What Causes the Asymmetric Correlation in Stock Returns?

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Abstract

The literature indicates that the correlations between the returns of individual stocks and the aggregate market are significantly larger during negative market-wide movements than during positive market-wide movements. Yet the cause(s) of this asymmetric correlation in stock returns remains largely unknown. We find that firms' cash flow news and other indicators of firm operating performance exhibit asymmetric correlations that are significantly similar to that of stock returns. We also find that other potential causes of asymmetric correlation, such as trading activities, arbitrage constraints, conditional conservatism, and earnings management, do not exhibit significant asymmetric correlations. Our results further suggest that the asymmetric correlation observed in stock returns is significantly related to the asymmetry in firm operating performance. Finally, although a firm's ability to innovate can explain the increases in individual firms' operating performance during bull markets, this ability does not explain the aggregate decreases in firm performance during bear markets.

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1. Introduction

Stock prices tend to fall simultaneously, but rise independently (Christie (1982), French et al. (1987), Ang and Chen (2002), and Hong et al. (2007)). A significant body of literature documents that individual stock returns correlate more strongly with the aggregate market when the market return is negative relative to when the market return is positive (Karolyi and Stulz (1996), Bekaert and Wu (2000), Longin and Solnik (2001), Ang and Chen (2002), Bae et al. (2003), and Albuquerque (2012)). This pattern, dubbed "asymmetric correlation," poses a challenge for investors as this asymmetry suggests that most stocks tend to perform worse in times of need. Harvey and Siddique (1999, 2000) find that rational investors value stocks that do well in times of market crashes, but empirical findings indicate that few stocks possess this virtue. Harvey and Siddique (1999, 2000) and Ang and Chen (2002) show that investors demand compensation for holding stocks that perform poorly during recessions. As such, the asymmetric correlation is important in portfolio selection and risk management strategies. However, to our knowledge, no prior study has examined the underlying cause(s) of the asymmetric correlation in stock returns. Thus, there is little evidence as to why the asymmetric correlation in stock returns arises. Our study fills this gap in the literature.

The accounting and finance literature suggests three categories of causes that potentially affect the asymmetric correlation. The first is a firm's operating performance. Campbell (1991) and Vuolteenaho (2002) show that stock returns can be decomposed into three parts: the expected return, shocks to expected cash flows (*Cash Flow News*), and shocks to discount rates (*Discount Rate News*). Vuolteenaho (2002) and Campbell and Vuolteenaho (2004) further show that firm-level stock returns are primarily driven by cash flow news (i.e., new information about the expected cash flows for a firm). If firms experience negative cash flow shocks together during a bear market, but experience positive cash flow shocks individually during a bull market, meaning that firm operating performances deteriorate together, but improve independently, stock returns would mirror the asymmetric correlation.

The second category of causes is related to the attributes of reported earnings. If reported earnings show asymmetric correlation, stock returns may reflect the same pattern. Basu (1997) and Givoly and Hayn (2000) find that conditional conservatism can make reported earnings more sensitive to bad news than good news, potentially creating asymmetric correlation in reported earnings at the aggregate level.[1] That is, if firms report earnings in a timelier manner during a bear market, yet reflect positive earnings in a less timely manner after sufficiently verifying each piece of news during a bull market, this tendency can cause the asymmetric correlation in reported earnings: Firms' earnings numbers may appear to go down together during negative market-wide movements, but go up individually during positive market-wide movements. Penman and Zhang (2002) find that investors do not completely adjust for accounting conservatism when pricing equity suggesting that conditional conservatism may partially drive the asymmetric correlation in stock returns.

The third category of causes is related to trading activity. If aggregate investors sell stocks simultaneously, but buy them independently, an asymmetric correlation in stock returns can occur. A few models predict such a trading pattern. The international finance literature suggests a "contagion effect" model in the international setting. In this model, a negative shock to one country causes investors to become cash constrained inducing them to sell stocks in other countries to replenish cash. The simultaneous selling activities decrease the prices of assets in

[1] Accounting conservatism has been described as the tendency to require a higher verification for recognizing positive news than for negative news (Basu (1997) and Watts (2003)).

other countries (Kyle and Xiong (2001), Bae, Karolyi, and Stulz (2003), Yuan (2005), and Rodriguez (2007)). Similarly, the literature on "fire sales" indicates that a negative shock to an industry can cause investors to become cash constrained. Investors may sell other stocks to secure much needed cash and the selling pressure affects a wide spectrum of stocks (Coval and Stafford (2007), Brunnermeier and Pedersen (2009), and Schleifer and Vishny (2011)).

Building upon the above three potential explanations from the accounting and finance literature, we strive to posit a credible explanation for the asymmetric correlation in stock returns. We construct variables that represent the potential causes of asymmetric correlation in stock returns and formally test whether those underlying causes are also asymmetrically correlated. To measure the asymmetric correlations of the above potential causes, we employ the methodology of Ang and Chen (2002) and Hong et al. (2007). A positive conditional co-movement (or conditional beta) is the correlation between changes in an individual variable and changes in a market-wide variable when the market-wide variable is higher than a certain level. A negative conditional beta is derived when the market-wide variable is lower than the level. For example, Ang and Chen (2002) define "negative beta" as the stock return beta estimated using only the times when the market returns are below zero. We then test whether the average difference between the two conditional betas differs statistically from zero using the Generalized Method of Moments (GMM) equations. If a variable has a significantly larger negative beta than the positive beta, on average, the variable is asymmetrically correlated.

We show that firm operating performance measures, including cash flow news, sales, and operating cash flows, are all asymmetrically correlated in a way similar to that of stock returns.[2] These results suggest that firm performance is related to the asymmetric correlation in stock returns. Next, we find no evidence of significant asymmetric correlations in reported earnings, and the degree of conditional conservatism is not related to the asymmetric correlation in stock returns. We also find no evidence that earnings management differs significantly by market conditions. In addition, trading activities are not asymmetrically correlated. Trading imbalances, which measure the direction of trades, do not exhibit significant asymmetric correlation. Furthermore, we examine whether arbitrage constraints can be a cause and find that stock returns exhibit significant asymmetric correlations regardless as to the stock's liquidity and other proxies of arbitrage constraints suggesting that arbitrage constraints are not the main cause of the asymmetric correlation in stock returns. Finally, we find that only the asymmetric correlation in cash flow news has a significant and positive explanatory power for the asymmetric correlation in stock returns confirming that the asymmetric correlation in stock returns is firm performance related. In sum, among the plausible candidates suggested in the accounting and finance literature, our tests strongly indicate that the asymmetric correlation in firm performance is related to (and probably causes) the asymmetric correlation in stock returns.

Having established that firm operating performance may drive the asymmetric correlation in stock returns, we further examine why firm performance is asymmetrically correlated in the first place. Motivated by prior studies indicating that corporate innovative efficiency is a critical

[2] We construct the cash flow news variable from the vector autoregression (VAR) framework in Campbell and Vuolteenaho (2004) that dissects realized stock returns into three components: expected return, cash flow news, and discount rate news. Section 3 includes the details of the variable construction.

determinant of firm performance and survival (Hirshleifer et al. (2013) and Cohen et al. (2012)) and future stock returns (Cochrane (1991, 1996), and Liu et al. (2009)), we test whether corporate innovative efficiency is one of the major underlying explanations for the asymmetric correlation observed in firm performance. That is, we examine whether the effect of innovative efficiency on firm performance varies by market condition. We find that innovative efficiency has significant and positive effects on firm performance (cash flow news in particular) only for bull markets. This result suggests that corporate innovative efficiency contributes to the improvement of individual firm's performance during a bull market, yet this efficiency cannot withstand the market-wide negative shocks during a bear market.

Our results should be useful in portfolio selection and risk management strategies. Risk management strategies based on reported earnings or trading activity could have marginal success in reducing the negative effects of asymmetric correlation in stock returns on portfolio performance. Rather, portfolio management strategies should change their focus by market conditions. In bear markets, market-wide information would be more important, while the merits of individual firms would shine more in bull markets. Our results also have policy implications. In bear markets, regulators often seek remedies related to reported earnings or trading activity to mitigate the effect of market crashes. Examples include new disclosure rules or regulations on short selling. Our results suggest that such policies would have little effect on easing the negative asymmetric correlation in stock returns.

The rest of this paper is organized as follows. Section 2 reviews the literature and lays out our hypotheses. Section 3 explains the data and our empirical methodologies, while Section 4 presents our results. Section 5 provides a summary and our conclusions.

2. Review of the Literature in Accounting and Finance and Testable Hypotheses

2.1 Asymmetric Correlation in Stock Returns

Researchers have observed for more than four decades that stock prices tend to go down together, but go up independently. Christie (1982) and French et al.(1987) report that stock prices fall together in bear markets, but rise independently in bull markets suggesting that the correlation between individual stock returns and aggregated market returns in a downside market is stronger than in an upside market . However, formal academic documentation of such asymmetric correlation starts with Ang and Chen (2002), who use an improved econometric methodology to show that stock returns exhibit a statistically significant and economically important asymmetric correlation. However, their design is based on the assumption that stock returns follow normal distribution. Hong et al. (2007) develop an improved methodology that detects asymmetric correlation without assuming the normal distribution of the variables under examination. Our asymmetric correlation measure is based on Hong et al.'s (2007) methodology.

Note that the term "asymmetric correlation" has been interpreted in various ways in the literature. In one strand of the literature, asymmetric correlation is related to the third moment of stock returns, which is skewness in the return distribution. From the perspective of the Arrow-Pratt notion of risk aversion, ceteris paribus, investors are expected to favor right-skewed portfolios over left-skewed ones. Assets that increase a portfolio's left skewness are less desirable and should be expected to provide higher expected returns. Likewise, assets that increase a portfolio's right skewness should be expected to provide lower expected returns. Thus, ex post realized portfolio returns are negatively skewed suggesting that portfolio returns tend to have more frequent crashes than booms (Kraus and Litzenberger (1976) and Albuquerque

(2012)). Thus the skewness literature uses the term “asymmetry” because the distribution of stock returns is not symmetric, but skewed.

This skewness of stock return distribution differs from what this paper means by asymmetric correlation. Herein, asymmetric correlation refers to the movement of stock returns that are conditional upon market-wide returns. Some research on skewness has developed the term “co-skewness,” which is closer to the term asymmetric correlation used in this paper. Co-skewness is the tendency to have extremely low or high returns that are conditional upon market returns (Harvey and Siddique, 1999, 2000). The literature documents the importance of co-skewness to stock prices, but there are few explanations as to why some stocks have higher co-skewness than others.

2.2. Causes of Asymmetric Correlation in Stock Returns

We now discuss three plausible causes, suggested in the accounting and finance literature, for the asymmetric correlation observed in stock returns: firm performances, reported earnings, and trading activity.

2.2.a. Firm Performance

According to the standard dividend discount model, stock price today is the sum of the present values of expected future dividends. Future cash flows will determine future dividends in general, as volatile payout policies are rare. Therefore, stock price changes as investors change their expectations about future cash flows. We measure the change in a firm’s performance using the firm’s cash flow news, which is an unexpected change in future cash flows for the given firm. Campbell (1991), Campbell and Mei (1993), Vuolteenaho (2002), and Campbell and Vuolteenaho (2004) propose methodologies to measure a firm’s cash flow news and show that it is a main determinant of stock returns. Therefore, we examine whether this particular determinant of stock returns is asymmetrically correlated. We supplement this analysis with other accounting measures of changes in firm performance including changes in sales and operating cash flows.

2.2.b. Conditional Conservatism and Reported Earnings

As described previously, conditional conservatism can make earnings more sensitive to negative news (captured by negative aggregate stock returns) to positive news (captured by positive aggregate stock returns) potentially creating an asymmetric correlation in reported earnings. In addition, Ball and Shivakumar (2006) suggest that conditional conservatism is more likely to occur in financially distressed firms, potentially causing market-wide decreases in reported earnings during a bear market. To gauge the degree (i.e., conditional conservatism) to which earnings figures incorporate negative news in a timelier manner than they incorporate positive news, we use the Basu (1997) measure.

The accounting literature on conservatism principle implies that reported earnings generate asymmetric correlations in stock returns. Basu (1997) and Givoly and Hayn (2000) find that conservatism makes reported earnings reflect bad news more quickly than good news. At a macro level, Crawley (2015) confirms that annual estimates of aggregate corporate profits and gross domestic product (GDP) reported by the United States Bureau of Economic Analysis are more sensitive to negative market-wide news than to positive market-wide news. However, Penman and Zhang (2002), show that investors do not appreciate how conservatism and changes in firm investment interact, thus failing accurately and efficiently pricing conditional conservatism. Thus, equity investors may fail to fully comprehend and price reported earnings characterized with conservatism in prior years inducing asymmetric correlation in future equity returns.

We also examine asymmetric correlation in discretionary accruals, as managers' discretion on reported earnings can contribute to the observed asymmetric correlation in stock returns.[3] Prior studies indicate that during a bear market, financially distressed firms report extremely negative abnormal accruals in their financial reporting (e.g., DeAngelo et al. (1994) and Butler et al. (2004)). These extremely negative abnormal accruals during a bear market may cause a market-wide decrease in reported earnings. In contrast, firms smooth out their positive abnormal accruals upon an arrival of good news during a bull market (Kirschenheiter and Melumad (2002)).

This asymmetric reporting may stem from managers' career concerns. Previous research argues that the market rewards management for smoother earnings. When a manager reports a larger earnings surprise, outside investors infer that the earnings precision is lower (Kirschenheiter and Melumad (2002) and Cheng and Warfield (2005)). Accordingly, managers tend to under report earnings as much as possible for sufficiently bad earnings news, a behavior known as taking a big bath in the current period in order to report higher future earnings (Kirschenheiter and Melumad (2002)). This behavior can create a pattern in reported earnings similar to that of asymmetric correlation in stock returns. That is, upon receiving negative macro-economic shocks during a bear market, firms may take a big bath together. Additionally, given

[3] DeAngelo et al. (1994) and Butler et al. (2004) show that financially distressed firms have extremely negative abnormal accruals. The latter attribute this to 'liquidity enhancing transactions (such as factoring receivables)' while the former attribute it to earnings management. However, it also is consistent with timely loss recognition, which is more likely to occur in distressed firms. Dechow, Sloan and Sweeney (1995) and Kothari, Leone and Wasley (2005) find that accrual models are misspecified for firms with extreme performance, which in part could be due to timely loss recognition in the extremely poor-performing firms." (Ball and Shivakumar, 2006, p. 209).

that the performance of a management team is evaluated by comparing it with industry or market peers (Fee, Hadlock, Huang, and Pierce (2012)), a manager's incentive is stronger in a bear market. Even though a manager reports a firm's lower earnings during market-wide downside movements, it is less likely to harm the manager's career. In contrast, if firm-level good news arrives, the manager smooths reported earnings and the degree of smoothing is a function of the amount of cash flow observed by outside investors. He either overstates or partially understates for marginally positive news and increasingly understates the reported earnings as the news becomes more positive until he understates the maximum amount for sufficiently positive news (Kirschenheiter and Melumad, 2002). To summarize, in a theoretical model of financial reporting designed by Kirschenheiter and Melumad (2002), big bath and earnings smoothing co-exist in equilibrium contingent upon the market-wide movement of stock returns. During bear markets, managers are likely to report bad news all together to take a big bath. During bull markets, managers smooth out their reported earnings by reporting good news gradually and individually, contingent upon observed cash flows to outside investors, thereby creating an asymmetric correlation in reported earnings.

Prior research indicates that when investors are naïve, they fixate on reported earnings and fail to correct managed earnings when pricing equity (Cheng and Warfield, (2005)). In contrast, when investors are sophisticated, they rationally expect managers to engage in earnings management during financial distress. Thus, they price reported earnings by correcting the portion of earnings management in reported earnings. Nevertheless, it is also likely that investors cannot fully comprehend the earnings management of individual firms (Stein, 1989), and reported losses during a bear market may cause a market-wide decrease in stock returns.

2.2.c. Trading Activity

There are two strands of literature that predict the relationship between asymmetric correlation in stock returns and trading activity. In the international finance literature, the contagion effect uses investors' cash constraints to explain asymmetric correlations between each country's market and the world-wide market. In those models, a negative shock to a country places investors in need of cash. Investors sell their investments in other countries to replenish their cash and this selling pressure creates other negative shocks in other markets. As a result, global market returns become negative simultaneously. Kyle and Xiong (2001) and Yuan (2005) build models of contagion, while Bae et al. (2003) and Rodriguez (2007) document evidence of contagion.

The fire sales literature, including Coval and Stafford (2007), Brunnermeier and Pedersen (2009), and Schleifer and Vishny (2011), suggests a similar mechanism at a more micro level. A negative shock to an industry or a sector causes investors to become cash constrained forcing them to sell other stocks to acquire much needed cash, thereby generating negative returns across stocks in various industries or sectors. This cash constraint will not be as severe in a bull market and, as a result, trading activity will be less one directional in a bull market.

Both the contagion effect and the fire sale effect suggest that investors' trading activity makes stock returns more simultaneous when the market-wide trend is negative. We examine asymmetric correlations in trading imbalances to see whether investors are selling more simultaneously compared to buying. Trading imbalance is the signed volume (i.e., plus for buy and minus for sell) that reflects the direction of trading activities. Lee and Ready (1991), Chordia and Subrahmanyam (2004), and Kim and Stoll (2014) find that this measure accurately captures the direction of trades and correlates significantly with stock returns.

We note that the effect of trading activity on stock prices depends upon arbitrage constraints, such as stock liquidity (Kyle (1985)). If a stock is highly liquid, a selling activity will have little impact on the stock price as the seller would be able to find another buyer without significantly lowering their quote. Thus, if asymmetric correlation in stock returns is significantly related to stock trading activity, highly liquid stocks would show little asymmetric correlation as their trading activities wouldn't influence their prices. We examine whether asymmetric correlation in stock returns does not appear for highly liquid stocks. We also try other measures of arbitrage constraints documented in the literature.

3. Data and Methodology

3.1. Variables for Firm Performances

Our main variable for firm performance is *Cash Flow News* developed by Campbell (1991) and Campbell and Vuolteenaho (2004). Cash flow news is a stock return originating from a revision in the expectations of the entire spectrum of future cash flows. The dividend discount model of stock valuation suggests stock returns are a function of expected future cash flows. Campbell and Vuolteenaho (2004) show that their cash flow news variable is a main driver of realized stock returns.

Following Campbell and Vuolteenaho (2004), we decompose the monthly stock returns of the individual firm obtained from the Center for Research in Security Prices (CRSP) database into the cash flow component and the discount rate component. The decomposition can be conceptually expressed as follows:

$$r_{t+1} - E_t(r_{t+1}) = NCF_{t+1} - NDR_{t+1}, \tag{1}$$

where r_{t+1} is the next period stock return, E_t denotes a rational expectation at time t, NCF is news about future cash flows (*i.e., Cash Flow News*), and NDR is news about future discount rates.

The empirical decomposition is accomplished by estimating the cash flow news and discount rate news series using a Vector Autoregression (VAR) model. The model assumes that the data are generated by a first order VAR model:

$$Z_{t+l} = a + \Gamma \cdot Z_t + u_{t+1}, \tag{2}$$

where Z_{t+1} is an m-by-l state vector with r_{t+1} as its first element, a is m-by-l vector, Γ is m-by-m matrix of constant parameters, and u_{t+l} is an i.i.d. m-by-l vector of shocks. The other elements of the vector, Z_{t+1}, are the excess market return (measured as the log excess return on the CRSP value-weighted index over the Treasury bill rate), the yield spread between long-term and short-term bonds (measured as the difference between the ten-year constant maturity taxable bond yield and the yield on short-term taxable notes in annualized percentage points), the market's smoothed price-earnings ratio (measured as the log ratio of the S&P 500 price index to a ten-year moving average of the S&P 500 earnings), and the small stock value spread (measured as the difference between the log book-to-market ratios of small value and small growth stocks). We use the monthly excess market returns from the Ken French Data Library. The Treasury bill rates are obtained from the Federal Reserve Board website. The S&P price index level is from the CRSP database and ten-year moving average of the S&P 500 earnings is calculated from the S&P 500 earnings data in Bloomberg. The small stock value spread is acquired from six size and book-to-market portfolios in the Ken French Data Library. Our data period is monthly from 1970-2012.

After generating the data with the VAR equation, we calculate cash flow news, NCF_{t+1}, from a linear function of the $t + 1$ shock vector:

$$NCF_{t+1} = (\mathrm{el}' + \mathrm{el}'\lambda)u_{t+1} \qquad (3)$$

The e1 vector is a vector whose first element is one and all other elements are zero. This vector selects the stock return from the matrix of the VAR results. The VAR shocks (u_{t+1}) are mapped to the cash flow news variable by λ, defined as $\lambda \equiv \rho\Gamma\ (I - \rho\Gamma)^{-1}$. The parameter ρ is a discount coefficient set to 0.95 per year in Campbell and Vuolteenaho (2004) and Γ is a fitted coefficient from the VAR model. See Campbell and Vuolteenaho (2004) for more details.

Since the legitimacy of the cash flow news variable depends upon the validity of the model in Campbell (1991) or Campbell and Vuolteenaho (2004), we supplement our cash flow news analyses with other accounting measures of firm performance. Changes in firm performance can also be reflected in changes in quarterly accounting performance. We select change in quarterly sales and operating cash flows as alternative performance measures as these figures are less affected by factors other than firm performance. A performance measure such as net income (e.g., *IB* or *IBADJ* in the Compustat database) can be significantly influenced by non-performance factors such as depreciation or taxes. In addition, the sales or revenue figure has a merit of being almost always above zero so that we can calculate quarterly percentage changes, just like the way we calculate stock returns from stock prices. On the other hand, performance measure like net income or operating cash flows (e.g., *OANCF* in the Compustat database) frequently have negative values, and percentage changes would be misleading.[4] The sales figures are extracted from the Compustat quarterly data (*SALEQ*) and quarterly operating cash flows are calculated from the *OANCF* item in the Compustat database. The change in sales is defined as

[4] For example, a change in net income from -$10M in the previous quarter to $10M in the current quarter would be interpreted as -200% [(($10M-(-$10M)/(-$10M))].

the difference between sales in the previous and the current quarters divided by sales in the previous quarter.

Note that our alternative measures of firm performance, such as change in sales or operating cash flows, have a few defects to substitute the cash flow news, which is our main measure of firm operating performance. One issue is low frequency. As sales and operating cash flows are only available quarterly, the power of the statistical tests decreases significantly. Another shortcoming is that the two alternative measures represent past performance, rather than expected future performance. Stock prices reflect the latter not the former.

3.2. Variables for Reported Earnings

Our proxy for conditional conservatism is the Conservatism Coefficient (*Consv_coeff*). *Consv_coeff* denotes incremental timeliness for bad news defined as the coefficient b_3 in the regression in Basu (1997), $NI = b_0 + b_1 Neg_{it} + b_2 Ret_{it} + b_3 Neg_{it} * Ret_{it} + \varepsilon$, where *NI* is net income before extraordinary items scaled by the market value of equity at the beginning of the fiscal quarter, *Neg* is an indicator variable that is equal to one if *Ret* is negative and zero otherwise, and *Ret* is the buy-and-hold return during the fiscal quarter. The Basu (1997) regression is fitted over the five-year period (20 quarters).

Since our measure of conditional conservatism is subject to measurement errors, we try alternative proxies, such as Conservatism Negative Skewness (*Consv_negskew*) and Conservative Relative Coefficient (*Consv_relative_coeff*). *Consv_negskew* is defined as the time-series skewness of cash flows from operations minus the skewness of earnings. If operating cash flow from the cash flow statements is not available, we use (funds from operations – change in current assets – change in short-term debt + change in current liabilities + change in cash). The time-series skewness is measured over the five-year period (20 quarters). *Consv_relative_coeff* denotes timeliness for bad news relative to good news, defined as $b_3/(b_2+ b_3)$, and obtained from the Basu (1997) regression above.

The literature in accounting on discretionary accruals also raises caution in using measures of reported earnings. Kothari et al. (2005) in particular illustrate that extant discretionary accrual models (e.g., the Jones (1991) and modified Jones models) are biased toward rejecting the null hypothesis of no earnings management when used with firm samples undergoing non-random performance. They suggest the use of adjusted discretionary accruals by subtracting the discretionary accruals of control firms that are matched by previous year return-on-assets (ROA) and industry. Following their suggestion, we match each firm with other firms from the same industry (using the two-digit SIC code) that have the closest ROA (net income scaled by lagged total assets) per fiscal year. That is, the performance-adjusted discretionary accruals are the discretionary total accruals of the firm after subtracting the discretionary total accruals of the matched firms. Acknowledging Hribar and Collins's (2002) concern that studies using balance sheet data to calculate accruals are potentially contaminated when testing for earnings management, we calculate discretionary total accruals using data obtained directly from cash flow and income statements. Total accruals (*TACC*) of firm *i* at time *t* are defined as:

$$TACC_{it} = [EBXI_{it} - CFO_{it}]/(TOTAL\ ASSET_{it-1}), \tag{4}$$

where *EBXI* is earnings before extraordinary items and discontinued operations, *CFO* is operating cash flow (from continuing operations) taken directly from the cash flow statement, and *TOTAL ASSET* is total assets. We use the performance matched discretionary accruals of Kothari et al. (2005) as the main measure of variability in earnings. We calculate these discretionary accruals from the quarterly accounting figures in the Compustat database. We then test whether the change in the discretionary accruals is asymmetrically correlated. The change is defined as the quarterly difference in the discretionary accruals divided by the number of shares outstanding in the contemporaneous quarter. The data period is quarterly from 1970-2012.

3.3. Variables for Trading Activity

For a measure of trading activity, we obtain monthly trading imbalances from the Financial Markets Research Center of Vanderbilt University. Following the literature on trading activity, monthly trading imbalance is defined as the difference between the number of shares traded on the ask-side (buy transactions) and the number of shares traded on the bid-side (sell transactions) in a month divided by volume in the month. Lee and Ready (1991), Chordia and Subrahmanyam (2004), and Kim and Stoll (2014) find that the trading imbalance variable captures the direction of trading activity and the strength of the direction. We test whether an individual stock's trading imbalances have stronger correlations with the market-wide trading imbalance when the market-wide trading imbalance is negative (i.e., market-wide selling).

We try alternative measures of trading imbalance for robustness. We estimate daily trading imbalance instead of monthly trading imbalance. We also try imbalance in terms of the number of trades or dollar volume. For all of the trading activity measures we use, there are no price and quotes data available prior to 1993. As such, our data period for this particular variable is from 1993-2012, while the sample period for the other variables for this research is monthly or quarterly from January 1970-December 2012.

3.4. Estimating Asymmetric Correlation

Following Ang and Chen (2002) and Hong et al. (2007), we define asymmetric correlation as the difference in the conditional co-movements of two variables. The conditional co-movement (or conditional beta) is defined as the correlation between changes in an individual variable and changes in a market-wide variable under certain conditions. For example, Ang and

Chen (2002) estimate the negative beta (positive beta) of stock returns by estimating a beta using only times when the market-wide stock returns are negative (positive). If the negative beta is statistically larger than the positive beta, one can conclude that the stock tends to follow the market more when market returns are negative.

We estimate the conditional beta of each firm with the following equation:

$$\Delta\text{variable}_{i,t} = \alpha_i + \beta_i \cdot \Delta\overline{\text{variable}}_t + \varepsilon_{i,t}, \tag{5}$$

where changes in a variable for firm *i* at time *t* are regressed on changes in the market-wide average of the same variable at time *t*. As in Hong et al. (2007), all of the variables are standardized by subtracting a time-series average and dividing by a time-series standard deviation. We use the entire time-series data available to estimate beta β_i of firm *i*. Fama and French (1992) provide justifications for betas estimated from the entire time-series data.[5,6]

Let *c* represent a separation point of the market-wide conditions. For example, if $c = \{0\}$, the two conditions are when the market-wide average changes are above zero and below zero. The separation point can be any real number. Asymmetric correlation would be better measured if all possible market-wide conditions are taken into consideration. However, for the sake of practicality, researchers select only a manageable number of conditions. Ang and Chen (2002) and Hong et al. (2007) find that using any number of market-wide conditions between one and

[5] Fama and French (1992) demonstrate theoretically that full period beta estimates can well capture the true beta despite possible variations through time. In addition, they find that empirical results with full period beta are not very different from the results employing a five-year rolling period beta.

[6] Note that a strand of literature uses a slightly different measure of co-movement. Roll (1988), Nofsinger and Sias (1999), Durney et al. (2003), and Chung and Kim (2017) measure co-movement by the R^2 of Equation (5). We do not employ such a co-movement measure as we are unaware of studies on the statistical properties of the tests using conditional R^2.

five captures the asymmetric correlation in stock returns. In this paper, we use c = $\{p25, p50, p75\}$, where p indicates the time-series percentiles of the equally-weighted market returns. We estimate the conditional betas when an equally-weighted market-wide return is higher than or below its 25th, 50th, and 75th percentiles of its historical value.[7] We write the conditional beta as a beta with its condition as its subscript. For example, a conditional beta β_{p25+} means the beta is estimated under a condition that the market return is higher than the 25th percentile of its time series observations, and a conditional beta β_{p75-} means a beta is estimated under a condition that the market return is lower than the 75th percentile of its time series observations.

To test the significance of asymmetric correlations, we employ the statistical methodology designed by Hong et al. (2007). The measure is a Generalized Method of Moments (GMM) test on the difference between conditional betas. This estimation method can detect a significant asymmetric correlation in a given variable without imposing assumptions about the underlying distributions. As the distributional properties of variables differ, such a model-free test would allow us to compare the degree of asymmetric correlation in a range of alternative variables.[8]

The conditional betas for $c = \{0\}$ for a variable are compared by estimating the GMM estimation for the following equation:

$$\beta_{positive} - \beta_{negative} = d \tag{6}$$

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[7] Results with the value-weighted averages are qualitatively similar to those with our equally-weighted averages.

[8] An alternative measure of asymmetric correlation is the "H" measure of Ang and Chen (2002). However, the H measure assumes that a variable follows the normal distribution. As there is no prior history to assume that all of the variables (accounting and trading activity variables in particular) we test in this paper follow a normal distribution, a test that requires no distributional assumptions would be more appropriate.

If d is significantly negative, the negative beta (beta estimated when the market-wide average is below zero) is significantly larger than the positive beta (beta estimated when the market-wide average is above zero). The variable is negatively asymmetrically correlated suggesting that the variable has higher correlations with the market-wide average when the market-wide average is negative. In our tests, there are three separation points in estimating the betas, c = $\{p25, p50, p75\}$. As a result, we acquire three positive betas and three negative betas. One can test the difference between each pair with Equation (7).

$$\beta_{p25+} - \beta_{p25-} = d_1$$

$$\beta_{p50+} - \beta_{p50-} = d_2$$

$$\beta_{p75+} - \beta_{p75-} = d_3 \tag{7}$$

Following Hong et al. (2007), we test whether the difference in each pair of conditional betas is zero using the GMM estimation. We also employ the Wald test to determine whether the differences in the three pairs of betas are jointly zero. The hypothesis of the Wald test is:

$$\beta_{p25+} = \beta_{p25-} \ and \ \beta_{p50+} = \beta_{p50-} \ and \ \beta_{p75+} = \beta_{p75-}$$

$$\text{or, } d_1 = d_2 = d_3 = 0 \tag{8}$$

The null hypothesis of the Wald test is that all pairs of the conditional betas are symmetric implying that there is no asymmetric correlation. We report the results of both the GMM estimation and the Wald test.

According to Campbell and Vuolteenaho (2004), the cash flow news variable requires a different beta estimation method. Since the cash flow news variable is a component of the stock returns, its beta has to be estimated from the component of the stock returns, rather than the full returns. The beta of cash flow news should be calculated as:

$$\beta_{i,CF} = \frac{Cov(r_{i,t}, NCF_t)}{Var(r^e_{M,t} - E_{t-1}r^e_{M,t})}, \tag{9}$$

where $B_{i,CF}$ is the cash flow news beta, r_{it} is the stock return of firm i at month t, NCF is news about future cash flows estimated from the VAR model, $r^e_{M,t}$ is the market return in excess of the risk-free rate, and $E_{t-1}r^e_{Mt}$ is expected market excess return from the VAR model.[9] Thus, the cash flow beta is a covariance between stock returns and cash flow news divided by a variance of the unexpected market excess returns. We calculate conditional cash flow betas as betas when the market excess return is larger or smaller than the three separation points, c = $\{p25, p50, p75\}$.

4. Empirical Results and Interpretations

4.1. Asymmetric Correlation in Stock Returns

Table I reports the summary statistics for our variables of interest. Consistent with the literature, cash flow news and trading imbalance are positively and significantly correlated with contemporaneous stock returns. Note that trading imbalance has a much higher correlation (18.97%) than cash flow news (2.52%). However, change in sales or operating cash flows are not positively correlated with contemporaneous stock returns. It is not surprising since the accounting-based variables are backward-looking measures, while stock returns are a forward-looking measure. Also, our measures of conditional conservatism and discretionary accruals are not significantly correlated with stock returns.

[Insert Table I about here.]

We then test whether stock returns in our sample exhibit significant asymmetric correlations as documented in earlier studies. Table II presents the results. Panel A reports the averages of the conditional betas. Panel B provides the results from the GMM and Wald tests as

[9] See Equations (1), (2), and (3) for details.

to whether the conditional positive betas are statistically different from the conditional negative betas.

[Insert Table II about here.]

The results suggest that negative betas are significantly larger than positive betas for stock returns at all three separation points, c = {p25, p50, p75}. The Wald test rejects the notion that differences between all of the pairs of the two conditional betas are jointly zero. Thus, we confirm the previous research that asymmetric correlation in stock returns is real for the more recent sample with the newer and refined econometrics that we employ in our tests.

4.2. Asymmetric Correlations in Plausible Causes for Asymmetric Correlation in Stock Returns

4.2.1. Firm Performance

We now examine whether plausible causes suggested in the accounting and finance literature for the observed asymmetric correlation in stock returns are asymmetrically correlated.

[Insert Table III about here.]

We find that *Cash Flow News*, our main variable for firm performance is (negatively) asymmetrically correlated. Panel B in Table III suggests that the negative betas for cash flow news are significantly larger than the positive betas for cash flow news at all three separation points, c = $\{p25, p50, p75\}$. The Wald test rejects the hypothesis that differences between all of the pairs of the two conditional betas are jointly zero. As it is supposed to be a main determinant of stock returns (Campbell and Vuolteenaho (2004)), this result suggests that the asymmetric correlation in firm performance is related to the asymmetric correlation in stock returns.

Since our cash flow news variable is extracted from monthly stock returns, one may argue that our test here merely captures the variation in stock returns. To address this issue, we subtract cash flow news from monthly stock returns to extract stock returns not associated with the cash flow news variable. We then test the asymmetric correlation of this residual stock return (i.e., $r_{t+1} - NCF_{t+1} = E_t(r_{t+1}) - NDR_{t+1}$) from Equation (1). We find that the residual stock return does not exhibit negative asymmetric correlation. Thus, we are assured that we don't use a tautological argument when we relate the cash flow news results to the negative asymmetric correlation observed in the stock returns.

[Insert Table IV about here.]

We now supplement the analyses with cash flow news with a few typical accounting measures of firm performance. We examine the asymmetric correlation in changes in quarterly sales first. We measure whether a firm's sales tend to decrease more when other firms' sales decrease as well. Sales figures can contain seasonality. Thus, we employ a fix to reduce the effect of seasonality. From the entire sample, we calculate the average of sales change by each calendar quarter. The quarterly average is subtracted from individual firms' percentage change in sales in the corresponding particular quarter. We also examine asymmetric correlation in operating cash flows.

[Insert Table V about here.]

Table V reports the asymmetric correlation in the firm performance variables. Panel A is based on the original quarterly sales figures, while Panel B is based on the de-seasoned values. Panel C reports the results for the operating cash flows. In all cases, we find strongly significant and negative asymmetric correlation. The results echo the case for cash flow news suggesting that the negative asymmetric correlation is not specific to the cash flow news variable. Firm performance is worse simultaneously, while it improves independently.

4.2.2. Reported Earnings

Next, we determine whether reported earnings due to conditional conservatism may cause asymmetric correlation in stock returns. The accounting literature (Basu (1997) and Givoly and Hayn (2000)) implies that firms with higher conditional conservatism may exhibit greater asymmetric correlation in stock returns. Accordingly, we categorize the sample into two subgroups by the size of our conditional conservatism measure *Consv_coeff*. We rank the conditional conservatism of each firm every calendar year. We then separate stocks by their time-series average of conditional conservatism ranks (1^{st} or 2^{nd}). We estimate the asymmetric correlation in monthly stock returns for these two subgroups separately. Note that the conditional conservatism measure is not available for approximately 40% of the firms in the CRSP database. We also report the results for the firms without the conservatism data.

[Insert Table VI about here.]

Table VI reports the asymmetric correlations for the two conditional conservatism subgroups. We find that the asymmetric correlations are similarly significant between the two conservatism groups: The t-values and the Wald statistics are very similar between the two groups. This result suggests that accounting conservatism is not likely to contribute to the asymmetric correlation observed in the stock returns. Though not reported, the results with alternative measures of conditional conservatism are similar to those in Table VI indicating that our results are robust.

In Table VII, we test the asymmetric correlations in discretionary accrual changes. The table provides the results with performance-matched discretionary accruals (Kothari et al., 2005).[10] We find little evidence that discretionary accruals or earnings management are

[10] Note that tests with alternative measures of discretionary accrual measures yield similar results.

asymmetrically correlated. These results confirm that managerial discretion on reported earnings is unlikely to contribute to the asymmetric correlation in stock returns.

[Insert Table VII about here.]

4.3. Trading Activity and Arbitrage Constraints

Finally, we explore whether trading activity is a major cause of asymmetric correlation in stock returns by examining the asymmetric correlations in monthly trading imbalances that is our measure of trading activity.

[Insert Table VIII about here.]

Table VIII demonstrates that trading imbalance does not show an asymmetric correlation pattern similar to that of stock returns. Conditional betas have positive asymmetric correlations at the 25th percentile separation point, insignificant asymmetric correlations at the 50th percentile separation point, and negative asymmetric correlations at the 75th percentile separation point. Although not reported, we don't find significant asymmetric correlations with alternative measures of trading imbalance, such as daily imbalance or dollar-volume imbalance. Our results suggest that trading activity is not likely a main cause of asymmetric correlations in stock returns.

As noted earlier in Section 4.3, one can argue that stock returns are asymmetrically correlated due to arbitrage constraints. If arbitrage constraints are indeed a primary cause of asymmetric correlations in stock returns, we should observe the degree of asymmetric correlations that increase with arbitrage constraints. Stocks subject to more arbitrage constraints would have stronger asymmetric correlations. And, as suggested in the literature, we assume that a stock's liquidity is a good measure of constraints to arbitrage the stock.

We group our sample stocks by their Amihud (2002) illiquidity measure and examine the asymmetric correlation in stock returns for each illiquidity group. Each calendar year, we separate the stocks into three groups by their previous year's market value. After controlling for the size effect, each size group of stocks is ranked by its previous year's Amihud (2002) measure.[11]

[Insert Table IX about here.]

Table IX reports the asymmetric correlation of stock returns by the Amihud (2002) measure. We find that asymmetric correlation is significant in all of the illiquidity categories including the most liquid stocks. If arbitrage constraints, estimated by a stock's liquidity, are a main cause of asymmetric correlation in stock returns, we should find that the stocks with the highest liquidity have the lowest asymmetric correlation, as the price effect of liquidity will be minimal to most liquid stocks. In unreported results, we also try a more detailed stratification employing the liquidity measure. Instead of three groups, we separate the stocks into deciles. We find a significant asymmetric correlation pattern in the stock returns even for those (extremely liquid) stocks in the highest decile. Our results suggest that trading activity is not likely to be a main cause of asymmetric correlation. Although the lowest liquidity group has the strongest asymmetric correlation, this pattern can be explained by the results in Brunnermeier and Pedersen (2009) and Chung and Kim (2017). They find that low liquidity magnifies extreme stock price movement regardless as to the direction. In other words, low liquidity does not

[11] The Amihud (2002) measure is constructed by dividing the absolute value of stock returns by the dollar volume and employ the average of the ratio during a year:

$$ILLIQ_{iz} = 1/D_{iz} \sum_{d=1}^{D_{iz}} |R_{izd}| \,/VOL_{izd},$$

where D_{iz} is the number of days for which data are available for stock i in the quarter-length period z, d is the counter of days, R is the daily stock return, and VOL is dollar trading volume. We use the CRSP daily data to acquire the yearly Amihud (2002) measure.

determine the direction of stock price movement, but only magnifies the movement. Tests with other measures of liquidity, such as dollar volume or bid-ask spread, yield similar results.

4.4. Relationship between Asymmetric Correlations in Firm Performance and Stock Returns

The results thus far strongly suggest that the asymmetric correlation in stock returns is related to the asymmetric correlation in firm performance, but not to the (perhaps lack of) asymmetric correlation in other plausible candidates. In this subsection, we demonstrate further that it is indeed probably the case. Recall from Equation (7) that the difference between the positive beta and the negative beta measures asymmetric correlation. These *d* variables are $\beta_{p25+} - \beta_{p25-} = d_1$, $\beta_{p50+} - \beta_{p50-} = d_2$, and $\beta_{p75+} - \beta_{p75-} = d_3$. In Figure I, we draw scatterplots that have a *d* variable from cash flow news in the x-axis and the corresponding *d* variable from the stock returns in the y-axis. The scatterplots also contain information about a regression line between the two asymmetric correlation measures. The *t*-statistics of the slope measure the significance of the correlation between the two measures of asymmetric correlation.

[Insert Figure I about here.]

We find a positive and significant relationship between the asymmetric correlation in cash flow news and the asymmetric correlation in stock returns. The *t*-statistics of the slopes are significantly positive at all three separation points, c = {p25, p50, p75}, ranging from 32.8-67.3.

We extend the test further and run a horse race among those plausible candidates with a multivariate regression model. The dependent variable is a *d* variable from the stock returns, and the explanatory variables are the *d* variables from cash flow news, earnings management, and trading imbalances. Each explanatory variable represents the asymmetric correlation measured from firm performance, reported earnings, and trading activity, respectively. We also include several control variables suggested in the literature. Ang and Chen (2002) suggest that firm size, the book-to-market (BTM) ratio, and market leverage are related to the degree of asymmetric correlation in stock returns. We rank a firm's size every calendar year and take the time-series average of the yearly rankings. The average rankings of size, BTM, and market leverage are included in the regression as control variables. We use OLS estimations corrected for heteroskedasticity.

[Insert Table X about here.]

We find that only the asymmetric correlation in cash flow news has a significant and positive explanatory power for the asymmetric correlation in stock returns regardless as to whether we include the control variables or not. The results confirm that the asymmetric correlation in stock returns is firm performance related. Overall, among the plausible candidates suggested in the accounting and finance literature, our tests indicate that only the asymmetric correlation in firm performance is related to (and probably causes) the asymmetric correlation in stock returns.[12]

4.5. Innovative Efficiency and Firm Performance: Why is Firm Performance Asymmetrically Correlated?

A natural question now is why firm performance demonstrates negative asymmetric correlation. We seek to delve into the underlying explanations for the asymmetry in firm performance. One can conjecture that some determinants of firm performance have different effects on performance by market conditions.

[12] We find similar, but weaker results when we use alternative firm performance measures (i.e., change in sales or operating cash flows).

Motivated by a significant body of research that indicates that a firm's ability to innovate is a vital factor in the firm's long-term success and survival (Schumpeter (1939), Solow (1957), Romer (1990), and Levine and Zervos (1998)), we examine the effect of a firm's innovation ability on the firm's operating performance. The efficiency of a firm's innovative activity may asymmetrically contribute to firm performance contingent upon the market conditions, such as bull vs. bear markets.

During bear markets, a market-wide negative shock, such as the financial crisis in 2008, may exacerbate all firms' operating performance regardless as to their differing degrees of innovative success. Securities prices plummet and market-wide pessimism among investors may induce the stock market's downward spiral to be self-supporting. Outside investors anticipate losses as pessimism and selling become pervasive. A market-wide negative shock may constrain the supply of external capital for firms to experiment with innovative and risky projects and shrink consumers' consumption of new innovative products and technologies. However, during a bull market, a market-wide positive shock may provide more opportunities, means, and time for firms with greater innovative efficiency to experiment with innovative and risky projects. Lowery (2003) finds that high tech firms can raise more capital during a bull market. A market-wide positive shock also increases financial market liquidity, and this increased market liquidity can facilitate long-term investment in high return technologies without requiring individual investors to commit their resources to the long-term (Levine, 1997). These firms also can convert their innovative success into financial success in a more efficient and timely manner, as consumers' demand and consumption of these new innovative products increase.

We obtain data on a firm's innovative efficiency and examine whether innovative efficiency works differently on firm performance depending upon market conditions. Hirshleifer et al. (2013) find that a firm's ability to innovate is a vital factor in their future performance and survival, and provide a quantified measure of a firm's innovative efficiency (IE) by using the number of patents per dollar of research and development (R&D) expenditures. That is, the IE measure proxies a firm's ability to transfer dollars of R&D investment into patents. The denominator, R&D, measures resource input to innovation. Patents are proxies for innovative output, as innovations are typically officially known to the public through approved patents. U.S. firms have increasingly recognized the necessity to patent their innovations and, as such, have been especially active in patenting activities since the early 1980s (Hall and Ziedonis (2001) and Hall et al. (2005)) owing to the creation of the Court of Appeals for the Federal Circuit in 1982 and several well-documented patent lawsuits (e.g., the Kodak-Polaroid case). Patents are thus the most useful proxy for firms' innovative output (Griliches (1990)), and are actively traded in the intellectual property market (Gu and Lev (2004)).An alternative measure of innovative efficiency would be the number of citations, and we obtain similar results from a citation-based innovation measure.

Following Hirshleifer et al. (2013), we match the innovative efficiency (IE) variable in fiscal year y with firm performance in fiscal year y+1 for the sample period from 1993-2012.[13] IE interacts with our indicator of the market condition. *Pos* indicates positive market-wide cash flow news and *Neg* is a negative indicator.

We use the standard control variables of firm performance discussed in Ahmed et al. (2011). The control variables include lagged firm performance, contemporaneous stock returns, book leverage, advertising and R&D, and book value. Stock returns are from the monthly CRSP database. Other measures are from the quarterly Compustat database. We define book leverage

[13] Note that the innovative efficiency measure is not available prior to 1993 (Hirshleifer et al., 2013).

as long-term debt divided by assets. Advertising and R&D is calculated as the sum of advertising expenses and R&D expenses divided by sales. Book value is the total asset value. As many of the control variables have a quarterly frequency, we accumulative monthly cash flow news when it is used as firm performance in the contemporaneous quarter and use it as the dependent variable. Monthly stock returns are also accumulated in the same way to derive the quarterly stock returns. Our test equation is as follows:

$$\text{Firm Performance}_{i,t} = \alpha + b1 \cdot Pos \cdot IE_{i,t} + b2 \cdot Neg \cdot IE_{i,t}$$
$$+\text{c1} \cdot \text{Firm Performance}_{i,t-1} + \text{c2} \cdot \text{Stock Return}_{i,t} + \text{c3} \cdot \text{Book Leverage}_{i,t} + \text{c4} \cdot$$
$$\text{Ads and R\&D}_{i,t} + \text{c5} \cdot \text{Book Value}_{i,t} + \varepsilon, \tag{10}$$

where *i* is an individual firm, *t* is the contemporaneous quarter, and *t-1* is the previous quarter. We estimate OLS regressions and use heteroskedasticity-consistent standard errors. Following Hirshleifer et al. (2013), we focus on five R&D intensive industries from 1993-2012. Their two-digit SIC codes are 28, 35, 36, 37, or 38. However, we acquire qualitatively similar results from the expanded sample of all non-financial firms.

[Insert Table XI about here.]

The results indicate that the effect of innovative efficiency on firm performance varies by market condition. The innovative efficiency variable is significantly and positively correlated with cash flow news only when market-wide performance is positive. Innovative efficiency is not significantly correlated with a change in sales when market-wide performance is positive. Alternatively, innovative efficiency has a negative impact on both cash flow news and change in sales when market-wide performance is negative. This observation is consistent with our conjecture. An individual firm's ability to innovate enhances firm performances in good times. However, an individual firm's ability cannot mitigate the effect of market-wide downturns.

Rather, the output of corporate innovative activities are intangible assets (i.e., patents) that have less collateral value and take a range of time to convert into monetary assets, depending upon the types of intangibles, in the event of a firm's financial distress. To the extent that these intangible assets replace other tangible assets, such as property, plant, and equipment, the intangible assets may exacerbate firms' downside risk in a bear market. Overall, our results provide us with just a partial answer to the question of why firm performance is asymmetrically correlated. Please note that we try an alternative measure of the firm's innovative ability, *Research Quotient* (*RQ*), extracted from the Wharton Research Data Services (WRDS) database and obtain very similar results, which are available upon request. A firm's *RQ* is the percentage increase in a firm's revenue from a 1% increase in its R&D when other inputs and their elasticities are held constant. Thus, it measures a firm's ability to generate revenue from its R&D expenditures. Please see Knott (2012) for details.

5. Conclusion

To determine the main cause of the asymmetric correlation observed in stock returns, we examine asymmetric correlations in plausible causes suggested by the accounting and finance literature. We find the firms' cash flow news variable is significantly asymmetrically correlated, as well as other accounting measures of firm operating performance. Also, the conditional betas of stock returns are positively and significantly correlated with the conditional betas of cash flow news. Finally, only the asymmetric correlation in firm performance has significant and positive explanatory power for the asymmetric correlation in stock returns. Thus, our results demonstrate that the asymmetric correlation in stock returns is related to (and probably is caused by) the asymmetric correlation in firm performance. Other plausible causes, such as conditional conservatism, earnings management, trading activity, and arbitrage constrains do not show similar asymmetric correlations nor do they explain the asymmetric correlation in stock returns suggesting that they are unlikely cause the asymmetric correlation in stock returns.

Our paper is the first study that reports that the asymmetric correlation in stock returns is related to the asymmetric correlation in firm performance. Our results suggest that risk management strategies focusing only on managerial behavior or trading activity would have only limited success in defying the effect of asymmetric correlation in stock returns on portfolio performance. Of course, a natural, perhaps larger, question remains. Why is firm performance asymmetrically correlated? We provide some evidence that a combination of cross-sectional differences in a firm's innovative efficiency and market conditions can partially answer this question. The asymmetric correlation of firm performance is explained by corporate innovation efficiency during a bull market, but not during a bear market. Further research on the effect of the dynamics of firm performance or business cycle perspectives may shed additional light on this.

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Table I. Correlations Among Stock Returns and Measures of Firm Performance, Reported Earnings, and Trading Activity

This table presents the Pearson correlations among the stock returns, the cash flow news, the change in sales, operating cash flows, the conditional conservatism measure (*Consv_coeff* variable in Basu (1997)), the performance-matched discretionary accruals (Kothari et al. (2005)), and the trading imbalance (Lee and Ready (1991), Chordia and Subrahmanyam (2004), or Kim and Stoll (2014)). As accounting variables, such as change in sales, operating cash flows, conservatism, and discretionary accruals, have quarterly or yearly frequencies, more frequent variables, like stock returns, cash flow news, and trading imbalance, are averaged by quarter or year when calculating their correlation with the accounting variables. *P*-values are in the parentheses. Correlation coefficients significant at the 1%, 5%, and 10% levels are marked with a, b, and c, respectively.

	Stock Return	Cash Flow News	Change in Sales	Operating Cash Flows	Conditional Conservatism	Discretionary Accruals	Trading Imbalance
Stock Return		**2.52%**[a] **(0.01)**	**-0.17%**[b] **(0.04)**	**-0.29%**[a] **(0.01)**	-0.14% (0.13)	0.01% (0.91)	**18.97%**[a] **(0.00)**
Cash Flow News			-0.02% (0.91)	-0.07% (0.91)	**-0.43%**[a] **(0.01)**	0.00% (0.98)	**0.58%**[a] **(0.01)**
Change in Sales				-0.06% (0.00)	0.01% (0.92)	-0.01% (0.89)	-0.11% (0.32)
Operating Cash Flows					0.04 (0.70)	**-0.45%**[a] **(0.01)**	**3.33%**[a] **(0.01)**
Conditional Conservatism						0.00% (0.99)	**-1.12%**[a] **(0.00)**
Discretionary Accruals							**0.39%**[a] **(0.00)**
Trading Imbalance							

Table II. Asymmetric Correlations in Monthly Stock Returns

This table presents a test of asymmetric correlations in monthly stock returns from January 1980-December 2012. We calculate the conditional betas of monthly stock returns and test whether their negative betas are larger than their positive betas. Panel A reports the summary statistics of the conditional betas at three separation points, c = {*p*25, *p*50, *p*75} where *p* indicates the percentile of equally-weighted market returns. That is, we estimate conditional betas when an equally-weighted market-wide return is higher or lower than its 25th, 50th, and 75th percentiles of its historical value. Panel B provides the difference between the positive betas and the negative betas along with the Wald test results on the null hypothesis that positive and negative betas are identical at all separation points. Coefficients significant at the 1%, 5%, and 10% levels are marked with a, b, and c, respectively.

Panel A

Separation Point	Positive and Negative Betas	Mean	Median	Std. Dev.	Obs.
P25	β^{+}	**0.36**[a]	0.36	0.29	24,835
	β^{-}	**0.40**[a]	0.4	0.43	23,575
P50	β^{+}	**0.35**[a]	0.35	0.39	24,468
	β^{-}	**0.39**[a]	0.39	0.31	24,995
P75	β^{+}	**0.34**[a]	0.33	0.65	22,821
	β^{-}	**0.38**[a]	0.39	0.27	25,089

Panel B

Test statistic	$\boldsymbol{\beta_{p25+} - \beta_{p25-} = d_1}$	$\boldsymbol{\beta_{p50+} - \beta_{p50-} = d_2}$	$\boldsymbol{\beta_{p75+} - \beta_{p75-} = d_3}$
Average difference	**-0.06**[a]	**-0.05**[a]	**-0.06**[a]
t-value of the difference	**-15.50**	**-15.97**	**-11.89**
Null Equation Wald Statistic (***p***-value)		$d_1 = d_2 = d_3 = 0$ **280.80**[a] (0.01%)	

Table III. Asymmetric Correlations in Cash Flow News

This table presents a test of the asymmetric correlations in monthly *Cash Flow News* from January 1980-December 2012 estimated from the method of Campbell and Vuolteenaho (2004). We calculate conditional betas of the cash flow news variable and test whether its negative betas are larger than its positive betas. Panel A provides the summary statistics of the conditional betas at three separation points, c = {*p*25, *p*50, *p*75} where *p* indicates the percentile of the market-wide average. That is, we estimate the conditional betas when the market-wide average is higher than or below its 25th, 50th, and 75th percentiles of its historical value. Panel B reports the difference between the positive betas and the negative betas along with the Wald test results on the null hypothesis that positive and negative betas are identical at all separation points. Coefficients significant at the 1%, 5%, and 10% levels are marked with a, b, and c, respectively.

Panel A

Separation Point	Positive and Negative Betas	Mean	Median	Std. Dev.	Obs.
P25	β^{+}	**0.24^{a}**	0.26	0.30	5,975
	β^{-}	**0.48^{a}**	0.46	0.57	4,912
P50	β^{+}	**0.21^{a}**	0.18	0.37	5,968
	β^{-}	**0.27^{a}**	0.29	0.25	5,941
P75	β^{+}	**0.28^{a}**	0.26	0.35	5,241
	β^{-}	**0.31^{a}**	0.33	0.23	5,975

Panel B

Test statistic	$\boldsymbol{\beta_{p25+} - \beta_{p25-} = d_1}$	$\boldsymbol{\beta_{p50+} - \beta_{p50-} = d_2}$	$\boldsymbol{\beta_{p75+} - \beta_{p75-} = d_3}$
Average difference	**-0.05^{a}**	**-0.13^{a}**	**-0.06^{a}**
t-value of the difference	**-11.81**	**-32.98**	**-14.98**
Null Equation Wald Statistic (***p***-value)		$d_1 = d_2 = d_3 = 0$ **1482.2^{a}** (0.01%)	

Table IV. Asymmetric Correlations in Monthly Residual Stock Returns

This table presents a test of the asymmetric correlations in the monthly residual stock returns, which is the monthly stock return minus the monthly cash flow news from January 1980-December 2012. See Table III and related discussions for details regarding the cash flow news variable. Panel A reports the summary statistics of the conditional betas at three separation points, c = {*p*25, *p*50, *p*75} where *p* indicates the percentile of the equally-weighted market-wide average of the residual stock returns. That is, we estimate the conditional betas when an equally-weighted market-wide average of the residual stock returns is higher or lower than its 25th, 50th, and 75th percentiles of its historical value. Panel B provides the difference between the positive betas and the negative betas along with Wald test results on the null hypothesis that positive and negative betas are identical at all separation points. Coefficients significant at the 1%, 5%, and 10% levels are marked with a, b, and c, respectively.

Panel A: Average of Conditional Betas

Separation Point	Positive and Negative Betas	Mean	Median	Std. Dev.	Obs.
P25	β^+	**0.01**^{b}	-0.02	0.22	5,975
	β^-	**0.02**^{a}	-0.02	0.37	5,377
P50	β^+	**0.03**^{a}	0.02	0.29	5,968
	β^-	**0.02**^{a}	-0.05	0.31	5,941
P75	β^+	**-0.09**^{a}	-0.11	0.34	5,241
	β^-	**-0.02**^{a}	-0.13	0.29	5,975

Panel B: Difference between Conditional Betas

Test statistic	$\boldsymbol{\beta_{p25+} - \beta_{p25-} = d_1}$	$\boldsymbol{\beta_{p50+} - \beta_{p50-} = d_2}$	$\boldsymbol{\beta_{p75+} - \beta_{p75-} = d_3}$
Average difference	0.00	**0.09**^{a}	**-0.01**^{c}
***t*-value of the** difference	0.89	**23.64**	**-1.75**
Null Equation Wald Statistic (***p***-value)		$d_1 = d_2 = d_3 = 0$ **1226.0**^{a} (0.01%)	

Table V. Asymmetric Correlations in Changes in Accounting Performance Measures

This table presents a test of the asymmetric correlations in quarterly changes in sales and operating cash flows from January 1980-December 2012. We calculate the conditional betas of changes in sales and operating cash flows and test whether their negative betas are larger than their positive betas at three separation points, c = {*p*25, *p*50, *p*75} where *p* indicates the percentile of the market-wide average. That is, we estimate the conditional betas when the market-wide average is higher than or below its 25th, 50th, and 75th percentiles of its historical value. We find the difference between the positive betas and the negative betas along with the Wald test results on the null hypothesis that the positive and negative betas are identical at all separation points. Panel A reports the changes in the original sales figures from Compustat. Panel B provides the changes in de-seasoned sales, while Panel C presents the operating cash flows. Coefficients significant at the 1%, 5%, and 10% levels are marked with a, b, and c, respectively.

Panel A: Changes in Quarterly Sales

Test statistic	$\boldsymbol{\beta_{p25+} - \beta_{p25-} = d_1}$	$\boldsymbol{\beta_{p50+} - \beta_{p50-} = d_2}$	$\boldsymbol{\beta_{p75+} - \beta_{p75-} = d_3}$
Average difference	**-3.13**[a]	**-1.96**[a]	**-1.28**[a]
t-value of the difference	**-14.91**	**-14.98**	**-16.11**
Null Equation Wald Statistic (***p***-value)		$d_1 = d_2 = d_3 = 0$ **384.0**[a] (0.01%)	

Panel B: Changes in Seasonality-fixed Sales

Test statistic	$\boldsymbol{\beta_{p25+} - \beta_{p25-} = d_1}$	$\boldsymbol{\beta_{p50+} - \beta_{p50-} = d_2}$	$\boldsymbol{\beta_{p75+} - \beta_{p75-} = d_3}$
Average difference	**-2.63**[a]	**-2.21**[a]	**-1.67**[a]
t-value of the difference	**-13.99**	**-18.50**	**-21.13**
Null Equation Wald Statistic (***p***-value)		$d_1 = d_2 = d_3 = 0$ **629.2**[a] (0.01%)	

Panel C: Operating Cash Flows

Test statistic	$\beta_{p25+} - \beta_{p25-} = d_1$	$\beta_{p50+} - \beta_{p50-} = d_2$	$\beta_{p75+} - \beta_{p75-} = d_3$
Average difference	**-0.06**[b]	**-0.16**[a]	**-0.16**[a]
t-value of the difference	**-2.38**	**-10.12**	**-9.66**
Null Equation Wald Statistic (***p***-value)		$d_1 = d_2 = d_3 = 0$ **115.2**[a] (0.01%)	

Table VI. Asymmetric Correlations in Stock Returns Stratified by Conditional Conservatism

This table presents a test of the asymmetric correlations in monthly stock returns for two subgroups with annual low and high conditional conservatism measures. We use *Consv_coeff*, which denotes incremental timeliness for bad news, defined as the coefficient b_3 in the Basu (1997) regression, $NI = b_0 + b_1 Neg_{it} + b_2 Ret_{it} + b_3 Neg_{it} * Ret_{it} + \varepsilon$. *NI* is net income before extraordinary items scaled by the market value of equity at the beginning of the fiscal quarter, *Neg* is an indicator variable that is equal to one if *Ret* is negative and zero otherwise, and *Ret* is the buy-and-hold return during the fiscal quarter. The Basu (1997) regression is fitted over the five-year period (20 quarters). See Section 2.1 for the details. We calculate the conditional betas of the monthly stock returns and test whether their negative betas are larger than their positive betas. Panels A and B provide the difference between the positive betas and the negative betas along with the Wald test results on the null hypothesis that positive and negative betas are identical at all separation points, c = {*p*25, *p*50, *p*75} where *p* indicates the percentile of equally-weighted market returns. That is, we estimate the conditional betas when an equally-weighted market-wide return is higher or lower than its 25th, 50th, and 75th percentiles of its historical value. Panel C reports the results for firms that have no data for our measure of conditional conservatism. Coefficients significant at the 1%, 5%, and 10% levels are marked with a, b, and c, respectively.

Panel A: *Consv_coeff* = Low (7,151 firms)

Test statistic	$\boldsymbol{\beta_{p25+} - \beta_{p25-} = d_1}$	$\boldsymbol{\beta_{p50+} - \beta_{p50-} = d_2}$	$\boldsymbol{\beta_{p75+} - \beta_{p75-} = d_3}$
Average difference	**-0.07**^{a}	**-0.08**^{a}	**-0.07**^{b}
t-value of the difference	**-17.52**	**-21.29**	**-11.76**
Null Equation Wald Statistic (***p***-value)		$d_1 = d_2 = d_3 = 0$ **479.95**^{a} (0.01%)	

Panel B: *Consv_coeff* = High (7,154 firms)

Test statistic	$\boldsymbol{\beta_{p25+} - \beta_{p25-} = d_1}$	$\boldsymbol{\beta_{p50+} - \beta_{p50-} = d_2}$	$\boldsymbol{\beta_{p75+} - \beta_{p75-} = d_3}$
Average difference	**0.09**^{a}	**-0.09**^{a}	**-0.08**^{a}
t-value of the difference	**-19.42**	**-21.89**	**-11.65**
Null Equation Wald Statistic (***p***-value)		$d_1 = d_2 = d_3 = 0$ **536.5**^{a} (0.01%)	

Panel C: *For Firms with no data on conditional conservatism* (8,294 firms)

Test statistic	$\boldsymbol{\beta_{p25+} - \beta_{p25-} = d_1}$	$\boldsymbol{\beta_{p50+} - \beta_{p50-} = d_2}$	$\boldsymbol{\beta_{p75+} - \beta_{p75-} = d_3}$
Average difference	**-0.09**^{a}	**-0.09**^{a}	**-0.09**^{b}
t-value of the difference	**-17.43**	**-17.83**	**-11.85**
Null Equation Wald Statistic (***p***-value)		$d_1 = d_2 = d_3 = 0$ **389.5**^{a} (0.01%)	

Table VII. Asymmetric Correlations in Earnings Management

This table presents a test of the asymmetric correlations in our proxy for earnings management. We take the difference between the contemporaneous quarterly discretionary accruals and the previous quarter discretionary accruals and divide it by the number of shares outstanding. We calculate the conditional betas of the earnings management variable and test whether its negative betas are larger than its positive betas. Panel A provides the summary statistics of the conditional betas at three separation points, c = {*p*25, *p*50, *p*75} where *p* indicates the percentile of the market-wide average. That is, we estimate the conditional betas when the market-wide average is higher or below its 25^{th}, 50^{th}, and 75^{th} percentiles of its historical value. Panel B reports the difference between the positive betas and the negative betas along with the Wald test results on the null hypothesis that the positive and negative betas are identical at all separation points. Note that this table reports the results with the performance-matched discretionary accruals (Kothari et al. (2005)). Coefficients significant at the 1%, 5%, and 10% levels are marked with a, b, and c, respectively.

Panel A

Separation Point	Positive and Negative Betas	Mean	Median	Std. Dev.	Obs.
P25	β^+	**1.50**[a]	0.38	15.48	5,871
	β^-	0.71	-0.01	24.1	2,929
P50	β^+	**1.00**[a]	0.15	20.01	5,289
	β^-	**0.69**[b]	0.01	20.67	5,247
P75	β^+	-0.06	-0.16	24.26	3,327
	β^-	**1.20**[a]	0.01	16.48	5,788

Panel B

Test statistic	$\beta_{p25+} - \beta_{p25-} = d_1$	$\beta_{p50+} - \beta_{p50-} = d_2$	$\beta_{p75+} - \beta_{p75-} = d_3$
Average difference	0.44	-0.15	**-0.63**[c]
t-value of the difference	0.90	-0.55	**-1.72**
Null Equation		$d_1 = d_2 = d_3 = 0$	
Wald Statistic		4.45	
(P-value)		(21.67%)	

Table VIII. Asymmetric Correlations in Trading Imbalances

This table presents a test of the asymmetric correlations in the monthly trading imbalances (Lee and Ready (1991), Chordia and Subrahmanyam (2004), or Kim and Stoll (2014)) from 1993-2012. Trading imbalance is measured as the difference between the ask-side volume and the bid-side volume divided by the monthly total trading volume. We calculate the conditional betas of the trading imbalances and test whether their negative betas are larger than their positive betas. Panel A reports the summary statistics of the conditional betas at three separation points, c = {*p*25, *p*50, *p*75} where *p* indicates the percentile of the market-wide average. That is, we estimate the conditional betas when the market-wide average is higher or lower than its 25th, 50th, and 75th percentiles of its historical value. Panel B provides the difference between the positive betas and the negative betas along with the Wald test results on the null hypothesis that the positive and negative betas are identical at all separation points. Coefficients significant at the 1%, 5%, and 10% levels are marked with a, b, and c, respectively.

Panel A

Separation Point	Positive and Negative Betas	Mean	Median	Std. Dev.	Obs.
P25	β^+	**0.23**[a]	0.23	0.26	8,085
	β^-	**0.23**[a]	0.22	0.64	7,773
P50	β^+	**0.22**[a]	0.23	0.38	8,060
	β^-	**0.25**[a]	0.25	0.36	8,062
P75	β^+	**0.23**[a]	0.23	0.65	7,754
	β^-	**0.24**[a]	0.24	0.27	8,081

Panel B

Test statistic	$\boldsymbol{\beta_{p25+} - \beta_{p25-} = d_1}$	$\boldsymbol{\beta_{p50+} - \beta_{p50-} = d_2}$	$\boldsymbol{\beta_{p75+} - \beta_{p75-} = d_3}$
Average difference	**0.02**[b]	-0.01	**-0.01**[c]
***t*-value of the difference**	**2.53**	-1.51	**-1.82**
Null Equation		$d_1 = d_2 = d_3 = 0$	
Wald Statistic		**22.7**[a]	
(*p*-value)		(0.01%)	

Table IX. Asymmetric Correlations in Stock Returns Stratified by Stock Liquidity

This table presents a test of asymmetric correlations in monthly stock returns from January 1980-December 2012 stratified by the liquidity of stocks. We use Amihud's (2002) illiquidity measure, which is constructed by dividing the absolute value of returns by dollar volume. Each calendar year, we separate stocks into three groups by their previous year's market value. After controlling for the size effect, each size group of stocks is ranked by its previous year's Amihud (2002) measure. For each subgroup (high, mid, and low liquidity), we first calculate the conditional betas of the monthly stock returns and test whether their negative betas are larger than their positive betas. Each panel below provides the summary statistics of the conditional betas at three separation points, c = {*p*25, *p*50, *p*75} where *p* indicates the percentile of equally-weighted market returns. That is, we estimate the conditional betas when an equally-weighted market-wide return is higher or below its 25th, 50th, and 75th percentiles of its historical value and then present the difference between the positive betas and the negative betas along with the Wald test results on the null hypothesis that the positive and negative betas are identical at all separation points. Coefficients significant at the 1%, 5%, and 10% levels are marked with a, b, and c, respectively.

Panel A: *Amihud* = Low (High Liquidity - 4,937 firms)

Test statistic	$\beta_{p25+} - \beta_{p25-} = d_1$	$\beta_{p50+} - \beta_{p50-} = d_2$	$\beta_{p75+} - \beta_{p75-} = d_3$
Average difference	**-0.04**^{a}	**-0.04**^{a}	**-0.06**^{b}
t-value of the difference	**-8.87**	**-10.04**	**-8.69**
Null Equation Wald Statistic (*p*-value)		$d_1 = d_2 = d_3 = 0$ **128.8**^{a} (0.01%)	

Panel B: *Amihud* = Mid (Mid Liquidity – 5,037 firms)

Test statistic	$\beta_{p25+} - \beta_{p25-} = d_1$	$\beta_{p50+} - \beta_{p50-} = d_2$	$\beta_{p75+} - \beta_{p75-} = d_3$
Average difference	**-0.06**^{b}	**-0.07**^{a}	**-0.06**^{a}
t-value of the difference	**-13.14**	**-17.07**	**-8.59**
Null Equation Wald Statistic (*p*-value)		$d_1 = d_2 = d_3 = 0$ **307.9**^{a} (0.01%)	

Panel C: *Amihud* = High (Low Liquidity – 4,610 firms)

Test statistic	$\beta_{p25+} - \beta_{p25-} = d_1$	$\beta_{p50+} - \beta_{p50-} = d_2$	$\beta_{p75+} - \beta_{p75-} = d_3$
Average difference	**-0.12**^{a}	**-0.11**^{a}	**-0.09**^{a}
t-value of the difference	**-24.07**	**-22.61**	**-10.81**
Null Equation Wald Statistic (*p*-value)		$d_1 = d_2 = d_3 = 0$ **676.9**^{a} (0.01%)	

Table X. Relationships Among Asymmetric Correlations

This table presents a multivariate regression between asymmetric correlations. The dependent variable is the *d* variable from the stock returns, where the *d* variable is the difference between the positive beta and the negative beta, $\beta_{p25+} - \beta_{p25-} = d_1$, $\beta_{p50+} - \beta_{p50-} = d_2$, and $\beta_{p75+} - \beta_{p75-} = d_3$. The main explanatory variables are the corresponding *d* variables from cash flow news, earnings management, and trading imbalances. We rank a firm's size every calendar year and take the time-series average of the yearly rankings. The average rankings of size, BTM, and market leverage are included in the regression as control variables following Ang and Chen (2004). The estimation method is OLS with corrections for heteroskedasticity. *T*-values are in parentheses. Coefficients significant at the 1%, 5%, and 10% levels are marked with a, b, and c, respectively.

Panel A: Without Control Variables

Dependent Variable	d_1 ($\beta_{p25+} - \beta_{p25-}$) *from Stock Return*	d_2 ($\beta_{p50+} - \beta_{p50-}$) *from Stock Return*	d_3 ($\beta_{p75+} - \beta_{p75-}$) *from Stock Return*
Corresponding d value from ***Cash Flow News***	**1.13**[a] **(49.55)**	**1.12**[a] **(40.23)**	**1.25**[a] **(47.78)**
Corresponding d value from ***Earnings Management***	0.20 (0.76)	-0.01 (-0.04)	-0.29 (-1.03)
Corresponding d value from ***Trading Imbalance***	**-1.58**[b] **(-2.14)**	-9.84 (-0.93)	4.92 (0.41)
Adjusted-R^2	73.9%	61.3%	77.7%
Observations	1,030	1,451	1,042

Panel B: With Control Variables

Dependent Variable	d_1 ($\beta_{p25+} - \beta_{p25-}$) *from Stock Return*	d_2 ($\beta_{p50+} - \beta_{p50-}$) *from Stock Return*	d_3 ($\beta_{p75+} - \beta_{p75-}$) *from Stock Return*
Corresponding d value from ***Cash Flow News***	**1.10**[a] **(46.35)**	**1.10**[a] **(46.35)**	**1.07**[a] **(38.64)**
Corresponding d value from ***Earnings Management***	0.16 (0.63)	0.02 (0.63)	0.13 (0.51)
Corresponding d value from ***Trading Imbalance***	**-2.98** **(-0.37)**	-2.98 (-0.37)	4.57 (0.45)
Size	**1.13**[a] **(49.55)**	**-0.61**[a] **(3.32)**	**-1.79**[a] **(-10.37)**
Book-to-Market	0.20 (0.76)	0.13 (0.31)	**-0.83**[c] **(-1.76)**
Leverage	**-1.58**[b] **(-2.14)**	**-0.82**[b] **(-2.33)**	0.59 (1.40)
Adjusted-R^2	73.9%	74.5%	65.6%
Observations	1,030	1,451	1,042

Table XI. Firm Performance and Innovative Efficiency

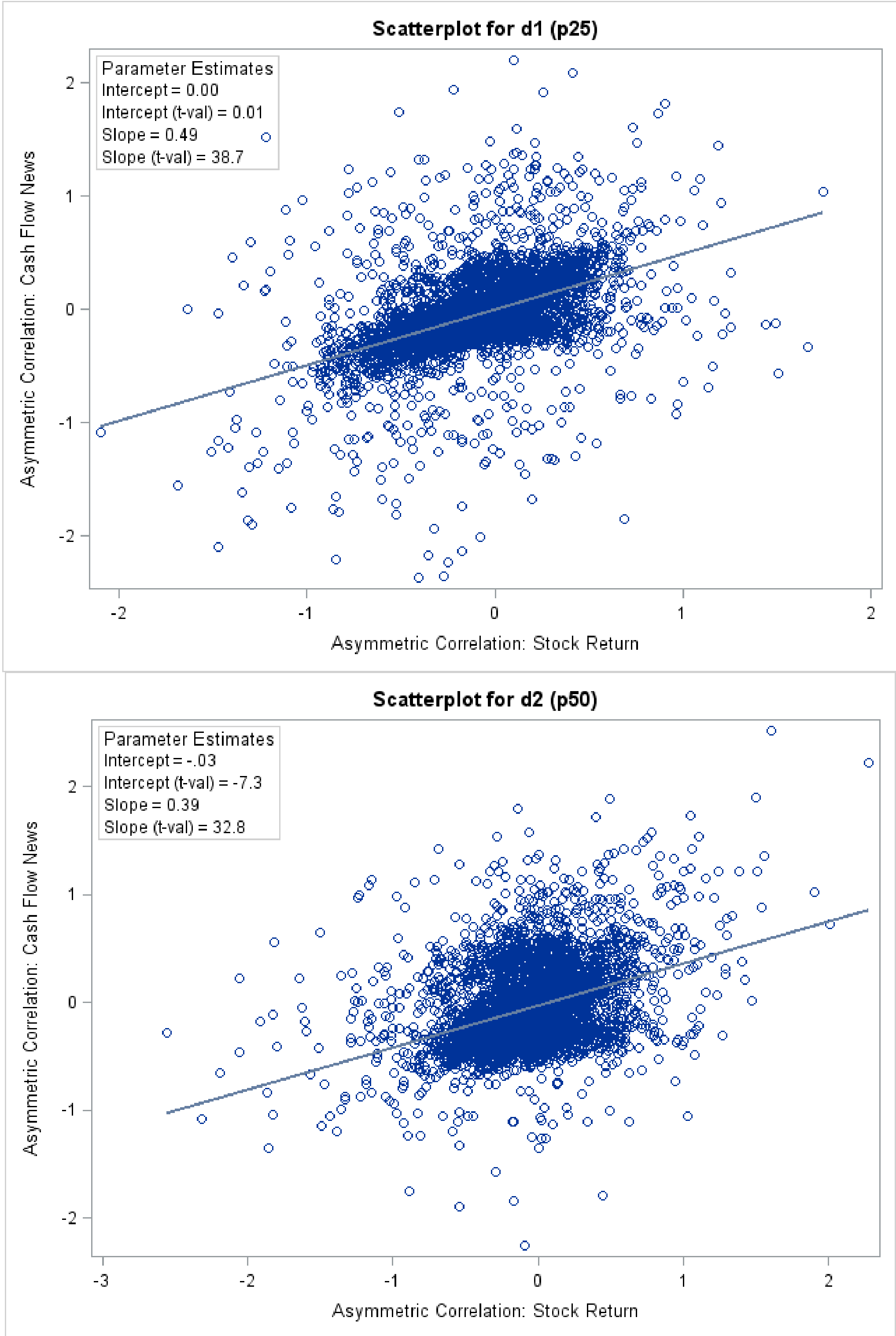
This table presents a test as to whether innovative efficiency works differently on firm performance by market conditions. The dependent variable is the accumulated cash flow news (or change in quarterly sales, operating cash flows) of a firm *i* in a quarter *t*. The innovative efficiency of a firm in year y is measured as the number of patents per dollar of R&D expenditures following the method used in Hirshleifer et al. (2013). We match the innovative efficiency variable in the fiscal year y with firm performance variables in fiscal year $y+1$. The positive (negative) indicator takes a value of one if the average market-wide operating performance in the contemporaneous quarter is positive (negative) zero and zero otherwise. Following Plumlee et al. (2015), we focus on five R&D intensive industries from 1993- 2012. Their SIC two-digit codes are 28, 35, 36, 37, or 38. For control variables, we include firm performance in the previous quarter, cumulative stock returns between the previous and the contemporaneous quarters, book leverage in the contemporaneous quarter, advertising and R&D expenses in the contemporaneous quarter, and size (i.e., book value of the firm) in the contemporaneous quarter. For details of these control variables, see Ahmed et al. (2011).We estimate OLS regressions and use heteroskedasticity-consistent standard errors. t-statistics are in parentheses and 1%, 5%, and 10% statistical significance levels are indicated with a, b, and c, respectively.

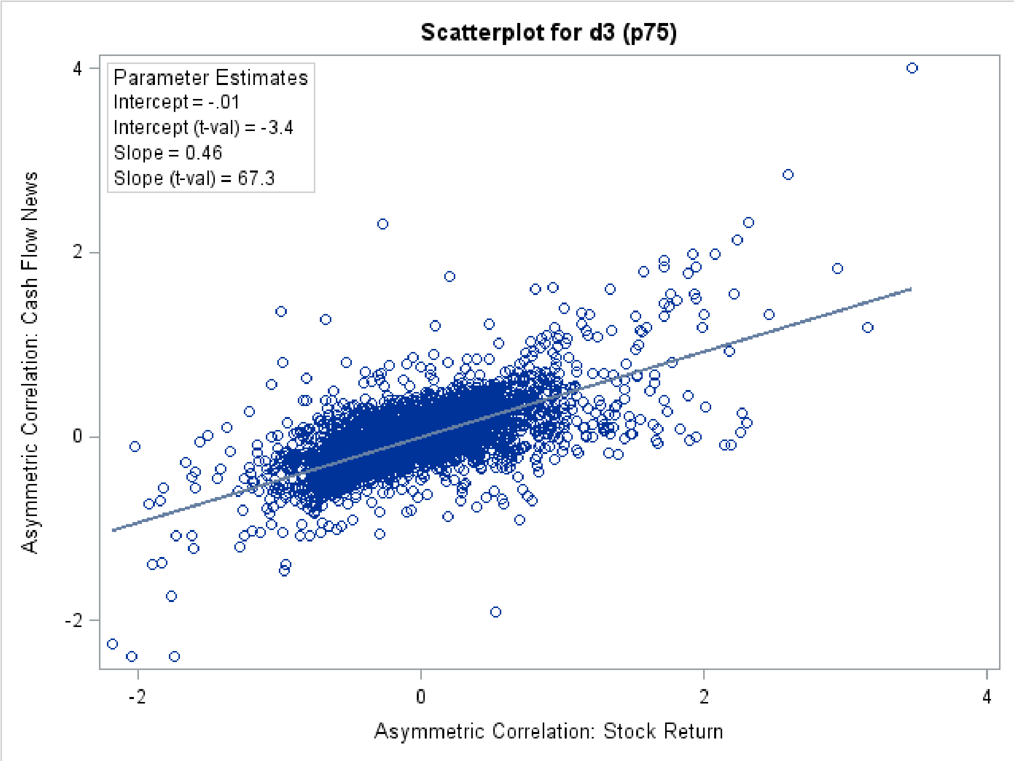
$$\text{Firm Performance}_{i,t} = a + b_1 \cdot Pos \cdot IE_{i,t-1} + b_2 \cdot Neg \cdot IE_{i,t-1} + c_1 \cdot Cash\ Flow\ News_{i,t-1} + c_2 \cdot Stock\ Return_{i,t} + c_3 \cdot Book\ Leverage_{i,t-1} + c_4 \cdot Ads\ and\ R\&D_{i,t-1} + c_5 \cdot Book\ Value_{i,t-1} + \varepsilon\ , \tag{11}$$

where *i* is the individual firm, *t* is the contemporaneous quarter, and *t-1* is the previous quarter.

Dependent Variable	Cash Flow News	Cash Flow News	Change in Sales	Change in Sales	Op. Cash Flows	Op. Cash Flows
*Positive Indicator * Innovation Efficiency*	**0.03**[a] **(3.26)**	**0.26**[b] **(2.40)**	-0.01 (-0.75)	-0.01 (-0.75)	**0.01**[a] **(4.87)**	**0.01**[a] **(4.98)**
*Negative Indicator * Innovation Efficiency*	**-0.14**[a] **(-3.29)**	**-0.14**[a] **(-3.64)**	**-0.08**[b] **(-2.92)**	**-0.07**[b] **(-2.54)**	**-0.02**[a] **(-5.84)**	**-0.02**[b] **(-6.02)**
Firm Performance$_{t-1}$	0.03 (0.60)	**0.08**[c] **(1.70)**	**-0.15**[a] **(-3.26)**	**-0.15**[a] **(-3.22)**	**-0.25**[a] **(-6.09)**	**-0.25**[a] **(-6.03)**
Cumulative Stock Return$_t$	**1.21**[a] **(15.52)**		**0.10**[a] **(8.16)**		**0.02**[a] **(8.28)**	
Book leverage	-0.03 (-0.79)	0.03 (0.63)	**-0.04**[b] **(-2.19)**	**-0.03**[c] **(-1.84)**	**-0.01**[a] **(-3.47)**	**-0.01**[a] **(-3.27)**
Advertising and R&D	**-19.06**[a] **(-3.18)**	**-15.36**[b] **(-2.26)**	2.85 (1.00)	3.06 (1.05)	-0.08 (-0.15)	-0.02 (-0.04)
Size	**0.01**[a] **(2.59)**	0.01 (0.83)	-0.01 (-1.13)	-0.01 (-1.47)	-0.01 (-1.09)	-0.01 (-1.40)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted-R^2	32.45%	12.14%	4.70%	3.44%	10.53%	9.41%
Number of Observations	5,719	5,719	5,719	5,719	5,719	5,719

Figure I. Relationship Between the Asymmetric Correlation in Monthly Stock Returns and the Asymmetric Correlation in Monthly Cash Flow News from January 1980-December 2012




Scatterplot for d3 (p75)
Parameter Estimates
Intercept = -.01
Intercept (t-val) = -3.4
Slope = 0.46
Slope (t-val) = 67.3
Asymmetric Correlation: Cash Flow News
Asymmetric Correlation: Stock Return
4
2
0
-2
-2
0
2
4