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Conditional Persistence of Earnings Components and Accounting Anomalies

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Abstract: We suggest that the failure of investors to distinguish between an earnings component's autocorrelation coefficient (unconditional persistence) and the marginal contribution of that component's persistence to the persistence of earnings (conditional persistence) provides a partial explanation of post-earnings-announcement drift, post-revenue-announcement drift, and the accrual anomaly. When the conditional persistence of revenue surprises is high (low) relative to its unconditional persistence, both the post-earnings-announcement drift and the post-revenue-announcement drift are high (low), because investors' under-reaction to revenues and earnings is stronger when the persistence of revenue surprises is more strongly associated with the persistence of earnings surprises. Also, the mispricing of accruals decreases substantially when the conditional persistence of accruals is high relative to its unconditional persistence, because investors' over-reaction to accruals is mitigated when the persistence of accruals is indeed more strongly associated with the persistence of earnings. Our findings also suggest that financial analysts' failure to distinguish between unconditional and conditional persistence of revenues and accruals results in more biased revenue and earnings predictions.

Keywords: earnings components, persistence, post-earnings-announcement drift, accrual anomaly, forecast errors

1. INTRODUCTION

Investors' failure to fully recognize that the various components of earnings differ in their persistence and that each component contributes differently to the overall persistence of earnings is a common driver behind the post-earnings-announcement drift, the post-revenue-announcement drift, and the accrual anomaly. Richardson et al. (2010) argue that post-announcement drifts are linked to investors' misconception of earnings persistence and to their inability to assign different persistence measures to the various earnings components. Sloan (1996) and Richardson et al. (2005) argue that the accrual anomaly occurs because investors fail to recognize that the

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accrual and cash flow components of earnings have different persistence, and that a larger accrual component reduces the overall persistence of earnings.[1] The post-earnings-announcement drift (Bernard and Thomas, 1989, 1990; and Chan et al., 1996) occurs because investors incorrectly assess earnings persistence (Ball and Bartov, 1996; Rangan and Sloan, 1998; and Cao and Narayanamoorthy, 2012) and partially ignore the differential contributions of the various earnings components to earnings persistence (Ertimur et al., 2003; Jegadeesh and Livnat, 2006a; and Shivakumar, 2006). Jegadeesh and Livnat (2006b) and Kama (2009) argue that the failure of investors to recognize the contribution of revenue surprises to the persistence of earnings surprises drives the post-revenue-announcement drift.

Amir et al. (2011) distinguish between conditional and unconditional persistence measures. Unconditional persistence, traditionally used in the literature, is the autocorrelation coefficient obtained from the time series of a component variable. Conditional persistence of an earnings component (for instance, revenues or accruals) is defined as the marginal contribution of the component's persistence to the overall persistence of earnings.[2] Hence, conditional persistence, as recently introduced by Amir et al. (2011), recognizes that the persistence of earnings depends on the persistence of the earnings components.

The persistence of an earnings component is important in security pricing because it explains the overall persistence of earnings. The traditional unconditional persistence of each component is measured independently from the persistence of the other components and the overall persistence of earnings (Lipe, 1986), and hence it is less useful than the conditional persistence in security pricing (Amir et al., 2011; Bauman, 2014; Esplin et al., 2014; and Lim, 2014).

Insofar as it is more difficult to measure the conditional persistence of earnings components than the traditional unconditional persistence, investors may be partially fixated on the traditional and relatively easy to measure unconditional persistence of an earnings component in pricing securities. Given that the three accounting anomalies that we study – the post-earnings-announcement drift, the post-revenue-announcement drift and the accrual anomaly – are partly driven by incorrect estimation of the persistence of earnings components and their contribution to the overall persistence of earnings, we suggest that the fixation of investors on a component's unconditional persistence and their tendency to neglect its conditional persistence provide another explanation for the three anomalies.

To examine our assertion, we use two decompositions of earnings. In the first one, we decompose standardized unexpected earnings into standardized unexpected revenue and standardized unexpected expenses. In the second one, we decompose earnings into operating cash flows and accruals. We compute the unconditional and conditional persistence of each component and construct a measure of the distance between the conditional and unconditional persistence, which we label the adjusted conditional persistence (ACP).

We focus our empirical analysis on standardized unexpected revenue growth (SURG), and the accrual component of earnings (ACC). We focus on SURG because

1 Xie (2001) and Cheng et al. (2012) show that a greater mispricing exists with respect to discretionary accruals, which are usually characterized by lower persistence relative to other accruals.

2 The slope coefficient obtained when the persistence of earnings is regressed on the persistence of earnings components multiplied by the mean of the explanatory variable is used as a measure of the component's conditional persistence.

prior studies have focused on revenue growth, and argue that the market fails to fully recognize the contribution of revenue growth to the persistence of earnings growth, which in turn drives the post-announcement drifts (Ghosh et al., 2005; and Jegadeesh and Livnat, 2006a, 2006b). The focus on the accrual component of earnings is motivated by the negative relationship between accruals and future stock returns, which is driven by investors' failure to correctly use accrual information in assessing the persistence of earnings (Sloan, 1996; and Dechow and Ge, 2006).

To measure the adjusted conditional persistence (ACP) of unexpected revenue growth (SURG), we begin by ranking all firms, each quarter, by their conditional persistence of SURG, and assign integers for each firm, starting with a value of "1" for the firm with the lowest conditional persistence of SURG. We do the same for unconditional persistence. Then, we measure for each firm/quarter the difference between the conditional and unconditional persistence of SURG, and divide this difference by the number of firms in the quarter. This way, we obtain a measure of the distance between the conditional and unconditional persistence of SURG, denoting it ACP(SURG). We repeat this procedure for the accrual component of earnings, obtaining a measure of the distance between the conditional and unconditional persistence of accruals, denoted ACP(ACC).

In our analysis we examine whether the adjusted conditional persistence of SURG explains the post-earnings-announcement and post-revenue-announcement drifts. In addition, we examine whether the adjusted conditional persistence of accruals explains the accrual anomaly. We find that both the post-earnings-announcement drift and the post-revenue-announcement drift increase almost monotonically with ACP(SURG). That is, the drifts are greater when the distance between the conditional and unconditional persistence of SURG is larger. This result is consistent with investors over-emphasizing the unconditional persistence of SURG, while under-emphasizing its conditional persistence. Moreover, the under-reaction of investors to the marginal contribution of revenue to earnings' persistence, documented in prior studies, is less (more) pronounced when the adjusted conditional persistence of SURG is low (high).[3]

We also find that when ACP(ACC) is in its lowest quintile, the difference in subsequent abnormal returns, for a 1-year window, between the lowest and the highest quintiles of accruals is 5.9%, compared with 2.2% for the highest quintile of ACP(ACC). That is, the accrual anomaly is much smaller when ACP(ACC) is high, because when ACP(ACC) is high the negative effect of accruals on earnings persistence diminishes, resulting in negligible negative excess returns for high accruals.[4] Furthermore, when both ACC and ACP(ACC) are in their highest quintile, the subsequent abnormal returns are not significantly different from zero.

Prior studies find that analysts' forecasts do not fully incorporate the information in earnings components about future earnings growth. For instance, Jegadeesh and Livnat (2006a) find that analysts do not fully incorporate information about revenues in forecasting earnings. Bradshaw et al. (2001) and Barth and Hutton (2004) find that information on the accrual component of earnings is not fully incorporated into earnings forecasts. Also, Bilinski (2014) finds that analysts do not issue cash flow

3 When the adjusted conditional persistence of SURG is high the conditional persistence of SURG is relatively high and the unconditional persistence of SURG is relatively low.

4 High adjusted conditional persistence of accruals does not simply mean that the accrual component is large; it means that the association between the persistence of accruals and earnings persistence is strong.

forecasts to supplement earnings forecasts when the accuracy of those earnings forecasts is reduced by accruals. We investigate whether analysts consider the conditional persistence of earnings components in their predictions. We find that the bias in revenue predictions in quarter *t*, measured by forecast errors, increases with the ACP(SURG) of the preceding quarter. Specifically, financial analysts tend to over-estimate future revenues when ACP(SURG) is low, but rather under-estimate future revenues when ACP(SURG) is high. This result suggests that analysts over-emphasize the unconditional persistence measure, and do not fully incorporate the conditional persistence of revenue growth. We also find that ACP(ACC) in quarter *t*–1 is negatively associated with the bias in earnings predictions in quarter *t*. Specifically, when ACP(ACC) is high the negative effect of the accrual component on earnings persistence diminishes. Therefore, the failure of analysts to fully incorporate the effect of accruals on earnings persistence becomes less material, resulting in less biased earnings predictions.

We contribute to the literature by documenting the pricing implications of investors' failure to distinguish between conditional and unconditional persistence of earnings components. In particular, investors' and analysts' failure to fully recognize the implications of conditional persistence of earnings components on future earnings might lead investors and analysts to incorrect estimates of earnings persistence, and hence to incorrect assessments of future earnings, which in turn may result in security mispricing.

2. PREDICTIONS

Under-estimation of both future earnings and the persistence of expected earnings growth are the main drivers behind the post-earnings-announcement drift. In particular, investors' incorrect assessment of the contribution of earnings components to earnings persistence causes inaccuracies in the estimated persistence of earnings growth. Thus, Ghosh et al. (2005) and Jegadeesh and Livnat (2006a), for instance, find that the contribution of revenue growth to the persistence of earnings growth is partly overlooked by investors.

Since the conditional persistence of SURG captures the marginal contribution of the persistence of revenue growth to the persistence of earnings growth, we examine whether the market's under-reaction to earnings is associated with ACP(SURG). If investors are indeed fixated on the unconditional persistence of SURG, as we propose here, and do not fully consider the implications of the conditional persistence of SURG on the persistence of earnings growth, then they will place a low persistence measure on predicted earnings when ACP(SURG) is high, whereas in fact, the persistence of earnings is high. This, in turn, will result in larger subsequent abnormal stock returns.

In addition to the delayed market reaction to earnings surprise, Jegadeesh and Livnat (2006b) and Kama (2009) have also documented a delayed market reaction to revenue surprise (post-revenue-announcement drift). They argue that the revenue-related drift is also driven by the market under-estimation of the marginal contribution of revenue growth to earnings persistence. When ACP(SURG) is low, the unconditional persistence of SURG is relatively high, while the conditional persistence of SURG is relatively low. Hence, the marginal contribution of the persistence of revenue to the persistence of earnings is expected to be low, resulting in a lower post-revenue-announcement drift. As ACP(SURG) increases, the marginal contribution of the persistence of revenue to the persistence of earnings increases. So, if investors fail to recognize this, their under-reaction to revenue surprises will be more pronounced, resulting in a stronger post-revenue-announcement drift.

Prediction 1: Investors over-emphasizing the unconditional persistence of SURG, while under-emphasizing its conditional persistence will lead to: a) a positive association between ACP(SURG) and the post-revenue-announcement drift; and b) a positive association between ACP(SURG) and the post-earnings-announcement drift.

Sloan (1996) decomposes earnings into accruals and operating cash flows and finds a negative association between the magnitude of the accrual component of earnings and the persistence of earnings. He argues that the market does not fully appreciate the negative effect of accruals on earnings persistence, resulting in a negative association between the magnitude of the accrual component of earnings and subsequent abnormal stock returns.

We expect to find a negative association between the magnitude of the accrual-related drift and ACP(ACC). When ACP(ACC) is low, the conditional persistence of accruals will be relatively low, which means that the accrual component of earnings will have a large negative impact on the persistence of earnings. Consequently, investors' expectations of earnings persistence and future earnings will be too high, and the accrual-related drift will be high. On the other hand, when ACP(ACC) is high, the conditional persistence of accruals will be relatively high, which means that accruals will have a smaller negative effect on the persistence of earnings. Hence, even if investors ignore the differential effect of accruals and cash flows on the persistence of earnings, this misconception becomes less material, and the accrual-related drift will be smaller.

Prediction 2: If investors over-emphasize the unconditional persistence of accruals while under-emphasizing its conditional persistence, the accrual-related drift will be negatively associated with ACP(ACC).

Following prior studies showing that analysts' forecasts do not fully incorporate the information in earnings components, if analysts over-emphasize the unconditional persistence of revenue surprises and accruals when issuing revenue and earnings forecasts, respectively, we will observe more biased revenue and earnings forecasts. In particular, when ACP(SURG) is high, analysts will view revenue as less persistent, whereas in fact revenue persistence will contribute more to the persistence of earnings. This could lead to under-estimation of future revenues. Also, when ACP(ACC) is high, the conditional persistence of accruals is high relative to its unconditional persistence. Therefore, the negative effect of the accrual component on earnings' persistence is weaker, and the failure of analysts to price the accrual components of earnings differently is mitigated. In this case, earnings forecasts will be less biased. This argument is summarized in Prediction 3:

Prediction 3: If financial analysts over-emphasize the unconditional persistence of revenue surprises and the unconditional persistence of accruals while under-emphasizing the conditional persistence of revenue surprises and accruals we will find: (a) a negative association between ACP(SURG) and the quality of revenue forecasts; and (b) a positive association between ACP(ACC) and the quality of earnings forecasts.

3. SAMPLE, VARIABLES AND DESCRIPTIVE STATISTICS

(i) Key Variables

Our measure of earnings surprise is similar to that used by Jegadeesh and Livnat (2006a). We use standardized unexpected earnings (SUE_{it}), measured as:

$$SUE_{it} = \frac{EPS_{it} - E(EPS_{it})}{S_{it}},$$

where EPS_{it} is firm i's earnings per share in quarter t; $E(EPS_{it})$ is expected earnings per share for firm i in quarter t, measured as earnings per share in the same quarter of the previous year plus an average drift (D_{it}) over the preceding eight quarters; and S_{it} is the standard deviation of the unexpected earnings per share:

$$E(EPS_{it}) = EPS_{it-4} + D_{it}$$

$$D_{it} = \frac{1}{8}\sum_{j=1}^{8}(EPS_{it-j} - EPS_{it-j-4}), \quad \text{and}$$

$$S_{it} = \frac{1}{7}\sqrt{\sum_{j=1}^{8}(EPS_{it-j} - E(EPS)_{it-j})^2}.$$

We compute standardized unexpected revenue ($SURG_{it}$) and standardized unexpected expenses ($SUXP_{it}$) in a similar manner, using sales per share, and expenses per share (sales per share minus earning per share), respectively, instead of earnings.

We also decompose earnings into its cash flow and accrual components. As a measure of earnings, we use earnings before extraordinary items and discontinued operations ($EARN_{it}$), divided by average total assets. The cash flow component of earnings (CFO_{it}) is equal to cash flows from continuing operations divided by average total assets; the accrual component of earnings (ACC_{it}) is equal to the difference between earnings and the cash flow components ($ACC_{it} = EARN_{it} - CFO_{it}$).

Following the arguments of prior studies that the market fails to recognize the marginal contribution of revenue and accruals to the persistence of earnings, we focus here on the adjusted conditional persistence of revenue surprises and accruals. To estimate the conditional persistence of unexpected revenue for each firm/quarter, we use a three-step procedure. First, for each firm/quarter, we estimate the unconditional persistence of standardized unexpected earnings (SUE), standardized unexpected revenue ($SURG$) and standardized unexpected expenses ($SUXP$), as the first-degree auto-correlation coefficient over the previous eight quarters. We denote these unconditional persistence measures as $P(SUE)_{it}$, $P(SURG)_{it}$ and $P(SUXP)_{it}$, respectively. Second, we estimate the following regression for each firm using the preceding eight quarters:

$$P(SUE)_{it} = \alpha_{0it} + \alpha_{1it}P(SURG)_{it} + \alpha_{2it}P(SUXP)_{it} + \varepsilon_{it}. \tag{1}$$

Because we always use the preceding eight quarters in estimating equation (1), we obtain a slope coefficient for each firm/quarter. We also compute the mean of each independent variable. Third, we compute the conditional persistence of revenue as follows:

$$CP(SURG)_{it} = \alpha_{1it} \times Mean[P(SURG)_{it}].$$

Recall that our main argument is that investors and analysts focus on the unconditional persistence in addition to the conditional persistence. Hence, we are interested in identifying the cases where the conditional persistence is substantially different than the unconditional persistence. Therefore, we measure the distance between the conditional and unconditional persistence of revenue surprises for each firm/quarter.

We start out by ranking all firms, each quarter, by their unconditional persistence, $P(SURG)_{it}$, assigning integer values starting with "1" for the firm with the lowest $P(SURG)_{it}$. Then, we rank all firms, each quarter by their conditional persistence, $CP(SURG)_{it}$, assigning integer values starting with "1" for the firm with the lowest conditional persistence. Finally, we compute the difference between the rankings and divide by the number of firms in the quarter, N_t. This way, we obtain a measure of the distance between unconditional and conditional persistence, denoted $ACP(SURG)$:

$$ACP(SURG)_{it} = \{Rank[CP(SURG)_{it}] - Rank[P(SURG)_{it}]\}/N_t.$$

We apply a similar procedure to the accrual and cash flow components of earnings. First, we compute the unconditional persistence of earnings, cash flows and accruals, denoting them $P(EARN)_{it}$, $P(CFO)_{it}$ and $P(ACC)_{it}$, respectively. Second, we compute the conditional persistence of accruals by estimating the following regression for each firm using the preceding eight quarters:

$$P(EARN)_{it} = \delta_{0it} + \delta_{1it}P(CFO)_{it} + \delta_{2it}P(ACC)_{it} + \eta_{it} \tag{2}$$

Third, we compute the conditional persistence of accruals as follows:

$$CP(ACC)_{it} = \delta_{2it} \times Mean[P(ACC)_{it}].$$

Finally, we compute the distance between the conditional and unconditional persistence in a manner similar to that used for revenue, obtaining $ACP(ACC)_{it}$:

$$ACP(ACC)_{it} = \{Rank[CP(ACC)_{it}] - Rank[P(ACC)_{it}]\}/N_t.$$

The adjusted conditional persistence (ACP) measures could in theory range between –1 and 1, although in practice their distribution is narrower.

To measure the post-earnings-announcement returns, we compute excess size-adjusted buy-and-hold stock returns for each firm/quarter using a window of 180 days, starting 2 days after the current preliminary earnings announcement [denoted $AR(180)_{it}$]. While most studies on the post-earnings-announcement drift use a 180-day window, studies on the accrual anomaly often use a 365-day window. So, consistent with prior studies, we compute size-adjusted excess buy-and-hold stock returns for a window of 365 days starting 2 days after the SEC filing date [denoted

Table 1
Sample Selection

Year	*Full Sample*
1993	3,950
1994	5,233
1995	5,608
1996	5,904
1997	6,036
1998	6,199
1999	6,259
2000	6,439
2001	6,351
2002	6,748
2003	7,136
2004	7,331
2005	7,183
2006	7,165
2007	7,191
2008	6,847
2009	6,321
2010	6,687
2011	6,661
2012	6,245
2013	1,844
Observations	129,338
Firms	5,133

Notes:
The sample includes all firms with complete stock returns and financial data available on Compustat and CRSP with market value of equity above US$ 10 million at quarter-end and stock price over US$ 1. We exclude financial institutions (1-digit SIC = 6) and public utilities (2-digit SIC = 49). We also remove the extreme 1% of observations (on both sides) in terms of the estimated variables.

$AR(365)_{it}$]. We use the post-SEC filing window to ensure the availability of the cash flow and accrual components of earnings (Chen et al., 2002).[5]

(ii) Sample Selection and Descriptive Statistics

The sample includes all firms with complete stock returns and financial data available on Compustat and CRSP during 1993–2013 with market value of equity above US$ 10 million at quarter-end, and share price above US$ 1. Similarly to Jegadeesh and Livnat (2006a), we exclude financial institutions (1-digit SIC = 6) and public utilities (2-digit SIC = 49) because these firms and their financial reporting are subject to industry-specific regulation. To limit the effect of extreme observations, each quarter we rank the sample according to each of the estimated variables, and remove the extreme 1% of the observations on each side. Table 1 lists the number of observations each year. The full sample includes 129,338 firm/quarter observations for 5,133 different firms.

Table 2 contains descriptive statistics. In addition to the main research variables described above, we report statistics for book-to-market ratios (*BM*), measured as book

5 We repeated the analysis using beta-adjusted returns instead of size-adjusted returns obtaining similar results.

Table 2
Descriptive Statistics

Variable	*N*	*Mean*	*Std. Dev.*	*5th Pctl.*	*25th Pctl.*	*Median*	*75th Pctl.*	*95th Pctl.*
AR(180)	129,338	0.00	0.28	−0.42	−0.17	−0.02	0.14	0.49
AR(365)	127,416	0.00	0.45	−0.61	−0.28	−0.05	0.20	0.79
SUE	129,338	−0.15	3.86	−6.24	−1.69	0.00	1.69	5.78
SURG	129,338	0.33	3.63	−5.72	−2.04	0.49	2.71	6.05
SUXP	129,338	0.32	3.56	−5.62	−1.83	0.42	2.46	6.02
EARN	127,416	0.01	0.03	−0.05	0.00	0.01	0.02	0.04
CFO	127,416	0.02	0.04	−0.04	0.00	0.02	0.04	0.08
ACC	127,416	−0.01	0.03	−0.06	−0.03	−0.01	0.00	0.04
P(SURG)	129,338	0.40	0.33	−0.21	0.18	0.43	0.63	0.89
CP(SURG)	129,338	0.19	0.91	−0.88	−0.12	0.03	0.34	1.81
ACP(SURG)	129,338	0.00	0.40	−0.72	−0.28	0.04	0.30	0.61
P(ACC)	127,416	−0.17	0.30	−0.66	−0.37	−0.16	0.03	0.33
CP(ACC)	127,416	0.03	0.47	−0.65	−0.11	0.00	0.15	0.81
ACP(ACC)	127,416	0.00	0.41	−0.62	−0.29	−0.05	0.27	0.75
BM	129,338	0.59	0.43	0.11	0.30	0.49	0.76	1.40
SIZE	129,338	2,623.8	6,791.1	26.9	118.8	465.8	1,853.3	12,746.9

Notes:
AR(180) is excess buy-and-hold size-adjusted stock returns for a 180-day (calendar) window, starting 2 days after the preliminary earnings announcement date; ***AR*(365)** is excess buy-and-hold size-adjusted stock returns for a 365-day (calendar) window, starting 2 days after the SEC filing date; *SUE* is standardized unexpected earnings, measured as quarterly earnings per share minus earnings per share in the same quarter of the previous year minus a drift, scaled by the standard deviation of earnings in the prior eight quarters; *SURG* (standardized unexpected revenue) is similar to *SUE* but with sales per share; *SUXP* (standardized unexpected expenses) is similar to *SUE* but with expenses per share; *EARN* is earnings before extraordinary items and discontinued operations, divided by average total assets; *CFO* is cash from continuing operations, divided by average total assets; *ACC* is the accrual component of earnings, measured as the difference between earnings before extraordinary items and discontinued operations and cash from continuing operations, divided by average total assets; *P(X)* is the unconditional persistence; *CP(X)* is the conditional persistence; *ACP(X)* is the adjusted conditional persistence (see Appendix for details)**;** *BM* is book value of common equity at quarter-end divided by market value of common equity; *SIZE* is market value of common equity at quarter-end (in millions of dollars).

value of equity at quarter-end divided by market value of common equity, and firm size, measured as market value of common equity at quarter-end (*SIZE*).

Mean buy-and-hold excess returns are zero for both the 180 and 365 return windows, but the distributions of *AR*(180) and *AR*(365) are both skewed to the right, as the median is negative. Consistent with Jegadeesh and Livnat (2006b), mean *SUE* is negative (–0.15), while its median is zero.

The distributions of revenue and expense surprises are quite similar to each other. Specifically, mean *SURG* and *SUEX* are 0.33 and 0.32, respectively, while the medians are 0.49 and 0.42, respectively. Earnings deflated by total assets have a mean of 0.01, while the average cash flow component is 0.02, and the average accrual component is –0.01 ($EARN = CFO + ACC$ by construction). Also consistent with prior studies, the distribution of the book-to-market ratio is skewed to the right. Finally, the adjusted conditional persistence of revenue and accruals, *ACP*(*SURG*) *and ACP*(*ACC*), are centred around zero. While in theory these variables could range from –1 to 1, 90% of the observations are within the interval (–0.72, 0.61) for *ACP*(*SURG*), and within the interval (–0.62, 0.75) for *ACP*(*ACC*).

Table 3
Rank Correlations of Scaled-Quintile Variables

		$ACP(SURG)^{quin}$	$ACP(ACC)^{quin}$
1.	$ACP(SURG)^{quin}$		0.02
2.	$ACP(ACC)^{quin}$	0.02	
3.	SUE^{quin}	0.01	−0.01
4.	$SURG^{quin}$	−0.01	−0.01
5.	$EARN^{quin}$	0.04	0.04
6.	ACC^{quin}	0.02	−0.01
7.	$BETA^{quin}$	0.04	0.03
8.	BM^{quin}	−0.01	−0.02
9.	$SIZE^{quin}$	−0.04	0.03

Notes:
The table presents average quarterly pair-wise Spearman correlation key variables. All the variables were transformed into a scaled-quintile format with values ranging from 0 to 1. The variables are: (1) adjusted conditional persistence of *SURG* [*ACP(SURG)*], (2) adjusted conditional persistence of *ACC* [*ACP(ACC)*], (3) standardized unexpected earnings (*SUE*), (4) standardized unexpected revenue (*SURG*), (5) earnings before extraordinary items and discontinued operations, divided by average total assets (*EARN*), (6) the accrual component of earnings divided by average total assets (*ACC*), (7) systematic risk (*BETA*), (8) book-to-market ratio (*BM*), and (9) firm size (*SIZE*).

Table 3 presents Spearman correlations for scaled-quintile variables. To convert a variable to a scaled-quintile format, we rank, each quarter, all firms according to the value of each specific variable and assign them into quintiles. The variable is then transformed into a scaled-quintile variable with values ranging from zero to one, as in Rajgopal et al. (2003): “0” in the bottom quintile, “0.25” in the second quintile, “0.50” in the third quintile, “0.75” in the fourth quintile, and “1” in the highest quintile.

As the table shows, the rank correlations between the adjusted conditional persistence measures *ACP*(*SURG*) and *ACP*(*ACC*) on one side and earnings, revenue, and accruals on the other side are small, ranging from –0.01 to 0.04. This result suggests that the adjusted conditional persistence measures are not merely proxies for earnings and earnings components. Also, the rank correlations between the adjusted conditional persistence measures *ACP*(*SURG*) and *ACP*(*ACC*) on one side and the three risk factors (*BETA*, *BM* and *SIZE*), are close to zero, ranging between –0.04 and 0.04.

4. RESULTS

(i) The Association Between ACP(SURG) and the Post-Revenue-Announcement Drift

To test whether the post-revenue-announcement drift anomaly is associated with the adjusted conditional persistence of *SURG* [*ACP*(*SURG*)] we use a univariate portfolio analysis and a multivariate regression analysis. Panel A of Table 4 presents post-announcement excess returns for portfolios based on combinations of *ACP*(*SURG*) and standardized unexpected revenue (*SURG*). To form these portfolios, we rank all companies, each quarter, according to their *ACP*(*SURG*) or *SURG*, and assign them into quintiles. Then, we construct portfolios of observations that fall into a specific combination. For instance, a combination denoted as *ACP*(*SURG*)1/*SURG1* includes observations in the lowest quintile of both *ACP*(*SURG*) and *SURG*. If investors fixate on the unconditional persistence of revenue surprises in addition to the conditional

Table 4
Post-Revenue-Announcement Drift and Adjusted Conditional Persistence of *SURG*

Panel A: Portfolio Analysis (N = 129,338)

		SURG1	*SURG5*	*SURG5 – SURG1*
	Full Sample	*−1.28****	*0.60****	*1.88****
$ACP(SURG)1$	−0.07	−0.88**	0.35	1.23**
$ACP(SURG)2$	0.15	−0.71*	0.80**	1.51***
$ACP(SURG)3$	−0.31*	−1.41***	0.20	1.60***
$ACP(SURG)4$	−0.14	−1.88***	0.43	2.30***
$ACP(SURG)5$	−0.23	−1.86***	1.36***	3.22***
$ACP(SURG)5 - ACP(SURG)1$	0.16	−0.98*	1.01*	1.99***

Panel B: Regression Analysis (*N*= 129,338)

Coefficient	*Spec. 1*	*Spec. 2*	*Spec. 3*
Intercept	−7.56	−7.16	−7.40
	(−3.8***)	(−3.3***)	(−3.6***)
$D_{ACP(SURG)5}$			−0.90
			(−2.2**)
$ACP(SURG)^{quin}$		−0.74	
		(−1.3)	
$SURG^{quin}$	1.77	1.13	1.51
	(5.1***)	(1.8*)	(4.1***)
$ACP(SURG)^{quin}SURG^{quin}$		1.31	
		(1.7*)	
$D_{ACP(SURG)5}SURG^{quin}$			1.45
			(2.5***)
$BETA^{quin}$	1.38	1.33	1.37
	(0.8)	(0.8)	(0.8)
B/M^{quin}	3.51	3.51	3.53
	(3.0***)	(3.0***)	(3.0***)
$SIZE^{quin}$	6.80	6.77	6.80
	(3.5***)	(3.5***)	(3.5***)
Adj-R^2	0.03	0.03	0.03

Notes:
1. The table presents the association between the post-revenue-announcement drift anomaly and the adjusted conditional persistence of *SURG*.
2. Panel A presents the market reaction to combinations of portfolios formed based on adjusted conditional persistence of $SURG[ACP(SURG)]$ and standardized unexpected revenue (*SURG*). To form portfolios, we begin by ranking all firms, each quarter, according to their $ACP(SURG)$ or *SURG*, and assign them into quintiles. Then, we construct portfolios of observations that fall into the two-variable combination of quintiles. For example, a combination of $ACP(SURG)1/SURG1$ includes observations in the lowest quintile of both $ACP(SURG)$ and *SURG*. We report mean size-adjusted abnormal returns (in percentages) for a 180-day window starting on the second day after the preliminary earnings announcement date.
3. Panel B presents results for the association between $ACP(SURG)$, *SURG* and post buy-and-hold abnormal returns of 180 days, starting 2 days after the preliminary earnings announcement date. We present average coefficients and corresponding *t*-statistics (in parentheses) from estimating equation (3) each quarter (*t*-statistics are based on the time-series of the quarterly regression coefficient estimates using the Fama and MacBeth, 1973 approach augmented by the Newey and West, 1987 correction for autocorrelation):

(*Continued*)

Table 4
Continued

$$AR(180)_{it} = \lambda_{0t} + \lambda_{1t}D_{ACP(SURG)5,it} + \lambda_{2t}ACP(SURG)_{it}^{quin} + \lambda_{3t}SURG_{it}^{quin} + \lambda_{4t}ACP(SURG)_{it}^{quin}SURG_{it}^{quin} + \lambda_{5t}D_{ACP(SURG)5,it}SURG_{it}^{quin} + \lambda_{6t}BETA_{it}^{quin} + \lambda_{7t}BM_{it}^{quin} + \lambda_{8t}SIZE_{it}^{quin} + \zeta_{it}. \quad (3)$$

$D_{ACP(SURG)5,it}$ is an indicator variable equal to "1" if *ACP*(*SURG*) is in the highest quintile for firm i in quarter *t*; See Appendix for definitions of other variables. Explanatory variables are transformed into a scaled-quintile variable with values ranging from 0 to 1. Coefficient estimates are multiplied by 100.
4 *, **, *** indicates significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

persistence of revenue surprises, as we propose here, then post-announcement excess returns will be positively correlated with *ACP*(*SURG*).

As Panel A of Table 4 shows, selling stocks of firms in the lowest quintile of *SURG* and buying stocks of firms in the highest quintile of *SURG* yields an excess return of 1.88% in the 180 days after the preliminary earnings announcement date (significant at the 0.01 level). However, the excess return increases monotonically with the quintile of *ACP*(*SURG*). When *ACP*(*SURG*) is in its lowest quintile, the difference in excess return between the lowest and the highest quintiles of *SURG* is 1.23% (significant at the 0.05 level). The drift increases monotonically to 3.22% (significant at the 0.01 level) when *ACP*(*SURG*) is in its highest quintile. This difference in differences (3.22% – 1.23% = 1.99%) is significant at the 0.01 level. In fact, the post-revenue-announcement drift associated with low *ACP*(*SURG*) is less than 40% of the drift associated with high *ACP*(*SURG*). This result supports Prediction 1(a).

Next, we use a multivariate regression analysis. We estimate equation (3) each quarter and report average coefficients and corresponding *t*-statistics (in parentheses); *t*-statistics are based on the time-series of the quarterly regression coefficient estimates using the Fama and MacBeth (1973) approach augmented by the Newey and West (1987) correction for autocorrelation:

$$AR(180)_{it} = \lambda_{0t} + \lambda_{1t}D_{ACP(SURG)5,it} + \lambda_{2t}ACP(SURG)_{it}^{quin} + \lambda_{3t}SURG_{it}^{quin} + \lambda_{4t}ACP(SURG)_{it}^{quin}SURG_{it}^{quin} + \lambda_{5t}D_{ACP(SURG)5,it}SURG_{it}^{quin} + \lambda_{6t}BETA_{it}^{quin} + \lambda_{7t}BM_{it}^{quin} + \lambda_{8t}SIZE_{it}^{quin} + \zeta_{it}. \quad (3)$$

The dependent variable in equation (3) is the excess return for a 180-day window starting after the preliminary earnings announcement date. $D_{ACP(SURG)5,it}$ is an indicator variable, which obtains the value of "1" if *ACP*(*SURG*) is in the highest quintile for firm *i* in quarter *t*, and "0" otherwise. In addition to $D_{ACP(SURG)5}$, *ACP*(*SURG*) and *SURG*, we also include in the model two interaction variables, [$D_{ACP(SURG)5}$ X *SURG*] and [*ACP*(*SURG*) X *SURG*], and control for *BETA*, *BM* and *SIZE*. All the explanatory variables in the model are transformed to scaled-quintile variables with values ranging from 0 to 1, as explained above.

Table 4, Panel B, presents results for three specifications of equation (3). The results in the first specification confirm the existence of the post-revenue-announcement drift documented in prior studies (the coefficient on *SURG* is positive and significant at the 0.01 level).

The second specification includes the interaction between *ACP*(*SURG*) and *SURG*. The coefficient λ_4 on [*ACP*(*SURG*) X *SURG*] is positive and significant at the 0.10 level, suggesting that the magnitude of the drift is associated with the adjusted conditional persistence of revenue surprises, as we predicted. The third specification further includes an interaction between the highest quintile of *ACP*(*SURG*) and *SURG*. The coefficient on this interaction variable is 1.45 (significant at the 0.01 level), suggesting that the post-revenue-announcement drift is (λ_3=) 1.51% for the first four quintiles of *ACP*(*SURG*), but increases to (λ_3+ λ_5= 1.51% + 1.45% =) 2.96% for the fifth quintile of *ACP*(*SURG*). Overall, the results in Table 4 support Prediction 1(a), that the post-revenue-announcement drift is positively associated with the adjusted conditional persistence of revenue surprises.

(ii) The Association Between ACP(SURG) and the Post-Earnings-Announcement Drift

Next we examine the association between the post-earnings-announcement drift and *ACP*(*SURG*). As Panel A of Table 5 shows, selling stocks of firms in the lowest quintile of *SUE* and buying stocks of firms in the highest quintile of *SUE* yields an excess return of 2.66% in the 180 days after the preliminary earnings announcement date (significant at the 0.01 level). However, when *ACP*(*SURG*) is in the lowest quintile, the drift is 1.45% (significant at the 0.05 level), and it increases almost monotonically to 4.18% (significant at the 0.01 level) when *ACP*(*SURG*) is in the highest quintile, as we predicted. Also, the difference in differences (4.18% – 1.45% = 2.73%) is significant at the 0.01 level. Moreover, the post-earnings-announcement drift associated with low *ACP*(*SURG*) is about one-third of the drift associated with high *ACP* (*SURG*).

Panel B of Table 5 presents regression results for equation (4), which is similar to equation (3), but with *SUE* instead of *SURG*:

$$\begin{aligned} AR(180)_{it} = {} & \lambda_{0t} + \lambda_{1t} D_{ACP(SURG)5,it} + \lambda_{2t} ACP(SURG)_{it}^{quin} + \lambda_{3t} SUE_{it}^{quin} \\ & + \lambda_{4t} ACP(SURG)_{it}^{quin} SUE_{it}^{quin} + \lambda_{5t} D_{ACP(SURG)5,it} SUE_{it}^{quin} \\ & + \lambda_{6t} BETA_{it}^{quin} + \lambda_{7t} BM_{it}^{quin} + \lambda_{8t} SIZE_{it}^{quin} + \zeta_{it}. \qquad (4) \end{aligned}$$

In the first specification, the coefficient on *SUE* is positive (significant at the 0.01 level), confirming the post-earnings-announcement drifts documented in prior studies. The second specification includes the interaction between *ACP*(*SURG*) and *SUE*. The coefficient λ_4 on [*ACP*(*SURG*) X *SUE*] is positive and significant at the 0.01 level, suggesting that the drift is positively associated with the adjusted conditional persistence of revenue surprises [*ACP*(*SURG*)], as we predicted. The third specification includes an interaction between the highest quintile of *ACP*(*SURG*) and *SUE*. The coefficient on this interaction variable is positive, as predicted, and significant at the 0.01 level. This specification suggests that the post-earnings-announcement drift is (λ_3=) 2.10% for the first four quintiles of *ACP*(*SURG*), but increases (at the 0.01 level) to (λ_3+ λ_5= 2.10% + 2.04% =) 4.14% for the fifth quintile of *ACP*(*SURG*), consistent with Prediction 1(b).

Table 5

Post-Earnings-Announcement Drift and Adjusted Conditional Persistence of *SURG*

Panel A: Portfolio Analysis ($N = 129{,}338$)

		SUE1	*SUE5*	*SUE5 – SUE1*
	Full Sample	−1.51***	1.15***	2.66***
ACP(*SURG*)1	−0.07	−0.71*	0.74*	1.45**
ACP(*SURG*)2	0.15	−1.09***	1.29**	2.38***
ACP(*SURG*)3	−0.31*	−1.80***	1.06***	2.86***
ACP(*SURG*)4	−0.14	−1.52***	0.80**	2.32***
ACP(*SURG*)5	−0.23	−2.36***	1.82***	4.18***
ACP(*SURG*)5 – *ACP*(*SURG*)1	0.16	−1.65***	1.08**	2.73***

Panel B: Regression Analysis ($N = 129{,}338$)

Coefficient	*Spec. 1*	*Spec. 2*	*Spec. 3*
Intercept	−7.89	−7.20	−7.63
	(−3.9***)	(−3.4***)	(−3.7***)
$D_{ACP(SURG)5}$			−1.17
			(−2.4**)
$ACP(SURG)^{quin}$		−1.27	
		(−2.1**)	
SUE^{quin}	2.51	1.37	2.10
	(5.3***)	(2.0**)	(3.8***)
$ACP(SURG)^{quin} SUE^{quin}$		2.28	
		(2.8***)	
$D_{ACP(SURG)5} SUE^{quin}$			2.04
			(2.6***)
$BETA^{quin}$	1.37	1.33	1.36
	(0.8)	(0.8)	(0.8)
B/M^{quin}	3.43	3.42	3.42
	(3.0***)	(2.9***)	(2.9***)
$SIZE^{quin}$	6.80	6.77	6.79
	(3.5***)	(3.4***)	(3.4***)
Adj-R^2	0.03	0.03	0.03

Notes:

1. The table presents the association between the post-earnings-announcement drift anomaly and adjusted conditional persistence of *SURG*.
2. Panel A presents the market reaction to combinations of portfolios formed based on adjusted conditional persistence of *SURG* [*ACP*(*SURG*)] and standardized unexpected earnings (*SUE*). To form portfolios, we begin by ranking all firms, each quarter, according to their *ACP*(*SURG*) or *SUE*, and assign them into quintiles. Then, we construct portfolios of observations that fall into the two-variable combination of quintiles. For example, a combination of *ACP*(*SURG*)1/ *SUE*1 includes observations in the lowest quintile of both *ACP*(*SURG*) and *SUE*. We report mean size-adjusted abnormal returns (in percentages) for a 180-day window starting on the second day after the preliminary earnings announcement date.
3. Panel B presents results for the association between *ACP*(*SURG*), *SUE* and post buy-and-hold abnormal returns of 180 days, starting 2 days after the earnings announcement date. We present average coefficients and corresponding *t*-statistics (in parentheses) from estimating equation (3) each quarter (*t*-statistics are based on the time-series of the quarterly regression coefficient estimates using the Fama and MacBeth, 1973 approach augmented by the Newey and West, 1987 correction for autocorrelation):

$$
\begin{aligned}
AR(180)_{it} = {} & \lambda_{0t} + \lambda_{1t} D_{ACP(SURG)5,it} + \lambda_{2t} ACP(SURG)_{it}^{quin} + \lambda_{3t} SUE_{it}^{quin} \\
& + \lambda_{4t} ACP(SURG)_{it}^{quin} SUE_{it}^{quin} + \lambda_{5t} D_{ACP(SURG)5,it} SUE_{it}^{quin} + \lambda_{6t} BETA_{it}^{quin} \\
& + \lambda_{7t} BM_{it}^{quin} + \lambda_{8t} SIZE_{it}^{quin} + \zeta_{it}. \qquad (4)
\end{aligned}
$$

$D_{ACP(SURG)5,\ it}$ is an indicator variable equal to "1" if *ACP*(*SURG*) is in the highest quintile for firm i in quarter t. See Appendix for definitions of other variables. Explanatory variables are transformed into a scaled-quintile variable with values ranging from 0 to 1. Coefficient estimates are multiplied by 100.

4. *, **, *** indicates significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

(iii) The Association between ACP(ACC) and the Accrual Anomaly

Table 6 provides results for the association between the adjusted conditional persistence of the accrual component of earnings [*ACP*(*ACC*)] and the magnitude of the accrual anomaly. As Panel A shows, buying stocks of firms in the lowest accruals quintile and selling stocks of firms in the highest accruals quintile yields an excess return of 4.10% in the post-SEC filing window (significant at the 0.01 level). However, when *ACP*(*ACC*) is in its lowest quintile, the difference in post-SEC filing excess returns between the lowest and the highest accruals quintiles is 5.94%, and this difference in excess return decreases to 2.23% when *ACP*(*ACC*) is in its highest quintile. That is, the accrual-related drift associated with high conditional persistence of accruals is much lower. The difference in differences (5.94% – 2.23% = 3.71%) is significant at the 0.01 level.

Consistent with Sloan (1996), the results in Panel A also indicate that when accruals are in their highest quintile (i.e., *ACC*5), post-SEC filing excess returns are mostly negative. However, when *ACP*(*ACC*) is in its highest quintile [i.e., *ACP*(*ACC*)5], and *ACC*is in its highest quintile (i.e., *ACC5*), post-SEC filing excess return is not significantly different from zero. That is, firms that report high accruals do not experience negative post-SEC filing returns if *ACP*(*ACC*) is high, because the marginal contribution of the persistence of accruals to the persistence of earnings is relatively high.

Following the argument of Green et al. (2011) and Mohanram (2014) that the accrual anomaly weakened after 2000, we divide our sample period into two sub-periods (1993–2000 and 2001–2013) and re-examine the association between *ACP*(*ACC*) and *ACC*. The results in Panel B of Table 6 indeed suggest that the accrual-related drift was 7.92% in 1993–2000, and decreased substantially to 1.91% in 2001–2013. Also, during 1993–2000, the drift is 10.29% when *ACP*(*ACC*) is in its lowest quintile, but only 4.82% when *ACP*(*ACC*) is in its highest quintile, a difference of 5.47% (significant at the 0.01 level). During 2001–2013, the drift is 3.44% when *ACP*(*ACC*) is in its lowest quintile, and 0.84% (not significantly different from zero) when *ACP*(*ACC*) is in its highest quintile, a difference of 2.60% (significant at the 0.05 level). While the magnitude of the accrual anomaly has clearly decreased in recent years, it is still associated with *ACP*(*ACC*) in both sub-periods, as we predicted.

Next, we estimate equation (5), which is similar to equation (3) and equation (4). We define $D_{ACP(ACC)5,it}$ as an indicator variable, which obtains the value of "1" if *ACP*(*ACC*) is in the highest quintile for firm *i* in quarter *t*, and "0" otherwise:

$$\begin{aligned} AR(365)_{it} = {} & \lambda_{0t} + \lambda_{1t} D_{ACP(ACC)5,it} + \lambda_{2t} ACP(ACC)_{it}^{quin} + \lambda_{3t} ACC_{it}^{quin} \\ & + \lambda_{4t} ACP(ACC)_{it}^{quin} ACC_{it}^{quin} + \lambda_{5t} D_{ACP(ACC)5,it} ACC_{it}^{quin} \\ & + \lambda_{6t} BETA_{it}^{quin} + \lambda_{7t} B/M_{it}^{quin} + \lambda_{8t} SIZE_{it}^{quin} + \zeta_{it}. \end{aligned} \tag{5}$$

Table 6, Panel C, presents average coefficients and corresponding *t*-statistics (in parentheses) from estimating equation (5)each quarter. In the first specification, the coefficient on *ACC* is negative (significant at the 0.01 level), which confirms the accrual anomaly: stocks with higher accruals earn smaller excess returns in the year after the SEC filing. The second specification includes the interaction between *ACP*(*ACC*) and *ACC*. The coefficient λ_4 on [*ACP*(*ACC*) X *ACC*] is positive

Table 6

The Accrual Anomaly and Adjusted Conditional Persistence of Accruals

Panel A: Portfolio Analysis (*N* = 127,416)

		ACC1	*ACC5*	*ACC1 – ACC5*
	Full Sample	*1.94****	*−2.16****	*4.10****
ACP(*ACC*)1	−0.36	1.98***	−3.96***	5.94***
ACP(*ACC*)2	0.08	1.37**	−2.08***	3.45***
ACP(*ACC*)3	−0.42	1.97***	−2.69***	4.66***
ACP(*ACC*)4	0.48	2.39***	−1.78***	4.17***
ACP(*ACC*)5	0.85***	1.95***	−0.28	2.23**
ACP(*ACC*)5 – *ACP*(*ACC*)1	1.21***	−0.03	3.68***	−3.71***

Panel B: Portfolio Analysis in Sub-periods

	ACC1–ACC5		
	1993–2013 (N = 127,416)	*1993–2000 (N = 46,322)*	*2001–2013 (N = 81,094)*
Full Sample	4.10***	7.92***	1.91***
ACP(*ACC*)1	5.94***	10.29***	3.44***
ACP(*ACC*)5	2.23**	4.82***	0.84
ACP(*ACC*)5 – *ACP*(*ACC*)1	−3.71***	−5.47***	−2.60**

Panel C: Regression Analysis (*N* = 127,416)

Coefficient	*Spec. 1*	*Spec. 2*	*Spec. 3*
Intercept	−17.74	−17.34	−17.53
	(−3.9***)	(−3.8***)	(−3.9***)
$D_{ACP(ACC)5}$			−1.27
			(−1.5)
$ACP(ACC)^{quin}$		−1.00	
		(−1.0)	
ACC^{quin}	−3.96	−5.60	−4.61
	(−4.1***)	(−3.8***)	(−4.3***)
$ACP(ACC)^{quin}ACC^{quin}$		3.40	
		(1.7*)	
$D_{ACP(ACC)5}ACC^{quin}$			3.22
			(2.1**)
$BETA^{quin}$	4.00	3.96	3.97
	(1.2)	(1.2)	(1.2)
B/M^{quin}	10.86	10.92	10.90
	(4.3***)	(4.3***)	(4.3***)
$SIZE^{quin}$	20.27	20.24	20.28
	(4.5***)	(4.5***)	(4.5***)
Adj-R^2	0.05	0.05	0.05

Notes:
1. The table presents the association between the accrual anomaly and the adjusted conditional persistence of *ACC*.

(*Continued*)

Table 6
Continued

2. Panel A presents the market reaction to combinations of portfolios formed based on the adjusted conditional persistence of *ACC*[*ACP*(*ACC*)] and the level of the accrual component (*ACC*). To form portfolios, we initially rank all firms, each quarter, according to their *ACP*(*ACC*) or *ACC*, and assign them into quintiles. Then, we construct portfolios of observations that fall into the two-variable combination of quintiles. For example, a combination of *ACP*(*ACC*)1/*ACC1* includes observations in the lowest quintile of both *ACP*(*ACC*) and *ACC*. We report mean size-adjusted abnormal returns (in percentages) for a 365-day window starting on the second day after the SEC filing date. Panel B presents the portfolio analysis for two sub-periods: 1993–2000 and 2001–2013.
3. Panel C presents results for the association between *ACP*(*ACC*), *ACC* and post-SEC filing buy-and-hold abnormal returns of 365 days, starting 2 days after the SEC filing date. We present average coefficients and corresponding *t*-statistics (in parentheses) from estimating equation (4) each quarter (*t*-statistics are based on the time-series of the quarterly regression coefficient estimates using the Fama and MacBeth, 1973 approach augmented by the Newey and West, 1987 correction for autocorrelation).

$$\begin{aligned}AR(365)_{it} = {} & \lambda_{0t} + \lambda_{1t} D_{ACP(ACC)5,it} + \lambda_{2t} ACP(ACC)_{it}^{quin} + \lambda_{3t} ACC_{it}^{quin} \\ & + \lambda_{4t} ACP(ACC)_{it}^{quin} ACC_{it}^{quin} + \lambda_{5t} D_{ACP(ACC)5,it} ACC_{it}^{quin} + \lambda_{6t} BETA_{it}^{quin} \\ & + \lambda_{7t} B/M_{it}^{quin} + \lambda_{8t} SIZE_{it}^{quin} + \zeta_{it} \qquad (5)\end{aligned}$$

$D_{ACP(ACC)5,\,it}$ is an indicator variable equal to "1" if *ACP*(*ACC*) is in the highest quintile for firm *i* in quarter *t*. See Appendix for definitions of other variables. Explanatory variables are transformed into a scaled-quintile variable with values ranging from 0 to 1. Coefficient estimates are multiplied by 100.
4. *, **, *** indicates significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

and significant at the 0.10 level, which is consistent with our prediction. The third specification includes an interaction between the highest quintile of *ACP*(*ACC*) and *ACC*. According to this specification, the accrual related drift is (λ_3=) –4.61% for the first four quintiles of *ACP*(*ACC*), but drops (in absolute terms) to (λ_3+ λ_5= –4.61% + 3.22% =) –1.39% for the fifth quintile of *ACP*(*ACC*), significant at the 0.04 level.[6]

Overall, the results in Table 6 indicate that the accrual anomaly is most noticeable when *ACP*(*ACC*) is at its lowest level and decreases as *ACP*(*ACC*) increases. Furthermore, when *ACP*(*ACC*) is high, firms that report high accruals do not experience negative post-SEC filing returns. That is, when the marginal contribution of the persistence of accruals to the persistence of earnings is relatively high, the failure of investors to price the accruals and cash components of earnings differently becomes immaterial. Taken as a whole, the results in Table 6 reinforce our second prediction, suggesting the accrual anomaly is negatively associated with the adjusted conditional persistence of accruals.

The results in Tables 4–6 suggest that the fixation of investors on the unconditional persistence of earnings components, while under-reacting to their conditional persistence, provides a plausible explanation for the post-earnings-announcement drift, the post-revenue-announcement drift, and the accrual anomaly.[7]

6 Consistent with the pattern observed in Panel A of Tables 4–6, we find (not tabulated) that the coefficients on the interactions between the lowest quintile of *ACP*(*SURG*) and *SURG*, the lowest quintile of *ACP*(*SURG*) and *SUE*, and between the lowest quintile of *ACP*(*ACC*) and *ACC* are negative and significant (at the 0.10 level or better), while the coefficients on the interaction with the middle quintile of *ACP* are not significantly different from zero.
7 When we estimate regression equations (3), (4) and (5)separately for the unconditional persistence and the conditional persistence we find that for the post-revenue-announcement drift both the interactions between *P*(*SURG*) and *SURG* and between *CP*(*SURG*) and *SURG* are significant (at the 0.10 level or better). For the post-earnings-announcement drift only the interaction between *P*(*SURG*) and *SUE*is significant (at the 0.05 level). As for the accrual anomaly, both the interactions between *P*(*ACC*) and *ACC* and between

(iv) The Adjusted Conditional Persistence and Analysts' Forecast Errors

The empirical analysis thus far has focused on investors' pricing of accounting information. Do financial analysts, who provide revenue and earnings predictions, also fixate on the unconditional persistence of earnings components, or do they use the conditional persistence of earnings components in predicting revenue and earnings? To answer this question, we examine whether the adjusted conditional persistence of *SURG* in quarter t–1 is associated with the bias of revenue forecasts in quarter t. In addition, we examine whether the adjusted conditional persistence of accruals in quarter t–1 is associated with the bias of earnings forecasts in quarter t.

We compute the earnings (and revenue) forecast errors, denoted $FE(EPS)_{it}$ and $FE(RPS)_{it}$, respectively, for firm i in quarter t, as reported earnings (revenue) per share minus the average of all forecasts announced in the month immediately preceding that of the earnings announcement (as reported in I/B/E/S), deflated by the stock price at the end of the prior quarter. Consistent with Gu and Wu (2003), we require a stock price of at least US$ 3 to avoid small deflators. We measure forecast bias as the signed average forecast error (*FE*). We estimate equation (6a)and equation (6b)each quarter and report average coefficients and corresponding t-statistics (in parentheses); t-statistics are based on the time-series of the quarterly regression coefficient estimates using the Fama and MacBeth 1973 approach augmented by the Newey and West (1987) correction for autocorrelation:

$$FE(EPS)_{it} = \gamma_{0t} + \gamma_{1t}ACP(SURG)_{it-1} + \gamma_{2t}SURG_{it-1} + \gamma_{3t}BM_{it} + \gamma_{4t}SIZE_{it} + \mu_{it} \quad (6a)$$

$$FE(RPS)_{it} = \gamma_{0t} + \gamma_{1t}ACP(ACC)_{it-1} + \gamma_{2t}ACC_{it-1} + \gamma_{3t}BM_{it} + \gamma_{4t}SIZE_{it} + \mu_{it}. \quad (6b)$$

The dependent variable in equation (6a)is analysts' revenue forecast errors, and the dependent variable in equation (6b)is the analysts' earnings forecast errors. Equation (6a)includes revenue surprises (*SURG*) and the adjusted conditional persistence of revenue surprises [*ACP*(*SURG*)] as explanatory variables; equation (6b)includes accruals (*ACC*) and the adjusted conditional persistence of accruals [*ACP*(*ACC*)] as explanatory variables. Consistent with prior studies, we control for the book-to-market ratio (*BM*) and firm size (*SIZE*).[8] Table 7 contains the results, with coefficient estimates multiplied by 1,000.

Focusing on equation (6a) in the left section of the table, higher *ACP*(*SURG*) is associated with more pessimistic forecasts (significant at the 0.02 level). This result suggests analysts over-estimate future revenue when *ACP*(*SURG*) is low, and under-estimate future revenue when *ACP*(*SURG*) is high. Turning to equation (6b), we find a negative association between *ACP*(*ACC*) in quarter t–1 and signed forecast errors in period quarter t (significant at the 0.01 level). These results suggest that analysts' forecasts are more informative about future earnings when *ACP*(*ACC*) is high. Recall that high *ACP*(*ACC*) occurs when the conditional persistence of accruals is relatively high and the unconditional persistence of accruals is relatively low. Hence, when *ACP*(*ACC*) is high the negative effect of the accrual component on earnings'

CP(*ACC*) and *ACC* are not significantly different from zero (not tabulated for brevity), which highlights the importance in using the difference between conditional and unconditional persistence rather than conditional and unconditional persistence separately.

8 See Atiase (1985), Bhushan (1989), Collins et al. (1987), and Lang and Lundholm (1996).

Table 7
The Association Between Adjusted Conditional Persistence and Analysts' Forecast Errors

	Equation (6a) – *Revenue Forecasts Errors*	*Equation* (6b) – *Earnings Forecast Errors*
Intercept	0.97	0.45
	(4.5***)	(4.5***)
ACP(*SURG*)	0.51	
	(2.4**)	
SURG	0.31	
	(11.5***)	
ACP(*ACC*)		−0.11
		(−3.8***)
ACC		−2.01
		(−2.5***)
BM	0.65	−0.17
	(0.8)	(−2.0**)
SIZE	0.00	0.00
	(0.3)	(0.3)
Adj-R^2	0.02	0.01
Observations	37,524	60,367

Notes:
The table presents results of estimating equation (6a)in the left panel, and equation (6b)in the right panel. The equations are estimated each quarter and we present average coefficients and corresponding *t*-statistics (in parentheses); *t*-statistics are based on the time-series of the annual regression coefficient estimates using the Fama and MacBeth approach augmented by the Newey and West (1987) correction for autocorrelation.

$$FE(EPS)_{it} = \gamma_{0t} + \gamma_{1t}ACP(SURG)_{it-1} + \gamma_{2t}SURG_{it-1} + \gamma_{3t}BM_{it} + \gamma_{4t}SIZE_{it} + \mu_{it} \quad (6a)$$

$$FE(RPS)_{it} = \gamma_{0t} + \gamma_{1t}ACP(ACC)_{it-1} + \gamma_{2t}ACC_{it-1} + \gamma_{3t}BM_{it} + \gamma_{4t}SIZE_{it} + \mu_{it} \quad (6b)$$

The dependent variable in equation (6a)is the analysts' revenue forecast errors, and in equation (6b)it is the analysts' earnings forecast errors (the signed forecast errors, deflated by the stock price at the end of the prior quarter).
2. See Appendix for definitions of the explanatory variables.
3. Coefficient estimates are multiplied by 1,000.
4. *, **, *** indicates significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.

persistence decreases, and analysts' failure to price accruals is less pronounced, resulting in less biased forecasts.

The results in Table 7 support our third prediction. *ACP*(*SURG*) is negatively associated with the quality of revenue forecasts, while *ACP*(*ACC*) is positively associated with the quality of earnings forecasts. The results in Table 7 are also consistent with those reported in Tables 4–6 we expect the anomalies to be weaker when analysts' forecasts are more informative about future revenue and earnings growth.

5. SUMMARY

The mispricing of accounting information is often linked to investors' misperception of the differential persistence of earnings components such as revenue and accruals. Recently it has been suggested that the market reaction to an earnings component should depend not on the component's autocorrelation coefficient (unconditional persistence), but on the marginal contribution of the component's persistence to the persistence of overall earnings (conditional persistence). The rationale is that information on the persistence of an earnings component is valuable for investors and analysts if it explains the persistence of a variable higher in the hierarchy, namely earnings. We therefore examine whether the market mispricing of accounting information is explained by investors' failure to distinguish between the unconditional and conditional persistence of earnings components.

We focus on three accounting-based stock price anomalies that have been attributed to incorrect estimation of the persistence of earnings components: the post-earnings-announcement drift, the post-revenue-announcement drift, and the accrual anomaly. We find that the magnitudes of these anomalies are significantly associated with the distance between the conditional persistence and the unconditional persistence of revenue and accruals (labeled here, adjusted conditional persistence). We also find that the bias of analysts' revenue and earnings forecasts is associated with the adjusted conditional persistence of revenue surprises and accruals, respectively.

Our findings suggest that under-emphasizing the marginal contribution of a component's persistence to the persistence of earnings (i.e., its conditional persistence) might lead investors and analysts to incorrect estimates of earnings persistence, and hence to incorrect assessments of future earnings. This incorrect assessment of future earnings, in turn, could lead to the market mis-pricing documented here. However, in case we fail to properly account for risk in stock returns, risk factors may explain our findings.[9]

9 For general discussion, see Fama (1991). For a specific example regarding the anomalies we consider, see Khan (2013), who shows that when true betas are empirically unobserved, the use of CAPM can generate the accrual anomaly, even when the true abnormal returns are zero.

APPENDIX

Variable Definitions

	Excess Return Measure
AR(180)	Excess buy-and-hold size-adjusted stock returns for a 180-day (calendar) window, starting 2 days after the preliminary earnings announcement date.
AR(365)	Excess buy-and-hold size-adjusted stock returns for a 365-day (calendar) window, starting 2 days after the SEC filing date.
	Unexpected Earnings, Revenue and Expenses
SUE	Standardized unexpected earnings, measured as earnings per share in quarter $t(EPS_t)$ minus earnings per share in the same quarter of the previous year (EPS_{t-4}) plus an average drift (D_t), deflated by the standard deviation of unexpected earnings per share over the previous eight quarters (S_t). $SUE_{i,t} = \frac{EPS_{i,t}-E(EPS_{i,t})}{S_{i,t}},\ E(EPS_{i,t}) = EPS_{i,t-4} + D_{i,t},$ $D_{i,t} = \frac{1}{8}\sum_{j=1}^{8}(EPS_{i,t-j} - EPS_{i,t-j-4}),$ $S_{i,t} = \frac{1}{7}\sqrt{\sum_{j=1}^{8}(EPS_{i,t-j} - E(EPS)_{i,t-j})^2}$
SURG	Standardized unexpected revenue, measured as revenue per share in quarter $t(RPS_t)$ minus revenue per share in the same quarter last year (RPS_{t-4}) plus an average drift (D_t), deflated by the standard deviation of unexpected revenue per share over the previous eight quarters (S_t). $SURG_{i,t} = \frac{RPS_{i,t}-E(RPS_{i,t})}{S_{i,t}},\ E(RPS_{i,t}) = RPS_{i,t-4} + D_{i,t},$ $D_{i,t} = \frac{1}{8}\sum_{j=1}^{8}(RPS_{i,t-j} - RPS_{i,t-j-4}),$ $S_{i,t} = \frac{1}{7}\sqrt{\sum_{j=1}^{8}(RPS_{i,t-j} - E(RPS)_{i,t-j})^2},$
SUXP	Standardized unexpected expenses, measured as expenses per share in quarter $t(XPS_t)$ minus expenses per share in the same quarter last year (XPS_{t-4}) plus an average drift (D_t), deflated by the standard deviation of unexpected expenses per share over the previous eight quarters (S_t). $XPS_{i,t} = RPS_{i,t} - EPS_{i,t},\ SUXP_{i,t} = \frac{XPS_{i,t}-E(XPS_{i,t})}{S_{i,t}},$ $E(XPS_{i,t}) = XPS_{i,t-4} + D_{i,t},$ $D_{i,t} = \frac{1}{8}\sum_{j=1}^{8}(XPS_{i,t-j} - XPS_{i,t-j-4}),$ $S_{i,t} = \frac{1}{7}\sqrt{\sum_{j=1}^{8}(XPS_{i,t-j} - E(XPS)_{i,t-j})^2}$

Cash Flow and Accrual Components of Earnings	
EARN	Earnings before extraordinary items and discontinued operations, divided by average total assets.
CFO	Cash flows from continuing operations, divided by average total assets.
ACC	The accrual component of earnings, measured as the difference between earnings before extraordinary items and discontinued operations and operating cash flows from continuing operations, divided by average total assets. $ACC = EARN - CFO$.
Persistence Measures	
$P(X)$	Unconditional persistence of *X*, measured for each firm/quarter as the first auto regression of *X* over the previous eight quarters.
$CP(SURG)$	Conditional persistence of *SURG*. $CP(SURG)$ is measured for each firm/quarter by estimating the following regression on a firm-by-firm basis using the previous eight quarters: $P(SUE)_{it} = \alpha_{0it} + \alpha_{1it}P(SURG)_{it} + \alpha_{2it}P(SUXP)_{it} + \varepsilon_{it}$ We obtain slope coefficients for each firm/quarter. We also compute the mean of $P(SURG)$ using the previous eight quarters [Mean $P(SURG)_{it}$]. Then, we compute the conditional persistence for each firm/quarter as: $CP(SURG)_{it} = \alpha_{1it} \times Mean[P(SURG)]_{it}$
$CP(ACC)$	Conditional persistence of accruals (ACC). $CP(ACC)$ is measured for each firm/quarter by estimating the following regression on a firm-by-firm basis using the previous eight quarters: $P(EARN)_{it} = \alpha_{0it} + \alpha_{1it}P(ACC)_{it} + \alpha_{2it}P(CFO)_{it} + \varepsilon_{it}$ We obtain slope coefficients for each firm/quarter. We also compute the mean of $P(ACC)$ using the previous eight quarters [Mean $P(ACC)_{it}$]. Then, we compute the conditional persistence for each firm/quarter as: $CP(ACC)_{it} = \alpha_{1it} \times Mean[P(ACC)]_{it}$
$ACP(SURG)$	We rank all firms, each quarter, according to their unconditional persistence, $P(SURG)$, assigning integer values starting with "1" for the firm with the lowest $P(SURG)$. Then, we rank all firms, each quarter, according to their conditional persistence, $CP(SURG)$, assigning integer values starting with "1" for the firm with the lowest conditional persistence. We compute the difference between the ranks and divide by the number of firms in the quarter, N_t: $ACP(SURG)_{it} = \{Rank[CP(SURG)_{it}] - Rank[P(SURG)_{it}]\}/N_t$ Thus, we obtain a measure of the distance between conditional and unconditional persistence and refer to it as adjusted conditional persistence of *SURG*, or $ACP(SURG)$.

ACP(*ACC*)	We rank all firms, each quarter, according to their unconditional persistence of accruals, *P*(*ACC*), assigning integer values starting with "1" for the firm with the lowest *P*(*ACC*). Then, we rank all firms, each quarter, according to their conditional persistence, *CP*(*ACC*), assigning integer values starting with "1" for the firm with the lowest conditional persistence. We compute the difference between the ranks and divide by the number of firms in the quarter, N_t: $ACP(ACC)_{it} = \{Rank[CP(ACC)_{it}] - Rank[P(ACC)_{it}]\}/N_t$ Thus, we obtain a measure of the distance between conditional and unconditional persistence and refer to it as adjusted conditional persistence of accruals, or *ACP*(*ACC*).
	Scaled-Quintile Transformation
X^{quin}	A variable *X* transformed into a scaled-quintile format, ranging from 0 to 1. The variable is ranked each quarter and the observations in the lowest quintile are assigned the value "0", the observations in the highest quintile are assigned the value "1", and the middle quintiles are assigned the values 0.25, 0.50 and 0.75, respectively. For instance, $SURG^{quin}$ is *SURG* transformed into a scaled-quintile format, ranging from 0 to 1.
	Indicator Variables
$D_{ACP(SURG)5}$	An indicator variable equal to "1" if *ACP*(*SURG*) is in the highest quintile for firm *i* in quarter *t*.
$D_{ACP(ACC)5}$	An indicator variable equal to "1" if *ACP*(*ACC*) is in the highest quintile for firm *i* in quarter *t*.
	Analysts' Forecast Errors
FE(*EPS*)	Earnings forecast error, computed as reported earnings per share (*EPS*) minus the average of all forecasts announced in the month immediately preceding that of the earnings announcement (as reported in I/B/E/S), deflated by the stock price at the end of the prior quarter.
FE(*RPS*)	Revenue forecast error, computed as reported revenue per share (*RPS*) minus the average of all forecasts announced in the month immediately preceding that of the earnings announcement (as reported in I/B/E/S), deflated by the stock price at the end of the prior quarter.
	Control Variables
BM	The book-to-market ratio, measured as book value of common equity at quarter-end divided by the market value of common equity.
SIZE	Market value of common equity at quarter-end (in millions of dollars).
BETA	Systematic market risk, as reported by *the Center for Research in Security Prices* (CRSP)

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