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Abstract

This paper documents pervasive evidence of intra-industry reversals in monthly returns. Unlike the conventional reversal strategy based on stock returns relative to the market portfolio, we document intra-industry return reversals that are larger in magnitude, consistently present over time, and prevalent across sub-group of stocks, including large and liquid stocks. These return reversals are driven by order imbalances and non-informational shocks. Consistent with reversals representing compensation for supplying liquidity, intra-industry reversals are stronger following aggregate market declines and volatile times, reflecting binding capital constraints and limited risk bearing capacity of liquidity providers.

Keywords: Return reversals, Industry effects, Liquidity Provision, Contrarian strategies, Industry momentum.

JEL Classification: D14, D21, G24

I. Introduction

The presence of short-term reversals in stock returns is well documented. Jegadeesh (1990) and Lehmann (1990) show that a contrarian strategy of buying stocks that underperformed the market (losers) and shorting stocks that outperformed the market (winners) yields economically significant returns. One plausible explanation for short term reversals is that these are related to compensation for providing liquidity. Campbell, Grossman and Wang (1993) present a model in which risk-averse market makers step in to address imbalances in the demand and supply for the security arising from liquidity shocks. If there is excess selling of a stock due to an exogenous shock, liquidity providers would step in to absorb the excess supply, but would do so only at a lower price and in expectation of a positive return. The subsequent reversal in the stock price, hence, reflects the premium required by liquidity providers. Conrad, Hameed and Niden (1994) provide supportive evidence that market-adjusted return reversals are stronger for stocks that experience a large increase in volume, representing pressure emanating from liquidity shocks. More recently, Hameed, Kang and Viswanathan (2010) and Nagel (2012) use the short-term reversals as a proxy for returns to supplying liquidity and show that the time-variation in these returns corresponds to changing market conditions that affect the provision of liquidity. Avramov, Chordia and Goyal (2006), however, argue that while return reversals are related to liquidity shocks, they are confined to a subset of illiquid stocks.[2]

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[2] Kaul and Nimalendran (1990), Conrad, Gultekin and Kaul (1997) and Jegadeesh and Titman (1995) find that a significant part of short term reversals is related to market frictions due to the bid-ask bounce in transaction prices. Alternatively, Lehmann (1990), Cooper (1999) and Subrahmanyam (2005) view short-term reversals as overreaction

In this paper, we argue for benchmarking stock returns with the returns on peer firms in the industry to better identify short-term return reversals. Returns on firms in the same industry are highly contemporaneously correlated as they are similarly affected by common shocks arising from shifts in demand and supply for their products and services, as well as from technological, regulatory and other macroeconomic changes. If return reversals represent deviations from fundamental values and subsequent convergence due to liquidity shocks, matching firms with similar fundamentals (or industries) provides a more natural framework to identify short-term reversals. To formalize the link between the unconditional (market-adjusted) and intra-industry (industry-adjusted) reversals, we decompose the unconditional reversal strategy into two components, using the portfolio weighting scheme in Lehmann (1990) and Nagel (2012). The first component is the within industry return reversals, where loser and winner stocks are defined based on their performance relative to their industry benchmark. The second component is the inter-industry reversals which involve buying (selling) the industry portfolios that have underperformed (outperformed) the market portfolio. Our decomposition shows that the magnitude of the intra-industry reversals exceeds the unconditional reversals if (a) inter-industry reversals earn negative profits (i.e. if there is momentum in the industry portfolios), and (b) if the cross-sectional dispersion in portfolio weights is smaller in the intra-industry strategy relative to the unconditional strategy. [3]

in stock prices to firm-specific information shocks stemming from behavioral biases. We evaluate these explanations in our empirical analyses.

[3] Roll (1992) provides evidence that a large proportion of an individual stock's return is explained by industry membership, which implies a smaller cross-sectional variation in returns in the intra-industry reversal portfolios.

We implement the return reversal strategies, where we take a one dollar long (short) position on stocks that are losers (winners) in the past month, and hold the portfolio over the next month. Assuming 50 percent margin requirement, the reversal strategy involves an investment of one dollar each month. We find that intra-industry reversal strategy yields a highly significant (risk-adjusted) return of 0.97 percent per month over the 1968-2010 period. The corresponding return on the unconditional reversal is significantly lower at 0.63 percent. Our decomposition exercise reveals that the primary driver of the difference in returns is the extraction of the inter-industry reversal component in unconditional reversals. Specifically, we find significant inter-industry momentum in monthly returns, consistent with the evidence uncovered in Moskowitz and Grinblatt (1999). Hence, an intra-industry reversal strategy isolates short-term reversals from across-industry momentum.[4]

Unlike the unconditional reversals, the intra-industry reversals survive a battery of robustness checks, are pervasive across sub-groups of stocks and are consistently present over time. Kaul and Nimalendran (1990), Jegadeesh and Titman (1995), and Conrad, Gultekin and Kaul (1997) argue that short-term (weekly) reversals are dominated by reversals due to the bid-ask bounce. Similar to Jegadeesh (1990), we skip a day between the formation and holding months to account for any bid-ask effects and find that our intra-industry reversal profits remain significant. Avramov, Chordia and Goyal (2006) show that the unconditional return reversal is confined to illiquid stocks. While we find that reversals are clearly stronger in stocks that are exposed to greater market frictions, we obtain significant intra-industry reversals even among stocks that have large market capitalization, are liquid, or have high institutional ownership. The

[4] Our results are also consistent with a contemporaneous paper by Da, Liu and Schaumburg (2011), who report short-term return reversals within industries and momentum across industries.

intra-industry reversals are also present in all sub-periods, including the recent decades which have recorded declines in transaction costs arising from changes in minimum tick size arrangements and increased turnover. In contrast, the profits from the unconditional reversal strategy are more fragile and do not survive these robustness tests.

Our evidence of intra-industry reversals provides a fresh setting to reexamine the economic sources of the monthly reversals. We explore the notion that the liquidity based explanation for intra-industry reversals necessarily involves a predictive relation between order flows and subsequent reversals. Using high frequency transaction data to measure buy and sell order flows, we find that intra-industry winners (losers) revert more when accompanied by buy (sell) order imbalances. On the other hand, predictions of return reversals using stock returns relative to the market portfolio are less correlated with order imbalances. For the 1993-2008 NYSE sample, the risk-adjusted return on the intra-industry reversal strategy of buying past losers with larger sell orders and selling past winners with greater buy orders is economically significant at 0.70 percent per month. When price movements in the industry winners and losers stocks are not accompanied by price pressure from order imbalances, we do not find significant reversals. Our findings support the hypothesis that liquidity provision is costly for stocks with greater order imbalances as these stocks have a bigger impact on the market makers' inventory risks (see Chordia, Roll and Subrahmanyam (2001, 2005) for supportive evidence at daily and intra-day frequency). Hence, the evidence indicates that short-term reversals are driven by imperfectly elastic supply of liquidity. On the other hand, the inter-industry reversals (or industry momentum) are unrelated to order imbalances, suggesting that these returns are largely driven by public information (Nagel (2012)).

If return reversals are related to compensation for providing liquidity, collateral-based models in Garleanu and Pedersen (2007), Brunnermeier and Pedersen (2009), and others suggest that declines in the aggregate value of securities or increases in market volatility also increases the expected return to supplying liquidity. In Brunnermeier and Pedersen (2009), for example, the market making sector faces capital constraints and obtain funding by pledging the securities they hold as collateral and posting margins. Declines in aggregate market valuations and increases in volatility of asset prices lower the value of the securities pledged and increases the margin requirements (i.e. bigger haircuts), which in turn makes financially constrained liquidity providers less willing to make markets during distress periods. Using unconditional reversal strategies, Hameed, Kang, and Viswanathan (2010) report that returns to supplying liquidity are higher following market declines while the evidence in Nagel (2012) indicates that higher market volatility captures a similar tightening of funding constraints.

Consistent with the predictions in these models and the evidence in Hameed, Kang and Viswanthan (2010) and Nagel (2012), we find that intra-industry reversals are larger following market declines and volatile periods. Specifically, we find a strong positive relation between the intra-industry reversals and declines in aggregate market valuations and higher implied market volatility (measured by *VIX* index of implied volatilities of S&P 500 index options). Our evidence points to higher premium associated with liquidity provision when funding liquidity is likely to be binding.

Finally, we examine if intra-industry reversals are affected by the release of (public) earnings information about the firm. If the reversals are related to non-informational (liquidity) factors, the arrival of public news about the firm should increase the noise in past returns as a proxy for non-informational shocks, leading to a weakening of the reversal returns (Nagel

(2012)). An alternative explanation of short-term reversals is that they represent overreaction of stock prices to firm specific news (Lehmann (1990), Cooper (1999) and Subrahmanyam (2005)), which implies greater reversals following periods of earnings news. After controlling for the drift in stock prices associated with the announcement of company's quarterly earnings (Bernard and Thomas (1989)), we find that intra-industry loser (winner) stocks revert less after an earnings announcement, particularly after negative (positive) earnings news. Our findings of significantly lower intra-industry reversals following the announcement of earnings news demonstrates that short-term reversals are likely to stem from non-informational shocks, confirming the link between reversals and returns to providing liquidity. More broadly, our evidence reinforces the findings in Asparouhova, Bessembinder and Kalcheva (2012) that there are significant temporary price impacts of order imbalances even in returns sampled at monthly horizon.

The rest of the paper is organized as follows. Section II decomposes analytically the unconditional reversals to see how they are linked to intra-industry and inter-industry reversal strategies. Section III presents the main empirical findings on the monthly reversal strategies while Section IV explores the sources of the intra-industry reversals. We provide our concluding remarks in Section V.

II. Unconditional and Intra-Industry Reversals: A Decomposition of Return Reversal Profits

In this section, we decompose the conventional return reversal profits into its components to show the link between unconditional return reversals and intra-industry reversals. We begin with the contrarian portfolio strategy employed in Lehmann (1990) and Nagel (2012). The strategy involves assigning portfolio weights, w_{jt}, to security j at time t based on the past return of security j (R_{jt-1}) relative to the returns on the equal-weighted market portfolio (R_{mt-1}):

(1) $$w_{jt} = -\frac{1}{H_{t-1}}(R_{jt-1} - R_{mt-1})$$

where $R_{mt-1} = \sum_{j=1}^{N} R_{jt-1}$ and N is the number of securities in the market. The weights of the unconditional reversal strategy imply buying the past loser securities (whose returns are less than the market return) and selling short the past winner securities (whose returns are greater than the market return). The weight of each stock j in month t is proportional to the stock's market-adjusted return in month t-1. The investment in each security is scaled by the inverse of the sum of absolute deviations of stock returns from the market portfolio so that the strategy is one dollar long the loser securities and one dollar short the winner securities. Assuming a 50% margin on the long and short positions, the strategy requires one dollar capital each period.[5] Consequently, the scaling factor in equation (1) is defined as:

(2) $$H_{t-1} = \frac{1}{2}\sum_{j=1}^{N} |R_{jt-1} - R_{mt-1}|$$

The profit from this long-short unconditional reversal strategy at time t, π_t, is given by:

(3) $$\pi_t = -\frac{1}{H_{t-1}} \sum_{j=1}^{N}\left(R_{jt-1} - R_{mt-1}\right)R_{jt}.$$

As in Nagel (2012), the profits in (3) represent return per dollar of investment in the long-short strategy.

[5] A 50% margin is assumed to be appropriate by others, see Lehmann (1990) and Nagel (2012).

To analyze the effect of deviations of stock returns from their industry peers on the reversal profits, we subtract and add the return on the portfolio of stocks in industry i (R_{it-1}), where $R_{it-1} = 1/N_i \sum_{j=1}^{N_i} R_{jt-1}$, N_i is the number of securities in industry i and $i=1,\ldots,L$ industries,

(4) $$\pi_t = -\frac{1}{H_{t-1}} \sum_{j=1}^{N} \left(R_{jt-1} - R_{mt-1} + R_{it-1} - R_{it-1}\right) R_{jt}.$$

Equation (4) can be rewritten as:

(5) $$\pi_t = -\frac{1}{H_{t-1}} \left[\sum_{j=1}^{N} (R_{jt-1} - R_{it-1}) R_{jt} + \sum_{i=1}^{L} N_{it-1} \left(R_{it-1} - R_{mt-1}\right) R_{it}\right]$$

The first term in (5) represents the returns to a strategy that buys stocks that underperform the industry portfolio and sell stocks that outperform the industry average. The second term in (5) involves taking long (short) positions in the industry portfolio if the industry returns are higher (lower) than the market portfolio in the formation period. In order to scale the investment in each of these two components to one dollar long and one dollar short, we multiply the profits by the factor of proportionality as follows:

(6) $$\pi_t = -\frac{H_{t-1}^{intra}}{H_{t-1}} \frac{1}{H_{t-1}^{intra}} \sum_{j=1}^{N} \left(R_{jt-1} - R_{it-1}\right) R_{jt} -$$

$$\frac{H_{t-1}^{inter}}{H_{t-1}} \frac{1}{H_{t-1}^{inter}} \sum_{i=1}^{L} (R_{it-1} - R_{mt-1}) N_{it-1}\, R_{it}$$

where

(7) $$H_{t-1}^{intra} = \frac{1}{2}\sum_{j=1}^{N} |R_{jt-1} - R_{it-1}|$$

(8) $$H_{t-1}^{inter} = \frac{1}{2}\sum_{i=1}^{L} |R_{it-1} - R_{mt-1}|\ N_{it-1}$$

Equation (6) provides the decomposition of the unconditional reversal profits into two parts: an intra-industry reversal profits and an inter-industry reversal profits. The return to an intra-industry reversal strategy of buying within industry losers (i.e. stocks that underperformed the industry portfolio) and selling within industry winners, and averaged across all securities in the market at time *t*, is given by:

(9) $$\pi_t^{intra} = -\frac{1}{H_{t-1}^{intra}}\sum_{j=1}^{N}\left(R_{jt-1} - R_{it-1}\right) R_{jt}$$

Assuming a 50 percent margin requirement for both the long and short sides of the strategy, the return per dollar invested in this strategy at time t is given by π_t^{intra}. Similarly, the inter-industry reversal profit per dollar investment, π_t^{inter}, comes from taking long positions in the (equal-weighted) portfolios of stocks in loser industries (industries that underperformed the market portfolio) and shorting the winner industry portfolios, and averaging the returns across all industries at time *t*:

(10) $$\pi_t^{inter} = -\frac{1}{H_{t-1}^{inter}}\sum_{i=1}^{L} N_i(R_{it-1} - R_{mt-1})\ R_{it}$$

As shown in equation (6), the unconditional reversal profit (π_t) is a weighted average of $\pi_t^{intra}$and π_t^{inter} where the weights depend on the scaling factors for the different strategies. The decomposition allows us to examine the relation between return reversals and liquidity provision. Nagel (2012) presents a model depicting the return to liquidity provision, where the short-term reversals are positively related to the ratio of variation in the unexpected return due to order flow and the cross-sectional variation in stock returns (see equation 11 in Nagel (2012), page 2014). Since past returns contain public information unrelated to market makers' inventory imbalances, high cross-sectional variation in returns adds noise to the market makers' strategy. A reversal strategy that removes the variation in returns that is not related to liquidity supply improves the signal-to-noise ratio and provides a sharper measure of return to the maker making sector.

Looking at the decomposition in equation (6), there are two possible reasons for intra-industry reversals to be a less noisy measure of returns to providing liquidity than the unconditional reversals. First, it is less likely that the profits from the reversal in industry portfolio returns, π^{inter}, if any, stem from liquidity effects since inventory induced reversals are more common at the individual stock level.[6] In fact, the evidence in Moskowitz and Grinbaltt (1999) points to significant inter-industry momentum profits in monthly returns, arising from under-reaction to public information. Hence, the persistence in industry portfolio returns related to public information adds noise to the detection of market makers' returns to liquidity provision. Second, the cross-sectional variation in returns for the unconditional strategy is expected to be not more than the intra-industry strategy, suggesting that the ratio of the scaling factors in (6), H_{t-1}^{intra}/H_{t-1}, is possibly less than one.[7] Together, these observations suggest that intra-industry

[6] We exclude the time subscript in the notation to indicate time-series average of the reversal returns.

[7] Note that in an un-scaled weighting scheme, H_{t-1}^{intra}/H_{t-1} represents the amount of capital invested in the intra-industry reversal strategy relative to that in the unconditional reversal strategy. A ratio of less than one denotes that lesser (market maker) capital is employed in the intra-industry reversal strategy.

reversals may be more closely related to the returns to supplying liquidity, in line with the arguments in Nagel (2012).

III. Empirical Evidence

We start our analyses by computing monthly returns from an unconditional (long-short) contrarian strategy as depicted in equation (3). Next, we estimate the components of the unconditional reversal strategy in equation (6). Specifically, we estimate the profits to the intra-industry and inter-industry reversal strategies, as well as the relative scaling weights that add up to the unconditional reversals. Besides reporting the raw monthly returns to the strategy, we also report the risk-adjusted returns, where raw monthly returns are regressed on several pre-specified common factors. We consider three factor-model specifications. First, we use the excess return on the value-weighted CRSP market index over the one-month T-bill return as the sole factor for the CAPM risk adjustment. In the second model, we add the small minus big return premium (SMB) and the high book-to-market minus low book-to-market return premium (HML) for the Fama-French risk adjustments.[8] In the final model, we add the liquidity factor introduced in Pastor and Stambaugh (2003) as the fourth factor to arrive at the four-factor risk-adjusted returns.[9]

A. Data

[8] We thank Ken French for making available the time-series data for the Fama-French three factor model. These factors are described in Fama and French (1993).

[9] The liquidity factor returns are also obtained from WRDS. For details on the construction of the liquidity factor, please refer to Pastor and Stambaugh (2003).

Our primary data consist of common stocks traded on the NYSE, AMEX and NASDAQ stock exchanges. Information on the common stocks, which have share codes 10 and 11, is obtained from the Center for Research on Security Prices (CRSP) database. To classify stocks into industries, we employ the widely used Fama and French (1997) system of classifying companies into 17 industry groups based on four-digit SIC codes.[10] We also consider the Fama-French 48 industry grouping to check for robustness of our results. The sample is obtained for the time period from January 1968 to December 2010.[11]

Table 1 provides the summary statistics of the monthly returns for the stocks in our sample in each of the 17 industry groups. We exclude stocks with a month-end price of below $5 to mitigate market microstructure effects associated with low priced stocks. The average number of stocks in an industry varies from 39 stocks in Mining to 808 (884) stocks in Financials (Other). Industry portfolio returns exhibit positive autocorrelations, ranging from 0.08 (Utilities) to 0.28 (Textiles and Apparel). The individual stock returns within each industry are more volatile, and autocorrelations are smaller and generally negative, averaging between 0.0 and -0.14. These return characteristics are consistent with those reported for earlier sample periods (see Lo and MacKinlay (1990), Moskowitz and Grinblatt (1999) and others).

{Insert Table 1 here.}

[10] In additional analysis, we find that our results remain robust when we classify stocks into industries using the four-digit Global Industry Classification Standard (GICS) scheme.

[11] Our start date for our main sample period is based on the availability of the Pastor-Stambaugh (2003) liquidity factor in CRSP. We obtain similar results if we extend the sample to earlier years.

B. Profitability of Reversal Strategies

Panel A of Table 2 reports the raw and risk-adjusted monthly returns for the loser, winner, and loser minus winner portfolios for the unconditional reversal strategy in equation (3). Consistent with the prior work, we find significant unconditional contrarian raw returns of 0.81 percent per month for our extended sample that includes the recent years. The risk-adjusted return per dollar of investment is lower, but continues to be significant. The four-factor risk-adjusted return is 0.63 percent.

{Insert Table 2 here.}

Panels B of Table 2 provides the estimates of the individual components that make up the unconditional reversal profits as shown in equation (6), namely, $\pi^{intra}$and π^{inter} as well as the time-series average of the cross-products: $\frac{H_{t-1}^{intra}}{H_{t-1}}\pi_t^{intra}$and $\frac{H_{t-1}^{inter}}{H_{t-1}}\pi_t^{inter}$. We obtain substantially higher returns for the intra-industry reversal strategy. The raw (risk-adjusted) π^{intra} is 1.14 percent (0.97) percent per month. The differential profit is primarily driven by the term $(\frac{H^{inter}}{H}\pi^{inter})$ in equation (6), which averages to -0.30 percent per month and, hence, accounts for almost 90 percent of the additional profit in π^{intra}. A negative π^{inter} indicates momentum rather than reversals in industry returns. The strong monthly across-industry momentum profits ($\pi^{inter} = -1.30$ percent) are consistent with Moskowitz and Grinblatt (1999). The remaining difference between π^{intra} and π comes from a lower cross-sectional dispersion in industry-adjusted returns ($\frac{H_{t-1}^{intra}}{H_{t-1}} < 1$). From Table 2 Panel B, the average $\frac{H^{intra}}{H}$ is 0.97, and contributes to the higher π^{intra}. Viewed in the context of the model in Nagel

(2012), using industry-adjusted returns as portfolio weights lowers the fluctuations in returns due to public information shocks, and gets us closer to the return reversals due to liquidity effects.

To verify if the intra-industry reversals are pervasive, we report the π^{intra} for each of the 17 industries in our sample. As shown in Figure 1, we find evidence of significant return reversals in every industry. The largest intra-industry reversals are observed in the Chemicals industry, where $\pi^{intra}$is 1.42 percent per month. The smallest π^{intra} of 0.71 percent occur in Consumer Durables.[12] The significant return reversal within each industry contributes to a strong and consistent overall intra-industry reversal.

{Insert Figure 1 here.}

C. Robustness Checks

1. Extreme Returns

Since the weights assigned to each stock *j* in month *t*, w_{jt}, is proportional to the stock's past return relative to the market or industry returns, larger weight is given to extreme winners and losers. It is possible that the strategies place greater weight on highly volatile stocks with extreme formation period returns. To gauge the influence of extreme returns on the reversal profits, each month, we sort stocks based on their formation month returns and exclude the top and bottom 5 percent of the stocks. Next, we re-compute the various components in equation (6) for this sub-sample. As reported in Table 3, Panel A, this reduces the magnitude of both π^{intra} and π, consistent with the notion that extreme returns are likely to be a result of price pressure

[12] To standardize the reversal returns within each industry, the intra-industry reversal strategy reported in Figure 1 is scaled to be one dollar long the losers and one dollar short the winners within each industry.

and hence revert in the next period. For example, (four-factor) risk-adjusted π drops to 0.38 percent while the risk-adjusted π^{intra} declines to 0.71 percent, but remain significant. Interestingly, the differential return attributable to the intra-industry strategy ($\pi^{intra} - \pi$) remains similar in magnitude to that in Table 2.

{Insert Table 3 here.}

2. Bid-ask Effects

Several researchers, including Kaul and Nimalendran (1990), Conrad, Gultekin and Kaul (1997) and Jegadeesh and Titman (1995), point out that because transaction prices fluctuate between bid and ask quotes, the bid-ask bounce contributes significantly to short-term return reversals. However, Nagel (2012) explains that the reversal strategy is designed to capture the returns to liquidity provision by the market making sector, broadly defined to include both specialized market makers and others such as hedge funds. Since the strategy absorbs the excess demand or supply for the stock, the trades by market makers are executed at transaction prices. Consequently, the negative autocorrelation in consecutive prices due to transactions between the bid and ask prices (i.e. the non-adverse selection component of the bid-ask spread) becomes part of returns earned by the liquidity providers. Nevertheless, it would be useful to assess the relative contribution of the bid-ask bounce to the unconditional and intra-industry reversals. To do so, we re-compute the reversal profits after skipping one day between the portfolio formation period and the holding period, similar to Jegadeesh (1990). Specifically, we apply the same stock weights in the formation month *t-1* as in equations (3) and (6), but exclude the first trading day in month *t* when measuring the holding period returns (R_{jt}). This approach purges the negative autocorrelation in contiguous returns induced by the bid-ask bounce.

The returns to the reversal strategies, after skipping a trading day, are reported in Panel B of Table 3. We find a significant reduction in the returns from both the unconditional (π) and intra-industry (π^{intra}) reversal strategies. In particular, π decline from 0.81 percent per month to 0.43 percent. Moreover, this profit figure goes down further to 0.27 percent, and is statistically indistinguishable from zero, after adjusting for common risk factors. More importantly, π^{intra} is more robust and we continue to observe an economically and statistically significant 0.57 percent risk-adjusted return per month. This indicates that the return to liquidity provision measured by intra-industry reversals reflects more than the bid-ask bounce.

3. January Seasonality

It is well documented that there are strong return reversals in the month of January and several papers argue that this turn-of-the-year effect is due to tax-loss selling (see George and Hwang (2004) and others). We separately examine the returns from the reversal strategies in January and the remaining months of February to December. Consistent with the presence of a strong January seasonal, Panel C of Table 3 shows that both the unconditional and intra-industry strategies yield large risk-adjusted returns of 2.4 and 2.7 per cent, respectively, during the month of January. More importantly, though, we find that the intra-industry strategy continues to produce economically significant returns in the non-January months. On the other hand, the inter-industry reversals generate slightly lesser negative returns (weaker momentum) in January compared to other months, consistent with other evidence on momentum in stock prices.

4. Reversals Using Value-weights

Treating each firm as being equal in size in the long-short portfolios has a potential problem of the portfolios being dominated by microcaps, such as stocks with market capitalization below the 20th NYSE percentile. On the other hand, larger sized firms may take up a bigger dollar-value of the market maker's inventory and hence the capital in providing liquidity. To examine if our results are sensitive to cross-sectional differences in firm size, we modify the long-short reversal strategies in equations (3), (9) and (10) by multiplying the weights assigned to each stock *j* by its market capitalization in month *t-1* (M_{jt-1}), similar to Nagel (2012):

$$\pi_t^{vw} = -\frac{1}{\frac{1}{2}\sum_{j=1}^{N}(R_{jt-1} - R_{mt-1})M_{jt-1}} \sum_{j=1}^{N}\left(R_{jt-1} - R_{mt-1}\right)M_{jt-1}R_{jt}. \tag{11}$$

$$\pi_t^{intra,vw} = -\frac{1}{\frac{1}{2}\sum_{j=1}^{N}(R_{jt-1} - R_{it-1})M_{jt-1}} \sum_{j=1}^{N}\left(R_{jt-1} - R_{it-1}\right)M_{jt-1}R_{jt} \tag{12}$$

$$\pi_t^{inter,vw} = -\frac{1}{\frac{1}{2}\sum_{i=1}^{L}(R_{it-1} - R_{mt-1})M_{it-1}} \sum_{i=1}^{L}(R_{it-1} - R_{mt-1})M_{it-1}R_{it} \tag{13}$$

As shown in Table 4, we find that the unconditional reversal returns (π^{vw}) are not significantly different from zero when the portfolios are value-weighted, with a mean raw return of 0.28 percent. This suggests that the unconditional reversals are heavily dependent on reversals among the smaller firms. More importantly, the value-weighted intra-industry reversal returns ($\pi^{intra,vw}$) are significant at 0.53 percent per month and are not dominated by small firms. The inter-industry reversal strategy ($\pi^{inter,vw}$) yields returns which are similar to the equal-weighted one reported in Table 2.[13]

5. Robustness to Alternative Industry Classification Scheme And Variation in Reversals Across Time

To check if our findings on the returns to supplying liquidity, measured by the intra-

[13] The value-weighted strategy in (11), however, does not decompose exactly into the intra and inter-industry reversal components, as with the equal-weighted strategy in (6).

industry reversal strategies, are robust across time periods and across alternative industry classification schemes, we examine the reversal strategies for four sub-periods: 1968-1979, 1980-1989, 1990-1999 and 2000-2009 for the finer 48-industries classification scheme of Fama-French.

Table 5 reports the returns for the unconditional (π), intra- (π^{intra}), and inter-(π^{inter}) industry strategies based on the Fama-French 48 industries over the full sample period and the four sub-periods. For the full sample period 1968-2010, π^{intra} increases to 1.28 percent with the finer industry groupings, supporting the idea that industry grouping helps to improve the signal of future return reversals. Furthermore, π^{intra} is significant in each of the sub-periods, and the risk-adjusted return ranges between 0.68 to 1.90 percent per month. For instance, π^{intra} continues to generate a significant 0.94 percent during the recent period of 2000-2010, suggesting that improvements in the trading mechanisms in the stock market and the growth in trading activity have not drastically reduced the return reversals. On the other hand, π has declined in magnitude over the past few decades, and is not different from zero in the recent decades. The weighted contribution from π^{inter} towards the unconditional reversals (see equation (6)) has also declined in the recent decade. The main message from Table 5 is that π^{intra} provides a strong measure of return reversals and is reliably significant across time.

{Insert Table 5 here.}

Figure 1 plots the 12-month moving average of the monthly series of π and π^{intra} reported in Table 5. The plots show that the profitability of the reversal strategies appears to be related to periods of liquidity crisis. For example, the spikes in π^{intra} appear to coincide with episodes of market stress such as the oil crisis in November 1973, the stock market crash of

October 1987, the LTCM crisis in 1998, the terrorist attacks of September 11, 2001, and the Euro crisis in 2010. In addition, π^{intra} also appear to be less volatile and more reliably positive than π.

{Insert Figure 2 here.}

6. Cross-Sectional Variation in Reversals

The higher profitability of the intra-industry contrarian strategy appears to come from selection of fundamentally correlated stocks that initially diverge in value, possibly in response to liquidity shocks, and subsequently converge to their fundamental values. Theoretical models of liquidity supply suggest that returns to supplying liquidity vary in the cross-section of stocks. In Garleanu and Pedersen (2007) and Brunnermeier and Pedersen (2009), for example, more risk capital is required to meet the higher margin requirements (higher haircuts) in market making for more volatile stocks. At the same time, prior evidence suggests that a large portion of the unconditional short-run reversals may be attributed to stocks that are illiquid (Avramov, Chordia and Goyal (2006)). To examine the pervasiveness of the intra-industry reversals, we check if the intra-industry contrarian strategy tilts the portfolio exclusively towards stocks that are small, illiquid, or have low institutional ownership. Specifically, we investigate the robustness of our findings by applying the contrarian strategies separately within subsample of firms sorted on each of these firm characteristics into the top and bottom 30 percent of firms in the formation month.

In Panel A of Table 6, we report the return reversals associated with the large and small stocks. Large (small) stocks are those that, at the end of the formation month, fall among the largest (smallest) 30 percent of the stocks in terms of market capitalization using the NYSE breakpoints. As expected, both unconditional (π) and intra-industry (π^{intra}) reversals yield higher returns for small stocks. On the other hand, for the sub-sample of large stocks, π becomes indistinguishable from zero, while π^{intra} continues to yield significant risk-adjusted monthly return of 0.47 percent. This confirms that the intra-industry reversals are pervasive, even among the large cap stocks.[14]

{Insert Table 6 here.}

Using the Amihud (2002) illiquidity measure, Avramov, Chordia and Goyal (2006) find that the short-term unconditional return reversals are limited to illiquid stocks. Amihud's (2002) measure is defined as $[1/n \sum \{|R_{j,d}| / (P_{j,d} * N_{j,d})\}]$, where n is the number of trading days in each month, $|R_{j,d}|$ is the absolute return of stock j on day d, $P_{j,d}$ is the daily closing price of stock j and $N_{j,d}$ is the number of shares of stock j traded during day d. The greater the change in stock price for a given trading volume, the higher would be the value of the Amihud illiquidity measure.

As the reporting mechanism for trading volume differs between NYSE/AMEX and NASDAQ stock exchanges (Atkins and Dyl (1997)), we sort stocks traded in each exchange separately. Panel B of Table 6 reports the returns to the unconditional and intra-industry reversal strategies applied to the liquid and illiquid group of stocks. Consistent with the findings of Avramov, Chordia and Goyal (2006), we find that π is strong at 1.53 percent per month for stocks that have low liquidity, but becomes insignificant for the high liquidity stocks. On the other hand, risk-adjusted π^{intra} remains significant at 0.32 per cent per month for the high liquidity stocks.

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[14] As reported in Table 6, the *t*-statistics for the test of the difference between π^{intra} and π indicate significance in each of the three panels.

Greater institutional ownership could lead to more efficient pricing of stocks; for example, by facilitating more informed institutional trading (Boehmer and Kelley (2009)) and by increasing the supply of loanable shares and mitigating constraints on short-selling (Nagel (2005)). As reported in Panel C of Table 6, we find that π^{intra} remains profitable for the stocks with high institutional ownership, which implies that institutional trading consumes liquidity and hence, contributes to short-term return reversals (Kaniel, Saar and Titman (2008) and Campbell, Ramadorai, Schwartz (2009)).[15]

To summarize, the unconditional strategy generates returns that are consistent with the established evidence that short-term reversals are not so conspicuous and are generally confined to a subset of stocks that are likely to be affected by illiquidity. The intra-industry reversals that we document in this paper, however, are economically significant, and are pervasive among sub-samples of large and liquid stocks, and are also persistent over time. We provide a more detailed analysis of the relation between the intra-industry reversals and liquidity provision in the following section.

IV. Intra-Industry Reversals and Returns to Providing Liquidity

A. Reversals and Order Flow Imbalances

The liquidity provision explanation involves a predictive relation between order flows and subsequent reversals. Chordia, Roll and Subrahmanyam (2001, 2005) and Hendershott and

[15] In unreported results, we find that return reversals are pervasive even among the low volatility stocks—π^{intra} is significant at 0.87 percent per month for this group of stocks.

Seasholes (2007) argue that the return reversals are related to inventory effects, where the market makers demand a risk premium for bearing inventory risk, which in turn depends on the order flow. If intra-industry rather than unconditional reversals better capture the returns to supplying liquidity, we should find a stronger relation between order imbalances and the intra-industry portfolio weights ($R_{jt-1} - R_{it-1}$) than ($R_{jt-1} - R_{mt-1}$) in predicting the future returns (R_{jt}).[16] A smaller effect of ($R_{jt-1} - R_{mt-1}$) on reversals may arise, for example, because industry returns are largely driven by public information rather than order imbalances (Nagel (2012)). Moreover, the imperfect elasticity of liquidity supply implies that intra-industry reversals should be present mostly when order imbalances accompany the price movement in the formation period.

We turn to high frequency data to measure order flow imbalance and gauge its relation to return reversals. We rely on NYSE Trades and Automated Quotations (TAQ) database to obtain high frequency transactions data for the period 1993 to 2008. The data filters and computation methods used in extracting the intraday transactions records to compute daily measures of order imbalance and bid-ask spreads correspond to those in Chordia, Roll and Subrahmanyam (2001 and 2005).[17] For example, the sign of each trade (i.e. buy or sell initiated trade) is decided by the Lee and Ready (1991) algorithm, which matches a trade to the most recent quote preceding the

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[16] Several papers such as Campbell, Grossman and Wang (1993), Conrad, Hameed and Niden (1994), Pastor and Stambaugh (2003) and Avramov, Chordia and Goyal (2006) use changes in (unsigned) trading volume to measure liquidity shocks. We use order imbalance to measure variations in demand for liquidity.

[17] Chordia, Roll and Subrahmanyam (2005) explain the filter rules used to eliminate anomalous records in the intraday data in the TAQ database. We thank Tarun Chordia for generously sharing the daily data extracted from the TAQ database.

trade by at least five seconds.[18] For each stock, the intra-day buy and sell orders are aggregated to obtain the daily buyer and seller initiated trades. Following Chordia, Roll and Subrahmanyam (2005), we define order imbalance for stock *j*, OIB_{jt-1}, as the monthly dollar value of buyer initiated trades less the monthly dollar value of seller initiated trades divided by the total value of trades during month *t-1*. The monthly observations of buyer and seller initiated trades are constructed by summing the corresponding daily values over the month, for each stock.

To provide an idea of the transaction costs associated with the securities in our portfolio, we use two measures of bid-ask spread for each stock using the TAQ database. *PQSPR*, the proportional quoted spread, is defined as the difference between the bid and ask quotes divided by the midpoint of the bid-ask prices, averaged across all trades during the trading day. The proportional effective spread, or *PESPR*, is obtained as two times the absolute difference between the transaction price and the midpoint of the prevailing bid and ask quotes, again averaged over the day. Both daily *PQSPR* and *PESPR* measures follow those reported in Chordia, Roll and Subrahmanyam (2005), which we average over each month to obtain monthly indicators of transaction costs.

To examine the relation between order imbalance and portfolio weights in intra and unconditional reversal strategies, we run the following Fama-McBeth regressions on monthly stock returns (R_{jt}):

$$(14) \quad R_{jt} = a_j + \ b \quad D_{Sell,jt-1} + c_{11}\left(R_{jt-1} - R_{it-1}\right)^{+} D_{Buy,jt-1}$$

[18] The Lee and Ready (1991) method classifies a trade as a buyer (seller) initiated order if a transaction occurs at a price that is closer to ask (bid) quote. If the trade is at the quote midpoint, it is signed according to the tick test; i.e. the trade is classified as a buyer (seller) initiated if the price is higher (lower) than the previous trade.

$$+c_{12}\left(R_{jt-1}-R_{it-1}\right)^{+}D_{Sell,jt-1}+c_{13}\left(R_{jt-1}-R_{it-1}\right)^{-}D_{Buy,jt-1}$$

$$+\,c_{14}\left(R_{jt-1}-R_{it-1}\right)^{-}D_{Sell,jt-1}+g'controls+\epsilon_{jt}$$

$$(15)\quad R_{jt}=a_j+\ b\quad D_{Sell,jt-1}+c_{11}\left(R_{jt-1}-R_{mt-1}\right)^{+}D_{Buy,jt-1}$$

$$+c_{12}\left(R_{jt-1}-R_{mt-1}\right)^{+}D_{Sell,jt-1}+c_{13}\left(R_{jt-1}-R_{mt-1}\right)^{-}D_{Buy,jt-1}$$

$$+\,c_{14}\left(R_{jt-1}-R_{mt-1}\right)^{-}D_{Sell,jt-1}+g'controls+\epsilon_{jt}$$

where $D_{Buy,jt-1}$ ($D_{Sell,jt-1}$) is a dummy variable that takes the value of 1 if stock *j*'s order imbalance (OIB_{jt-1}) is positive (negative); the superscript '+' ('-') associated with the industry adjusted returns $\left(R_{jt-1}-R_{it-1}\right)$ in (14) and market-adjusted returns $\left(R_{jt-1}-R_{mt-1}\right)$ in (15) indicates that the returns are positive (negative). Our main focus is on the interaction terms in equations (14) and (15), which gauge the joint effect of order-imbalances and intra-industry and market-adjusted portfolio weights on future returns. The vector of control variables (*controls*) consists of the following firm-specific variables in month *t-1*: *Log (Size)* is the logarithm of market capitalization; *IdioVol* is the idiosyncratic volatility of stock returns computed as the standard deviation of the daily residuals from a standard market model regression; $Return_{t-6:t-1}$ is the average monthly return from month *t-6* through month *t-1*; and *Amihud* is the logarithm of Amihud illiquidity measure.

The time-series averages of the monthly estimates of equations (14) and (15) are produced in Table 7 for the *NYSE-TAQ* merged sample. The estimated coefficients for the control variables are consistent with prior expectations: smaller firms earn higher returns (Banz (1981)); high idiosyncratic volatility is associated with low future returns (Ang, Hodrick, Xing and Zhang (2009)); loser and winner stocks over the previous six months exhibit momentum in returns (Jegadeesh and Titman (1993)). The surprising result here is that we find a negative relation between Amihud illiquidity and future returns, inconsistent with the notion that illiquid stocks are expected to earn higher returns, a finding that is also noted in Ang et al (2009).

We find that past stock returns relative to the market or industry portfolio predict future reversals, consistent with our earlier evidence on unconditional and intra-industry reversals. Both industry-adjusted and market-adjusted returns revert only when the order imbalances also indicate similar pressure on the inventory balances. More interestingly, negative net order imbalance ($D_{Sell,jt-1}$) accompanied by negative industry-relative stock returns reverts more strongly in the next period than when accompanied by negative market-relative returns.[19] The latter finding confirms the intuition that industry-relative weights provide a superior weighting scheme to capture imbalances in demand and supply for the stock in the formation month. Market-relative returns appear to be a noisier proxy for order imbalances since it is also affected by industry returns, which are more likely to be driven by public information.

{Insert Table 7 here}

Next, we evaluate the joint effects of order imbalances and past returns on intra and inter-industry reversals. We sort stocks in the industry loser and winner portfolios in Table 8 into two equal groups, based on *OIB* in the formation month. The notion of return to liquidity provision implies that the reversal return ought to be higher when buying loser securities that also face selling pressure (low *OIB*) and shorting winner securities that exhibit greater buying pressure

[19] The regression coefficient of -0.045 associated with $\left(R_{jt-1} - R_{it-1}\right)^{-}$ is significantly different than the coefficient of -0.036 associated with $\left(R_{jt-1} - R_{mt-1}\right)^{-}$ (t-statistic = 2.10).

(high *OIB*). Supportive evidence is provided in Panel A of Table 8, where the risk-adjusted return on the intra-industry strategy that takes the offsetting position in stocks that experience large order imbalances is a significant return of 0.7 percent per month. The return is also economically significant when compared to the one-way transaction costs estimate (*PESPR*) of between 0.41 to 0.46 percent. Note that *PESPR* is likely to overstate trading costs for institutions and market makers, who may adjust their trades to minimize actual costs. On the other hand, the intra-industry reversal strategy applied to stocks that have low price pressure does not yield significant profits.

{Insert Table 8 here}

Panel B of Table 8 presents the breakdown of inter-industry reversal profits within sub-groups sorted by order imbalances. Consistent with the assertion that inter-industry reversals are driven by public information, we find that the inter-industry profits are unrelated to the level of order imbalance. Hence, these findings provide further support to the proposition that intra-industry return reversals reflect compensation for accommodating imbalances in order flows, even at monthly horizon.[20]

B. Intra-Industry Reversals and Market Conditions

Recent theoretical models posit that the cost of supplying liquidity increases following market declines or volatile market prices due to either an increase in aggregate demand for liquidity or a decrease in the market making sector's ability to absorb liquidity shocks or both.

[20] We obtain qualitatively similar results when order imbalance is defined as the difference in the number of buyer and seller initiated trades during the month divided by the total number of trades. However, this measure ignores the size of the trade.

For example, in Brunnermeier and Pedersen (2009), liquidity providers obtain financing by posting margins and pledging their inventory of securities as collaterals. During periods of decline in aggregate market valuations or high market volatility, falling asset values and binding margin requirements generate a "liquidity spiral" which tightens funding constraints, and restricts the market's capacity to supply liquidity. Garleanu and Pedersen (2007) show that tightening of risk bearing capacity due to heightened market volatility, which is a standard feature of risk management models, lowers funding liquidity during market stress. Vayanos (2004) suggests that if transactions costs are higher during volatile times, the impact of market volatility on liquidity would be even stronger. Consistent with the central predictions in these models, Hameed, Kang and Viswanathan (2010) and Nagel (2012) find that the profit from the unconditional (weekly) return reversal strategy is higher during bad times, i.e. when constraints on the market making sector is likely to be binding.

We expand our analyses by exploring the relation between intra-industry reversals and changes in market conditions. Similar to Hameed, Kang and Viswanathan (2010), we employ a dummy variable, $DOWN_{mkt}$, which takes the value of one only if the past 3-month return on the CRSP value-weighted market index is negative, to capture the effect of down market states on funding liquidity. As in Nagel (2012), we use the implied volatility of S&P 500 index options (*VIX*) to proxy for periods of market turmoil. Since *VIX* measures the risk neutral implied aggregate volatility, we follow Nagel (2012) and decompose *VIX* into two components—the physical volatility measure (VOL_{mkt}) and the variance risk premium. As shown in Bollerslev, Gibson and Zhou (2011), the difference between implied and realized volatilities ($VIX\text{-}VOL_{mkt}$) reflects a volatility risk premium (or risk aversion index) that appears to respond to economic state variables.[21] To explore the relative importance of the two components that drive the relation between *VIX* and intra-industry reversals, we obtain monthly realized volatility from Bollerslev, Gibson and Zhou (2011), who show that VOL_{mkt} is efficiently estimated by summing five-minute squared returns on the S&P 500 index within the month.[22] Our empirical specification of the time-series regression takes the following form:

$$(16) \quad \pi_t^{intra} = a + b_1\, DOWN_{mkt,t-2} + b_2\big(VIX_{t-2} - VOL_{mkt,t-2}\big) + b_3\, VOL_{mkt,t-2} + c'controls_t + \beta' F_t + e_{It}$$

where π_t^{intra} is the intra-industry reversal returns in month t, the value of *VIX*, realized volatility on the market index (VOL_{mkt}) and $DOWN_{mkt}$ is lagged two months since the reversal strategy portfolio weights are obtained in month t-1, and $controls_t$ is a vector of control variables that include a January dummy and a pre-decimalization dummy to denote the institutional change in the tick size to decimals in April 2001. We also consider the effect of controlling for common risk factors (F_t) via the four risk factors described in Section III. Our sample period is limited by the availability of data on *VIX* from 1990 to 2010.

Estimates of several variations of equation (16) are presented in Table 9. The salient finding in Table 9 is that both the down market state and *VIX* are positively related to π^{intra}. The

[21] Garleanu, Pedersen and Poteshman (2009) find that the market makers' ability to accommodate demand pressures from end-users in the options market is reflected in the variance risk premium.

[22] We thank Hao Zhou for making available the data on his website at http://sites.google.com/site/haozhouspersonalhomepage. We obtain similar results if we use the realized volatility measured using daily returns on the S&P 500 index within the month,

intra-industry reversal returns, for example, increases to above 1 percent per month during down market states. When we include both $DOWN_{mkt}$ and *VIX* in the regression, the coefficients on each of them become smaller but remain significant, suggesting that both proxies have a role to play in capturing the effect of market conditions on liquidity provision. When we replace *VIX* by its two components as in equation 16, the point estimate of the coefficient on variance risk premium proxy ($VIX\text{-}VOL_{mkt}$) is the same magnitude as the point estimate of the coefficient on realized market volatility (VOL_{mkt}), although we obtain significance only for VOL_{mkt}. It is possible that the tests lack statistical power to disentangle the two components. The estimated coefficients indicate that a one percent increase in market volatility predicts a significant 0.24 per cent increase in π^{intra}per month (see Model 6 in Table 9). These results are robust to control for common factor risks.

In sum, consistent with the notion that high values of *VIX* and market declines are associated with constraints on liquidity supply, as in Brunnermeier, Nagel and Pedersen (2008), Brunnermeier and Pedersen (2009), Hameed, Kang and Vishwanthan (2010) and Nagel (2012), our findings suggest that intra-industry reversals are related to liquidity dry-ups during market downturns and volatile times.

{Insert Table 9 here.}

C. Are Intra-Industry Reversals Related to Earnings Information?

So far, the evidence points to return to liquidity provision as the likely source of intra-industry reversals. An alternative explanation of the short-term return reversals is that it is linked investor overreaction (e.g. Lehmann (1990) and Subrahmanyam (2005)). To explore this possibility, we examine if intra-industry reversals are related to the release of earnings information. In Nagel (2012), arrival of public information makes past returns a noisier proxy for non-informational (liquidity) shocks and, hence, weakens return reversals. On the other hand, if investors overreact to firm-specific public information, followed by correction in prices in the following period, we expect reversals to be stronger following the announcement of earnings news.

Our proxy for the arrival of public information about the firm is the incidence of quarterly earnings announcements. Besides being themselves informative about firm's future fundamentals, earnings announcements are often accompanied by other firm level news from corporate managers (e.g., the announcements of future earnings targets, dividends and splits) and analysts (e.g., revisions in forecasts of future earnings and recommendations). We compute a three-day, size, and book-to-market adjusted cumulative abnormal return (*CAR*), over the days -1 to +1, around the earnings announcement date (day 0).[23] We separate the positive and negative earnings information using the *CAR* calculated in the formation month, depending on whether *CAR*>0 (denoted as *PosCAR*) or *CAR*<0 (denoted as *NegCAR*). The quarterly earnings announcement dates for the sample period 1972 to 2010 are obtained from Compustat and IBES following the procedure outlined by DellaVigna and Pollet (2009).

To examine if the magnitude of reversals is related to earnings news, we run Fama-McBeth cross-sectional regressions of the following general form:

(17) $R_{jt} = a_0 + b_1 D_{Loser,jt-1} + b_2 D_{Winner,jt-1} + c_1 D_{NegCAR,jt-1} + c_2 D_{PosCAR,jt-1} +$

[23] We follow Daniel, Grinblatt, Titman and Wermers (1997) who suggest that matching firms to portfolios based on size and book-to-market characteristics, rather than factor betas, provides a better specification and tests.

$$d_1 D_{Loser,jt-1} \times D_{NegCAR,jt-1} + d_2 D_{Winner,jt-1} \times D_{PosCAR,jt-1} + g' controls_{jt-1} + e_{jt}$$

where the dependent variable, R_{jt}, is the return on stock *j* in month *t*. The profits from the intra-industry contrarian strategy are captured in equation (17) via two dummy variables, $D_{Loser,jt-1}$ and $D_{Winner,jt-1}$. $D_{Loser,jt-1}$ takes the value of one if stock *j* is among the bottom 30 percent of stocks within its industry based on the returns in month *t-1* and zero otherwise. Similarly, $D_{Winner,jt-1}$ is set to one if the stock belongs to the top 30 percent of returns in its industry. $D_{NegCAR,jt-1}$ and $D_{PosCAR,jt-1}$ denote dummy variables that take the value of one if there is negative (*NegCAR*) or positive (*PosCAR*) firm-specific earnings information for firm *j* in month *t-1*, and zero otherwise. These variables capture the established finding on post-earnings announcement drift, that there is undereaction in stock prices to earnings announcements so that the *NegCAR* (*PosCAR*) stocks earn low (high) returns in the following period (e.g., Bernard and Thomas (1989)). Our primary focus in the regression is on the interaction variables, $D_{Loser,jt} \times D_{NegCAR,jt}$ and $D_{Winner,jt} \times D_{PosCAR,jt}$, that allow us to examine how the intra-industry reversals are related to the arrival of earnings news. If reversals are adversely affected by the presence of public (earnings) information, we expect to see a negative coefficient on the interaction term $D_{Loser,jt} \times D_{NegCAR,jt}$ in regression equation (17) and a positive coefficient on $D_{Winner,jt} \times D_{PosCAR,jt}$. Alternatively, if the reversals are reinforced by overreaction to earnings information, these interaction terms are expected to have the opposite sign. The vector of control variables (*controls*) in equation (17) includes the firm-specific variables defined in equation (14) in Section IV.A.

The time series averages of the regression coefficients in equation (17) are reported in Table 10. The estimated coefficients associated with $D_{Loser,jt-1}$ and $D_{Winner,jt-1}$ in Model 1 indicate that the intra-industry reversals for the sample is 1.32 percent [= 0.71% + 0.61%] per month using this alternative specification of reversal portfolios. The monthly reversals remain highly significant after inclusion of the firm specific control variables in a multivariate setting.

{Insert Table 10 here.}

The estimate of Model 2 in Table 10 confirms the presence of post-earnings announcement drift: stocks with *NegCAR* (*PosCAR*) register an incremental -0.3 (0.3) percent return in the following month. More importantly, the interaction variable involving the loser portfolio and negative earnings news, *Loser* x *NegCAR*, indicates that the arrival of negative (public) earnings news lowers the return reversal of loser stocks by 0.23 percent. Similarly, the reduction in the reversal of past winner stocks with *PosCAR* is significant at +0.19 percent. For completeness, Table 10 also presents the estimates of equation (17) separately for the winner and loser portfolios in the intra-industry strategy and the results are consistent with those in Model 2. Our results in Table 10 show that the return reversals are weakened by the arrival of (public) information about the firm, confirming that non-informational shocks are the primary source of return reversals.

V. Conclusion

If short-term return reversals represent deviations from fundamental values emanating from liquidity (non-informational) shocks and the subsequent convergence to fundamentals, then focusing on loser and winner stocks relative to industry benchmark provides a more natural framework to identify returns to supplying liquidity. We formalize this intuition by decomposing the returns from the unconditional (i.e. conventional) reversal strategy into two components: returns from an *intra-industry* reversal strategy and the returns from an *inter-industry* reversal strategy.

We uncover striking evidence of intra-industry return reversals that are significantly stronger and more pervasive than the unconditional reversals. We find that the reversal strategy that invests one dollar in taking long (short) positions in stocks that under- (over-) performed the industry portfolio generates a return of 1.14 percent (or 0.97 percent risk-adjusted) per month. Moreover, while the unconditional return reversals are fragile, the reversals conditioned on industry membership are pervasive both in the cross-section and across time.

The evidence we accumulate in this paper supports the idea that short term reversals are related to compensation for providing liquidity (Campbell, Grossman and Wang (1993), Brunnermeier and Pedersen (2009) and Nagel (2012)). We find that the intra-industry reversal strategy generates significant profits only when the price movements are accompanied by large imbalances in the buy and sell orders. We also document stronger intra-industry reversals following periods of market declines and heightened market volatility, supporting the recent models of liquidity in which providers of liquidity become constrained and liquidity supply becomes more inelastic during periods of market stress. Finally, we find that intra-industry reversals are attenuated when firms release earnings information, consistent with the notion that past returns are noisier proxies for imbalances in demand and supply of securities in the presence of more public information. Overall, the evidence in this paper is consistent with return reversals representing imperfectly elastic supply of liquidity in equity markets, due to capital constraints and limited risk-bearing capacity of liquidity providers.

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TABLE 1
Descriptive Statistics for the Individual Stock and Industry Returns

This table reports the summary statistics for the stocks included in our sample during the period from 1968 to 2010. We include all common stocks listed on NYSE, AMEX and NASDAQ. Stocks with month-end prices of less than $5 are excluded.

			Portfolio (Equal-weighted) Returns			Individual Stock Returns	
Industry Group		Number of Stocks/Month	Mean	Standard Deviation	Auto-Correlation	Avg. Standard Deviation	Avg. Auto-Correlation
1	Food	127	1.626	4.635	0.203	13.791	-0.043
2	Mining	39	1.906	6.828	0.108	16.022	-0.091
3	Oil	132	2.006	7.352	0.100	16.480	-0.057
4	Textiles & Apparel	98	1.858	6.473	0.278	14.807	-0.031
5	Consumer Durables	114	1.793	6.453	0.245	16.060	-0.098
6	Chemicals	71	1.735	5.767	0.151	15.274	0.000
7	Consumables	136	2.355	7.016	0.186	20.290	-0.144
8	Construction	159	1.726	6.203	0.222	14.591	-0.060
9	Steel	63	1.591	7.076	0.124	14.286	-0.040
10	Fabricated Products	46	1.949	6.302	0.188	15.300	-0.032
11	Machinery	455	2.166	7.528	0.190	18.946	-0.044
12	Automobiles	60	1.727	6.656	0.223	15.238	-0.015
13	Transportation	127	1.741	6.111	0.206	14.569	-0.038
14	Utilities	159	1.138	3.709	0.081	10.029	-0.060
15	Retail	234	1.933	6.481	0.254	15.957	-0.028
16	Financials	808	1.581	4.797	0.274	11.474	-0.031
17	Other	884	2.168	6.751	0.214	19.814	-0.018
Market Portfolio (Equal-weighted)		3,711	1.874	5.620	0.214	16.385	-0.038

TABLE 2
Unconditional Reversal Strategy and Its Decomposition

This table reports the monthly returns from the unconditional reversal strategy (π) and its decomposition into intra-industry (π^{intra}) and inter-industry (π^{inter}) reversal return components as depicted in equation (6). In Panel A, we report the return for π, where the strategy takes long (short) positions in the stocks that underperformed (outperformed) the market in the previous month, and we group these stocks as *Losers* (*Winners*). π is defined as *Losers* minus *Winners.* In Panel B, we report π^{intra}, where the strategy takes long (short) positions in the stocks that underperformed or (outperformed) the industry portfolio in the previous month. H^{intra} and H are the scaling factors for the unconditional and intra-industry strategies, so that the portfolio weights add to one dollar long and one dollar short in the respective strategies. Panel C reports π^{inter}, where the strategy takes long (short) positions in the industry portfolios that underperformed (outperformed) the market portfolio. H^{inter} is the scaling factor for the inter-industry strategy. We report the holding period returns for each portfolio, which include raw return as well as risk-adjusted returns using CAPM, Fama-French three-factor model, and a four-factor model which further includes the Pastor-Stambaugh liquidity factor. The sample period is from 1968 to 2010. Newey-West adjusted *t*-statistics are reported in parentheses.

Portfolio	Raw Return	Risk-adjusted Returns		
		CAPM	Three-Factor	Four-Factor
Panel A: Unconditional Reversal				
Losers	1.298	0.301	0.147	0.146
	(4.28)	(2.08)	(1.51)	(1.48)
Winners	0.491	-0.423	-0.504	-0.481
	(1.8)	(-2.73)	(-4.78)	(-4.69)
π (Losers − Winners)	0.806	0.725	0.651	0.627
	(4.55)	(4.40)	(3.51)	(3.43)
Panel B: Intra-Industry Reversal				
Losers	1.479	0.485	0.333	0.336
	(4.93)	(3.45)	(4.11)	(4.10)
Winners	0.343	-0.574	-0.659	-0.637
	(1.27)	(-3.85)	(-7.21)	(-7.13)
π^{intra} (Losers − Winners)	1.136	1.059	0.993	0.974
	(7.76)	(7.66)	(6.55)	(6.52)
$\pi^{intra} \times H^{intra}/H$	1.101	1.026	0.963	0.944
	(7.87)	(7.68)	(6.57)	(6.54)
Panel C: Inter-Industry Reversal				
Losers	0.378	-0.529	-0.706	-0.721
	(1.49)	(-3.79)	(-6.62)	(-6.75)
Winners	1.679	0.795	0.630	0.643
	(6.74)	(5.92)	(6.10)	(6.16)
π^{inter} (Losers − Winners)	-1.301	-1.324	-1.336	-1.364
	(-7.84)	(-7.72)	(-7.02)	(-7.15)
$\pi^{inter} \times H^{inter}/H$	-0.295	-0.302	-0.311	-0.317
	(-6.13)	(-6.23)	(-5.63)	(-5.68)

TABLE 3
Unconditional Reversal Strategy and Its Decomposition: Robustness Checks

This table examines the robustness of the return from the unconditional reversal strategy (π) and its decomposition into intra-industry (π^{intra}) and inter-industry (π^{inter}) reversal return components as depicted in equation (6), and described in Table 2. $\pi = [\pi^{intra} \text{ x } H^{intra}/H] + [\pi^{inter} \text{ x } H^{inter}/H]$, where H, H^{intra}, and H^{inter} are the scaling factors for the unconditional, intra-industry and inter-industry reversal strategies, so that the portfolio weights add to one dollar long and one dollar short in the respective strategies. We report the average raw return as well as risk-adjusted returns using CAPM, Fama-French three-factor model, and a four-factor model which further includes the Pastor-Stambaugh liquidity factor. In Panel A, we exclude the top and bottom 5% of the stocks with extreme returns in the formation month *t-1*. In Panel B, we compute returns after skipping a day between the formation month *t*-1 and the holding month *t*. Panel C examines the reversals during the month of January and Panel D looks at the reversals during the remaining months of February to December. The sample period is from 1968 to 2010. Newey-West adjusted *t*-statistics are reported in parentheses.

Portfolio		Risk-adjusted Returns		
	Raw Return	CAPM	Three-Factor	Four-Factor
Panel A: Exclude Top and Bottom 5% Extreme Returns				
π	0.532	0.462	0.412	0.383
	(3.96)	(3.74)	(2.97)	(2.75)
π^{intra}	0.844	0.780	0.731	0.708
	(7.8)	(7.74)	(6.61)	(6.36)
$\pi^{intra} \times H^{intra}/H$	0.816	0.755	0.706	0.684
	(7.91)	(7.77)	(6.66)	(6.41)
$\pi^{inter} \times H^{inter}/H$	-0.284	-0.292	-0.295	-0.301
	(-6.94)	(-7.12)	(-6.40)	(-6.48)
Panel B: Skip One Day				
π	0.426	0.351	0.285	0.268
	(2.66)	(2.26)	(1.62)	(1.55)
π^{intra}	0.713	0.642	0.581	0.569
	(5.32)	(4.98)	(4.10)	(4.06)
$\pi^{intra} \times H^{intra}/H$	0.692	0.624	0.565	0.553
	(5.33)	(4.99)	(4.12)	(4.08)
$\pi^{inter} \times H^{inter}/H$	-0.266	-0.273	-0.281	-0.285
	(-5.86)	(-6.05)	(-5.46)	(-5.52)
Panel C: January Only				
π	3.237	3.114	2.411	2.363
	(6.10)	(6.61)	(4.16)	(5.34)
π^{intra}	3.594	3.467	2.738	2.695
	(7.74)	(8.75)	(5.54)	(7.14)
$\pi^{intra} \times H^{intra}/H$	3.506	3.378	2.665	2.622
	(7.69)	(8.72)	(5.50)	(7.12)
$\pi^{inter} \times H^{inter}/H$	-0.269	-0.264	-0.254	-0.260
	(-1.75)	(-1.66)	(-1.49)	(-1.59)
Panel D: February to December Only				
π	0.585	0.510	0.459	0.466
	(3.37)	(3.00)	(2.21)	(2.26)
π^{intra}	0.913	0.843	0.802	0.813
	(6.24)	(5.89)	(4.77)	(4.86)
$\pi^{intra} \times H^{intra}/H$	0.883	0.815	0.777	0.787
	(6.25)	(5.89)	(4.79)	(4.89)
$\pi^{inter} \times H^{inter}/H$	-0.297	-0.305	-0.318	-0.322
	(-6.15)	(-6.39)	(-5.33)	(-5.36)

TABLE 4
Reversal Returns Using Value-weighted Strategies

This table reports the value-weighted unconditional reversals (π^{VW}), intra-industry reversals ($\pi^{VW,intra}$), and inter-industry reversals ($\pi^{VW,inter}$). π^{VW} and $\pi^{VW,intra}$ denote the value-weighted unconditional and intra-industry reversals, respectively. In π^{VW} ($\pi^{VW,intra}$), the weight of each stock in the portfolio in month t is proportional to (-1) times the stock's market-adjusted (industry-adjusted) return in month t-1, multiplied by the stock's market capitalization at the end of month t-1. In $\pi^{VW,inter}$, the weight of each stock in the portfolio in month t is proportional to (-1) times the returns on the stock's industry portfolio relative to that of the market in month t-1, multiplied by the stock's market capitalization at the end of month t-1. All portfolio weights in each strategy are scaled to be one dollar long and one dollar short. We report the average raw monthly return as well as risk-adjusted returns using CAPM, Fama-French three-factor model, and a four-factor model which further includes the Pastor-Stambaugh liquidity factor. The sample period is from 1968 to 2010. Newey-West adjusted t-statistics are reported in parentheses.

Portfolio		Risk-adjusted Returns		
	Raw Return	CAPM	Three-Factor	Four-Factor
π^{VW}	0.284	0.215	0.170	0.128
	(1.57)	(1.43)	(1.05)	(0.78)
$\pi^{VW,intra}$	0.534	0.467	0.431	0.390
	(3.67)	(3.76)	(3.24)	(2.89)
$\pi^{VW,inter}$	-1.442	-1.461	-1.467	-1.502
	(-7.94)	(-7.86)	(-7.10)	(-7.24)
$\pi^{VW,intra} - \pi^{VW}$	0.250	0.252	0.261	0.262
	(3.99)	(4.20)	(4.17)	(4.03)

TABLE 5
Sub-Period Analysis of the Reversal Strategies, Using Fama-French 48 Industries

This table reports the monthly reversal returns for stocks sorted into industry groups based on Fama-French 48 industry classification. π, π^{intra}, and π^{inter} denote the unconditional, intra-industry and inter-industry reversal strategy returns, respectively. $\pi = [\pi^{intra} \times H^{intra}/H] + [\pi^{inter} \times H^{inter}/H]$, where H, H^{intra}, and H^{inter} are the scaling factors for the unconditional, intra-industry and inter-industry reversal strategies, so that the portfolio weights add to one dollar long and one dollar short in the respective strategies. We separately report the raw returns and the four-factor (three Fama-French factors and the Pastor-Stambaugh liquidity factor) risk-adjusted returns for full sample period 1968 to 2010, as well as four sub-periods: 1968−1979, 1980−1989, 1990−1999 and 2000−2010. Newey-West adjusted *t*-statistics are reported in parentheses.

	1968 − 2010		1968 − 1979		1980 − 1989		1990 − 1999		2000 − 2010	
	Raw Return	Four-Factor Alpha	Raw Return	Four-Factor Alpha	Raw Return	Four-Factor Alpha	Raw Return	Four-Factor Alpha	Raw Return	Four-Factor Alpha
π	0.816	0.637	1.554	1.446	0.810	0.712	0.210	0.029	0.567	0.598
	(4.61)	(3.49)	(6.19)	(5.46)	(3.68)	(2.66)	(0.7)	(0.10)	(1.06)	(1.54)
π^{intra}	1.284	1.129	2.018	1.897	1.199	1.074	0.875	0.684	0.932	0.943
	(9.49)	(8.26)	(9.06)	(7.67)	(6.91)	(4.71)	(3.8)	(3.19)	(2.43)	(2.92)
$\pi^{intra} \times H^{intra}/H$	1.224	1.076	1.929	1.806	1.147	1.029	0.852	0.666	0.865	0.870
	(9.66)	(8.30)	(9.08)	(7.72)	(6.92)	(4.72)	(3.9)	(3.28)	(2.45)	(2.93)
π^{inter}	-1.386	-1.460	-1.315	-1.294	-1.165	-1.070	-2.154	-2.141	-0.965	-0.904
	(-7.68)	(-6.81)	(-6.35)	(-6.35)	(-4.15)	(-3.48)	(-6.74)	(-6.32)	(-1.78)	(-2.07)
$\pi^{inter} \times H^{inter}/H$	-0.408	-0.439	-0.375	-0.360	-0.336	-0.317	-0.642	-0.637	-0.297	-0.273
	(-6.24)	(-5.69)	(-5.91)	(-5.72)	(-4.09)	(-3.88)	(-5.23)	(-4.96)	(-1.44)	(-1.86)

TABLE 6
Reversal Returns: Cross-Sectional Differences

This table reports the returns from the unconditional (π), intra-industry (π^{intra}) and inter-industry (π^{inter}) reversal strategies when implemented within sub-groups of stocks sorted on firm characteristics. $\pi = [\pi^{intra} \text{ x } H^{intra}/H] + [\pi^{inter} \text{ x } H^{inter}/H]$, where H, H^{intra}, and H^{inter} are the scaling factors for the unconditional, intra-industry and inter-industry reversal strategies, so that the portfolio weights add to one dollar long and one dollar short in the respective strategies. In Panel A, we sort stocks based on market capitalization into large (top 30 percent using NYSE breakpoints) and small (bottom 30 percent using NYSE breakpoints) stocks. Panel B sorts stocks on Amihud illiquidity measure, and create groups of liquid stocks (bottom 30 percent in NYSE/AMEX and NASDAQ separately) and illiquid stocks (top 30 percent in NYSE/AMEX and NASDAQ separately). Panel C sorts stocks on institutional ownership and groups the top and bottom 30 percent of stocks into high and low institutional ownership stocks, respectively. We report the raw returns and the four-factor (three Fama-French factors and the Pastor-Stambaugh liquidity factor) risk-adjusted returns. The sample period is from 1968 to 2010, and Newey-West adjusted *t*-statistics are reported in parentheses.

Portfolio	# of Stocks / Month	Raw Return	Four-Factor Alpha	# of Stocks / Month	Raw Return	Four-Factor Alpha
Panel A: Size						
	Large Stocks			Small Stocks		
π	485	0.313	0.122	1850	1.173	0.996
		(1.80)	(0.66)		(6.11)	(4.94)
π^{intra}	485	0.638	0.469	1850	1.504	1.343
		(4.48)	(3.16)		(9.09)	(7.95)
$\pi^{intra} \times H^{intra}/H$	485	0.580	0.422	1850	1.464	1.310
		(4.42)	(3.11)		(9.16)	(8.02)
$\pi^{inter} \times H^{inter}/H$	485	-0.267	-0.299	1850	-0.291	-0.313
		(-3.92)	(-4.11)		(-5.58)	(-5.34)
Panel B: Liquidity						
	Liquid Stocks			Illiquid Stocks		
π	969	0.182	-0.024	971	1.627	1.532
		(0.94)	(-0.12)		(9.37)	(8.52)
π^{intra}	969	0.502	0.324	971	1.885	1.795
		(3.22)	(2.00)		(11.52)	(10.70)
$\pi^{intra} \times H^{intra}/H$	969	0.466	0.298	971	1.845	1.757
		(3.18)	(1.96)		(11.52)	(10.71)
$\pi^{inter} \times H^{inter}/H$	969	-0.284	-0.322	971	-0.218	-0.225
		(-4.20)	(-4.38)		(-7.46)	(-7.11)
Panel C: Institutional Ownership						
	High Institutional Ownership Stocks			Low Institutional Ownership Stocks		
π	1129	0.641	0.406	1118	0.559	0.461
		(3.30)	(2.12)		(2.26)	(1.78)
π^{intra}	1129	0.872	0.652	1118	1.009	0.914
		(5.25)	(3.99)		(5.15)	(4.48)
$\pi^{intra} \times H^{intra}/H$	1129	0.833	0.623	1118	0.975	0.888
		(5.25)	(3.98)		(5.24)	(4.58)
$\pi^{inter} \times H^{inter}/H$	1129	-0.192	-0.216	1118	-0.415	-0.427
		(-3.53)	(-3.87)		(-4.34)	(-4.19)

TABLE 7
Return Reversals and Order Imbalance: Regression Analysis

This table reports the estimates of the following monthly Fama-MacBeth regressions,

$$R_{jt} = a_j + b\, D_{Sell,jt-1} + c_{11}\, RelRet^{+}_{jt-1}\, D_{Buy,jt-1} + c_{12} RelRet^{+}_{jt-1}\, D_{Sell,jt-1} + c_{13} RelRet^{-}_{jt-1}\, D_{Buy,jt-1}$$
$$+ c_{14} RelRet^{-}_{jt-1}\, D_{Sell,jt-1} + g\,'\ controls + \epsilon_{jt}$$

where, R_{jt}, is the return on stock *j* in month *t*. $OIB_{Buy,jt-1}$ ($OIB_{Sell,jt-1}$) represents stock *j*'s dollar order imbalance (buy orders minus sell orders) in month *t*-1 and is set to zero if the order imbalance is negative (positive). $RelRet_{jt-1}$ is relative return for stock *j* either with respect to the market benchmark ($R_{jt-1} - R_{mt-1}$) or the industry benchmark ($R_{jt-1} - R_{it-1}$); the superscript '+' ('-') associated with it signifies the sign of the relative return. The vector of control variables (*controls*) includes the following firm-specific variables in month *t-1*: *Log (Size)* is the logarithm of market capitalization; *IdioVol* is the idiosyncratic volatility of stock returns computed as the standard deviation of the daily residuals from a one factor model comprising market returns; $Return_{t-1:t-6}$ is the average monthly return from month *t-6* through month *t-1*; and *Log (Amihud)* is the logarithm of average daily Amihud illiquidity. The numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively, and the corresponding Newey-West adjusted *t*-statistics are in brackets. The sample consists of NYSE stocks during the period 1993 to 2008.

	Dependent Variable: r_{jt}			
Explanatory Variables	Model 1	Model 2	Model 3	Model 4
Intercept	2.122***	2.097***	2.098***	2.061***
	(3.53)	(3.38)	(3.55)	(3.43)
D_{sell}			0.054	0.060
			(0.54)	(0.53)
$R_{jt-1} - R_{mt-1}$	-0.022***			
	(-2.72)			
$R_{jt-1} - R_{it-1}$		-0.028***		
		(-3.26)		
$(R_{jt-1} - R_{mt-1})^{+} \times D_{Buy}$			-0.028***	
			(-2.7)	
$(R_{jt-1} - R_{mt-1})^{+} \times D_{Sell}$			-0.019	
			(-1.27)	
$(R_{jt-1} - R_{mt-1})^{-} \times D_{Buy}$			-0.001	
			(-0.12)	
$(R_{jt-1} - R_{mt-1})^{-} \times D_{Sell}$			-0.036***	
			(-3.27)	
$(R_{jt-1} - R_{it-1})^{+} \times D_{Buy}$				-0.030***
				(-3.23)
$(R_{jt-1} - R_{it-1})^{+} \times D_{Sell}$				-0.024
				(-1.6)
$(R_{jt-1} - R_{it-1})^{-} \times D_{Buy}$				-0.008
				(-0.73)
$(R_{jt-1} - R_{it-1})^{-} \times D_{Sell}$				-0.045***
				(-3.52)
Log (Size)	-0.267**	-0.262**	-0.281**	-0.273**
	(-2.48)	(-2.38)	(-2.55)	(-2.44)
IdioVol	-0.202**	-0.201**	-0.188**	-0.194**
	(-2.29)	(-2.27)	(-2.35)	(-2.39)
$Return_{t-1:t-6}$	0.060***	0.064***	0.060***	0.063***
	(3.28)	(3.47)	(3.29)	(3.42)
Log (Amihud)	-0.161**	-0.158**	-0.181**	-0.177**
	(-2.11)	(-2.05)	(-2.3)	(-2.21)
Adj R-squared	0.048	0.046	0.051	0.049
Obs	264,577	264,577	264,577	264,577

TABLE 8
Return Reversals and Order Imbalance: Two-Way Sorts

This table reports the returns from the intra- and inter-industry reversal strategies, for stocks grouped by order imbalance in dollar value (*OIB*) in the previous month. Panel A reports the results for the intra-industry reversal. For stocks classified as Losers and Winners under the intra-industry strategy (see Table 2 for definitions), we sort the stocks into *High* (top 50 percent) and *Low* (bottom 50 percent) *OIB* in the formation month to generate the four portfolios in Panel A. We apply the portfolio weights to each stock as described in Table 2, so that we are invested one dollar (long the Losers and short the Winners) in each of the four portfolios. We compute the returns for the two intra-industry reversal strategies: (a) long (*Losers* and *Low OIB*) and short (*Winners* and *High OIB*); (b) long (*Losers* and *High OIB*) and short (*Winners* and *Low OIB*). We report raw returns and the four-factor risk-adjusted returns (Fama-French three-factor and Pastor-Stambaugh liquidity factor). The same portfolio weights are used to compute the average relative quoted spread (*RQSPR*), relative effective spread (*RESPR*), and *OIB* in the formation month for each group. Panel B reports similar statistics for the inter-industry reversal strategy. The sample consists of NYSE stocks during the period 1993 to 2008. Newey-West adjusted *t*-statistics are reported in parentheses.

Portfolio		Formation Period PQSPR	PESPR	OIBP	Holding Period Raw Return	Four-Factor Alpha
Panel A: Intra-Industry Reversal						
Losers	Low OIB	0.691	0.464	-7.000	1.126	0.112
					(2.73)	(0.66)
	High OIB	0.555	0.376	13.381	0.614	-0.411
					(1.4)	(-2.30)
Winners	Low OIB	0.729	0.496	-5.350	0.594	-0.260
					(1.78)	(-1.73)
	High OIB	0.608	0.414	15.860	0.255	-0.588
					(0.72)	(-4.10)
Losers&Low OIB − Winners&High OIB					0.872	0.700
					(4.06)	(3.29)
Losers&High OIB − Winners&Low OIB					0.019	-0.151
					(0.09)	(-0.79)
Panel B: Inter-Indsutry Reversal						
Losers	Low OIB	0.568	0.384	3.390	0.524	-0.412
					(1.41)	(-2.27)
	High OIB	0.563	0.381	3.739	0.518	-0.422
					(1.39)	(-2.27)
Winners	Low OIB	0.567	0.384	5.199	0.982	0.055
					(2.88)	(0.39)
	High OIB	0.561	0.379	5.605	1.001	0.077
					(2.87)	(0.48)
Losers&Low OIB − Winners&High OIB					-0.477	-0.489
					(-1.96)	(-2.37)
Losers&High OIB − Winners&Low OIB					-0.464	-0.477
					(-2.02)	(-2.31)

TABLE 9
Intra-Industry Reversals and Market Conditions

This table presents the results of the following time-series regression:

$$\pi_t^{intra} = a + b_1\, DOWN_{mkt,t-2} + b_2\left(VIX_{t-2} - VOL_{mkt,t-2}\right) + b_3\, VOL_{mkt,t-2} + c'controls_t + \beta' F_t + e_{It}$$

where π_t^{intra}, is the return from the intra-industry reversal strategy in month t. $DOWN_{mkt}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past three months is negative, and zero otherwise; *VIX* is the CBOE S&P 500 implied volatility index, Vol_{mkt} is the realized market volatility and ($VIX-Vol_{mkt}$) the volatility risk premium. These variables are measured prior to the formation month. The vector of control variables (*controls*) includes *January*, which is a dummy variable that takes the value of one if month *t* is January and zero otherwise; and *Pre-decimalization*, a dummy variable that takes the value of one if month *t* is before April 2001 and zero otherwise. The vector *F* stacks Fama-French three-factors (market factor (RMRF), size factor (SMB), and book-to-market factor (HML)) and the Pastor-Stambaugh liquidity factor (PS). The sample period is from 1990 to 2010. The numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively. Newey-West adjusted *t*-statistics are reported in parentheses.

	Dependent Variable: π_t^{intra}							
Explanatory Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-0.627	-1.126*	-0.212	-0.987*	-1.004**	-1.173*	-1.088*	-0.852*
	(-1.13)	(-1.90)	(-0.71)	(-1.91)	(-2.08)	(-1.75)	(-1.72)	(-1.78)
VIX	0.233**	0.234**		0.142**	0.122*			
	(2.17)	(2.26)		(2.00)	(1.90)			
VOL_{mkt}						0.236**	0.144**	0.117*
						(2.37)	(2.04)	(1.72)
$VIX-VOL_{mkt}$						0.269	0.219	0.007
						(0.96)	(0.75)	(0.03)
$DOWN_{mkt}$			1.355**	1.072*	1.195*		1.096**	1.159*
			(2.23)	(1.84)	(1.88)		(2.03)	(1.90)
January		3.404***	3.595***	3.524***	3.978***	3.396***	3.508***	4.004***
		(5.91)	(5.87)	(6.04)	(5.00)	(6.05)	(6.16)	(4.89)
Pre-decimalization		0.417	0.419	0.495	0.284	0.402	0.464	0.326
		(1.29)	(1.32)	(1.54)	(1.14)	(1.43)	(1.58)	(1.32)
RMRF					0.264***			0.271***
					(3.50)			(3.35)
SMB					-0.207			-0.205
					(-1.37)			(-1.38)
HML					0.126			0.128
					(1.21)			(1.21)
LIQ					0.053			0.054
					(1.03)			(1.05)
Adj R-Squared	0.018	0.074	0.082	0.087	0.193	0.074	0.088	0.194
Obs	250	250	250	250	250	250	250	250

TABLE 10
Intra-Industry Reversals and Earnings Information

This table presents the estimates of the following monthly Fama-MacBeth regressions, as well as the corresponding Newey-West adjusted *t*-statistics in brackets:

$$R_{jt} = a_0 + b_1 D_{Loser,jt-1} + b_2 D_{Winner,jt-1} + c_1 D_{NegCAR,jt-1} c_2 D_{PosCAR,jt-1} + d_1 D_{Loser,jt-1} \times D_{NegCAR,jt-1}$$

$$+ d_2 D_{Winner,jt-1} \times D_{PosCAR,jt-1} + g' controls_{jt-1} + e_{jt}$$

where R_{jt}, is the return on stock *j* in month *t*. $D_{Loser,jt-1}$ is a dummy variable that takes the value of one if stock *j* is among the bottom top 30 percent of stocks within its industry based on the returns in month *t-1*,and is zero otherwise. Similarly, $D_{Winner,jt-1}$ is set to one if the stock belongs to the top 30 percent of returns in its industry, and is zero otherwise. $D_{NegCAR,jt-1}$ and $D_{PosCAR,jt-1}$ denote dummy variables that take the value of one if there is negative (*NegCAR*) or positive (*PosCAR*) firm-specific earnings information for firm *j* in month *t-1*, and zero otherwise, depending on whether the three-day CAR around earnings announcement is negative or positive. The vector of control variables (*controls*) includes the following firm-specific variables in month *t-1*: *Earnings* is a dummy variable that takes the value of one if there is an earnings announcement and zero otherwise; *Log (Size)* is the logarithm of market capitalization; *IdioVol* is the idiosyncratic volatility of stock returns computed as the standard deviation of the daily residuals from a one factor model comprising market returns; $Return_{t-1:t-6}$ is the average monthly return from month *t-6* through month *t-1*; and *Log (Amihud)* is the logarithm of average daily Amihud illiquidity. The sample period is from 1972 to 2010. The numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Explanatory Variables	Dependent Variable: r_{jt}							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	3.169***	3.180***	3.064***	3.072***	3.061***	3.528***	3.539***	3.540***
	(9.34)	(9.36)	(9.06)	(9.08)	(9.06)	(10.17)	(10.19)	(10.19)
Loser	0.706***	0.766***	0.993***	0.967***	1.001***			
	(13.46)	(14.25)	(15.57)	(15.67)	(15.48)			
Winner	-0.610***	-0.673***				-0.916***	-0.958***	-0.965***
	(-12.74)	(-13.84)				(-14.96)	(-15.82)	(-15.05)
NegCAR		-0.318***	-0.608***		-0.270***	-0.697***		-0.372***
		(-5.72)	(-11.69)		(-4.81)	(-13.10)		(-6.79)
PosCAR		0.312***		0.738***	0.360***		0.594***	0.222***
		(5.94)		(13.86)	(7.00)		(10.29)	(4.09)
Loser × NegCAR		-0.229***	-0.270***		-0.277***			
		(-2.77)	(-3.25)		(-3.26)			
Loser × PosCAR				-0.095	-0.128			
				(-1.00)	(-1.30)			
Winner × NegCAR						-0.028		0.02
						(-0.29)		(0.20)
Winner × PosCAR		0.189***					0.272***	0.279***
		(2.64)					(3.78)	(3.76)
Earnings	-0.01		0.336***	-0.388***		0.337***	-0.370***	
	(-0.24)		(7.20)	(-7.65)		(7.24)	(-7.30)	
Log (Size)	-0.373***	-0.377***	-0.377***	-0.376***	-0.376***	-0.409***	-0.408***	-0.408***
	(-6.44)	(-6.50)	(-6.49)	(-6.49)	(-6.49)	(-7.02)	(-7.01)	(-7.01)
IdioVol	-0.209***	-0.207***	-0.259***	-0.259***	-0.259***	-0.173***	-0.173***	-0.173***
	(-4.48)	(-4.45)	(-5.70)	(-5.72)	(-5.70)	(-3.73)	(-3.73)	(-3.73)
$\text{Return}_{t-1:t-6}$	0.025*	0.023	0.01	0.01	0.01	0.011	0.011	0.011
	(1.72)	(1.61)	(0.71)	(0.71)	(0.71)	(0.73)	(0.73)	(0.74)
Amihud	-0.142***	-0.144***	-0.141***	-0.141***	-0.141***	-0.164***	-0.164***	-0.164***
	(-3.29)	(-3.34)	(-3.25)	(-3.25)	(-3.25)	(-3.76)	(-3.75)	(-3.75)
Adj R-Squared	0.047	0.047	0.046	0.046	0.046	0.045	0.045	0.045
Obs	1,437,442	1,437,442	1,437,442	1,437,442	1,437,442	1,437,442	1,437,442	1,437,442

FIGURE 1
Intra-Industry Reversal Returns for Fama-French 17 Industries

This figure reports the monthly returns on the intra-industry reversal strategy for each of the 17 Fama-French industries over the period 1968-2010.

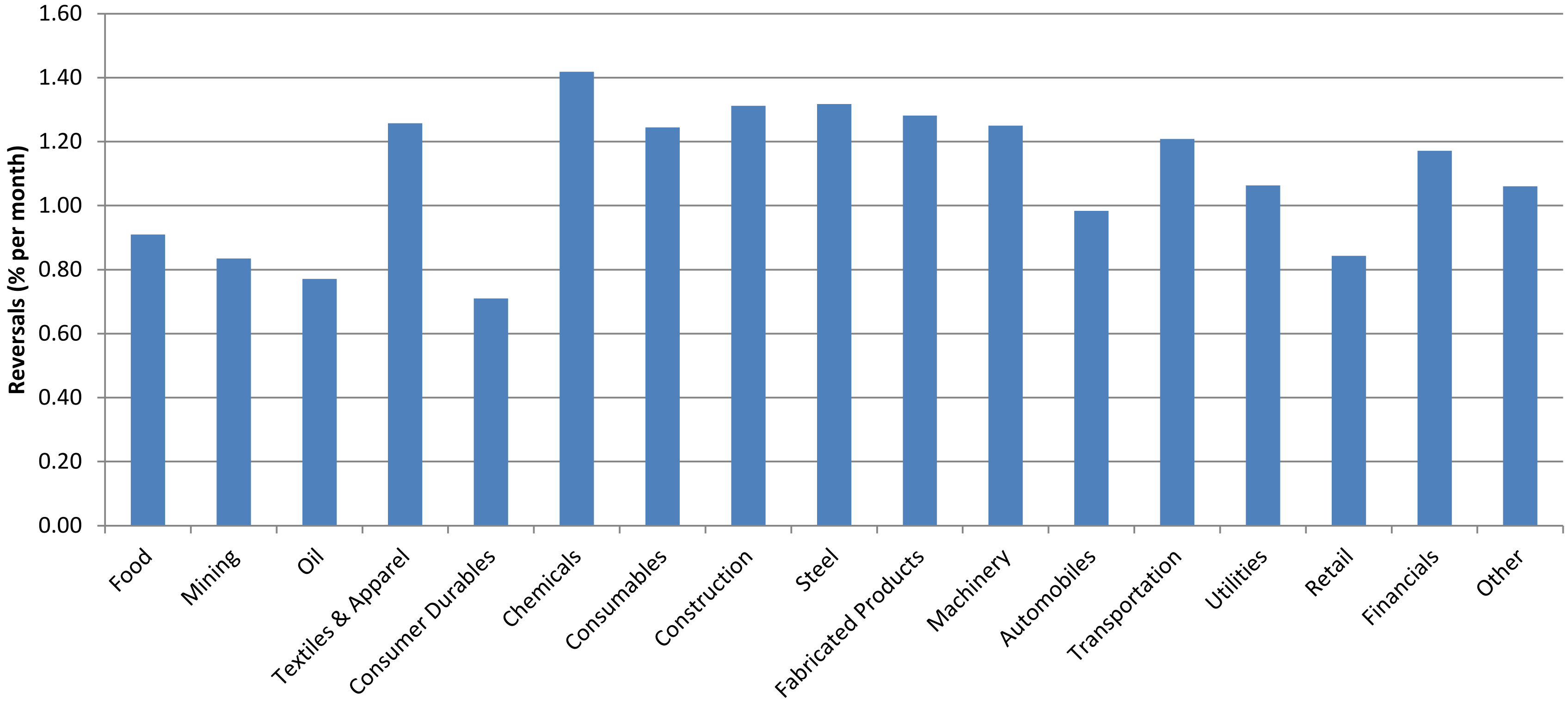

FIGURE 2
Time Series of Returns from the Unconditional and Intra-Industry Reversal Strategies (1968-2010)

This figure plots the 12-month moving averages of the returns from the unconditional and intra-industry (using Fama-French 48-industries classification) reversal strategies over the period 1968-2010.