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Aggregate Accruals and Market Returns: The Role of Aggregate M&A Activity

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Abstract

Extant literature documents that aggregate accruals positively predict future market returns and attributes this relation to either changes in discount rates or systematic earnings management. We offer an alternative explanation: aggregate merger and acquisition (M&A) activity drives this relation. M&A activity affects the magnitude of accruals, which in turn drives the market return predictability of aggregate accruals. We find that the ability of both aggregate accruals and discretionary aggregate accruals (a measure of systematic earnings management) to predict market returns disappears after controlling for aggregate M&A activity. Furthermore, aggregate M&A activity predicts future market returns, consistent with a price response to improvements in macroeconomic outcomes due to aggregate M&A activity.

Aggregate Accruals and Market Returns: The Role of Aggregate M&A Activity

1. Introduction

Hirshleifer, Hou, and Teoh (2009) document an intriguing finding – aggregate accruals positively predict future market returns. This finding is puzzling for two reasons: 1) there is no relationship between aggregate earnings and future market returns (e.g., Kothari, Lewellen, and Warner, 2006; Sadka and Sadka, 2009), and 2) at the firm level, accruals *negatively* predict future stock returns in the cross-section (Sloan, 1996). Prior research (e.g., Hirshleifer et al., 2009; Kang, Liu, and Qi, 2010; Guo and Jiang, 2011) offers two explanations for the positive relation between aggregate accruals and future market returns. First, aggregate accruals convey information about discount rate shocks. Second, managers systematically manipulate accruals in response to market-wide undervaluation. We offer an alternative explanation. We posit and find evidence that aggregate merger and acquisition (M&A) activity drives aggregate accruals' ability to predict market returns because accruals include changes in balance sheet accounts related to M&A activity. More important, aggregate M&A activity positively predicts market returns and subsumes aggregate accruals' predictive ability. The relation between M&A activity and future market returns is consistent with economic theory that predicts improvements in macroeconomic outcomes stemming from aggregate M&A activity.

Economic theory suggests that aggregate M&A activity improves economic efficiency through capital reallocation in the economy (e.g., Gort, 1969; Jovanovic and Rousseau, 2002, 2008; Yang, 2008; Levis, 2011; Gomes and Livdan, 2004; Eckbo, 2014; David, 2017). In particular, M&A activity reallocates capital from underperforming and low-productivity firms to better-performing, high-productivity, and better-managed firms (Jovanovic and Rousseau, 2008), thereby improving economic efficiency. Furthermore, synergies from economies of scope could also improve aggregate efficiency (Gomes and Livdan, 2004; Rhodes-Kropf and Robinson, 2008). However, it is unclear whether market returns immediately incorporate expected efficiency improvements. In addition to these direct channels, M&A activity may predict future aggregate returns because of merger anticipation and the associated premium for potential targets. This premium, on average, is roughly 10% of potential targets' stock price (Bennett and Dam, 2018). Yet other literature suggests that M&A activity is value-destroying because of managers' empire-building considerations, overconfidence, and hubris (e.g., Jensen, 1986; Roll, 1986; Morck, Shleifer, and Vishny, 1990; Lang, Stulz, and Walking, 1991; Malmendier and Tate, 2008; Curtis and Oh, 2018). Therefore, ex-ante, the relationship between aggregate M&A activity and future market returns is unclear.

Furthermore, M&A activity also affects the magnitude of accruals because the balance sheet method of measuring accruals uses data from the income statement and changes in the balance sheet non-cash working capital accounts (e.g., Sloan, 1996; Hirshleifer et al., 2009; Kang et al., 2010). That is, the balance sheet method includes accruals arising from M&A activity.[1] Therefore, it is plausible that the relation between aggregate accruals and future market returns is due to accruals capturing information about M&A activities.

We test this explanation in four ways. First, we use an alternative approach to measure accruals. Specifically, we estimate accruals using the cash flow statement method, i.e., directly from the cash flow statement (net income *minus* cash flows from operations), and accruals measured in this way do not include balance sheet accruals related to M&A activities (Hribar and Collins, 2002). If aggregate M&A activity drives accruals' return predictability, then aggregate

[1] The balance sheet method incorporates non-articulating events beyond M&A activities, such as discontinued operations and foreign currency translations. We also consider the impact of discontinued operations and foreign currency translations on return predictability in section 5.1.

accruals based on the cash flow statement method should have little or no return predictability. In contrast, if systematic earnings management drives the return predictability of aggregate accruals, then aggregate accruals estimated from cash flow statements (hereafter, CF-based) should predict future market returns just as well as aggregate accruals estimated from the balance sheet method (hereafter, BS-based). Second, we explicitly control for aggregate M&A activity in return prediction tests to examine whether BS-based aggregate accruals have any residual predictive ability. Third, we attempt to isolate M&A-related accruals by using the difference between BS-based aggregate accruals and CF-based aggregate accruals and expect M&A-related accruals to predict market returns. Finally, we consider two distinct components of BS-based aggregate accruals by separating firms with and without M&A activity. Our explanation suggests that the aggregate accruals of firms with M&A activities should drive the return predictability.

Before proceeding to the return prediction tests, we analyze the role of M&A activity on the measurement of accruals by focusing on the difference between BS-based and CF-based accruals (i.e., accruals spread). Note that the accruals spread contains three main non-articulating events: mergers and acquisitions, discontinued operations, and foreign currency translations. We find that of the three non-articulating events, M&A activity is the dominant driver of the accruals spread. In particular, we find that firms with M&A activity display a more positive accrual spread because M&A activity, on average, increases the net assets of the acquiring firms.

Next, we move to the return prediction tests. We begin by replicating the findings from Hirshleifer et al. (2009) for our sample period (1988-2015) in which cash flow statement data are also available. As in prior literature, we find that aggregate earnings do not predict future market returns. However, when we decompose earnings into accruals and cash flows, we find that BS-based aggregate accruals positively predict future market returns. Thus, the return predictability of aggregate accruals is robust for our sample period as well.

In testing our explanation, we first use the cash flow method to measure accruals. If systematic earnings management is the primary driver of the return-predictive ability of aggregate accruals, CF-based aggregate accruals should also predict future aggregate returns. We hold the sample and research design constant and replace BS-based with CF-based aggregate accruals. We find that, unlike BS-based aggregate accruals, CF-based aggregate accruals have no association with future market returns.

Second, we introduce aggregate M&A activity as an additional predictor. If aggregate M&A activity drives the return predictability of aggregate accruals, then controlling for M&A activity should attenuate or even eliminate the positive relationship between BS-based aggregate accruals and future aggregate returns. Consistent with this prediction, we find that when we control for aggregate M&A activity, the BS-based aggregate accruals have no incremental predictive ability. At the same time, we document that aggregate M&A activity positively predicts market returns. Our findings are robust to several alternative measures of aggregate M&A activity.

Lastly, we find interesting insights when we decompose BS-based aggregate accruals in two ways. First, we decompose aggregate accruals into articulating accruals (i.e., CF-based aggregate accruals) and non-articulating accruals (i.e., the difference between the BS-based and CF-based aggregate accruals). Consistent with our explanation, we find that non-articulating accruals positively predict future market returns. Second, when we separate aggregate accruals into two components, one based on firms with M&A activities and the other based on firms without M&A activities, we find that the former component predicts market returns, whereas the latter component is not associated with future market returns. Taken together, our findings from various alternative approaches thus far provide consistent and persuasive evidence that accruals stemming from aggregate M&A activity drive the aggregate returns-accruals relationship.

Does M&A activity subsume the systematic earnings management explanation supported by Kang et al. (2010)? To answer this question, we test whether the relation between aggregate discretionary accruals (the measure of systematic earnings management from Kang et al. (2010)) and future market returns holds after we control for aggregate M&A activity. As with the previous findings, when we control for the aggregate M&A activity, the return predictability of aggregate discretionary accruals disappears. Furthermore, when we estimate discretionary accruals using the cash flow statement method, aggregate discretionary accruals are unrelated to subsequent market returns. Thus, we do not find support for systematic earnings management as an explanation for aggregate accruals' return predictability.

Finally, we explore the underlying channel for the return predictability of aggregate M&A activity. If increased economic efficiency is the channel, we expect a positive relation between M&A activity and future aggregate economic activity. Consistent with economic theory, we find that higher aggregate M&A activity is associated with increases in future total factor productivity, real GDP growth, industrial production growth, and investment growth.

Our paper makes the following contributions to the literature. First, we document that the puzzling association between aggregate accruals and future aggregate market returns is a manifestation of aggregate M&A activity. Second, we offer new evidence on the role of aggregate M&A activity in predicting future market returns. While extensive literature documents the firm-level effects of M&A activity, we are unaware of a study that documents the ability of aggregate M&A activity to predict future aggregate returns. Also, we document that aggregate M&A activity is associated with higher future economic outcomes, consistent with theoretical predictions (e.g., David, 2017). Finally, an extensive literature advocates that scholars use CF-based accruals (e.g., Hribar and Collins, 2002; Casey et al., 2017) because BS-based accruals contain measurement error. Yet our evidence documents that BS-based accruals do contain important information about firm-specific economic activities, as suggested in Nallareddy, Sethuraman, and Venkatachalam (2020) and Larson, Sloan, and Giedt (2018).

2. Data and Descriptive Analysis

2.1 Sample Selection and Descriptive Statistics

We obtain annual stock return data for firms listed on NYSE/AMEX/NASDAQ from CRSP for the period 1988 to 2017 and accounting data from Compustat for 1988 to 2015.[2] We drop firm-year observations that are missing price, returns, and shares outstanding. Consistent with Hirshleifer et al. (2009), we restrict our sample firms to those with December fiscal year ends to better align annual returns with the annual frequency of accounting data. Finally, we require that firms have prior year data available to be included in the sample to estimate accruals based on changes in balance sheet accounts.

We calculate firm-level accruals in two ways: 1) using the balance sheet method (BS-based), and 2) using the cash flow statement method (CF-based). Before cash flow statements became mandatory in 1987, firms were not required to disclose different classifications of changes in cash during the year. Therefore, the literature has predominantly used the balance sheet method (BS-based) to estimate accruals. We calculate BS-based accruals following prior literature (e.g., Sloan, 1996; Hirshleifer et al., 2009) as follows:

$$ACC\_BSM = \Delta CA - \Delta CL - \Delta Cash + \Delta STDEBT + \Delta TP - DEP \qquad (1)$$

where Δ is the change operator, *CA* is current assets, *CL* is current liabilities, *Cash* is cash and cash equivalents, *STDEBT* is short-term debt, *TP* is taxes payable, and *DEP* is depreciation expense.

[2] We begin our sample in 1988 because cash flow data are unavailable prior to this year. Consistent with Hirshleifer et al. (2009), we define the period of our return calculations for period *t* to be from May of year *t* to April of year *t*+1, and the future return period (*t*+1) from May of year *t*+1 to April of year *t*+2. This limits our panel to the period of 1988 to 2015.

In contrast, following the recommendation in Hribar and Collins (2002), more recent literature uses CF-based accruals estimated as follows:

$$ACC\_CFM = IBC - CF\_CFM \quad (2)$$

where *ACC_CFM* is accruals using the cash flow statement method, *IBC* is earnings before extraordinary items and discontinued operations (Compustat item *ibc*), and *CF_CFM* is cash flows from operations before extraordinary items (Compustat items *oancf* minus *xidoc*).[3]

Following Hirshleifer et al. (2009), we compute aggregate accruals and cash flows by value-weighting firm-level accruals and cash flows using market capitalization at the beginning of the year as weights. For market returns in year *t*, we use two measures based on annual firm-level stock returns from May of year *t* through April of year *t*+1. First, we calculate the CRSP value-weighted returns (*CRSPRET*) using all CRSP firms in each period. Second, we estimate the value-weighted returns (*SAMPRET*) using only our sample firms.

We construct the M&A activity variable (*MA_ACT*) using the proportion of target firms that were merged or acquired during a year. Specifically, in each fiscal year, we identify the firms that are no longer followed by Compustat due to a merger or acquisition using Compustat data item "*DLRSN"* (defined as "Reason for Deletion" and coded as "01"). We then estimate *MA_ACT* as the number of Compustat firms that are delisted within our sample (just prior to aggregation) due to a merger or acquisition divided by the total number of Compustat firms in year *t*.[4]

With respect to control variables, dividend yield (*DYIELD*) and the 30-day treasury yield (*TBILL*) are from CRSP. Macroeconomic data for default spread (*DEF)*, term spread (*TERM)*, total factor productivity (*TFP)*, real gross domestic product (*RGDP)*, real private domestic investment (*INVEST)*, industrial production (*IND PROD*), and unemployment (*UNEMP*) are obtained from

[3] Our results are robust to using earnings before extraordinary items from the income statement instead of *IBC*.
[4] Our findings are robust to several alternative measures of M&A activity (see Section 5.3 and Table A3).

the St. Louis Federal Reserve Economic Data (FRED). The Chicago Fed National Activity Index (*CFNAI*) is a weighted-average index of 85 various monthly indicators of economic activity. We take the average 12-month calendar year value of the index. Data on new equity issued relative to total new debt and equity issued (*ESHARE)* are mainly from Baker and Wurgler (2000).[5] Aggregate book-to-market (*BE/ME*) is the value-weighted book-to-market ratio for year *t*. See the Appendix for more details on variable definitions.

Table 1 provides descriptive statistics. The average market return across our sample period using both CRSP value-weighted and sample value-weighted returns is approximately 11%. The mean BS-based aggregate accruals (*ACC_BSM*) is −0.054, whereas the mean operating cash flows (*CF_BSM*) is 0.132, consistent with prior literature. The mean CF-based aggregate accruals (*ACC_CFM*) is −0.064, whereas the mean aggregate cash flows (*CF_CFM*) is 0.142. All other control variables are consistent with those reported in Hirshleifer et al. (2009).

2.2 Non-articulation Events and the Accrual Spread

The difference between BS-based accruals and CF-based accruals stems largely from three main events: 1) mergers and acquisitions, 2) divestitures and discontinued operations, and 3) foreign currency translations (Hribar and Collins, 2002). In particular, the BS-based accruals incorporate these events, whereas the CF-based accruals do not. Therefore, we analyze how these three non-articulating events affect the magnitude of the spread (i.e., the difference between the BS-based accruals and the CF-based accruals) for our sample. Consistent with Hribar and Collins (2002), we expect M&A activity to positively affect the spread because net current assets for the acquiring firm tend to increase. That is, M&A activity will increase BS-based accruals relative to

[5] We thank Jeffrey Wurgler for providing *ESHARE* data on his website: http://people.stern.nyu.edu/jwurgler/. The data are available through April 2008. We update this measure for the period of May 2008 through December 2015 using the data provided by the Federal Reserve System: https://www.federalreserve.gov/data/corpsecure/default.htm. (Date retrieved: March 6, 2019.)

CF-based accruals. Similarly, we expect discontinued operations to affect the spread negatively. We do not have ex-ante predictions for foreign currency translations.

We estimate *ACC_BSM* and *ACC_CFM* based on equations (1) and (2) for three mutually *non-exclusive* groups of firms: (i) firms with at least one acquisition, (ii) firms with discontinued operations, and (iii) firms with foreign currency translations. Panel A of Table 2 presents the descriptive statistics for *ACC_BSM* and *ACC_CFM*, and the spread for each of the sub-groups. In the univariate analysis, we find that M&A activity results in considerable spread between *ACC_BSM* and *ACC_CFM*. In particular, we find that for firms with acquisitions, *ACC_BSM* is −0.033, and *ACC_CFM* is −0.077. The difference (i.e., spread) between *ACC_BSM* and *ACC_CFM* is 0.043, which is statistically different from zero at the 1% level. This finding is consistent with the conjecture that M&A activity produces a positive spread between *ACC_BSM* and *ACC_CFM*, as M&A activity, on average, should be associated with positive net current assets for the acquiring firm. For comparison, Panel A of Table 2 also provides descriptive statistics for firms without M&A activity. The spread for non-M&A firms is 0.024, which is statistically different from zero at the 1% level. More important, the spread is higher for M&A firms relative to non-M&A firms by 0.019, which is statistically significant at the 1% level.

For the sample of firms with discontinued operations, the difference between *ACC_BSM* and *ACC_CFM* is 0.015 and statistically different from zero at the 1% level, whereas for foreign currency translations, we find the spread to be 0.023 during our sample period, also significant at the 1% level. While we do not have a clear ex-ante prediction for the foreign currency translation sample, our finding for the discontinued operations sample is inconsistent with the expectation that discontinued operations provide a negative spread between *ACC_BSM* and *ACC_CFM* as net current assets decrease when a firm has discontinued operations. However, note that the samples are not mutually exclusive in that other non-articulating events can contaminate the spread estimates. With this caveat in mind, we document that the firms with discontinued operations have an average spread of 0.015, which is lower than the average spread of the sample without discontinued operations (0.031). For the sample of firms with foreign currency translation, we find that the average spread is 0.023, whereas the average spread of the sample without foreign currency translation is 0.031.

In addition to the firm-level descriptive statistics, we present the value-weighted (using the weights from within each subgroup) time-series descriptive statistics for each sub-sample in Panel B. The findings using the value-weighted analysis are similar to those using the firm-level analysis. However, as with the firm-level analysis reported in Panel A, a limitation of the univariate analysis in Panel B is that the samples are not mutually exclusive, which makes it difficult to compare across subgroups. To address this issue, we conduct a multivariate analysis at the firm level, in which we regress the accrual spread on each of the three non-articulation event indicators.

Panel C of Table 2 presents regression estimates from multivariate analysis. We find that M&A activity is positively associated with the spread, whereas discontinued operations are negatively related to the spread. The latter result is consistent with expectations and different from the univariate analysis. Foreign currency translations are also negatively related to the spread. The explanatory power of all three non-articulation events is 1%, but a majority of the explanatory power comes from M&A activity.

Using an M&A indicator variable does not take into account the size of the target company acquired or the number of acquisitions during the year by the same acquirer. To address this limitation, we perform additional analysis using direct measures of M&A activity, in particular the sales contribution of acquisitions for the acquirer and the inventory contribution of acquisitions for the acquirer. Unfortunately, these data are not available in Compustat until

2011. Nonetheless, with the available data, we find that the incremental explanatory power of the continuous measures of M&A activity is significantly higher. In particular, we find that the incremental explanatory power of the sales contribution using the acquisitions measure is 4.7% (columns 3 and 4 of Table 2, Panel B), and it is 18.2% when we use the inventory contributions from the acquisitions measure (refer to columns 5 and 6). Collectively, the evidence suggests that M&A activity is one of the key drivers of the spread between *ACC_BSM* and *ACC_CFM*. The lower explanatory power of the spread models suggests that there are other differences between *ACC_BSM* and *ACC_CFM*, beyond M&A activity, divestitures and discontinued operations, and foreign currency translations.

3. Results

3.1 Aggregate Accruals and Return Predictability: Balance Sheet Approach

We begin by replicating the findings of Hirshleifer et al. (2009) for our sample period (1988-2015). For the return-predictability regressions, we standardize all independent variables with a mean of zero and a variance of one for ease of interpretability and comparability to Hirshleifer et al. (2009). We present our full model as follows:

$$AGGVWRET_{t+1} = \alpha + \beta_1 ACC\_BSM_t + \beta_2 CF\_\ BSM_t + \sum \beta_k Controls_t + \epsilon_{t+1} \qquad (3)$$

where *AGGVWRET* is aggregate stock returns (*CRSPRET* or *SAMPRET*), *ACC_BSM* is BS-based aggregate accruals, *CF_BSM* is BS-based aggregate cash flows, and controls include *BE/ME*, *ESHARE*, *DYIELD*, *DEF*, *TERM*, and *TBILL*. All regression estimates are reported with Newey-West heteroskedasticity- and autocorrelation-consistent standard errors.[6] We expect β_1 to be

[6] Durbin-Watson (1950, 1951, 1971) tests indicate sufficient autocorrelation to warrant the use of Newey-West (1987) standard errors. We determine three lags as appropriate based on the formula, $4*(T/100)^{2/9}$, where T is the number of observations in the regression model.

positive and significant, as documented in Hirshleifer et al. (2009).

Table 3, Panel A, reports the results. Consistent with prior literature, we find that aggregate earnings do not predict future market returns. In particular, columns (1) and (5) show a statistically insignificant coefficient estimate on aggregate earnings (*EARN*) for both CRSP and sample index market returns. Decomposing the earnings into accruals and cash flows improves the return-prediction model significantly. The results in columns (2) and (6) indicate that the explanatory power of the model improves dramatically from an adjusted R^2 of below 0% using earnings to 14-17% for the model that disaggregates aggregate earnings into aggregate accruals and aggregate cash flows. More importantly, consistent with the findings in Hirshleifer et al. (2009), we find that aggregate accruals positively predict future market returns in our sample, while aggregate cash flows negatively predict future market returns. We include the full battery of controls in columns (3) and (7) and find that the predictive ability of accruals is robust. In economic terms, we find that a one standard deviation increase in aggregate accruals increases future CRSP value-weighted returns (*CRSPRET*) by 5.2% and future sample value-weighted returns (*SAMPRET*) by 6.4%. We find that the predictive ability of *CF_BSM* is not robust to alternative specifications.

We estimate the models reported in columns (3) and (7) following Hirshleifer et al. (2009), but one of the main concerns about these models is multicollinearity between book-to-market and dividend yield, as indicated by a high variance inflation factor (VIF).[7] Therefore, we omit book-to-market from these specifications to address multicollinearity concerns. Diagnostic tests suggest that excluding book-to-market alleviates the issue.[8] Results presented in columns (4) and (8), where we estimate equation (3) after omitting *BE/ME*, indicate that the coefficient estimates for

[7] For example, in model (3) the VIF is 8.64 for *BE/ME* and 10.23 for *DYIELD*. A VIF above 5 represents a significant multicollinearity issue (Montgomery, Peck, and Vining, 2012).
[8] Once we remove *BE/ME* from the specification, all VIFs are below 5.

BS-based accruals (*ACC_BSM*) are similar. Thus, our regression estimates are robust to excluding *BE/ME*.[9]

Overall, consistent with prior literature, we find that aggregate earnings are not associated with future market returns. Aggregate accruals estimated using the balance sheet approach positively predict future market returns, and these findings are robust to alternative specifications. Aggregate cash flows are negatively related to future market returns; however, the evidence is not robust.

3.2 M&A Activity as an Explanation for Aggregate Accruals' Return Predictability

In this section, we explore whether M&A activity drives accruals' return predictability at the aggregate level. We conduct four analyses. First, we estimate and substitute accruals based on the cash flow statements. Second, we explicitly control for aggregate M&A activity in the BS-based accrual-return prediction model. Third, we decompose aggregate accruals into articulating accruals and accruals pertaining to non-articulating events, and we examine the return predictability of the two components. Fourth, we compute aggregate accruals for firms with and without M&A activities and examine which of these two components are related to future market returns.

3.2.1 Aggregate Accruals and Return Predictability: Cash Flow Statement Approach

To test our prediction that M&A-related accruals explain the return predictability, we rerun the aggregate return-predictability model using CF-based aggregate accruals and cash flows. As discussed in section 2.2, the largest difference between the BS-based accruals and CF-based accruals is due to M&A activity. Therefore, if M&A-related accruals drive accruals' return

[9] We present Table 2 with and without *BE/ME* to facilitate comparison with prior literature. For subsequent analyses of return predictability, we omit *BE/ME* as a predictor to avoid multicollinearity in our regression estimates.

predictability documented in section 3.1, we expect the ability of CF-based aggregate accruals to predict future market returns to attenuate. To test this prediction, we estimate the following model:

$$AGGVWRET_{t+1} = \alpha + \beta_1 ACC\_CFM_t + \beta_2 CF\_CFM_t + \sum \beta_k Controls_t + \epsilon_{t+1} \quad (4)$$

where *AGGVWRET* is aggregate stock returns (*CRSPRET* or *SAMPRET*), *ACC_CFM* is CF-based aggregate accruals, *CF_CFM* is CF-based aggregate cash flows, and controls include *BE/ME*, *ESHARE*, *DYIELD*, *DEF*, *TERM*, and *TBILL*. For this analysis, we maintain the same sample and research design as in section 3.1 but replace the BS-based aggregate accruals and cash flows with CF-based aggregate accruals and cash flows.

Table 3, Panel B, presents the results using CF-based aggregate accruals and cash flows. Strikingly, we do not find reliable evidence that aggregate accruals calculated using data from the cash flow statement have significant predictive power for future market returns. These findings are suggestive that the M&A activity-related accruals embedded in BS-based aggregate accruals drive the return predictability of aggregate accruals.

3.2.2 Market Return Predictability: Controlling for M&A Activity

In this section, we explicitly control for aggregate M&A activity in the empirical specification. Because M&A activity affects the magnitude of BS-based accruals, controlling for M&A activity should considerably diminish or even eliminate the predictive ability of BS-based accruals. To test this prediction, we modify equation (3) by including the proxy for the level of aggregate M&A activity *(MA_ACT)*:

$$AGGVWRET_{t+1} = \alpha + \beta_1 ACC\_BSM_t + \beta_2 CF\_BSM_t + \beta_3 MA\_ACT_t + \sum \beta_k Controls_t + \epsilon_{t+1} \quad (5)$$

If M&A activity is a driver of aggregate accruals' return predictability, the coefficient on β_1 will attenuate. We expect β_3 to be positive, consistent with predictions from economic theory (e.g., David, 2017).

In Table 4, columns (1) and (3) repeat the results from Table 3, Panel A for comparison. When we add *MA_ACT* to the regression specification, we find that the coefficient on *ACC_BSM* loses statistical significance (see columns (2) and (4)). Also, the coefficient on *MA_ACT* is positive and statistically significant. *CF_BSM* is also affected by M&A activity because *CF_BSM* is imputed as earnings (*IBC*) minus the BS-based accruals (*ACC_BSM*). Recall that that *CF_BSM* was negatively related to future market returns, but this relation was not robust. However, when we include M&A activity in the regression, we find that *CF_BSM* becomes significant and broadly robust. We are not able to come up with a rational explanation for this finding.

We draw two main conclusions from the above analysis. First, the predictive ability of BS-based aggregate accruals for future returns disappears when we include aggregate M&A activity, consistent with our prediction. Second, our evidence suggests that the aggregate level of M&A activity is a positive predictor of future market returns.

3.2.3 Aggregate Accrual Components and Return Predictability

One disadvantage of the analysis in section 3.2.2 is that the evidence using the M&A measure is indirect because it focuses on the target firms rather than the acquiring firms. That is, this measure does not directly capture accruals stemming from M&A activity for the acquirers. To address this limitation, and to further understand the source of the predictive ability of BS-based aggregate accruals for future market returns, we drill down on M&A-related accruals in two ways. First, we proxy for M&A-related accruals using the difference between BS-based aggregate accruals and CF-based aggregate accruals (i.e., accrual spread).[10] If aggregate M&A activity drives the aggregate accruals' predictive ability, then this accruals component should be potent in

[10] Note that the difference between BS-based accruals and CF-based accruals also contains information about discontinued operations and foreign currency translations. In section 5.1, we investigate the role of discontinued operations and foreign currency translations. We find that these events, unlike M&A activity, do not subsume accruals' predictive ability of future market returns.

predicting future market returns. Table 5, Panel A (columns (1) and (2)) presents the results. Consistent with expectations, aggregate M&A-related accruals (i.e., the accrual spread: *ACC_BSM* − *ACC_CFM*) positively predict future market returns. In particular, the coefficient estimate on the aggregate M&A-related accruals is 0.061 when we use the CRSP value-weighted returns, and it is 0.078 when we use the sample value-weighted returns. Furthermore, as Columns (3) and (4) show, when we control for the aggregate M&A activity, the predictability of the accrual spread is insignificant. At the same time, the coefficient on the aggregate M&A activity (*MA_ACT*) is positive and statistically significant, as before (see columns (3) and (4) of Panel A, Table 5). We note that the coefficient on *ACC_CFM* is statistically significant in columns (1) and (2), which is inconsistent with the findings in Table 3, Panel B. The correlation between *ACC_CFM* and non-articulating accruals (i.e., *ACC_BSM* − *ACC_CFM*) is quite high ($\rho = -0.62$). We believe that this high correlation may drive the positive relation between *ACC_CFM* and future market returns, because when we exclude the non-articulating accruals variable, *ACC_CFM* is not associated with future market returns. At the same time, when we exclude *ACC_CFM* from the regression estimation, the non-articulating accruals remain positively related to future market returns.

In our second analysis, we measure aggregate accruals for two sets of firms: 1) firms with M&A activities, and 2) firms without M&A activities. For each year, we classify firms that have an M&A footnote in Compustat (footnote code "AA") as M&A firms (following Hribar and Collins, 2002). The remaining firms are classified as non-M&A firms. We then separately aggregate the accruals for M&A and non-M&A firms each year. If the M&A activity drives aggregate accruals' ability to predict future market returns, then the aggregate accruals of M&A firms should predict future market returns, while the aggregate accruals of non-M&A firms should have no predictive ability. Table 5, Panel B, presents the results. In Columns (1) and (2), we find that the aggregate accruals of M&A firms (*ACQ_ACC_BSM)* positively predict future market returns. These results are robust to using CRSP value-weighted returns or sample value-weighted returns as the dependent variable. In contrast, aggregate accruals of non-M&A firms (*NON_ACQ_ACC_BSM)* are not associated with future market returns.

This analysis has two limitations. First, the difference in coefficient estimates between *ACQ_ACC_BSM* and *NON_ACQ_ACC_BSM* is not statistically significant. Second, M&A firms are fundamentally different from non-M&A firms. Therefore, comparing the return predictability of aggregate accruals of M&A firms to the aggregate accruals of non-M&A firms may not offer dispositive evidence in support of our explanation. To address these limitations, we repeat all our tests using the same sample and research design but replacing the BS-based accrual components with CF-based accruals components, again splitting aggregate accruals between M&A and non-M&A firms. This way, we ensure that the fundamentals are constant, and any differences in findings can be attributed solely to the measurement of accounting attributes. Columns (3) and (4) present the results. We find that CF-based accrual components do not predict future market returns, whereas BS-based accrual components do. These results provide corroborative evidence that it is likely the M&A activity, rather than the fundamental differences between M&A and non-M&A firms, that drives the return predictability.

3.3 Discretionary Accruals and Aggregate M&A Activity

Hirshleifer et al. (2009) propose that aggregate accruals' predictive ability is due to either information about discount rate shocks encapsulated in aggregate accruals or systematic earnings management by firms in response to market undervaluation. Subsequent work by Kang et al. (2010) concludes that the predictive ability is due mainly to systematic earnings management by documenting that aggregate *discretionary* accruals (a proxy for earnings management), rather than aggregate *non-discretionary* accruals, drive return predictability.

Like Hirshleifer et al. (2009), Kang et al. (2010) use the balance sheet method to estimate discretionary accruals. They estimate discretionary accruals as the difference between total accruals and non-discretionary accruals (e.g., accruals expected by model estimates). They estimate non-discretionary accruals as a linear function of typical firm-level variables such as sales growth and property, plant, and equipment. Furthermore, Hribar and Collins (2002) suggest that the BS-based accruals introduce measurement error into non-discretionary accrual estimation. To the extent that the economic determinants of non-discretionary accruals capture the measurement error in total accruals, the measurement error problem may not translate directly to discretionary accruals. Therefore, it is an open empirical question whether our findings for total accruals apply to discretionary accruals as well.

We estimate firm-level discretionary accruals (*DAC*) using both methods: 1) the balance sheet method (*DAC_BSM*), and 2) the cash flow statement method (*DAC_CFM*). For both calculations, we first estimate the following model by industry and year (Jones, 1991):

$$ACC\_BSM \text{ or } ACC\_CFM_{it} = \alpha_1 \frac{1}{TA_{it}} + \beta_1 \frac{\Delta Rev_{it}}{TA_{it}} + \beta_2 \frac{PPE_{it}}{TA_{it}} + \epsilon_{it} \tag{6}$$

where *ΔRev* is the change in revenue from *t*-1 to *t*, *PPE* is property, plant, and equipment, and *TA* is average total assets in year *t* for firm *i*. To estimate non-discretionary firm-level accruals (*NAC_BSM* or *NAC_CFM*), we require at least five observations in each two-digit SIC industry-year. To mitigate the influence of outliers, we delete firm-year observations with BS-based accruals below the 0.5 percentile and above the 99.5 percentile (following Kang et al., 2010).[11] Thus:

$$NAC\_BSM \text{ or } NAC\_CFM_{it} = \left[\widehat{\alpha_1} \frac{1}{TA_{it}} + \widehat{\beta_1} \frac{\Delta Rev_{it}}{TA_{it}} + \widehat{\beta_2} \frac{PPE_{it}}{TA_{it}}\right] \tag{7}$$

[11] Kang et al. (2010) require at least 10 observations for each firm and estimate discretionary accruals using firm-specific time-series regressions. We deviate from their methodology and pool observations within two-digit SIC industry and year to estimate discretionary accruals. We believe this reduces survivorship bias in the sample. This also allows us to relax the required sample size to five observations within an industry and year.

$$DAC\_BSM = ACC\_BSM - NAC\_BSM \text{ or } DAC\_CFM = ACC\_CFM - NAC\_CFM \tag{8}$$

where $\widehat{\alpha_1}$, $\widehat{\beta_1}$, and $\widehat{\beta_2}$ are the fitted coefficient estimates from specification (6) above. As with aggregate accruals, we compute aggregate discretionary and non-discretionary accruals using market capitalization as weights.

We begin by re-estimating the main specification (3) by substituting total aggregate accruals with discretionary and non-discretionary aggregate accruals. Table 6, Panel A reports the regression estimates of future returns on BS-based discretionary and non-discretionary accruals. Consistent with the findings in Kang et al. (2010), we find that aggregate discretionary accruals positively predict future market returns, while aggregate non-discretionary accruals have no predictive ability. That is, the coefficients on *DAC_BSM* are positive and statistically significant, whereas the coefficients on *NAC_BSM* are not significant (see columns (1) and (3)). Thus, the findings from Kang et al. (2010) are robust to the extended sample.

Next, we repeat our analysis after including the aggregate M&A activity measure as an additional predictor. When we include the M&A activity measure in the model, we find that the predictive ability of aggregate discretionary accruals becomes insignificant. At the same time, the coefficient on the aggregate M&A activity (*MA_ACT*) is positive and statistically significant (see columns (2) and (4) of Panel A, Table 6). Overall, these results provide evidence that, like the predictive ability of aggregate total accruals, the predictive ability of aggregate discretionary accruals is also driven by M&A activity.

To buttress our findings, we next examine whether computing discretionary accruals using CF-based aggregate accruals predicts future market returns. In other words, we estimate *NAC_CFM* and *DAC_CFM* and substitute these alternative accrual calculations for *NAC_BSM* and *DAC_BSM* in equation (3). We report the results in Panel B, Table 6. Consistent with our prediction and the results reported earlier, we find that CF-based aggregate discretionary accruals have no significant predictive ability for future aggregate returns. That is, the coefficient on *DAC_CFM* is not statistically significant across specifications. Collectively, the evidence documented here is not consistent with the systematic earnings management explanation after we account for aggregate M&A activity.

4. M&A Activity and Future Macroeconomic Outcomes

Our finding that the level of aggregate M&A activity (*MA_ACT*) predicts future market returns is consistent with a price response to aggregate economic effects of M&A activity. Economic theory suggests that aggregate M&A activity improves aggregate economic outcomes (David, 2017). Braguinsky, Ohyama, Okazaki, and Syverson (2015) echo this prediction by showing that higher-productivity firms buy lower-productivity firms, which leads to better capital productivity in the aggregate. Furthermore, synergies emanating from economies of scope could also improve economic efficiency (Gomes and Livdan, 2004). Consistent with theoretical predictions, Dimopoulos and Sacchetto (2017) document that firm-level productivity increases by 4.8% following M&A activity, on average. Therefore, we predict that aggregate M&A activity is related to future aggregate economic outcomes.

To test our prediction, we examine the relationship between current-period aggregate M&A activity and future macroeconomic outcomes. We consider five macroeconomic outcomes that capture aggregate economic efficiency: 1) *TFP* – the annual percent change in total factor productivity: a measure of aggregate output productivity from capital and labor; 2) *RGDP* – the annual percent change in real gross domestic product: the value of aggregate output adjusted for price changes; 3) *IND PROD* – the annual percent change in industrial production; 4) *INVEST* – the annual percent change in the amount of real gross private domestic investment; and 5) *UNEMP* – the unemployment rate. Consistent with predictions from economic theory (e.g., Braguinsky et al., 2015; David, 2017), we expect aggregate M&A activity to be positively related to *TFP*, *RGDP*, *IND PROD*, and *INVEST*, and negatively related to *UNEMP*. We estimate the following empirical specification:

$$MACRO\ OUTCOME_{t+i} = \alpha + \beta_1 MA\_ACT_t + \beta_2 CFNAI_t + \sum \beta_k MACRO\ OUTCOME_t + \epsilon_{t+i} \quad (9)$$

where i = 1 or 2 years ahead, *MACRO OUTCOME* = {*TFP*, *RGDP*, *IND PROD, INVEST*, *UNEMP*}, and *MA_ACT* is the number of firms for which Compustat stopped coverage due to a merger or acquisition divided by the total number of Compustat firms in year t. Note that when estimating equation (9), we compute the *MA_ACT* measure using all Compustat firms since it more comprehensively captures the effect of M&A activity on macroeconomic outcomes, whereas, for our return prediction tests, we compute the measure using only our sample firms. We control for the state of the economy with *CFNAI*, the Chicago Fed National Activity Index – a composite weighted-average index of 85 economic indicators.[12]

Table 7 presents our empirical findings. In Panel A, we consider one-year-ahead macroeconomic outcomes. We find that current M&A activity is positively related to one-year-ahead increases in economic activity. In particular, aggregate M&A activity is positively related to subsequent one-year-ahead total factor productivity (column (1)), real GDP growth (column (2)), industrial production growth (column (3)), and aggregate investment (column (4)). We do not find that M&A activity is related to one-year-ahead unemployment rate (column (5)). As expected, *CFNAI* is positively related to future real GDP, industrial production growth, and aggregate investment, and negatively related to unemployment. Thus, M&A activity predicts future macroeconomic outcomes after we control for *CFNAI* and lagged macroeconomic indicators.

[12] *CFNAI* data are obtained from the Chicago Fed: https://www.chicagofed.org/publications/cfnai/index (retrieved March 7, 2019).

Panel B presents the results using two-year-ahead macroeconomic outcomes. We find that M&A activity is not robustly related to two-year-ahead macroeconomic outcomes.

The evidence suggests that, consistent with economic theory, aggregate M&A activity is associated with improvements in overall economic efficiency. The relation between M&A activity and future macroeconomic outcomes provides suggestive evidence that the association between M&A activity and future market returns is consistent with a risk-based explanation (Liew and Vassalou, 2000; and Petkova, 2006). For example, Liew and Vassalou (2000) use the relation between size and value factor for future GDP growth to support a risk-based explanation, consistent with the intertemporal capital asset pricing (ICAPM) model. Albeit, our evidence does not rule out market inefficiency as an explanation for our findings.

5. Additional Analyses

5.1 Effects of Other Events - Discontinued Operations & Foreign Currency Translations

Besides M&A activity, two other main economic events drive the difference between BS-based accruals and CF-based accruals: 1) discontinued operations and divestitures, and 2) foreign currency activities. These events may also explain the relation between aggregate accruals and market returns. However, ex-ante, we do not have clear theoretical predictions for how these events will relate to future market returns. Additionally, M&A activity is the main difference between accruals calculated using the balance sheet statement and those calculated using the cash flow statement. For completeness, we explore whether including discontinued operations or foreign currency activities in the baseline model also attenuates the effect of BS-based aggregate accruals on future market returns.

In Table 8, we present regression estimates of future returns on BS-based aggregate accruals, after incorporating information about foreign currency activities and discontinued operations. The analysis here is similar to that reported in Table 4. Specifically, following Hribar and Collins (2002), we use the fraction of firms with discontinued operations/divestitures (*DO_ACT*) and the fraction of firms with foreign currency activities (*FCA_ACT*) as additional variables. We find that including aggregate discontinued operations or aggregate foreign currency activities does not subsume the predictive ability of the aggregate accruals. We find that aggregate discontinued operations are not associated with future returns (columns (2) and (5)), and aggregate foreign currency activities (columns (3) and (6)) are negatively related to future market returns only for *SAMPRET*. More importantly, the coefficient on aggregate accruals continues to be positive and statistically significant.[13]

Collectively, the evidence in Table 8 suggests that the accruals stemming from events other than M&A activity are not significant enough to influence the effect of aggregate accruals on future market returns. Thus, we conclude that aggregate M&A activity is the key driver that explains the relation between aggregate accruals and market returns.

5.2 Alternative Accrual Measurement

In our primary analysis, we define *ACC_BSM* using equation (1) and *ACC_CFM* using equation (2). This design choice is to keep the same broad sample in our analysis but change only the measurement of accruals in our research design. In particular, in our sample period, after restricting our data to NYSE/AMEX/Nasdaq firms with December year-ends, we can estimate *ACC_BSM* for 70,326 firm-year observations, and *ACC_CFM* for 69,357 firm-year observations.[14] We further restrict our sample by omitting observations with 1) no coverage in CRSP (6,957

[13] Larson et al. (2018) suggest that capital expenditures are another item that drives the difference between BS-based and CF-based accruals. Therefore, we also consider aggregate capital expenditures as an additional control variable in the empirical specification. In untabulated results, we find that including aggregate capital expenditures has very little effect on the relation between aggregate accruals and future returns.

[14] The difference in sample size is attributable to missing earnings before extraordinary items (341 firm-year observations) and operating cash flow figures (879 firm-year observations). These missing variable observations are not mutually exclusive. We replace missing extraordinary items with zero.

observations), 2) missing future return data (10,652 observations), and 3) missing market capitalization data in Compustat (3,402 observations). These restrictions collectively reduce our sample for our primary analyses to 48,346 firm-year observations. A limitation of this approach is that *ACC_CFM* contains certain components beyond those contained in *ACC_BSM*. For example, accruals related to stock-based compensation and write-downs are part of *ACC_CFM* but not *ACC_BSM*. Therefore, *ACC_CFM*'s lack of predictive ability could be attributable to these other components of accruals. To address this limitation, we consider definitionally consistent accruals. In particular, to maintain consistency with the definition of *ACC_BSM*, we change the measurement of cash flow-based accruals as follows:

$$ACC\_CFM = -(RECCH + INVCH + APLACH + AOLOCH + DPC) \qquad (10)$$

where *RECCH* is decrease (increase) in receivables, *INVCH* is decrease (increase) in inventory, *APLACH* is increase (decrease) in payable, *AOLOCH* is net increase (decrease) in other assets and liabilities, and *DPC* is depreciation expense. Even though estimating *ACC_CFM* using equation (10) is definitionally consistent with *ACC_BSM*, this method restricts the sample to 30,591 firm-year observations because of the missing data.[15] This constitutes a sample reduction of 37% relative to the sample used in the main analysis. Nonetheless, for completeness, we repeat our main analyses using this reduced sample and present the results in Tables A1 and A2.

Overall, our inferences remain robust. We find that CF-based accruals estimated using equation (10) do not predict future aggregate returns. Furthermore, we find that non-articulating accruals (i.e., *ACC_BSM* − *ACC_CFM*) positively predict future market returns. Finally, aggregate BS-based accruals of M&A firms positively predict future market returns, whereas aggregate BS-

[15] The reduction in the sample is attributable to missing amounts for change in receivable (6,231 firm-year observations), change in inventory (7,221 firm-year observations), change in payable (19,260 firm-year observations), change in other assets and liabilities (628 firm-year observations), and depreciation expense (835 firm-year observations). These missing variable observations are not mutually exclusive.

based accruals of non-M&A firms are not associated with future market returns. However, when we change the measurement to CF-based accruals, we find that neither the aggregate CF-based accruals of M&A firms nor those of non-M&A firms are significantly related to future market returns. Together, these findings suggest that our main analysis is robust to alternative accrual definitions and that it is the non-articulating component of accruals that explains return predictability.

5.3 Alternative M&A Activity Measures

We investigate the robustness of our findings to alternative M&A activity measures that are derived using different data sources and deflators. In particular, in our primary analysis, we employ a measure estimated as the number of firms delisted because of M&A activity divided by the total number of sample firms. We consider several alternative measures of M&A activity to ensure the robustness of our findings. First, we use the sum of the market capitalization of target firms divided by total market capitalization from Compustat. Using this measure, we find that, as before, M&A activity subsumes the predictive ability of *ACC_BSM*. However, M&A activity is not significant at conventional levels. Second, we consider measures from an alternative dataset (SDC Platinum's M&A dataset). A major difference between SDC- and Compustat-based measures is that SDC includes private and subsidiary target firm deals as well. We employ the following measures using the SDC dataset: i) natural log of the number of deals, (ii) square root of the number of deals, (iii) number of deals divided by the total number of Compustat firms, and (iv) number of deals divided by the total number of CRSP-listed firms. Using these four alternative measures of M&A activity from SDC, we consistently find that M&A activity positively predicts future market returns and attenuates the predictive ability of aggregate accruals from our main analyses. The results from the aforementioned alternative measures are reported in Table A3.

5.4 Industry Analysis

We perform industry-level cross-sectional tests similar to those of Hirshleifer et al. (2009) (untabulated). Specifically, we estimate the BS-based aggregate accruals at the industry level and investigate the relationship between aggregate industry accruals and future industry returns by estimating specification (3) for each of the Fama-French 48 industries. The results in Table 8 (page 403) of Hirshleifer et al. (2009) are inconclusive. They document that the relationship between BS-based accruals and industry returns is positive for seven industries at the 5% significance level or better, is negative for five industries, and is statistically insignificant for the remaining 36 industries.

Similarly, we do not find a robust relationship between industry-level accruals and industry returns in our sample. This evidence suggests that cross-industry merger activities are crucial for the return predictability of aggregate M&A activity overall. In other words, industry-specific analyses do not fully account for the effects of M&A activities with targets from other industries. Consistent with this notion, in our sample period, we find that cross-industry M&A accounts for 43.7% of total M&A activity.

6. Conclusion

Hirshleifer et al. (2009) document an intriguing and puzzling finding: aggregate accruals positively predict future market returns. This is in stark contrast to the negative cross-sectional relation between accruals and future returns documented by Sloan (1996). Further work by Kang et al. (2010) provides evidence that the Hirshleifer et al. (2009) result is primarily due to the discretionary component of accruals, and they conclude that systematic earnings management in response to undervaluation is the reason for this positive relationship.

We offer an alternative explanation. We posit that aggregate M&A activity is the reason aggregate accruals positively predict future market returns. We provide evidence in support of this explanation in several ways. First, we use a different measurement technique to estimate accruals such that M&A activity–related non-articulating accruals are excluded. Specifically, we compute accruals using the cash flow statement and document that aggregate accruals do not predict future market returns under this alternative measurement. Second, when we control for the aggregate M&A activity in the Hirshleifer et al. (2009) specification, aggregate accruals no longer predict future market returns. Third, we document that aggregate non-articulating accruals (computed as the difference between BS-based aggregate accruals and CF-based aggregate accruals) positively predict future market returns. Finally, aggregate accruals for firms with M&A activity predict future market returns, whereas aggregate accruals for firms without M&A activity do not. Collectively, the evidence indicates that the previously documented relation between aggregate accruals and future aggregate market returns is attributable primarily to aggregate M&A activity, rather than systematic earnings management. However, we caution readers that our findings cannot reject the discount-rate hypothesis. In other words, it is plausible that M&A activity predicts returns because it is correlated with changes in discount rates.

Our finding that aggregate M&A activity positively predicts future market returns is new to the literature. This finding implies that the market reacts to the economic effects signaled by aggregate M&A activity. In particular, we document that aggregate M&A activity presages macroeconomic outcomes such as real GPD growth, aggregate investment, industrial production, and total factor productivity, consistent with economic theory. Thus, the future market returns associated with M&A activity reflect improvements in economic efficiency stemming from M&A activity.

References

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. 2013. Value and momentum everywhere. *The Journal of Finance*, *68*(3), 929-985.

Baker, M. & Wurgler, J., 2000. The equity share in new issues and aggregate stock returns. *The Journal of Finance* 55, 2219-2257.

Ball, R. & Brown, P., 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research*, 159-178.

Bennett, B. & Dam, R. A., 2018. Merger activity, stock prices, and measuring gains from M&A. Working paper.

Bernard, V. L. & Thomas, J. K., 1989. Post-earnings-announcement drift: delayed price response or risk premium?. *Journal of Accounting Research* 27, 1-36.

Bernard, V. L. & Thomas, J. K., 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics* 13, 305-340.

Braguinsky, S., Ohyama, A., Okazaki, T. & Syverson, C., 2015. Acquisitions, productivity, and profitability: evidence from the Japanese cotton spinning industry. *American Economic Review* 105, 2086-2119.

Casey, R., Gao, F., Kirschenheiter, M., Li, S., & Pandit, S., 2017. Articulation-based accruals. *Review of Accounting Studies* 22:288-319.

Curtis, A., & Oh. H.I., 2020. Why are aggregate investing activities negatively associated with future market returns? The role of accounting measurement. Working paper.

David, J., 2017. The Aggregate Implications of Mergers and Acquisitions. Working paper.

Desai, H., Rajgopal, S., & Venkatachalam, M. (2004). Value-glamour and accruals mispricing: One anomaly or two?. *The Accounting Review*, 79(2), 355-385.

Dimopoulos, T. & Sacchetto, S., 2017. Merger activity in industry equilibrium. *Journal of Financial Economics* 126, 200-226.

Doidge, C., Karolyi, G. A. & Stulz, R. M., 2017. The US listing gap. *Journal of Financial Economics* 123, 464-487.

Durbin, J., & Watson, G., 1950, 1951, 1971. "Testing for Serial Correlation in Least Squares Regression I, II, III," *Biometrika* 37 (1950), 409-428; 38 (1951), 159-178; 58 (1971), 1-42.

Eckbo, B. E., 2014. Corporate takeovers and economic efficiency. *Annual Review Financial Economics* 6, 51-74.

Feenstra, R. C., Inklaar, R. & Timmer, M. P., 2015. The next generation of the Penn World Table. *American Economic Review* 105, 3150-82.

Gomes, J. & Livdan, D., 2004. Optimal diversification: Reconciling theory and evidence. *The Journal of Finance* 59, 507-535.

Gort, M., 1969. An economic disturbance theory of mergers. *The Quarterly Journal of Economics*, 624-642.

Guo, H., & Jiang, X. 2011. Accruals and the conditional equity premium. *Journal of Accounting Research*, *49*(1), 187-221.

Harford, J., 2005. What drives merger waves?. *Journal of Financial Economics* 77, 529-560.

Harford, J., 2018. Connections and Context in Finance Research. *Asia-Pacific Journal of Financial Studies* 47, 7-20.

Hirshleifer, D., Hou, K. & Teoh, S. H., 2009. Accruals, cash flows, and aggregate stock returns. *Journal of Financial Economics* 91, 389-406.

Hribar, P. & Collins, D. W., 2002. Errors in estimating accruals: Implications for empirical research. *Journal of Accounting Research* 40, 105-134.

Jensen, M., 1986, Agency costs of free cash flow, corporate finance, and takeovers. *American Economic Review* 76, 323–329.

Jones, J. J., 1991. Earnings management during import relief investigations. *Journal of Accounting Research* 29, 193-228.

Jovanovic, B. & Rousseau, P. L., 2002. The Q-theory of mergers. *American Economic Review* 92, 198-204.

Jovanovic, B. & Rousseau, P. L., 2008. Mergers as reallocation. *The Review of Economics and Statistics* 90, 765-776.

Kang, Q., Liu, Q. & Qi, R., 2010. Predicting stock market returns with aggregate discretionary accruals. *Journal of Accounting Research* 48, 815-858.

Kothari, S. P., Lewellen, J. & Warner, J. B., 2006. Stock returns, aggregate earnings surprises, and behavioral finance. *Journal of Financial Economics* 79, 537-568.

Lang, L., Stulz, R., & Walkling, R., 1991, A test of the free cash flow hypothesis: The case of bidder returns. *Journal of Financial Economics* 29, 315–336.

Larson, C. R., Sloan, R., & Giedt, J. Z. 2018. Defining, measuring, and modeling accruals: a guide for researchers. *Review of Accounting Studies*, 23(3), 827-871.

Levis, M., 2011. The performance of private equity-backed IPOs. *Financial Management* 40(1), 253-277.

Liew, J., & Vassalou, M. 2000. Can book-to-market, size and momentum be risk factors that predict economic growth?. *Journal of Financial Economics*, *57*(2), 221-245.

Malmendier, U., & Tate, G., 2008. Who makes acquisitions? CEO overconfidence and the market's reaction. *Journal of financial Economics*, *89*(1), 20-43.

Montgomery, Douglas C., Elizabeth A. Peck, and G. Geoffrey Vining, 2, Introduction to linear regression analysis. *John Wiley & Sons,* Vol 821.

Morck, R., Shleifer, A., & Vishny, R., 1990. Do managerial incentives drive bad acquisitions? *Journal of Finance* 45, 31–48.

Nallareddy, S., Sethuraman, M., & Venkatachalam, M., 2020. Changes in accrual properties and operating environment: Implications for cash flow predictability. *Journal of Accounting and Economics*, 101313.

Newey, W. K. & West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. *Econometrica* 55, 703-708.

Petkova, R., 2006. Do the Fama–French factors proxy for innovations in predictive variables?. *The Journal of Finance*, *61*(2), 581-612.

Rhodes-Kropf, M., & Robinson, D., 2008. The market for mergers and the boundaries of the firm. *Journal of Finance* 63, 1169-1211.

Rhodes-Kropf, M., Robinson, D. T. & Viswanathan, S., 2005. Valuation waves and merger activity: The empirical evidence. *Journal of Financial Economics* 77, 561-603.

Rhodes-Kropf, M. & Viswanathan, S., 2004. Market valuation and merger waves. *The Journal of Finance* 59, 2685-2718.

Roll, R., 1986. The hubris hypothesis of corporate takeovers. *Journal of Business*, 197-216.

Sadka, G. & Sadka, R., 2009. Predictability and the earnings--returns relation. *Journal of Financial Economics* 94, 87-106.

Shleifer, A. & Vishny, R. W., 2003. Stock market driven acquisitions. *Journal of Financial Economics* 70, 295-311.

Sloan, R. G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting Review,* 289-315.

Yang, L., 2008. The real determinants of asset sales. *The Journal of Finance* 63, 2231-2262.

Appendix: Variable Definitions

Variable	Definition
CRSPRET *Source*: CRSP	Aggregate annual returns for the value-weighted index of all CRSP firms for the 12-month period of May t to April t+1.
SAMPRET *Source*: CRSP; Compustat	Aggregate annual returns for the value-weighted index of CRSP-Compustat sample firms for the 12-month period of May t to April t+1.
EARN *Source*: Compustat	The aggregate sample firm value-weighted earnings (scaled by beginning total assets) in a fiscal year.
ACC_BSM *Source*: Compustat	Aggregate accruals (scaled by beginning total assets) calculated using changes in working capital accounts of the balance sheet. Firm-level accruals are calculated as described below and aggregated using value-weighting: Accruals (BSM) $=\Delta CA - \Delta CL - \Delta Cash + \Delta STDEBT + \Delta TP - DEP$
CF_BSM *Source*: Compustat	Aggregate cash flows (scaled by beginning total assets) calculated using changes in working capital accounts of the balance sheet and earnings. Firm-level cash flows are calculated as described below and aggregated using value-weighting: Cash Flows (BSM) = IBC − Accruals (BSM)
ACC_CFM *Source*: Compustat	Aggregate accruals (scaled by beginning total assets) calculated using the cash flow statement (following Hribar and Collins, 2002). Firm-level accruals are calculated as described below and aggregated using value-weighting: Accruals (CFM) = $IBC - (OANCF - XIDOC)$
CF_CFM *Source*: Compustat	Aggregate cash flows from operations excluding extraordinary items and discontinued operations (scaled by beginning total assets) as reported by the firm in the cash flow statement. Firm-level cash flows are calculated as described below and aggregated using value-weighting: Cash Flows (CFM) = $OANCF - XIDOC$
MA_ACT *Source*: Compustat	M&A activity is the number of Compustat firms that are delisted within our sample due to a merger or acquisition divided by the total number of Compustat firms in year t. A firm is considered to be merged or acquired if it is no longer covered by Compustat due to a merger or acquisition (refer Compustat data item "*DLRSN*" (defined as "Reason for Deletion" and coded as "01")). *MA_ACT* = # of firms with *DLRSN*=1 in year t (from Compustat) / # of total Compustat firms in year t
ACQ_ACC_BSM *Source*: Compustat	The aggregate value of *ACC_BSM* for firms that engaged in M&A activity during the year, per Compustat Footnote Code "AA".

Appendix: Variable Definitions (continued)

NON_ACQ_ACC_BSM *Source*: Compustat	The aggregate value of *ACC_BSM* for firms that did not engage in M&A activity during the year.
ACQ_ACC_CFM *Source*: Compustat	The aggregate value of *ACC_CFM* for firms that engaged in M&A activity during the year, per Compustat Footnote Code "AA".
NON_ACQ_ACC_CFM *Source*: Compustat	The aggregate value of *ACC_CFM* for firms that did not engage in M&A activity during the year.
BE/ME *Source*: Compustat	The aggregate book-to-market in a fiscal year. Firm-level book-to-market is calculated as described below and aggregated using value-weighting: Book-to-market = *(SEQ* + *TXDITC* − *PS*) / (*PRCC_F* * *CSHO*)
ESHARE *Source*: Baker and Wurgler (2000); Board of Governors of the Federal Reserve System	The ratio of equity to total debt and equity issuances made in the U.S. in a calendar year. *ESHARE* = Equity Issuances / (Debt Issuances + Equity Issuances)
DYIELD *Source*: CRSP	The aggregate dividend yield on the CRSP index measured from May of year t to April of year t+1.
DEF *Source*: FRED	The default spread defined as the difference in yield between Moody's Baa yield and Aaa yield at the start of May in year t.
TBILL *Source*: CRSP	The rate on 30-day t-bills at the start of May in year t.
TERM *Source*: FRED	The term spread defined as the difference in yield between the 10-year and one-year treasury constant maturity at the start of May in year t.
TFP *Source*: FRED	The annual percentage change in total factor productivity at constant national prices during year t (see Feenstra, Inklaar, and Timmer, 2015 for details of the total factor productivity measurement).
RGDP *Source: FRED*	The annual percentage change real gross domestic product during year t.
IND PROD *Source: FRED*	The percentage change in industrial production in year t.
INVEST *Source: FRED*	The annual percentage change in real gross private domestic investment during year t.
UNEMP *Source: FRED*	The percentage of workers unemployed at the end of year t.

Appendix: Variable Definitions (continued)

CFNAI *Source*: Federal Reserve Bank of Chicago	A weighted-average index of 85 various monthly indicators of economic activity. We take the average 12-month calendar year value of the index. The Federal Reserve Bank of Chicago provides the composition of this index: https://www.chicagofed.org/publications/cfnai/index (retrieved March 7, 2019).
FCA_ACT *Source*: Compustat	The proportion of firms with foreign currency activities (FCA) in a fiscal year. A firm is considered to engage in FCA if the absolute value of *fca* in Compustat is above $10,000. *FCA_ACT* = # firms with FCA / # total firms in Compustat at the end of year *t-1*
DO_ACT *Source*: Compustat	The proportion of firms with discontinued operations (DO) in a fiscal year. A firm is considered to have discontinued operations if the absolute value of *DO* in Compustat is above $10,000. *DO_ACT* = # firms with *DO* / # total firms in Compustat at the end of year *t-1*

Table 1: Descriptive Statistics

Variable	N	Mean	Median	Std Dev	P25	P75
CRSPRET	28	0.112	0.140	0.159	0.040	0.184
SAMPRET	28	0.114	0.126	0.161	0.055	0.186
EARN	28	0.078	0.079	0.016	0.073	0.088
ACC_BSM	28	-0.054	-0.052	0.012	-0.056	-0.049
CF_BSM	28	0.132	0.131	0.011	0.123	0.140
BE/ME	28	0.464	0.464	0.107	0.388	0.518
ESHARE	28	0.117	0.117	0.040	0.084	0.142
DYIELD	28	0.022	0.021	0.007	0.018	0.025
DEF	28	0.010	0.008	0.005	0.007	0.010
TERM	28	0.016	0.017	0.011	0.007	0.027
TBILL	28	0.003	0.003	0.002	0.000	0.004
ACC_CFM	28	-0.064	-0.059	0.015	-0.065	-0.057
CF_CFM	28	0.142	0.140	0.012	0.133	0.152
MA_ACT	28	0.065	0.056	0.029	0.047	0.080
NAC_BSM	28	-0.044	-0.043	0.005	-0.046	-0.040
DAC_BSM	28	-0.010	-0.007	0.013	-0.011	-0.005
NAC_CFM	28	-0.052	-0.056	0.026	-0.061	-0.048
DAC_CFM	28	-0.012	-0.005	0.025	-0.012	-0.002
TFP	27	0.883	0.759	0.804	0.132	1.674
RGDP	28	2.597	2.804	1.630	1.859	3.786
IND PROD	28	2.061	2.982	3.698	0.940	4.475
INVEST	28	3.793	5.965	7.521	0.801	8.625
UNEMP	28	6.043	5.604	1.510	5.012	6.879
CFNAI	28	-0.144	-0.070	0.615	-0.249	0.234
FCA_ACT	28	0.299	0.262	0.151	0.189	0.382
DO_ACT	28	0.140	0.141	0.075	0.083	0.176

Table 1 presents descriptive statistics for the key variables of interest. See the Appendix for variable definitions, data sources, and calculations.

Table 2: Firm-level Differences between BS-based and CF-based Accruals

Panel A: Firm-level descriptive statistics for alternative sub-samples

	M&A Sample				**Non-M&A Sample**			
	N	**Mean**	**Median**	**Std Dev**	**N**	**Mean**	**Median**	**Std Dev**
ACC_BSM_t	10,611	-0.033	-0.037	0.108	37,735	-0.043	-0.042	0.084
ACC_CFM_t	10,611	-0.077	-0.058	0.139	37,735	-0.067	-0.056	0.115
$ACC\_BSM_t - ACC\_CFM_t$	10,611	0.043	0.021	0.121	37,735	0.024	0.013	0.091
	Discontinued Operations Sample				**Non-discontinued Operations Sample**			
	N	**Mean**	**Median**	**Std Dev**	**N**	**Mean**	**Median**	**Std Dev**
ACC_BSM_t	6,392	-0.046	-0.042	0.082	41,954	-0.040	-0.041	0.091
ACC_CFM_t	6,392	-0.062	-0.050	0.100	41,954	-0.070	-0.057	0.123
$ACC\_BSM_t - ACC\_CFM_t$	6,392	0.015	0.010	0.100	41,954	0.031	0.015	0.099
	FX Sample				**Non-FX Sample**			
	N	**Mean**	**Median**	**Std Dev**	**N**	**Mean**	**Median**	**Std Dev**
ACC_BSM_t	13,676	-0.042	-0.042	0.077	34,670	-0.040	-0.041	0.095
ACC_CFM_t	13,676	-0.065	-0.054	0.101	34,670	-0.071	-0.057	0.127
$ACC\_BSM_t - ACC\_CFM_t$	13,676	0.023	0.012	0.085	34,670	0.031	0.015	0.104

Panel B: Value-weighted time-series descriptive statistics for alternative sub-samples

	M&A Sample				**Non-M&A Sample**			
	N	**Mean**	**Median**	**Std Dev**	**N**	**Mean**	**Median**	**Std Dev**
ACC_BSM_t	28	-0.051	0.014	-0.056	28	-0.052	0.005	-0.055
ACC_CFM_t	28	-0.068	0.020	-0.075	28	-0.060	0.007	-0.064
$ACC\_BSM_t - ACC\_CFM_t$	28	0.017	0.012	0.009	28	0.008	0.006	0.005
	Discontinued Operations Sample				**Non-discontinued Operations Sample**			
	N	**Mean**	**Median**	**Std Dev**	**N**	**Mean**	**Median**	**Std Dev**
ACC_BSM_t	28	-0.050	0.013	-0.059	28	-0.053	0.006	-0.056
ACC_CFM_t	28	-0.053	0.013	-0.059	28	-0.064	0.010	-0.067
$ACC\_BSM_t - ACC\_CFM_t$	28	0.003	0.015	-0.003	28	0.011	0.007	0.007
	FX Sample				**Non-FX Sample**			
	N	**Mean**	**Median**	**Std Dev**	**N**	**Mean**	**Median**	**Std Dev**
ACC_BSM_t	28	-0.053	0.007	-0.057	28	-0.050	0.010	-0.052
ACC_CFM_t	28	-0.061	0.010	-0.064	28	-0.063	0.014	-0.066
$ACC\_BSM_t - ACC\_CFM_t$	28	0.008	0.006	0.004	28	0.013	0.011	0.008

Panel C: Regression estimates of *ACC_BSM − ACC_CFM* on M&A, discontinued operations, and FX indicators

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	***Spread:*** $\boldsymbol{ACC\_BSM_t - ACC\_CFM_t}$					
M&A Var_t	0.019***		0.116***		0.698***	
	(13.35)		(3.28)		(7.54)	
D_DiscOp_t	-0.015***	-0.015***	-0.001	-0.001	-0.012**	-0.011*
	(-11.19)	(-10.88)	(-0.09)	(-0.09)	(-2.17)	(-1.83)
D_FX_t	-0.008***	-0.007***	-0.008	-0.011*	-0.012**	-0.015***
	(-6.65)	(-6.43)	(-1.59)	(-1.93)	(-2.28)	(-2.69)
M&A Var =	***D_M&A***	***D_M&A***	***ACQSC***	***ACQSC***	***ACQINVT***	***ACQINVT***
# Obs	48,346	48,346	1,139	1,139	1,071	1,071
Adj R^2	0.010	0.004	0.048	0.001	0.189	0.007
Incremental R^2 of M&A		0.006		0.047		0.182

Table 2 presents BS-based accruals, CF-based accruals, and the accrual spread (the difference between BS-based and CF-based accruals) at the firm level across various sub-samples for fiscal years 1988-2015. In Panel A, the acquisition sample contains firms that had an M&A event during the year, the discontinued operations sample comprises firms that have greater than $10,000 in discontinued operations, and the FX sample includes firms that have more than $10,000 in foreign currency gains/losses. Panel B reports value-weighted (within each sub-sample) time-series descriptive statistics of *ACC_BSM*, *ACC_CFM*, and *ACC_BSM − ACC_CFM*. Panel C presents regression estimates of the accrual spread on the three non-articulating events. Columns (1), (3), and (5) report regression estimates of spread on M&A activity, discontinued operations indicators, and FX indicators. Columns (2), (4), and (6) report regression estimates of accrual spread on discontinued operations indicators and FX indicators only. Columns (1) and (2) use *D_M&A* as the M&A variable, which is an indicator variable that is equal to 1 if the firm is flagged as having an M&A activity (with footnote code "AA") in the Compustat Annual file. Columns (3) and (4) use Compustat variable *ACQSC* (scaled by lagged total assets) as the M&A variable, which is the sales contribution of acquisitions. Columns (5) and (6) use Compustat variable *ACQINVT* (scaled by lagged total assets) as the M&A variable, which is an inventory contribution of acquisitions. The incremental R^2 of M&A represents the incremental explanatory power of the corresponding M&A variable. *t*-statistics are calculated using standard errors clustered by firm. ***, **, and * represent the 1%, 5%, and 10% (two-tailed) levels of significance.

Table 3: Aggregate Accruals and Future Market Returns

Panel A: *BS-based aggregate accruals* and future market returns

	(1) $CRSPRET_{t+1}$	(2) $CRSPRET_{t+1}$	(3) $CRSPRET_{t+1}$	(4) $CRSPRET_{t+1}$	(5) $SAMPRET_{t+1}$	(6) $SAMPRET_{t+1}$	(7) $SAMPRET_{t+1}$	(8) $SAMPRET_{t+1}$
$EARN_t$	**-0.004**				**0.012**			
	(-0.09)				**(0.29)**			
ACC_BSM_t		**0.051*****	**0.052****	**0.044****		**0.059*****	**0.064*****	**0.058*****
		(3.64)	**(2.50)**	**(2.22)**		**(4.06)**	**(3.46)**	**(3.21)**
CF_BSM_t		-0.059**	-0.045*	-0.047*		-0.046*	-0.036	-0.037
		(-2.37)	(-1.84)	(-1.95)		(-1.87)	(-1.31)	(-1.39)
BE/ME_t			0.063				0.046	
			(1.34)				(0.85)	
$ESHARE_t$			0.065	0.066			0.055	0.055
			(1.68)	(1.67)			(1.35)	(1.35)
$DYIELD_t$			-0.028	0.035			-0.027	0.018
			(-0.61)	(1.47)			(-0.53)	(0.69)
DEF_t			-0.018	-0.011			0.003	0.008
			(-0.77)	(-0.45)			(0.12)	(0.30)
$TERM_t$			-0.005	-0.010			0.005	0.002
			(-0.13)	(-0.22)			(0.11)	(0.03)
$TBILL_t$			-0.022	-0.043			-0.004	-0.019
			(-0.48)	(-0.83)			(-0.07)	(-0.32)
Constant	0.112***	0.112***	0.112***	0.112***	0.114***	0.114***	0.114***	0.114***
	(3.94)	(5.21)	(4.06)	(4.30)	(4.27)	(5.05)	(3.79)	(4.00)
# Obs	28	28	28	28	28	28	28	28
Adj R^2	-0.038	0.167	0.227	0.241	-0.033	0.143	0.123	0.154

Panel B: *CF-based aggregate accruals* and future market returns

	(1) $CRSPRET_{t+1}$	(2) $CRSPRET_{t+1}$	(3) $CRSPRET_{t+1}$	(4) $CRSPRET_{t+1}$	(5) $SAMPRET_{t+1}$	(6) $SAMPRET_{t+1}$	(7) $SAMPRET_{t+1}$	(8) $SAMPRET_{t+1}$
$\boldsymbol{EARN_t}$	**-0.004**				**0.012**			
	(-0.09)				**(0.29)**			
$\boldsymbol{ACC\_CFM_t}$		**0.024**	**0.030**	**0.011**		**0.032**	**0.035**	**0.023**
		(0.99)	**(0.98)**	**(0.37)**		**(1.10)**	**(0.94)**	**(0.69)**
CF_CFM_t		-0.043	-0.027	-0.020		-0.023	-0.008	-0.004
		(-1.64)	(-0.89)	(-0.76)		(-0.89)	(-0.26)	(-0.13)
BE/ME_t			0.078				0.047	
			(1.07)				(0.59)	
$ESHARE_t$			0.060	0.064			0.051	0.053
			(1.35)	(1.39)			(1.11)	(1.14)
$DYIELD_t$			-0.048	0.042			-0.024	0.029
			(-0.60)	(1.21)			(-0.27)	(0.79)
DEF_t			-0.019	-0.016			-0.001	0.001
			(-0.73)	(-0.62)			(-0.04)	(0.02)
$TERM_t$			0.014	0.007			0.024	0.020
			(0.28)	(0.15)			(0.43)	(0.37)
$TBILL_t$			-0.010	-0.040			0.000	-0.017
			(-0.23)	(-0.82)			(0.00)	(-0.32)
Constant	0.112***	0.112***	0.112***	0.112***	0.114***	0.114***	0.114***	0.114***
	(3.94)	(4.61)	(3.71)	(4.08)	(4.27)	(4.51)	(3.54)	(3.81)
# Obs	28	28	28	28	28	28	28	28
Adj R^2	-0.038	0.044	0.084	0.101	-0.033	-0.001	-0.042	0.000

Table 3 presents regression estimates of one-year-ahead aggregate returns on current aggregate earnings, accruals, cash flows, and other aggregate predictors. Panel A uses accruals and cash flows calculated using the balance sheet. Panel B uses accruals and cash flows calculated using the cash flow statement. *CRSPRET* is the one-year-ahead CRSP value-weighted index returns. *SAMPRET* is the CRSP/Compustat matched sample one-year-ahead value-weighted index returns. All explanatory variables are standardized to have a mean of zero and variance of one. See the Appendix for variable definitions, data sources, and calculations. *t*-statistics are calculated using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors to correct for serial correlation. ***, **, and * represent the 1%, 5%, and 10% (two-tailed) levels of significance.

Table 4: Aggregate Accruals, Aggregate M&A Activity, and Future Market Returns

	(1) $CRSPRET_{t+1}$	(2) $CRSPRET_{t+1}$	(3) $SAMPRET_{t+1}$	(4) $SAMPRET_{t+1}$
ACC_BSM_t	**0.044****	**0.011**	**0.058*****	**0.019**
	(2.22)	**(0.41)**	**(3.21)**	**(0.75)**
MA_ACT_t		**0.149****		**0.174****
		(2.67)		**(2.80)**
CF_BSM_t	-0.047*	-0.088***	-0.037	-0.085**
	(-1.95)	(-2.95)	(-1.39)	(-2.52)
$ESHARE_t$	0.066	0.050	0.055	0.037
	(1.67)	(1.35)	(1.35)	(0.98)
$DYIELD_t$	0.035	0.147***	0.018	0.149**
	(1.47)	(2.94)	(0.69)	(2.72)
DEF_t	-0.011	-0.009	0.008	0.011
	(-0.45)	(-0.38)	(0.30)	(0.47)
$TERM_t$	-0.010	0.036	0.002	0.055
	(-0.22)	(0.94)	(0.03)	(1.36)
$TBILL_t$	-0.043	-0.021	-0.019	0.007
	(-0.83)	(-0.60)	(-0.32)	(0.17)
Constant	0.112***	0.113***	0.114***	0.115***
	(4.30)	(4.95)	(4.00)	(4.72)
# Obs	28	28	28	28
Adj R^2	0.241	0.461	0.154	0.457

Table 4 presents regression estimates of aggregate future returns on BS-based aggregate accruals, M&A activity, and controls. *MA_ACT* is the number of Compustat firms that are delisted within our sample due to a merger or acquisition divided by the total number of Compustat firms in year *t*. *CRSPRET* is the one-year-ahead CRSP value-weighted index returns. *SAMPRET* is the CRSP/Compustat matched sample one-year-ahead value-weighted index returns. All explanatory variables are standardized to have a mean of zero and variance of one. See the Appendix for variable definitions, data sources, and calculations. *t*-statistics are calculated using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors to correct for serial correlation. ***, **, and * represent the 1%, 5%, and 10% (two-tailed) levels of significance.

Table 5: Aggregate Accrual Components and Future Market Returns

Panel A: Aggregate accrual components: Spread and CF-based aggregate accruals

	(1)	(2)	(3)	(4)
	$CRSPRET_{t+1}$	$SAMPRET_{t+1}$	$CRSPRET_{t+1}$	$SAMPRET_{t+1}$
$\boldsymbol{ACC\_BSM_t - ACC\_CFM_t}$	**0.061***	**0.078****	**0.044**	**0.059**
	(1.84)	**(2.31)**	**(1.16)**	**(1.57)**
$\boldsymbol{ACC\_CFM_t}$	**0.053***	**0.069****	**0.011**	**0.020**
	(1.90)	**(2.49)**	**(0.31)**	**(0.59)**
$\boldsymbol{MA\_ACT_t}$			**0.151*****	**0.177*****
			(2.99)	**(3.17)**
CF_BSM_t	-0.034	-0.020	-0.074**	-0.067*
	(-1.28)	(-0.73)	(-2.29)	(-1.96)
$ESHARE_t$	0.072*	0.063*	0.057	0.045
	(2.06)	(1.81)	(1.62)	(1.33)
$DYIELD_t$	0.060**	0.050*	0.176***	0.186***
	(2.38)	(1.82)	(5.23)	(5.00)
DEF_t	-0.023	-0.007	-0.022	-0.006
	(-1.47)	(-0.43)	(-1.42)	(-0.37)
$TERM_t$	-0.016	-0.006	0.030	0.048
	(-0.36)	(-0.13)	(0.70)	(1.09)
$TBILL_t$	-0.052	-0.030	-0.030	-0.005
	(-1.29)	(-0.67)	(-1.27)	(-0.22)
Constant	0.112***	0.114***	0.113***	0.115***
	(4.33)	(4.09)	(5.27)	(5.23)
# Obs	28	28	28	28
Adj R^2	0.241	0.172	0.482	0.506

Panel B: Aggregate accrual components: Aggregate accruals for M&A and non-M&A firms

	(1) $CRSPRET_{t+1}$	(2) $SAMPRET_{t+1}$	(3) $CRSPRET_{t+1}$	(4) $SAMPRET_{t+1}$
$ACQ\_ACC\_BSM_t$	**0.048***	**0.063****		
	(1.83)	**(2.59)**		
$NON\_ACQ\_ACC\_BSM_t$	**0.039**	**0.044**		
	(1.33)	**(1.33)**		
$ACQ\_ACC\_CFM_t$			**0.022**	**0.037**
			(0.65)	**(1.03)**
$NON\_ACQ\_ACC\_CFM_t$			**-0.025**	**-0.026**
			(-0.71)	**(-0.68)**
CF_BSM_t	-0.050*	-0.040		
	(-1.89)	(-1.35)		
CF_CFM_t			-0.011	0.007
			(-0.33)	(0.20)
$ESHARE_t$	0.068	0.057	0.062	0.052
	(1.61)	(1.29)	(1.53)	(1.28)
$DYIELD_t$	0.039	0.022	0.040	0.028
	(1.24)	(0.64)	(1.35)	(0.88)
DEF_t	-0.007	0.012	-0.028	-0.014
	(-0.25)	(0.44)	(-1.39)	(-0.69)
$TERM_t$	-0.000	0.010	-0.014	-0.006
	(-0.01)	(0.18)	(-0.27)	(-0.11)
$TBILL_t$	-0.033	-0.011	-0.055	-0.036
	(-0.68)	(-0.19)	(-1.26)	(-0.71)
Constant	0.715**	0.592	0.112***	0.114***
	(2.28)	(1.69)	(4.22)	(4.02)
# Obs	28	28	28	28
Adj R^2	0.209	0.116	0.092	0.003

Table 5 presents regression estimates of the return predictability of the aggregate accrual components. In Panel A, aggregate BS-based accruals are decomposed into the accrual spread (i.e., the difference between *ACC_BSM* and *ACC_CFM*) and CF-based aggregate accruals. *CRSPRET* is the one-year-ahead CRSP value-weighted index returns. *SAMPRET* is the CRSP/Compustat matched sample one-year-ahead value-weighted index returns. In Panel B, aggregate accruals are decomposed into aggregate accruals of acquiring firms and non-acquiring firms. *ACQ_ACC_BSM* (*ACQ_ACC_CFM*) is the aggregate balance sheet method (cash flow method) accruals of the sample firms with mergers and acquisitions. *NON_ACQ_ACC_BSM* (*NON_ACQ_ACC_CFM*) is the balance sheet method (cash flow method) aggregate accruals of the sample firms without mergers and acquisitions. All explanatory variables are standardized to have a mean of zero and variance of one. See the Appendix for variable definitions, data sources, and calculations. *t*-statistics are calculated using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors to correct for serial correlation. ***, **, and * represent the 1%, 5%, and 10% (two-tailed) levels of significance.

Table 6: Aggregate Discretionary Accruals, Aggregate M&A Activity, and Future Market Returns

Panel A: ***BS-based aggregate discretionary accruals*****, aggregate M&A activity, and future market returns**

	(1)	(2)	(3)	(4)
	$CRSPRET_{t+1}$	*$CRSPRET_{t+1}$*	*$SAMPRET_{t+1}$*	*$SAMPRET_{t+1}$*
DAC_BSM_t	**0.051***	**0.016**	**0.066****	**0.026**
	(1.94)	**(0.45)**	**(2.70)**	**(0.75)**
MA_ACT_t		**0.150****		**0.175*****
		(2.77)		**(2.93)**
NAC_BSM_t	**0.028**	**0.020**	**0.034**	**0.024**
	(0.79)	**(0.43)**	**(0.92)**	**(0.54)**
CF_BSM_t	-0.051	-0.094**	-0.041	-0.092**
	(-1.47)	(-2.54)	(-1.14)	(-2.29)
$ESHARE_t$	0.065	0.049	0.055	0.036
	(1.63)	(1.35)	(1.30)	(0.96)
$DYIELD_t$	0.030	0.141**	0.014	0.142**
	(1.07)	(2.43)	(0.43)	(2.28)
DEF_t	-0.005	0.000	0.015	0.021
	(-0.19)	(0.01)	(0.47)	(0.80)
$TERM_t$	-0.007	0.041	0.005	0.060
	(-0.15)	(1.19)	(0.10)	(1.58)
$TBILL_t$	-0.037	-0.012	-0.013	0.016
	(-0.71)	(-0.33)	(-0.21)	(0.38)
Constant	0.112***	0.113***	0.114***	0.115***
	(4.23)	(4.93)	(3.92)	(4.67)
# Obs	28	28	28	28
Adj R^2	0.204	0.436	0.113	0.433

Panel B: ***CF-based aggregate discretionary accruals*, aggregate M&A activity, and future market returns**

	(1)	(2)
	$CRSPRET_{t+1}$	$SAMPRET_{t+1}$
DAC_CFM$_t$	**0.020**	**0.044**
	(0.35)	**(0.69)**
NAC_CFM$_t$	**0.018**	**0.036**
	(0.34)	**(0.62)**
CF_CFM$_t$	-0.019	-0.001
	(-0.69)	(-0.05)
$ESHARE_t$	0.063	0.052
	(1.35)	(1.11)
$DYIELD_t$	0.042	0.032
	(1.21)	(0.87)
DEF_t	-0.018	-0.003
	(-0.67)	(-0.11)
$TERM_t$	0.006	0.016
	(0.11)	(0.27)
$TBILL_t$	-0.042	-0.023
	(-0.81)	(-0.41)
Constant	0.112***	0.114***
	(3.98)	(3.72)
# Obs	28	28
Adj R^2	0.054	-0.049

Table 6 presents regression estimates of aggregate future returns on aggregate discretionary and non-discretionary accruals. Panel A provides regression estimates of aggregate future returns on BS-based aggregate discretionary and non-discretionary accruals. Panel B provides regression estimates of future market returns on the CF-based aggregate discretionary and non-discretionary accruals. Discretionary accruals for both the balance sheet method and the cash flow statement method are generated using the Jones (1991) model at the firm level and then aggregated using value weighting. *MA_ACT* is the number of Compustat firms that are delisted within our sample due to a merger or acquisition divided by the total number of Compustat firms in year *t*. *CRSPRET* is the one-year-ahead CRSP value-weighted index returns. *SAMPRET* is the CRSP/Compustat matched sample one-year-ahead value-weighted index returns. All explanatory variables are standardized to have a mean of zero and variance of one. See the Appendix for variable definitions, data sources, and calculations. *t*-statistics are calculated using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors to correct for serial correlation. ***, **, and * represent the 1%, 5%, and 10% (two-tailed) levels of significance.

Table 7: Aggregate M&A Activity and Macroeconomic Outcomes

Panel A: Aggregate M&A activity and one-year-ahead macroeconomic outcomes

	(1)	(2)	(3)	(4)	(5)
	TFP_{t+1}	$RGDP_{t+1}$	$IND\ PROD_{t+1}$	$INVEST_{t+1}$	$UNEMP_{t+1}$
MA_ACT$_t$	**0.330***	**0.620****	**1.482****	**3.094*****	**-0.069**
	(1.74)	**(2.44)**	**(2.20)**	**(3.29)**	**(-1.01)**
$CFNAI_t$	0.721	3.058***	7.222***	13.799***	-1.937***
	(1.08)	(3.92)	(3.92)	(4.09)	(-5.08)
TFP_t	0.415*	0.340	0.299	2.134*	0.003
	(1.78)	(1.43)	(0.70)	(1.97)	(0.03)
$RGDP_t$	-0.418	-0.119	-0.208	-1.558	0.128
	(-0.87)	(-0.24)	(-0.27)	(-1.20)	(0.98)
$IND\ PROD_t$	-0.041	-0.154	-0.623	-0.709	0.158*
	(-0.30)	(-0.80)	(-1.43)	(-0.80)	(2.08)
$INVEST_t$	-0.024	-0.089	-0.095	-0.328	-0.039
	(-0.57)	(-1.45)	(-0.57)	(-1.20)	(-1.21)
$UNEMP_t$	-0.089	0.249	1.150**	3.074***	0.775***
	(-0.36)	(0.88)	(2.28)	(3.14)	(9.49)
Constant	2.401	2.119	-2.061	-8.022	0.558
	(0.88)	(0.72)	(-0.44)	(-0.83)	(0.64)
# Obs	26	27	27	27	27
Adj R^2	0.060	0.534	0.595	0.660	0.939

Panel B: Aggregate M&A activity and two-year-ahead macroeconomic outcomes

	(1)	(2)	(3)	(4)	(5)
	TFP_{t+2}	$RGDP_{t+2}$	$IND\ PROD_{t+2}$	$INVEST_{t+2}$	$UNEMP_{t+2}$
MA_ACT$_t$	**0.128**	**0.404**	**1.145**	**1.929**	**-0.256**
	(0.92)	**(1.08)**	**(1.41)**	**(1.33)**	**(-1.33)**
$CFNAI_t$	-1.496**	-0.962	-4.345	-10.470*	-2.032***
	(-2.52)	(-0.81)	(-1.57)	(-1.88)	(-3.15)
TFP_t	0.577*	0.969*	0.760	3.835	-0.264
	(2.10)	(1.78)	(0.65)	(1.73)	(-1.04)
$RGDP_t$	-0.174	-0.520	1.096	-1.545	0.397
	(-0.50)	(-0.59)	(0.52)	(-0.40)	(0.77)
$IND\ PROD_t$	0.261*	0.226	0.203	1.092	0.250
	(1.97)	(0.62)	(0.26)	(0.79)	(1.01)
$INVEST_t$	-0.024	0.035	-0.022	0.258	-0.127
	(-0.57)	(0.37)	(-0.09)	(0.62)	(-1.44)
$UNEMP_t$	-0.116	0.125	1.550	2.297	0.473
	(-0.56)	(0.27)	(1.62)	(1.25)	(1.64)
Constant	0.800	1.428	-12.056	-14.521	2.034
	(0.37)	(0.30)	(-1.19)	(-0.75)	(0.69)
# Obs	25	27	27	27	27
Adj R^2	0.209	-0.068	-0.029	0.211	0.582

Table 7 presents regression estimates of aggregate future macroeconomic outcomes and aggregate M&A activity. Panel A provides regression estimates of one-year-ahead aggregate macroeconomic outcomes on aggregate M&A

activity, and Panel B provides regression estimates of two-year-ahead aggregate macroeconomic outcomes on aggregate M&A activity. *MA_ACT* is the M&A deals identified from all Compustat firms divided by the total number of Compustat firms in year *t*. *MA_ACT* is standardized to have a mean of zero and variance of one. See the Appendix for variable definitions, data sources, and calculations. *t*-statistics are calculated using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors to correct for serial correlation. ***, **, and * represent the 1%, 5%, and 10% (two-tailed) levels of significance.

Table 8: Discontinued Operations, Foreign Currency Translation, and Future Market Returns

	(1) $CRSPRET_{t+1}$	(2) $CRSPRET_{t+1}$	(3) $CRSPRET_{t+1}$	(4) $SAMPRET_{t+1}$	(5) $SAMPRET_{t+1}$	(6) $SAMPRET_{t+1}$
ACC_BSM_t	**0.044****	**0.043***	**0.046****	**0.058*****	**0.056*****	**0.061*****
	(2.22)	**(2.06)**	**(2.52)**	**(3.21)**	**(2.93)**	**(3.92)**
DO_ACT_t		**0.016**			**0.020**	
		(0.29)			**(0.32)**	
FCA_ACT_t			**-0.124**			**-0.166****
			(-1.66)			**(-2.43)**
CF_BSM_t	-0.047*	-0.053	-0.029	-0.037	-0.044	-0.013
	(-1.95)	(-1.52)	(-1.06)	(-1.39)	(-1.13)	(-0.52)
$ESHARE_t$	0.066	0.073*	0.058	0.055	0.064	0.044
	(1.67)	(1.85)	(1.46)	(1.35)	(1.59)	(1.12)
$DYIELD_t$	0.035	0.033	0.080*	0.018	0.015	0.079*
	(1.47)	(1.23)	(2.01)	(0.69)	(0.52)	(1.97)
DEF_t	-0.011	-0.016	-0.005	0.008	0.002	0.016
	(-0.45)	(-0.54)	(-0.23)	(0.30)	(0.08)	(0.69)
$TERM_t$	-0.010	-0.006	-0.082**	0.002	0.007	-0.095**
	(-0.22)	(-0.12)	(-2.10)	(0.03)	(0.12)	(-2.26)
$TBILL_t$	-0.043	-0.033	-0.199*	-0.019	-0.007	-0.228**
	(-0.83)	(-0.54)	(-1.98)	(-0.32)	(-0.10)	(-2.28)
Constant	0.112***	0.112***	0.112***	0.114***	0.114***	0.114***
	(4.30)	(4.22)	(5.06)	(4.00)	(3.93)	(5.16)
# Obs	28	28	28	28	28	28
Adj R^2	0.241	0.205	0.332	0.154	0.115	0.339

Table 8 presents regression estimates of aggregate future returns on the BS-based aggregate accruals with events other than M&A activities included in the model. *DO_ACT* is the percentage of firms in the current year that had material discontinued operations, and *FCA_ACT* is the percentage of firms in the current year that had material foreign currency adjustments. *CRSPRET* is the one-year-ahead CRSP value-weighted index returns. *SAMPRET* is the CRSP/Compustat matched sample one-year-ahead value-weighted index returns. All explanatory variables are standardized to have a mean of zero and variance of one. See the Appendix for variable definitions, data sources, and calculations. *t*-statistics are calculated using Newey-West heteroskedasticity and autocorrelation-consistent standard errors to correct for serial correlation. ***, **, and * represent the 1%, 5%, and 10% (two-tailed) levels of significance.

Table A1: Aggregate Accruals, Future Market Returns, and M&A Activity

	(1) $CRSPRET_{t+1}$	(2) $SAMPRET_{t+1}$	(3) $CRSPRET_{t+1}$	(4) $SAMPRET_{t+1}$	(5) $CRSPRET_{t+1}$	(6) $SAMPRET_{t+1}$
ACC_BSM_t	**0.044****	**0.057*****			**-0.014**	**-0.011**
	(2.17)	**(3.11)**			**(-0.36)**	**(-0.30)**
ACC_CFM_t			**0.029**	**0.041**		
			(1.06)	**(1.67)**		
MA_ACT_t					**0.133****	**0.156****
					(2.21)	**(2.63)**
CF_BSM_t	-0.047*	-0.038			-0.077***	-0.072**
	(-1.95)	(-1.42)			(-2.91)	(-2.83)
CF_CFM_t			-0.003	0.012		
			(-0.07)	(0.28)		
$ESHARE_t$	0.066	0.054	0.070	0.054	0.001	-0.022
	(1.66)	(1.32)	(1.65)	(1.23)	(0.02)	(-0.47)
$DYIELD_t$	0.035	0.019	0.044	0.031	0.133**	0.134**
	(1.46)	(0.70)	(1.21)	(0.84)	(2.35)	(2.41)
DEF_t	-0.011	0.009	-0.023	0.001	0.026	0.053
	(-0.45)	(0.34)	(-0.83)	(0.04)	(0.91)	(1.73)
$TERM_t$	-0.010	0.001	0.011	0.015	-0.047	-0.041
	(-0.23)	(0.02)	(0.21)	(0.27)	(-1.27)	(-1.07)
$TBILL_t$	-0.043	-0.019	-0.025	-0.014	-0.131*	-0.122*
	(-0.83)	(-0.32)	(-0.36)	(-0.21)	(-2.06)	(-1.80)
Constant	0.112***	0.113***	0.112***	0.113***	0.112***	0.113***
	(4.27)	(3.96)	(4.24)	(4.03)	(6.26)	(6.28)
# Obs	28	28	28	28	28	28
Adj R^2	0.239	0.153	0.112	0.055	0.438	0.434

Table A1 presents regression estimates of one-year-ahead aggregate returns on an alternative accrual measure, cash flows, M&A activity, and other aggregate predictors. Columns (1) and (2) use accruals and cash flows calculated using the balance sheet. Columns (3) and (4) use accruals and cash flows calculated using individual components of cash flow statement items for accounts receivable, inventory, accounts payable, other assets/liabilities, and depreciation. *MA_ACT* is the number of Compustat firms that are delisted within our sample due to a merger or acquisition divided by the total number of Compustat firms in year *t*. *CRSPRET* is the one-year-ahead CRSP value-weighted index returns. *SAMPRET* is the CRSP/Compustat matched sample one-year-ahead value-weighted index returns. All explanatory variables are standardized to have a mean of zero and variance of one. See the Appendix for variable definitions, data sources, and calculations. *t*-statistics are calculated using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors to correct for serial correlation. ***, **, and * represent the 1%, 5%, and 10% (two-tailed) levels of significance.

Table A2: Aggregate Accrual Components and Future Market Returns

Panel A: Aggregate accrual components: Spread and CF-based aggregate accruals

	(1) $CRSPRET_{t+1}$	(2) $SAMPRET_{t+1}$	(3) $CRSPRET_{t+1}$	(4) $SAMPRET_{t+1}$
$ACC\_BSM_t - ACC\_CFM_t$	**0.025**	**0.030***	**0.022**	**0.027**
	(1.62)	**(1.86)**	**(1.24)**	**(1.50)**
ACC_CFM_t	**0.035***	**0.048****	**-0.002**	**0.005**
	(1.96)	**(2.73)**	**(-0.07)**	**(0.23)**
MA_ACT_t			**0.157*****	**0.183*****
			(2.99)	**(3.14)**
CF_BSM_t	-0.046*	-0.036	-0.086**	-0.083**
	(-1.81)	(-1.30)	(-2.87)	(-2.44)
$ESHARE_t$	0.067	0.056	0.053	0.039
	(1.62)	(1.29)	(1.36)	(0.99)
$DYIELD_t$	0.038	0.021	0.157***	0.160***
	(1.49)	(0.74)	(3.22)	(3.00)
DEF_t	-0.011	0.009	-0.008	0.012
	(-0.42)	(0.33)	(-0.34)	(0.47)
$TERM_t$	-0.012	0.000	0.034	0.053
	(-0.25)	(0.00)	(0.88)	(1.31)
$TBILL_t$	-0.049	-0.025	-0.035	-0.009
	(-0.94)	(-0.41)	(-1.04)	(-0.22)
Constant	0.112***	0.113***	0.112***	0.113***
	(4.18)	(3.88)	(4.98)	(4.78)
# Obs	28	28	28	28
Adj R^2	0.202	0.111	0.451	0.452

Panel B: Aggregate accrual components: Aggregate accruals for M&A and non-M&A firms

	(1) $CRSPRET_{t+1}$	(2) $SAMPRET_{t+1}$	(3) $CRSPRET_{t+1}$	(4) $SAMPRET_{t+1}$
$ACQ\_ACC\_BSM_t$	**0.048***	**0.063****		
	(1.85)	**(2.60)**		
$NON\_ACQ\_ACC\_BSM_t$	**0.038**	**0.043**		
	(1.29)	**(1.30)**		
$ACQ\_ACC\_CFM_t$			**0.029**	**0.042**
			(1.07)	**(1.67)**
$NON\_ACQ\_ACC\_CFM_t$			**-0.008**	**0.005**
			(-0.30)	**(0.15)**
CF_BSM_t	-0.051*	-0.041		
	(-1.89)	(-1.37)		
CF_CFM_t			0.001	0.015
			(0.01)	(0.32)
$ESHARE_t$	0.068	0.056	0.068	0.053
	(1.60)	(1.25)	(1.62)	(1.21)
$DYIELD_t$	0.038	0.022	0.043	0.031
	(1.26)	(0.65)	(1.19)	(0.82)
DEF_t	-0.007	0.013	-0.025	0.000
	(-0.25)	(0.49)	(-0.85)	(0.01)
$TERM_t$	-0.000	0.010	-0.003	0.007
	(-0.01)	(0.18)	(-0.05)	(0.10)
$TBILL_t$	-0.033	-0.011	-0.048	-0.027
	(-0.68)	(-0.18)	(-0.67)	(-0.34)
Constant	0.112***	0.113***	0.112***	0.113***
	(4.06)	(3.78)	(4.21)	(3.96)
# Obs	28	28	28	28
Adj R^2	0.206	0.114	0.073	0.007

Table A2 presents regression estimates of the return predictability of aggregate accrual components estimated using an alternative accrual measure. In Panel A, aggregate BS-based accruals are decomposed into the spread (i.e., the difference between *ACC_BSM* and *ACC_CFM*) and CF-based aggregate accruals. *CRSPRET* is the one-year-ahead CRSP value-weighted index returns. *SAMPRET* is the CRSP/Compustat matched sample one-year-ahead value-weighted index returns. In Panel B, aggregate accruals are decomposed into aggregate accruals of acquiring firms and non-acquiring firms. *ACQ_ACC_BSM* (*ACQ_ACC_CFM*) is the aggregate balance sheet method (cash flow method) accruals of the sample firms with mergers and acquisitions. *NON_ACQ_ACC_BSM* (*NON_ACQ_ACC_CFM*) is the aggregate balance sheet method (cash flow method) accruals of the sample firms without mergers and acquisitions. All explanatory variables are standardized to have a mean of zero and variance of one. See the Appendix for variable definitions, data sources, and calculations. *t*-statistics are calculated using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors to correct for serial correlation. ***, **, and * represent the 1%, 5%, and 10% (two-tailed) levels of significance.

Table A3: Aggregate Accruals and Alternative Aggregate M&A Activity Measures

	(1) $CRSPRET_{t+1}$	(2) $SAMPRET_{t+1}$	(3) $CRSPRET_{t+1}$	(4) $SAMPRET_{t+1}$	(5) $CRSPRET_{t+1}$	(6) $SAMPRET_{t+1}$
ACC_BSM_t	**0.044****	**0.058*****	**0.034**	**0.043**	**0.025**	**0.035**
	(2.22)	**(3.21)**	**(1.19)**	**(1.61)**	**(1.02)**	**(1.57)**
MA_ACT_t			**0.040**	**0.061**	**0.144****	**0.173*****
			(0.70)	**(1.08)**	**(2.63)**	**(2.99)**
CF_BSM_t	-0.047*	-0.037	-0.056**	-0.051*	-0.056**	-0.048*
	(-1.95)	(-1.39)	(-2.14)	(-1.78)	(-2.32)	(-1.94)
$ESHARE_t$	0.066	0.055	0.055	0.039	0.034	0.017
	(1.67)	(1.35)	(1.20)	(0.84)	(0.97)	(0.47)
$DYIELD_t$	0.035	0.018	0.056	0.051	0.142***	0.147***
	(1.47)	(0.69)	(1.45)	(1.31)	(2.92)	(2.92)
DEF_t	-0.011	0.008	-0.001	0.023	0.045	0.076**
	(-0.45)	(0.30)	(-0.05)	(0.80)	(1.64)	(2.66)
$TERM_t$	-0.010	0.002	-0.004	0.011	0.036	0.057
	(-0.22)	(0.03)	(-0.09)	(0.28)	(0.77)	(1.20)
$TBILL_t$	-0.043	-0.019	-0.042	-0.018	-0.014	0.016
	(-0.83)	(-0.32)	(-0.86)	(-0.33)	(-0.40)	(0.42)
Constant	0.112***	0.114***	0.112***	0.114***	0.112***	0.114***
	(4.30)	(4.00)	(4.32)	(4.10)	(5.34)	(5.27)
MA_ACT_t =			$MA\_MCAP\_ACT_t$	$MA\_MCAP\_ACT_t$	$LN(SDC\_NUM)_t$	$LN(SDC\_NUM)_t$
# Obs	28	28	28	28	28	28
Adj R^2	0.241	0.154	0.248	0.216	0.025	0.035

Table A3: Aggregate Accruals and Alternative Aggregate M&A Activity Measures (cont'd)

	(7) $CRSPRET_{t+1}$	(8) $SAMPRET_{t+1}$	(9) $CRSPRET_{t+1}$	(10) $SAMPRET_{t+1}$	(11) $CRSPRET_{t+1}$	(12) $SAMPRET_{t+1}$
ACC_BSM_t	**0.025**	**0.036**	**0.034**	**0.046***	**0.030**	**0.042****
	(0.97)	**(1.51)**	**(1.38)**	**(2.09)**	**(1.31)**	**(2.13)**
MA_ACT_t	**0.136****	**0.161****	**0.104***	**0.124****	**0.076***	**0.086****
	(2.46)	**(2.63)**	**(2.06)**	**(2.10)**	**(1.98)**	**(2.21)**
CF_BSM_t	-0.057**	-0.049*	-0.059**	-0.051*	-0.054*	-0.045
	(-2.27)	(-1.85)	(-2.34)	(-1.88)	(-2.03)	(-1.57)
$ESHARE_t$	0.032	0.015	0.042	0.027	0.048	0.035
	(0.81)	(0.37)	(1.00)	(0.62)	(1.10)	(0.76)
$DYIELD_t$	0.137**	0.138**	0.108**	0.105**	0.080**	0.069*
	(2.66)	(2.57)	(2.39)	(2.18)	(2.39)	(2.05)
DEF_t	0.039	0.067**	0.022	0.048	0.025	0.048
	(1.37)	(2.20)	(0.76)	(1.50)	(0.80)	(1.41)
$TERM_t$	0.033	0.053	0.017	0.034	0.029	0.045
	(0.73)	(1.13)	(0.40)	(0.76)	(0.59)	(0.87)
$TBILL_t$	-0.031	-0.005	-0.059	-0.038	-0.009	0.019
	(-0.85)	(-0.12)	(-1.38)	(-0.78)	(-0.20)	(0.34)
Constant	0.112***	0.114***	0.112***	0.114***	0.112***	0.114***
	(5.18)	(4.97)	(4.87)	(4.61)	(4.43)	(4.14)
***MA_ACT_t* =**	$SQRT(SDC\_NUM)_t$	$SQRT(SDC\_NUM)_t$	$SDC\_NUM\_COMP_t$	$SDC\_NUM\_COMP_t$	$SDC\_NUM\_CRSP_t$	$SDC\_NUM\_CRSP_t$
# Obs	28	28	28	28	28	28
Adj R^2	0.351	0.314	0.323	0.278	0.249	0.170

Table A3 presents regression estimates of aggregate future returns on BS-based aggregate accruals, alternative M&A activity measures, and controls. $MA\_MCAP\_ACT_t$ is the total market capitalization of M&A target firms in our sample during the year, as identified in Compustat, divided by the total market capitalization of sample firms. $LN(SDC\_NUM)_t$ is the natural log of the total number of deals in SDC Platinum. $SQRT(SDC\_NUM)_t$ is the square root of the total number of deals in SDC Platinum. $SDC\_NUM\_COMP_t$ is the total number of deals in SDC Platinum during a calendar year divided by the total number of Compustat firms. $SDC\_NUM\_CRSP_t$ is the total number of deals in SDC Platinum during a calendar year divided by the total number of listed firms in CRSP. *CRSPRET* is the one-year-ahead CRSP value-weighted index returns. *SAMPRET* is the CRSP/Compustat matched sample one-year-ahead value-weighted index returns. All explanatory variables are standardized to have a mean of zero and variance of one. See the Appendix for variable definitions, data sources, and calculations. *t*-statistics are calculated using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors to correct for serial correlation. ***, **, and * represent the 1%, 5%, and 10% (two-tailed) levels of significance.