, the t-statistics for the event dummies are all significant in most specifications.¹⁵

The bad news for the model of the last section is that it does not eliminate all of this underreaction. In regressions of its residuals on the event dummies (which we omit) the coefficient on stock-financed mergers does become insignificant. But the SEO coefficient is only lowered slightly in magnitude, and the share-repurchase one actually increases. This apparently indicates that these events lead to return drift beyond that attributable to the contemporaneous changes they cause in earnings expectations.

The picture changes fundamentally, however, when, in addition to the contem-

¹²Some of the primary work on these can be found in Asquith and Mullins (1986), Loughran and Ritter (1995) and Speiss and Affleck-Graves (1995) (for SEOs), Ikenberry, Lakonishok, and Vermaelen (1995) (for buybacks), and Travlos (1987) and Loughran and Vjih (1997) (for mergers). Collectively, these were also the basis for the study of long-horizon inference in Mitchell and Stafford (2000), and the study of underreaction by Kadiyala and Rau (2001).

¹³See Appendix 5 for details on our selection criteria and definition of events.

¹⁴We don't use the announcement returns for anything below, so this is immaterial.

¹⁵We have also used a design where the dummy variable in the regressions is set equal to the sign of the (three-day) announcement return. The only important difference in our results with this alteration is that the drift following all-stock mergers fails to be significant with either the returns or the model residuals.

poraneous correlation, lagged correlations are taken into account. It turns out that analyst forecasts also drift in periods following our events. Or, equivalently, lagged values of the event dummies enter significantly in Δi regressions. Statistically, this means equation (3) is now mis-specified (and the derivation of the subsequent model equations needs to be modified). Intuitively, it means that the corrected expectational innovations (our ξ) ought to react to the occurrence of one of our events so as to incorporate all future predictable revisions in the uncorrected series. That is, we must un-do the underreaction of the analysts.

To see how this works mathematically, write the amended version of (3) as

$$(9) \quad \Delta i_t = \mu + A(L)\Delta i_{t-1} + a(L)r_{t-1} + b(L)x_{t-1} + \epsilon_t^{(2)}$$

where now x_t is the event indicator process. (For the exposition we will assume there is only one type of event. In the version we fit there will be a separate process, and a separate lag polynomial, for each of our three types.) Next, assume x_t is a martingale. This is also for simplicity, but it is not far off.¹⁶ Then, as shown in Appendix 5, equations (4), (5), and (6) are formally unchanged. But now (7) becomes

$$(10) \quad \lambda_t = \epsilon_t^{(2)} + a(1)r_t + b(1)x_t.$$

As with the return term, the event correction now involves the sum of all the regression coefficients in (9) multiplied by the current value of the indicator. Table 6 shows our estimates of these coefficient sums. For equity-financed mergers, we do not detect any significant analyst underreaction. But for buy-backs and SEOs we find significant coefficients, nearly all of the same sign, out to lags of nearly six years for revisions to both year-one estimates and long-term growth forecasts. This finding, though ancillary to the main purpose of our study, is nevertheless remarkable in its own right. We have documented a long-horizon post-event drift in analysts' forecasts

¹⁶In fact, previous buy-backs tend to predict buy-backs, and momentum predicts SEOs. But the effects are weak. Correcting for this slightly strengthens our results.

which parallels closely the pattern in returns.¹⁷

Continuing now with our program, incorporating the lags of the event indicators in our Δi specification, we use the new estimates of the parameters in (9) to again construct the innovation series λ_t .¹⁸ As before, we then use λ_t to simultaneously estimate the return response coefficients α and build the corrected news process ξ_t . Residuals from our return model are then tested for remaining predictability. The results are shown in Table 7.

The first panel shows various specifications for the raw returns themselves, and demonstrates the significance of the post-event drift. Interestingly, the post-merger drift is almost all accounted for by the raw IBES revisions, whereas the other two event types are not. The fact that analysts revisions also seem to respond correctly to mergers, but not to buybacks and SEOs, strongly suggests that our model is indeed isolating the true informational component of the forecast series.

The second of the table panel runs the same regressions with the model residuals. All the event dummies – as well as momentum itself again – are now reduced to levels indistinguishable from zero. A χ^2 test for the hypothesis that they are jointly zero fails to reject at any level for any specification (the worst p-value is 0.4054). On this basis, we conclude that our cleaned expectational variables, together with the simple return model (2), explain both classes of underreaction phenomenon.

It is thus reasonable to infer that both anomalies are manifestations of the same basic mechanism, and do not present separate puzzles. News that causes fundamental earnings expectations to change has persistent effects on returns. Holding these expectations fixed, neither momentum nor the corporate actions examined here alter expected returns.

¹⁷The predictable downgrading of firms after SEOs is studied in Teoh and Wong (2002) and Dechow, Hutton, and Sloan (1999). We are not aware of similar work on repurchasing firms.

¹⁸Because of the long lags required of the event variables, this series now starts in 1985. Neither the new estimates of A , a , and α , nor their standard errors differ appreciably from the values reported in Section 3.

5 Concluding Remarks

This paper has argued that return persistence – following either significant corporate news or exceptional past returns – occurs if and only if those events coincide with changes in earnings (or earnings growth) expectations. We have not attempted to explain why even this type of fundamental news should produce persistence. But we think the fact that it does advances our understanding and narrows the focus of the search for a theoretical explanation.

We see at least two interpretations of our findings. On the one hand, behavioralists will not fail to note that in building our “corrected” expectational proxies from reported forecasts, we uncover precisely the same biases in the IBES data that are observed in returns themselves: analysts appear to significantly underreact to 6 to 12 months of stock returns and to up to 5 or 6 years of corporate actions. Certainly a natural interpretation of this coincidence is that the analysts’ errors were, in fact, the market’s errors, and that our adjusted expectational measures, while summarizing the informational content of those errors, are merely a mechanical construct.

On the other hand, if one views our derived variables as legitimately correcting noisy proxies in the direction of actual expectations, the outlook for a purely rational theory of return persistence seems promising. Under this interpretation, if better observations of agents’ true expectations were available (or perhaps if analysts forecasts were not distorted by institutional factors), the econometric complexities of our model would unwind (Δi would be the same as ξ in our notation), and we would be left with a much-consolidated ordinary factor representation of the cross-section of expected returns.

Either way, linking the underreaction anomalies to expectations (even if perhaps mistaken ones) about fundamental quantities such as earnings and earnings growth appears to us to cast these puzzles in a much simpler light than they have appeared heretofore. We may perhaps now be able to dispense with the more abstruse and exotic theories that have sometimes seemed necessary to explain them.

Finally, on a basic level, we think our work also bolsters the case for accepting the

existence of both of the underreaction anomalies themselves. It is always important to apply rigorous and stringent critiques to reports of new asset pricing “puzzles”. But the direct channel we have demonstrated between fundamental variables and both momentum and post-event drift would seem to make it increasingly difficult to maintain the position that either or both are merely a product of data-mining or inferential errors. Both coincide with expectational revisions, and the magnitude of those revisions exactly matches the magnitude needed to account for the subsequent return persistence.

Table 5: *Corporate Events in IBES Sample*

Year:	Number of events		
	SEO	BBK	EFM
1983	1156	156	460
1984	391	435	487
1985	594	210	91
1986	912	238	122
1987	593	830	132
1988	281	339	90
1989	362	600	152
1990	310	903	109
1991	748	402	169
1992	875	534	256
1993	1202	550	329
1994	836	950	411
1995	1007	999	479
1996	1335	1335	544
1997	1118	1195	662
1998	758	1739	631
1999	850	1363	533
<hr/>			
Mean event return	-.0069	.0186	.0030
Mean one year return	-.0359	.0215	-.0357

The table describes the corporate action sample used in Section 4. Announcement dates for secondary equity offerings (SEO), share buy-backs (BBK), and equity-financed mergers (EFM) are taken from SDC for all firms for which we have the IBES fields used in Section 3. Also shown are the mean 3-day announcement return across the whole sample, and the mean 12-month return commencing in the first post-announcement month. Both returns numbers are excesses over the S&P500 return for the same period.

Table 6: *Corporate Events as Predictors of Forecast Revisions*

	Event Type		
	SEO	BBK	EFM
Coefficient sum:			
Dependent=DFY1	-0.0958	0.0699	0.0000
Dependent=DLTG	-0.2157	0.0574	0.0000
Lags selected:	11	9	0
χ^2 drop lag :	.0440	.0085	—
χ^2 add lag :	.0785	.3921	.4470

The table shows the sum of the estimated coefficients on lags of corporate event indicator variables (c.f. equation (9)). Lags are included until χ^2 tests reject the significance of an additional lag at the 95% level. The three event types are secondary equity offerings (SEO), share buy-backs (BBK), and equity-financed mergers (EFM).

Table 7: *Return Regressions*

R6	SEO	BBK	EFM	DFY1	DLTG	E/P	SIZE
DEPENDENT VARIABLE=6-MONTH RETURNS							
.0547	-.0174	.0083	-.0201				
(5.10)	(3.05)	(1.40)	(3.47)				
.0595	-.0170	.0110	-.0084	.0644	.0138		
(3.75)	(2.96)	(2.43)	(1.30)	(5.23)	(3.51)		
.0602	-.0169	.0085	-.0098	.0611	.0137	.0056	.0095
(4.65)	(3.18)	(2.62)	(1.53)	(7.03)	(3.71)	(0.23)	(0.55)
DEPENDENT VARIABLE=MODEL RESIDUALS							
.0200	-.0016	.0053	-.0038				
(1.14)	(0.26)	(1.18)	(0.54)				
.0140	-.0033	.0049	-.0043	.0111	.0017		
(0.83)	(0.54)	(1.13)	(0.64)	(0.88)	(0.40)		
.0154	-.0035	.0021	-.0064	.0054	.0015	.0092	.0157
(1.12)	(0.61)	(0.64)	(0.93)	(0.62)	(0.37)	(0.38)	(0.88)

The table shows results from Fama-Macbeth regressions for monthly stock returns (top panel) and estimated model return residuals (bottom panel), for different specifications of independent variables. R6 is the six-month trailing return. SEO, BBK, and EFM are dummy variables which indicate that the announcement of the relevant corporate action (secondary equity offering, share buy-back, or equity-financed merger) occurred in the preceding six months. E/P and SIZE are as defined in Table 4. The data are monthly observations from 1985 through 1999. Standard errors are adjusted for induced six-month autocorrelation. The resulting t statistics are in parentheses.

Appendix

A. Derivation of Equation (4)

For ease of exposition, equation 5 is proved using $A(L) = A$, $\alpha_0 = 0$, $\mu = 0$.

Assume:

$$r_t = \alpha \xi_{t-1} + \varepsilon_t^{(1)}$$

$$\Delta i_t = A \Delta i_{t-1} + a(L)r_{t-1} + b(L)x_{t-1} + \varepsilon_t^{(2)}$$

$$\xi_t = M_t - M_{t-1} + \Delta i_{t-1}$$

$$M_t = E_t \left[\sum_{k=0}^{\infty} \Delta i_{t+k} \right]$$

where x_t is a martingale and the other variables are defined in the text.

Now:

$$E_t(\Delta i_t) = \Delta i_t$$

$$E_t(\Delta i_{t+1}) = A \Delta i_t + a(L)r_t + b(L)x_t$$

$$\begin{aligned} E_t(\Delta i_{t+2}) &= A E_t(\Delta i_{t+1}) + a(L)E_t(r_{t+1}) + b(L)E_t(x_{t+1}) \\ &= A E_t(\Delta i_{t+1}) + a_1 \alpha \xi_t + a_2 r_t + \dots + b_2 x_t + b_3 x_{t-1} + \dots \end{aligned}$$

$$E_t(\Delta i_{t+3}) = AE_t(\Delta i_{t+2}) + a_2\alpha\xi_t + a_3r_t + \dots + b_3x_t + \dots$$

and

$$E_t(\Delta i_{t+k}) = AE_t(\Delta i_{t+k-1})$$

for $k > (\text{max order of } a(L) \text{ and } b(L)) + 3$

Thus:

$$M_t = (1 - A)^{-1} [\Delta i_t + a_1r_t + a_2r_t + \dots + b_1x_t + b_2x_t + \dots + a_1\alpha\xi_t + a_2\alpha\xi_t + \dots]$$

$$M_t = (1 - A)^{-1} [\Delta i_t + a(1)r_t + b(1)x_t + a(1)\alpha\xi_t]$$

where $a(1)$ is defined as $a(L)$ with $L = 1$.

It follows that:

$$\xi_t = M_t - M_{t-1} + \Delta i_{t-1}$$

$$\xi_t = (1-A)^{-1} [\Delta i_t - \Delta i_{t-1} + a(1)(r_t - r_{t-1}) + b(1)(x_t - x_{t-1}) + a(1)\alpha(\xi_t - \xi_{t-1})] + \Delta i_{t-1}$$

Substituting Δi_t :

$$\xi_t = (1 - A)^{-1} [\varepsilon_t^{(2)} + a(1)r_t + b(1)x_t + a(1)\alpha(1 - L)\xi_t]$$

$$(1 - A - a(1)\alpha)\xi_t - a(1)\alpha L\xi_t = \varepsilon_t^{(2)} + a(1)r_t + b(1)x_t$$

Define:

$$\lambda_t = \varepsilon_t^{(2)} + a(1)r_t + b(1)x_t$$

$$F = (1 - A - a(1)\alpha')^{-1}$$

$$E = Fa(1)\alpha'$$

Therefore:

$$\xi_t = [1 + EL]^{-1} F\lambda_t$$

$$r_t = \alpha' [1 + EL]^{-1} F\lambda_{t-1} + \varepsilon_t^{(1)}$$

The generalization to the case where $A(L)$ is an arbitrary polynomial with roots inside the unit circle, though not used in the text, can be similarly established by straightforward calculation.

B. Description of Data and Variable Definitions

IBES Normalisations

IBES monthly consensus forecast record fields are transformed into the two variables DFY1 and DLTG used in the text as follows.

For DFY1,

$$\text{DFY1}(t) = k(n) \frac{\text{FYE}(t) - \text{FYE}(t-6)}{P(t-6)}$$

where t indexes the month where the forecasts are made, $\text{FYE}(t)$ is the mean earnings estimate for the next full fiscal year following the one that was underway at $t-6$.

$P(t)$ is the stock price at month t , and $k(n)$ is a normalising constant to ensure that the forecast changes at t are comparable across firms with different fiscal years. Specifically, if the “next” fiscal year is already underway at $t - 6$, then k is the reciprocal of the amount of that year remaining, up to a maximum value of 3.

For DLTG,

$$\text{DLTG}(t) = \text{LTG}(t) - \text{LTG}(t - 6)$$

where $\text{LTG}(t)$ is the mean long term growth rate estimate at time t .

Both DFY1 and DLTG are expressed as a percentile rank relative to the other firms existing in the cross section at time t . These are then centered at zero by subtracting the median, to yield a number between $-1/2$ and $1/2$.

SDC Event Definitions

Secondary Equity Offerings: These are obtained from the SDC Global New Issues database from 1978 to 1999, searching for all public & private issues of common stock by a US company where the issue is not an IPO. Announcement dates were taken from the D (issue date) data field. This is defined as the date when the securities were offered.

Buybacks: These are obtained from the SDC domestic mergers database for all US stocks from 1978 to 1999. Included are all deals in which the company buys back its equity securities or securities convertible into equity, either on the open market, through privately negotiated transactions, or through a tender offer. Announcement dates were taken from the DA (date announced) data field.

Equity Financed Mergers: These are obtained from the SDC domestic mergers database for all US stocks from 1978 to 1999 where the form of the deal is a merger or acquisition. Only completed deals are included in the database. All events where the payment form contained no cash were used in the sample. The Announcement date is defined as the date when either target or acquiror makes

a public announcement that it held negotiations, or received a formal proposal to combine, acquire, recapitalize, etc.

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