Predicting Stock Market Returns with Aggregate Discretionary Accruals*

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Predicting Stock Market Returns with Aggregate Discretionary Accruals

Abstract

We find that the positive relation between aggregate accruals and one-year-ahead market returns documented in Hirshleifer, Hou and Teoh [2009] is driven by discretionary accruals but not normal accruals. The return forecasting power of aggregate discretionary accruals is robust to choices of sample periods, return measurements, estimation methods, business condition and risk premium proxies, and accrual models used to isolate discretionary accruals. Our extensive analysis shows that aggregate discretionary accruals, in sharp contrast to aggregate normal accruals, contain little information about overall business conditions or aggregate cash flows and display little co-movement with ICAPM-motivated risk premium proxies. Our findings imply that aggregate discretionary accruals likely reflect aggregate fluctuations in earnings management, thereby favoring the behavioral explanation that managers time aggregate equity markets to report earnings.

JEL Classification: G1, M4

Keywords: aggregate discretionary accruals, return predictive regressions, ICAPM-motivated risk premium proxies, managerial market timing
1 Introduction

Numerous studies document the time-varying nature of aggregate stock returns. Against the backdrop of return predictability, Hirshleifer, Hou and Teoh [2009] document that operating accruals at the aggregate level positively predict aggregate stock returns and that innovations in aggregate accruals are negatively correlated with contemporaneous market returns. Their analysis suggests that either changes in accruals contain information about changes in discount rates or that firms manage earnings in response to market-undervaluation, i.e., “lean against wind” in earnings management.

In this study we examine the market return predicability with aggregate discretionary accruals. Our motivations for this inquiry are two fold. First, at the disaggregate level, Teoh, et al. [1998] and Xie [2001] have shown that the return forecasting power of accruals is mainly due to discretionary accruals. We test whether this discretionary accrual-return relation extends to the aggregate level. Second, because the literature typically uses discretionary accruals as a measure of earnings management, examination of the relation between aggregate discretionary accruals and aggregate returns provides a vehicle to distinguish between the two potential explanations advanced by Hirshleifer, Hou and Teoh [2009].

Our study consists of several parts. We first provide robust evidence that the aggregate accrual-return relation documented by Hirshleifer, Hou and Teoh [2009] derives mainly from the discretionary component of accruals. We decompose operating accruals into normal accruals, which reflect business conditions, and discretionary accruals, which most likely characterize managerial earnings management. When we run a horse race between aggregate discretionary accruals and aggregate normal accruals, we find that the former overwhelmingly dominates the latter in their abilities to predict future aggregate stock returns. Moreover, innovations in aggregate discretionary accruals are contemporaneously and negatively correlated with aggregate returns, but innovations in aggregate normal accruals are not related with aggregate returns either contemporaneously or intertemporally. These findings are robust to controlling for various commonly used return predictors such as book-to-market, dividend yields, term premiums, default premiums, short-term interest rates, consumption-wealth ratio, and investment plan. The results also survive a number of robustness checks. Estimating the aggregate-level accrual-return relation using either Amihud...
and Hurvich's [2004] reduced-bias estimator or a Bayesian approach, annualizing market returns over different time windows, and examining this relation across various subperiods all yield similar results.

We then assess what accounts for the positive predictive relation between aggregate discretionary accruals and aggregate returns. Our analysis is subject to a notable caveat. Because any measures of earnings management are unavoidably subject to a “bad model” problem — that is, the accrual decomposition models may classify accrual components other than earnings management into discretionary accruals — aggregate discretionary accruals may not necessarily reflect aggregate fluctuations in earnings management. Our analysis hence falls short of providing direct evidence that firms manage earnings in response to market undervaluation. Instead, we take an alternative approach by conducting a battery of tests of risk-based explanations. We provide strong evidence that these risk-based stories lack empirical support, thereby paving the way for a behavioral explanation. As Hirshleifer, Hou and Teoh (2009) conclude that the investors’ earnings-fixation hypothesis, which has been used by Sloan (1996) to account for the cross-sectional accrual-return relation, is not a valid explanation for the aggregate accrual-return relation, our analysis points to the hypothesis of “lean-against-wind” in earnings management.

We begin by assessing the validity of our accrual decomposition model. To address the potential bad model problem, we apply various accrual models available in the literature to calculate discretionary accruals. These models, building on the Jones' [1991] model and controlling for additional variables such as past, present, and/or future cash flows, firm performance, and rising conservatism in financial reporting, arguably produce more reliable measures of earnings management. We find that the resulting aggregate discretionary accruals retain economically and statistically significant power to forecast future market returns but the aggregate normal accruals continue to lack such power.

Despite these efforts, we are aware that our accrual model might still misclassify certain information on business cycles and business conditions into discretionary accruals, thereby rendering aggregate discretionary accruals the power to forecast market returns. We thus examine relations among aggregate discretionary accruals, aggregate normal accruals, and business conditions. If this concern is valid, we expect aggregate discretionary accruals to be somewhat correlated with macroeconomic variables characterizing business condition fluctuations. Contradicting this
explanation, we find that aggregate discretionary accruals do not have any power in predicting future macroeconomic activity, nor do their innovations have a contemporaneous correlation with innovations in macroeconomic variables. In contrast, aggregate normal accruals correlate both intertemporally and contemporaneously with gross domestic product growth rates.

As Campbell and Shiller [1988] and Campbell [1991] show, changes in stock price are caused by either changes in discount rates, i.e., discount-rate news, or changes in expected future cash flows, i.e., cash-flow news, or both. Therefore, another plausible risk-based explanation is that aggregate discretionary accruals contain information about future cash flows above and beyond the control variables used in our analysis. We study the relations between aggregate discretionary accruals and the two news series. We report that aggregate discretionary accruals are significantly related to the discount-rate news but not to the cash-flow news. Moreover, we find only very weak evidence, if any, that aggregate discretionary accruals have an intertemporal relation with future earnings or future cash flows.

Given the finding that aggregate discretionary accruals are significantly related to discount-rate news, one might further concern that aggregate discretionary accruals may contain information about discounts rates above and beyond control variables used in our analysis. In particular, Guo and Jiang [2009] argue that aggregate accruals forecast market returns because they co-move with the conditional equity premium that is represented by market variance and CAPM-based average idiosyncratic variance. To address this concern, we use a set of risk premium proxies motivated by Merton’s [1973] intertemporal capital asset pricing model (ICAPM), namely, Campbell and Vuolteenaho’s [2004] discount-rate news and cash-flow news, and the two variance measures used in Guo and Jiang [2009]. We find that aggregate discretionary accruals still have the power beyond that of these risk premium proxies to strongly and significantly forecast aggregate returns.

In a further analysis, we examine the contemporaneous co-movement between firm-level discretionary accruals versus normal accruals and the aforementioned ICAPM-motivated risk premium proxies, and test whether the discretionary accruals unrelated to the co-movement exhibit the power to forecast returns at the aggregate level. We find that firm-level discretionary accruals demonstrate little co-movement with the four risk premium proxies but firm-level normal accruals do. We also find that the components of firm-level discretionary accruals that do not co-move with these risk premium proxies retain return forecasting power at the aggregate level. However, the
components of firm-level discretionary accruals that co-move with the risk premium proxies have almost no return forecasting power at the aggregate level. This evidence corroborates our early inference that aggregate normal accruals reflect business conditions and aggregate discretionary accruals appear not.

Taking all the evidence together, we conclude that aggregate discretionary accruals do not have or contain little information about business conditions or future cash flows and display little co-movement with the ICAPM-motivated risk premium proxies. Although our analysis does not rule out a co-movement of aggregate discretionary accruals with discount rates, to the extent that the risk-based explanations receive little empirical support, a behavioral explanation begins to emerge.

In a further support of behavioral explanations, we analyze the relation between aggregate discretionary accruals and aggregate stock returns in cross-section. If the relation reflects a risk-based explanation, firm-level discretionary accruals and hence aggregate discretionary accruals will capture certain information that is systematically related to business cycles and macroeconomic conditions. Therefore, we will be able to observe prevalent return forecasting power of discretionary accruals across boards. However, cross-sectional examinations of the relations between discretionary accruals and returns shows evidence to the contrary. The return forecasting power of aggregate discretionary accruals is limited to firms with certain characteristics, namely large firms and/or growth firms, and to certain sectors, which contradicts a risk-based explanation. Given Hirshleifer, Hou and Teoh’s (2009) study, we thus narrow our search down to the hypothesis of “lean-against-the-wind” in earnings management. That is, managers time aggregate markets to manage earnings — when the aggregate equity market’s valuation falls, managers report improved earnings by adjusting up current-period accruals, discretionary accruals in particular, and vice versa.

We discuss several plausible incentives for managers to conduct this kind of earnings management. Given the mix of accounting earnings and stock returns as determinants of managerial compensations, managers have incentives to manage earnings to shield themselves from market shocks. Such an incentive for earnings management is likely to be strong when the market is perceived to be weak. Also, investors and financial analysts widely use accounting information to analyze the firms they follow and value their stocks. This may create an incentive for managers to manage earnings in order to avoid adverse effects of reported losses or earnings declines, and to influence the short-term stock price performance. When a negative shock hits the stock market
and causes a gap between firm performance and analysts’ or investors’ expectations, the managerial incentives to manage earnings are likely to be high. It is worth noting that earnings management is potentially costly to firms and managers. Increased worries over potential litigations and reputation damage due to mis-reporting can place constraints on the exercise of managerial opportunism — firm managers thus might choose to time the aggregate equity market rather than their own stock performance to manage earnings.\footnote{Nevertheless, why firms are more prone to timing the aggregate market than their own firm-specific undervaluation is an important and open area for future research. A related research question is what types of firms are more prone to doing so. In Section 5, we provide some preliminary evidence that bellwether firms (i.e., large firms in our context) are more likely to time the aggregate market.}

Finally, we offer an analysis toward reconciling the positive accrual-return relation at the aggregate level with the negative accrual-return relation at the disaggregate level. By regressing each firm’s annual stock returns against its one-period-lagged discretionary accruals and/or one-period-lagged aggregate discretionary accruals, we find that the average predictive coefficient estimates on firm-level discretionary accruals and the average predictive coefficient estimates on aggregate discretionary accruals are significant but of opposite signs, consistent with the evidence when the two accrual-return relations are examined separately. This result suggests that the two distinct accrual-return relations are driven by different economic rationales. Notably, the power of aggregate discretionary accruals is much stronger than that of the firm-level discretionary accruals in predicting firm-level returns. Moreover, there is considerable cross-sectional heterogeneity. The negative predictive coefficients capturing the disaggregate-level accrual-return relation are significant only in the two smallest size quintiles. In contrast, aggregate discretionary accruals remain as a robust and positive predictor of firm-level returns in all five quintiles, and their power to forecast firm-level returns increases monotonically from the smallest quintile to the largest quintile. A potential explanation is that bellwether firms are more prone to timing the aggregate market because their managers likely bear higher risks when managing earnings in response to fluctuations in their own stock prices.

Our paper contributes to the accounting and finance literatures in several ways. First, this study deepens our understanding of the accrual-return relation at both the aggregate and disaggregate levels. We report robust evidence that the aggregate-level accrual-return relation identified by Hirshleifer, Hou and Teoh \citeyear{HirshleiferHT2009} is mainly driven by aggregate discretionary accruals. Our extensive
analysis to account for this relation provides evidence in favor of a behavioral explanation. Second, our study contributes to the growing literature on opportunistic managerial behavior. On top of managerial decisions such as equity and debt issues, dividend payouts, and corporate investments (e.g., Baker and Wurgler [2000], Lamont [2000], and Baker et al. [2003]), we find that earnings management is another decision managers are prone to timing the market to make. Third, our paper provides a new perspective to the empirical asset pricing literature via examining the relations among cash flows, discount rates, and stock returns. Although cash-flow news and discount-rate news are known to be important sources of stock return variations, the effects of aggregate earnings or aggregate cash flows on aggregate stock returns remain inconclusive (e.g., Fama [1990], Schwert [1990], Kothari and Shanken [1992], Kothari, Lewellen, and Warner [2006]). We show that one important component of aggregate earnings, namely aggregate discretionary accruals, relates to aggregate stock returns both contemporaneously and intertemporally.

The remainder of the paper is structured as follows. Section 2 summarizes data, discusses our empirical methods, and conducts a Monte Carlo analysis to cope with econometric issues associated with a typical predictive regression. In Section 3, we run a horse race between aggregate normal accruals and aggregate discretionary accruals to evaluate their respective return forecasting power. In Section 4 we assess potential risk-based explanations for the relation between aggregate discretionary accruals and market returns, and we find that these explanations lack empirical support. In Section 5 we explore a behavioral explanation for the aggregate-level accrual-return relation. Section 6 concludes.

2 Data and Empirical Methods

2.1 Aggregate Discretionary Accruals Measures

We obtain accounting data and returns data from Standard & Poor’s Compustat database and the Center for Research in Security Prices (CRSP) database. We choose NYSE/AMEX non-financial firms with December fiscal year-ends. (Including NASDAQ firms does not change our results qualitatively.) Because the statement-of-cash-flow data are available only after 1987, we use the
balance-sheet method to calculate operating accruals (Sloan [1996]):

\[
\text{Accruals} = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - Dep,
\]

where \(\Delta CA\) is change in current assets (Compustat item 4), \(\Delta Cash\) is change in cash/cash equivalents (Compustat item 1), \(\Delta CL\) is change in current liabilities (Compustat item 5), \(\Delta STD\) equals change in debt included in current liabilities (Compustat item 34), \(\Delta TP\) is change in income taxes payable (Compustat item 71), and \(Dep\) is depreciation and amortization expense (Compustat item 14). We scale a firm’s accruals by its average total assets (\(TA\), Compustat item 6) from the beginning to the end of a fiscal year. We delete firms with accrual values ranked below the 0.5 percentile or above the 99.5 percentile. We then weight each firm’s accruals by its beginning-of-year market capitalization to calculate the value-weighted aggregate accruals (\(AC\)).

We use the time-series Jones’ [1991] model to compute firm-level discretionary accruals.\(^2\) The model is specified as follows:

\[
\frac{\text{Accruals}_{it/TA_{it}}}{TA_{it}} = a_1/TA_{it} + a_2\Delta Rev_{it}/TA_{it} + a_3PPE_{it}/TA_{it} + e_{it},
\]

where \(\Delta Rev_{it}\) is the change in revenues in year \(t\) (Compustat item 12) and \(PPE_{it}\) is gross property, plant, and equipment in year \(t\) (Compustat item 7). We estimate Equation (2) firm by firm in the full sample period, and we require a firm to have a minimum of ten observations.\(^3\) We compute normal accruals and discretionary accruals respectively as the predicted values and the residuals of Equation (2). Similar to aggregate accruals, we compute the value-weighted aggregate normal accruals (\(NAC\)) and the value-weighted aggregate discretionary accruals (\(DAC\)). Due to the availability of accounting information sufficient to calculate accruals, normal accruals, and discretionary accruals, our sample covers the period from 1965 to 2004.

\(^2\)Our empirical results are robust to the selection of accrual decomposition models. In earlier versions of this paper, we have used the cross-sectional Jones’ [1991] model and the modified Jones’ model to estimate discretionary accruals. The results are similar and are available upon request. Moreover, as we will show in Section 4.1, we apply a number of accrual decomposition models commonly used in the literature (e.g., Dechow and Dichev [2002], McNichols [2002], and Ball and Shivakumar [2006]), and the results are again similar.

\(^3\)This restriction introduces a survivor bias into the study. As a robustness check, we use cross-sectional versions of the accrual decomposition models as mentioned in Footnote 2, which are not subject to this restriction. The results are qualitatively similar, suggesting that the survivor bias is not severe enough to compromise our inference.
2.2 Aggregate Market Returns and Forecasting Variables

We measure aggregate stock returns ($EXC_{VW}$) by CRSP’s calendar-year returns on the value-weighted NYSE/AMEX index in excess of the one-month Treasury bill rate. For robustness, we also use the returns on the NYSE/AMEX index annualized over other twelve-month periods, e.g., February to January, March to February, and May to April.

We use a set of variables that are known to have power in forecasting aggregate returns: dividend yield (Campbell and Shiller [1988], Fama and French [1988]), term spread (Keim and Stambaugh [1986], Fama and French [1989]), book-to-market ratio (Kothari and Shanken [1997], Pontiff and Schall [1998]), default premium (Keim and Stambaugh [1986], Fama and French [1989]), short-term interest rate and its stochastically-detrended variant (Fama and Schwert [1977], Campbell [1987]), consumption-wealth ratio (Lettau and Ludvigson [2001]), aggregate corporate investment plan (Lamont [2000]), realized market variance and CAPM-based average idiosyncratic variance (Guo and Savickas [2008]). These variables are arguably able to capture changes in business conditions and investment opportunities, and thus serve as proxies for time-varying equity premiums. We calculate the dividend yield ($DP$) as the dividends on the CRSP’s value-weighted NYSE/AMEX index accumulated over the prior year (current month included) divided by the current month’s index level. The term premium ($TERM$) is the yield spread of a ten-year Treasury bond over a one-month Treasury bill. The default premium ($DEF$) is the yield spread of corporate bonds with Moody’s Baa and Aaa ratings. The short rate ($TB1M$) is the yield of a one-month Treasury bill, and we also calculate the stochastically-detrended short rate ($SHORT$) by subtracting from the year-end short rate the average short rate over the year prior to the current month (current month excluded). We obtain the consumption-wealth ratio ($CAY$) and aggregate corporate investment plan ($GHAT$) from Martin Lettau’s and Owen Lamont’s websites, respectively. Like Guo and Savickas [2008], we construct the average idiosyncratic variance ($IV$) as the value-weighted average of firm-level standard deviations in CAPM-based idiosyncratic shocks across 500 largest stocks and we estimate the CAPM using daily stock returns in a given year. We calculate the realized market variance ($MV$) as the standard deviation of daily market excess returns in that year. Alternatively, defining $IV$ and $MV$ as the sum of squared daily CAPM-based

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4We include the two variance measures in the set of control variables to distinguish our results from those reported in Guo and Jiang [2009]. Please see Section 4.4 for our detailed analysis.
shocks and daily market excess returns in a given year yields qualitatively similar results.

Campbell and Shiller [1988] and Campbell [1991], by applying a loglinear approximate
decomposition to a simple present-value formula, show that a change in stock prices is due either
to a change in expected cash flows or a change in discount rates or both. Because the two
news series directly measure the temporal changes in market returns, we follow Campbell and
Vuolteenaho [2004] to construct discount-rate news \((NDR)\) and cash-flow news \((NCF)\) and use
them as another set of proxies for time-varying risk premiums.

Table 1 summarizes the variables used in our study. Their summary statistics are in line with
those reported in prior studies. Notably, these variables display distinctly different persistence
levels. The market return has close to zero and slightly negative autocorrelation. For the three
aggregate accrual measures, \(AC\), \(NAC\), and \(DAC\), their first-order autocorrelations are 0.201,
0.673, and 0.026, respectively. For the control variables, \(BTM\) and \(DP\) have high persistence
with autocorrelation coefficients exceeding 0.8; \(TERM\), \(DEF\), \(CAY\), \(IV\) and \(MV\) have modest
persistence with autocorrelation coefficients ranging from 0.4 to 0.6; \(SHORT\) and \(GHAT\) have very
low persistence with close to zero autocorrelation. For the two news variables, their autocorrelation
coefficients are respectively almost zero for \(NDR\) and 0.217 for \(NCF\). Figure 1 plots the time series
of the aggregate returns and the three aggregate accrual measures.

As documented in the return predictability literature, some of the return predictors used in
our analysis are quite persistent and close to being unit-root, \(BTM\) and \(DP\) in particular, thereby
causing several statistical issues for return predictive regressions (e.g., Nelson and Kim [1993],
Stambaugh [1999]). However, for the key predictors of our interest, \(DAC\) and \(NAC\), the unit-root
possibility is not a serious concern. In an unreported analysis we reject unit-root possibility for
\(DAC\) easily and \(NAC\) with borderline statistics. Also in Section 2.4 we conduct a Monte Carlo
exercise to address one related statistical issue of return predictive regressions.

2.3 Empirical Methods

We primarily use the ordinary least squares (OLS) estimator in our analysis. We apply the
generalized method of moments (GMM) estimator to cases in which we specify a system of equations
to examine the joint dynamics of variables of interest. Whenever applicable, we calculate and report Newey-West heteroscedasticity and autocorrelation consistent (HAC) standard errors for parameter estimates. Following Newey and West [1987, 1994], we set the bandwidth of the Bartlett kernel, i.e., the number of lags used in corrections, to the integer part of $4 \times \left( \frac{T}{100} \right)^{\frac{3}{9}}$, where $T$ is the number of observations used in regressions. Hence, the number of lags is set to three for most of our regressions as $T$ is equal to 40. We also experiment with regressions using different numbers of lags such as one, two, three, four, etc., and we compare the regression statistics, namely the Akaike information criterion $AIC$, of each regression. We find that regressions with 40 observations have the lowest $AIC$ value when the number of lags is set to three.

The return predictability literature has documented various econometric issues associated with predictive regressions (e.g., Nelson and Kim [1993], Stambaugh [1999]). To address those issues, in addition to the OLS estimator, we also use two other approaches to estimate the predictive regressions in our study: one is Amihud and Hurvich’s [2004] reduced-bias estimator, and the other is a Bayesian analysis. The essence of the Amihud and Hurvich method is to employ an augmented regression, which orthogonalizes the error series of the dependent variable (i.e., market returns) against the error series of the autoregressive regressors (i.e., return predictors), and to add a proxy for the error of each return predictor in the return predictability model. Amihud and Hurvich’s [2004] simulation analyses show that the reduced-bias estimates behave well in both the bias reduction and the standard error adjustment. In the case of the Bayesian analysis, we use the Markov Chain Monte Carlo (MCMC) method with Gibbs sampling to generate many random draws of data. We then examine the posterior means and standard deviations of estimated coefficients of interest. For brevity the results of the Bayesian analysis are available upon request.

### 2.4 A Monte-Carlo Study

Stambaugh (1999) shows that there is a bias in the estimated predictive coefficient in a common empirical framework to study stock return predictability with scaled-price variables. The bias arises because innovations in these scaled-price variables are contemporaneously correlated (negatively oftentimes) with stock returns. This bias is more pronounced when the contemporaneous correlation

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5For consistency in expositions, we could stick to the OLS estimator throughout the paper, using the innovations in variables of interest in regressions. However, the GMM estimation is more efficient than the OLS method in controlling for estimation errors from the first-step calculation of those innovation terms.
between the innovation terms is strong, the persistence of the predictors is high, or the sample size is small.

In our study, aggregate accruals measures are not scaled-price variables, and the persistence of the three aggregate accrual measures is at most mild relative to other popular scaled-price variables like dividend yield and book-to-market ratio. The bias thus is less of a concern. However, we have a small sample size. We follow Baker et al. [2006] to conduct a Monte Carlo analysis under the null hypothesis of zero return predictability.

We first simulate 50,000 series of aggregate stock returns, $EXC_{VW}$, based on the following system of equations:

$$EXC_{VW_t} = a + u_t, \quad \text{with} \quad u_t \sim i.i.d.(0, \sigma_u^2), \quad \text{and}$$

$$DAC_t = c + d \times DAC_{t-1} + v_t, \quad \text{with} \quad v_t \sim i.i.d.(0, \sigma_v^2) \quad \text{and} \quad Corr(u, v) = \rho_{u,v}. \quad (3)$$

Here, $EXC_{VW}$ and $DAC$ are the value-weighted stock market return and the value-weighted aggregate discretionary accruals; the parameters $a$ and $\sigma_u$ are set according to the empirical distribution of $EXC_{VW}$, the parameters $c$, $d$, and $\sigma_v$ are determined according to the empirical values of $DAC$, the correlation coefficient $\rho_{u,v}$ is set to its empirical value, and the sample size is $T$. In our analysis, $a=5.864$, $\sigma_u=16.550$, $c=-8.477e-3$, $d=2.859e-2$, $\sigma_v=0.838$, $\rho_{u,v}=-0.397$, and $T=40$. We then regress each series of the simulated returns against $DAC$, and we use the OLS estimates of the predictive coefficient $b$ from each of the 50,000 samples. We report the average estimated coefficient and compare it with the actual estimation result from regressing $EXC_{VW}$ against $DAC$.

Figure 2 presents the results of the Monte Carlo analysis. Panel A reports the average estimated predictive coefficient from the 50,000 simulations versus the actual coefficient estimate from regressing $EXC_{VW}$ against the one-period-lagged $DAC$. Under the null hypothesis of zero return predictability ($b=0$), the average estimated predictive coefficient from the 50,000 simulations is 0.158. In contrast, as reported for Model (2) in Panel A of Table 2, the actual OLS estimate of the predictive coefficient is 6.341 with a Newey-West HAC standard error of 1.798. Thus, as a point estimate, the bias accounts for only 2.49% of discretionary aggregate accruals’ actual coefficient estimate. The one-sided $p$-value shows that there is a less than 0.01% probability that the bias
would lead to a coefficient as large as the actual one.

To better illustrate the distribution of the simulated estimates of the predictive coefficient, we plot its histogram in Panel B of Figure 2. The actual estimate of the predictive coefficient falls in the far right tail of the simulated distribution, leading to an outright rejection of the hypothesis that the OLS estimation results are severely affected by this bias.

3 Return Predictability: Aggregate Discretionary Accruals vs. Aggregate Normal Accruals

In this section, we run a horse race between aggregate discretionary accruals and aggregate normal accruals, and we examine which one plays a more important role in causing the power of aggregate accruals to predict market returns, as documented in Hirshleifer, Hou and Teoh [2009].

3.1 Predictive Relation

We first examine the intertemporal relation between the two aggregate accrual measures and the aggregate returns. We specify the model as follows:

\[ R_t = a + bX_{t-1} + u_t, \]  

(4)

where \( R \) is the excess market return (\( EXC_{VW} \)), and \( X \) represents a set of predictors including the lagged excess market return, various aggregate accrual measures (\( AC \), \( NAC \), or \( DAC \)), and other well-known predictors such as aggregate book-to-market ratio (\( BTM \)), dividend yield (\( DP \)), term premium (\( TERM \)), default premium (\( DEF \)), stochastically-detrended one-month T-bill yield (\( SHORT \)), consumption-wealth ratio (\( CAY \)), and investment plan (\( GHAT \)).

3.1.1 OLS Estimates with Newey-West HAC Standard Errors

We first estimate Equation (4) using OLS, and we calculate the Newey-West HAC standard errors. Panel A of Table 2 reports the results.

We begin by using aggregate accruals (\( AC \)) as the sole return predictor (Model (0)). We find that \( AC \) is positively related with one-year-ahead aggregate stock returns, corroborating the finding
of Hirshleifer, Hou and Teoh [2009]. Our focus is however on the forecasting power of aggregate discretionary accruals (DAC) and aggregate normal accruals (NAC). Several results stand out. First, aggregate normal accruals (NAC) have no power to predict future market returns at all (Model (1)). Second, as shown in Model (2), aggregate discretionary accruals (DAC) exhibit significant power in forecasting one-year-ahead stock market returns. The relevant predictive coefficient estimate is 6.341 and is significant at the 1% level. The regression’s adjusted $R^2$ is as high as 8.9%. The economic magnitude of this predictive relation is non-trivial too. A one-standard-deviation increase in DAC, which is 0.887%, is associated with a 5.624 percentage point increase in the next year’s market return. Third, when we include both aggregate normal accruals and aggregate discretionary accruals in the predictive regression (Model (3)), aggregate discretionary accruals retain its significant power in forecasting returns, but the estimated coefficient on aggregate normal accruals is still nonsignificant.

We extend our analysis by including in regressions control variables that are known to predict the equity premium. When we control for the return predictors such as lagged market returns, dividend yield, term premium, default premium, stochastically-detrended short rate, aggregate book-to-market ratio, and consumption-wealth ratio in the predictive regressions (Models (4) and (5)), DAC remains as a significant return predictor. In both models, the coefficient estimates on DAC are positive and significant at the 1% level, but the coefficient estimates on NAC are nonsignificant. After we add GHAT in the regression (Model (6)), which reduces the sample period to 1965-1994, the estimated coefficient on DAC is still statistically significant.

### 3.1.2 Reduced-Bias Estimates

Return predictive regressions are inherently associated with various econometric issues. Our Monte Carlo analysis in Section 2.4 has shown that the Stambaugh [1999] bias is not severe in our study. Here, we follow Amihud and Hurvich [2004] to conduct reduced-bias estimations. We employ an augmented regression, which essentially orthogonalizes error series of market returns against error series of the return predictors, and adds a proxy for the error of each return predictor in the original return predictive regression. As in Amihud and Hurvich [2004], we calculate the bias-corrected error series of each return predictor, assuming that each return predictor follows an AR(1) process. Panel B of Table 2, sharing a similar structure to Panel A, reports the reduced-bias estimates.
Similar to the OLS estimation results, aggregate normal accruals exhibit no power to predict future market returns at all, but aggregate discretionary accruals demonstrate significant power in forecasting one-year-ahead stock market returns. Further, the aggregate discretionary accrual measure retains its forecasting power in the presence of other return predictors.

Notably, when we do not control for business-condition variables (i.e., Models (0)-(3)), the reduced-bias estimates are quite similar to the OLS estimates. When we control for those variables, (i.e., Models (4)-(6)), some of the reduced-bias estimates differ markedly from their OLS counterparts. Our explanation is that the reduced-bias estimator adds the proxies for errors in return predictors to the predictive regression, thereby doubling the number of regressors. With a small sample like ours, increasing the number of regressors appears to compromise the performance of the reduced-bias estimator. Despite the difference, the key results of the reduced-bias estimation are similar to those of the OLS regressions.\footnote{In an earlier version of the paper, we also use a Bayesian approach, which employs the MCMC method and Gibbs sampling to estimate the predictive regression as specified in Equation (4), assuming the error term \( u_t \) to follow an AR(1) process:
\[
    u_t = \rho u_{t-1} + v_t \quad \text{with} \quad v_t \sim N(0, \sigma^2).
\]

We use non-informative priors for \( b, \rho \) and \( \sigma^2 \). We generate 10,000 random draws and drop the first 2,000 draws. We then compute posterior means of the coefficients of interest, \( b \), and standard errors. The Bayesian analysis yields similar results to the OLS regression and the reduced-bias estimation. The details of the Bayesian analysis and the results are available upon request.}

3.1.3 Robustness Checks

We conduct several robustness checks. First, because financial statements are usually released one to three months after the end of a fiscal year, our use of the December year-end accrual measures to predict calendar-year returns might cause a spurious relation. To address this concern, we use returns on the NYSE/AMEX index annualized over different twelve-month periods, e.g., February to January, March to February, April to March, and May to April. As shown in Panel A of Table 3, the power of aggregate discretionary accruals to predict market returns stands regardless of how the market returns are annualized. Second, because Figure 1 indicates there might exist outliers in the pre-1975 period, we study the predictive relation between aggregate discretionary accruals and aggregate stock returns in various subperiods: 1975-2004, 1985-2004, and 1965-1984. As shown in Panel B of Table 3, the predictive relation documented in our above analysis is quite stable across these subperiods. Note that 1965-1984 and 1985-2004 are two non-overlapping subperiods and that
the return forecasting power of aggregate discretionary accruals is stronger in the latter subperiod.
All in all, our subperiod analysis indicates that our findings are not primarily driven by outliers.

We also undertake other robustness analyses. For example, besides the time-series Jones’ [1991]
model, we apply other accrual decomposition models available in the literature, and we defer a
detailed discussion to Section 4.1. We extend our analysis by including the NASDAQ firms with
sufficient accounting information. We also use returns on the NYSE/AMEX/NASDAQ index as
the dependent variable. All these analyses yield qualitatively similar results.

3.2 Contemporaneous Relations

We examine the contemporaneous relations between the two aggregate accrual measures and the
aggregate market returns. We specify the following system of equations:

\[ R_t = \alpha + \beta v_t + \epsilon_t, \]  \hspace{1cm} (5)
\[ F_t = \theta + \gamma F_{t-1} + v_t, \]  \hspace{1cm} (6)

where \( R \) stands for the value-weighted market return (\textit{EXC.VW}) and \( F \) represents the following
set of variables: aggregate accruals measures (\textit{NAC}, and \textit{DAC}), term premium (\textit{TERM}), default
premium (\textit{DEF}), short-term interest rate (\textit{TB1M}), and consumption-wealth ratio (\textit{CAY}). The
variable \( v \) represents innovations in \( F \). Note that we do not observe these innovations and can
only estimate them from Equation (6). To avoid introducing estimation errors into estimation
of Equation (5), we estimate Equations (5) and (6) simultaneously with GMM. We calculate the
GMM Newey-West HAC standard errors for the parameter estimates.

Table 4 reports the estimation results. We first conduct the analysis without including
innovations in business condition variables (Models (1)-(3)). Innovations in aggregate normal
accruals and aggregate returns appear to be unrelated contemporaneously: Model (1) shows that
the coefficient on \( NAC \) is nonsignificant and negative. In contrast, as Model (2) shows, innovations
in aggregate discretionary accruals are significantly and negatively correlated with current market
returns. When we include innovations in both \( NAC \) and \( DAC \) (Model (3)), the coefficient estimate
on \( NAC \) remains nonsignificant and the coefficient estimate on \( DAC \) is still significantly negative.
We then conduct the multivariate analysis by adding innovations in business-condition variables in
the system (Models (4)-(5)). In both models, the coefficient estimates on DAC remain negative and significant. Interestingly, the coefficient estimates on NAC become significant and negative (only) in the presence of innovations in business-condition variables.

4 Accounting for Return Forecasting Power of Aggregate Discretionary Accruals

In this section we assess what accounts for the positive predictive relation between aggregate discretionary accruals and aggregate returns. We focus our analysis on distinguishing risk-based explanations from behavioral explanations, especially the two representative ones proposed in Hirshleifer, Hou and Teoh [2009] — either changes in aggregate accruals contain information about changes in discount rates (a risk-based explanation) or firms manage earnings in response to market-undervaluation (a behavioral explanation). We conduct a battery of tests of risk-based explanations, which takes us to behavioral explanations, especially the “lean-against-wind” in earnings management explanation.

4.1 The Validity of Accrual Decomposition Models

One potential explanation for the power of aggregate discretionary accruals in forecasting market returns is that the Jones’ [1991] model fails to isolate discretionary accruals; and that even if the model does it perfectly, discretionary accruals, i.e., accruals not driven by revenues and depreciation on fixed assets, may represent managerial operating adjustments to anticipated changes in discount rates, which are ignored in the Jones model and have nothing to do with earnings management. As a first step to assess this explanation, we use other accrual decomposition models, which augment the Jones’ [1991] model with additional variables, so that we are better able to isolate discretionary accruals and control for managers’ rational operating adjustments.

Following Dechow and Dichev [2002] and McNichols [2002], we add firm-level cash flows to the Jones’ [1991] model to remove the impact of cash flows on discretionary accruals estimation. We have three model variants and label them “DD1”, “DD1-HC”, and “DD2”, respectively. Model “DD1” extends the Jones model by including one-period lagged and current cash flows; Model

7We thank an anonymous referee and the editor for suggesting this potential explanation.
“DD1-HC” is primarily Model “DD1”, but deletes firms experiencing extreme events/performance as discussed in Hribar and Collins [2002]; Model “DD2” further extends Model “DD1” by including one-period-lead cash flows. We extend the Jones model by including two performance measures, ROA, and squared ROA, to control for the effects of firm performance on discretionary accruals estimation, and we label this model “DD3”. Also, we follow Ball and Shivakumar (2006) to incorporate accounting conservatism in accrual decompositions. We extend the Jones model by adding three additional variables: stock return less market return (the relative return), a dummy taking the value of one if the relative return is negative and zero otherwise, and the interaction of the relative return to the dummy; we label this model “BS”.

We estimate all these accrual models in time series and require a firm to have at least ten observations over the sample period. We denote the fitted values and the residuals as normal accruals and discretionary accruals, respectively. We then use a value-weighting method to obtain aggregate normal accruals and aggregate discretionary accruals. To the extent that managerial operating adjustments affect a firm’s cash flows or performance or financial reporting, the aggregate discretionary accruals obtained from these extended Jones models contain less or no components that potentially capture managerial rational operating adjustments, and hence better represent managerial earnings management.

To have a glimpse into the quality of these accrual models, we report in Panel A of Table 5 the cross-sectional distributions of adjusted $R^2$s for these models. For the baseline Jones’ [1991] model, the adjusted $R^2$s over 2,450 firms have a mean of 0.479 and a median of 0.502. The adjusted $R^2$s vary considerably in cross-section, ranging from -0.393 to 0.998. The majority of firms have moderate adjusted $R^2$s with the first quartile equal to 0.253 and the third quartile equal to 0.732.

We observe similar cross-sectional distributions of adjusted $R^2$s for the augmented models as well. For Model “DD1”, the adjusted $R^2$s over 2,436 firms have a mean of 0.686 and a median of 0.770; the average adjusted $R^2$s are even higher for Model “DD1-HC” and Model “DD2”, both exceeding 0.70. For Model “DD3”, the adjusted $R^2$s over 2,450 firms have a mean of 0.516 and a median of 0.562. For Model “BS”, the adjusted $R^2$s over 2,429 firms average at 0.486. These accrual models appear to perform reasonably well.

Panel B of Table 5 reports the results of predicting aggregate returns with value-weighted aggregate normal accruals and/or value-weighted aggregate discretionary accruals obtained from
these extended Jones’ [1991] models. The results are similar to those reported in Table 2, that is, aggregate discretionary accruals display significant power in forecasting future equity premiums but aggregate normal accruals have no power. In particular, relative to aggregate discretionary accruals obtained from the baseline Jones’ [1991] model, aggregate discretionary accruals from Model “DD1-HC”, Model “DD2”, and Model “DD3” have about the same power in predicting market returns, and aggregate discretionary accruals from either Model “DD1” or Model “BS” exhibit about two times stronger power. This result implies that controlling for the effects of past and current cash flows or accounting conservatism on discretionary accrual estimation strengthens the return forecasting power of aggregate discretionary accruals.

In summary, our analysis indicates that the return forecasting power of aggregate discretionary accruals is robust to use of accrual decomposition models. Thus, the validity of accrual models in estimating discretionary accruals is less of a concern. For ease of exposition we focus on using only the baseline Jones’ [1991] model for accrual decompositions in the ensuing discussions. Moreover, because these extended accrual models more or less control for factors reflecting managerial operating adjustments, the evidence prompts us to lean toward interpreting the resulting discretionary accruals as a measure of earnings management.

4.2 Do Aggregate Discretionary Accruals Reflect Business Conditions?

Despite the use of various accrual models in our above analysis, we acknowledge that our accrual decompositions might still misclassify some information about business conditions into discretionary accruals, thus rendering aggregate discretionary accruals the power to forecast market returns. To address this concern, we examine in this section the relations between the two aggregate accrual measures and business conditions.

We first study the intertemporal relation:

\[ y_t = a + bX_{t-1} + v_t, \]  

(7)

where \( y \) is the dependent variable measuring business conditions. Here, we use the annual U.S. gross domestic product growth rate (\( GDPG \)).\(^8\) The explanatory variable \( X \) is a set of one-period-

\(^8\)Besides the GDP growth rate, we also use other macroeconomic variables such as industrial product growth
lagged predictors including the industrial product growth rate ($IPG$) and the two aggregate accrual measures ($NAC$, $DAC$). Because $IPG$ is a well-documented predictor of future macroeconomic activities, we include it as a control variable in each specification of Equation (7). Data on $GDPG$ and $IPG$ are from the Bureau of Economic Analysis website.

We first estimate Equation (7) using OLS, and report the estimates with the Newey-West HAC standard errors in Panel A of Table 6. There are several interesting findings. First, industrial product growth rate $IPG$ consistently forecasts the GDP growth rate with substantial power, confirming its role as one of the lead indicators of the macroeconomy. Second, aggregate normal accruals ($NAC$) have some power in predicting the GDP growth rate, consistent with the argument that normal accruals reflect business conditions. Third, aggregate discretionary accruals ($DAC$) exhibit no power in predicting future macroeconomic activity. When we include both $NAC$ and $DAC$ in the predictive regression, the coefficient estimate on $NAC$ remains significant at the 1\% level and the coefficient estimate on $DAC$ remains nonsignificant.

For robustness we also apply Amihud and Hurvich’s [2004] reduced-bias estimator to Equation (7) and report the estimation results in Panel B of Table 6. Similar to the results in Panel A, aggregate normal accruals exhibit some power in predicting the GDP growth rate, but aggregate discretionary accruals show no power at all.

We next examine the contemporaneous relations between the two aggregate accrual measures and the GDP growth rates with the following system of equations:

\[
GDPG_t = \alpha + \beta v_t + \epsilon_t, \tag{8}
\]

\[
F_t = \theta + \gamma F_{t-1} + v_t. \tag{9}
\]

Here, $F$ represents the set of variables including the aggregate accruals measures ($NAC$ and/or $DAC$) and business-condition variables such as term premium, default premium, short-term interest rate, and consumption-wealth ratio, and $v$ represents innovations in the set of variables $F$. We do not observe these innovations and can only estimate them from Equation (9). To avoid the errors-in-variable problem due to estimation of $v$, we estimate Equations (8) and (9) simultaneously rate, term premium, default premium, short-term interest rate, and inflation rate as dependent variables, and find qualitatively similar results. To save space we do not report these results in the paper.
with GMM. To save space, we only report the estimates on the aggregate accrual measures of Equation (8) in Panel C of Table 6. It is clear that innovations in aggregate normal accruals positively and significantly correlate with current GDP growth rates even after we control for the impact of innovations in business-condition variables. In contrast, innovations in aggregate discretionary accruals are uncorrelated with current GDP growth rates.

In summary, we find that aggregate normal accruals are correlated with GDP growth rates both intertemporally and contemporaneously, while aggregate discretionary accruals are not. In an unreported analysis, we find that this result holds when we use other macroeconomic variables such as industrial product growth rate, term premium, default premium, short-term interest rate, and inflation rate as dependent variables. This analysis suggests that aggregate normal accruals contain information about the overall business conditions, but that aggregate discretionary accruals do not. This evidence helps further alleviate the misclassification concern about the estimation of accrual models.

### 4.3 Do Aggregate Discretionary Accruals Contain Information about Future Cash Flows?

Another potential explanation for the return forecasting power of aggregate discretionary accruals is that they contain information about future cash flows above and beyond the control variables used. By applying a loglinear approximate decomposition to a simple present-value formula, Campbell and Shiller [1988] and Campbell [1991] show that a change in stock prices is due either to a change in discount rates or a change in expected future cash flows or both. To better understand the source of differential return forecasting power of aggregate discretionary accruals versus aggregate normal accruals, we examine the intertemporal and contemporaneous relations of the two aggregate accrual measures with the discount-rate news ($NDR$) and the cash-flow news ($NCF$). We follow Campbell and Vuolteenaho [2004] to construct the two news variables.

Panel A of Table 7 reports the results of the intertemporal predictive regressions. Aggregate discretionary accruals exhibit strong power in predicting future discount-rate news: $DAC$ alone predicts 13.5% of variation in future discount-rate news. The coefficient on $DAC$ is significantly negative, implying that a higher $DAC$ is associated with a decrease in discount-rate news and a higher market return in the next year. This finding is consistent with our earlier evidence
that aggregate discretionary accruals positively predict market returns. Also, $DAC$ has much weaker power in predicting future cash-flow news with an adjusted $R^2$ of only 2.5%. Mirroring Campbell’s [1991] finding that discount-rate news dominates cash-flow news in moving aggregate market prices, our result suggests that the return forecasting power of aggregate discretionary accruals derives mainly from their power in predicting future discount-rate news.

Studies of the contemporaneous relations (Panel B of Table 7) show that aggregate discretionary accruals are positively and significantly related to current discount-rate news. The significantly positive relation between $DAC$ and $NDR$ is consistent with our earlier finding of a negative relation between innovations in $DAC$ and current market returns. Interestingly, neither $DAC$ nor $NAC$ is related to current cash-flow news.

Having shown that aggregate discretionary accruals are related to discount-rate news but not cash-flow news, our analysis indicates that aggregate discretionary accruals more likely predict market returns through a discount-rate channel instead of a cash-flow channel. For further evidence, we directly investigate the intertemporal relations among aggregate discretionary accruals, aggregate normal accruals, aggregate cash flows, and aggregate earnings. Table 8 reports the OLS results on the predictive regressions. Due to availability of the cash flow data, the sample period reduces to 1972-2004. As evidenced in Panel A of Table 8, aggregate normal accruals are able to predict a substantial amount of one-year-ahead value-weighted aggregate earnings — the coefficient estimate is significantly positive and the adjusted $R^2$ is as high as 23.2%. Aggregate normal accruals also have weak power in predicting one-year-ahead aggregate cash flows. On the contrary, aggregate discretionary accruals predict neither value-weighted aggregate earnings nor value-weighted aggregate cash flows. Using equal-weighted aggregate earnings and aggregate cash flows as dependent variables yields largely similar results (see Panel B of Table 8).

In sum, the results in Table 8, in conjunction with the findings in Table 7, offer little support to the proposed explanation that aggregate discretionary accruals forecast market returns because they contain information on future earnings or future cash flows. Although there is evidence showing that aggregate discretionary accruals predict market returns through a discount-rate channel, our analysis below argues that such a channel is more likely to be behavioral rather than risk-based.
4.4 Controlling for ICAPM-Motivated Risk Premium Proxies

Another risk-based explanation is that the set of commonly-used control variables in our multivariate analysis are not as powerful as the aggregate discretionary accruals in predicting time-varying equity premiums, so that aggregate discretionary accruals contain information about discount rates above and beyond the control variables used. Building on Guo and Savickas’ [2008] finding that market variance and idiosyncratic variance have superior forecasting power relative to commonly used proxies, Guo and Jiang [2009] suggest that aggregate accruals forecast market returns because they co-move with the conditional equity premium that is represented by the two variance variables.

To address this concern, we use the market variance (MV) and idiosyncratic variance (IV) in Guo and Jiang [2009], together with Campbell and Vuolteenaho’s [2004] discount-rate news (NDR) and cash-flow news (NCF), as proxies for conditional equity premiums. The four proxies are all motivated by Merton’s [1973] Intertemporal capital asset pricing model (ICAPM). Either IV or NCF is arguably related to a risk-averse long-term investor’s demand to hedge against the changing investment opportunities.\(^9\) With these risk premium proxies at hands, we conduct two analyses. We first examine whether aggregate discretionary accruals retain the power to forecast market returns when we control for these risk premium proxies. We then study the contemporaneous co-movement between firm-level discretionary accruals versus normal accruals and this set of risk premium proxies, and we test whether the components of discretionary accruals unrelated to such co-movement exhibit power in forecasting market returns.

4.4.1 Predictive Regressions with Alternative Risk Premium Proxies

Table 9 reports the estimation results of regressing excess market returns against aggregate normal accruals and/or aggregate discretionary accruals, using the four ICAPM-motivated risk premium proxies as control variables. As in Guo and Jiang [2009], we also include a time trend in the predictive regressions to accommodate the statistical property of IV. Use of this trend variable also

\(^9\)The interpretation of IV as a risk premium proxy is still debatable. The literature has mixed evidence on whether or not idiosyncratic variance is related to stock returns in cross-section and/or in time-series. A detailed discussion on the interpretations of IV is beyond the scope of this study. Here, taking at face value Guo and Jiang’s [2009] finding based on their use of MV and IV, we present evidence to defend our interpretation of findings in our earlier draft.
alleviates the concern over a potential time trend in either aggregate normal accruals or aggregate discretionary accruals due to the documented rising conservatism in accounting reporting (Givoly and Hayn [2000]).

We first examine the results when $MV$ and $IV$ are used as the control variables (Models (1)-(6)). Consistent with the literature, we find that the coefficients on $IV$ are all significantly negative and the coefficients on $MV$ are all significantly positive. The trend variable also has a significantly positive loading. Interestingly, the inclusion of $MV$ and $IV$ in the return predictive regressions does not materially change our earlier finding that it is aggregate discretionary accruals but not aggregate normal accruals that have power to forecast future market returns. We then analyze the results when $NDR$ and $NCF$ are used as controls. As shown in Models (7)-(9), both news series lack power in predicting future market return; and again, aggregate discretionary accruals but not aggregate normal accruals demonstrate strong power in forecasting next-period market returns. In Models (10)-(11), we include all of the four risk premium proxies as controls and find similar results: aggregate discretionary accruals retain considerable return forecasting power but aggregate normal accruals do not.

Clearly, although the four alternative risk premium proxies do help predict future equity premiums, aggregate discretionary accruals have return forecasting power that is robust to controlling for such risk premium proxies as market variance, idiosyncratic variance, discount-rate news, and cash-flow news.

4.4.2 Co-movement of Firm-level Discretionary versus Normal Accruals with Risk Premium Proxies

As a further test of whether aggregate discretionary accruals forecast market returns because they co-move with risk premium proxies, we study the contemporaneous co-movement between firm-level discretionary accruals versus firm-level normal accruals and the four ICAPM-motivated risk premium proxies.

For each firm in our sample, we separately regress its discretionary accruals and normal accruals against the current risk premium proxies. We estimate each co-movement regression in time series and require a firm to have at least ten observations over 1965-2004. We gather the fitted values, residuals, and the adjusted $R^2$s for each of the co-movement regressions. The $R^2$ of a co-movement
regression reflects the amount of variation in firm-level discretionary accruals or normal accruals that can be explained by the variation in the fitted values, which are further determined by their co-movement with the risk premium proxies. Thus, a higher $R^2$ indicates a higher level of co-movement.

Table 10, Panel A presents the summary statistics of the adjusted $R^2$ s of the firm-level co-movement regressions across a sample of 2,450 firms. A careful look at these statistics shows that the firm-level discretionary accruals have little co-movement, but firm-level normal accruals do exhibit moderate co-movement. For example, when $IV$ and $MV$ are used as the risk premium proxies in the co-movement regressions of firm-level discretionary accruals, the adjusted $R^2$ s have a mean of -0.017 and a median of -0.040. In contrast, for the co-movement regressions of firm-level normal accruals, the adjusted $R^2$ s have a mean of 0.085 and a median of 0.037. Using $NDR$ and $NCF$ as the risk premium proxies yields similar results. The adjusted $R^2$ s of the co-movement regressions of firm-level discretionary accruals (normal accruals) have a mean of -0.004 (0.081) and a median of -0.030 (0.053). If we use all the risk premium proxies in the co-movement regressions of firm-level discretionary accruals (normal accruals), then the adjusted $R^2$ s average at -0.023 (0.164) with a median of -0.042 (0.151).

Building on the firm-level co-movement regressions, we assess whether the components of firm-level discretionary accruals that do not co-move with the risk premium proxies, i.e., the residuals of the co-movement regressions, still exhibit power in forecasting future market returns. Using the fitted values and the residuals of co-movement regressions of firm-level discretionary accruals, we respectively calculate the value-weighted averages of the fitted values ($FDAC$) and the value-weighted averages of the residuals ($RDAC$). The former captures the components of discretionary accruals explained by their co-movement with the risk premium proxies, and the latter captures the components orthogonal to the risk premium proxies.

Panel B of Table 10 reports the predictive regression results when $FDAC$ and/or $RDAC$ are used as explanatory variables. The panel clearly shows that $RDAC$ exhibits modest return forecasting power with a positive and statistically significant coefficient. If constructed from the co-movement regressions with $IV$ and $MV$ as the risk premium proxies, $RDAC$ predicts future equity premium with an adjusted $R^2$ of 4%. If constructed from the co-movement regressions with $NDR$ and $NCF$ as the risk premium proxies, $RDAC$ predicts future equity premium with an
adjusted $R^2$ of 10.8%. If constructed from the co-movement regressions with all the four variables as the risk premium proxies, $RDAC$ predicts future equity premium with an adjusted $R^2$ of 5.1%. In contrast, the components of discretionary accrual that co-move with the risk premium proxies, $FDAC$, exhibit no power in predicting future equity premiums with one notable exception. When constructed from the co-movement regressions with $IV$ and $MV$ as the risk premium proxies, $FDAC$ predicts future equity premium with a significantly positive estimated coefficient and an adjusted $R^2$ of 0.126. However, when we include in the firm-level co-movement regressions all the four ICAPM-motivated risk premium proxies, $FDAC$ loses its return forecasting power.

In summary, we find that firm-level discretionary accruals exhibit little co-movement with ICAPM-motivated risk premium proxies but firm-level normal accruals do. We also find that the components of firm-level discretionary accruals that do not comove with risk premium proxies retain modest return forecasting power at the aggregate level, but the other components of firm-level discretionary accruals have no such power at the aggregate level. These findings corroborate our inference in Section 4.2 that aggregate normal accruals reflect business conditions but aggregate discretionary accruals do not. This evidence further suggests that aggregate discretionary accruals do not achieve the power to forecast market returns by reflecting shifts in business conditions and investment opportunities, thereby pointing to certain behavioral channels.

5 Discussion: Behavioral Explanations

Having firmly established that the return forecasting power of aggregate accruals documented in Hirshleifer, Hou and Teoh (2009) is driven by aggregate discretionary accruals (see Section 3), our analysis in Section 4 examines various risk-based explanations. Showing that those risk-based explanation in general lack empirical support from the data, our analysis naturally turns to behavioral explanations. Moreover, as Hirshleifer, Hou and Teoh’s (2009) analysis has narrowed potential explanations for the aggregate-level accruals-return relation to that either changes in

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10 As Guo and Jiang [2009] do not tabulate their result, we believe this notable exception is one of the evidence that they use to challenge the interpretation of findings in our earlier draft. In page 5, they claim to “find that the predictive power of discretionary accruals mainly comes from the systematic component of firm-level discretionary accruals that are positively related to the conditional equity premium”. However, a further analysis, unreported for brevity, illustrates that $FDAC$ obtains the significant return forecasting power in this particular framework of co-movement regressions mainly through the co-movement of firm-level discretionary accruals with $IV$ but not $MV$. As discussed in Footnote 9, the literature still debates whether $IV$ is a valid risk premium proxy.
accruals contain information about changes in discount rates (a risk-based explanation) or that firms manage earnings in response to market-undervaluation (a behavioral explanation), the latter emerges as the more likely explanation. Before we proceed with this explanation, we have to acknowledge one caveat of our analysis, though. Because any measure of earnings management may contain elements other than earnings management, it is difficult to test this behavioral explanation directly.\textsuperscript{11}

As one indication of a behavioral explanation, in an untabulated analysis, we obtain five negative predicted values of the equity market risk premium in 1966, 1968, 1969, 1970, and 2002 when using aggregate discretionary accruals as the sole predictor of the one-year-ahead excess market return. (The actual excess market returns were all negative for those five years except 1968.) Because the stock market must be a hedge against aggregate consumption for a rational asset pricing model to predict negative market risk premiums, researchers have used this return forecasting approach to test market efficiency (e.g., Fama and Schwert [1977], Fama and French [1988], Kothari and Shanken [1997], Baker and Wurgler [2000]). The result that aggregate discretionary accruals sometimes predict negative market risk premiums casts a doubt on market efficiency.

5.1 Return Forecasting Power of Discretionary Accruals in Cross-Section

We examine the relation between aggregate discretionary accruals and aggregate returns in cross-section. If the relation reflects a risk-based explanation, then firm-level discretionary accruals and hence aggregate discretionary accruals will capture information that is systematically related to fluctuations in overall business conditions. As a result, we will be able to observe prevalent power of discretionary accruals to forecast returns in cross-section.

We conduct two sets of exercises. We run univariate regressions of excess market returns against one-period-lagged discretionary accruals aggregated across different cohorts of firms. We form these cross-sections by classifying firms into groups using both a one-way sorting by beginning-of-year firm size or book-to-market and a two-way sorting by size and book-to-market. We construct the value-weighted averages of discretionary accruals for each of these cross-sections. Table 11 reports the estimated predictive coefficients, the Newey-West standard errors, and the adjusted $R^2$'s in the first,\textsuperscript{11}

\textsuperscript{11}Our extensive use of accrual decomposition models in Section 4.1 alleviates but does not completely resolve this concern.
second, and third rows of each cell, respectively. The table clearly shows that the return forecasting power of aggregate discretionary accruals concentrates in large and/or growth firms. The aggregate discretionary accruals of these firms significantly and positively predict future aggregate returns with the adjusted $R^2$s hovering around 10%. In contrast, the aggregate discretionary accruals of medium firms, small firms and value firms show little power in forecasting returns.

We also examine the return forecasting power of discretionary accruals at the sector and industry level. Following Hirshleifer, Hou and Teoh [2009], for each sector or industry, we construct the value-weighted averages of firm-level cash flows, normal accruals, and discretionary accruals. We use these aggregate measures at the sector level to predict one-year-ahead market returns or sector returns. Table 12 reports the results. When sector returns are used as the dependent variable (Panel A), we find that the sector-level discretionary accruals are significant predictors in only two sectors: Health and Others. In Panel B where excess market returns are used as the dependent variable, the sector-level discretionary accruals are significant predictors in High-tech and Others.

In summary, the cross-sectional analysis shows that the return forecasting power of discretionary accruals is limited to certain portfolios and sectors. The finding casts a further doubt on risk-based explanations and favors a behavior-based explanation.

5.2 Managerial Incentives to Time the Market

Although we fail to provide direct evidence for the hypothesis of “lean-against-wind” in earnings management, our analysis so far has illustrated that likely risk-based explanations receive little empirical support. In this section we briefly discuss various managerial incentives to engage in market-timing earnings management. We build our discussion on the growing finance and accounting literatures that investigate the behavioral rationales behind various managerial decisions.

To ameliorate the agency problems facing modern firms, managerial compensation schemes rely on both accounting earnings and stock returns. Given these compensation schemes, managers have incentives to manage earnings to shield themselves from aggregate market shocks. For example,

\[12\text{In an unreported analysis, we also regress one-year-ahead industry value-weighted earnings against the current-year industry value-weighted cash flows, normal accruals, and discretionary accruals. We find that the industry value-weighted discretionary accruals are not a reliable predictor of future earnings except for High-tech and Health sectors. Moreover, when we extend the five-sector analysis to the Fama-French 48 industries, we obtain similar results. For ease of exposition, we make the results available upon request.}\]
Watts and Zimmerman [1978], Healy [1985], McNichols and Wilson [1988], and Defeo et al. [1989] all find that CEOs report accounting income so as to increase their compensation and that the relation is causal. Sloan [1993] shows that accounting earnings are much less sensitive to macroeconomic risk than stock returns and accounting profits are more closely correlated with market-adjusted stock returns than with raw returns. Kothari et al. [2009] provide systematic evidence that managers tend to delay dissemination of bad news. With all sorts of contractual arrangements in practice, the managerial incentives to manage earnings are likely stronger when the aggregate market is perceived to be weak.

Also, investors and financial analysts widely use accounting information to analyze the firms they follow and value their stocks. Managers thus might have incentives to manage earnings in order to avoid adverse effects on stock returns of reported losses or earnings declines, and to influence short-term stock price performance. Dye [1988] and Trueman and Titman [1988] develop analytical models showing that contracting frictions may cause earnings management intended to influence the decisions of external capital providers. Burgstahler and Dichev [1997], and Degeorge et al. [1999] report evidence that firms use earnings management to avoid reporting negative earnings, earnings declines, or failing short of market expectations. Teoh et al. [1998] find that firms report positive discretionary accruals prior to initial public offers. Graham et al. [2005] survey Chief Financial Officers (CFOs) and report that CFOs indicate they manage earnings to maintain or increase the stock price of their firms. Finally, Kothari, Loutskina, and Nikolaev [2006] argue that managers of overvalued firms are likely to manage their firms’ accruals upwards to prolong the overvaluation. In summary, when a negative shock hits the stock market and causes a gap between firm performance and analysts’ or investors’ expectations, the managerial incentives to manage earnings are likely to be high. It is worth noting that earnings management is potentially costly to firms and managers. Increased worries over potential litigations and reputation damage due to mis-reporting can place constraints on firm managers, so that they might choose to time the aggregate equity market performance rather than their own stock performance to manage earnings.
5.3 A Dichotomy of Discretionary Accrual-Return Relations: Macro versus Micro

The positive relation between discretionary accruals and stock returns at the aggregate level contrasts sharply with the negative relation at the firm- and portfolio-level. Here we offer an exploratory analysis as a first step toward reconciling the two qualitatively different relations. We regress each firm’s annual stock returns against its one-period-lagged discretionary accruals ($dac$) and/or the one-period-lagged aggregate discretionary accruals. For ease of comparison, both $dac$ and $DAC$ are standardized to have zero mean and unit variance in the return predictive regressions. Table 13 reports the cross-sectional averages ($t$-statistics in parentheses) and the cross-sectional medians of each parameter estimate from the firm-level regressions. We adjust the $t$-values with White’s heteroskedasticity-consistent standard errors.

We first study the pooled-sample results. When we include firm-level discretionary accruals $dac$ as the sole predictor of firm-level returns (Model (1)), both the mean and the median of the coefficient estimates on $dac$ are significantly negative, mirroring the well-documented accruals anomaly. We then include both the firm-level discretionary accruals and aggregate discretionary accruals as return predictors (Model (2)). The cross-sectional averages of the two predictive coefficient estimates are respectively -2.165 and 8.152, and both are strongly significant. The cross-sectional medians of the two estimates are -1.956 and 6.604, respectively. This result highlights that the disaggregate-level accrual-return relation and the aggregate-level accrual-return relation are qualitatively different but can coexist in a unified empirical framework.

In a further analysis, we sort firms by size into quintiles and summarize the corresponding regression statistics in Table 13. Several interesting results surface. When serving as the sole predictor of firm-level returns (Models (1)), the firm-level discretionary accruals retain significant and negative coefficients only in the two smallest size quintiles but not in the other three quintiles; it remains to be the case even when aggregate discretionary accruals also enter the firm-level return predictive regressions (Models (2)). This result corroborates the finding that the accruals anomaly is more significant in small firms than in large firms. On the other hand, aggregate discretionary accruals remain as a robust and positive predictor of firm-level returns across all five size quintiles. Moreover, aggregate discretionary accruals have an increasingly larger role in predicting firm-level
returns as the firm size increases.

The finding that the two qualitatively opposite discretionary accrual-return relations coexist has two implications. First, the firm-level discretionary accruals and aggregate discretionary accruals predict stock returns through different channels, and the underlying economic rationales are likely to differ. To the extent that discretionary accruals serve as a measure of earnings management, the evidence implies that firms might manage earnings in response to both firm-specific shocks and market-wide shocks. Second, the evidence also appears to echo Samuelson’s [1998] dictum that mispricing at the disaggregate level can be quickly arbitraged away whereas mispricing at the aggregate market level tends to persist (see also Jung and Shiller [2005], Lamont and Stein [2006]). Along this line of thinking, if discretionary accruals indeed reflect earnings management, the behavior of “lean-against-wind” in earnings management will become pronounced at the macro level. Our evidence thus lends support to Samuelson’s conjecture.

6 Conclusion

In this paper we examine the power of aggregate discretionary accruals to forecast market returns. We document robust evidence that aggregate accruals derive return forecasting power primarily from discretionary accruals rather than from normal accruals. Specifically, aggregate discretionary accruals positively predict future market returns and negatively correlate with current market returns. In contrast, aggregate normal accruals exhibit no power in predicting future market returns, nor are they correlated with current market returns.

We conduct an extensive analysis to account for the return forecasting power of aggregate discretionary accruals, and the body of analysis provides strong evidence that risk-based explanations lack empirical support. We show that aggregate discretionary accruals contain little information about overall business conditions or aggregate cash flows. We find that aggregate discretionary accruals forecast market returns via a discount-rate channel, but our further analysis documents that aggregate discretionary accruals display little co-movement with ICAPM-motivated risk premium proxies and retain modest return forecasting power beyond these risk premium proxies. To the extent that discretionary accruals reflects earnings management, our study helps distinguish between the two potential explanations raised in Hirshleifer, Hou and Teoh [2009], and
favors the behavioral explanation that managers time aggregate equity markets to report earnings.

Not only do we document a positive relation between discretionary accruals and stock returns at the aggregate level, which is qualitatively opposite to the negative relation at the disaggregate level, but we also show that the two different relations coexist in one empirical framework and are likely driven by different rationales. We also offer a first step toward reconciling the two qualitatively different accrual-return relations.

Our study has one notable caveat — we do not provide a direct test of the behavioral explanation in our analysis because we are unable to construct a precise measure of earnings management. As well known in the accounting literature, discretionary accruals are a crude measure of earnings management and might capture things other than earnings management. Nonetheless, we use a variety of accrual decomposition models available in the literature, and we turn to the behavioral explanation after assessing the validity of various risk-based explanations. Our results suggest that aggregate discretionary accruals likely represent aggregate fluctuations in earnings management and that firm managers time the aggregate market to manage earnings. It is worth noting that why and what types of firms are prone to timing the aggregate market performance instead of their own stock performance remains an open and interesting question for future research.
References


### Table 1. Summary Statistics

This table reports summary statistics of variables used in our empirical study: value-weighted annual NYSE/AMEX market returns in excess of one-month T-Bill rates (EXC_VW), aggregate accruals (AC), aggregate normal accruals (NAC), aggregate discretionary accruals (DAC), book-to-market ratio (BTM), annual dividend yield (DP), term premium of ten-year T-Bond yields over one-month T-Bill yields at year-end (TERM), default premium defined as Baa-rated corporate bond yields over Aaa-rated corporate bond yields at year-end (DEF), stochastically-detrended one-month T-Bill yield (SHORT), consumption-wealth ratio (CAY), realized volatility in value-weighted market returns (MV), discount rate news (NDR), cash flow news (NCF), value-weighted aggregate earnings (EARN), and aggregate cash flows (CF). We use the time-series Jones’ (1991) model to decompose accruals into normal and discretionary accruals. Market returns, dividend yields, and one-month T-Bill rates are calculated using the CRSP database. Accrual measures, book-to-market ratio, earnings, and cash flows are calculated using the Compustat database. Term premium and default premium are obtained using the DRI database. Consumption-wealth ratio and planned investment growth are downloaded from Martin Lettau’s website and Owen Lamont’s website, respectively. We calculate IV as the standard deviation in CAPM-based residuals using daily firm returns within a year, and MV as the standard deviation in daily market returns within a year. We estimate NDR and NCF following Campbell and Vuolteenaho (2004). We calculate firm-level earnings as Compustat item 172 scaled by average asset (item 6) over the year. We follow Hribar and Collins (2002) to define firm-level cash flows as the total cash flow (item 308) minus the cash portion of discontinued operations and extraordinary items (item 124), scaled by average asset in that year; because item 308 is only available from 1987, we use the balance sheet approach to calculate cash flows prior to 1987. The sample period is 1965-2004 (40 observations) except for CAY (1965-2001, 37 observations), GHAT (1965-1994, 30 observations), and CF (1971-2004, 34 observations). All variables except BTM are quoted in percentages. The last column reports the first-order autocorrelation coefficients, with p-values in parentheses.

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<th>Variable</th>
<th>Mean</th>
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<th>Std. Dev.</th>
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<th>Maximum</th>
<th>Autocorr. (p-value)</th>
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Table 2. Aggregate Accrual Measures as Return Predictors: Univariate and Multivariate Analysis

This table reports estimates of regressing value-weighted market excess returns against various one-period-lagged predictors. The sample periods are 1965-2004 for models (0)-(4), 1965-2002 for model (5), and 1965-1994 for model (6), respectively. Variables are defined in Table 1. Panel A reports the OLS estimates with Newey-West statistics. We set the Newey-West bandwidth to the integer part of \( \frac{4 \times (T/100)^{2/9}}{T} \), where T is the number of observations used in regressions. We report the Newey-West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors in parentheses. *, **, and *** denote (two-sided) significance at the 10%, 5%, and 1% levels, respectively. Panel B reports the regression results using the Amihud and Hurvich (2004) reduced-bias estimator, with standard errors in parentheses.

Panel A: OLS estimates with Newey-West HAC standard errors

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Panel B: Reduced-bias estimates

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<td>1.263</td>
<td>-0.452</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(16.918)</td>
<td>(1.978)</td>
<td>(1.561)</td>
<td>(0.114)</td>
<td>(54.970)</td>
<td>(7.782)</td>
<td>(1.198)</td>
<td>(6.802)</td>
<td>(1.316)</td>
<td>(1.686)</td>
<td>(0.301)</td>
<td></td>
</tr>
</tbody>
</table>
Table 3. Predictive Regressions with Alternative Return Measures and across Sub-periods

This table reports estimates of regressing value-weighted NYSE/AMEX index excess returns against one-period-lagged value-weighted aggregate discretionary accruals for NYSE/AMEX firms. We follow Sloan’s (1996) method to calculate accruals and apply the time-series version of Jones’ (1991) model to decompose accruals. Panel A uses market returns annualized over different periods as the dependent variable. Panel B reports the time series regression results across different subperiods. The full sample period is 1965-2004. We set the Newey-West bandwidth to the integer part of \(4 \times (T/100)^{2/9}\), where \(T\) is the number of observations used in regressions, and we report the Newey-West HAC standard errors in parentheses.

*, **, and *** denote (two-sided) significance at the 10%, 5%, and 1% levels, respectively.

Panel A: NYSE/AMEX value-weighted index excess returns annualized over different 12 month horizons

<table>
<thead>
<tr>
<th>HORIZON</th>
<th>INTERCEPT</th>
<th>NAC</th>
<th>DAC</th>
<th>ADJ. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>February-January</td>
<td>-2.579</td>
<td>-1.654</td>
<td>6.817***</td>
<td>0.114</td>
</tr>
<tr>
<td></td>
<td>(13.935)</td>
<td>(2.957)</td>
<td>(1.741)</td>
<td></td>
</tr>
<tr>
<td>March-February</td>
<td>-1.120</td>
<td>-1.346</td>
<td>5.627***</td>
<td>0.065</td>
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<tr>
<td></td>
<td>(13.001)</td>
<td>(2.728)</td>
<td>(1.808)</td>
<td></td>
</tr>
<tr>
<td>April-March</td>
<td>-0.335</td>
<td>-1.179</td>
<td>7.286***</td>
<td>0.101</td>
</tr>
<tr>
<td></td>
<td>(13.457)</td>
<td>(2.849)</td>
<td>(2.100)</td>
<td></td>
</tr>
<tr>
<td>May-April</td>
<td>-1.600</td>
<td>-1.381</td>
<td>7.516***</td>
<td>0.142</td>
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<tr>
<td></td>
<td>(13.622)</td>
<td>(2.918)</td>
<td>(1.902)</td>
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Panel B: Sub-period Analysis

<table>
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<tr>
<th>PERIODS</th>
<th>INTERCEPT</th>
<th>NAC</th>
<th>DAC</th>
<th>ADJ. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1965-2004</td>
<td>-0.530</td>
<td>-1.322</td>
<td>6.432***</td>
<td>0.089</td>
</tr>
<tr>
<td></td>
<td>(15.858)</td>
<td>(3.309)</td>
<td>(1.806)</td>
<td></td>
</tr>
<tr>
<td>1975-2004</td>
<td>-3.618</td>
<td>-2.736</td>
<td>8.750**</td>
<td>0.112</td>
</tr>
<tr>
<td></td>
<td>(17.163)</td>
<td>(3.604)</td>
<td>(3.777)</td>
<td></td>
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<tr>
<td>1985-2004</td>
<td>12.736</td>
<td>0.526</td>
<td>17.455***</td>
<td>0.239</td>
</tr>
<tr>
<td></td>
<td>(25.934)</td>
<td>(5.117)</td>
<td>(5.112)</td>
<td></td>
</tr>
<tr>
<td>1965-1984</td>
<td>-1.299</td>
<td>-0.686</td>
<td>5.259**</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>(16.041)</td>
<td>(3.242)</td>
<td>(2.680)</td>
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</tr>
</tbody>
</table>
Table 4. Contemporaneous Relations Between Innovations in Aggregate Accrual Measures and Market Returns
This table reports GMM estimates on the following system of equations:

\[ R_t = \alpha + \beta_1 F_t + \epsilon_t \]
\[ F_t = \theta + \gamma F_{t-1} + \nu_t, \]

where the symbol \( F \) represents the set of variables such as aggregate accrual measures (NAC,DAC), term premium (TERM), default premium (DEF), short-term interest rate (TB1M), and consumption-wealth ratio (CAY). The sample periods is 1965-2004 except for regressions including the variable CAY, where the sample period is 1965-2002. We set the Newey-West bandwidth to the integer part of \( (4 \times (T/100)^{2/9}) \), where \( T \) is the number of observations used in regressions, and we report the Newey-West HAC standard errors in parentheses.

*, **, and *** denote (two-sided) significance at the 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Model</th>
<th>INTERCEPT</th>
<th>NAC</th>
<th>DAC</th>
<th>TERM</th>
<th>DEF</th>
<th>TB1M</th>
<th>CAY</th>
<th>ADJ. R²</th>
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<tbody>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>(1)</td>
<td>6.557***</td>
<td>-5.141</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.020</td>
</tr>
<tr>
<td></td>
<td>(2.121)</td>
<td>(4.260)</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>(2)</td>
<td>5.675**</td>
<td></td>
<td>-7.240***</td>
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<td></td>
<td></td>
<td></td>
<td>0.248</td>
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<tr>
<td></td>
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<td></td>
<td>(1.420)</td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>(3)</td>
<td>5.723**</td>
<td>-0.625</td>
<td></td>
<td>-7.103***</td>
<td></td>
<td></td>
<td></td>
<td>0.227</td>
</tr>
<tr>
<td></td>
<td>(2.319)</td>
<td>(3.851)</td>
<td></td>
<td>(1.638)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4)</td>
<td>6.024***</td>
<td>-4.533*</td>
<td>-6.615***</td>
<td>-2.597**</td>
<td>-15.245***</td>
<td>0.988</td>
<td></td>
<td>0.410</td>
</tr>
<tr>
<td></td>
<td>(1.816)</td>
<td>(2.356)</td>
<td>(1.106)</td>
<td>(1.212)</td>
<td>(5.045)</td>
<td>(1.659)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5)</td>
<td>6.142***</td>
<td>-5.250***</td>
<td>-2.890***</td>
<td>-2.579**</td>
<td>-9.609***</td>
<td>0.174</td>
<td>-5.980***</td>
<td>0.643</td>
</tr>
<tr>
<td></td>
<td>(1.164)</td>
<td>(1.678)</td>
<td>(0.968)</td>
<td>(1.166)</td>
<td>(3.582)</td>
<td>(1.368)</td>
<td>(1.112)</td>
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</table>
Table 5. Return Predictive Regressions Using Various Accrual Decomposition Models
Panel A reports the cross-sectional distributions of adjusted $R^2$s of various accrual decomposition models. The baseline model is Jones’ (1991) model. Models “DD1”, “DD1-HC”, and “DD2” are all based on Dechow and Dichev (2002). DD1 extends the Jones model by including one-period lagged and current cash flows. DD1-HC is primarily DD1 but deletes firms experiencing extreme events/performance as discussed in Hribar and Collins (2002). DD2 further extends DD1 by also including one-period-lead cash flows. The model “DD3” extends the Jones model by including two performance measures: ROA, and squared ROA. The model “BS”, based on Ball and Shivakumar (2006), extends the Jones model by adding three additional variables to incorporate accounting conservatism in accrual decomposition models: stock return less market return for the fiscal year (RRET), dummy which equals one if RRET is negative and zero otherwise, and the interaction between RRET and the dummy. We estimate all accrual models in time series and require a firm to have at least ten observations. We denote the fitted values and the residuals of each regression by normal accruals and discretionary accruals, respectively. Panel B reports the results of predicting aggregate returns with value-weighted aggregate normal accruals (NAC) and/or value-weighted aggregate discretionary accruals (DAC) obtained from these augmented accrual decomposition models. The sample period is 1965-2004 for Jones, DD3, and BS, and is 1973-2004 for DD1, DD1-HC, and DD2. The predictive regression results based on the Jones model are reported in Table 2, Panel A, Models 1-3, and are included in this table. We set the Newey-West bandwidth to the integer part of $(4 \times (T/100)^{2/9})$, where $T$ is the number of observations used in regressions, and we report the Newey-West HAC standard errors in parentheses.

*, **, and *** denote (two-sided) significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary Statistics of Adjusted $R^2$s of Various Accrual Decomposition Models

<table>
<thead>
<tr>
<th>Accrual Models</th>
<th>Number of Firms</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Q1</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jones (1991)</td>
<td>2,450</td>
<td>0.479</td>
<td>0.502</td>
<td>0.306</td>
<td>-0.393</td>
<td>0.253</td>
<td>0.732</td>
<td>0.998</td>
</tr>
<tr>
<td>DD1 (2002)</td>
<td>2,436</td>
<td>0.686</td>
<td>0.770</td>
<td>0.275</td>
<td>-0.792</td>
<td>0.574</td>
<td>0.884</td>
<td>0.999</td>
</tr>
<tr>
<td>DD1-HC</td>
<td>2,104</td>
<td>0.709</td>
<td>0.802</td>
<td>0.303</td>
<td>-1.473</td>
<td>0.610</td>
<td>0.912</td>
<td>0.999</td>
</tr>
<tr>
<td>DD2 (2002)</td>
<td>2,159</td>
<td>0.709</td>
<td>0.793</td>
<td>0.271</td>
<td>-1.291</td>
<td>0.611</td>
<td>0.897</td>
<td>0.999</td>
</tr>
<tr>
<td>DD3</td>
<td>2,450</td>
<td>0.516</td>
<td>0.562</td>
<td>0.318</td>
<td>-0.742</td>
<td>0.318</td>
<td>0.776</td>
<td>0.998</td>
</tr>
<tr>
<td>BS (2006)</td>
<td>2,429</td>
<td>0.486</td>
<td>0.536</td>
<td>0.344</td>
<td>-1.742</td>
<td>0.274</td>
<td>0.762</td>
<td>0.999</td>
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### Panel B. Return Predictive Regressions

<table>
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<th>ACCRUAL MODELS</th>
<th>INTERCEPT</th>
<th>NAC</th>
<th>DAC</th>
<th>ADJ. R²</th>
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<tr>
<td>DD1</td>
<td>4.648</td>
<td>-0.360</td>
<td>-0.033</td>
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</tr>
<tr>
<td></td>
<td>(11.913)</td>
<td>(2.353)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>5.623**</td>
<td>16.456**</td>
<td>0.146</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.576)</td>
<td>(6.937)</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>-15.465</td>
<td>21.168**</td>
<td>0.176</td>
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<tr>
<td></td>
<td>(13.439)</td>
<td>(8.748)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DD1-HC</td>
<td>15.503</td>
<td>1.928</td>
<td>-0.020</td>
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<tr>
<td></td>
<td>(9.822)</td>
<td>(2.166)</td>
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<td></td>
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<tr>
<td></td>
<td>5.052*</td>
<td>13.938***</td>
<td>0.072</td>
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<tr>
<td></td>
<td>(2.606)</td>
<td>(5.015)</td>
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<tr>
<td></td>
<td>7.032</td>
<td>13.633**</td>
<td>0.041</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(11.206)</td>
<td>(5.198)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DD2</td>
<td>8.379</td>
<td>0.440</td>
<td>-0.033</td>
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</tr>
<tr>
<td></td>
<td>(10.942)</td>
<td>(2.200)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>5.855**</td>
<td>14.202**</td>
<td>0.077</td>
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<tr>
<td></td>
<td>(2.547)</td>
<td>(7.000)</td>
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</tr>
<tr>
<td></td>
<td>-7.854</td>
<td>17.816**</td>
<td>0.070</td>
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<tr>
<td></td>
<td>(14.936)</td>
<td>(9.185)</td>
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<td></td>
</tr>
<tr>
<td>DD3</td>
<td>10.797</td>
<td>1.017</td>
<td>-0.023</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(14.743)</td>
<td>(2.890)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4.955**</td>
<td>7.156***</td>
<td>0.075</td>
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</tr>
<tr>
<td></td>
<td>(2.199)</td>
<td>(2.148)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2.636</td>
<td>7.307***</td>
<td>0.051</td>
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</tr>
<tr>
<td></td>
<td>(16.495)</td>
<td>(2.435)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BS</td>
<td>-0.927</td>
<td>-1.396</td>
<td>-0.020</td>
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</tr>
<tr>
<td></td>
<td>(12.073)</td>
<td>(2.437)</td>
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<td>5.462**</td>
<td>7.747***</td>
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<td>(1.287)</td>
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<tr>
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<td>0.456</td>
<td>7.685***</td>
<td>0.129</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(13.090)</td>
<td>(1.344)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 6. Aggregate Accrual Measures and Macroeconomic Activity
This table reports the intertemporal (Panels A and B) and contemporaneous (Panel C) relations between aggregate accrual measures and annual U.S. GDP growth rates (GDPG) over the 1965-2004 period. Panel A predicts GDPG with one-period-lagged aggregate accrual measures and industrial product growth rates (IPG). Panel B replicates the analysis in Panel A by using the reduced-bias estimator proposed in Amihud and Hurvich (2004). Panel C presents GMM estimation results on the following system of equations: GDPGt = α + βyt + εt and Ft = θ + γFt-1 + ut, where the symbol F represents a set of aggregate normal and discretionary accruals and business-condition variables such as term premium, default premium, short-term interest rate, and consumption-wealth ratio. We set the Newey-West bandwidth to the integer part of \(4 \times (T / 100)^{2/9}\), where T is the number of observations used in regressions, and we report the Newey-West HAC standard errors in parentheses. *, **, and *** denote (two-sided) significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Intertemporal predictive relation: OLS estimates with Newey-West standard errors

<table>
<thead>
<tr>
<th>Model</th>
<th>INTERCEPT</th>
<th>IPG</th>
<th>NAC</th>
<th>DAC</th>
<th>ADJ. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>2.511***</td>
<td>0.226***</td>
<td>-0.734***</td>
<td>0.247</td>
<td>0.374</td>
</tr>
<tr>
<td></td>
<td>(0.285)</td>
<td>(0.049)</td>
<td>(0.247)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2)</td>
<td>0.671</td>
<td>0.243***</td>
<td>-0.364</td>
<td>0.294</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.577)</td>
<td>(0.035)</td>
<td></td>
<td>(0.331)</td>
<td></td>
</tr>
<tr>
<td>(3)</td>
<td>0.965</td>
<td>0.222***</td>
<td>-0.715***</td>
<td>-0.327</td>
<td>0.380</td>
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<tr>
<td></td>
<td>(1.321)</td>
<td>(0.051)</td>
<td>(0.215)</td>
<td>(0.257)</td>
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</table>

Panel B. Intertemporal predictive relation: Reduced-bias estimates

<table>
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<tr>
<th>Model</th>
<th>INTERCEPT</th>
<th>IPG</th>
<th>NAC</th>
<th>DAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>2.343***</td>
<td>0.292***</td>
<td>-0.291***</td>
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</tr>
<tr>
<td></td>
<td>(0.115)</td>
<td>(0.035)</td>
<td>(0.116)</td>
<td></td>
</tr>
<tr>
<td>(2)</td>
<td>2.611***</td>
<td>0.277***</td>
<td>0.050</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.489)</td>
<td>(0.031)</td>
<td>(0.098)</td>
<td></td>
</tr>
<tr>
<td>(3)</td>
<td>2.406***</td>
<td>0.286***</td>
<td>-0.266***</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.487)</td>
<td>(0.036)</td>
<td>(0.102)</td>
<td>(0.097)</td>
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</table>

Panel C. Contemporaneous relation

<table>
<thead>
<tr>
<th>Model</th>
<th>INTERCEPT</th>
<th>NAC</th>
<th>DAC</th>
<th>ADJ. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>3.097***</td>
<td>1.019**</td>
<td>0.029</td>
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<tr>
<td></td>
<td>(0.321)</td>
<td>(0.491)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2)</td>
<td>3.097***</td>
<td>0.011</td>
<td>-0.088</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.321)</td>
<td>(0.435)</td>
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<td></td>
</tr>
<tr>
<td>(3)</td>
<td>3.097***</td>
<td>1.404***</td>
<td>-0.224</td>
<td>-0.055</td>
</tr>
<tr>
<td></td>
<td>(0.279)</td>
<td>(0.517)</td>
<td>(0.417)</td>
<td></td>
</tr>
</tbody>
</table>
Table 7. Aggregate Accrual Measures, Discount Rate News, and Cash Flow News
This table reports the OLS estimates from the regressions that examine the intertemporal (Panel A) and contemporaneous (Panel B) relations between aggregate accrual measures (NAC,DAC) and discount rate news (NDR) and cash flow news (NCF) over 1965-2004. We set the Newey-West bandwidth to the integer part of \(4 \times (T / 100)^{2/9}\), where \(T\) is the number of observations used in regressions, and we report the Newey-West HAC standard errors in parentheses. *, **, and *** denote (two-sided) significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Intertemporal predictive relations

<table>
<thead>
<tr>
<th>Depend. Variable</th>
<th>Model</th>
<th>INTERCEPT</th>
<th>NAC</th>
<th>DAC</th>
<th>ADJ. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDR</td>
<td>(1)</td>
<td>14.250</td>
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Panel B. Contemporaneous relations

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Table 8. Predicting Aggregate Earnings or Cash Flows Using Aggregate Accrual Measures

This table reports the predictive regression results from regressing aggregating earnings (EARN) and cash flows (CF) against one-period-lagged value-weighted aggregate normal accruals and/or value-weighted aggregate discretionary accruals. The sample period is 1972-2004. We set the Newey-West bandwidth to the integer part of \( \left( \frac{4 \times (T/100)^{2/9}}{0.71} \right) \), where \( T \) is the number of observations used in regressions, and we report the Newey-West HAC standard errors in parentheses. *, **, and *** denote (two-sided) significance at the 10%, 5%, and 1% levels, respectively.

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Table 9. Aggregate Accrual Measures as Return Predictors: Using ICAPM-motivated Risk Premium Proxies as Controls

This table reports the estimation results of regressing value-weighted market excess returns against one-period-lagged aggregate accrual measures and one-period-lagged alternative risk premium proxies such as IV, MV, NDR, and NCF. Trend stands for the year trend, and the other variables are defined in Table 1. The sample period is 1965-2004. We set the Newey-West bandwidth to the integer part of \((4 \times (T/100)^{2/9})\), where \(T\) is the number of observations used in regressions. We report the Newey-West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors in parentheses. *, **, and *** denote (two-sided) significance at the 10%, 5%, and 1% levels, respectively.

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Table 10. Co-movement Regressions of Firm-level Normal/Discretionary Accruals against Alternative Risk Premium Proxies and Return Predictive Regressions

For each firm we respectively regress its normal/discretionary accruals, obtained using the time-series Jones’ (1991) model, against contemporaneous risk premium proxies such as IV, MV, NDR, and NCF. We estimate each regression in times series, requiring a firm to have at least ten observations over 1965-2004. We obtain the fitted values and the residuals of each co-movement regression and then aggregate them using a value-weighting method. Panel A reports the summary statistics of the adjusted R²s of the firm-level co-movement regressions across 2,450 firms. Panel B reports the OLS results from regressing the value-weighted market excess returns against the one-period-lagged aggregate fitted value (FDAC) and the aggregate residual (RDAC) of discretionary accruals. The sample period is 1965-2004. We set the Newey-West bandwidth to the integer part of \((4 \times (T/100)^{2/9})\), where T is the number of observations used in regressions, and we report the Newey-West HAC standard errors in parentheses. *, **, and *** denote (two-sided) significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary statistics of adjusted R²s of the firm-level co-movement regressions

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Panel B. Return Predictive Regressions with Decomposed Discretionary Accruals

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<td></td>
</tr>
<tr>
<td>(2.476)</td>
<td>(4.857)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.618</td>
</tr>
</tbody>
</table>
Table 11: Predicting Market Returns with Aggregate Discretionary Accruals Formed on Different Groups: Grouped by SIZE and/or Book-to-Market

This table reports univariate regression results from regressing market excess returns against one-period-lagged discretionary accruals aggregated in different groups of firms. We use the time-series Jones’ (1991) model to obtain firm-level discretionary accruals. Firms are classified into groups using either one-way sorting by beginning-of-year firm size (Size), or one-way sorting by beginning-of-year book-to-market (BM), or a two-way sorting by both size and BM. Each cell reports the estimated predictive coefficients, Newey-West HAC standard errors, and adjusted regression R²s in the first, second, and third rows, respectively. The sample periods are 1965-2004. *, **, and *** denote (two-sided) significance at the 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>SIZE/BM</th>
<th>GROWTH</th>
<th>BLEND</th>
<th>VALUE</th>
<th>SIZE ONLY</th>
</tr>
</thead>
<tbody>
<tr>
<td>SMALL</td>
<td>-0.452</td>
<td>-2.201</td>
<td>-2.564</td>
<td>-2.355</td>
</tr>
<tr>
<td></td>
<td>(2.774)</td>
<td>(3.065)</td>
<td>(3.518)</td>
<td>(3.621)</td>
</tr>
<tr>
<td></td>
<td>-0.026</td>
<td>-0.009</td>
<td>-0.006</td>
<td>-0.015</td>
</tr>
<tr>
<td></td>
<td>(2.477)</td>
<td>(2.779)</td>
<td>(2.699)</td>
<td>(3.062)</td>
</tr>
<tr>
<td>MEDIUM</td>
<td>1.463</td>
<td>1.878</td>
<td>1.246</td>
<td>2.177</td>
</tr>
<tr>
<td></td>
<td>(2.774)</td>
<td>(2.033)</td>
<td>(2.722)</td>
<td>(1.969)</td>
</tr>
<tr>
<td></td>
<td>-0.020</td>
<td>-0.016</td>
<td>-0.023</td>
<td>-0.017</td>
</tr>
<tr>
<td>LARGE</td>
<td>3.862***</td>
<td>4.227**</td>
<td>0.391</td>
<td>7.024***</td>
</tr>
<tr>
<td></td>
<td>(0.754)</td>
<td>(2.033)</td>
<td>(2.722)</td>
<td>(1.969)</td>
</tr>
<tr>
<td></td>
<td>0.106</td>
<td>0.031</td>
<td>-0.026</td>
<td>0.104</td>
</tr>
<tr>
<td>BM ONLY</td>
<td>3.921***</td>
<td>4.317*</td>
<td>-0.216</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.859)</td>
<td>(2.215)</td>
<td>(3.208)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.093</td>
<td>0.023</td>
<td>-0.027</td>
<td></td>
</tr>
</tbody>
</table>
Table 12. Predictive Relations at the Sector Level
This table reports the OLS estimation results from regressing value-weighted sector-level returns (Panel A) or value-weighted excess market returns (Panel B) against one-period-lagged sector-level discretionary accruals, normal accruals, and cash flows. We classify firms into sectors using Fama-French five-sector classifications. For each sector, we respectively construct the value-weighted averages of firm-level cash flows, normal accruals, and discretionary accruals within each sector, and we use the time-series Jones’ (1991) model to estimate firm-level normal accruals and discretionary accruals. In each predictive regression we also include commonly-used control variables such as book-to-market, dividend yield, default premium, term premium, short-term interest rate, and equity share. Table 1 defines all these control variables except equity share, which is the ratio of equity issues to total equity and debt issues. We download sector-level returns and equity shares from Ken French’s and Jeffery Wurgler’s websites. The sample period is 1965-2004. We use Newey-West HAC standard errors to calculate t-values. We set the Newey-West bandwidth to the integer part of \( \frac{4 \times (T / 100)^{2/9}}{\bar{T}} \), where \( \bar{T} \) is the number of observations used in regressions. *, **, and *** denote (two-sided) significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Predicting Sector-level Returns:
\[
\text{EXC}_t = \text{Intercept} + \beta_1 \cdot DAC_t + \beta_2 \cdot NAC_t + \beta_3 \cdot \text{CASHFLOW}_t + \text{Controls}
\]

<table>
<thead>
<tr>
<th>Sector</th>
<th>( \beta_1 )</th>
<th>( t(\beta_1) )</th>
<th>( \beta_2 )</th>
<th>( t(\beta_2) )</th>
<th>( \beta_3 )</th>
<th>( t(\beta_3) )</th>
<th>Adj. R(^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer</td>
<td>-1.626</td>
<td>-1.206</td>
<td>-6.241**</td>
<td>-2.278</td>
<td>-2.471***</td>
<td>-3.279</td>
<td>0.368</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>2.722</td>
<td>0.848</td>
<td>-2.259</td>
<td>-0.826</td>
<td>-0.553</td>
<td>-0.366</td>
<td>0.173</td>
</tr>
<tr>
<td>High-tech</td>
<td>3.976</td>
<td>1.406</td>
<td>5.736</td>
<td>1.516</td>
<td>2.753</td>
<td>1.240</td>
<td>0.136</td>
</tr>
<tr>
<td>Health</td>
<td>-4.361***</td>
<td>-2.860</td>
<td>-1.466</td>
<td>-1.210</td>
<td>-2.463*</td>
<td>-1.917</td>
<td>0.150</td>
</tr>
<tr>
<td>Other</td>
<td>11.884**</td>
<td>2.528</td>
<td>-6.631</td>
<td>-1.446</td>
<td>-2.815</td>
<td>-1.124</td>
<td>0.357</td>
</tr>
</tbody>
</table>

Panel B. Predicting Aggregate Returns:
\[
\text{EXC}_t = \text{Intercept} + \beta_1 \cdot DAC_t + \beta_2 \cdot NAC_t + \beta_3 \cdot \text{CASHFLOW}_t + \text{Controls}
\]

<table>
<thead>
<tr>
<th>Sector</th>
<th>( \beta_1 )</th>
<th>( t(\beta_1) )</th>
<th>( \beta_2 )</th>
<th>( t(\beta_2) )</th>
<th>( \beta_3 )</th>
<th>( t(\beta_3) )</th>
<th>Adj. R(^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer</td>
<td>-2.172</td>
<td>-1.176</td>
<td>-3.753</td>
<td>-1.477</td>
<td>-1.525**</td>
<td>-2.267</td>
<td>0.162</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>4.287</td>
<td>1.148</td>
<td>-3.420</td>
<td>-1.104</td>
<td>0.427</td>
<td>0.221</td>
<td>0.173</td>
</tr>
<tr>
<td>High-tech</td>
<td>3.935**</td>
<td>2.090</td>
<td>2.097</td>
<td>0.624</td>
<td>0.995</td>
<td>0.791</td>
<td>0.213</td>
</tr>
<tr>
<td>Health</td>
<td>-1.418</td>
<td>-0.923</td>
<td>-0.148</td>
<td>-0.163</td>
<td>-1.113</td>
<td>-0.956</td>
<td>0.140</td>
</tr>
<tr>
<td>Other</td>
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<td>2.363</td>
<td>-6.566*</td>
<td>-1.689</td>
<td>-2.343</td>
<td>-0.999</td>
<td>0.326</td>
</tr>
</tbody>
</table>
Table 13. Return-Discretionary Accrual Relation: Macro and Micro

We regress each firm’s annual stock returns against its one-period-lagged discretionary accruals (dac) and/or the one-period-lagged value-weighted aggregate discretionary accruals (DAC). Both dac and DAC are standardized to have zero mean and unit variance in the return regressions. We use the time-series Jones’ (1991) model to calculate discretionary accruals and, accordingly, the value-weighted aggregate discretionary accruals. We require a firm to have at least ten observations of data throughout the sample period. Firms are grouped by size into quintiles from the smallest to the largest ones. In each cell, we report the cross-sectional means, the t-statistics (in parentheses), and the cross-sectional medians of the regression results in the first, second, and third rows, respectively. The sample period is 1965-2004. *, **, and *** denote (two-sided) significance at the 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Models</th>
<th>Intercept</th>
<th>dac</th>
<th>DAC</th>
<th>ADJ. R²</th>
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<td></td>
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<tr>
<td>Pooled</td>
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<td></td>
</tr>
<tr>
<td>(1)</td>
<td>17.801***</td>
<td>-1.686***</td>
<td></td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(51.29)</td>
<td>(-3.79)</td>
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<td></td>
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<tr>
<td></td>
<td>16.715</td>
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<tr>
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<td>18.542***</td>
<td>-2.165***</td>
<td>8.152***</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td>(38.19)</td>
<td>(-5.04)</td>
<td>(9.23)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>16.631</td>
<td>-1.956</td>
<td>6.604</td>
<td>0.007</td>
</tr>
<tr>
<td>Smallest</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1)</td>
<td>17.577***</td>
<td>-3.318***</td>
<td></td>
<td>0.002</td>
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<tr>
<td></td>
<td>(15.95)</td>
<td>(-2.68)</td>
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<tr>
<td></td>
<td>15.550</td>
<td>-3.109</td>
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<td>-0.024</td>
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<tr>
<td>(2)</td>
<td>16.096***</td>
<td>-3.489***</td>
<td>5.658**</td>
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<tr>
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<td>-3.068</td>
<td>4.764</td>
<td>-0.014</td>
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<tr>
<td>(1)</td>
<td>18.346***</td>
<td>-3.828***</td>
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<td>17.465</td>
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<td>(23.26)</td>
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<td>17.789</td>
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<tr>
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<td>7.129***</td>
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<td>(19.62)</td>
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<td>(4.06)</td>
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<td></td>
<td>17.293</td>
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<td>6.525</td>
<td>0.009</td>
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<td>4</td>
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<td>(1)</td>
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<td>15.952</td>
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<td>-0.015</td>
</tr>
<tr>
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<td>7.901***</td>
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</tr>
<tr>
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<td>(16.05)</td>
<td>(-1.63)</td>
<td>(3.85)</td>
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<td>16.038</td>
<td>-0.480</td>
<td>6.659</td>
<td>0.009</td>
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<td>Largest</td>
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<tr>
<td>(1)</td>
<td>18.425***</td>
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<td>(36.66)</td>
<td>(-0.70)</td>
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<td></td>
<td>17.093</td>
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<td>-0.018</td>
</tr>
<tr>
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<td>21.643***</td>
<td>-1.312</td>
<td>12.424***</td>
<td>0.075</td>
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<tr>
<td></td>
<td>(19.92)</td>
<td>(-1.63)</td>
<td>(6.86)</td>
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</tr>
<tr>
<td></td>
<td>17.830</td>
<td>-2.147</td>
<td>8.569</td>
<td>0.040</td>
</tr>
</tbody>
</table>
Figure 1. Aggregate Accruals (AC), Aggregate Normal Accruals (NAC), Aggregate Discretionary Accruals (DAC), and Aggregate Market Returns (EXCVW)
Figure 2. Monte-Carlo Analysis under the Null Hypothesis of No Stock Return Predictability

We plot the histogram of estimated coefficients from regressing value-weighted excess market returns on value-weighted aggregate discretionary accruals. Following Baker, Taliaferro and Wurgler (2006), we first simulate 50,000 series of EXC_VW based on the following system of equations:

\[
\text{EXC}_{t} = a + u_{t}, \quad \text{with } u_{t} \sim \text{i.i.d.}(0, \sigma_{u}^{2}), \quad \text{and}
\]

\[
\text{DAC}_{t} = c + d \times \text{DAC}_{t-1} + v_{t}, \quad \text{with } v_{t} \sim \text{i.i.d.}(0, \sigma_{v}^{2}) \quad \text{and } \rho(u, v) \neq 0.
\]

Here, EXC_VW is the value-weighted excess market return; DAC is the value-weighted aggregate discretionary accruals; the parameters a and \( \sigma_{u} \) are set based on the empirical distribution of EXC_VW; the parameters c, d, and \( \sigma_{v} \) are determined based on the empirical dynamics of DAC; the correlation coefficient \( \rho(u, v) \) is set to its empirical value; the sample size is T. Specifically, a=5.864, \( \sigma_{u}=16.550 \); c= -8.477e-3, d=2.859e-2, \( \sigma_{v}=0.838 \); \( \rho(u, v)=-0.397 \); and T=40. We then regress each series of simulated returns against DAC, and we use OLS estimates of the predictive coefficient b from 50,000 separate samples, reporting the average estimated coefficient and compare it with the actual estimation result.

Panel A. Average Estimated Predictive Coefficient from Simulations and Actual Result

<table>
<thead>
<tr>
<th>Simulation versus Actual Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average b</td>
</tr>
<tr>
<td>0.158</td>
</tr>
</tbody>
</table>

Panel B. Histogram of Estimated Predictive Coefficients