Contrarian Profits of the Firm-specific Component on Stock Returns

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Abstract

Contrarian strategy using firm-specific component on stock returns can be more powerful than general strategy using total return, based on the literatures that argue that the contrarian profits are caused from investors' irrational behavior about information. We find that the weekly contrarian profits of firm-specific component on stock returns is higher, more significant and steadier than those of total returns. This result is neither due to size or idiosyncratic volatility effect nor due to very high profits in special periods. Furthermore, all stocks in contrarian portfolios based on past firm-specific component generate significantly and continuously positive profits regardless of whether they belong to total-return-based contrarian portfolios, while stocks both in total-return-based and not in firm-specific-component-based contrarian portfolios cannot earn significant positive profits. Also, we decompose the contrarian profits based on firm-specific component, applying Lo and MacKinlay (1990). As a result, the profits are attributed to negative autocovariances in individual stocks' firm-specific components rather than positive cross-serial covariances across securities'. Further decomposing Lo and MacKinlay's decomposition into each winners and losers and into between them to calculate their own and mutual relation in auto- and cross-serial covariances, we reveal that winners are strongly negatively autocorrelated although losers are positively autocorrelated and cross-serial correlated. Therefore, when we consider that size of winners is bigger than that of losers, it is one of the sources of contrarian profits based on firm-specific component that investors overreact to good firm-specific news of large stocks.

Keywords: Contrarian strategy, Firm-specific component on stock returns, Contrarian profit decomposition, Autocovariance, Cross-serial covariance, Information overreaction

I. Introduction

The predictability of stock returns based on their past performance has been significantly verified for a variety of strategies and periods. De Bondt and Thaler (1985, 1987) argues that contrarian strategies of buying past losers and selling past winners generate positive profits over long period, 3 to 5 years. Jegadeesh (1990), Lehmann (1990), Lo and MacKinlay (1990), Jegadeesh and Titman (1995) and Conrad and Kaul (1998) show return reversals for short period such as a week or a month. On the other hand, Levy (1967), Grinblatt, Titman, and Wermers (1994), Jegadeesh and Titman (1993,2001), Hendricks, Patel, and Zeckhauser (1993), and Conrad and Kaul (1998) provide the evidence of momentum at the intermediate-term horizon.[1]

Explanation for sources of momentum and reversal can be partitioned into two parts: whether investors' irrational behavior to new private information (or firm-specific information) drives them or not. Literatures that momentum and reversal are not due to investors' irrational reaction to information are as follows. Lo and MacKinlay (1990) show that weekly contrarian porfolio returns are caused from strongly positive cross-serial cavariances across securities despite negative autocorrelation in individual stock returns, using their decomposition of expected contrarian profits. They argue their results are evidence against overreaction as the only source of contrarian profits. Conrad and Kaul (1998) utilize Lo and MacKinlay's decomposition to analyze the profitable performance of contrarian and momentum, and then they obtain that the profit reflects cross-sectional variability in average returns. Ang, Chen, and Xing (2001) also assert that momentum profit is compensation from bearing negative skewness

[1] In addition, there are a large number of literatures that deal with predictability of return based on past return, momentum and return reversal, which are Gibbons and Ferson (1985), Fama and French (1988), Lo and MacKinlay (1988), Porterba and Summers (1988), Conrad and Kaul (1988, 1989), Boudoukh, Richardson, and Whitelaw (1994), Conrad, Hameed, and Niden (1994), and Chopra, Lakonishok and Ritter (1992).

of return. Recently, McLean (2010) assesses that whether the persistence of the momentum and long-term reversal effects is the result of idiosyncratic risk limiting arbitrage. And he shows that long-term reversal is prevalent only in high idiosyncratic risk stocks, suggesting that idiosyncratic risk limits arbitrage in reversal mispricing.

Although the cause of positive profits from trading strategy using past returns has been debatable, a number of litheratures account for this anomaly with behavioral biases of investors. [2] The models in theoretical papers such as Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) present that the momentum and/or reversal of stock return are induced by the revision of investors' expectations in response to new information. That is, these models imply that investors' underreaction or overreaction to firm-specific information can lead to momentum and/or reversal. Empirical studies also support these patterns in the stock price reaction to firm-specific information. Bernard (1992), Chan, Jegadeesh and Lakonishok (1996) and Grinblatt and Han (2005) document that the unnerreaction to firm-specific information causes momentum. Also, Lehmann (1990) show that predictable variation in equity returns such as return reversals reflects stock price overreaction, and Jegadeesh and Titman (1995) demonstrate that stock prices overreact to firm-specific information but react with a delay to common factors.

Considering literatures which show that price variation is caused by private information (or firm-specific information) which affects prices when informed investors trade, we can anticipate that investors' systematic behavior toward new information can generate the predictability of stock returns based on their past performance.

[2] As Chae and Eom (2009) mention that since the momentum profit is supposed to be the other side of a coin for the contrarian profit (negative momentum profit), I refer both studies to analyze the momentum profit and those to do the contrarian profit for research of contrarian profit.

If the investors' irrational behavior to firm-specific information is the source of these strategies' profits, the strategy that utilizes the firm-specific component of stock return will be more powerful, as opposed to the whole or risk-factor components of return. Fama and French (1996), Moskowitz and Grinblatt (1999), Jegadeesh and Titman (2001), Grundy and Martin (2001), Cooper, Gutierrez and Hameed (2004) show that momentum cannot be captured by factor exposure (e.g. Fama-French factors or microeconomic factors).

Meanwile, recent studies find that firm-specific momentum is more profitable. Grundy and Martin (2001) testfy that the momentum profitability reflects momentum in the stock-specific component of returns, and when risk adjusted, the momentm strategy's profitability is remarkably stable. In additional test, they find that the stock-specific return momentum strategy based on alphas of asset pricing model is significantly more profitable and stable than general momentum. However, that alpha for stock-specific component is not proper proxy for 'new information'. Gutierrez and Prinsky (2007) assess that the momentum profits using firm-specific abnormal return determined by stock's idiosyncratic return variation of market model continues for years, whereas total return momentum profit reverses strongly in a year. Simillarly, Blitz, Huij and Martens (2011) assert that momentum in residual from the Fama-French model earn more profits then total return momentum profits.

We examine the profitability of contrariran strategy based on weekly firm-specific component on stock returns estimated by asset pricing model with Korean stocks. The strategy follows Jegadeesh and Titman (1993, 2001)'s methology but buying past loser and selling past winner. The reason why we use Korean stocks is as follows. First, the returns on Korean stocks reverse at weekly and monthly horizon (Kho (1997) and Chae and Eom (2009)). And many literatures such as Grinblatt and Keloharju (2000), Jackson (2003), Kaniel, Saar, and Titman (2004), Choe, Kho, and Stulz (1999), and Khil, Kim, and Sohn (2006) observe that individual investors are contrarian traders in not only U.S. stock market but also various international market. Moreover, individual investor's ratio in Korean stock market is larger than any other stocks market (Choe, Kho, and Stulz (2005) and Kim(2012)). Generally, the individual traders are the uninformed, which may mistakenly react to information in firm-specific return. Therefore, we can certainly observe the investor's irrational reaction to firm-specific information with Korean stocks. In addition, analysis with short-term return is due to the literatures such as Sims (1984) and Lehmann (1990) which have emphasized that systematic short-run changes in fundamental values should be negligible in an efficient market with unpredictable information arrival even if there are predictable variations in expected security returns over longer horizons, thereby facilitating focusing on investors' reaction to firm-specific information far from change in expected return owing to firm-specific information. And we rank stocks on firm-specific component on stock returns that is calculated as firm-specific returns divided by its standard deviation, to form contrarian portfolios. According to Gutierrez and Prinsky (2007) and Blitz et al. (2011), standardizing the firm-specific component on stock returns yields an improved measure of the extent to which a given firm-specific return shock is actually news, as opposed to noise, thereby facilitating a better interpretation of that as firm-specific information.

As a result, contrariran strategy based on weekly firm-specific component on stock returns outperforms those based on the total returns and the expected returns. The profitablility of firm-specific-component-based contrarian strategy is larger, more significant and steadier. This result is not due to size or idiosyncratic volatility effect, despite the highest size of stocks with the highest past firm-specific component on stock returns. Also, the high average returns of firm-specific-component contrarian strategy are still significant, however, the significance of general total-return contrarian profits decreases. Furthermore, all contrarian portfolios based on past firm-specific component generate significantly and continuously positive profits whether they belong to total-return-based contrarian portfolios, while stocks both in total-return-based and not in firm-specific-component-based contrarian portfolios cannot earn significant positive profits.

We investigate our hypothesis that contrarian strategy based on firm-specific component on stock returns is more meaningful and powerful underlying that the profitability of stock returns based on their past performance is caused by investors' irrational reaction to firm-specific information. Thus, we additionally anaylize to uncover that underlying hypothesis decomposing the contrarian profit with Lo and MacKinlay (1990)'s methodology. They decompose the total-return-based contrarian profit into autocovariance, cross-serial covariance and cross-sectional variance of the mean returns. This decompostion enable to figure out whether the contrarian profit is caused by investors' overreaction to information or not but by cross-serial covariances across securities. We utilize their analytic frame to decompose the firm-specific-component-based contrarian profit into autocovariance of individual stocks and cross-serial covariance of securities. Morevoer, we decompose the portfolios of winner and loser as well as all stocks, and further do total autocovariances into winners' autocovariances and losers's autocovariances and do total cross-serial covariance into winners', losers and their mutual cross-serial covariance, referring Chae and Eom (2009). From this decomposition of decomposition, the detainled source of contrarian profit can be revealed.

We find that weekly standardized firm-specific component on stock returns and firm-specific component of individual stocks are negatively autocorrelated and insignificantly positively cross-serial correlated. This result implies that contrarian profits using firm-specific component on stock returns are induced by investors' overreaction to firm-specific information, not by cross-serial covariances across stocks' firm-specific component on stock returns.

Meanwhile, according to the decomposition of decomposition in winners and losers, autocovariances and cross-serial covariances in them are asymmetric. 1) firm-specific components of winners are negatively autocorrelated, 2) those of losers are positively autocorrelated, 3) those across stocks in winner portfolio are negatively cross-serial correlated, 4) those across stocks in loser portfolio are positively cross-serial correlated, 5) past firm-specific component of losers and current firm-specific component on stock returns of winners are positively cross-serial correlated, and 6) past firm-specific components on stock returns of winners and current firm-specific component of losers are negatively cross-serial correlated. These relationships do not change as the past is 1-week lag to 4-week lag from current week. Therefore, the contrarian profit primarily arises from negative autocovariances of winners, recalling that negative autocovariances of individual stocks is surce of contrarian profits in the first simple decomposition. And the conclusion suggests that investors overreact to good firm-specific news of large stocks, when it is considered that size of winners is the bigger than that of losers. On the contrary, investors underreact to stocks' bad firm-specific news, the extend of which is smaller than that of overreaction to good news of large stocks. In addition, the winners', losers' and their mutual cross-serial covariances have consistent signs, however, the total sum of them is insignificant.

The remainder of the paper is organized as follows. Section II describes the sample data used in this paper and the estimation of firm-specific component on stock returns. With estimated firm-specific component, we form the contrarian strategy portfolio following Jegadeesh and Titman (1993, 2001)'s methodology. Section III discusses the characteristics of the contrarian portfolio based on firm-specific components. Section IV presents the performance of contrarian strategy. Section V investigate the decomposition of the firm-specific-component-based contrarian profit. We utilize Lo and Mackinlay (1990)'s decomposition and expand their methodology further to decompose the decomposition. Also, we check the robustness of the decomposition and the decomposition of decomposition with additional factor. Section VI reviews the study's main conclusions.

II. Data and Methodology

A. Data

We use all firms traded on the Korea Stock Exchange (KSE) from January 1987 to July 2014, and obtain all data including weekly returns of stocks for this study from the DataGuide.[3] The DataGuide computes the weekly returns of each security as the return from Friday's closing price to the following Friday's close, which are adjusted the effect of stock split, dividend and capital increase.

To avoid survival bias, we encompass all delisted firms. Since the Fama-French three-factor model is used to estimate the expected returns on stocks, the sample selection in this study follows Fama and French (1992, 1993). That is, we exclude financial firms because the the leverage for these firms has the different meaning as for nonfinancial firms, and mutual funds, REITs, ETFs, and preferred stocks are excluded for the same reason. Also, we use only the December fiscal yearend firms, and negative book equity firms are eliminated. As we calculate the expected weekly returns with 52-week weekly return data of stocks from the regression of asset pricing model (i.e. the Fama-French model), only firms having weekly returns for at least 25 of the 52 weeks are included in the final data set.

[3] The DataGuide covers 364-day Monetary stabilization bond (MSB) data used as risk-free rate in this paper from 1987, which is the earliest one among interest rates reported in the DataGuide. Since we need the risk-free rate to estimate the excess returns of stocks, the first calendar year in our data is 1987.

To estimate the coefficients of asset pricing model, lagged returns data over 1-year are needed before the regression. Furthermore, our strategies having 12-week formation period again require lagged returns data over 23 weeks at least. Note that we use the methodolgy of Fama and French (1993) for modeling, in which the foctor mimicking portfolios are constructed in June and the regression start in July. Therefore, the first full calendar year for which we could investigate the portfolio returns of the strategies is 1989. As a result, 865 firms are totally included in this study during whole period, from 209 firms in january 1989 through 618 firms in the end of the analysis.

B. Estimation of Firm-specific Component on Stock Returns

Our contrarian strategy basically follows the momentum strategy of Jegadeesh and Titman (1993, 2001). Although their strategy is buying stocks with high returns and selling stocks with low returns, using raw return data, our strategy is buying stocks with low firm-specific component on stock returns and selling stocks with high firm-specific component such as Gutierrez and Pirinsky (2007). Thus, to obatin the firm-specific component on stock returns, we first must estimate the firm-specific abnormal return, which is real stock return minus the expected return. we use the Fama-French three-factor model to calculate the expected returns of stocks. To estimate the coefficients of the model in week *t*, we employ the time-series regression of the equation (1) over the previous 52-week rolling windows, [*t*-52, *t*-1].

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + \varepsilon_{it} \tag{1}$$

where R_{it} is the return of stock *i* in week *t*, R_{ft} is the 364-day MSB rate in week *t*, R_{mt} is the return on the Korea Composite Stock Price Index (KOSPI) in week *t*, SMB_t and HML_t

are the returns of the factor mimicking portfolios related to size and book-to-market equity ratio (BE/ME) in week *t*, α_i, β_i, s_i and h_i are the parameter to be estimated, and ε_{it} is the residual for stock *i* in week *t*.

SMB_t and HML_t are formed along with Fama and French (1993). The size for the size sort is measured at the end of June of year τ, the ME for the book-to-market equity sort is market capitalization of common stock at the end of December of $\tau - 1$ and the BE is book common equity for the fiscal year ending in calendar year $\tau - 1$. In June of each year τ, the securities with bigger size than median firm size are assigned into big group (*B*) and those with smaller size than median are into small group (*S*). And based on the BE/ME in December of $\tau - 1$, all stocks are divided into three book-to-market equity ratio groups: the bottom 30% (*L*), middle 40% (*M*) and top 30% (*H*). With these, we build six portfolios (*S/L, S/M, S/H, B/L, B/M, B/H*) from the intersections of the two size and the three BE/ME groups, and calculate value-weighted weekly returns on the six portfolios from July of τ to June of τ + 1 for July 1987 to June 2014. SMB_t is the simple average of the returns on the three small-stock portfolios (*S/L*, *S/M* and *S/H*) minus the simple average of the returns on the three big-stock portfolios (*B/L, B/M* and *B/H*). HML_t is the simple average of the returns on the two high-BE/ME portfolios (*S/H* and *B/H*) minus the simple average of the returns on the two low-BE/ME portfolios (*S/L* and *B/L*).

The firm-specific abnormal return of the stock *i* in week *t* is calculated with the estimated constant and factor loadings of equation (1) as follows.

$$\varepsilon_{it} = R_{it} - R_{ft} - [\hat{\alpha}_i + \hat{\beta}_i(R_{mt} - R_{ft}) + \hat{s}_i SMB_t + \hat{h}_i HML_t] \quad (2)$$

The alpha estimated, $\hat{\alpha}_i$, must be indistinguishable from zero for the Fama-French model to qualify as the well-specified asset-pricing model and most literatures interpret the non-zero alpha as pricing-error or abnormal return (Merton (1973), Fama and French (1993), Kim (2009), Kim and Chae (2015)). However, we include the alpha to calculate the expected return as Gutierrez and Prinsky (2007) and Blitz, Huij and Martens (2011) comment that the alpha from the estimation period serves as a general control for misspecification in the model of expected returns. Also, Kim and Chae (2015) document the significant alpha is often observed in the time-series regression of short term such as 1-year with Korean stock returns, which can be a part of expected returns for short period. In addition, we test without the estimated alpha and the findings are not changed. Precisely, almost profits of our strategies using the expected returns without the estimated alpha are slightly smaller than those of including alpha in each equivalent strategy.

We investigate the contrarian strategy based on the firm-specific component on stock returns in this paper. Thus, the firm-specific component is required, which is not the firm-specific abnormal return. As the creteria to make portfolios for the contrarian strategy, the firm-specific component on returns is that the firm-specific abnormal returns estimated from equation (2) are standardized, that is, the firm-specific abnormal returns are divided by their standard deviations, which is expressed as

$$\textit{Firm-specific Component on Stock Returns } (FC) = \frac{\varepsilon_{it}}{\sigma(\varepsilon_{it})} \qquad (3)$$

where $\sigma(\varepsilon_{it})$ is the standard deviation of ε_{it} for previous 52 weeks.

According to Gutierrez and Prinsky (2007) and Blitz et al. (2011), standardizing the firm-specific return yields an improved measure of the extent to which a given firm-specific return shock is actually news, as opposed to noise, thereby facilitating a better interpretation of that as firm-specific information. Also, although it is possible that ε_{it} has large positive correlation with idiosyncratic volatility of stock returns, we can control the effect induced from the idiosyncratic volatility on the contrarian profits with standardizing ε_{it}. Therefore, this helps the contrarian profits to be construed as caused from the unexpected firm-specific information or investors' reaction on unexpected firm-specific information, not from what is related with the idiosyncratic risk. Furthermore, we also analyze the equivalent contrarian strategy but based on the firm-specific abnormal returns which are not divided by their standard deviations. This additional analysis is not controlled the effect of idiosyncratic risk. Nevertheless, the findings are not significantly different with the results from our original test of contrarian strategy based on the firm-specific component on stock returns (FC), thus, to save space, we do not report these findings. This undifferentiated finding proves that the results from our contrarian strategy based on FC are not caused by the effect of the idiosyncratic volatility.

C. Formation of Contrarian Strategy Portfolio

We construct the long-shot portfolios with winner and loser based on the firm-specific component, applying Jegadeesh and Titman (1993, 2001). That is, at the end of each week (i.e. Friday) we rank the stocks in our sample based on their past *J*-week firm-specific components and then group the stocks into 10 equally weighted portfolios based on these ranks. P1 is the equal-weighted portfolio of 10 percent of the stocks with the highest firm-specific components over the previous *J* months, P2 is the equal-weighted portfolio of the 10 percent of the stocks with the next highest firm-specific components, and so on. Each portfolio is held for *K* weeks following the ranking week. Among the 10 portfolios based on firm-specific components for *J* weeks, we identify the top decile portfolio (P10) as “winner”, and bottom decile portfolio (P1) as “loser”. Our long-short portfolios are buying loser and selling winner in week *t* and holding this position for *K* weeks. This strategy is called as a *J*-week/*K*-week strategy here. The *J*s vary 1, 3, 6, 9 and 12 weeks, and the *K*s vary from 1 to 20 weeks. We conduct this forming and *K*-week holding the long-short portfolio in every week, both with and without skipping a week between the portfolio formation period and the holding period. Jegadeesh and Titman (1993) discuss that by skipping a week, we can reduce the bias related to the market-microstructure such as the bid-ask spread effect.

To increase the power of our tests, following Jegadeesh and Titman (1993, 2001), we build overlapping portfolios. In other words, we identify *K* portfolios of decile stocks respectively in any particular calendar week, which has a different vintage of the *J*-week strategy. we assign the equally weighted average returns of *K* portfolios as the average weekly returns of decile portfolios. For the average weekly returns on long-short portfolios of our contrarian strategy, we subtract the average weekly return on the winner portfolios from the average weekly return on the loser portfolios in each week.

we also analyze the same contrarian strategy with the total stock returns and the expected returns. To exactly compare with firm-specific component’s contrarian profits, the contrarian strategy with the raw returns and expected returns use the precisely equal sample, periods and methodology.

III. The Characteristics of Contrarian Strategy Portfolio

Table 1 reports summary statistics for these 10 portfolios based on past 1- and 3-week firm-specific components on stock returns. It shows informations about firm-specific component, size, BE/ME, the constant and coefficients of the Fama-French three-factor model and idiosyncratic volatility of each portfolio. Since Panel A presents the characteristics of *J*=1 contrarian portfolios, values of FC are 1-week lagged firm-specific components. Panel B presents the information of *J*=3 contrarian portfolios, thus the values of FC in Panel B are cumulated firm-specific components over 3 weeks prior to the formation of portfolios. Table 1 includes statistics of each portfolio's size and BE/ME which are main risk factors of the Fama-French three-factor model. Size is the market capitalization of stocks in billion won in week *t*. BE/ME is the book-to-market equity ratio of stocks. α, β, s and h are the constant and coefficients in the time-series regressions of the Fama-French three-factor model (equation (1)). IV is the idiosyncratic volatility, which is calculated in week *t* as the standard deviation of residuals in equation (1), $\sqrt{var(\varepsilon_{it})}$.

According to FC in Table 1, the distribution of firm-specific components is not too extremely biased to implement our contrarian strategy. While the mean or the median of the distribution is not zero and the distribution is biased toward slightly negative, the absolute values of firm-specific components in P1 and P10 are so simillar for both *J*=1 and especially *J*=3 to apply the contrarian strategy based on them.

Table 1 also shows that size increases from lower to higher firm-specific-component portfolios except the highest (P10) for both *J*=1 and *J*=3. This pattern may be caused from size effect to numerator (i.e., the firm-specific return) or denominator (i.e., the standard deviation of firm-specific returns) of the FC because some literatures discuss that there is the correlation between the variation of firm-specific returns and size on stocks. Kim and Chae (2015) reports that the firms with higher absolute value of firm-specific returns are bigger, and Kho and Kim (2012) documents that firms with higher R^2 have bigger asset than those with lower R^2 from the market model regression which is 1 minus the residual sum of squares over the total sum of squares in the model. In the sample of this paper, there is the relation between the variation of firm-specific return and size on stocks. For one thing, the bigger size of firms, the higher firm-specific returns. For another thing, as Kim and Chae (2015), the standard deviation of firm-specific returns and size on stocks are positively correlated. Therefore, by the asymmetric joint effect of two positive correlationship, size slightly increases from lower to higher firm-specific-component portfolios with the correlation coefficient of 0.013 between size and FC in this sample. Under this potential relation between them, the result from our contrarian strategy may be induced from the effect of size, not from the firm-specific component. Thus, we check whether the result is robust to size afterwards.

For other variables, the portfolios with higher firm-specific components have lower BE/ME, however, the differences of BE/ME among portfolios are not large. α, β, s and h of the Fama-French three-factor model gradually also decrease for firms with higher firm-specific component before P10, however, the changes are very small. Moreover, α, β, s and h of P10 that is included in our contrarian strategy are rather higher than those of other portfolios. Especially, there is little change of β among portfolios. In addition, dividing firm-specific returns by thier standard deviations to standardize, we consider the effect of idiosyncratic volatility to contrarian profits. However, the linear pattern that idiosyncratic volatility decrease with the firm-specific component until P9 is negligible. Overall, the promary variables except size do not have significant relationship with the firm-specific component on stock returns .

IV. The Performance of Contrarian Strategy

A. Contrarian Profits based on the Total Returns and the Expected Returns,

To compare the performances of contrarian strategies based on the firm-specific components, we analyze the performances of contrarian strategies based on the total returns and the expected returns with the equal sample, using Jegadeesh and Titman (1993, 2001)'s methodology. This comparison is expected to be helpful to reveal the source of the contrarian profits in the stock market.

First, panel A of Table 2 shows that the profits of contrarian long-short portfolios based on the total returns, general contrarian strategy, representing the average weekly returns of P1, P10 and P1−P10 for 45 strategies explained in previous section II. P1 is the equal-weighted portfolio of 10 percent of the stocks with the highest raw returns and P10 is the equal-weighted portfolio of the 10 percent of the stocks with the lowest raw returns over the previous *J* months. It includes all results both with and without 1-week jump between the formation and the holding period for portfolios. According to the panel A, almost profits are positive regardless of 1-week jump. only 1-week/1-week and 1-week/2-week strategies with 1-week jump have negative results, but they are insignificant. 30 of 45 strategies that do not skip 1 week between the formation and holding period are significantly positive. On the other hand, only 18 of 45 strategies that skip 1 week between the formation and holding period are statistically significant. In addition, the significance of total-return-based contrarian profits does not continue in longer holding period, which all weekly returns of the strategies whose holding period is 20 weeks are insignificant except only one strategy and those of J=6/K=16, J=9/K=16, J=12/K=9~16 in the "without 1-week Jump" column are also insignificant. It is stronger in the "with 1-week Jump" column that the significance of total-return-based contrarian profits dose not persist in longer holding period. This result from general contrarian strategy using the raw returns on stocks can be predicted by related literatures that utilize Korean stocks.[4]

Secondly, we investigate the contrarian strategy based on the expected returns on the securities to reveal the source of the contrarian profits as well. The expected returns are

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[4] Kho (1997) shows that Korean stocks from 1980 to 1995 insignificantly have the negative momentum profits in months, and Chae and Eom (2009) show that they have weakly negative momentum profits in months and significantly negative momentum profits in weeks from 1980 to 2005. Others also find the negative momentum effect or the return reversal in Korean stock market during short or intermediate periods.

estimated from the Fama-French three-factor model. First, we estimate the coefficients of the Fama-French model for stock *i* in week *t*, α_i, β_i, s_i and h_i, employing the time-series regression of the equation (1) over the previous 52-week rolling windows, [*t*-52, *t*-1]. And then the expected returns on stock *i* in week *t* are calculated with the estimated coefficients and real data of the risk factors. Applying Jegadeesh and Titman (1993, 2001)'s methodology, the long-short contrarian portfolios based on the expected returns is formed. Now, P1 is the equal-weighted portfolio of 10 percent of the stocks with the highest expected returns and P10 is the equal-weighted portfolio of the 10 percent of the stocks with the lowest expected returns over the previous *J* months. Panel B in Table 2 presents the contrarian profits based on the expected returns. According to this panel, the expected-return-based contrarian strategies can not generate any significant positive profits. This result suggests that the contrarian profits in the stock market are not caused from the investors' reaction to the expected returns on stocks estimated from the common risk factors. And it is consistent with the literatures which illustrate that the predictability of stock returns based on their past performance such as momentum cannot be captured by factor exposure (e.g. Fama-French factors or microeconomic factors).[5] As a result, investors do not irrationally react on the systematic information, consequently, the reaction of investors to this information do not induce contrarian or momentum profits in the stock market.

B. Contrarian Profits based on the Firm-specific Component

We calculate the average weekly returns on long-short contrarian portfolios based on the firm-specific component, which are displayed in Table 3. Panel A of Table 3 presents the profits

[5] See Fama and French (1996), Moskowitz and Grinblatt (1999), Jegadeesh and Titman (2001), Grundy and Martin (2001), Cooper, Gutierrez and Hameed (2004).

of the firm-specific-component contrarian strategy. The panel shows the interesting results that the all profits of this strategy are remarkably positive regardless of 1-week jump between formation period and holding period. Also, all these positive returns are statistically significant except the return of only one strategy. The highest profit of our contrarian strategy without 1-week jump is 0.719% (*t*-statistics of 5.66) for 9-week/1-week strategy and that with 1-week jump is 0.544% (*t*-statistics of 4.64) for 9-week/1-week strategy, which are considerably large. Overall, the average returns on the contrarian portfolios that does not skip a week are higher than those that skips a week but 6 of 45 strategies because return reversal is so strong in the next period (t+1). Especially, all returns in K=1 without a week jump is very higher than those with a week jump, which may be the reason of overall higher profits of strategies with 1-week jump. For same J, the returns of contrarian long-short portfolios largely incease with K. For the same K, the returns of long-short portfolios largely incease with J up to J=9.

The most important fact from Panel A of Table 3 is that the contrarian profits of firm-specific components are always bigger and more significant than those of the total returns and the expected returns, in Table 2. The profits of the total-return-based contrarian strategy are at most 67% of the firm-specific-components-based strategy's, on average 50%. Especially, the difference between the profits of firm-specific-component-based and total-return-based portfolios is larger for the contrarian strategy with 1-week jump than without 1-week jump, because the substantial source of contrarian profits using total returns is big return reversal in next week which may happen by the effect of market microstructure such as bid-ask spread. This more difference in "with 1-week jump" shows that firm-specific-component-based contrarian profits are caused from information or investors' systematic reaction not from the effect of market microstructure. Furthermore, in contrast with the firm-specific-component-based contrarian strategies, the significance of total returns' contrarian profits does not continue in longer holding period. In “without 1-week jump” of Panel A in Table 2, all average weekly returns of K=20 are insignificant except J=1 and those of J=6/K=16, J=9/K=16, J=12/K=9~16 are also insignificant. Moreover, the significance of the total-return-based contrarian profits dose not persist in longer holding period in “with 1-week jump” of Panel A in Table 2. Otherwise, the positive profits of the firm-specific-component-based contrarian strategy significantly continue in longer period for all J as Table 3. Note that the contrarian profits based on the expected returns are always tiny and insignificant as Panel B of Table 2 presents. Concluing from the results of Table 2 and Table 3, the firm-specific-component-based contrarian strategy generates larger, more significant and steadier than the total-return- or the expected-return-based strategies. This conclusion implies that the main resource of short-term contrarian profits can be the investors’ reaction to the firm-specific information, not to the common risk factors (i.e., systematic information) or to the total returns (i.e., total information).

Panel B in Table 3 displays the risk-adjusted returns of firm-specific-component contrarian portfolios. The risk-adjusted returns are the alphas estimated by regressing the weekly returns of portfolios minus the risk-free rate on the three Fama-French factors. As a result, all Fama-French alphas are also significantly positive and their magnitudes are similar with the average weekly returns in Panel A. Comparing results in Panel B with Panel A, almost alphas are larger than the corresponding average returns. only some alphas of longer J (J=9/K=1~6, and J=12/K=1~9) are smaller than the corresponding average returns. Overall alphas have little difference with average returns in Panel A.

We also assess the average holding period returns of the long-short contrarian portfolios based on the firm-specific component. The holding period returns are calculated following Conrad and Kaul (1993)’s holding period abnormal performance measure. That is,

$$\mathrm{AHPRF}_p(K) = \frac{1}{n}\sum_{i=1}^{n} \mathrm{HPR}_{pi}(K) - \frac{1}{N}\sum_{j=1}^{N} \mathrm{HPR}_j(K) \tag{4}$$

$$= \mathrm{AHPR}_p(K) - \mathrm{AHPR}_M(K) \qquad p = \mathrm{L}, \mathrm{W}$$

where $\mathrm{AHPRF}_p(K)$ is the average holding *K*-week period return for the portfolio of firm-specific-component-based losers (*p*=L) or winners (*p*=W), $\mathrm{AHPR}_p(K)$ is the average holding *K*-week period return for the portfolio of losers or winners, and $\mathrm{AHPR}_M(K)$ is the average holding *K*-week period return for the portfolio of all stocks in our sample. The holding period return of stock *i* over a *K*-week interval is calculated by compounding *K* single week returns as follows.

$$\mathrm{HPR}_i(K) = (1 + \mathrm{R}_1)(1 + \mathrm{R}_2) \cdots (1 + \mathrm{R}_K) - 1$$

Panel C in Table 3 shows the average holding period returns of our contrarian portfolios. The average holding period returns of P1 are estimated from $\mathrm{AHPRF}_L(K)$, and those of P10 are from $\mathrm{AHPRF}_W(K)$. The average returns in this panel are significantly positive and it is consistent with above results in other panels in Table 3. Especially, as the equal-weighted returns on all stocks, $\mathrm{AHPR}_M(K)$, are subtracted from $\mathrm{AHPR}_p(K)$ in calculation of $\mathrm{AHPRF}_p(K)$, we can observe the excess returns of winners and losers. According to the results in Panel C, the contrarian profits are induced from winner's negative abnormal returns since the absolute values of the average excess returns on winners are higher and more significant than those on losers. Although $\mathrm{AHPRF}_p(K)$s of winners and losers are similar or those of losers are higher in short *K*, almost absolute values of $\mathrm{AHPRF}_p(K)$s for winners are higher and more significant. Therefore, we can conjecture that the contrarian profits based on the firm-specific component are arisen more from investors' overreaction to winners who have better firm-specific information than that to losers.

Since Table 2 and Table 3 show only winner (P10) and loser (P1), the pattern of the returns of all portfolios including P2~P9 cannot be grasped. Table 4 reports the average weekly returns for all contrarian portfolios formed based on the past 3- and 6-week firm-specific components and total returns, and then held for 3, 6, 9, and 12 weeks. According to the result of Panel A in which contrarian portfolios are formed immediately after the lagged firm-specific-components used for forming these portfolios, without 1-week jump, the average returns of higher past firm-specific-component portfolios are lower except J=3/K=3. However, the average returns of contrarian portfolios based on past total returns without 1-week jump in Panel B have rarely linear relationship with the past returns for any J/K strategies although average returns of P1 are higher than those of P10. This result is similar in Panel C and D of contrarian strategies with 1-week jump, but the monotonic patterns are weaker in both panels. Practically, there is not linear relation between the returns on contrarian portfolios and contrarian ranks in Panel D of the total-return-based contrarian strategy, as opposed to the obvious monotonic linear relationship between the returns on firm-specific-component-based portfolios and contrarian ranks. This outcome implies the magnitude of the firm-specific component has the orderly and systematic relationship with future stock returns, whereas the contrarian profits based on the raw returns is caused not from the orderly reaction of investors to past returns but just from the difference between the future returns on winners and losers.

C. Contrarian Profits in Subperiod

We calculate the contrarian profits based on the firm-specific component in each of the subperiods in the total sample period to test whether the high contrarian outperformance is due to very high profits in particular periods. Table 5 shows the average weekly returns in subperiods for contrarian portfolios formed based on past 1-, 3-, 6-, and 9-week firm-specific components and total returns, and then held for 1, 3, 6, 9 weeks. The whole period is divided to three subperiods of 1989~1996, 1997~2005 and 2006~2013. Panel A in Table 5 shows that most of the firm-specific-component-based contrarian strategies can generate significantly positive average weekly returns in all subperiods, especially, the contrarian profits in 1997~2005 are the highest. However, almost contrarian strategies based on the total returns fail in subperiods as Panel B in Table 5. There are totally 48 strategies in one panel of Table 5 owing to 4 *J*s and 4 *K*s in 3 subperiods. 44 of 48 strategies earn significantly positive profits in Panel A, whereas only 13 strategies do that in Panel B. This result shows that the high outperformance of firm-specific-component-based contrarian strategy is not due to very high profits in particular periods and we can observe the high outperformance in all subperiods.

D. Size and Idiosyncratic Volatility Effect

Size effect to the firm-specific-component-based contrarian profits is examined because the firm size increase from lower to higher contrarian portfolios except P10 and size of P10 are bigger than that of P1 as Table 1 shows. We also investigate idiosyncratic volatility effect to the contrarian profits because the denominator and numerator of FC (equation (3)) for ranking the contrarian portfolios can be correlated with the idiosyncratic volatility. In particular, the denominator of FC is the standard deviation of idiosyncratic return which is naturally strongly correlated with the idiosyncratic volatility. To control their effect, we evaluate the profitability of contrarian strategy based on firm-specific component within three subsamples stratified on the basis of firm size and idiosyncratic volatility (IV). The subsample including the smallest firms is Size1, the subsample including the medium-sized firms is Size2, and Size3 contains the largest firms. Similarly, the subsample IV1, IV2, and IV3 contain the firms with the smallest, medium, and the largest idiosyncratic volatility. The idiosyncratic volatility is estimated with the Fama-French three-factor model as mentioned in Section III, that is, IV for stock *i* in week *t* is calculated as the standard deviation of residuals in equation (1), $\sqrt{var(\varepsilon_{it})}$ from the 52-week residual data prior to portfolio formation, [t-52, t-1].

Panel A of Table 6 shows the FC's contrarian profits of size-based subsample Size1, Size2, and Size3. Overall, the contrarian profits are not due to the cross-sectional differences in the size-related risk of firms, as all average returns in subsamples are not smaller than the average returns in the full sample. Rather, some of the average returns in subsamples are higher than those in the full sample. The contrarian profits in Size3 are higher than those in Size1, Size2 and full sample at *J*=1, although the contrarian profits in Size1 are higher than those in Size2, Size3 and full sample at *J*=9, and the profits of Size2 are highest at *J*=6. Briefly, when the formation period of contrarian portfolios is shorter, portfolios composed of bigger stocks earn higher returns. The investors may overreact on the firm-specific information of large firms more readily recognized than small firms in short-term observation.

In addition, the highest average returns of losers (P1) and the lowest average returns of winners (P10) are not in same size subsamples. While the losers in Size1 have higher average returns that in Size2 and Size3, the winners in Size3 have the lowest average returns. The extreme following returns of losers in Size1 and winners in Size3 are regardless of formation period and holding period. This suggests that the investors overreact to small loser and large winner. Consequentially, the contrarian profits based on the firm-specific component is robust to size effect, however, the degree of investors overreaction on the firm-specific information is related to size effect.

Panel B of Table 6 presents the contrarian profits in idiosyncratic-volatility-based subsample IV1, IV2, and IV3. Note that Table 1 shows that the higher contrarian rank is, the lower idiosyncratic volatility is, however, the strength of the linear relationship between contrarian ranks and idiosyncratic volatility is weak. According to Panel B in Table 6, the contrarian profits in IV2 are generally the highest and both winners and losers contribute these highest profits of IV2. Especially, when formation period is longer such as 6 or 9 weeks, the average weekly returns of IV2 are higher. Therefore, the high contrarian profits of firm-specific component are not compensation for the high idiosyncratic risk. Furthermore, since all of average returns in subsamples of IV are not smaller than average returns in the full sample and some returns in subsamples are higher than those in the full sample, the FC's contrarian profits are not caused from the cross-sectional differences in the risk related with idiosyncratic volatility of firms. In conclusion, FC's high contrarian profits are robust to idiosyncratic volatility.

E. Subsets of Firm-specific Component and Total Returns

Winners and losers based on the FCs are not necessarily to be same with those based on the total returns, although many of winners and losers based on the FCs are expected to belong to contrarain portfolios based on the total returns. To compare the performances of the FC contrarain strategy and the total return contrarain strategy, we identify three subset portfolios of winners and losers for the contrarain strategies as Gutierrez and Prinsky (2007). we define 'FC∩TR' as the intersection of the stocks in the FC contrarian portfolio with the stocks in the total return contrarian portfolio, 'only-FC' as the subset of the FC contrarian portfolio that are not in the top or bottom decile of lagged total returns, and 'only-TR' as the subset of the total return contrarian portfolio that are not also in the FC contrarian portfolio during the formation period.

Table 7 reports the average number in week *t* of stocks in subsets of contrarian portfolios, 'FC∩TR', 'only-FC', and 'only-TR'. For winners (P10), the number of stocks in FC∩TR is the most at all *Js* and each those in only-FC and only-TR are similar, yet the number of stocks in FC∩TR is not immoderately different with that in only-FC and only-TR. For losers (P1), the numbers of stocks in three subsets are similiar. For instance in *J*=6, FC∩TR averagely has 22.31 losers in a week, only-FC averagely has 21.95 losers in a week, and only-TR averagely has 22.34 losers in a week. Consequently, the numbers of stocks in subsets are not unreasonable to analyze separating the subsets.

Table 8 shows the average weekly returns of contrarian subsets, FC∩TR in Panel A, only-FC in Panel B, and only-TR in Panel C. As above contrarian portfolios, they are formed based on the past *J*-week firm-specific component and total returns and held for *K* weeks. Interestingly, most of contrarian profits of FC∩TR and only-FC are significantly high, whereas all contrarian profits of only-TR are insignificant except just one strategy of *J*=12/*K*=3 with 1-week jump. This result supports our hypothesis that firm-specific component contrarian strategy will be more profitable and significant than total-return-based strategy if return predictability based on past stock performance is induced from investors' overreaction to firm-specific information as many literatures discuss[6]. We can also infer that the resource of contrarian profits is not the investors' reaction to the total of systematic and firm-specific information.

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[6] Bernard (1992), Jegadeesh and Titman (1995), Chan, Jegadeesh and Lakonishok (1996), Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), Hong and Stein (1999), and Grinblatt and Han (2005).

Although overall performances of stocks in FC∩TR are similar with those in only-FC, they have a little difference. To be specific, the average returns on long-short portfolios of the only-FC are higher than those of the FC∩TR for shorter formation and holding period, however, stocks in the FC∩TR outperform stocks in the only-FC for longer formation period such as 9 and 12 weeks.

The difference among the subsets abviously reveals in long-term performance. Figure 1 exhibits the performances of three subsets for the contrarian long-short portfolios in 3 years. Y-axis is the CARs (cumulative average (weekly) abnormal returns) on long-short portfolios after contrarian ranking. CARs on stocks in only-TR are reversed, but the reversed returns (CARs) are very tiny. On the contrary, the CARs of FC∩TR and only-FC portfolios increase for about 90 weeks. Moreover, the value of their CARs are quite large. On average in 100 weeks, the only-FC subset generates the CARs of from 6.7% at J=1 to 14.1% at J=9. The FC∩TR subset generates CARs of from 4.8% at J=1 to 9.8% at J=9 on average in 100 weeks, which are similar with the sum of CARs on only-FC and on only-TR subset. Note that the stocks in only-FC subset may be extremely overreacted only to firm-specific information but not to total information. This result suggests that mispricing caused by overreaction to the firm-specific information is more slowly resolved for these period than total information.

In addition, since the magnitude of the firm-specific return is correlated with the idiosyncratic volatility, we may be able to get another hint from McLean(2010) about our result from Figure 1. He shows that idiosyncratic risk deters arbitrage regardless of the arbitrageur's diversification and return reversal is prevalent only in high idiosyncratic risk stocks, suggesting that idiosyncratic risk limits arbitrage in reversal mispricing.[7] According to his findings, the highest and steady outperformance of the only-FC subset can be induced from the limited

[7] See also Scholes (1972), Treynor and Black (1973) and Pontiff (2006) for further discussion that idiosyncratic risk limits arbitrage.

arbitrage in reversal mispricing by the idiosyncratic risk as stocks in the only-FC generate higher idiosyncratic risk.

V. The Decomposition of Contrarian Profits

A. Decomposition

To analyze the sources of firm-specific-component-based contrarian profits, we apply the decomposition in Lo and Mackinlay (1990). That is, we consider buying stocks in week *t* that were losers in week *t-k* and selling stocks in week *t* that were winners in week *t-k*. Let the realized stock return, $\tilde{R}_{it}$, be the return on stock *i* in week *t*, which is expressed as

$$\tilde{R}_{it} = E(R_{it}) + \tilde{\varepsilon}_{it}$$

where $E(R_{it})$ is the expected return on stock i in week t and $\tilde{\varepsilon}_{it}$ is the unexpected idiosyncratic return on stock i in week t. Mean of $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \cdots, \varepsilon_{Nt})'$ is zero, autocovariance matrix of ε_t is $\Gamma_k = E(\varepsilon_{t-k}\varepsilon_t{}')$ and variance of $\varepsilon_i = (\varepsilon_{it_1}, \varepsilon_{it_2}, \cdots, \varepsilon_{iT})'$ is $\sigma_{\varepsilon i}^2$. To model auto- and cross-serial correlation, we assume ε_{it} as follows.

$$E(\varepsilon_{it-1}\,\varepsilon_{it}) = \kappa\sigma_{\varepsilon i}^2 \neq 0$$

$$E\left(\varepsilon_{it-1}\varepsilon_{jt}\right) \neq 0$$

As $E(R_{it})$ is estimated from typical asset pricing models (e.g. the Fama-French three-factor model), the estimation error may be included as follows.

$$E(R_{it}) = \hat{E}(R_{it}) + \eta_{it} \tag{5}$$

$\hat{E}(R_{it})$ is the expected return estimated from asset pricing model, and η_{it} is the estimation error of the model on stock *i* in week *t*. η_{it} has zero mean with autocovariance matrix of $\Sigma_k = E(\eta_{t-k}\eta_t{}')$ and is not correlated with $\hat{E}(R_{it})$ and ε_{it}. Therefore, the realized stock return is

$$\tilde{R}_{it} \ = \ \hat{E}(R_{it}) + \eta_{it} + \tilde{\varepsilon}_{it}$$

As a result, the observed abnormal firm-specific return, r_{it} is $\eta_{it} + \varepsilon_{it}$. Mean of $r_t = (r_{1t}, r_{2t}, \cdots, r_{Nt})'$ is zero, autocovariance matrix of r_t is $\Omega_k = E(r_{t-k}r_t{}') = \Gamma_k + \Sigma_k$, and variance of $r_i = (r_{it_1}, r_{it_2}, \cdots, r_{iT})'$ is σ_{ri}^2. Thus, the standardized abnormal firm-specific return, that is, the firm-specific component, υ_{it}, which we use as main theme in this paper is

$$\upsilon_{it} = \frac{r_{it}}{\sigma_{ri}}$$

Applying the methodology of Lo and Mackinlay (1990), the portfolio weight for stock *i* in week *t* is

$$\omega_{it}(k) = -\frac{1}{N}(\upsilon_{it-k} - \bar{\upsilon}_{t-k}) \tag{6}$$

where $\bar{\upsilon}_{t-k} = (1/N)\sum_{i=1}^{N} \upsilon_{it-k}$ is the equal-weighted firm-specific component on market in week *t*, therefore, the expectation of $\bar{\upsilon}_{t-k}$ is zero. By construction, these weights lead to a zero cost portfolio since weights sum to zero.

$$\sum_{i=1}^{N} \omega_{it}(k) = 0$$

Therefore, the investment long (or short) at time *t* is given by

$$I_t(k) = \frac{1}{2}\sum_{i=1}^{N} |\omega_{it}(k)|$$

As many of literature discuss, since these weights are proportional to the differences between the security's firm-specific component and the equal-weighted portfolio’s, they capture the general belief that extreme price movements are followed by extreme movements (DeBondt and Thaler (1985), Lehmann (1990), Lo and MacKinlay (1990), and Jegadeesh and Titman (1993), Conrad and Kaul (1998)).

The contrarian profit from such a strategy in week *t* is

$$\pi_t(k) = \sum_{i=1}^{N} \omega_{it}(k) R_{it}$$

Rearranging this equation and taking expectations yields the following.

$$E[\pi_t(k)] = -\frac{1}{N} tr(\Psi_k) + \frac{1}{N^2}(i'\Psi_k i) \tag{7}$$

where matrix Ψ_k is expressed as follows,

$$\Psi_k = \begin{bmatrix} \rho_{11k}\sigma_{r1} & \rho_{12k}\sigma_{r2} & \rho_{13k}\sigma_{r3} & \cdots & \rho_{1Nk}\sigma_{rN} \\ \rho_{21k}\sigma_{r1} & \rho_{22k}\sigma_{r2} & \rho_{23k}\sigma_{r3} & \cdots & \rho_{2Nk}\sigma_{rN} \\ \rho_{31k}\sigma_{r1} & \rho_{32k}\sigma_{r2} & \rho_{33k}\sigma_{r3} & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho_{N1k}\sigma_{r1} & \cdots & \cdots & \cdots & \rho_{NNk}\sigma_{rN} \end{bmatrix}$$

or,

$$\Psi_k = \begin{bmatrix} Cov(r_{1t-k}, r_{1t})/\sigma_{r1} & Cov(r_{1t-k}, r_{2t})/\sigma_{r1} & \cdots & Cov(r_{1t-k}, r_{Nt})/\sigma_{r1} \\ Cov(r_{2t-k}, r_{1t})/\sigma_{r2} & Cov(r_{2t-k}, r_{2t})/\sigma_{r2} & \cdots & Cov(r_{2t-k}, r_{Nt})/\sigma_{r2} \\ \vdots & \vdots & \ddots & \vdots \\ Cov(r_{Nt-k}, r_{1t})/\sigma_{rN} & \cdots & \cdots & Cov(r_{Nt-k}, r_{Nt})/\sigma_{rN} \end{bmatrix}$$

and ρ_{ijk} is the correlation coefficient between r_{it-k} and r_{jt}. The derivation of equation (7) is included in Appendix.

Equation (7) can also be divided to two parts.

$$E[\pi_t(k)] = -O_k + C_k \tag{8}$$

where

$$O_k = \frac{N-1}{N^2} tr(\Psi_k)$$

and

$$C_k = \frac{1}{N^2} [i'\Psi_k i - tr(\Psi_k)]$$

Therefore, the profits of the firm-specific component contrarian strategy can be decomposed into two component, O_k, which is related to autocorrelation of firm-specific components for individual stocks, and C_k, which is related to cross-serial covariances among stocks' firm-specific components.

B. Lo and MacKinlay Type Contrarian Profits

Before the decomposition of expected contrarian profits, we assess the contrarian strategy builded by Lo and MacKinlay (1990) with firm-specific component. That is, the trading strategy is investing $\omega_{it}(k)$ of equation (6) in stock *i*. The weights are rescaled to have ₩1 long and ₩1 short. we reconstitute Lo and MacKinlay type five contrarian weighted portfolios with P1~P10. LS1 is the weighted portfolio buying P1 and selling P10 with each rescaled weight $\omega_{it}(k)$. LS2 is the weighted portfolio buying P2 and selling P9 with each rescaled weight $\omega_{it}(k)$, and so on.

Table 9 reports average weekly returns of Lo and MacKinlay type weighted portfolios, LS1~LS5, formed based on the past 1-, 3-, 6-, 9 and 12-week firm-specific component and held for 1-, 3-, 6-, 9 and 12-weeks. Average returns for the portfolios are calculated constructing overlapping portfolios using Jegadeesh and Titman (1993, 2001)'s methodology. Note that contrarian ranks have monotonic relationship with their performances in Table 4. we can predict that extreme price movements are followed by extreme movements of the firm-specific component. Since LS1 is from extreme portfolios, P1 and P10, it is natural that its performance is the highest among all weighted portfolios and always significant, however, the magnitudes of returns are smaller than Jegadeesh and Titman type contrarian performance in Table 3. All of contrarian profits in LS2 are significantly positive and smaller than those in LS1 for equal *J/K* strategy. Contrarian profits in LS3 are smaller than LS2, and the profits for 10 of 25 strategies with 1-week jump and 2 of 25 strategies without 1-week jump are not significant. For LS4, the profits for 13 of 25 strategies without 1-week jump and only 3 of 25 strategies with 1-week jump are significant. Most of contrarian profits in LS5 are positive but all of them are insignificant. Overall, the Lo and MacKinlay type contrarian strategy based on the firm-specific component earns the significantly positive profits as Jegadeesh and Titman type strategy, especially in LS1. Therefore, it can be confirmed that the firm-specific component contrarian profit does not depend on calculation methods.

C. Sources of the Contrarian Profits

we decompose the expected contrarian profits based on the firm-specific component using equation (8) to investigate the sources of these contrarian profits. we calculate the time-series values of O_k and C_k, O_{kt} and C_{kt}, using equation (A2) and (A4), and then $\hat{O}_k$ and $\hat{C}_k$ are estimated from equation (A1) and (A3).

Table 10 reports the estimated components of decomposition, $\hat{O}_k$ and $\hat{C}_k$, expected contrarian profits summed $\hat{O}_k$ and $\hat{C}_k$, and their ratios to profits, %-$\hat{O}_k$ and %-$\hat{C}_k$, for all stocks and the LS1 portfolio. %-$\hat{O}_k$ is the ratio of $-\hat{O}_k$ over the expected contrarian profit and %-$\hat{C}_k$ is the ratio of $\hat{C}_k$ over the expected contrarian profit. *z*-statistics are asymptotically N(0, 1) under the null hypothesis that the relevant parameter is zero and are robust to heteroscedasticity and autocorrelation.

According to the result for all stocks in Table 10, $\hat{O}_k$ is negative for 1-week lag, which means that there are negative autocorrelation of firm-specific returns for individual stocks, but insignificant. Also, since $\hat{C}_k$ is significantly positive in 1-week lag for all stocks, there are positive cross-serial covariances among stocks' firm-specific returns. That is, in this case, the source of the contrarian profits is mainly cross effect not overreaction. This result is very similar with literatures such as Chae and Eom (2009) that calculate autocorrelation for individual stocks and cross-serial covariances among stocks for 1-week lag with raw returns of all Korean stocks. However, in longer lag, the results are different with that. In 2-and 3-week lag, $\hat{O}_k$ is significantly negative and $\hat{C}_k$ is insignificantly negative. In 4-week lag, $\hat{O}_k$ and $\hat{C}_k$ are significantly negative. Note that positive $\hat{C}_k$ can be a help to positive contrarian profit but negative $\hat{C}_k$ reduce the contrarian profits and can cause rather momentum. These results show that the effect of strongly negative autocorrelation of firm-specific returns for individual stocks is more powerful than that of cross-serial covariances among stocks' firm-specific returns, which induces the positive contrarian profits. Therefore, the resource of contrarian profits is negative autocorrelation for individual stocks' firm-specific returns, that is, investors' overreaction to firm-specific information.

Since our contrarian portfolios consist of stocks with extreme firm-specific components, not all stocks in market, it is reasonable that I decompose the extreme contrarian portfolio, LS1, into O_k and C_k. The raw of *J*=1 LS1~ *J* =9 LS1 in Table 10 display these decomposition results. For 1- and 2-week lag of all portfolios, I cannot find significant relationship among $\hat{O}_k$, $\hat{C}_k$ and profits. However, for 3- and 4-week lag of all portfolios, both $\hat{O}_k$ and $\hat{C}_k$ are significantly negative and the effect of $\hat{O}_k$ is larger than that of $\hat{C}_k$, which leads the positive contrarian profits. In conclusion, investors' overreaction to firm-specific information causes positive contrarian profits despite the impediment of cross effect among stocks' firm-specific returns.

D. Decomposition of Decomposition

Although we decompose the contrarian portfolios to find the source of the profits in previous section, it cannot success to reveal the detailed relationship among autocovariances and cross-serial covariances of winners and losers. As it is perfectly possible that the propensity of winners is different with that of losers, the relationships among winners, among losers, and between winners and losers can vary. Moreover, the different relationships can cancel each other out so that the real source cannot emerge through decomposition. Thus, I further decompose total autocovariances in the extreme contrarian portfolios (LS1) into autocovariances between winners and between losers, and also do total cross-serial covariances in LS1 into winners', losers and their mutual cross-serial covariance, referring Chae and Eom (2009). From this decomposition of decomposition, the detailed source of contrarian profits based on firm-specific component can be revealed.

Table 11 shows the results for the decomposition of decomposition. O_k is divided up into $\hat{O}_{W,k}$ of autocovariances between winners at lag *k* and $\hat{O}_{L,k}$ of autocovariances between losers at lag *k*. Also, C_k is divided up into $\hat{C}_{W,k}$ of cross-serial covariances across winners' *k*-week previous firm-specific components and current firm-specific returns, $\hat{C}_{L,k}$ of cross-serial covariances across losers', $\hat{C}_{LW,k}$ of cross-serial covariances across *k*-week previous losers' and current winners', and $\hat{C}_{WL,k}$ of cross-serial covariances across *k*-week previous winners' and current losers'.

According to the results, every column of Table 11 has consistent tendency. Furthermore, almost all of covariances are significant. The autocovariances between winners, $\hat{O}_{W,k}$, are negative, and those between losers, $\hat{O}_{L,k}$, are positive. The cross-serial covariances across winners, $\hat{C}_{W,k}$, are negative, those across loser, $\hat{C}_{L,k}$, are positive, those across *k*-week previous losers and current winners, $\hat{C}_{LW,k}$, are positive, and finally those across *k*-week previous winners and current losers, $\hat{C}_{WL,k}$, are negative. Therefore, $\hat{O}_{W,k}$, $\hat{C}_{L,k}$ and $\hat{C}_{LW,k}$ are a help to the positive contrarian profits and sources of the profits. Considering that the total autocovariances ($\hat{O}_k$) and the total cross-serial covariances ($\hat{C}_k$) are negative, the autocovariances between winners ($\hat{O}_{W,k}$) are the most powerful to generate contrarian profits.

That is, investors' overreaction to winners is the main source of the profits, rather than systematic cross effect between stocks.

E. Robust Check of Decomposition with Liquidity Factor

It is possible that the decomposition of equation (8) cannot resolve the model misspecification like factor-missing as equation (5) involves estimation error, η_{it}. Thus, we examine whether the result from decomposition is robust even when other model is used to estimate the expected returns. Since I utilize the Fama-French three-factor model to estimate the expected returns, we add another factor, liquidity factor in our model.

Prior to constructing liquidity factor, I calculate Amihud (2002) illiquidity measure which represent the illiquidity of individual stock. Amihud (2002) illiquidity measure based on the Choe and Yang (2009) that study the liquidity with the Korean stock market is defined as

$$ILLIQ_{im} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} \frac{|R_{imd}|}{VOLD_{imd}}$$

where $|R_{imd}|$ is the return for stock *i* on day *d* in month *m*, $VOLD_{imd}$ is won volume (in 10 million won) for stock *i* on day *d* in month *m*, and D_{im} is the number of valid observation days for stock *i* in month *m*. To building the mimicking liquidity factor (*LIQF*), all sample firms are sorted based on the average of monthly $ILLIQ_{im}$ over the prior 1 year at the end of June of year τ, and divided into two average $ILLIQ_{it}$ groups: the bottom 50% and top 50%. Then I calculate value-weighted weekly returns on the two portfolios from July of τ to June of $\tau + 1$ for July 1987 to June 2014. Consequently, the mimicking liquidity factor, *LIQF*, is the returns on the highest-illiquidity-stock portfolios (top 50%) minus the returns on the lowest-illiquidity-stock portfolios (bottom 50%). Now I estimate the coefficients including *LIQF*'s coefficients, *l*, with following time-series regression of the equation (9) over the previous 52-week rolling windows, [*t*-52, *t*-1].

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + l_i LIQF_t + \varepsilon_{it} \tag{9}$$

In succession, the new firm-specific return of the stock *i* in week *t* with the estimated constant and factor loadings of equation (9) is calculated as follows.

$$\varepsilon_{it} = R_{it} - R_{ft} - [\hat{\alpha}_i + \hat{\beta}_i\left(R_{mt} - R_{ft}\right) + \hat{s}_i SMB_t + \hat{h}_i HML_t + \hat{l}_i LIQF_t] \tag{10}$$

As a result, we calculate the new firm-specific component using equation (3) with ε_{it} and $\sigma(\varepsilon_{it})$ from equation (10). And with this new firm-specific component, we decompose the expected contrarian profit applying equation (8) again. The result is presented in Table 12. Overall, the values and patterns of $\hat{O}_k$, $\hat{C}_k$ and profits in Table 12 are very similar with those in Table 10, which shows that model misspecification such as factor-missing does not cause the negative autocorrelation for individual stocks' firm-specific returns to be the resource of contrarian profits and that adding factors do not weaken the negative autocorrelation or not boost the positive cross-serial covariances among stocks' firm-specific returns. Rather, all of the positive cross-serial covariances decrease by adding liquidity factor whereas there is not systematic change in $\hat{O}_k$. That is, adding factors and then using more elaborative model support that the investors' overreaction to winners is the resource of contrarian profits, diminishing effects of systematic structure expressed by the cross-serial covariances, $\hat{C}_k$.

we also performs the decomposition of decomposition among winners and losers with 4-factor model including liquidity factor as above section D. Table 13 present the result from the decomposition of decomposition using liquidity factors. $\hat{O}_{W,k}$, $\hat{O}_{L,k}$, $\hat{C}_{W,k}$, $\hat{C}_{L,k}$, $\hat{C}_{LW,k}$ and $\hat{C}_{WL,k}$ in Table 13 are equally designated with those in Table 11. The result of the decomposition of decomposition with liquidity factor is similar with Table 11 as well. Nevertheless, all of $\hat{C}_{W,k}$, $\hat{C}_{L,k}$, $\hat{C}_{LW,k}$ and $\hat{C}_{WL,k}$ decrease compared to those in Table 11 while some of $\hat{O}_{W,k}$ and $\hat{O}_{L,k}$ increase and the others of them decrease. This result confirms again that our decomposition is valid regardless of used model and that more accurate model can diminish the effects from systematic structure in stock market without decrease of effect from the investors' irrational reaction. In conclusion, the decomposition and the result that investors' overreaction to winners is the resource of contrarian profits are robust even with liquidity factor.

VI. Conclusion

we examine the profitability of contrarian strategy based on weekly firm-specific component estimated by asset pricing model with Korean stocks. The strategy follows Jegadeesh and Titman (1993, 2001)'s methodology but buying past loser and selling past winner. And I rank stocks on firm-specific component that is calculated as firm-specific return divided by its standard deviation, to form contrarian portfolios. As a result, the contrarian strategy based on weekly firm-specific component outperforms that based on total returns. The profitability of firm-specific-component-based contrarian strategy is larger, more significant and steadier. This result is not due to size or idiosyncratic volatility effect, despite the highest size of stocks with the highest past firm-specific components. Also, the high average returns of firm-specific-component contrarian strategy are still significant, however, the significance of general total-return contrarian profits decreases. Furthermore, all contrarian portfolios based on past firm-specific component generate significantly and continuously positive profits whether they belong to total-return-based contrarian portfolios, while stocks both in total-return-based and not in firm-specific-component-based contrarian portfolios cannot earn significant positive profits.

we investigate our hypothesis that contrarian strategy based on firm-specific component is more meaningful and powerful underlying that the profitability of stock returns based on their past performance is caused by investors' irrational reaction to firm-specific information. Thus, we additionally anaylize to uncover that underlying hypothesis decomposing the contrarian profit with Lo and MacKinlay (1990)'s methodology. we utilize their analytic frame to decompose the firm-specific-component-based contrarian profit into autocovariance of individual stocks and cross-serial covariance of securities. Morevoer, we decompose the portfolios of winner and loser as well as all stocks, and further do total autocovariances into winners' autocovariances and losers's autocovariances and do total cross-serial covariance into winners', losers' and their mutual cross-serial covariance, referring Chae and Eom (2009). From this decomposition of decomposition, the detailed source of contrarian profits can be revealed.

we find that weekly firm-specific returns of individual stocks are negatively autocorrelated and insignificantly positively cross-serial correlated. This result implies that contrarian profits using firm-specific component are induced by investors' overreaction to firm-specific information, not by cross-serial covariances across stocks' firm-specific returns. Meanwhile, according to the decomposition of decomposition in winners and losers, autocovariances and cross-serial covariances in them are asymmetric. 1) past firm-specific components and current firm-specific returns of winners are negatively autocorrelated, 2) those of losers are positively autocorrelated, 3) those across stocks in winner portfolio are negatively cross-serial correlated, 4) those across stocks in loser portfolio are positively cross-serial correlated, 5) past firm-specific components of losers and current firm-specific returns of winners are positively cross-serial correlated, and 6) past firm-specific components of winners and current firm-specific returns of losers are negatively cross-serial correlated. These relationships do not change as the past is 1-week lag to 4-week lag from current week. Therefore, the contrarian profit primarily arises from negative autocovariances of winners, recalling that negative autocovariances of individual stocks is surce of contrarian profits in the first simple decomposition. And the conclusion suggests that investors overreact to big stocks' good firm-specific news, when it is considered that size of winners is the bigger. On the contrary, investors underreact to stocks' bad firm-specific news, the extend of which is smaller than that of overreaction to big stocks' good news. In addition, the winners', losers and their mutual cross-serial covariance have consistent signs, however, the total sum of them is insignificant.

Appendix

Derivation of equation (7) is

$$\pi_t(k) = \sum_{i=1}^{N} \omega_{it}(k) R_{it} = \sum_{i=1}^{N} -\frac{1}{N}(\upsilon_{it-k} - \bar{\upsilon}_{t-k}) R_{it}$$

$$= -\frac{1}{N}\sum_{i=1}^{N}(\upsilon_{it-k} R_{it}) + \frac{1}{N}\sum_{i=1}^{N}(\bar{\upsilon}_{t-k} R_{it})$$

$$= -\frac{1}{N}\sum_{i=1}^{N}(v_{it-k}\, R_{it}) + \bar{v}_{t-k}\,\frac{1}{N}\sum_{i=1}^{N} R_{it}$$

$$= -\frac{1}{N}\sum_{i=1}^{N}(v_{it-k}\, R_{it}) + \bar{v}_{t-k}\bar{R}_t$$

$$E[\pi_t(k)] = -\frac{1}{N}\sum_{i=1}^{N} E(v_{it-k}\, R_{it}) + E(\bar{v}_{t-k}\bar{R}_t)$$

$$= -\frac{1}{N}\sum_{i=1}^{N} E[\frac{r_{it-k}}{\sigma_{ri}}(\hat{E}(R_{it}) + r_{it}\,)] + E[\bar{v}_{t-k}(\hat{E}(\bar{R}_t) + \bar{r}_t\,)]$$

$$= -\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\sigma_{ri}} E[r_{it-k}\,\hat{E}(R_{it}) + r_{it-k}r_{it}] + E[\bar{v}_{t-k}\hat{E}(\bar{R}_t) + \bar{v}_{t-k}\bar{r}_t\,]$$

$$= -\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\sigma_{ri}}[E(r_{it-k}\,\hat{E}(R_{it})) + E(r_{it-k}r_{it})] + E[\bar{v}_{t-k}\hat{E}(\bar{R}_t)] + E(\bar{v}_{t-k}\bar{r}_t)$$

$$= -\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\sigma_{ri}}[E(r_{it-k})\,\hat{E}(R_{it}) + Cov\left(r_{it-k}, \hat{E}(R_{it})\right) + Cov(r_{it-k}, r_{it})$$

$$+ E(r_{it-k})E(r_{it})] + E(\bar{v}_{t-k})\hat{E}(\bar{R}_t) + Cov(\bar{v}_{t-k}, \hat{E}(\bar{R}_t))$$

$$+ Cov(\bar{v}_{t-k}, \bar{r}_t) + E(\bar{v}_{t-k})E(\bar{r}_t)$$

$$= -\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\sigma_{ri}} Cov(r_{it-k}, r_{it}) + Cov(\bar{v}_{t-k}, \bar{r}_t)$$

$$= -\frac{1}{N}\sum_{i=1}^{N}\frac{Cov(\,r_{it-k}, r_{it})}{\sigma_{ri}} + \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{Cov(\,r_{it-k}, r_{jt})}{\sigma_{ri}}$$

$$= -\frac{1}{N}\sum_{i=1}^{N}\rho_{iik}\sigma_{ri} + \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\rho_{ijk}\sigma_{rj}$$

$$E[\pi_t(k)] = -\frac{1}{N} tr(\Psi_k) + \frac{1}{N^2}(i'\Psi_k i) \qquad (7)$$

The elements of firm-specific-component-based contrarian profits are estimated by allowing auto and cross-serial covariances (equation (8)) to be time dependent as Lo and MacKinlay (1990) and Conrad and Kaul(1998). Then,

$$\hat{O}_k = \frac{1}{T-k}\sum_{t=k+1}^{T} O_{kt} \qquad (A1)$$

where

$$O_{kt} = \frac{N-1}{N^2}\sum_{i=1}^{N}\frac{1}{\sigma_{ri}}\left(r_{it-k}r_{it} - \hat{\mu}_i^2\right) \qquad (A2)$$

and $\hat{\mu}_i$ is the usual sample mean of the returns to security *i*. Also,

$$\hat{C}_k = \frac{1}{T-k}\sum_{t=k+1}^{T} C_{kt} \qquad (A3)$$

where

$$C_{kt} = \frac{1}{N^2}\left[\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{1}{\sigma_{ri}}\left(r_{it-k}r_{jt} - \hat{\mu}_i\hat{\mu}_j\right) - \sum_{i=1}^{N}\frac{1}{\sigma_{ri}}\left(r_{it-k}r_{it} - \hat{\mu}_i^2\right)\right] \qquad (A4)$$

We follow most of Lo and MacKinlay (1990)'s assumptions and methdology of derivation for the elements of contrarian profits, however, there are difference in equation (A4).

While Lo and MacKinlay (1990) use market return, $R_{mt-k},$ and mean of the market return, $\hat{\mu}_m,$ to calculate the sum of all elements in *k*th-order auto and cross-serial covariance matrix of stock returns in the first term of cross-serial covariances in time *t*, C_{kt}, we calculate the first term of C_{kt}, $i'\Psi_k i$, with all individual stocks at every time *t* as (A4) shows.

Finally, as Lo and MacKinlay (1990)'s Assumption A3, consistent estimators of the asymptotic variance of the estimators $\hat{O}_k$ and $\hat{C}_k$ which may be obtained along the lines of Newey and West (1987) are equivalent to (A16) and (A17) in Lo and MacKinlay (1990). As a result, these asymptotic variance estimators are robust to general forms of heteroskedasticity and autocorrelation in the O_{kt} and C_{kt} time series.

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Table 1. Summary Statistics of Contrarian Portfolios based on the Firm-specific Component

This table reports the summary statistics for contrarian portfolios formed based on the past 1-and 3-week firm-specific component on stock returns. Reported statistics are mean, standard deviation (*STD*) and median of every characteristics. The firm-specific component is produced from equation (2) and (3). That is, the firm-specific abnormal returns, real returns minus expected retursn estimated with the Fama-French three-factor model, are divided by standard deviations of firm-specific returns. P1 (loser) is the equal-weighted portfolio of 10 percent of the stocks with the highest firm-specific components over the previous *J* months, and P10 (winner) is the equal-weighted portfolio of the 10 percent of the stocks with the lowest firm-specific components. FC is the firm-specific component on stock returns in percentage. Size is the market capitalization of stock in billion won. BE/ME is book-to-market equity ratio which is BE for the fiscal year ending in calendar year $\tau - 1$ divided by ME (market equity) at the end of December of $\tau - 1$. α, β, s and h are the constant and coefficients in the time-series regressions (equation (1)) of the Fama-French three-factor model. α is the intercept, β is the coefficient of market factor, s is that of size factor, and h is that of BE/ME factor in the Fama-French model. IV is the idiosyncratic volatility, which is calculated as the standard deviation of residuals in equation (1), $\sqrt{var(\varepsilon_{it})}$. Panel A presents the characteristics of contrarian portfolios based on 1-week lagged firm-specific components, and Panel B presents those based on 3-week lagged firm-specific components. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

Panel A. *J*=1

		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
FC	Mean	-1.66	-1	-0.71	-0.48	-0.29	-0.1	0.12	0.39	0.78	1.93
	STD	0.75	0.45	0.4	0.38	0.37	0.37	0.39	0.43	0.51	1.45
	Median	-1.52	-0.94	-0.67	-0.46	-0.28	-0.11	0.09	0.34	0.7	1.6
Size	Mean	591.0	609.7	588.4	604.5	611.1	638.4	710.0	844.7	962.8	866.6
	STD	4001	4041	4204	4330	4426	4240	4557	5404	5832	5187
	Median	57.6	59.1	58.2	58.4	58.0	60.4	64.7	70.5	78.1	73.3
BE/ME	Mean	1.69	1.67	1.6	1.56	1.5	1.45	1.43	1.48	1.47	1.38
	STD	6.31	6.47	6.55	7.85	10.39	9.69	10.09	7.33	4.57	5.75
	Median	1.4	1.36	1.32	1.29	1.26	1.24	1.22	1.19	1.15	1.11
α	Mean	0.39	0.37	0.35	0.35	0.34	0.33	0.32	0.31	0.32	0.33
	STD	0.45	0.45	0.44	0.44	0.43	0.43	0.43	0.42	0.42	0.43
	Median	0.31	0.29	0.28	0.27	0.27	0.26	0.26	0.25	0.25	0.26
β	Mean	0.97	0.97	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
	STD	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
	Median	0.97	0.97	0.97	0.97	0.96	0.96	0.96	0.96	0.97	0.96
s	Mean	0.62	0.61	0.62	0.62	0.61	0.60	0.59	0.57	0.55	0.59
	STD	0.50	0.48	0.47	0.47	0.47	0.48	0.49	0.50	0.52	0.54
	Median	0.71	0.70	0.71	0.70	0.70	0.70	0.68	0.67	0.65	0.68
h	Mean	0.28	0.25	0.24	0.22	0.21	0.19	0.18	0.17	0.16	0.16
	STD	0.49	0.47	0.46	0.46	0.47	0.48	0.49	0.49	0.51	0.58
	Median	0.33	0.31	0.29	0.28	0.27	0.26	0.25	0.24	0.23	0.24
IV	Mean	2.27	2.26	2.26	2.26	2.26	2.25	2.24	2.2	2.19	2.23
	STD	1.1	1.08	1.06	1.07	1.08	1.08	1.09	1.09	1.12	1.21
	Median	1.97	1.95	1.96	1.96	1.95	1.95	1.93	1.91	1.89	1.91

Panel B. *J*=3											
		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
FC	Mean	-3.01	-1.89	-1.38	-0.99	-0.64	-0.29	0.10	0.57	1.26	3.20
	STD	1.28	0.83	0.75	0.71	0.69	0.70	0.72	0.77	0.89	2.35
	Median	-2.79	-1.80	-1.31	-0.95	-0.62	-0.30	0.06	0.50	1.15	2.64
Size	Mean	459.5	530.8	530.2	574.3	615.0	651.5	784.5	934.1	1068.6	890.1
	STD	3291	3593	3505	4606	4388	4212	5051	5788	5859	5484
	Median	53.8	55.8	55.8	56.2	57.5	61.7	66.4	74.2	85.0	79.1
BE/ME	Mean	1.80	1.74	1.70	1.54	1.49	1.43	1.46	1.39	1.38	1.31
	STD	5.98	5.05	5.23	10.27	10.17	10.92	7.95	7.79	6.32	4.19
	Median	1.52	1.42	1.36	1.32	1.28	1.24	1.20	1.15	1.10	1.03
α	Mean	0.41	0.37	0.36	0.35	0.33	0.33	0.31	0.31	0.31	0.34
	STD	0.46	0.45	0.44	0.43	0.42	0.43	0.42	0.42	0.41	0.43
	Median	0.32	0.29	0.28	0.27	0.26	0.26	0.25	0.25	0.25	0.27
β	Mean	0.97	0.97	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
	STD	0.18	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
	Median	0.97	0.97	0.97	0.97	0.96	0.96	0.96	0.96	0.96	0.96
s	Mean	0.64	0.62	0.62	0.62	0.61	0.60	0.58	0.56	0.53	0.65
	STD	0.50	0.47	0.46	0.46	0.46	0.48	0.49	0.50	0.52	0.55
	Median	0.72	0.71	0.71	0.71	0.70	0.69	0.68	0.67	0.63	0.68
h	Mean	0.33	0.28	0.26	0.23	0.21	0.19	0.17	0.15	0.13	0.14
	STD	0.51	0.46	0.44	0.44	0.45	0.47	0.49	0.51	0.52	0.58
	Median	0.37	0.32	0.31	0.29	0.27	0.25	0.24	0.22	0.21	0.22
IV	Mean	2.32	2.27	2.26	2.26	2.25	2.24	2.22	2.20	2.17	2.24
	STD	1.12	1.07	1.06	1.06	1.05	1.08	1.08	1.12	1.13	1.22
	Median	2.00	1.97	1.96	1.95	1.95	1.94	1.92	1.90	1.88	1.91

Table 2. Contrarian Profits based on Total Returns and Expected Returns

This table reports the average weekly returns for contrarian portfolios formed based on the past *J*-week total returns or expected returns, and held for *K* weeks, applying Jegadeesh and Titman (1993, 2001)'s methodology. The expected returns are estimated from the Fama-French three-factor model of equation (1). P1 (loser) is the equal-weighted portfolio of 10 percent of the stocks with the highest total returns or expected returns over the previous *J* months, and P10 (winner) is the equal-weighted portfolio of the 10 percent of the stocks with the lowest total returns or expected returns. Panel A presents the profits of the total-return-based contrarian strategy. Panel B presents the expected-return-based contrarian profits. The "without 1-week Jump" portfolios are formed immediately after the lagged raw returns and expected returns used for forming these portfolios. The "with 1-week Jump" portfolios are formed 1 week after the lagged returns and expected returns are measured for the purpose of portfolio formation. The *t*-statistics are reported in parentheses. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

Panel A : Total Returns Contrarian Profits																			
			without 1-week Jump									with 1-week Jump							
J		*K*=	1	2	3	4	6	9	12	16	20	1	2	3	4	6	9	12	16	20
1	P1		0.501	0.355	0.320	0.312	0.322	0.309	0.292	0.293	0.291	0.210	0.231	0.249	0.270	0.284	0.286	0.262	0.280	0.280
	P10		0.139	0.202	0.203	0.180	0.150	0.177	0.190	0.204	0.228	0.262	0.234	0.194	0.161	0.159	0.184	0.201	0.219	0.237
	P1−P10		0.361	0.153	0.117	0.131	0.172	0.132	0.102	0.089	0.063	-0.052	-0.003	0.055	0.109	0.125	0.102	0.061	0.061	0.043
	t-stat.		(2.69)	(1.62)	(1.57)	(2.07)	(3.35)	(3.15)	(2.75)	(2.70)	(2.10)	(-0.54)	(-0.04)	(0.90)	(2.61)	(2.72)	(2.58)	(1.73)	(1.92)	(1.50)
3	P1		0.367	0.283	0.288	0.305	0.318	0.303	0.285	0.284	0.273	0.198	0.247	0.283	0.296	0.301	0.289	0.278	0.277	0.267
	P10		0.244	0.210	0.138	0.091	0.082	0.134	0.164	0.168	0.194	0.175	0.084	0.041	0.040	0.077	0.135	0.156	0.181	0.198
	P1−P10		0.123	0.073	0.150	0.214	0.236	0.169	0.121	0.116	0.079	0.022	0.163	0.243	0.256	0.224	0.154	0.122	0.095	0.068
	t-stat.		(0.92)	(0.65)	(1.49)	(2.33)	(2.97)	(2.48)	(1.99)	(2.13)	(1.58)	(0.20)	(1.63)	(2.64)	(3.01)	(3.00)	(2.33)	(2.05)	(1.79)	(1.40)
6	P1		0.456	0.380	0.357	0.357	0.343	0.328	0.313	0.298	0.281	0.302	0.320	0.323	0.325	0.310	0.314	0.293	0.282	0.270
	P10		0.025	0.052	0.035	0.038	0.069	0.133	0.153	0.179	0.196	0.077	0.039	0.043	0.058	0.106	0.157	0.168	0.200	0.211
	P1−P10		0.431	0.328	0.322	0.319	0.275	0.195	0.160	0.119	0.086	0.225	0.280	0.280	0.267	0.203	0.157	0.125	0.082	0.059
	t-stat.		(3.23)	(2.73)	(2.95)	(3.00)	(2.81)	(2.24)	(2.00)	(1.64)	(1.28)	(1.92)	(2.55)	(2.67)	(2.65)	(2.16)	(1.86)	(1.61)	(1.17)	(0.90)
9	P1		0.460	0.397	0.395	0.387	0.374	0.362	0.341	0.315	0.291	0.333	0.361	0.362	0.362	0.356	0.344	0.321	0.303	0.276
	P10		0.052	0.069	0.073	0.080	0.126	0.168	0.183	0.195	0.211	0.086	0.084	0.090	0.115	0.159	0.190	0.199	0.214	0.222
	P1−P10		0.408	0.327	0.322	0.307	0.248	0.194	0.158	0.120	0.080	0.247	0.277	0.272	0.247	0.197	0.154	0.123	0.089	0.054
	t-stat.		(3.00)	(2.59)	(2.70)	(2.67)	(2.31)	(1.95)	(2.54)	(1.40)	(1.00)	(1.99)	(2.36)	(2.39)	(2.24)	(1.89)	(1.58)	(1.34)	(1.06)	(0.69)
12	P1		0.495	0.424	0.409	0.409	0.397	0.374	0.346	0.308	0.280	0.353	0.364	0.379	0.381	0.372	0.352	0.318	0.288	0.266
	P10		0.117	0.134	0.136	0.136	0.164	0.202	0.202	0.211	0.225	0.148	0.143	0.142	0.157	0.189	0.216	0.208	0.226	0.233
	P1−P10		0.378	0.291	0.273	0.273	0.233	0.172	0.144	0.097	0.055	0.204	0.220	0.237	0.225	0.183	0.136	0.110	0.062	0.033
	t-stat.		(2.77)	(2.27)	(2.24)	(3.13)	(2.06)	(1.61)	(1.42)	(1.03)	(0.62)	(1.63)	(1.84)	(2.02)	(1.96)	(1.66)	(1.30)	(1.10)	(0.67)	(0.38)

Panel B: Expected Return Contrarian Profits																			
		without 1-week Jump									with 1-week Jump								
J	*K*=	1	2	3	4	6	9	12	16	20	1	2	3	4	6	9	12	16	20
1	P1	0.321	0.323	0.324	0.326	0.327	0.316	0.308	0.313	0.320	0.367	0.333	0.354	0.328	0.336	0.322	0.312	0.311	0.315
	P10	0.339	0.343	0.342	0.342	0.340	0.330	0.326	0.324	0.325	0.323	0.323	0.324	0.317	0.319	0.326	0.320	0.327	0.328
	P1−P10	-0.018	-0.021	-0.017	-0.016	-0.013	-0.014	-0.018	-0.012	-0.005	0.044	0.011	0.029	0.011	0.017	-0.004	-0.008	-0.017	-0.012
	t-stat.	(-0.43)	(-0.60)	(-0.57)	(-0.56)	(-0.50)	(-0.56)	(-0.75)	(-0.50)	(-0.20)	(0.65)	(0.20)	(0.62)	(0.25)	(0.43)	(-0.12)	(-0.24)	(-0.53)	(-0.40)
3	P1	0.334	0.338	0.331	0.328	0.321	0.307	0.304	0.318	0.324	0.326	0.335	0.316	0.299	0.312	0.312	0.309	0.299	0.302
	P10	0.365	0.349	0.359	0.355	0.343	0.345	0.344	0.338	0.335	0.305	0.285	0.293	0.303	0.301	0.317	0.315	0.314	0.317
	P1−P10	-0.031	-0.012	-0.028	-0.027	-0.022	-0.038	-0.040	-0.020	-0.011	0.021	0.050	0.023	-0.004	0.011	-0.005	-0.006	-0.015	-0.015
	t-stat.	(-0.69)	(-0.30)	(-0.77)	(-0.79)	(-0.69)	(-1.28)	(-1.38)	(-0.71)	(-0.39)	(0.31)	(0.85)	(0.43)	(-0.07)	(0.23)	(-0.12)	(-0.14)	(-0.39)	(-0.40)
6	P1	0.347	0.344	0.344	0.331	0.311	0.310	0.312	0.320	0.325	0.290	0.316	0.318	0.323	0.321	0.330	0.309	0.295	0.293
	P10	0.343	0.344	0.336	0.330	0.324	0.333	0.332	0.327	0.330	0.316	0.308	0.320	0.307	0.314	0.325	0.320	0.315	0.321
	P1−P10	0.005	0.000	0.007	0.001	-0.012	-0.022	-0.020	-0.008	-0.005	-0.027	0.008	-0.003	0.016	0.006	0.005	-0.011	-0.019	-0.027
	t-stat.	(0.11)	(-0.01)	(0.19)	(0.03)	(-0.34)	(-0.66)	(-0.62)	(-0.25)	(-0.17)	(-0.42)	(0.13)	(-0.05)	(0.30)	(0.13)	(0.10)	(-0.25)	(-0.44)	(-0.65)
9	P1	0.327	0.324	0.315	0.308	0.307	0.317	0.322	0.324	0.328	0.350	0.336	0.328	0.327	0.334	0.321	0.294	0.290	0.286
	P10	0.331	0.344	0.348	0.349	0.346	0.340	0.334	0.329	0.330	0.296	0.313	0.330	0.329	0.327	0.325	0.317	0.320	0.322
	P1−P10	-0.004	-0.020	-0.033	-0.041	-0.039	-0.022	-0.012	-0.005	-0.002	0.053	0.022	-0.003	-0.002	0.006	-0.005	-0.025	-0.032	-0.037
	t-stat.	(-0.10)	(-0.49)	(-0.84)	(-1.08)	(-1.05)	(-0.63)	(-0.35)	(-0.15)	(-0.06)	(0.32)	(0.14)	(-0.02)	(-0.02)	(0.04)	(-0.03)	(-0.16)	(-0.20)	(-0.23)
12	P1	0.308	0.314	0.308	0.305	0.314	0.330	0.326	0.323	0.327	0.318	0.336	0.334	0.326	0.309	0.285	0.263	0.263	0.265
	P10	0.353	0.334	0.337	0.335	0.339	0.340	0.332	0.326	0.325	0.359	0.339	0.342	0.343	0.340	0.331	0.326	0.327	0.328
	P1−P10	-0.045	-0.020	-0.028	-0.030	-0.025	-0.010	-0.006	-0.002	0.002	-0.043	-0.005	-0.009	-0.018	-0.032	-0.048	-0.064	-0.065	-0.064
	t-stat.	(-1.05)	(-0.48)	(-0.70)	(-0.76)	(-0.64)	(-0.26)	(-0.16)	(-0.07)	(0.05)	(-0.26)	(-0.03)	(-0.06)	(-0.11)	(-0.21)	(-0.31)	(-0.40)	(-0.41)	(-0.41)

Table 3. Contrarian Profits based on the Firm-specific Component

This table reports the average weekly returns for contrarian portfolios formed based on past *J*-week firm-specific components and held for *K* weeks. The firm-specific component is produced from equation (2) and (3). That is, the firm-specific abnormal returns, real returns minus expected returns estimated with the Fama-French three-factor model, are divided by standard deviations of the firm-specific returns. P1 (loser) is the equal-weighted portfolio of 10 percent of the stocks with the highest firm-specific component over the previous *J* months, and P10 (winner) is the equal-weighted portfolio of the 10 percent of the stocks with the lowest firm-specific component. Panel A presents the profits of the firm-specific-component-based contrarian strategy, applying Jegadeesh and Titman (1993, 2001)'s methodology. Panel B presents the risk-adjusted returns of the firm-specific-component contrarian portfolios which are formed applying Jegadeesh and Titman (1993, 2001)'s methodology. The risk-adjusted returns are the intercepts from Fama-French three-factor regressions. Also, Panel C presents the holding period returns of the firm-specific-component contrarian portfolios. The holding period returns are calculated following Conrad and Kaul (1993)'s holding period abnormal performance measure of equation (4). The "without 1-week Jump" portfolios are formed immediately after the lagged firm-specific components used for forming these portfolios. The "without 1-week Jump" portfolios are formed 1 week after the lagged firm-specific components are measured for the purpose of portfolio formation. The *t*-statistics are reported in parentheses. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

Panel A : Firm-specific Component Contrarian Profits

			without 1-week Jump									with 1-week Jump								
J		*K*=	1	2	3	4	6	9	12	16	20	1	2	3	4	6	9	12	16	20
1	P1		0.704	0.506	0.462	0.435	0.421	0.394	0.367	0.349	0.348	0.381	0.387	0.393	0.396	0.385	0.381	0.342	0.337	0.340
	P10		0.072	0.187	0.196	0.175	0.153	0.177	0.198	0.215	0.242	0.269	0.232	0.187	0.171	0.187	0.205	0.220	0.242	0.254
	P1−P10		0.632	0.320	0.266	0.260	0.268	0.218	0.169	0.134	0.106	0.112	0.155	0.206	0.225	0.198	0.176	0.123	0.096	0.086
	t-stat.		(5.41)	(4.02)	(4.29)	(4.92)	(6.20)	(6.11)	(5.38)	(4.94)	(4.39)	(1.12)	(2.15)	(3.45)	(4.24)	(4.55)	(4.70)	(3.83)	(3.41)	(3.36)
3	P1		0.627	0.495	0.475	0.469	0.445	0.410	0.375	0.364	0.358	0.400	0.436	0.459	0.455	0.431	0.410	0.373	0.370	0.364
	P10		0.155	0.160	0.104	0.078	0.088	0.139	0.172	0.193	0.217	0.145	0.056	0.023	0.053	0.092	0.138	0.172	0.196	0.214
	P1−P10		0.471	0.335	0.371	0.390	0.357	0.271	0.203	0.171	0.140	0.255	0.380	0.436	0.401	0.340	0.271	0.201	0.174	0.149
	t-stat.		(4.09)	(3.47)	(4.25)	(4.90)	(5.19)	(4.53)	(3.83)	(3.72)	(3.38)	(2.31)	(3.81)	(4.82)	(4.85)	(4.77)	(4.34)	(3.69)	(3.66)	(3.47)
6	P1		0.672	0.546	0.522	0.494	0.465	0.434	0.407	0.388	0.383	0.488	0.501	0.501	0.490	0.470	0.438	0.406	0.392	0.386
	P10		-0.003	0.014	0.010	0.017	0.057	0.127	0.171	0.195	0.206	-0.006	-0.029	-0.019	0.030	0.099	0.151	0.173	0.202	0.210
	P1−P10		0.675	0.532	0.512	0.477	0.408	0.307	0.236	0.193	0.177	0.494	0.530	0.519	0.460	0.371	0.287	0.233	0.189	0.177
	t-stat.		(5.89)	(5.19)	(5.35)	(5.25)	(4.88)	(4.11)	(3.53)	(3.23)	(3.23)	(4.52)	(5.13)	(5.22)	(4.81)	(4.17)	(3.64)	(3.32)	(3.04)	(3.04)
9	P1		0.651	0.591	0.575	0.571	0.519	0.486	0.445	0.415	0.398	-0.533	-0.539	-0.545	-0.516	-0.486	-0.453	-0.417	-0.398	-0.383
	P10		-0.068	-0.042	-0.026	-0.002	0.053	0.113	0.146	0.163	0.176	-0.011	0.001	0.025	0.060	0.103	0.154	0.173	0.183	0.194
	P1−P10		0.719	0.633	0.601	0.573	0.466	0.373	0.299	0.252	0.222	0.544	0.538	0.520	0.456	0.383	0.299	0.244	0.215	0.188
	t-stat.		(5.66)	(5.43)	(5.45)	(5.35)	(6.20)	(4.11)	(5.38)	(4.94)	(3.22)	(4.64)	(4.85)	(4.79)	(4.35)	(3.93)	(3.36)	(3.02)	(2.94)	(2.75)
12	P1		0.713	0.630	0.580	0.550	0.508	0.464	0.422	0.395	0.375	0.549	0.513	0.495	0.481	0.456	0.418	0.389	0.367	0.353
	P10		0.030	0.034	0.041	0.054	0.092	0.138	0.154	0.167	0.179	0.043	0.053	0.067	0.084	0.125	0.164	0.164	0.176	0.186
	P1−P10		0.683	0.597	0.539	0.497	0.416	0.326	0.268	0.228	0.196	0.505	0.461	0.428	0.396	0.332	0.254	0.225	0.191	0.166
	t-stat.		(5.30)	(5.00)	(4.75)	(5.25)	(4.03)	(3.37)	(2.99)	(2.79)	(3.23)	(4.24)	(4.08)	(3.91)	(3.72)	(3.29)	(2.68)	(2.56)	(2.37)	(2.21)

Panel B : FF Alpha of Firm-specific Component Contrarian Profits																			
		without 1-week Jump									with 1-week Jump								
J	*K*=	1	2	3	4	6	9	12	16	20	1	2	3	4	6	9	12	16	20
1	P1	0.658	0.461	0.402	0.372	0.337	0.305	0.274	0.246	0.245	0.292	0.285	0.288	0.291	0.285	0.280	0.243	0.237	0.240
	P10	-0.072	0.047	0.056	0.037	0.045	0.079	0.086	0.107	0.129	0.154	0.120	0.083	0.068	0.089	0.107	0.123	0.143	0.155
	P1−P10	0.731	0.414	0.346	0.335	0.292	0.226	0.188	0.139	0.116	0.138	0.166	0.206	0.223	0.196	0.174	0.120	0.094	0.084
	t-stat.	(5.64)	(4.57)	(5.01)	(5.78)	(6.25)	(5.91)	(5.58)	(4.82)	(4.50)	(1.38)	(2.30)	(3.44)	(4.19)	(4.50)	(4.63)	(3.73)	(3.33)	(3.30)
3	P1	0.586	0.434	0.409	0.404	0.368	0.329	0.287	0.275	0.265	0.314	0.342	0.365	0.358	0.332	0.311	0.274	0.271	0.266
	P10	0.046	0.040	-0.018	-0.049	-0.028	0.019	0.048	0.074	0.097	0.040	-0.039	-0.068	-0.039	-0.002	0.043	0.077	0.100	0.120
	P1−P10	0.540	0.394	0.427	0.453	0.397	0.310	0.239	0.201	0.169	0.275	0.381	0.433	0.398	0.334	0.268	0.197	0.171	0.146
	t-stat.	(4.11)	(3.62)	(4.35)	(5.13)	(5.31)	(4.85)	(4.25)	(4.14)	(3.87)	(2.50)	(3.82)	(4.79)	(4.80)	(4.67)	(4.27)	(3.59)	(3.59)	(3.38)
6	P1	0.628	0.498	0.462	0.442	0.402	0.357	0.322	0.300	0.284	0.400	0.403	0.400	0.388	0.369	0.336	0.304	0.294	0.289
	P10	-0.163	-0.130	-0.137	-0.127	-0.060	0.007	0.041	0.072	0.081	-0.094	-0.119	-0.110	-0.064	0.001	0.053	0.075	0.106	0.116
	P1−P10	0.791	0.628	0.599	0.570	0.462	0.350	0.281	0.227	0.202	0.494	0.522	0.510	0.452	0.368	0.282	0.229	0.187	0.173
	t-stat.	(6.18)	(5.64)	(5.76)	(5.72)	(5.06)	(4.34)	(3.90)	(3.57)	(3.46)	(4.51)	(5.04)	(5.11)	(4.70)	(4.12)	(3.56)	(3.24)	(2.99)	(2.96)
9	P1	0.528	0.468	0.452	0.448	0.397	0.364	0.325	0.295	0.278	0.445	0.442	0.447	0.415	0.384	0.351	0.319	0.277	0.259
	P10	-0.167	-0.141	-0.124	-0.103	-0.049	0.008	0.041	0.059	0.071	-0.109	-0.100	-0.077	-0.042	0.003	0.055	0.077	0.071	0.085
	P1−P10	0.695	0.609	0.575	0.551	0.446	0.356	0.284	0.236	0.207	0.554	0.542	0.524	0.457	0.381	0.296	0.241	0.206	0.175
	t-stat.	(5.46)	(5.22)	(5.21)	(5.14)	(4.49)	(3.93)	(3.44)	(3.20)	(3.02)	(4.70)	(4.87)	(4.81)	(4.33)	(3.89)	(3.31)	(2.97)	(2.76)	(2.53)
12	P1	0.595	0.514	0.461	0.430	0.387	0.338	0.302	0.274	0.254	0.514	0.521	0.461	0.430	0.387	0.338	0.292	0.270	0.256
	P10	-0.072	-0.065	-0.058	-0.047	-0.011	0.039	0.051	0.064	0.076	-0.065	-0.034	-0.058	-0.047	-0.011	0.039	0.075	0.086	0.095
	P1−P10	0.667	0.580	0.518	0.478	0.397	0.299	0.251	0.211	0.178	0.580	0.556	0.518	0.478	0.397	0.299	0.218	0.184	0.162
	t-stat.	(5.16)	(4.85)	(4.56)	(4.35)	(3.85)	(3.11)	(2.80)	(2.58)	(2.35)	(4.85)	(4.56)	(4.56)	(4.35)	(3.85)	(3.11)	(2.46)	(2.27)	(2.14)

Panel C : Holding Period Return of Firm-specific Component Contrarian Portfolio

		without 1-week Jump									with 1-week Jump								
J	*K*=	1	2	3	4	6	9	12	16	20	1	2	3	4	6	9	12	16	20
1	P1	0.390	0.381	0.443	0.462	0.571	0.641	0.557	0.535	0.647	0.056	0.133	0.183	0.273	0.290	0.434	0.109	0.010	0.266
	t-stat.	(6.91)	(5.26)	(4.72)	(4.24)	(4.45)	(4.16)	(3.23)	(2.56)	(2.53)	(0.97)	(1.41)	(1.64)	(2.02)	(1.98)	(2.55)	(0.54)	(0.04)	(0.78)
	P10	-0.242	-0.253	-0.360	-0.587	-1.083	-1.384	-1.484	-1.610	-1.433	-0.056	-0.170	-0.411	-0.602	-0.866	-1.099	-1.091	-1.307	-1.252
	t-stat.	(-3.22)	(-2.73)	(-3.50)	(-5.34)	(-8.18)	(-9.01)	(-8.31)	(-7.73)	(-5.62)	(-0.86)	(-1.82)	(-3.55)	(-4.26)	(-5.18)	(-5.84)	(-4.73)	(-4.98)	(-3.48)
	P1−P10	0.632	0.634	0.802	1.050	1.654	2.025	2.041	2.145	2.080	0.112	0.303	0.594	0.875	1.156	1.533	1.201	1.316	1.518
	t-stat.	(5.41)	(4.48)	(4.83)	(5.79)	(7.76)	(8.26)	(7.23)	(6.34)	(5.09)	(1.12)	(1.96)	(3.23)	(3.92)	(4.68)	(5.51)	(3.47)	(3.26)	(2.73)
3	P1	0.309	0.351	0.466	0.582	0.730	0.876	0.683	0.807	0.772	0.073	0.225	0.399	0.536	0.622	0.656	0.379	0.492	0.666
	t-stat.	(5.17)	(4.17)	(4.44)	(4.72)	(5.13)	(5.20)	(3.46)	(2.96)	(2.70)	(1.20)	(2.44)	(3.23)	(3.44)	(3.68)	(3.73)	(1.74)	(1.79)	(1.72)
	P10	-0.162	-0.305	-0.627	-0.953	-1.459	-1.699	-1.699	-1.956	-1.930	-0.182	-0.515	-0.887	-1.101	-1.464	-1.659	-1.721	-1.878	-2.076
	t-stat.	(-2.29)	(-3.29)	(-5.84)	(-7.64)	(-9.97)	(-9.75)	(-8.19)	(-8.42)	(-6.89)	(-2.47)	(-4.70)	(-6.36)	(-6.91)	(-7.88)	(-7.56)	(-6.90)	(-6.67)	(-6.25)
	P1−P10	0.471	0.656	1.093	1.535	2.188	2.575	2.382	2.763	2.702	0.255	0.740	1.285	1.637	2.086	2.315	2.100	2.370	2.742
	t-stat.	(4.09)	(4.27)	(6.05)	(7.34)	(9.13)	(9.14)	(7.15)	(6.59)	(5.75)	(2.31)	(4.47)	(5.93)	(6.30)	(7.17)	(7.33)	(5.62)	(5.27)	(4.72)
6	P1	0.358	0.474	0.632	0.735	0.897	1.101	1.114	1.116	1.440	0.166	0.371	0.560	0.716	0.908	0.955	0.854	0.737	1.124
	t-stat.	(6.14)	(5.57)	(5.75)	(5.56)	(6.17)	(5.73)	(4.43)	(4.53)	(4.16)	(2.68)	(3.84)	(4.31)	(4.64)	(5.32)	(4.51)	(2.94)	(2.80)	(2.55)
	P10	-0.317	-0.600	-0.920	-1.205	-1.573	-1.699	-1.709	-1.855	-2.271	-0.328	-0.688	-0.995	-1.136	-1.276	-1.556	-1.684	-1.881	-2.428
	t-stat.	(-4.37)	(-6.11)	(-8.08)	(-9.25)	(-9.74)	(-9.13)	(-8.10)	(-7.99)	(-8.00)	(-4.65)	(-6.61)	(-7.18)	(-7.07)	(-6.54)	(-6.92)	(-6.65)	(-6.32)	(-7.27)
	P1−P10	0.675	1.074	1.552	1.940	2.470	2.800	2.823	2.970	3.711	0.494	1.058	1.555	1.852	2.184	2.512	2.538	2.618	3.552
	t-stat.	(5.89)	(6.76)	(8.14)	(8.76)	(9.58)	(8.66)	(7.03)	(7.32)	(6.94)	(4.52)	(6.40)	(7.01)	(7.07)	(7.23)	(6.97)	(5.53)	(5.64)	(5.52)
9	P1	0.377	0.428	0.639	0.798	0.899	1.131	0.995	1.115	1.352	0.214	0.473	0.712	0.837	0.960	0.960	0.690	0.691	0.959
	t-stat.	(4.43)	(4.75)	(5.44)	(5.66)	(5.66)	(5.62)	(4.38)	(4.48)	(3.79)	(3.26)	(4.58)	(5.20)	(5.11)	(5.17)	(4.58)	(3.54)	(2.84)	(2.30)
	P10	-0.342	-0.556	-0.781	-0.972	-1.254	-1.411	-1.369	-1.660	-1.971	-0.330	-0.608	-0.816	-0.943	-1.272	-1.480	-1.656	-2.263	-2.691
	t-stat.	(-4.32)	(-5.87)	(-6.78)	(-7.01)	(-7.69)	(-7.42)	(-6.58)	(-6.83)	(-6.76)	(-4.43)	(-5.46)	(-5.28)	(-5.29)	(-6.57)	(-6.26)	(-6.30)	(-7.64)	(-7.82)
	P1−P10	0.719	0.984	1.420	1.770	2.153	2.542	2.364	2.775	3.323	0.544	1.081	1.528	1.780	2.232	2.440	2.346	2.954	3.650
	t-stat.	(4.98)	(6.09)	(7.01)	(7.34)	(7.76)	(7.53)	(6.35)	(6.66)	(5.98)	(4.64)	(6.08)	(6.33)	(6.30)	(7.14)	(6.47)	(6.22)	(6.60)	(5.69)
12	P1	0.376	0.544	0.720	0.923	1.206	1.293	1.196	1.373	1.447	0.238	0.420	0.568	0.693	0.771	0.573	0.329	0.202	0.422
	t-stat.	(5.46)	(5.78)	(5.98)	(6.00)	(6.54)	(6.03)	(5.10)	(5.24)	(3.92)	(3.55)	(3.91)	(4.11)	(4.24)	(4.47)	(3.32)	(1.72)	(0.83)	(0.98)
	P10	-0.308	-0.371	-0.541	-0.707	-0.960	-0.996	-1.153	-1.517	-1.746	-0.268	-0.501	-0.695	-0.891	-1.122	-1.300	-1.831	-2.409	-2.950
	t-stat.	(-2.94)	(-3.82)	(-4.70)	(-5.24)	(-5.97)	(-5.46)	(-5.53)	(-5.90)	(-5.73)	(-3.51)	(-4.55)	(-4.77)	(-5.37)	(-5.63)	(-5.44)	(-6.89)	(-7.58)	(-8.24)
	P1−P10	0.683	0.915	1.261	1.629	2.166	2.289	2.349	2.890	3.193	0.505	0.921	1.263	1.584	1.893	1.874	2.160	2.612	3.372
	t-stat.	(4.65)	(5.41)	(6.09)	(6.51)	(7.38)	(6.86)	(6.25)	(6.53)	(5.55)	(4.24)	(5.11)	(5.37)	(5.85)	(6.30)	(5.64)	(5.68)	(5.62)	(5.11)

Table 4. Contrarian Returns of All Portfolios

This table reports the average weekly returns for all contrarian portfolios formed based on past 3- and 6-week firm-specific components and total returns, and then held for 3, 6, 9, and 12 weeks, applying Jegadeesh and Titman (1993, 2001)'s methodology. The firm-specific component is produced from equation (2) and (3), that is, the firm-specific returns are divided by their standard deviation. P1 is the equal-weighted portfolio of 10 percent of the stocks with the highest firm-specific components or total returns over the previous *J* months, P2 is the equal-weighted portfolio of the 10 percent of the stocks with the next highest firm-specific components or total returns, and so on. Panel A and C present the profit results of the firm-specific-component contrarian strategy. Also, Panel B and D present the profit results of the general contrarian strategy, using real stock returns. Panel A and B are formed immediately after the lagged firm-specific components and total returns used for forming these portfolios. Panel C and D are formed 1 week after the lagged firm-specific components and total returns are measured for the purpose of portfolio formation. The *t*-statistics are reported in parentheses. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

			Panel A : Firm-specific-component Portfolio without 1-week Jump				Panel B : Total-return Portfolio without 1-week Jump			
J		*K*=	3	6	9	12	3	6	9	12
3	P1		0.475	0.445	0.410	0.375	0.288	0.318	0.303	0.285
	P2		0.481	0.433	0.399	0.371	0.418	0.401	0.373	0.352
	P3		0.417	0.413	0.385	0.364	0.389	0.378	0.359	0.339
	P4		0.378	0.364	0.347	0.335	0.391	0.382	0.362	0.343
	P5		0.322	0.328	0.329	0.320	0.359	0.351	0.343	0.338
	P6		0.272	0.304	0.309	0.307	0.315	0.341	0.339	0.334
	P7		0.265	0.298	0.293	0.290	0.363	0.352	0.349	0.340
	P8		0.236	0.257	0.262	0.265	0.284	0.301	0.302	0.301
	P9		0.194	0.200	0.226	0.243	0.241	0.252	0.275	0.293
	P10		0.104	0.088	0.139	0.172	0.138	0.082	0.134	0.164
	P1−P10		0.371	0.357	0.271	0.203	0.150	0.236	0.169	0.121
	t-stat.		(4.25)	(5.19)	(4.53)	(3.83)	(1.49)	(2.97)	(2.48)	(1.99)
6	P1		0.522	0.465	0.434	0.407	0.357	0.343	0.328	0.313
	P2		0.476	0.427	0.396	0.383	0.441	0.400	0.370	0.361
	P3		0.433	0.403	0.374	0.370	0.422	0.398	0.367	0.349
	P4		0.371	0.373	0.357	0.344	0.388	0.377	0.359	0.349
	P5		0.341	0.333	0.319	0.318	0.340	0.345	0.324	0.320
	P6		0.317	0.330	0.310	0.310	0.350	0.345	0.328	0.319
	P7		0.298	0.293	0.284	0.292	0.335	0.338	0.327	0.326
	P8		0.178	0.206	0.234	0.257	0.290	0.296	0.317	0.318
	P9		0.171	0.190	0.215	0.234	0.219	0.248	0.286	0.283
	P10		0.010	0.057	0.127	0.171	0.035	0.069	0.133	0.153
	P1−P10		0.512	0.408	0.307	0.236	0.322	0.275	0.195	0.160
	t-stat.		(5.35)	(4.88)	(4.11)	(3.53)	(2.95)	(2.81)	(2.24)	(2.00)

		Panel C : Firm-specific-component Portfolio with 1-week Jump				Panel D : Total-return Portfolio with 1-week Jump			
J	*K*=	3	6	9	12	3	6	9	12
3	P1	0.459	0.431	0.410	0.373	0.283	0.301	0.289	0.278
	P2	0.474	0.428	0.395	0.372	0.406	0.372	0.360	0.334
	P3	0.435	0.425	0.386	0.368	0.399	0.369	0.351	0.330
	P4	0.385	0.368	0.366	0.357	0.374	0.357	0.346	0.331
	P5	0.323	0.341	0.342	0.344	0.352	0.344	0.333	0.331
	P6	0.314	0.322	0.309	0.315	0.347	0.344	0.345	0.334
	P7	0.331	0.328	0.315	0.308	0.377	0.365	0.352	0.339
	P8	0.285	0.277	0.280	0.280	0.332	0.325	0.314	0.310
	P9	0.221	0.230	0.243	0.256	0.284	0.293	0.298	0.306
	P10	0.023	0.092	0.138	0.172	0.041	0.077	0.135	0.156
	P1−P10	0.436	0.340	0.271	0.201	0.243	0.224	0.154	0.122
	t-stat.	(4.82)	(4.77)	(4.34)	(3.69)	(2.64)	(3.00)	(2.33)	(2.05)
6	P1	0.501	0.470	0.438	0.406	0.323	0.310	0.314	0.293
	P2	0.460	0.410	0.387	0.373	0.402	0.371	0.356	0.347
	P3	0.422	0.400	0.375	0.376	0.402	0.375	0.346	0.333
	P4	0.397	0.388	0.356	0.352	0.390	0.362	0.344	0.336
	P5	0.345	0.331	0.323	0.324	0.346	0.336	0.318	0.312
	P6	0.356	0.340	0.323	0.329	0.360	0.348	0.328	0.315
	P7	0.328	0.294	0.295	0.307	0.360	0.341	0.333	0.328
	P8	0.224	0.244	0.263	0.274	0.328	0.321	0.328	0.325
	P9	0.197	0.196	0.222	0.245	0.241	0.277	0.301	0.292
	P10	-0.019	0.099	0.151	0.173	0.043	0.106	0.157	0.168
	P1−P10	0.519	0.371	0.287	0.233	0.280	0.203	0.157	0.125
	t-stat.	(5.22)	(4.17)	(3.64)	(3.32)	(2.67)	(2.16)	(1.86)	(1.61)

Table 5. Contrarian Profits in Subperiod.

This table reports the average weekly returns in subperiod for contrarian portfolios formed based on past 1-, 3-, 6-, and 9-week firm-specific components and total returns, and then held for 1, 3, 6, 9 weeks without 1-week jump, applying Jegadeesh and Titman(1993, 2001)'s methodology. The firm-specific component is produced from equation (2) and (3). P1 is the equal-weighted portfolio of 10 percent of the stocks with the highest firm-specific components or total returns over the previous *J* months, and P10 is the equal-weighted portfolio of the 10 percent of the stocks with the lowest firm-specific components or total returns. Panel A presents the profits of the firm-specific-component contrarian strategies. Also, Panel B presents the profits of general contrarian strategies, using real stock returns. The *t*-statistics are reported in parentheses. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014..

Panel A: Firm-specific Component Contrarian Profits

		1989~1996				1997~2005				2006~2013			
J	*K*=	1	3	6	9	1	3	6	9	1	3	6	9
1	P1	0.831	0.527	0.405	0.347	0.876	0.582	0.537	0.497	0.607	0.437	0.420	0.423
	P10	0.016	0.061	0.091	0.100	-0.057	0.209	0.139	0.210	0.153	0.233	0.244	0.257
	P1−P10	0.815	0.466	0.314	0.247	0.933	0.373	0.398	0.287	0.454	0.204	0.176	0.166
	t-stat.	(4.09)	(4.40)	(4.27)	(4.09)	(3.32)	(2.56)	(4.17)	(3.61)	(2.78)	(2.16)	(2.61)	(3.06)
3	P1	0.789	0.529	0.393	0.308	0.741	0.523	0.562	0.547	0.544	0.510	0.497	0.483
	P10	0.153	0.059	0.013	0.036	-0.054	0.013	0.044	0.115	0.377	0.210	0.169	0.232
	P1−P10	0.635	0.470	0.381	0.272	0.796	0.510	0.519	0.432	0.167	0.301	0.329	0.251
	t-stat.	(3.28)	(3.11)	(3.25)	(2.58)	(2.83)	(2.47)	(3.20)	(3.15)	(0.95)	(2.24)	(3.52)	(3.15)
6	P1	0.741	0.489	0.346	0.242	0.845	0.662	0.673	0.674	0.639	0.577	0.542	0.491
	P10	0.022	-0.047	-0.026	0.026	-0.273	-0.134	-0.007	0.114	0.075	0.071	0.150	0.204
	P1−P10	0.719	0.536	0.372	0.216	1.117	0.797	0.680	0.560	0.564	0.505	0.392	0.287
	t-stat.	(3.81)	(3.30)	(2.51)	(1.60)	(4.06)	(3.60)	(3.53)	(3.35)	(3.33)	(3.65)	(3.25)	(2.63)
9	P1	0.650	0.385	0.251	0.216	0.707	0.711	0.731	0.713	0.592	0.604	0.552	0.498
	P10	-0.064	-0.081	-0.001	0.057	-0.155	-0.065	0.050	0.119	0.021	0.084	0.122	0.187
	P1−P10	0.714	0.465	0.252	0.159	0.862	0.776	0.681	0.594	0.571	0.520	0.430	0.312
	t-stat.	(3.64)	(2.59)	(1.52)	(1.00)	(3.15)	(3.37)	(3.32)	(3.27)	(3.50)	(3.52)	(3.25)	(2.52)

Panel B: Total Returns Contrarian Profits

		1989~1996				1997~2005				2006~2013			
J	*K*=	1	3	6	9	1	3	6	9	1	3	6	9
1	P1	0.709	0.392	0.315	0.273	0.408	0.270	0.328	0.331	0.403	0.308	0.327	0.322
	P10	0.218	0.195	0.167	0.152	-0.006	0.150	0.058	0.126	0.219	0.281	0.238	0.249
	P1−P10	0.491	0.197	0.148	0.121	0.414	0.119	0.270	0.205	0.184	0.027	0.089	0.073
	t-stat.	(2.32)	(1.65)	(1.74)	(1.70)	(1.40)	(0.73)	(2.41)	(2.23)	(1.15)	(0.31)	(1.51)	(1.55)
3	P1	0.525	0.366	0.302	0.235	0.209	0.140	0.283	0.311	0.387	0.372	0.382	0.365
	P10	0.320	0.218	0.130	0.141	0.138	0.046	-0.026	0.056	0.285	0.173	0.154	0.208
	P1−P10	0.205	0.148	0.172	0.094	0.072	0.094	0.309	0.255	0.102	0.199	0.228	0.157
	t-stat.	(0.97)	(0.85)	(1.26)	(0.78)	(0.24)	(0.44)	(1.78)	(1.73)	(0.63)	(1.69)	(2.69)	(2.09)
6	P1	0.578	0.337	0.221	0.172	0.355	0.312	0.366	0.383	0.449	0.444	0.441	0.416
	P10	0.237	0.150	0.116	0.151	-0.203	-0.100	-0.035	0.069	0.069	0.074	0.129	0.173
	P1−P10	0.341	0.187	0.105	0.020	0.558	0.413	0.401	0.315	0.381	0.370	0.313	0.243
	t-stat.	(1.61)	(1.00)	(0.62)	(0.13)	(1.91)	(1.68)	(1.91)	(1.72)	(2.44)	(3.01)	(2.83)	(2.41)
9	P1	0.457	0.293	0.192	0.179	0.415	0.374	0.432	0.440	0.510	0.503	0.491	0.452
	P10	0.150	0.150	0.192	0.187	-0.053	-0.003	0.061	0.125	0.072	0.087	0.129	0.188
	P1−P10	0.307	0.144	0.000	-0.008	0.468	0.377	0.370	0.314	0.438	0.416	0.361	0.265
	t-stat.	(1.35)	(0.69)	(0.00)	(-0.04)	(1.60)	(1.50)	(1.66)	(1.56)	(2.79)	(3.00)	(2.87)	(2.24)

Table 6. Contrarian Profits of Size- and Idiosyncratic Volatility-Based Subsamples

This table reports the average weekly returns of size- and idiosyncratic volatility-based subsamples for contrarian portfolios formed based on past 1-, 3-, 6-, and 9-week firm-specific components and held for 1, 3, 6, 9 weeks without 1-week jump, applying Jegadeesh and Titman(1993, 2001)'s methodology. The firm-specific component is produced from equation (2) and (3). P1 is the equal-weighted portfolio of 10 percent of the stocks with the highest firm-specific components over the previous *J* months, and P10 is the equal-weighted portfolio of the 10 percent of the stocks with the lowest firm-specific components. Panel A presents the average weekly returns of the contrarian strategy in size-based subsamples. The subsample Size1 contains the smallest firms, Size2 contains the medium-sized firms, and Size3 contains the largest firms. Panel B presents the average weekly returns of the contrarian strategy in idiosyncratic volatility-based subsamples. The subsample IV1, IV2, and IV3 contain the firms with the smallest, medium, and the largest idiosyncratic volatility estimated using the Fama-French three-factor model with the 52-week returns data prior to portfolio formation. The *t*-statistics are reported in parentheses. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

Panel A: Contrarian Profits of Size-based Subsamples

		Size1				Size2				Size3			
J	*K*=	1	3	6	9	1	3	6	9	1	3	6	9
1	P1	0.844	0.619	0.611	0.564	0.769	0.466	0.418	0.396	0.628	0.432	0.318	0.292
	P10	0.257	0.426	0.361	0.372	-0.021	0.155	0.143	0.184	-0.192	-0.015	-0.003	0.067
	P1−P10	0.587	0.193	0.250	0.192	0.790	0.311	0.275	0.212	0.820	0.447	0.321	0.225
	t-stat.	(2.57)	(1.45)	(2.68)	(2.42)	(4.34)	(3.39)	(4.18)	(4.11)	(5.59)	(5.32)	(5.39)	(4.32)
3	P1	0.818	0.550	0.537	0.525	0.677	0.597	0.541	0.485	0.634	0.407	0.356	0.316
	P10	0.430	0.270	0.210	0.275	0.161	0.126	0.080	0.110	-0.105	-0.090	-0.011	0.055
	P1−P10	0.387	0.280	0.327	0.250	0.515	0.471	0.461	0.375	0.739	0.497	0.368	0.261
	t-stat.	(2.07)	(2.20)	(2.87)	(2.62)	(2.94)	(3.71)	(4.74)	(4.56)	(5.00)	(4.69)	(4.52)	(3.78)
6	P1	0.861	0.638	0.620	0.591	0.769	0.626	0.552	0.479	0.635	0.472	0.399	0.376
	P10	0.151	0.139	0.216	0.258	-0.084	-0.092	-0.044	0.034	-0.207	-0.040	0.048	0.111
	P1−P10	0.710	0.499	0.404	0.333	0.853	0.718	0.596	0.445	0.842	0.513	0.351	0.265
	t-stat.	(3.25)	(2.81)	(2.69)	(2.47)	(5.03)	(5.28)	(5.15)	(4.51)	(5.04)	(4.41)	(3.48)	(2.95)
9	P1	0.936	0.681	0.654	0.622	0.557	0.580	0.497	0.452	0.552	0.457	0.395	0.385
	P10	-0.047	0.072	0.196	0.216	-0.038	-0.055	-0.020	0.056	-0.089	-0.005	0.095	0.141
	P1−P10	0.983	0.609	0.458	0.405	0.596	0.635	0.517	0.396	0.641	0.462	0.300	0.244
	t-stat.	(4.34)	(3.23)	(2.67)	(2.63)	(3.33)	(4.25)	(4.18)	(3.74)	(4.24)	(3.61)	(2.63)	(2.31)

Panel B: Contrarian Profits of Idiosyncratic Volatility-based Subsamples

		IV1				IV2				IV3			
J	*K*=	1	3	6	9	1	3	6	9	1	3	6	9
1	P1	0.800	0.490	0.400	0.359	0.824	0.571	0.526	0.487	0.743	0.495	0.443	0.418
	P10	-0.125	0.097	0.104	0.132	-0.055	0.179	0.158	0.187	0.115	0.183	0.159	0.194
	P1−P10	0.925	0.393	0.296	0.227	0.879	0.392	0.368	0.300	0.627	0.312	0.284	0.224
	t-stat.	(5.79)	(4.50)	(5.37)	(4.99)	(5.27)	(4.53)	(5.60)	(5.36)	(2.99)	(2.48)	(3.04)	(2.84)
3	P1	0.698	0.475	0.434	0.424	0.871	0.694	0.609	0.512	0.489	0.488	0.414	0.395
	P10	0.131	0.072	0.050	0.103	0.091	0.032	0.078	0.136	0.322	0.155	0.074	0.130
	P1−P10	0.567	0.403	0.384	0.320	0.780	0.662	0.531	0.376	0.168	0.333	0.340	0.265
	t-stat.	(3.59)	(2.87)	(3.50)	(3.13)	(4.27)	(4.82)	(5.20)	(4.64)	(0.97)	(2.09)	(2.99)	(2.99)
6	P1	0.711	0.518	0.410	0.397	0.840	0.691	0.598	0.485	0.550	0.442	0.450	0.467
	P10	0.099	0.021	0.069	0.117	-0.203	-0.067	0.044	0.158	-0.020	-0.059	0.017	0.118
	P1−P10	0.612	0.497	0.341	0.279	1.043	0.758	0.554	0.327	0.570	0.502	0.434	0.349
	t-stat.	(3.72)	(3.63)	(2.62)	(2.44)	(6.03)	(5.35)	(4.53)	(3.27)	(2.78)	(3.10)	(3.18)	(2.95)
9	P1	0.524	0.444	0.422	0.416	0.781	0.664	0.581	0.511	0.588	0.566	0.548	0.523
	P10	0.087	0.058	0.136	0.161	-0.167	-0.087	-0.017	0.075	-0.130	-0.045	0.067	0.150
	P1−P10	0.438	0.385	0.286	0.255	0.947	0.751	0.598	0.435	0.718	0.610	0.481	0.373
	t-stat.	(2.86)	(2.97)	(2.49)	(2.41)	(5.68)	(5.37)	(4.88)	(4.17)	(3.48)	(3.52)	(3.20)	(2.74)

Table 7. Number of Stocks in Intersections and Mutually Exclusive Subsets of the Firm-specific Component and Total Returns

This table reports the average number of stocks in subsets for contrarian portfolios formed based on the past *J*-week firm-specific component and total returns. The firm-specific component is produced from equation (2) and (3). P1 is the equal-weighted portfolio of 10 percent of the stocks with the highest firm-specific component or total returns over the previous *J* weeks, and P10 is the equal-weighted portfolio of the 10 percent of the stocks with the lowest firm-specific component or total returns over the previous *J* weeks. 'FC∩TR' portfolio is the intersection of the stocks in the FC-based contrarian portfolio with the stocks in the total-return-based contrarian portfolio. 'only-FC' portfolio is comprised of the subset of FC-based contrarian portfolio that are not in the top or bottom decile of lagged total returns during the formation period. Finally, 'only-TR' is comprised of the subset of the total return contrarian portfolio that are not also in the FC-based contrarian portfolio during the formation period. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

	FC∩TR		only-FC		only-TR	
J	P1	P10	P1	P10	P1	P10
1	28.05	35.07	16.60	9.68	16.60	9.68
3	24.96	34.44	19.6	10.23	19.72	10.37
6	22.31	33.31	21.95	11.05	22.34	11.45
9	20.67	32.38	23.36	11.75	23.97	12.38
12	19.44	31.47	24.37	12.42	25.21	13.29

Table 8. Average Returns on Subsets of Contrarian Portfolios based on the Firm-specific component and Total Returns

This table reports the average weekly returns of subsets for contrarian portfolios formed based on the past *J*-week firm-specific component and total returns and then held for *K* weeks, following Jegadeesh and Titman(1993, 2001)'s methodology. The firm-specific component is produced from equation (2) and (3). P1 is the equal-weighted portfolio of 10 percent of the stocks with the highest firm-specific component or total returns over the previous *J* months, and P10 is the equal-weighted portfolio of the 10 percent of the stocks with the lowest firm-specific component or total returns. Panel A presents the contrarian profits of 'FC∩TR' portfolio, which is the intersection of the stocks in the total-return contrarian portfolio with the stocks in the firm-specific-component contrarian portfolio. Panel B presents the contrarian profits of 'only-FC' portfolio, which is comprised of the subset of firm-specific-component contrarian portfolio that are not in the top or bottom decile of lagged total returns during the formation period. Finally, Panel C presents the contrarian profits of 'only-TR' portfolio, which is comprised of the subset of total-return contrarian portfolio that are not also in the firm-specific-component contrarian portfolio during the formation period. All Panels show both result without and with 1-week jump after contrarian portfolio formation. The *t*-statistics are reported in parentheses. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

Panel A : FC∩TR																			
		without 1-week Jump									with 1-week Jump								
J	*K*=	1	2	3	4	6	9	12	16	20	1	2	3	4	6	9	12	16	20
1	P1	0.739	0.507	0.437	0.401	0.390	0.374	0.339	0.321	0.313	0.280	0.290	0.291	0.304	0.327	0.338	0.293	0.291	0.296
	P10	0.136	0.199	0.182	0.142	0.146	0.177	0.186	0.208	0.233	0.260	0.206	0.144	0.137	0.160	0.184	0.199	0.225	0.241
	P1−P10	0.603	0.307	0.254	0.259	0.244	0.196	0.153	0.112	0.080	0.021	0.084	0.146	0.167	0.168	0.154	0.094	0.065	0.055
	t-stat.	(3.71)	(2.70)	(2.94)	(3.66)	(4.40)	(4.39)	(4.06)	(3.65)	(3.34)	(0.13)	(2.70)	(2.04)	(2.66)	(3.26)	(3.56)	(2.77)	(2.52)	(2.53)
3	P1	0.559	0.400	0.372	2.665	0.367	0.351	0.331	0.327	0.320	0.300	0.310	0.353	0.364	0.353	0.366	0.344	0.336	0.336
	P10	0.242	0.201	0.116	0.074	0.067	0.121	0.153	0.176	0.204	0.095	-0.010	-0.027	0.017	0.060	0.116	0.153	0.179	0.194
	P1−P10	0.317	0.199	0.256	2.592	0.299	0.230	0.178	0.151	0.116	0.205	0.320	0.380	0.348	0.293	0.249	0.191	0.158	0.142
	t-stat.	(2.16)	(1.66)	(2.41)	(3.12)	(3.60)	(3.20)	(2.77)	(2.68)	(2.28)	(1.45)	(2.59)	(3.41)	(3.40)	(3.33)	(3.21)	(2.78)	(2.62)	(2.62)
6	P1	0.631	0.449	0.437	0.404	0.394	0.382	0.368	0.353	0.344	0.384	0.410	0.393	0.412	0.418	0.406	0.390	0.366	0.357
	P10	0.031	0.016	-0.006	-0.010	0.031	0.103	0.151	0.179	0.190	-0.056	-0.078	-0.063	0.000	0.072	0.128	0.148	0.179	0.185
	P1−P10	0.601	0.433	0.444	0.413	0.362	0.279	0.217	0.173	0.154	0.440	0.488	0.456	0.413	0.346	0.278	0.241	0.187	0.172
	t-stat.	(4.07)	(3.34)	(3.69)	(3.64)	(3.47)	(2.99)	(2.55)	(2.28)	(2.21)	(2.85)	(3.49)	(3.48)	(3.30)	(2.99)	(2.71)	(2.71)	(2.53)	(2.59)
9	P1	0.647	0.586	0.598	0.612	0.556	0.517	0.480	0.431	0.398	0.526	0.575	0.601	0.578	0.532	0.487	0.451	0.413	0.380
	P10	-0.092	-0.101	-0.088	-0.070	0.005	0.079	0.107	0.126	0.145	-0.105	-0.081	-0.057	0.001	0.062	0.116	0.135	0.147	0.162
	P1−P10	0.739	0.687	0.687	0.682	0.552	0.438	0.374	0.305	0.254	0.631	0.656	0.658	0.577	0.470	0.371	0.316	0.266	0.218
	t-stat.	(4.17)	(4.30)	(4.57)	(4.66)	(4.14)	(3.62)	(3.29)	(3.11)	(2.83)	(4.17)	(4.30)	(4.57)	(4.66)	(4.14)	(3.62)	(3.29)	(3.11)	(2.83)
12	P1	0.769	0.651	0.589	0.542	0.542	0.514	0.481	0.430	0.403	0.527	0.489	0.460	0.483	0.494	0.471	0.450	0.390	0.363
	P10	-0.001	-0.008	-0.012	0.010	0.051	0.116	0.126	0.145	0.161	-0.008	-0.010	0.020	0.040	0.091	0.138	0.137	0.157	0.168
	P1−P10	0.770	0.659	0.601	0.532	0.491	0.398	0.355	0.285	0.242	0.535	0.499	0.440	0.443	0.403	0.333	0.312	0.233	0.195
	t-stat.	(4.24)	(3.92)	(3.81)	(3.49)	(3.43)	(2.91)	(2.77)	(2.37)	(2.07)	(3.12)	(3.17)	(2.91)	(2.97)	(2.88)	(2.51)	(2.47)	(1.94)	(1.71)

	Panel B : only-FC																			
		without 1-week Jump									with 1-week Jump									
J	*K*=	1	2	3	4	6	9	12	16	20	1	2	3	4	6	9	12	16	20
1	P1	0.796	0.614	0.554	0.515	0.478	0.426	0.401	0.374	0.378	0.459	0.445	0.441	0.444	0.399	0.385	0.347	0.351	0.351
	P10	-0.234	0.042	0.128	0.173	0.179	0.218	0.244	0.269	0.289	0.352	0.261	0.299	0.274	0.318	0.328	0.329	0.342	0.344
	P1−P10	1.031	0.572	0.426	0.342	0.299	0.207	0.157	0.105	0.089	0.107	0.184	0.142	0.170	0.081	0.057	0.018	0.009	0.007
	t-stat.	(9.66)	(7.21)	(6.53)	(6.11)	(6.67)	(5.51)	(4.66)	(3.51)	(3.02)	(0.98)	(2.23)	(2.13)	(2.59)	(1.71)	(2.35)	(1.40)	(1.22)	(1.36)
3	P1	0.738	0.621	0.603	0.574	0.523	0.466	0.427	0.410	0.403	0.524	0.536	0.517	0.507	0.469	0.433	0.392	0.389	0.372
	P10	-0.116	0.022	0.068	0.106	0.171	0.206	0.242	0.255	0.275	0.107	0.110	0.110	0.120	0.139	0.204	0.222	0.279	0.341
	P1−P10	0.854	0.598	0.535	0.468	0.351	0.259	0.185	0.155	0.128	0.416	0.426	0.408	0.387	0.331	0.229	0.170	0.110	0.032
	t-stat.	(8.33)	(7.22)	(7.32)	(7.11)	(6.00)	(5.04)	(4.01)	(3.77)	(3.41)	(2.87)	(3.59)	(3.73)	(3.40)	(3.09)	(2.20)	(2.13)	(2.11)	(1.46)
6	P1	0.742	0.643	0.610	0.580	0.532	0.476	0.447	0.423	0.416	0.589	0.557	0.547	0.524	0.484	0.432	0.402	0.398	0.389
	P10	-0.046	0.028	0.091	0.119	0.148	0.209	0.238	0.254	0.274	0.139	0.180	0.168	0.177	0.209	0.224	0.281	0.305	0.376
	P1−P10	0.788	0.615	0.519	0.460	0.385	0.267	0.209	0.169	0.142	0.449	0.377	0.379	0.347	0.275	0.207	0.122	0.093	0.013
	t-stat.	(7.15)	(6.78)	(6.30)	(5.91)	(5.41)	(4.28)	(3.75)	(3.34)	(3.05)	(3.05)	(3.01)	(3.36)	(3.40)	(2.79)	(2.19)	(1.68)	(1.33)	(0.91)
9	P1	0.680	0.606	0.567	0.555	0.500	0.461	0.428	0.403	0.393	0.535	0.513	0.515	0.485	0.466	0.423	0.397	0.387	0.383
	P10	0.243	0.265	0.238	0.247	0.203	0.273	0.341	0.389	0.429	0.302	0.255	0.254	0.208	0.233	0.292	0.327	0.381	0.446
	P1−P10	0.437	0.342	0.329	0.308	0.297	0.188	0.087	0.015	-0.036	0.233	0.258	0.261	0.276	0.232	0.131	0.070	0.006	-0.063
	t-stat.	(2.71)	(2.71)	(2.87)	(2.99)	(2.93)	(2.59)	(2.08)	(1.76)	(1.71)	(2.71)	(2.71)	(2.87)	(2.39)	(2.26)	(2.05)	(1.73)	(1.46)	(1.39)
12	P1	0.676	0.622	0.581	0.565	0.510	0.447	0.411	0.385	0.380	0.570	0.533	0.527	0.511	0.458	0.409	0.379	0.364	0.362
	P10	0.322	0.236	0.306	0.270	0.269	0.255	0.275	0.273	0.302	0.137	0.270	0.220	0.237	0.202	0.236	0.263	0.275	0.288
	P1−P10	0.354	0.386	0.275	0.295	0.240	0.192	0.136	0.111	0.078	0.433	0.263	0.307	0.274	0.257	0.173	0.116	0.088	0.073
	t-stat.	(2.29)	(3.18)	(2.64)	(2.82)	(2.83)	(2.22)	(1.73)	(1.91)	(1.81)	(3.06)	(2.65)	(2.65)	(2.75)	(2.58)	(1.60)	(1.47)	(1.29)	(1.75)

Panel C : only-TR																			
		without 1-week Jump									with 1-week Jump								
J	*K*=	1	2	3	4	6	9	12	16	20	1	2	3	4	6	9	12	16	20
1	P1	0.325	0.267	0.226	0.226	0.217	0.204	0.195	0.213	0.218	0.281	0.274	0.263	0.271	0.280	0.286	0.298	0.330	0.245
	P10	0.025	0.050	0.123	0.168	0.167	0.183	0.198	0.205	0.217	0.012	0.082	0.062	0.084	0.103	0.093	0.145	0.212	0.223
	P1−P10	0.300	0.216	0.102	0.058	0.050	0.020	-0.003	0.009	0.001	0.269	0.192	0.200	0.187	0.176	0.193	0.153	0.118	0.022
	t-stat.	(1.86)	(1.87)	(1.10)	(0.73)	(0.81)	(0.42)	(0.05)	(0.11)	(0.16)	(1.33)	(1.45)	(1.83)	(1.73)	(1.54)	(1.80)	(1.17)	(2.39)	(1.27)
3	P1	0.168	0.172	0.204	0.223	0.237	0.223	0.216	0.226	0.219	0.144	0.210	0.238	0.218	0.311	0.276	0.286	0.241	0.229
	P10	0.363	0.290	0.236	0.174	0.136	0.180	0.198	0.162	0.187	0.078	0.068	0.053	0.035	0.072	0.065	0.078	0.049	0.060
	P1−P10	-0.195	-0.118	-0.033	0.049	0.100	0.043	0.018	0.064	0.031	0.066	0.142	0.186	0.184	0.239	0.211	0.208	0.193	0.169
	t-stat.	(1.17)	(0.85)	(0.27)	(0.46)	(1.12)	(0.58)	(0.27)	(1.06)	(0.56)	(0.28)	(0.72)	(1.11)	(1.17)	(1.94)	(1.41)	(1.74)	(1.76)	(1.29)
6	P1	0.318	0.322	0.304	0.309	0.288	0.271	0.268	0.259	0.233	0.283	0.282	0.309	0.306	0.283	0.305	0.274	0.257	0.243
	P10	0.074	0.165	0.158	0.181	0.187	0.207	0.191	0.210	0.233	0.344	0.205	0.208	0.202	0.178	0.150	0.165	0.196	0.254
	P1−P10	0.244	0.157	0.145	0.128	0.101	0.064	0.077	0.049	0.000	-0.060	0.077	0.102	0.104	0.105	0.155	0.109	0.062	-0.010
	t-stat.	(1.60)	(1.17)	(1.17)	(1.11)	(0.96)	(0.70)	(0.91)	(0.63)	(0.00)	(0.28)	(0.47)	(0.36)	(0.51)	(0.55)	(1.12)	(1.32)	(0.37)	(0.04)
9	P1	0.416	0.358	0.330	0.323	0.319	0.313	0.311	0.289	0.254	0.345	0.370	0.364	0.389	0.395	0.369	0.349	0.321	0.292
	P10	0.195	0.260	0.236	0.222	0.235	0.247	0.239	0.242	0.253	0.372	0.307	0.315	0.271	0.249	0.253	0.260	0.285	0.344
	P1−P10	0.222	0.098	0.094	0.100	0.084	0.067	0.071	0.047	0.001	-0.027	0.062	0.050	0.118	0.146	0.115	0.088	0.037	-0.052
	t-stat.	(1.45)	(0.69)	(0.73)	(0.82)	(0.75)	(0.65)	(0.74)	(0.52)	(0.01)	(0.44)	(0.08)	(0.01)	(0.60)	(1.00)	(0.96)	(0.61)	(0.22)	(0.37)
12	P1	0.383	0.335	0.320	0.317	0.311	0.311	1.988	0.260	0.233	0.432	0.456	0.448	0.449	0.427	0.404	0.341	0.309	0.280
	P10	0.248	0.270	0.257	0.240	0.263	0.287	0.271	0.255	0.273	0.149	0.154	0.145	0.173	0.264	0.272	0.234	0.224	0.232
	P1−P10	0.135	0.065	0.063	0.076	0.048	0.025	1.717	0.006	-0.040	0.283	0.302	0.304	0.277	0.163	0.132	0.108	0.085	0.048
	t-stat.	(0.88)	(0.46)	(0.47)	(0.60)	(0.40)	(0.22)	(0.27)	(0.06)	(0.42)	(1.52)	(1.87)	(2.00)	(1.79)	(1.16)	(0.95)	(0.70)	(0.45)	(0.21)

Table 9. Lo and MacKinlay Type Contrarian Profits

This table reports the average weekly returns for contrarian portfolios formed based on past *J*-week firm-specific component and held for *K* weeks. The methodology of portfolio formation follows Lo and MacKinlay(1990). Thus, the trading strategy is investing $\omega_{it}(k) = -(1/N)(\upsilon_{it-k} - \bar{\upsilon}_{t-k})$ in stock *i*, where $\upsilon_{it-k} - \bar{\upsilon}_{t-k}$ is the stock *i*'s *k*-lag firm-specific component in excess of the equal-weighted firm-specific component for market. The weights are rescaled to have ₩1 long and ₩1 short. The firm-specific component is produced from equation (2) and (3). LC1 is the weighted portfolio of top decile and bottom decile of the firm-specific components over the previous *J* months, and LC2 is the weighted portfolio of the next decile ranks from top and bottom of the firm-specific components, and so on. Average returns for portfolios are calculated using Jegadeesh and Titman (1993, 2001)'s method of overlapping portfolios. Portfolios in Panel A is formed immediately after the lagged firm-specific component used for forming these portfolios. Portfolios in Panel B is formed 1 week after the lagged firm-specific component which is measured for the purpose of portfolio formation. The *t*-statistics are reported in parentheses. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

		Panel A : without 1-week Jump					Panel B : with 1-week Jump				
J	*K*=	1	3	6	9	12	1	3	6	9	12
1	LC1	0.245	0.150	0.156	0.120	0.096	0.076	0.126	0.126	0.102	0.074
	t-stat.	(3.15)	(3.77)	(6.00)	(5.71)	(5.23)	(1.38)	(3.75)	(5.26)	(5.07)	(4.27)
	LC2	0.263	0.148	0.107	0.068	0.044	0.105	0.081	0.066	0.038	0.020
	t-stat.	(5.91)	(5.45)	(5.57)	(4.20)	(2.99)	(2.68)	(3.30)	(3.54)	(2.39)	(1.42)
	LC3	0.189	0.090	0.057	0.043	0.031	0.037	0.025	0.025	0.019	0.019
	t-stat.	(5.18)	(4.12)	(3.52)	(3.21)	(2.59)	(1.12)	(1.20)	(1.63)	(1.46)	(1.61)
	LC4	0.055	0.019	0.007	-0.044	-0.037	-0.086	0.020	-0.032	-0.063	-0.028
	t-stat.	(1.27)	(0.41)	(0.23)	(-1.03)	(-1.00)	(-1.04)	(0.43)	(-0.72)	(-1.37)	(-0.70)
	LC5	0.586	0.116	0.555	0.872	0.417	-0.560	-0.221	0.288	0.534	0.010
	t-stat.	(0.72)	(0.09)	(0.90)	(1.46)	(1.43)	(-1.08)	(-0.33)	(0.79)	(1.23)	(1.05)
3	LC1	0.222	0.232	0.222	0.170	0.129	0.188	0.253	0.194	0.150	0.111
	t-stat.	(3.07)	(4.33)	(5.41)	(4.83)	(4.13)	(3.13)	(5.08)	(4.95)	(4.34)	(3.64)
	LC2	0.302	0.190	0.145	0.105	0.071	0.123	0.124	0.101	0.071	0.050
	t-stat.	(6.67)	(5.38)	(5.32)	(4.46)	(3.52)	(2.76)	(3.68)	(3.81)	(3.12)	(2.58)
	LC3	0.131	0.097	0.085	0.066	0.048	0.078	0.075	0.074	0.049	0.037
	t-stat.	(3.38)	(3.67)	(4.18)	(3.75)	(3.11)	(2.22)	(2.92)	(3.71)	(2.90)	(2.49)
	LC4	0.145	0.077	0.048	0.038	0.032	0.073	0.033	0.022	0.023	0.021
	t-stat.	(4.22)	(3.46)	(2.95)	(2.85)	(2.71)	(2.30)	(1.55)	(1.40)	(1.76)	(1.88)
	LC5	-0.097	-0.502	-0.116	0.373	0.319	-0.095	-0.223	0.093	0.448	0.433
	t-stat.	(-1.13)	(-1.28)	(-0.44)	(1.27)	(1.39)	(-1.14)	(-0.74)	(0.40)	(1.58)	(1.95)
6	LC1	0.394	0.331	0.253	0.187	0.146	0.287	0.281	0.200	0.150	0.115
	t-stat.	(5.72)	(5.72)	(5.01)	(4.15)	(3.58)	(4.75)	(5.04)	(4.05)	(3.37)	(2.86)
	LC2	0.230	0.174	0.137	0.104	0.077	0.148	0.134	0.105	0.076	0.056
	t-stat.	(5.02)	(4.50)	(4.26)	(3.72)	(3.12)	(3.16)	(3.58)	(3.37)	(2.80)	(2.35)
	LC3	0.166	0.125	0.109	0.071	0.057	0.112	0.104	0.084	0.055	0.042
	t-stat.	(4.42)	(4.39)	(4.69)	(3.48)	(3.11)	(3.18)	(3.79)	(3.71)	(2.76)	(2.32)
	LC4	0.080	0.044	0.053	0.041	0.019	0.027	0.027	0.049	0.026	0.015
	t-stat.	(2.36)	(1.79)	(2.71)	(2.55)	(1.27)	(0.80)	(1.10)	(2.58)	(1.69)	(1.01)
	LC5	0.082	0.235	0.178	-0.089	-0.082	0.648	0.240	0.133	-0.045	-0.030
	t-stat.	(0.11)	(0.71)	(0.67)	(-0.44)	(-0.44)	(1.24)	(0.87)	(0.52)	(-0.22)	(-0.15)
9	LC1	0.355	0.300	0.219	0.169	0.126	0.286	0.247	0.177	0.130	0.097
	t-stat.	(5.18)	(4.94)	(3.96)	(3.30)	(2.68)	(4.52)	(4.14)	(3.25)	(2.58)	(2.09)
	LC2	0.232	0.172	0.127	0.090	0.063	0.141	0.126	0.089	0.062	0.043
	t-stat.	(4.94)	(4.27)	(3.72)	(2.88)	(2.16)	(2.91)	(3.32)	(2.68)	(2.00)	(1.51)
	LC3	0.151	0.112	0.087	0.058	0.037	0.104	0.082	0.060	0.042	0.024
	t-stat.	(3.86)	(3.68)	(3.40)	(2.55)	(1.76)	(2.82)	(2.73)	(2.41)	(1.88)	(1.14)
	LC4	0.068	0.070	0.045	0.027	0.019	0.046	0.070	0.030	0.019	0.009
	t-stat.	(2.07)	(3.03)	(2.39)	(1.64)	(1.25)	(1.45)	(3.05)	(1.62)	(1.16)	(0.60)
	LC5	-0.428	0.047	0.394	0.442	0.396	-0.517	0.404	0.559	0.503	0.370
	t-stat.	(-0.60)	(0.04)	(0.59)	(0.90)	(1.02)	(-1.10)	(0.34)	(0.84)	(1.02)	(0.95)
12	LC1	0.302	0.250	0.183	0.130	0.105	0.249	0.202	0.141	0.101	0.085
	t-stat.	(4.28)	(3.98)	(3.17)	(2.40)	(2.06)	(3.85)	(3.32)	(2.49)	(1.88)	(1.70)
	LC2	0.223	0.150	0.109	0.076	0.057	0.090	0.109	0.071	0.045	0.036
	t-stat.	(4.63)	(3.60)	(2.98)	(2.22)	(1.77)	(1.88)	(2.72)	(1.99)	(1.33)	(1.14)
	LC3	0.129	0.098	0.082	0.053	0.036	0.071	0.073	0.063	0.037	0.025
	t-stat.	(3.33)	(3.19)	(3.08)	(2.16)	(1.54)	(1.81)	(2.46)	(2.39)	(1.52)	(1.09)
	LC4	0.108	0.049	0.033	0.015	0.009	0.030	0.020	0.013	0.003	-0.002
	t-stat.	(3.21)	(2.08)	(1.65)	(0.85)	(0.54)	(0.94)	(0.83)	(0.67)	(0.15)	(0.12)
	LC5	0.185	0.346	-0.486	-0.990	0.003	0.147	-0.487	-0.480	-0.393	0.833
	t-stat.	(1.24)	(0.33)	(-0.95)	(-0.67)	(0.00)	(0.92)	(-0.84)	(-1.74)	(-0.44)	(0.30)

Table 10. The Decomposition of Contrarian Profits

This table reports the decomposition of the expected contrarian profit based on the firm-specific component, following Lo and MacKinlay (1990)'s methodology. The expected profit are given by

$$E[\pi_t(k)] = E[\sum_{i=1}^{N} -\frac{1}{N}(\upsilon_{it-k} - \bar{\upsilon}_{t-k})R_{it}] = -O_k + C_k$$

where O_k depends on the effect from autocovariances of individual stocks' firm-specific components, C_k depends on the effect from cross-serial covariances among firm-specific components of individual stocks. The contrarian trading strategy is investing $\omega_{it}(k) = -(1/N)(\upsilon_{it-k} - \bar{\upsilon}_{t-k})$ in stock *i*, where $\upsilon_{it-k} - \bar{\upsilon}_{t-k}$ is the stock *i*'s *k*-lag firm-specific component in excess of the equal-weighted firm-specific components on market. The weights are rescaled to have ₩1 long and ₩1 short. 'All' of portfolio column is the whole sample in this study. LC1 is the weighted portfolio of top decile and bottom decile of the firm-specific components over the previous *J* months. %-$\hat{O}_k$ is the ratio of $-\hat{O}_k$ over the profit and %-$\hat{C}_k$ is the ratio of $\hat{C}_k$ over the profit. The numbers in parentheses are z-statistics that are asymptotically N(0, 1) under the null hypothesis that the relevant parameter is zero and are robust to heteroscedasticity and autocorrelation. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

Portfolio	Lag *k*	$\hat{O}_k$	$\hat{C}_k$	Profit	%-$\hat{O}_k$	%-$\hat{C}_k$
All	1	-0.047	0.080	0.126	36.90	63.10
	z-stat.	(0.74)	(2.32)	(3.02)		
	2	0.009	0.032	0.023	-37.12	137.12
	z-stat.	(0.13)	(0.69)	(0.74)		
	3	-0.139	-0.062	0.077	179.49	-79.49
	z-stat.	(2.18)	(1.41)	(2.36)		
	4	-0.105	-0.027	0.078	135.13	-35.13
	z-stat.	(2.30)	(0.94)	(2.84)		
J=1 LC1	1	-0.159	-0.105	0.055	292.19	-192.19
	z-stat.	(0.68)	(2.99)	(0.25)		
	2	-0.084	-0.130	-0.046	-180.39	280.39
	z-stat.	(0.70)	(4.23)	(0.43)		
	3	-0.468	-0.247	0.221	211.85	-111.85
	z-stat.	(3.75)	(7.06)	(1.98)		
	4	-0.468	-0.189	0.279	167.74	-67.74
	z-stat.	(4.54)	(6.27)	(2.91)		
J=3 LC1	1	0.091	-0.052	-0.142	63.97	36.60
	z-stat.	(0.41)	(1.43)	(0.70)		
	2	-0.068	-0.072	-0.004	-1800.64	1900.64
	z-stat.	(0.65)	(2.45)	(0.04)		
	3	-0.428	-0.195	0.233	183.72	-83.72
	z-stat.	(3.72)	(5.49)	(2.30)		
	4	-0.414	-0.139	0.275	150.54	-50.54
	z-stat.	(4.56)	(4.67)	(3.34)		
J=6 LC1	1	0.194	0.012	-0.182	106.48	-6.48
	z-stat.	(0.88)	(0.32)	(0.92)		
	2	-0.070	-0.029	0.040	173.25	-73.25
	z-stat.	(0.69)	(0.80)	(0.47)		
	3	-0.349	-0.122	0.227	153.83	-53.83
	z-stat.	(3.24)	(3.47)	(2.47)		
	4	-0.330	-0.073	0.257	128.32	-28.32
	z-stat.	(3.94)	(2.71)	(3.38)		
J=9 LC1	1	0.323	0.052	-0.272	119.00	-19.00
	z-stat.	(1.49)	(1.30)	(1.39)		
	2	-0.032	-0.007	0.025	126.83	-26.83
	z-stat.	(0.34)	(0.21)	(0.31)		
	3	-0.315	-0.122	0.193	163.11	-63.11
	z-stat.	(3.04)	(3.55)	(2.18)		
	4	-0.247	-0.062	0.185	133.60	-33.60
	z-stat.	(3.02)	(2.08)	(2.54)		

Table 11. The Decomposition of Decomposition in Winners and Losers

This table reports the detailed decomposition of the expected contrarian profit based on the firm-specific component of winners and losers, expanding Lo and MacKinlay (1990)'s methodology. The expected profit are given by $E[\pi_t(k)] = -O_k + C_k$, where O_k depends on the effect from autocovariances of individual stocks' firm-specific components, C_k depends on the effect from cross-serial covariances among stocks' firm-specific components. O_k is divided up into $\hat{O}_{W,k}$ of autocovariances between winners at lag *k* and $\hat{O}_{L,k}$ of autocovariances between losers at lag *k*. Also, C_k is divided up into $\hat{C}_{W,k}$ of cross-serial covariances across winners' *k*-week previous firm-specific components and current firm-specific returns, $\hat{C}_{L,k}$ of cross-serial covariances across losers', $\hat{C}_{LW,k}$ of cross-serial covarianc-es across *k*-week previous losers' and current winners', and $\hat{C}_{WL,k}$ of cross-serial covariances across *k*-week previous winners' and current losers'. The numbers in parentheses are z-statistics that are asymptotically N(0, 1) under the null hypothesis that the relevant parameter is zero and are robust to heteroscedasticity and autocorrelation. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

J	Lag k	$\hat{O}_{W,k}$	$\hat{O}_{L,k}$	$\hat{C}_{W,k}$	$\hat{C}_{L,k}$	$\hat{C}_{LW,k}$	$\hat{C}_{WL,k}$
1	1	-0.90	0.59	-1.45	0.52	1.33	-0.82
	z-stat.	(-2.18)	(2.94)	(-6.62)	(2.71)	(8.11)	(-4.15)
	2	-1.29	1.13	-1.12	1.08	0.98	-1.46
	z-stat.	(-7.19)	(5.73)	(-6.98)	(5.60)	(6.91)	(-7.88)
	3	-1.69	0.77	-1.47	0.85	1.06	-1.41
	z-stat.	(-8.88)	(3.96)	(-9.08)	(4.68)	(7.92)	(-8.32)
	4	-1.81	0.89	-1.56	0.91	1.30	-1.40
	z-stat.	(-10.41)	(5.75)	(-9.62)	(5.97)	(9.74)	(-8.54)
3	1	-0.18	0.37	-0.76	0.41	0.79	-0.64
	z-stat.	(-0.47)	(2.27)	(-5.32)	(2.74)	(7.22)	(-4.78)
	2	-0.78	0.64	-0.76	0.56	0.74	-0.82
	z-stat.	(-5.37)	(4.01)	(-6.68)	(3.69)	(6.39)	(-6.41)
	3	-1.18	0.34	-1.11	0.36	0.76	-0.79
	z-stat.	(-7.61)	(2.00)	(-10.57)	(2.39)	(8.70)	(-6.55)
	4	-1.25	0.43	-0.95	0.45	0.77	-0.83
	z-stat.	(-9.01)	(3.72)	(-8.85)	(4.12)	(8.88)	(-7.93)
6	1	-0.10	0.28	-0.58	0.33	0.72	-0.42
	z-stat.	(-0.27)	(1.93)	(-4.84)	(2.63)	(7.38)	(-4.02)
	2	-0.58	0.44	-0.60	0.37	0.70	-0.59
	z-stat.	(-4.48)	(2.88)	(-7.22)	(2.56)	(6.09)	(-6.32)
	3	-0.88	0.19	-0.73	0.21	0.58	-0.55
	z-stat.	(-6.30)	(1.19)	(-8.80)	(1.49)	(7.18)	(-6.19)
	4	-0.98	0.33	-0.58	0.38	0.54	-0.62
	z-stat.	(-8.29)	(3.11)	(-7.55)	(3.93)	(7.48)	(-8.15)
9	1	-0.26	0.38	-0.41	0.40	0.61	-0.39
	z-stat.	(-0.67)	(2.69)	(-3.88)	(3.29)	(6.86)	(-4.43)
	2	-0.48	0.42	-0.46	0.37	0.54	-0.47
	z-stat.	(-4.06)	(2.95)	(-6.29)	(2.74)	(5.33)	(-5.58)
	3	-0.73	0.11	-0.56	0.12	0.40	-0.45
	z-stat.	(-5.53)	(0.75)	(-7.97)	(0.94)	(5.56)	(-5.71)
	4	-0.73	0.24	-0.41	0.28	0.39	-0.51
	z-stat.	(-6.54)	(2.30)	(-5.74)	(2.92)	(6.12)	(-6.84)

Table 12. The Decomposition of Contrarian Profits with Liquidity Factor

This table reports the decomposition of the expected contrarian profit based on the firm-specific component estimated using 4-factor model of equation (9) and (10) which includes Fama-French's three-factors and liquidity factor, following Lo and MacKinlay (1990)'s methodology. The expected profit are given by $E[\pi_t(k)] = -O_k + C_k$, where O_k depends on the effect from autocovariances of individual stocks' firm-specific-returns, C_k depends on the effect from cross-serial covariances among stocks' firm-specific-returns. The contrarian trading strategy is investing $\omega_{it}(k) = -(1/N)(\upsilon_{it-k} - \bar{\upsilon}_{t-k})$ in stock *i*, where $\upsilon_{it-k} - \bar{\upsilon}_{t-k}$ is the stock *i*'s *k*-lag firm-specific component in excess of the equal-weighted firm-specific component on market. The weights are rescaled to have ₩1 long and ₩1 short. 'All' of the portfolio column is the whole sample in this study. LC1 is the weighted portfolio of top decile and bottom decile of the firm-specific component over the previous *J* months. %-$\hat{O}_k$ is the ratio of $-\hat{O}_k$ over the profit and %-$\hat{C}_k$ is the ratio of $\hat{C}_k$ over the profit. The numbers in parentheses are z-statistics that are asymptotically N(0, 1) under the null hypothesis that the relevant parameter is zero and are robust to heteroscedasticity and autocorrelation. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

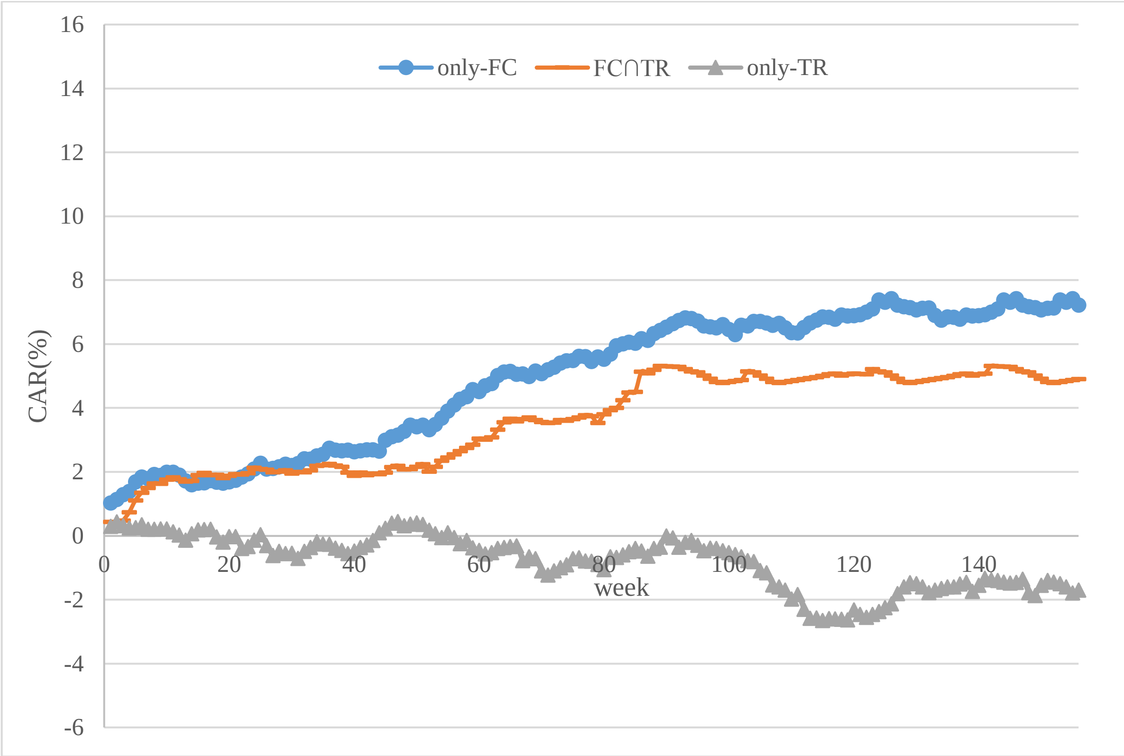
Portfolio	Lag *k*	$\hat{O}_k$	$\hat{C}_k$	Profit	%-$\hat{O}_k$	%-$\hat{C}_k$
J=1 LC1	1	-0.157	-0.080	0.076	205.26	-105.26
	z-stat.	(-0.09)	(-2.16)	(0.31)		
	2	-0.173	-0.095	0.078	221.78	-121.78
	z-stat.	(1.76)	(2.96)	(0.91)		
	3	-0.529	-0.208	0.321	164.84	-64.84
	z-stat.	(5.06)	(6.50)	(3.46)		
	4	-0.512	-0.175	0.337	151.77	-51.77
	z-stat.	(5.74)	(5.66)	(4.04)		
J =3 LC1	1	0.140	0.002	-0.138	101.31	-1.31
	z-stat.	(0.68)	(0.05)	(0.73)		
	2	-0.155	-0.037	0.117	131.82	-31.82
	z-stat.	(1.77)	(1.00)	(1.67)		
	3	-0.429	-0.137	0.292	146.82	-46.82
	z-stat.	(4.42)	(4.21)	(3.50)		
	4	-0.416	-0.096	0.319	130.16	-30.16
	z-stat.	(4.25)	(3.25)	(3.36)		
J =6 LC1	1	-0.201	0.028	0.230	87.68	12.32
	z-stat.	(1.99)	(1.83)	(2.04)		
	2	-0.053	0.017	0.070	75.13	24.87
	z-stat.	(0.63)	0.36	(1.17)		
	3	-0.308	-0.069	0.238	129.10	-29.10
	z-stat.	(3.11)	(1.94)	(2.85)		
	4	-0.319	-0.067	0.252	126.56	-26.56
	z-stat.	(4.15)	(2.20)	(3.71)		
J =9 LC1	1	0.236	0.099	-0.136	172.71	-72.71
	z-stat.	(1.19)	(2.61)	(0.77)		
	2	-0.004	0.038	0.043	10.18	89.82
	z-stat.	(0.05)	0.68	(0.76)		
	3	-0.246	-0.073	0.173	142.41	-42.41
	z-stat.	(2.26)	(1.63)	(1.98)		
	4	-0.294	-0.041	0.253	116.31	-16.31
	z-stat.	(3.22)	(1.25)	(3.16)		

Table 13. The Decomposition of Decomposition in Winners and Losers with Liquidity Factor

This table reports the detailed decomposition of the expected contrarian profit based on the firm-specific component of winners and losers estimated from 4-factor model of equation (9) and (10) which includes Fama-French's three-factors and liquidity factor, expanding Lo and MacKinlay (1990)'s methodology. The expected profit are given by $E[\pi_t(k)] = -O_k + C_k$, where O_k depends on the effect from autocovariances of individual stocks' firm-specific-returns, C_k depends on the effect from cross-serial covariances among stocks' firm-specific-returns. O_k is divided up into $\hat{O}_{W,k}$ of winners' autocovariances at lag k and $\hat{O}_{L,k}$ of losers' autocovariances at lag k. Also, C_k is divided up into $\hat{C}_{W,k}$ of cross-serial covariances across winners' k-week previous firm-specific component and current firm-specific-returns, $\hat{C}_{L,k}$ of cross-serial covariances across losers', $\hat{C}_{LW,k}$ of cross-serial covarianc-es across k-week previous losers' and current winners', and $\hat{C}_{WL,k}$ of cross-serial covariances across k-week previous winners' and current losers'. The numbers in parentheses are z-statistics that are asymptotically N(0, 1) under the null hypothesis that the relevant parameter is zero and are robust to heteroscedasticity and autocorrelation. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

	Lag k	$\hat{O}_{W,k}$	$\hat{O}_{L,k}$	$\hat{C}_{W,k}$	$\hat{C}_{L,k}$	$\hat{C}_{LW,k}$	$\hat{C}_{WL,k}$
J=1 LC1	1	-0.915	0.601	-0.824	0.296	0.746	-0.493
	z-stat.	(-2.01)	(2.95)	(-6.74)	(3.12)	(8.30)	(-4.76)
	2	-0.815	0.557	-0.709	0.481	0.565	-0.661
	z-stat.	(-6.79)	(5.16)	(-7.66)	(4.80)	(7.33)	(-6.54)
	3	-0.965	0.503	-0.894	0.354	0.602	-0.724
	z-stat.	(-8.55)	(5.16)	(-9.75)	(3.76)	(8.31)	(-7.65)
	4	-1.209	0.445	-0.904	0.435	0.701	-0.766
	z-stat.	(-10.81)	(5.15)	(-9.22)	(5.30)	(9.51)	-8.21)
J =3 LC1	1	0.092	0.113	-0.350	0.174	0.434	-0.261
	z-stat.	(0.27)	(1.42)	(-5.20)	(2.70)	(7.27)	(-4.24)
	2	-0.505	0.272	-0.444	0.182	0.369	-0.256
	z-stat.	(-5.26)	(3.02)	(-7.85)	(2.17)	(6.03)	(-4.61)
	3	-0.982	0.355	-0.497	0.078	0.315	-0.320
	z-stat.	(-9.27)	(4.36)	(-9.76)	(0.98)	(6.92)	(-5.82)
	4	-0.837	0.200	-0.406	0.170	0.316	-0.358
	z-stat.	(-8.80)	(3.30)	(-7.64)	(3.33)	(6.66)	(-7.01)
J =6 LC1	1	-0.210	0.110	-0.162	0.157	0.327	-0.125
	z-stat.	(-0.74)	(0.53)	(-3.51)	(2.94)	(1.97)	(-3.37)
	2	-0.254	0.162	-0.207	0.104	0.261	-0.141
	z-stat.	(-3.12)	(1.88)	(-5.67)	(1.30)	(4.25)	(-4.23)
	3	-0.973	0.294	-0.235	0.003	0.181	-0.176
	z-stat.	(-8.48)	(3.94)	(-6.87)	(0.04)	(4.56)	(-4.95)
	4	-0.871	0.058	-0.222	0.070	0.171	-0.214
	z-stat.	(-7.53)	(1.04)	(-6.41)	(1.55)	(4.45)	(-6.33)
J =9 LC1	1	0.249	0.147	-0.045	0.169	0.266	-0.089
	z-stat.	(0.76)	(2.15)	(-1.09)	(3.47)	(5.17)	(-2.94)
	2	-0.165	0.222	-0.110	0.086	0.197	-0.079
	z-stat.	(-2.21)	(1.80)	(-3.49)	(1.14)	(3.32)	(-2.37)
	3	-0.765	0.142	-0.189	-0.004	0.086	-0.133
	z-stat.	(-5.21)	(1.68)	(-6.20)	(-0.06)	(2.06)	(-3.62)
	4	-0.874	0.070	-0.156	0.048	0.132	-0.145
	z-stat.	(-7.02)	(1.30)	(-5.03)	(1.12)	(3.41)	(-4.49)

A. *J*=1



B. *J*=3

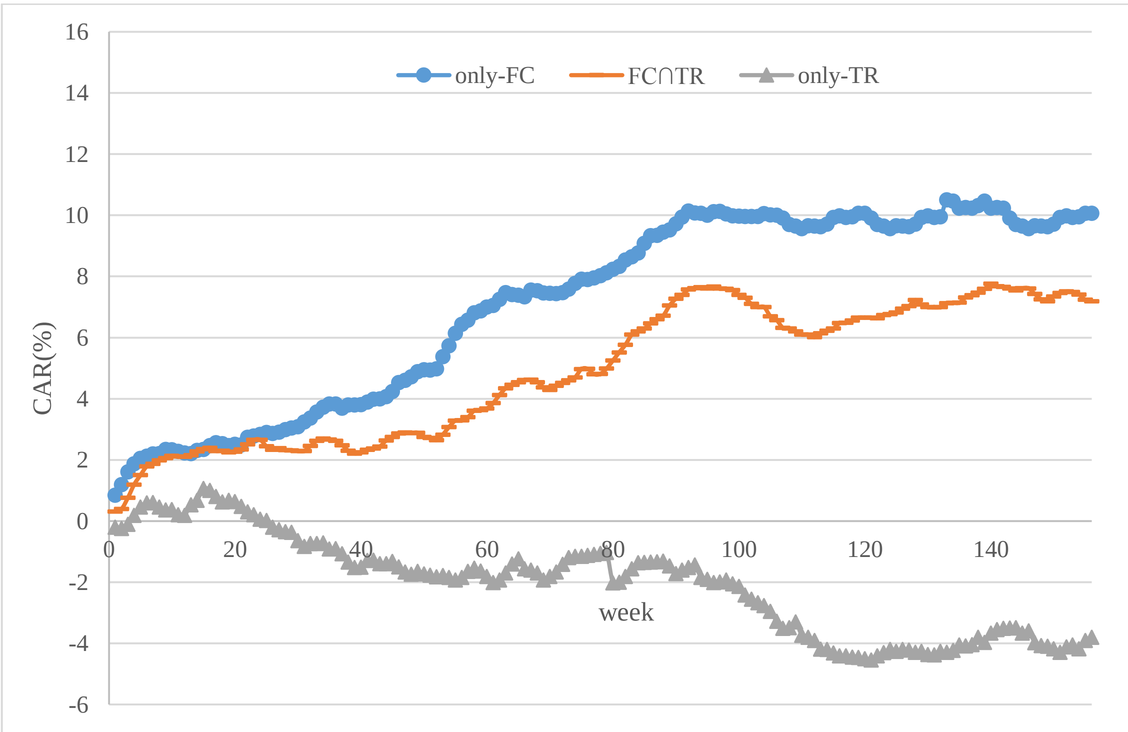
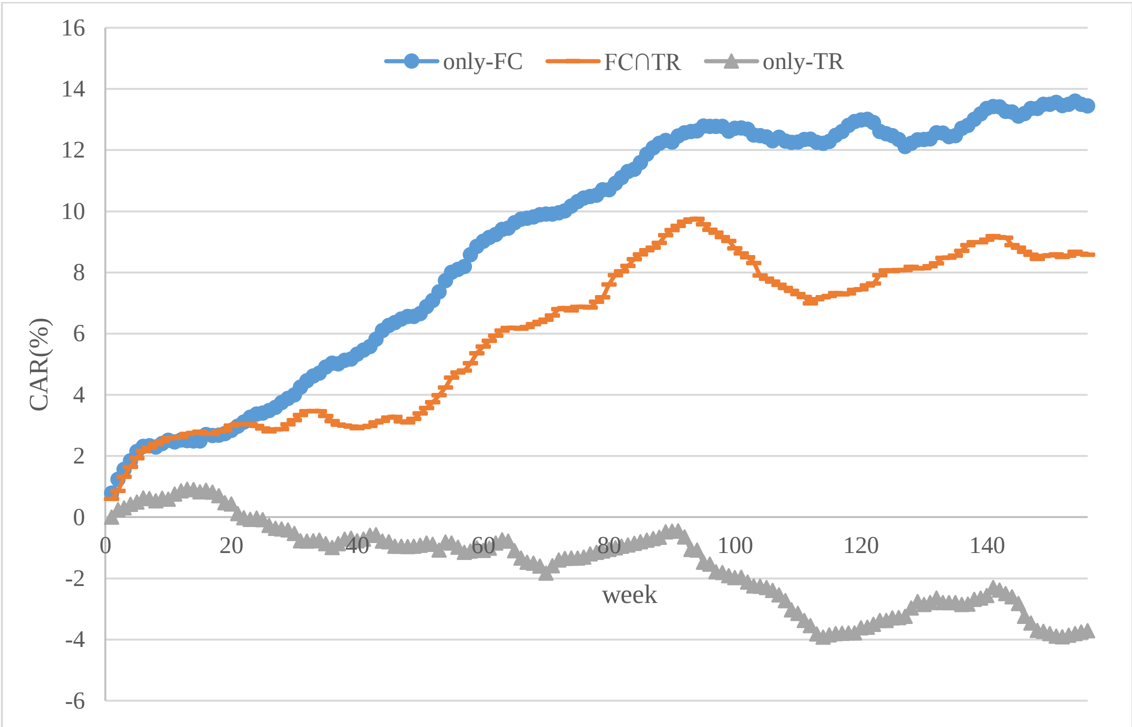


Figure 1. Contrarian Profits of Subsets. This figure presents the cumulative performance of subsets for contrarian portfolios formed based on past *J*-week firm-specific component and total returns, and held for 156 weeks (3 years). See Table 3 for a description of contrarian portfolio construction and Table 7 for the construction of three subsets. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.

C. *J*=6



D. *J*=9

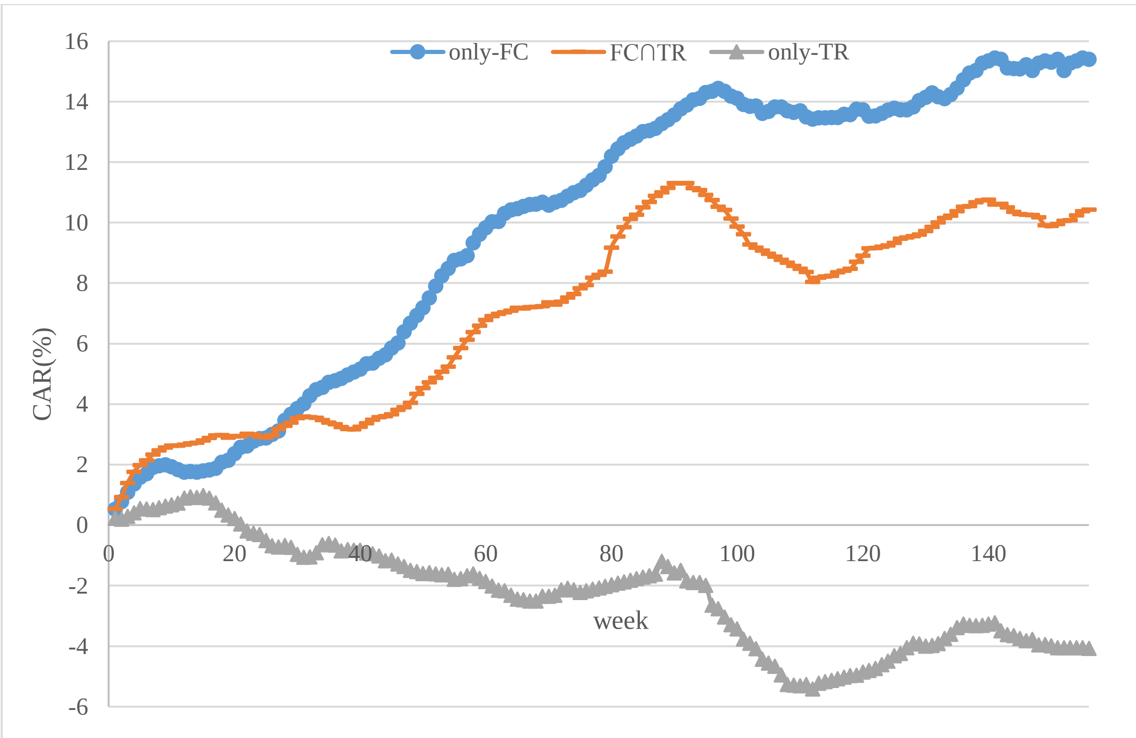


Figure 1(continued). This figure presents the cumulative performance of subsets for contrarian portfolios formed based on past *J*-week firm-specific component and total returns, and held for 156 weeks (3 years). See Table 3 for a description of contrarian portfolio construction and Table 7 for the construction of three subsets. The sample includes all non-financial stocks traded on KRX from January 1989 to July 2014.