Preliminary and Incomplete
Comments Welcome

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

John C. Heater
Duke University
john.heater@duke.edu

Suresh Nallareddy
Duke University
suresh.nallareddy@duke.edu

Mohan Venkatachalam
Duke University
vmohan@duke.edu

July 8, 2019

We would like to thank Jenny Zha Giedt, Xu Jiang, Campbell Harvey, Maria Ogneva, Gil Sadka, and participants of research seminar at George Washington University for their helpful comments and suggestions. Any remaining errors are our own.

Abstract

Extant literature documents that aggregate accruals positively predict future market returns and attribute this to change in discount rates or systematic earnings management. We offer an alternative explanation and provide supporting evidence that the positive relation between aggregate accruals and future market returns is due to aggregate merger and acquisition (M&A) activity. Aggregate M&A activity affects the magnitude of aggregate accruals estimated from the balance sheet, and drives the market return predictability of accruals. Controlling for the aggregate M&A activity, we find that the robust positive relation between aggregate accruals and future market returns disappears, and instead aggregate M&A activity predicts future market returns. Moreover, the positive relation between discretionary aggregate accruals (a measure of systematic earnings management) and market returns also disappears after controlling for the aggregate M&A activity.

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

1. Introduction

In influential work, Hirshleifer, Hou, and Teoh (2009) document an intriguing finding – aggregate accruals positively predict future market returns. This finding is puzzling because prior literature documents no relationship between aggregate earnings and future market returns (e.g., Kothari, Lewellen, and Warner, 2006; Sadka and Sadka, 2009). It is further perplexing that accruals *negatively* predict future stock returns in the cross-section (Sloan, 1996). Extant literature (e.g., Hirshleifer et al., 2009; Kang, Liu, and Qi, 2010; Guo and Jiang, 2010) 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 undervaluation. In this paper, we offer an alternative explanation. We posit that aggregate merger and acquisition (M&A) activity drives accruals' ability to predict aggregate returns because accruals include changes in balance sheet accounts related to M&A activity. In particular, we document that accruals' ability to predict aggregate returns is subsumed by 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 emanating from economies of scope could improve economic efficiency (Gomes and Livdan, 2004). However, it is unclear whether market returns immediately incorporate such efficiency improvements. In addition to these direct channels, M&A potentially predicts future aggregate returns because of merger anticipation, creating a premium for potential targets. This premium, on average, is roughly 10% of potential targets' stock price (Bennett and Dam, 2018).

M&A activity affects the magnitude of accruals. In particular, estimating accruals using the balance sheet method (e.g., Sloan, 1996; Hirshleifer et al., 2009; Kang et al., 2010), entails calculating accruals by using data from the income statement and changes in the balance sheet non-cash working capital accounts. This method of estimating accruals is comprehensive because it also includes events that generate non-articulation between the balance sheet and the income statement, e.g., mergers and acquisitions, discontinued operations, foreign currency translations (Larson, Sloan, and Giedt, 2018). On the other hand, accruals estimated directly from the cash flow statement (net income *minus* cash flows from operations) do not include these items. M&A activity is the main non-articulation event that drives differences in accruals estimated using the balance sheet method versus the cash flow method (Larson et al., 2018). If aggregate M&A activity is the main driver of the accruals' return predictability, then cash flow method based aggregate accruals should display little or no return predictability. In contrast, if systematic earnings management or discount rate shocks drive the return predictability of aggregate accruals, then accruals estimated using either approach should equally predict future market returns. Similar predictions should hold for aggregate discretionary accruals (proxy for systematic earnings management) as well.

We begin by replicating the key findings from Hirshleifer et al. (2009) using an extended sample period spanning 1965-2015. Consistent with the findings in Hirshleifer et al. (2009), we find that aggregate earnings do not predict future market returns. Next, we decompose the earnings into accruals and cash flows and find that aggregate accruals estimated using the balance sheet method positively predict future returns. Thus, we find that the market return predictability of aggregate accruals is robust and stronger in the recent time-period.

When we use the cash flow statement approach to measure accruals, a different picture emerges. As mentioned earlier, if either systematic earnings management or discount rate shocks is the main driver of return predictive ability of accruals, cash flow statement based accruals should also predict future aggregate returns. However, we find that cash flow method aggregate accruals do not predict market returns over the 1988-2015 time-period.[1] Over the same time-period, balance sheet method based aggregate accruals do predict future market returns. This evidence is suggestive that M&A activity drives market return predictability of accruals.

To offer more direct evidence, we examine the predictive ability of balance sheet based accruals after controlling for the aggregate M&A activity. If aggregate M&A activity is the main driver of return predictability of accruals, then controlling for M&A activity should attenuate or even eliminate the positive relationship between aggregate accruals and future aggregate returns. Consistent with this prediction, we find that when separately controlling for aggregate M&A activity the balance sheet method aggregate accruals display no predictive ability. That is, we document that aggregate M&A activity positively predicts market returns, while the predictive ability of aggregate accruals dissipates.

Next, we test whether the relation between aggregate discretionary accruals and future market returns documented by Kang et al. (2010) holds after controlling for M&A activity. While the findings in Kang et al. (2010) holds for the extended sample period using the balance sheet approach accruals, when we control for the aggregate M&A activity, the predictability of the aggregate discretionary accruals disappears. At the same time, as with the findings for aggregate

[1] Note that cash flow statement information was not available until 1987 under SFAS 95.

accruals, when we estimate discretionary accruals using the cash flow method, we document that aggregate discretionary accruals are unrelated to subsequent market returns. Together, our results provide consistent and persuasive evidence that accruals stemming from the aggregate M&A activity rather than systematic earnings management drive the aggregate returns-accruals relationship.

Lastly, we explore the underlying channel for 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. To test this prediction, we investigate the relation between aggregate M&A activity and future macroeconomic outcomes – total factor productivity, economic growth, investment growth, and unemployment rate. Consistent with expectations, we find that higher aggregate M&A activity is associated with increases in future total factor productivity, future economic growth, future investment growth, and decreases in future unemployment rate.

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 provide evidence on the role of aggregate M&A activity for future market returns. While a large literature documents firm-level effects of M&A activity, we are unaware of studies that document the predictive ability of aggregate M&A activity for future aggregate market returns. In addition, we document that this relation is due to aggregate M&A activity conveying information about higher economic growth and lower unemployment. Finally, an extensive literature in accounting advocates scholars to use cash flow method accruals (e.g., Hribar and Collins, 2002; Casey et al., 2017) because balance sheet accruals contain measurement error. Our evidence suggests that balance sheet method accruals do contain important information about firm-specific economic activities (e.g., Larson et al., 2018) that are relevant for return predictability.

2. Data, Sample Selection & Descriptive Statistics

We obtain annual stock return data for firms listed on NYSE/AMEX/NASDAQ from CRSP and accounting data from COMPUSTAT for firm-years 1965 to 2015. We drop firm-year observations that are missing price, returns, and shares outstanding. We restrict our sample firms to December fiscal year to better align annual returns with annual frequency accounting data. Finally, we impose that a firm should have prior year data available to be included in the sample to estimate accruals based on changes in balance sheet accounts.

Firm-level accruals are calculated in two ways, using 1) the balance sheet method and 2) the cash flow method. Prior to the requirement of the cash flows statement in 1987, firms were not required to disclose different classifications of changes in cash during the year. We calculate the balance sheet method accruals following prior literature (e.g., Sloan, 1996) as follows:

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

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. The balance sheet method for calculating accruals potentially includes three main non-articulation events between the balance sheet and income statement (Hribar and Collins, 2002): 1) mergers and acquisitions, 2) divestitures and discontinued operations, and 3) foreign currency translations.

The cash flow statement method based accruals are measured as follows:

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

where ACC_CFM is accruals using cash flow method, $EBXI$ 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-xidoc*). Note that because cash flow statement data is not available the entire sample period, cash flow method based accruals cover a period of 1988-2015.[2]

To compute aggregate measures of the accruals and cash flow variables, we value-weight with CRSP market capitalization as the weights. For market returns, we use two measures based on annual firm-level stock returns starting May of year *t* through April of year *t*+1 (Hirshleifer et al., 2009). First, we calculate the CRSP value-weighted returns ($CRSPVWRT_{t+1}$) using all CRSP firms in each period. Second, we estimate the value-weighted returns ($SAMPVWRT_{t+1}$) using only our sample firms. See the Appendix for more details on variable estimation.

With respect to control variables, dividend yield (*DYIELD*) and the 30-day treasury yield (*TBILL*) are collected 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)*, and unemployment (*UNEMP*) are collected from the St. Louis Federal Reserve Economic Data (FRED). Equity issuance relative to total issuance data (*ESHARE)* is obtained from Baker and Wurgler (2000).[3] Aggregate book-to-market (*BE/ME*) is the value-weighted book-to-market ratio for fiscal year *t*.

Finally, we construct our mergers and acquisitions (M&A) activity variable (*AGG_MA*) following Hribar and Collins (2002). We identify a firm-year observation as part of a merger or acquisition if Compustat reports a “01” code under “DLRSN” (defined as “Reason for Deletion”). We then count the number of firms deleted in a fiscal year and divide it by the total number of

[2] The Financial Accounting Standards Board (FASB) issued FAS 95 in November 1987, which established standards for reporting firms’ cash flow activities. This statement requires that firms report their cash-related activities classified into three main components: 1) cash changes from operations; 2) cash changes from investing activities; and 3) cash changes from financing activities. We, however, omit fiscal year 1987 because data is not available for a substantial number of firms.

[3] We thank Jeffrey Wurgler for providing *ESHARE* data on his website: http://people.stern.nyu.edu/jwurgler/. This data is available through April 2008. We update this measure for the periods 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)

firms at the start of year *t* to generate the percentage of firms merged or acquired in fiscal year *t*. For firms deleted from Compustat because of a merger or acquisition, we first identify the last annual fiscal year a firm's financial reports are available, and count the M&A year for the firm to be the following calendar year. For example, if a firm's final financial report available in Compustat is December 31, 2011, we identify 2012 to be the year the firm is merged with or acquired by another firm. This results in the final fiscal year of a company deleted from Compustat to be the year prior to the actual M&A date. Survivor/acquirer firms will continue to exist in the fiscal period *t*, which aligns with balance sheet effects that occur with respect to the M&A activity.

Table 1 provides descriptive statistics. The average market return across our sample period using both CRSP value-weighted and sample value-weighted is approximately 11%. Mean balance sheet method aggregate accruals (*ACC_BSM*) are -0.051 and operating cash flows (*CF_BSM*) are 0.207. The cash flow method based aggregate accruals (*ACC_CFM*) for the reduced sample period are -0.063, whereas aggregate cash flows (*CF_CFM*) are, on average, 0.140. During our sample period, on average, 4.1% of firms merged or were acquired (*AGG_MA*) each year. This M&A frequency is consistent with prior literature (e.g., Doidge, Karolyi, and Stulz, 2017; Bennet and Dam, 2018). All other control variables are consistent with those reported in Hirshleifer et al. (2009).

3. Results

3.1 Aggregate Accruals and Return Predictability: Balance Sheet Approach

We start our analysis by first replicating Hirshleifer et al. (2009) for the extended sample period of 1965 to 2015. For our return predictability regressions, we standardize all independent variables to have a mean of zero and variance of one for ease of interpretability and comparability to Hirshleifer et al. (2009). We present our full model as follows:

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

where *AGGVWRET* are aggregate stock returns (*CRSPVWRT* or *SAMPVWRT*), *ACC_BSM* is balance sheet method aggregate accruals, *CF_BSM* is balance sheet method 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 to correct for serial correlation. We expect β_1 to be positive, consistent with Hirshleifer et al. (2009).

Table 2, 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 (4) show a statistically insignificant coefficient estimate on aggregate earnings ($EARN_t$) for both CRSP and sample market returns. Decomposing the earnings into accruals and cash flows improves the return prediction model significantly. Results in columns (2) and (5) indicate that the explanatory power of the model improves dramatically from below 0% using earnings to 13-15% for the decomposed model that separately includes aggregate accruals and cash flows. More importantly, consistent with the findings in Hirshleifer et al. (2009), in our extended sample, we find that aggregate accruals positively predict future market returns, while aggregate cash flows negatively predict future market returns. We include the full battery of controls in columns (3) and (6) 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 ($CRSPVWRT_{t+1}$) by 3.4% and sample value-weighted returns ($SAMPVWRT_{t+1}$) by 4.1%.

Overall, consistent with prior literature, current aggregate earnings and cash flows do not consistently predict future market returns. In contrast, current aggregate accruals estimated using the balance sheet approach positively predict future market returns, and these findings are robust to alternative controls and sample periods.

3.2 Aggregate Accruals and Return Predictability: Cash Flow Statement Approach

To test the effect of aggregate M&A activity in accruals on market return predictability, we rerun the aggregate return predictability model, but instead use cash flow statement information to generate aggregate accruals and cash flows. The main difference between balance sheet method and cash flow method accruals is M&A activity (Larson et al., 2018). Therefore, if M&A activity is descriptive of return predictability, we expect that the ability of cash flow based aggregate accruals to predict future market returns should attenuate. To test this prediction, we estimate the following model:

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

where *AGGVWRET* are aggregate stock returns (*CRSPVWRT* or *SAMPVWRT*), *ACC_CFM* are cash flow method aggregate accruals, *CF_CFM* are cash flow method aggregate cash flows and controls include *BE/ME*, *ESHARE*, *DYIELD*, *DEF*, *TERM*, and *TBILL*. As mentioned earlier, cash flow statement based accruals is computed for years starting from 1988, and hence, estimation of equation (4) is restricted to years 1988 to 2015.

Before we explore the role of M&A activity on the return predictability, we first ensure that the aggregate balance sheet accruals predict future market returns for the reduced sample period of 1988-2015. This ensures that the Hirshleifer et al. (2009) results are robust for this sub-sample. As with results reported in Panel A of Table 2, we find that aggregate current earnings do not predict future stock returns for the sub-sample as well (see columns (1) and (4) of Panel B, Table 2). More important, we continue to observe a strong positive relation between balance sheet method aggregate accruals and future market returns across specifications with and without control variables (see columns (2), (3), (5), and (6) of Panel B, Table 2). Thus, we conclude that the 1988 to 2015 sample period provides an appropriate setting to assess whether M&A activity related accruals integral in the balance sheet method accruals is a contributing factor in future return predictability.

Table 2, Panel C presents the results using the cash flow method aggregate accruals and cash flows. Strikingly, and in contrast to findings in Hirshleifer et al. (2009), we find that aggregate accruals calculated using data from the cash flow statement have no predictive power for future returns. The lack of significance in coefficients is not attributable to differences in the sample period since we demonstrate that balance sheet method accruals provide consistent estimates with prior literature using the same sample and research design. These findings are indicative that M&A activity related accruals inherent in the balance sheet method aggregate accruals drives return predictability.[4]

3.3 Market Return Predictability: Controlling for M&A Activity

In this section, we provide direct evidence on the role of aggregate M&A activity on the relation between aggregate accruals and future market return by controlling for M&A activity in the empirical specification. Because M&A activity affects the magnitude of the balance sheet method accruals, controlling for M&A activity should considerably diminish or even eliminate the predictive ability of balance sheet based accruals. To test this, we modify the regression specification in (3) by including aggregate merger and acquisition activity (*AGG_MA*):

$$AGGVWRET_{t+1} = \alpha + \beta_1 ACC\_BSM_t + \beta_2 CF\_BSM_t + \beta_3 AGG\_MA_t + \sum \beta_k Controls_t + \epsilon_{t+1} \qquad (5)$$

Consistent with our M&A activity explanation, we expect the coefficient on β_1 to be attenuated. We expect β_3 to be positive consistent with predictions from economic theory (e.g., David, 2017).

[4] In section 3.6, we document that other non-articulation events, such as discontinued operations and foreign currency translations, are unrelated to subsequent market returns.

In Table 3, Panel A, Columns (1) and (4) reports the results from Table 2, Panel A for comparison purposes. When we add M&A activity (*AGG_MA_t)* into the regression specification, we find that the coefficient on ACC_BSM_t loses statistical significance (see Columns (2) and (5)). Also, the coefficient on AGG_MA_t is positive and statistically significant, indicating that aggregate M&A activity predicts future market returns.[5] Table 3, Panel B repeats the analysis for the sub-period, 1988-2015 (periods in which cash flow statement data is available), for completeness. Interestingly, we find stronger effects for AGG_MA_t during this period, with equally strong attenuations of balance sheet method accruals. This evidence further corroborates the aggregate M&A activity as the main driver for the relation between aggregate accruals and market returns.

Overall, we draw two conclusions from the above analysis. First, the predictive ability of balance sheet method accruals on future returns disappears when including aggregate M&A activity, consistent with our prediction. Second, our evidence suggests that aggregate M&A activity is a positive predictor for future market returns.

3.4 Discretionary Accruals and Aggregate M&A Activity

Hirshleifer et al. (2009) conclude that the 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. Kang et al. (2010) conclude that the predictive ability is mainly due to systematic earnings management by documenting that aggregate *discretionary* accruals (a proxy for earnings management), rather than aggregate non-discretionary accruals, drive return predictability.

[5] Rhodes-Kropf and Viswanathan (2004) document a firm-level association with market-to-book and misvaluation. Hence, it is possible that M&A activity at the aggregate level is correlated with aggregate book-to-market leading to inappropriate inferences for M&A activity variable. Consistent with this, we find that BE/ME_t is correlated with AGG_MA_t (ρ=-0.446, p-value=0.001). Therefore, we conduct additional analysis where we omit book-to-market in this specification to ensure that multicollinearity is not an issue. Coefficient estimates (reported in columns (3) and (6) of Table 3, Panel A) for M&A activity are unchanged when omitting *BE/ME*, suggesting our estimates are robust.

Like Hirshleifer et al. (2009), Kang et al. (2010) also use the balance sheet method for estimating discretionary accruals. Discretionary accruals are estimated 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. Non-articulation events in the balance sheet method accruals introduce the measurement error in non-discretionary accrual estimation (Hribar and Collins, 2002). 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 to discretionary accruals. Therefore, it is an open empirical question as to whether our findings for total accruals will apply for discretionary accruals as well.

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

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

where ΔRev is the change in revenue from t-1 to t, *PPE* is property, plant, and equipment, and *TA* is average total assets at t. To estimate non-discretionary firm-level accruals (*NAC_BSM* | *NAC_CFM*), we impose the restriction of at least 5 observations in each two-digit SIC industry. To mitigate the influence of outliers, we delete firms with balance sheet method accruals below the 0.5 percentile and above the 99.5 percentile (Kang, Liu, and Qi, 2010).[6] Thus:

[6] Kang et al. (2010) requires at least 10 observations be available for each firm, and estimate discretionary accruals using firm-specific time-series regressions. We deviate from their methodology, and pool observations across industry and year to estimate discretionary accruals. We believe this reduces survivorship bias in the sample, especially because surviving firms from M&A events will be more likely to not exit their sample. This also allows us to relax the required sample size to 5 observations within an industry and year. In addition, the accruals variable is not susceptible to changes in measurement following the promulgation of SFAS 95. We are able to replicate their results in Table 5 using these assumptions and the balance sheet method for calculating accruals.

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

$$DAC\_BSM \mid DAC\_CFM_{it} = ACC\_BSM \mid ACC\_CFM_{it} - NAC\_BSM \mid NAC\_CFM_{it} \tag{8}$$

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

We re-estimate specification (5) by substituting total aggregate accruals with discretionary and non-discretionary aggregate accruals. Table 4, Panel A, provides regression estimates of future returns on balance sheet method discretionary accruals and normal accruals for the sample period 1965-2015, and Panel B for the sample period 1988-2015. 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 (4)). Thus, Kang et al. (2010) findings are robust to different sample partitions.

Next, we repeat our analysis after including aggregate M&A activity as an additional predictor. For both panels A and B, when we include M&A activity in the model, we find the predictive ability of the aggregate discretionary accruals becomes insignificant. More important, the coefficient on aggregate M&A activity is positive and statistically significant (see columns 2-3 and 4-6) of Panels A and B, Table 4). As before, omitting BE/ME_t does not alter our inferences. Overall, these results provide evidence that like total accruals and market return relation, discretionary accruals and market returns relation at the aggregate level is driven by M&A activity.

To buttress our findings, we next examine whether computing discretionary accruals using cash flow statement based total accruals predict future market returns. In other words, we estimate

NAC_CFM and *DAC_CFM* and substitute for *NAC_BSM* and *DAC_BSM* in the empirical specification (3) and report the results in Panel C, Table 4. Consistent with our prediction, we find no significant predictive ability of cash flow statement method aggregate discretionary accruals for future aggregate returns. That is, the coefficient on *DAC_CFM* is not statistically significant across all specifications.

Collectively, the evidence suggests that it is M&A activity, rather than systematic earnings management, that drives the market return predictive ability of accruals. Also, as before, aggregate M&A activity continues to predict future market returns.

3.5 Why does aggregate M&A Activity predict future market returns?

Our finding that aggregate M&A activity predicts future market returns is consistent with a delayed 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 buys lower productivity" firms within an industry, leading 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 the predictions from theory, Dimopoulos and Sacchetto (2017) documents that firm-level productivity increases 4.8% with M&A activity, on average. Therefore, we predict that aggregate M&A activity is related to future economic outcomes.

To test this prediction, we begin by first examining univariate correlations between current period aggregate M&A activity and future macroeconomic outcomes. Specifically, we investigate four macroeconomic outcomes: 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 adjusting for price changes;

3) *INVEST* – the annual percent change in the amount of real gross private domestic investment; and 4) *UNEMP* – the unemployment rate. Although we examine these variables individually, these are by no means independent. Pearson correlations across various macroeconomic variables are statistically significant, except for the unemployment rate (see Panel A of Table 5).

Panel B, Table 5 presents the correlations between aggregate M&A activity and future macroeconomic outcomes. We find a positive correlation between current period M&A activity and one-year-ahead total factor productivity (TFP_{t+1}: ρ=0.238, p-value=0.050), real GDP ($RGDP_{t+1}$: ρ=0.144, p-value=0.156), and real investment activity ($INVEST_{t+1}$: ρ=0.199, p-value=0.081), however highlight that the relation with real GDP is marginal. The correlation with one-year-head unemployment rate is marginally negative ($UNEMP_{t+1}$: ρ=-0.153, p-value=0.142). With respect to two-years-ahead macroeconomic outcomes, we find a significantly positive correlation with *TFP* and strong negative correlation with *UNEMP*. For *RDP* and *INVEST*, the correlations are marginally positive. Together, these correlations are suggestive that aggregate M&A activity portends positive future macroeconomic outcomes. To ensure that these results are not spurious due to correlated omitted variables, we consider placebo tests that examine correlations between current M&A activity and lagged (*t*-1) macroeconomic outcomes. We do not observe any systematic correlations. These findings provide comfort that the correlated omitted variables are less likely to drive the relation between current M&A activity and future macroeconomic outcomes.

Next, using multivariate regressions, we explore the relation between current M&A activity and future macroeconomic outcomes. As a control for the current macroeconomic conditions, we employ two benchmarks: (i) lagged macroeconomic factor, and (ii) the Chicago Fed National

Activity Index (CFNAI) – a composite weighted-average index of 85 economic indicators.[7] We present these models as follows:

$$MACRO\_OUTCOME_{t+i}=\alpha+\beta_1 MERGACTV_t+\beta_2 MACRO\_OUTCOME_t+\epsilon_{t+i} \quad (8a)$$

$$MACRO\_OUTCOME_{t+i}=\alpha+\beta_1 MERGACTV_t+\beta_2 CFNAI_t+\epsilon_{t+i} \quad (8b)$$

where i=1 or 2 years ahead, $MACRO\_OUTCOME$ = {TFP, $RGDP$, $INVEST$, $UNEMP$}, AGG_MA is aggregate M&A activity, and $CFNAI$ is the Chicago Fed National Activity Index.

Table 6 presents the results. Panel A presents the relation between current aggregate M&A activity and one-year ahead macroeconomic outcomes. We find that current M&A activity is positively related to one-year ahead economic activity. That is, aggregate M&A activity is positively related to subsequent one year ahead total factor productivity (column 1), aggregate investment (column 3), and negatively related to unemployment rates (column 4). Current aggregate M&A activity is positively related to one-year ahead real GDP after controlling for the CFNAI index (column 6), but not after controlling for the lagged real GDP (column 2).

Panel B presents the results using the two-year ahead macroeconomic outcomes. We find the predictive power of aggregate M&A activity is persistent for total factor productivity (unemployment rate) with a positive (negative) and significant coefficient estimate. We find no association of current M&A activity on two-year-ahead real GDP and investment growth. Together, the evidence suggests that consistent with the economic theory, aggregate M&A activity improves the overall economic efficiency, and hence, supports the previously documented relation between aggregate M&A activity and future market returns.

3.6 Additional Analysis: Effects of other Balance Sheet Method Non-articulation Events: Discontinued Operations & Foreign Currency Translations

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

Hribar and Collins (2002) discuss two additional non-articulation events between the income statement and balance sheet: 1) discontinued operations/divestitures, and 2) foreign currency activities. These events could also explain the relation between aggregate accruals and market returns. However, ex-ante, we do not have clear theoretical predictions for how these aggregate events will be related to future market returns. Additionaly, Larson et al. (2018) highlight that M&A activity is the main difference between accruals calculated using the balance sheet versus cash flows statement. In this section, for completeness, we explore whether including discontinued operations or foreign currency acitivites into the baseline model also attenuates the effect of balance sheet method accruals on future returns.

In Table 7, we present regression estimates of future returns on balance sheet method accruals, including the fraction of firms with discontinued operations/divestitures ($DOACTV_t$) and the fraction of firms with foreign currency activities ($FCAACTV_t$) as additional variables. The analysis here is similar to that reported in Table 3. We run the analysis for both the full sample and the reduced sample. For the full sample with available data for *DOACTV* and *FCAACTV*, we find that including aggregate discontinued operations does reduce the statistical significance of aggregate accruals coefficient estimates, but does not substantially reduce its magnitude (see column (1)). More important, we find no predictive ability of aggregate discontinued operations for future returns for the full sample. Including aggregate foreign currency activities (refer column (2)) does not affect aggregate accruals ability nor predicts future returns for the full sample. Moving to the reduced sample over the period 1988-2015, the results are broadly consistent with those for the full sample.[8]

[8] Larson et al. (2018) suggest that capital expenditures is another item that drive the difference between balance sheet based and cash flow statement based accruals. Therefore, we also consider aggregate capital expenditures as an additional control variable in the empirical specification. However, the inclusion of aggregate capital expenditures has very little effect on the relation between aggregate accruals and future returns.

Collectively, the evidence in Table 7 suggests that the accruals stemming from non-articulation events other than M&A activity are not significant enough to influence the effect of aggregate accruals on future market returns. Nor can we conclude that these additional non-articulation events have predictive power for future aggregate returns. Thus, we conclude that aggregate M&A activity is the key driver that explains the relation between aggregate accruals and market returns.

4. 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 relation between accruals and future returns in the cross-section as documented by Sloan (1996). Further work by Kang et al. (2010) provide evidence that the Hirshleifer et al. (2009) result is primarily due to the discretionary component of accruals, and conclude that systematic earnings management in response to unvervaluation is the reason for this positive relation.

We offer an alternative explanation. We posit that aggregate M&A activity is the reason why we observe market return predictability of aggregate accruals. We provide evidence in two ways. First, we use a different measurement technique to estimate accruals such that non-articulating M&A activity related accruals are excluded. Specifically, we compute accruals using the cash flow statement and document that aggregate accruals do not predict future market returns. 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. Furthermore, aggregate M&A activity positively predicts future aggregate market returns. Collectively, we conclude that the previously documented relation between aggregate accruals and future aggregate market returns is primarily due to aggregate M&A activity rather than systematic earnings management or discount rate shocks.

Our finding that aggregate M&A activity positively predicts future market returns is new to the literature. This finding implies that the market reacts in a delayed manner 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, total factor productivity, and unemployment rate, consistent with economic theory. Thus, the future market returns associated with M&A activity is reflective of improvements in economic efficiency stemming from M&A activity.

References

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. Unpublished working paper. Ohio State University and University of Colorado at Boulder.

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

David, J., 2017. The Aggregate Implications of Mergers and Acquisitions. Unpublished working paper. University of Southern California.

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.

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.

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.

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.

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

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.

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
CRSPVWRT *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.
SAMPVWRT *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 (after depreciation) in a fiscal year.
ACC_BSM *Source*: Compustat	Aggregate accruals calculated using changes in working capital accounts of the balance sheet. Firm level accruals are calculated as described below, and aggregated to the annual level via value-weighting: Accruals (BSM) $=\Delta CA-\Delta CL-\Delta Cash+\Delta STDEBT+\Delta TP- DEP$
CF_BSM *Source*: Compustat	Aggregate cash flows calculated using changes in working capital accounts of the balance sheet. Firm level accruals are calculated as described below, and aggregated to the annual level via value-weighting: Cash Flows (BSM) = *OIADP* - Accruals (BSM)
ACC_CFM *Source*: Compustat	Aggregate accruals calculated using the cash flows statement (Hribar and Collins, 2002). Firm level accruals are calculated as described below, and aggregated to the annual level via value-weighting: Accruals (CFM) = $(IBC-(OANCF-XIDOC))/AT_{t-1}$
CF_CFM *Source*: Compustat	Aggregate cash flows from operations excluding Extraordinary Items and Discontinued Operations as reported by the firm in the cash flows statement. Firm level cash flows are calculated as described below, and aggregated to the annual level via value-weighting: Cash Flows (CFM) = $(OANCF-XIDOC)/AT_{t-1}$
AGG_MA *Source*: Compustat	The percentage of firms merged or acquired in a fiscal year. *AGG_MA* = # Firms Acquired / # Total Firms at the start of year *t*
FCAACTV *Source*: Compustat	The percentage 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. *FCAACTV* = # Firms with FCA / # Total Firms at the end of year *t*
DOACTV *Source*: Compustat	The percentage 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.

	DOACTV = # Firms with DO / # Total Firms at the end of year *t*
BE/ME *Source*: Compustat	The aggregate sample firm value-weighted book-to-market in a fiscal year. Book-to-market = *(SEQ+TXDITC-PS*)/(*PRCC_F**CSHO*)
ESHARE *Source*: Baker and Wurgler (2000); Board of Governors of the Federal Reserve System	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.
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 ten-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 for United States during year *t* (see also Feenstra, Inklaar, and Timmer, 2015 for Total Factor Productivity measurement).
RGDP *Source*: FRED	The annual percentage change in Real Gross Domestic Product during year *t*.
INVEST *Source*: FRED	The annual percentage change in Real Gross Private Domestic Investment during year *t*. (GPDIC1 from FRED)
UNEMP *Source*: FRED	The percent of workers unemployed at the end of year *t*.
CFNAI *Source*: Federal Reserve Bank of Chicago	A weighted average index of 85 various monthly indicators of economic activity in the U.S. We take the average 12-month calendar year value of the index, except for 1965, which begins in March. The Federal Reserve Bank of Chicago provides the composition of this index here: https://www.chicagofed.org/publications/cfnai/index (retrieved March 7, 2019).

Table 1: Descriptive Statistics

Variable	N	Mean	Median	Std.Dev	P25	P75
CRSPVWRT	51	0.110	0.116	0.158	0.011	0.196
SAMPVWRT	51	0.114	0.117	0.154	0.042	0.204
EARN	51	0.155	0.145	0.030	0.136	0.174
ACC_BSM	51	-0.051	-0.051	0.015	-0.057	-0.045
CF_BSM	51	0.207	0.203	0.027	0.190	0.217
ACC_CFM	28	-0.063	-0.058	0.016	-0.065	-0.055
CF_CFM	28	0.140	0.140	0.013	0.128	0.150
NAC_BSM	51	-0.041	-0.042	0.009	-0.046	-0.036
DAC_BSM	51	-0.010	-0.008	0.011	-0.012	-0.005
NAC_CFM	28	-0.052	-0.056	0.026	-0.061	-0.048
DAC_CFM	28	-0.012	-0.004	0.025	-0.013	0.000
AGG_MA	51	0.041	0.041	0.023	0.023	0.048
FCAACTV	44	0.143	0.136	0.055	0.088	0.205
DOACTV	48	0.056	0.050	0.026	0.041	0.077
BE/ME	51	0.594	0.510	0.219	0.418	0.743
ESHARE	51	0.170	0.144	0.087	0.113	0.209
DYIELD	51	0.029	0.028	0.011	0.021	0.037
DEF	51	0.010	0.009	0.005	0.007	0.012
TERM	51	0.011	0.012	0.012	0.001	0.019
TBILL	51	0.004	0.004	0.003	0.002	0.005
TFP	50	0.008	0.008	0.011	0.001	0.017
RGDP	51	0.030	0.032	0.021	0.019	0.044
UNEMP	51	0.061	0.058	0.016	0.049	0.072
INVEST	51	0.042	0.060	0.089	-0.009	0.095
CFNAI	49	-0.003	0.083	0.709	-0.259	0.395

Table 1 presents descriptive statistics for the key variable of interest. All variables are for years 1965 to 2015 (51 yearly observations) with the following exceptions. Variables constructed using cash flow statement data (*ACC_CFM, CF_CFM, NAC_CFM*, *DAC_CFM)* are limited to 1988 to 2015 due to data availability. Foreign currency activities data is available (*FCAACTV*) for the period 1972 to 2015. Data on discontinued operations (*DOACTV)* is from 1968 to 2015 because of a lack of consistent data for the prior years. Variable *TFP* is restricted to 50 observations due to data limits from FRED through 2014. Variable *CFNAI* is restricted to 49 observations as data from the Federal Reserve Bank of Chicago starts in 1967. See Appendix for variable definitions, data sources, and calculations.

Table 2: Aggregate Accruals and Future Market Returns

Panel A: ***Balance Sheet Method Aggregate Accruals*** **and Future Market Returns: Sample Years 1965-2015**

	(1) $CRSPVWRT_{t+1}$	(2) $CRSPVWRT_{t+1}$	(3) $CRSPVWRT_{t+1}$	(4) $SAMPVWRT_{t+1}$	(5) $SAMPVWRT_{t+1}$	(6) $SAMPVWRT_{t+1}$
$EARN_t$	**-0.013**			**-0.009**		
	(-0.67)			**(-0.46)**		
ACC_BSM_t		**0.051*****	**0.034***		**0.049*****	**0.041****
		(3.91)	**(1.71)**		**(3.07)**	**(2.07)**
CF_BSM_t		**-0.042****	**-0.045***		**-0.037****	**-0.032**
		(-2.51)	**(-1.98)**		**(-2.23)**	**(-1.42)**
BE/ME_t			0.015			0.004
			(0.30)			(0.08)
$ESHARE_t$			0.023			0.019
			(0.56)			(0.47)
$DYIELD_t$			0.031			0.022
			(0.70)			(0.49)
DEF_t			-0.022			-0.008
			(-0.81)			(-0.27)
$TERM_t$			0.028			0.039
			(0.98)			(1.24)
$TBILL_t$			-0.015			0.005
			(-0.31)			(0.09)
Constant	0.110***	0.112***	0.111***	0.114***	0.116***	0.115***
	(5.53)	(6.30)	(5.73)	(5.81)	(6.51)	(6.09)
# Obs	51	51	51	51	51	51
Adj R^2	-0.014	0.148	0.116	-0.017	0.133	0.091

Panel B: *Balance Sheet Method Aggregate Accruals* and Future Market Returns: Sample Years 1988-2015

	(1) $CRSPVWRT_{t+1}$	(2) $CRSPVWRT_{t+1}$	(3) $CRSPVWRT_{t+1}$	(4) $SAMPVWRT_{t+1}$	(5) $SAMPVWRT_{t+1}$	(6) $SAMPVWRT_{t+1}$
$EARN_t$	**-0.001**			**0.011**		
	(-0.03)			**(0.31)**		
ACC_BSM_t		**0.051*** **	**0.060*** **		**0.060*** **	**0.074*** **
		(3.37)	**(2.99)**		**(4.59)**	**(3.65)**
CF_BSM_t		**-0.054**	**-0.055***		**-0.046**	**-0.047**
		(-1.57)	**(-1.85)**		**(-1.57)**	**(-1.49)**
BE/ME_t			0.111			0.088
			(1.67)			(1.09)
$ESHARE_t$			0.065			0.053
			(1.71)			(1.34)
$DYIELD_t$			-0.083			-0.079
			(-1.19)			(-0.94)
DEF_t			-0.027			-0.002
			(-1.03)			(-0.08)
$TERM_t$			0.001			0.011
			(0.02)			(0.22)
$TBILL_t$			-0.003			0.015
			(-0.06)			(0.25)
Constant	0.112***	0.118***	0.114***	0.112***	0.118***	0.115***
	(3.74)	(5.28)	(4.00)	(3.83)	(5.08)	(3.79)
# Obs	28	28	28	28	28	28
Adj R^2	-0.038	0.133	0.235	-0.034	0.153	0.160

Panel C: *Cash Flow Statement Method Aggregate Accruals* and Future Market Returns: Sample Years 1988-2015

	(1) $CRSPVWRT_{t+1}$	(2) $CRSPVWRT_{t+1}$	(3) $CRSPVWRT_{t+1}$	(4) $SAMPVWRT_{t+1}$	(5) $SAMPVWRT_{t+1}$	(6) $SAMPVWRT_{t+1}$
$EARN_t$	**-0.001**			**0.011**		
	(-0.03)			**(0.31)**		
ACC_BSM_t		**0.027**	**0.038**		**0.036**	**0.046**
		(1.07)	**(1.29)**		**(1.27)**	**(1.31)**
CF_BSM_t		**-0.043**	**-0.035**		**-0.024**	**-0.017**
		(-1.51)	**(-0.93)**		**(-0.87)**	**(-0.42)**
BE/ME_t			0.085			0.057
			(0.97)			(0.59)
$ESHARE_t$			0.057			0.047
			(1.29)			(1.02)
$DYIELD_t$			-0.066			-0.046
			(-0.66)			(-0.42)
DEF_t			-0.015			0.004
			(-0.54)			(0.14)
$TERM_t$			0.012			0.023
			(0.24)			(0.41)
$TBILL_t$			-0.010			0.005
			(-0.19)			(0.08)
Constant	0.112***	0.115***	0.112***	0.112***	0.115***	0.112***
	(3.74)	(4.52)	(3.69)	(3.83)	(4.43)	(3.53)
# Obs	28	28	28	28	28	28
Adj R^2	-0.038	0.057	0.098	-0.034	0.022	-0.020

Table 2 presents regression estimates of one-year-ahead aggregate returns on current aggregate earnings, accruals, cash flows, and other aggregate predictors. Panel A provides regression estimates of aggregate future returns on the aggregate balance sheet method accruals for the full sample (years 1965 to 2015). Panel B provides regression estimates of aggregate future returns on aggregate balance sheet method accruals for the sub-period 1988 to 2015. Panel C provides regression estimates of aggregate future returns on the aggregate cash flow method accruals for the cash flow statement period sample, years 1988 to 2015. Accruals in Panels A and B are calculated using changes in balance sheet working capital accounts (*ACC_BSM)*, and accruals in Panel C are calculated using the cash flow method (*ACC_CFM)*. *CRSPVWRT* is one-year ahead CRSP value-weighted index returns. *SAMPVWRT* is one-year-ahead CRSP/Compustat matched sample one-year ahead value-weighted index returns. See 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-tail) levels of significance.

Table 3: Aggregate Accruals, Aggregate M&A Activity, and Future Market Returns

Panel A: *Balance Sheet Method Aggregate Accruals*, Aggregate M&A Activity, and Future Market Returns: Sample Years 1965-2015

	(1)	(2)	(3)	(4)	(5)	(6)
	$CRSPVWRT_{t+1}$	$CRSPVWRT_{t+1}$	$CRSPVWRT_{t+1}$	$SAMPVWRT_{t+1}$	$SAMPVWRT_{t+1}$	$SAMPVWRT_{t+1}$
ACC_BSM_t	**0.034***	**0.021**	**0.021**	**0.041****	**0.026**	**0.026**
	(1.71)	**(0.95)**	**(0.96)**	**(2.07)**	**(1.35)**	**(1.34)**
AGG_MA_t		**0.064***	**0.064***		**0.068****	**0.067****
		(1.83)	**(1.85)**		**(2.13)**	**(2.10)**
CF_BSM_t	**-0.045***	**-0.035**	**-0.035**	**-0.032**	**-0.021**	**-0.018**
	(-1.98)	**(-1.34)**	**(-1.25)**	**(-1.42)**	**(-0.85)**	**(-0.70)**
BE/ME_t	0.015	-0.004		0.004	-0.016	
	(0.30)	(-0.09)		(0.08)	(-0.37)	
$ESHARE_t$	0.023	0.022	0.021	0.019	0.017	0.016
	(0.56)	(0.65)	(0.64)	(0.47)	(0.54)	(0.51)
$DYIELD_t$	0.031	0.106	0.103*	0.022	0.102	0.088
	(0.70)	(1.55)	(1.71)	(0.49)	(1.52)	(1.51)
DEF_t	-0.022	-0.014	-0.014	-0.008	0.001	-0.001
	(-0.81)	(-0.54)	(-0.56)	(-0.27)	(0.05)	(-0.03)
$TERM_t$	0.028	0.001	0.001	0.039	0.011	0.011
	(0.98)	(0.04)	(0.04)	(1.24)	(0.30)	(0.32)
$TBILL_t$	-0.015	-0.057	-0.056	0.005	-0.040	-0.039
	(-0.31)	(-1.03)	(-1.03)	(0.09)	(-0.67)	(-0.66)
Constant	0.111***	0.110***	0.110***	0.115***	0.113***	0.113***
	(5.73)	(6.24)	(6.31)	(6.09)	(6.64)	(6.62)
# Obs	51	51	51	51	51	51
Adj R^2	0.116	0.174	0.193	0.091	0.163	0.182

Panel B: *Balance Sheet Method Aggregate Accruals*, Aggregate M&A Activity, and Future Market Returns: Sample Years 1988-2015

	(1) $CRSPVWRT_{t+1}$	(2) $CRSPVWRT_{t+1}$	(3) $CRSPVWRT_{t+1}$	(4) $SAMPVWRT_{t+1}$	(5) $SAMPVWRT_{t+1}$	(6) $SAMPVWRT_{t+1}$
ACC_BSM_t	**0.060*****	**0.003**	**-0.005**	**0.074*****	**0.012**	**0.004**
	(2.99)	**(0.12)**	**(-0.13)**	**(3.65)**	**(0.52)**	**(0.13)**
AGG_MA_t		**0.165*****	**0.105****		**0.179*****	**0.123****
		(4.08)	**(2.17)**		**(4.06)**	**(2.85)**
CF_BSM_t	**-0.055***	**-0.052***	**-0.028**	**-0.047**	**-0.044**	**-0.022**
	(-1.85)	**(-1.76)**	**(-0.81)**	**(-1.49)**	**(-1.57)**	**(-0.70)**
BE/ME_t	0.111	0.217***		0.088	0.204***	
	(1.67)	(4.23)		(1.09)	(3.24)	
$ESHARE_t$	0.065	-0.005	0.027	0.053	-0.023	0.007
	(1.71)	(-0.15)	(0.73)	(1.34)	(-0.72)	(0.18)
$DYIELD_t$	-0.083	-0.058	0.117*	-0.079	-0.051	0.113**
	(-1.19)	(-1.05)	(1.98)	(-0.94)	(-1.01)	(2.10)
DEF_t	-0.027	0.012	0.014	-0.002	0.040*	0.042
	(-1.03)	(0.66)	(0.47)	(-0.08)	(1.99)	(1.31)
$TERM_t$	0.001	-0.027	-0.020	0.011	-0.020	-0.013
	(0.02)	(-0.90)	(-0.54)	(0.22)	(-0.61)	(-0.33)
$TBILL_t$	-0.003	-0.027	-0.071	0.015	-0.010	-0.052
	(-0.06)	(-0.76)	(-1.59)	(0.25)	(-0.28)	(-1.06)
Constant	0.114***	0.105***	0.111***	0.115***	0.105***	0.110***
	(4.00)	(5.01)	(5.01)	(3.79)	(4.94)	(5.02)
# Obs	28	28	28	28	28	28
Adj R^2	0.235	0.514	0.315	0.160	0.485	0.317

Table 3 presents regression estimates of aggregate future returns on aggregate balance sheet method accruals, M&A activity and controls. Panel A provides regression estimates for the full sample, years 1965 to 2015, and Panel B provides regression estimates for the cash flow statement period sample, years 1988 to 2015. Accruals are calculated using the balance sheet method. M&A activity is measured by the percent of firms deleted in Compustat under DLRSN "01"—mergers & acquisitions—in the preceding period. *CRSPVWRT* is one-year ahead CRSP value-weighted index returns. *SAMPVWRT* is one-year-ahead CRSP/Compustat matched sample one-year ahead value-weighted index returns. See 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-tail) levels of significance.

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

Panel A: *Balance Sheet Method Aggregate Discretionary Accruals*, Aggregate M&A Activity, and Future Market Returns: Sample Years 1965-2015

	(1) $CRSPVWRT_{t+1}$	(2) $CRSPVWRT_{t+1}$	(3) $CRSPVWRT_{t+1}$	(4) $SAMPVWRT_{t+1}$	(5) $SAMPVWRT_{t+1}$	(6) $SAMPVWRT_{t+1}$
DAC_BSM_t	**0.039***	**0.023**	**0.023**	**0.048*****	**0.032**	**0.032**
	(1.99)	**(0.96)**	**(0.97)**	**(2.93)**	**(1.53)**	**(1.56)**
NAC_BSM_t	-0.001	0.002	0.002	-0.005	-0.002	-0.002
	(-0.04)	(0.09)	(0.11)	(-0.23)	(-0.10)	(-0.12)
AGG_MA_t		**0.060**	**0.060***		**0.062***	**0.061***
		(1.66)	**(1.70)**		**(1.87)**	**(1.89)**
CF_CFM_t	-0.045*	-0.035	-0.036	-0.031	-0.021	-0.021
	(-1.82)	(-1.31)	(-1.26)	(-1.27)	(-0.82)	(-0.75)
BE/ME_t	0.025	0.003		0.018	-0.005	
	(0.51)	(0.05)		(0.37)	(-0.11)	
$ESHARE_t$	0.029	0.025	0.025	0.026	0.022	0.022
	(0.73)	(0.73)	(0.74)	(0.71)	(0.70)	(0.69)
$DYIELD_t$	0.029	0.101	0.103*	0.020	0.094	0.089
	(0.71)	(1.44)	(1.75)	(0.49)	(1.39)	(1.60)
DEF_t	-0.034	-0.020	-0.020	-0.024	-0.010	-0.011
	(-1.20)	(-0.75)	(-0.74)	(-0.82)	(-0.34)	(-0.39)
$TERM_t$	0.013	-0.005	-0.005	0.020	0.001	0.001
	(0.40)	(-0.13)	(-0.14)	(0.55)	(0.03)	(0.03)
$TBILL_t$	-0.030	-0.062	-0.062	-0.016	-0.049	-0.049
	(-0.62)	(-1.15)	(-1.16)	(-0.30)	(-0.83)	(-0.84)
Constant	0.142	0.139	0.140	0.137	0.134	0.132
	(1.29)	(1.38)	(1.46)	(1.35)	(1.49)	(1.56)
# Obs	51	51	51	51	51	51
Adj R^2	0.112	0.158	0.178	0.103	0.156	0.176

Panel B: *Balance Sheet Method Aggregate Discretionary Accruals*, Aggregate M&A Activity, and Future Market Returns: Sample Years 1988-2015

	(1) $CRSPVWRT_{t+1}$	(2) $CRSPVWRT_{t+1}$	(3) $CRSPVWRT_{t+1}$	(4) $SAMPVWRT_{t+1}$	(5) $SAMPVWRT_{t+1}$	(6) $SAMPVWRT_{t+1}$
DAC_BSM_t	**0.065****	**0.006**	**-0.009**	**0.080*****	**0.016**	**0.002**
	(2.80)	**(0.24)**	**(-0.21)**	**(3.33)**	**(0.73)**	**(0.05)**
NAC_BSM_t	0.029	0.013	-0.019	0.035	0.018	-0.013
	(1.26)	(0.79)	(-0.74)	(1.28)	(0.76)	(-0.45)
AGG_MA_t		**0.166*****	**0.108****		**0.180*****	**0.125*****
		(3.74)	**(2.25)**		**(3.74)**	**(2.92)**
CF_CFM_t	-0.058	-0.057	-0.022	-0.051	-0.050	-0.017
	(-1.59)	(-1.73)	(-0.59)	(-1.27)	(-1.52)	(-0.47)
BE/ME_t	0.116	0.226***		0.094	0.213**	
	(1.58)	(3.82)		(1.04)	(2.82)	
$ESHARE_t$	0.064	-0.006	0.027	0.052	-0.024	0.007
	(1.68)	(-0.18)	(0.73)	(1.29)	(-0.70)	(0.18)
$DYIELD_t$	-0.091	-0.071	0.126**	-0.088	-0.066	0.120**
	(-1.11)	(-1.22)	(2.17)	(-0.87)	(-1.01)	(2.17)
DEF_t	-0.024	0.018	0.007	0.001	0.046*	0.036
	(-1.06)	(0.82)	(0.21)	(0.03)	(1.76)	(0.98)
$TERM_t$	0.004	-0.022	-0.026	0.013	-0.015	-0.019
	(0.08)	(-0.65)	(-0.71)	(0.25)	(-0.39)	(-0.45)
$TBILL_t$	0.002	-0.017	-0.082*	0.021	-0.000	-0.061
	(0.04)	(-0.47)	(-1.86)	(0.31)	(-0.00)	(-1.17)
Constant	0.442*	0.236	-0.074	0.508*	0.284	-0.008
	(1.79)	(1.47)	(-0.28)	(1.78)	(1.27)	(-0.03)
# Obs	28	28	28	28	28	28
Adj R^2	0.194	0.490	0.285	0.115	0.460	0.285

Panel C: ***Cash Flow Statement Method Aggregate Discretionary Accruals*****, Aggregate M&A Activity, and Future Market Returns: Sample Years 1988-2015**

	(1) $CRSPVWRT_{t+1}$	(2) $CRSPVWRT_{t+1}$	(3) $SAMPVWRT_{t+1}$	(4) $SAMPVWRT_{t+1}$
$\boldsymbol{DAC\_CFM_t}$	**0.061**	**0.028**	**0.076**	**0.055**
	(1.22)	**(0.54)**	**(1.34)**	**(0.98)**
NAC_CFM_t	0.062	0.024	0.069	0.045
	(1.13)	(0.43)	(1.10)	(0.73)
CF_CFM_t	-0.035	-0.025	-0.014	-0.008
	(-0.88)	(-0.75)	(-0.35)	(-0.22)
BE/ME_t	0.084		0.054	
	(0.94)		(0.55)	
$ESHARE_t$	0.057	0.062	0.046	0.049
	(1.25)	(1.30)	(0.98)	(1.01)
$DYIELD_t$	-0.065	0.034	-0.042	0.022
	(-0.63)	(0.81)	(-0.37)	(0.48)
DEF_t	-0.015	-0.015	0.001	0.002
	(-0.56)	(-0.50)	(0.03)	(0.05)
$TERM_t$	0.011	0.005	0.020	0.016
	(0.21)	(0.10)	(0.33)	(0.28)
$TBILL_t$	-0.011	-0.042	-0.001	-0.021
	(-0.19)	(-0.76)	(-0.01)	(-0.34)
Constant	0.112***	0.113***	0.112***	0.113***
	(3.60)	(3.99)	(3.47)	(3.77)
# Obs	28	28	28	28
Adj R^2	0.048	0.065	-0.073	-0.031

Table 4 presents regression estimates of aggregate future returns on aggregate discretionary and non-discretionary accruals. Panel A (Panel B) provides regression estimates of aggregate future returns on aggregate balance sheet method discretionary and non-discretionary accruals for the full sample, years 1965 to 2015 (years 1988 to 2015). Panel C provides regression estimates of future returns on cash flow method discretionary and non-discretionary accruals for the cash flow statement period sample, years 1988 to 2015. Discretionary accruals for both the balance sheet method and cash flow method are generated using the Jones (1991) model at the firm level and then aggregated. CRSPVWRT is one-year ahead CRSP value-weighted index returns. *SAMPVWRT* is one-year-ahead CRSP/Compustat matched sample one-year ahead value-weighted index returns. See 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-tail) levels of significance.

Table 5: Univariate correlations of M&A Activity with macroeconomic outcomes

Panel A: Univariate correlations across macroeconomic outcomes

	(1) TFP_t	(2) $RGDP_t$	(3) $INVEST_t$
$RGDP_t$	0.743***		
	(0.000)		
$INVEST_t$	0.682***	0.859***	
	(0.000)	(0.000)	
$UNEMP_t$	-0.059	-0.367***	-0.114
	(0.341)	(0.004)	(0.214)

Panel B: Univariate correlations of Aggregate M&A Activity with alternative time period macroeconomic activity

	(1) *TFP*	(2) *RGDP*	(3) *INVEST*	(4) *UNEMP*
t+1	0.238**	0.144	0.199*	-0.153
	(0.050)	(0.156)	(0.081)	(0.142)
t+2	0.213*	0.138	0.123	-0.290**
	(0.073)	(0.167)	(0.196)	(0.020)
t-1	0.158	-0.095	0.062	0.096
	(0.134)	(0.255)	(0.334)	(0.251)

This table reports the univariate Pearson correlations among macroeconomic outcomes at time *t* and between M&A activity at time *t (AGG_MA)* and macroeconomic outcomes across various time periods. One-tailed p-values are reported in brackets below correlation coefficients. ***, **, and * represent the 1%, 5%, and 10% levels of significance. See Appendix for variable definitions, data sources, and calculations.

Table 6: Aggregate M&A Activity and Macroeconomic Outcomes

Panel A: Aggregate M&A Activity and One-year-ahead Macroeconomic Outcomes

	(1) TFP_{t+1}	(2) $RGDP_{t+1}$	(3) $INVEST_{t+1}$	(4) $UNEMP_{t+1}$	(5) TFP_{t+1}	(6) $RGDP_{t+1}$	(7) $INVEST_{t+1}$	(8) $UNEMP_{t+1}$
$\boldsymbol{AGG\_MA_t}$	**0.115****	**0.114**	**0.721****	**-0.104****	**0.128****	**0.146***	**0.655****	**-0.146**
	(2.10)	**(1.25)**	**(2.21)**	**(-2.10)**	**(2.39)**	**(1.97)**	**(2.23)**	**(-1.52)**
TFP_t	-0.047							
	(-0.38)							
$RGDP_t$		0.288**						
		(2.56)						
$INVEST_t$			0.050					
			(0.41)					
$UNEMP_t$				0.803***				
				(11.08)				
$CFNAI_t$					-0.135	1.487***	4.725***	-1.245***
					(-0.76)	(5.56)	(3.21)	(-4.36)
Constant	0.339	1.559**	0.726	1.644***	0.227	2.197***	1.179	6.851***
	(1.14)	(2.67)	(0.37)	(2.70)	(0.70)	(4.67)	(0.60)	(11.82)
# Obs	49	51	51	51	47	49	49	49
Adj R^2	0.018	0.071	0.002	0.660	0.033	0.290	0.146	0.349

Panel B: Aggregate M&A Activity and Two-year-ahead Macroeconomic Outcomes

	(1) TFP_{t+2}	(2) $RGDP_{t+2}$	(3) $INVEST_{t+2}$	(4) $UNEMP_{t+2}$	(5) TFP_{t+2}	(6) $RGDP_{t+2}$	(7) $INVEST_{t+2}$	(8) $UNEMP_{t+2}$
AGG_MA_t	**0.106****	**0.121**	**0.621**	**-0.199****	**0.124****	**0.171**	**0.594**	**-0.261*****
	(2.04)	**(1.13)**	**(1.64)**	**(-2.20)**	**(2.50)**	**(1.65)**	**(1.44)**	**(-2.81)**
TFP_t	-0.082							
	(-0.54)							
$RGDP_t$		-0.104						
		(-0.64)						
$INVEST_t$			-0.252*					
			(-1.86)					
$UNEMP_t$				0.475***				
				(3.79)				
$CFNAI_t$					-0.636***	-0.457	-5.427***	-0.979***
					(-2.92)	(-1.08)	(-3.65)	(-3.08)
Constant	0.381	2.614***	2.328	4.057***	0.229	2.032***	1.387	7.356***
	(1.28)	(3.27)	(1.11)	(3.52)	(0.81)	(3.31)	(0.61)	(12.91)
# Obs	48	51	51	51	46	49	49	49
Adj R^2	0.010	-0.009	0.040	0.287	0.185	0.017	0.162	0.347

Table 6 presents regression estimates of aggregate future macroeconomic outcomes and aggregate M&A activity. Panel A provides regression estimates of aggregate macroeconomic outcomes on aggregate M&A activity one period ahead, and panel B provides regression estimates of aggregate macroeconomic outcomes on aggregate M&A activity two periods ahead. See Appendix for variable definitions, data sources, and various 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-tail) levels of significance.

Table 7: Other Non-articulation Events and Future Market Returns

	(1) $CRSPVWRT_{t+1}$	(2) $CRSPVWRT_{t+1}$	(3) $SAMPVWRT_{t+1}$	(4) $SAMPVWRT_{t+1}$
ACC_BSM_t	**0.039**	**0.044****	**0.045***	**0.055*****
	(1.62)	**(2.13)**	**(1.83)**	**(2.73)**
$DOACT_t$	**-0.026**		**-0.022**	
	(-0.70)		**(-0.59)**	
$FCAACTV_t$		**-0.011**		**-0.024**
		(-0.23)		**(-0.52)**
CF_BSM_t	-0.081***	-0.092**	-0.063**	-0.076*
	(-3.11)	(-2.19)	(-2.38)	(-1.88)
BE/ME_t	0.111	0.103	0.089	0.105
	(1.46)	(1.09)	(1.20)	(1.14)
$ESHARE_t$	0.025	0.026	0.021	0.012
	(0.65)	(0.65)	(0.57)	(0.33)
D/P_t	-0.062	-0.053	-0.059	-0.064
	(-0.95)	(-0.96)	(-0.92)	(-1.12)
DEF_t	-0.014	-0.013	-0.001	0.009
	(-0.47)	(-0.41)	(-0.04)	(0.29)
$TERM_t$	0.018	0.028	0.031	0.036
	(0.59)	(0.79)	(0.88)	(0.90)
$TBILL_t$	-0.029	-0.018	-0.008	-0.008
	(-0.58)	(-0.25)	(-0.14)	(-0.10)
Constant	0.096***	0.088***	0.101***	0.088***
	(4.77)	(3.58)	(4.98)	(3.69)
# Obs	48	44	48	44
Adj R^2	0.179	0.125	0.135	0.138

This table presents regression estimates of aggregate future returns on aggregate balance sheet method accruals with other aggregate non-articulation events included into the model. *DOACTV* is the percentage of firms in the current year that had material discontinued operations and *FCAACTV* is the percentage of firms in the current year that had material foreign currency adjustments. *CRSPVWRT* is one-year ahead CRSP value-weighted index returns. *SAMPVWRT* is one-year-ahead CRSP/Compustat matched sample one-year ahead value-weighted index returns. Columns (1) and (3) provide estimates for sample years 1968 to 2015 and columns (2) and (4) provide estimates for sample years 1972 to 2015 because of data restrictions in Compustat. See 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-tail) levels of significance.