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TACTICAL ASSET ALLOCATION USING INVESTORS' SENTIMENT

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Abstract

We extend investor sentiment literature and apply it to tactical portfolio allocation in the Korean stock market. We first construct a Korean investors' sentiment index by considering prior literature and expert opinions. Second, we investigate whether the index can predict both time series and cross sectional variations of stock returns. Third, we attempt tactical asset allocation using the index. Our sentiment index predicts both time series and cross sectional variations of stock returns. In addition, the tactical asset allocation generates significant excess return after adjusting risks and transaction costs.

Keywords: investor sentiment, tactical asset allocation, Korean stock market, alpha
JEL Classification Codes: G02, G11, G12

Investor sentiment is an important consideration in asset allocation. Existing literature finds investor sentiment affects not only the time series, but also cross sectional variations of stock valuation. For example, Baker and Wurgler [2006, 2007] propose that sentiment affects cross sectional variations of stock returns because each stock faces different degrees of subjective valuation and arbitrage constraints. Such investor sentiment literature suggests that how to apply investor sentiment in asset allocation and stock selection can determine the performance of portfolios. In addition, investor sentiment may exhibit distinct dynamics in other countries depending on the extent of subjective valuation and arbitrage constraints arising from cultural and institutional factors. We explore such possibilities. In this paper, we demonstrate that using investor sentiment significantly improves the performance of tactical asset allocation in the

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Korean stock market. Therefore, our findings about the investment strategies using investor sentiment may benefit global investors as well as contributes to academic literature.

Investor sentiment is a serious issue in industry practice. For instance, JP Morgan published an investment confidence index to quantify how much investors feel confident in their investment environment. State Street has a similar investor confidence index to capture the attitude of investors about risk. In academia, many papers also demonstrate that investor sentiment is a significant issue in both corporate finance and asset pricing. Baker and Wurgler [2006, 2007] state, "*Investor sentiment, defined broadly, is a belief about future cash flows and investment risks that is not justified by the facts at hand*" and provide an excellent review on this subject. Baker and Wurgler describes a way to construct an investor sentiment index. They collect proxies of investor sentiment discussed in prior literature and extract the first principal component to define it into an investor sentiment index. Baker and Wurgler found that this index can predict cross sectional and time series variations of stock returns as conjectured by behavioral finance literature.

Baker and Wurgler summarizes two channels through which investor sentiment generates cross sectional variations in stock returns. First, investors value some stocks more subjectively than others. Subjective valuation is more likely to be influenced by speculative demands originating from varying investor confidence and emotion. Second, investors cannot easily construct arbitrage about some stocks. This sustains stock prices deviating from fundamental values.

Baker and Wurgler's reasoning suggests that investor sentiment can have larger effects on asset pricing in some countries more than others. If a stock market receives less attention from sophisticated investors and restricts arbitrage trading more than the U.S. market does, investor sentiment should generate a larger impact in the stock market than in the U.S. market. Moreover, if the valuation and arbitrage constraints are strong enough to overwhelm transaction costs, it is likely to generate excess return to identify investor sentiment and to trade on the dynamics of that sentiment.

The experiment on this possibility clearly suggests ramifications to the industry as well as the academic field. Tactical asset allocation (often called *TAA*) is a way of rebalancing portfolios dynamically in order to generate excess return based on short-term market predictions. Since investor sentiment can be temporary and lead stock prices to vary without any change in fundamental values, tactical asset allocation is an ideal technique to test the potential of applying investor sentiment to investment strategies.

We chose the Korean stock market for the experiment. The Korean stock market is a natural candidate for the reasons in line with the two forces of investor sentiment to asset pricing. First, it has received less attention than developed markets, but is important enough to be an option for global investors. For example, FTSE promoted South Korea to a developed market index only recently (September 2009) while MSCI still considers it an emerging market index. Second, several restrictions exist to make arbitrage trading costly in the Korean market. MSCI assesses Korea as unprepared to join the MSCI Developed Market index because of accessibility issues, such as less active offshore markets for the Korean won and limited trading hours of the onshore spot currency market. This forces global investors to conduct pre-fund trades. Such accessibility problems clearly make arbitrage trading costly in this market from the perspective of global investors. In addition, it bans short selling in most cases since a trading scandal in 2000 and more strictly since the 2008 financial crisis (as of November 2010).

In line with our conjecture, our results find that it is possible to generate significantly positive excess return in the Korean stock market upon investor sentiment. Our results remain robust after controlling systematic risks and transaction costs. We can generate excess return by predicting either time series or cross sectional variations of stock return and adjusting asset allocation accordingly.

Our results are useful to practitioners interested in the Korean market who can replicate our strategies to enhance their investment. Our strategies are generic, so that they can easily be applied in other markets. The results are also meaningful academically in that Baker and Wurgler's framework is extended to tactical asset allocation problems. This suggests that investor sentiment is important and useful for asset allocation in countries other than the U.S., making Baker and Wurgler's finding applicable in an international setting.

I. *Literature Review*

Baker and Wurgler [2006, 2007] provide a good review of literature on investor sentiment. Thus, we discuss the literature after Baker and Wurgler. Investor sentiment affects asset return and volatility. Public information affects market sentiment and as a result stock prices around IPO (Eng and Tan, 1998). Investor optimism predicts the returns of stocks with small size or low institutional ownership, but may not forecast value and momentum premiums (Lemmon and Portniaguina, 2006)[1]. However, investor sentiments can conditionally explain size, value, liquidity and momentum premiums (Ho and Hung, 2009). Rational and irrational sentiments are distinguishable and separately explain empirical patterns in return and volatility (Verma and Verma, 2007). Investors' mood and irrational behavior predict US equity returns (Lucas and Rebitzky, 2008). Various sources or components of investor sentiment include media content (Tetlock 2007), monetary policy (Kurov, 2010), sports outcomes (Edmans, Garcia and Norli, 2007; Palomino, Renneboog and Zhang, 2009), order flow (Burghardt and Riordan, 2009).

In addition, investor sentiment can affect the behavior of various entities such as retail investors (Alok and Lee, 2006; Franzzini and Lamont, 2008; Burghardt and Riordan, 2009), financial analysts (Glaum and Friedrich, 2006), high grey market (Cornelli, Goldreich and Ljungqvist, 2006) and even institutional investors (Luo and Li, 2008). Investor sentiment can drive IPO returns as investors overweight personal experiences (Kaustia and Knupfer, 2008). Firms use investor sentiment to foster optimistic earnings valuation (Bergman and Roychowdhury, 2008). Sentiment affects traders' behavior and therefore market liquidity (Kurov, 2008, 2010), the pattern of style investing (Froot and Teo, 2008; Kumar, 2009) and derivative market (Bandopadhyaya and Jones, 2008; Han, 2008).

Despite numerous papers about investor sentiment, few illustrate how to apply the literature to investment or trading and how to undertake asset allocation practically. Therefore, we extend investor sentiment literature and implement it for tactical portfolio allocation. We use the methodologies in the prior literature and insights of industry experts in order to construct investor-sentiment index. Then, we demonstrate that the index has the predictive power about future returns and their cross sectional variations. Such predictive power is

[1] Related results are Bandopadhyaya and Jones [2006], Schmeling [2007], Fung, Leung and Zhu [2008], Canbas and Kandir [2009]. Contrasting results are Derrien and Kecskes [2009] and Kaplanski and Levy [2010].

exploited in designing tactical portfolio allocation, which generates significant excess returns beyond traditional multi-factors and transaction costs. These results suggest that the investor sentiment index is a powerful tool to produce extra performance via trading in market portfolios or undertaking style investing. In conclusion, we present the powerful results contributing not only to academic researchers, but also to practitioners such as active fund managers, risk managers and traders. Next sections describe our framework and procedure step by step.

II. *Measuring Investor Sentiment*

The information used here to construct sentiment index is mostly market data, which are computed and released by the exchange in real-time basis. The only exception is *Nlist*, the growth rate of number of listed companies in KRX. However, all new stocks to be listed or to be de-listed are notified by the exchange in far advance; therefore, the information we used are available before the investment decision. Therefore, the index constructed upon the information is used for trading, and our trading strategy is robust.

We construct an investor sentiment index following Baker and Wurgler's methods. First, we list candidate proxies for sentiment based on the characteristics of the Korean market and prior literature. We interviewed several investment experts in Korea to ask how they measure investor sentiment and what proxies they recommend us to utilize. We also refer to Baker and Wurgler's papers to generate the list of candidate proxies. Second, we select proxies for sentiment from the list considering data availability. Third, we conduct a principal component analysis to extract the most important component out of the selected proxies and to define it as an investor sentiment index in the Korean market.

Table 1 describes how we select the variables to determine investor sentiment. Baker and Wurgler [2006, 2007] summarizes many proxies about sentiment to use as time-series conditioning variables. Thus, we start from Baker and Wurgler. Then, considering Korean market characteristics and experts opinions, we expand the list. Finally, we select appropriate variables. The first column denotes identification (id) of variables. The second briefly describes the variables. The third shows whether Baker and Wurgler [2006] included the variables or not. The fourth shows whether we include the variables or not. o, x and Δ means inclusion, exclusion and partial inclusion respectively. We obtain data from the FnGuide (http://www.fnguide.com).

Nlist refers to the growth rate of listed companies in the Korean Exchange (KRX; http://www.krx.co.kr). This is a proxy for *NIPO* (number of IPOs) in Baker and Wurgler [2006]. We use *Nlist* instead of *NIPO* because of data constraint. *Vol* is the implied volatility index in KRX (V-KOSPI 200 or simply VKOSPI). KRX computes V-KOSPI 200 using KOSPI 200 option data similar to VIX in the U.S.

Mom is the three-month momentum of KOSPI 200. While Baker and Wurgler excludes momentum, we find several asset management firms in Korea use momentum as a sentiment index. In addition, several interviewees strongly recommended its inclusion[2]. *Fore* is percentage of shares owned by foreign investors in the Korean market: 100* (# of shares owned by foreigners) / (# of shares outstanding in all listed firms). Foreign investors, most of whom are

[2] Our results remain robust without including this momentum factor. See Appendix.

Table 1. Variable Description

Variable	Description	Baker and Wurgler	Ours	Remark
Nlist	Growth rate of number of listed companies in the Korea stock exchange (KRX)	△	○	*Nlist* is a proxy for NIPO; Lack of reliable IPO data
Vol	Implied volatility, V-KOSPI 200 index	○	○	Option prices can include information about sentiment
Mom	Three month momentum of KOSPI200	x	○	This is very popular sentiment measure in Korea; may stand for inertia of sentiment
Fore	100*(# of foreign owned shares)/(# of shares outstanding in all listed firm)	△	○	Korean market has been heavily influenced by foreign investors; Foreign investors are regarded more sophisticated and informed than retail investors in Korea; Baker and Wurgler consider retail investors trade -- the opposite of foreign ownership
KKR	KOSPI200 index divided by KOSDAQ index	x	○	This may stand for preference for stable performers over risky performers
ETF	Discount rate of ETF: ETF market price-ETF net asset value (NAV)	△	○	ETF discount can measure investors' forecast for market return; Proxy for closed end fund discount (CEFD) in Baker and Wurgler
PCR	Put-Call Ratio	x	○	Sentiment can be implied in option market
Ab	% of stocks that is above 20-days moving average	x	○	*Ab* can include cross sectional upward sentiment among investors; Experts recommended this measure with similar reason to momentum
Turn	Turnover ratio in logarithm	○	○	High turnover may reflect investor sentiment and confidence
CEFD	Average discount on closed-end mutual funds	○	△	This is similar to ETF discount
S	Gross annual equity issuance divided by gross annual equity plus debt issuance	○	x	Financing activities can capture the sentiment of stock suppliers; Lack of data in Korea
NIPO	Annual number of IPOs	○	△	NIPO measures the sentiment of issuers. Lack of data especially at weekly frequency; May be proxied by *Nlist*
RIPO	Annual average first day return of IPOs	○	x	RIPO captures enthusiasm of investors. Lack of data at weekly frequency
$P^{D\text{-}ND}$	Log ratio of value-weighted average market-to-book ratios of dividend payers and non-payers	○	x	Investors' sentiment may affect the demand for bond like stocks, i.e. dividend payers; Lack of data before 2006

Note: ○ means inclusion. x means exclusion. △ denotes partial inclusion.

institutional, have been regarded as more sophisticated and informed than retail investors in the Korean market. Thus, the behavior of foreign investors can contain information about other investors' investment behaviors. Baker and Wurgler suggests using retail investor behaviors in order to measure sentiments of uninformed investors. Retail and foreign investors are polar cases of informed and uninformed trading in the Korean market. Thus, both can contain closely related information.

KKR is the ratio between the KOSPI 200 and KOSDAQ index. KOSPI 200 and KOSDAQ are Korean versions of the S&P500 and NASDAQ respectively. This has been a heuristic measure of sentiment among Korean brokerage and asset management firms. *KKR* captures investors' preference between stability and growth, or degree of risk aversion. Thus, we include it as a candidate proxy although Baker and Wurgler disregards it. *ETF* is the discount rate of exchange trade funds (ETFs): the ratio of ETF market price and ETF Net Asset Value minus one. PCR is the put-call ratio measured with their open interests. We include this variable in light of Han [2008] who finds a significant relationship between sentiment and the option market. Bandopadhyaya and Jones [2008] similarly recommend that the put-call ratio is superior to a volatility index in measuring investor sentiment.

Ab is included upon expert interviews and market practices although Baker and Wurgler excludes it. This is the percentage of stocks above 20-day moving average. It is intended to proxy cross sectional upward sentiment among investors. *Turn* is the turnover ratio (trading volume/ number of shares outstanding). We use this measure following Baker and Wurgler. CEFD is the average discount on closed-end mutual funds and is used by Baker and Wurgler. We replace it with ETF discount due to data constraint. *S* is total equity issuance, which we exclude also due to data constraint.

NIPO and *RIPO* are the number and first day return from IPO, but we use only the change of the number of total listed firms (*Nlist*) due to data issues. We exclude the premium of dividend payers ($P^{D\text{-}ND}$) as well because fewer than 250 firms pay dividends. Most dividend payers are large firms, and many firms have changed their dividend policy to serve foreign investors. Our data source, FnGuide, does not have this data before 2006 either. However, our results remain robust with these small number of data on dividend payer premiums.

Table 2 describes summary statistics of selected proxies in Table 1. We use weekly data from 2003.1 to 2010.9, producing sample weeks of 383. We design our sentiment index by extracting the first principal component of proxies and defining it as a sentiment index. We use two methods to construct this index. First, we use Baker and Wurgler's variables only (Panel A: SENTIMENT with 6 variables). Second, we use all proxies (SENTIMENT with 9 variables). Thus, the sentiment indexes are first principal components of six and nine variables during the data period respectively. Their correlation with proxies is in the sixth column.

We consider the proxies and their lags to construct sentiment indexes in line with Baker and Wurgler. First, we estimate the first principal component of both current and lags of the proxies (first-stage principal component analysis). Second, we compare the correlation between the first principal component and current and lags. Third, we choose one current and one lag of each variable depending on the size of their correlation with the first component. Forth, we conduct principal component analysis again with the chosen variables. We define the sentiment index as the first principal component of this second-stage principal component analysis. We have not orthogonalized the proxies on macroeconomic variables, which Baker and Wurgler finds unimportant. It is impractical as well to use quarterly macroeconomic data in estimating investor sentiment at a weekly frequency. The resulting sentiment indexes are:

$sentiment\_6 = -0.0294Turn_t + 0.0516Nlist_t + 0.5759Fore_t - 0.3713ETF_{t-1} - 0.5656Vol_{t-1} + 0.4550Mom_{t-1}$ (explaining 32% of sample variance[3]), (1)

$sentiment\_9 = -0.2036Turn_{t-1} - 0.0111Nlist_t - 0.4840Fore_t + 0.3447ETF_{t-1} + 0.3428Mom_t + 0.4676KKR_t - 0.1961PCR_t - 0.2873Ab_{t-1}$ (explaining 28% of sample variance), (2)

[3] The variance of this principal component over the sum of the variance of all the other principal components is 32%.

Table 2. Summary Statistics

Table 2 describes summary statistics of selected proxies in Table 1. We collect the data from the FnGuide (http://www.fnguide.com). We use weekly data from 2003.1 to 2010.9, making the sample period 383. Raw data is provided daily and we used a weekly average except for momentum. Momentum is recorded at the end-day of each week. We design a sentiment index upon Baker and Wurgler: extracting first principal component of proxies and defining it as a sentiment index. We use two methods to construct the sentiment index. First, we use Baker and Wurgler's variables only (Panel A: SENTIMENT with 6 variables). Second, we use all proxies (SENTIMENT with 9 variables). Thus, the sentiment indexes have a first principal component of six and nine variables during the data period respectively. Their correlations with proxies are in the sixth column. Sentiment indexes are: $sentiment\_6 = -0.0294Turn_t + 0.0516Nlist_t + 0.5759Fore_t - 0.3713ETF_{t-1} - 0.5656Vol_{t-1} + 0.4550Mom_{t-1}$ (explain 32% of sample variance), $senti\text{-}ment\_9 = -0.2036Turn_{t-1} - 0.0111Nlist_t - 0.4840Fore_t + 0.3447ETF_{t-1} + 0.3428Mom_t + 0.4676KKR_t - 0.1961PCR_t - 0.2873Ab_{t-1}$ (explain 28% of sample variance), where each of the index components has first been de-meanded and scaled to have unit variance. Superscript a, b and c stand for the significance level under 1%, 5%, and 10%, respectively.

	Mean	SD	Min	Max	Correlation with SENTIMENT	$Turn_t$	$Nlist_t$	$Fore_t$	ETF_{t-1}	Vol_{t-1}	Mom_{t-1}			
Panel A: SENTIMENT with 6 variables														
$Turn_t$	-0.12	0.37	-0.83	0.89	-0.04	1.00								
$Nlist_t$	0.02	0.13	-0.52	0.57	0.07	-0.09[c]	1.00							
$Fore_t$	38.30	5.16	29.65	47.33	0.79[a]	0.08[c]	0.02	1.00						
ETF_{t-1}	-0.33	0.36	-1.95	1.26	-0.51[a]	-0.23[a]	0.03	-0.50[a]	1.00					
Vol_{t-1}	26.26	10.06	14.23	81.27	-0.78[a]	0.41[a]	-0.02	-0.43[a]	0.05	1.00				
Mom_{t-1}	3.97	12.17	-40.83	36.23	0.63[a]	0.15[a]	0.06	0.19[a]	-0.05	-0.49[a]	1.00			
Panel B: SENTIMENT with 9 variables														
						$Turn_{t-1}$	$Nlist_t$	$Fore_t$	ETF_{t-1}	Vol_t	Mom_{t-1}	KKR_t	PCR_t	Ab_{t-1}
$Turn_{t-1}$	-0.12	0.37	-0.82	0.89	-0.55[a]	1.00								
$Nlist_t$	0.02	0.12	-0.52	0.57	-0.02	-0.04	1.00							
$Fore_t$	38.3	5.16	29.65	47.33	-0.77[a]	0.09[c]	0.03	1.00						
ETF_{t-1}	-0.33	0.36	-1.95	1.26	0.55[a]	-0.22[a]	0.03	-0.50[a]	1.00					
Vol_t	26.21	10.06	14.23	81.27	0.55[a]	0.39[a]	-0.21	-0.43[a]	0.04	1.00				
Mom_{t-1}	3.97	12.16	-40.83	36.23	-0.62[a]	0.20[a]	0.04	0.18[a]	-0.07	-0.50[a]	1.00			
KKR_t	0.31	0.07	0.16	0.49	0.75[a]	-0.40[a]	-0.07	-0.67[a]	0.42[a]	0.17[a]	-0.22[a]	1.00		
PCR_t	0.94	0.19	0.36	2.35	-0.31[a]	0.12[b]	-0.11[b]	0.02	0.07	-0.23[a]	0.29[a]	-0.03	1.00	
Ab_{t-1}	0.53	0.21	0.03	0.69	-0.46[a]	0.14[a]	-0.03	0.09[c]	-0.08	-0.26a	0.40[a]	-0.09[c]	0.31[a]	1.00

where each of the index components has first been de-meanded and scaled to have unit variance.

Figure 1 and Figure 2 plot sentiment proxies and sentiment index. They show that the proxies and constructed sentiment indexes correspond to the events in Korean economic history; Dropped sentiments during the Korean credit card crisis (2003–2004), steadily increasing sentiment during the stock market boom (2005–2007), sharply falling sentiment around the Lehman default (September 2008). Proxies also show similar patterns except the number of listed companies (*Nlist*) and percentage of listed companies whose stock prices are over a 20-day average (*Ab*). *Nlist* and *Ab* are found to correlate with the sentiment index insignificantly and significantly respectively in Table 2. Overall, our sentiment indexes and proxies capture the

FIGURE 1. SENTIMENT PROXIES AND SENTIMENT INDEX (2003-2010)

A sentiment index is constructed with six proxies described in Panel A to F: ETF discount rate; turnover ratio in logarithm; change in the growth rate of listed companies; implied volatility (VKOSPI), three-month momentum and % of foreign ownership of listed companies (see Table 2). Sentiment and other variables are all de-meaned and scaled to have zero mean and unit-variance. Raw data is provided daily and we used weekly averages except for momentum. Momentum is recorded at the end-day of each week. Dashed-lines is the sentiment index generated by 6 variables. The solid line is scaled data used for computing sentiment index. 'Unit' of index is not important numerically since our principal component analysis does not favor high variance variables: our principal component analysis takes the correlation matrix, not covariance matrix.

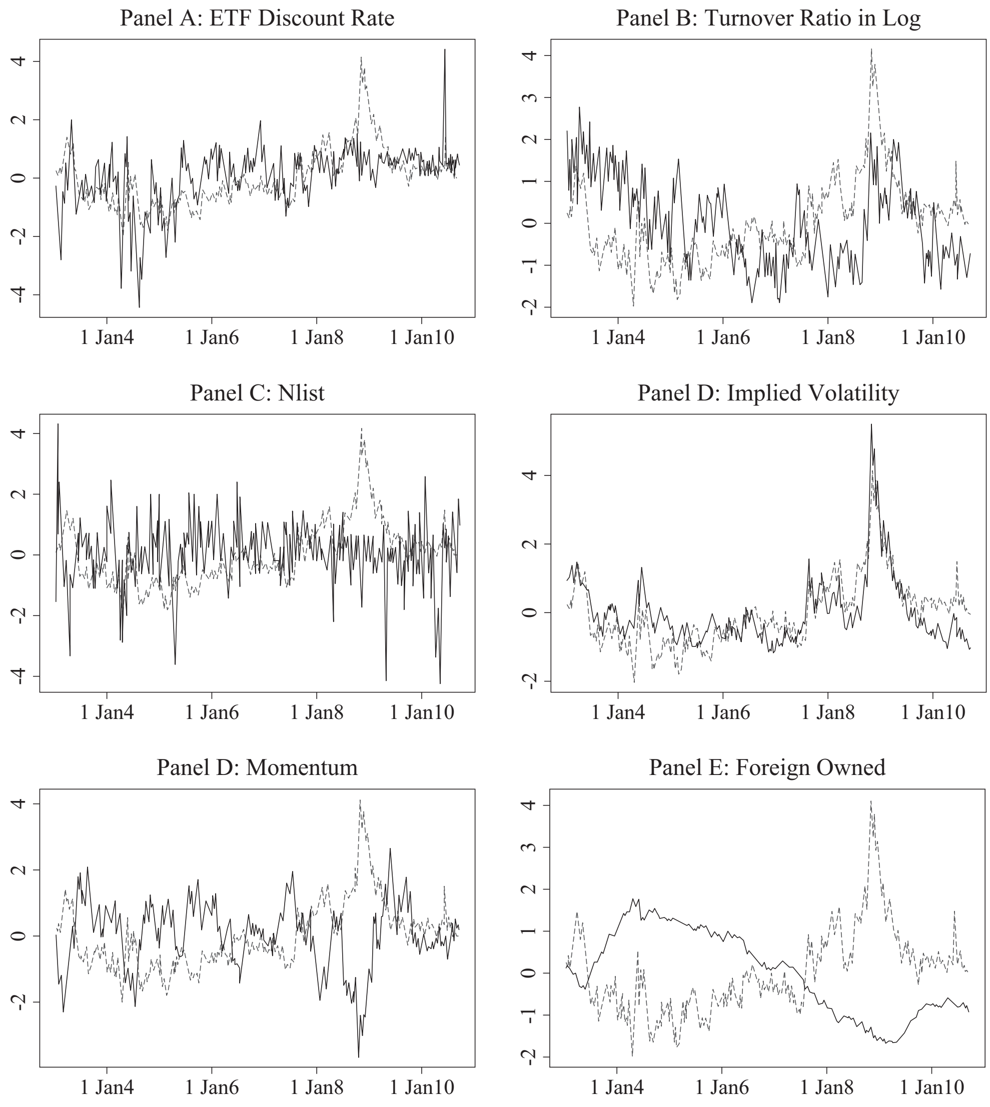
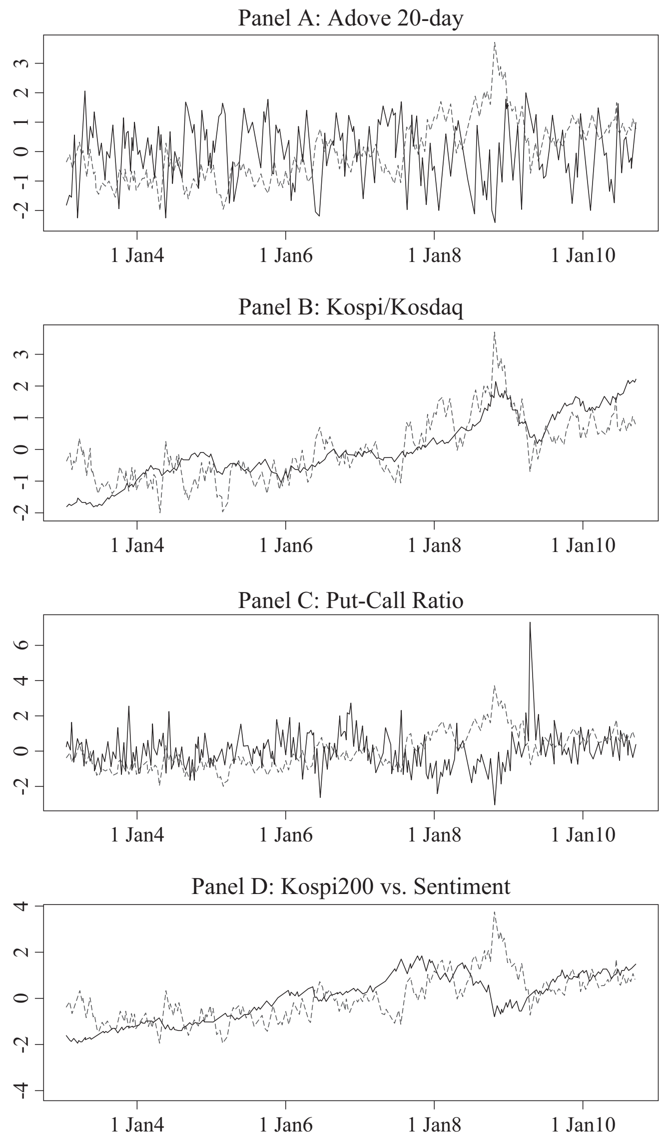


FIGURE 2. SENTIMENT PROXIES AND SENTIMENT INDEX (9 variables): 2003-2010

The dashed-line is the sentiment with 9 variables. The solid line is scaled data used for computing sentiment index. In Panel D, we compare sentiment index with KOSPI200 performance. We do not put sentiment with 6 variables since it almost coincides with sentiment with 9 variables as shown in Figure 1. For the further descriptions about variables, see Table 1 and Figure 1.



intuitive variation in the Korean economy.

Panel D of Figure 2 suggests that the constructed sentiment index is closely related with the dynamics of a market portfolio proxied with the KOSPI200 index performance. Graphically, the sentiment index looks like a lagged mirror image of the KOSPI200. In addition, Baker and Wurgler proposes that sentiment can explain cross sectional variation of stock return in terms of size, risk, profitability, distress, tangibility and growth options. We explore such possibilities in the Korean market with vector autoregression (VAR) analysis.

III. *Results*

In order to assess the predictive power of our sentiment index, we undertake VAR analysis. This analysis enhances the validity of our sentiment index in line with Baker and Wurgler (2006). In addition to our sentiment index[4], we use market premium, size premium, value premium and momentum premium for VAR. Thus, the vector for the VAR analysis is X_t = [*sentiment change(t), MKT Ret(t), SMB Ret(t), HML Ret(t), MOM Ret(t)*]^{T}. Weekly returns is used. *MKT Ret, SMB Ret, HML Ret* and *MOM Ret* stand for "Market premium", "Small minus Big (size premium)", "High minus Low (value premium)", and "Winner minus Loser (momentum premium)" factor returns as in the Fama-French factor (plus momentum factor) model. We use nine proxies to construct the sentiment index. It does not change results to use the sentiment index upon six proxies. To find market portfolio, we have tried both KOSPI200 and KOSPI composite indexes and find the results remain the same. The correlation between KOSPI200 and KOSPI composite indexes is 0.999. Thus, we use the KOSPI200 index to proxy market portfolio in order to make our results more practical; KOSPI200 related derivatives are popular and their markets are the most liquid in the world. The equation for our VAR analysis is:

$$X_{\mathrm{t}} = \alpha + \beta X_{\mathrm{t-1}} + \varepsilon_{\mathrm{t.}}, \tag{3}$$

Table 3 shows the results of VAR analysis. Table 3 shows that the sentiment index may contain information about future stock returns. Our results are consistent with Baker and Wurgler. First, the sentiment index is negatively correlated with future market returns. This suggests that investor sentiment can predict future variations of market portfolio returns. In addition, these results may allow portfolio managers to tactically adjust asset allocation between a market portfolio and cash. Second, the sentiment index is negatively correlated with size and value premium, implying that the sentiment index can predict cross sectional variations of stock return in terms of size (Small vs. Big) and growth option (Value vs. Growth). These results can allow asset managers to potentially alter allocation across various types of stocks or styles in order to generate excess return. Our results contrast Lemmon and Portniaguina [2006] in which investor sentiment does not forecast value and momentum premiums. We agree with Lemmon and Portniaguina [2006] on momentum premiums, but not on value premiums. Our findings partially correspond to Ho and Hung [2009] in which investor sentiments conditionally explain size, value, liquidity and momentum premiums.

[4] This is the sentiment index for entire period. When we develop trading strategies, we repeated estimating the sentiment index every period with the 'best' combination of underlying proxies. Detailed explanation will follow shortly.

TABLE 3. SENTIMENT INDEX AND STOCK RETURNS (VAR results)

This table is the result of vector autoregressive. The VAR model is $X_t = \alpha + \beta X_{t-1} + \varepsilon_t$, where X_t = [*sentiment change(t), MKT Ret(t), SMB Ret(t), HML Ret(t), MOM Ret(t)*]^T. Weekly return is computed. *MKT Ret, SMB Ret, HML Ret,* and *MOM Ret* stand for "Market premium", "Small minus Big (size premium)", "High minus Low (value premium)", and "Winner minus Loser (momentum premium)" factor return as in the Fama-French factor model. We use nine proxies to construct the sentiment index. It does not change results to use the sentiment index upon six proxies. To find a market portfolio, we have tried both KOSPI200 and KOSPI composite indexes and find the results remain the same. The correlation between KOSPI200 and KOSPI composite index is 0.999. Thus, we use KOSPI200 index to proxy market portfolio in order to make our results more practical: KOSPI200 related derivatives are popular and their market is one of the most liquid in the world. Estimates and p-value are provided. Superscript a, b, and c mean statistical significance under 1%, 5% and 10% level, respectively.

	$SENTIMENT_{t-1}$		MKT_{t-1}		SMB_{t-1}		HML_{t-1}		MOM_{t-1}	
	estimate	p-value	estimate	p-value	estimate	p-value	estimate	p-value	estimate	p-value
$SENTIMENT_t$	0.036	0.577	-1.124	0.505	2.325	0.462	-0.972	0.825	2.279	0.123
MKT_t	-0.012[a]	0.006	-0.081	0.480	-0.323	0.133	0.299	0.318	0.062	0.535
SMB_t	-0.008[c]	0.083	0.067	0.554	-0.415[c]	0.052	0.324	0.275	-0.102	0.306
HML_t	-0.009[b]	0.027	0.008	0.401	-0.313[c]	0.097	0.224	0.393	-0.052	0.554
MOM_t	0.004	0.213	-0.073	0.337	-0.031	0.830	0.019	0.924	0.030	0.656

FIGURE 3. PERFORMANCES OF TAA1 AND MARKET PORTFOLIO (KOSPI200)

We generate sentiment signal and conduct asset allocation between market portfolio and call loan (TAA1). Figure 3 graphically compares the performance between TAA1 (solid line) and market portfolio (dashed line). For the further description about performances, see Table 4.

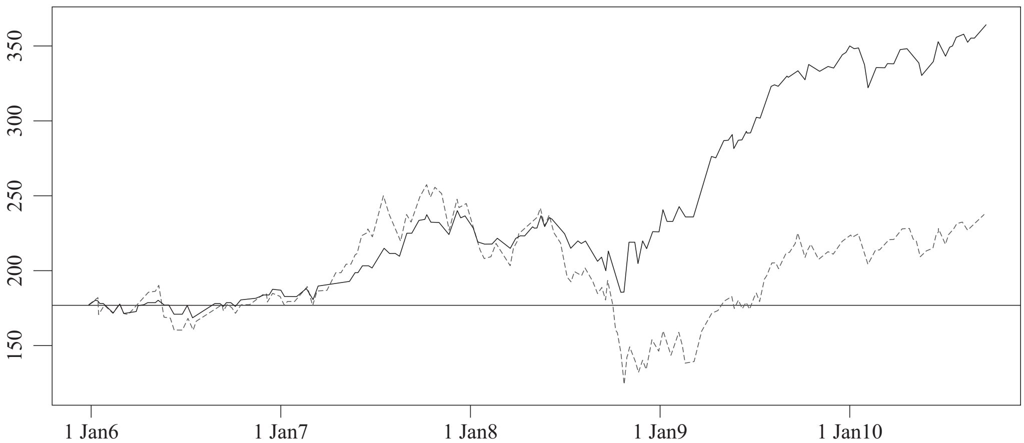


Table 4. Benefits from Tactical Asset Allocation Using Market Sentiment

We generate sentiment signal and conduct asset allocation between market portfolio and call loan in accordance to Table 3. Table 4 evaluates the performance of TAA1 and TAA2 after adjusting risks. For TAA1, we invest (1-PCT)% in KOSPI200 and PCT% in call loans. We consider transaction cost to compute our portfolio's performance: 10 bp per unit (brokerage fee + implied costs) whenever buying KOSPI200 and 40 bp per unit (brokerage fee + implied costs + transaction tax) whenever selling KOSPI200. In Korea, transaction tax (30 bp per unit) is imposed on sellers only. For TAA2, we invest (1-PCT)% of initial wealth in SMB+HML in addition to base allocation to market portfolio. Both SMB and HML are zero-cost portfolios. Thus, SMB+HML is also a zero-cost portfolio taking long positions on small and value stocks and short positions on large and growth stocks. Transaction cost for TAA2 is also considered: 25bp per unit (brokerage fee + implied costs+ transaction tax/2) whenever buying SMB+HML and 25bp per unit (brokerage fee + implied costs + transaction tax/2) whenever selling SMB+HML. Panel A shows the distribution of TAA1, TAA2 and KOSPI200 returns. Annualized Sharpe Ratio (SR) is also provided. We rebalanced the portfolio weekly. Panel B shows risk and excess return of our tactical portfolios. We regress the excess return of our tactical portfolio over weekly risk free rate (call rate) on Fama-French three factors and momentum factor: *Portfolio Ret – Risk Free rate* $= a + b_1$ **KOSPI200 Ret* $+ b_2$* *SMB Ret* $+ b_3$* *HML Ret* $+ b_4$**MOM Ret + error*. R^2 of TAA1 and TAA2 are 0.5748 and 0.9953, respectively.

Panel A: Descriptive Statistics of TAA1, TAA2 and KOSPI200

	Min	Max	Average	STD	Sharpe Ratio
TAA1	-6.405%	17.189%	0.330%	2.270%	0.922
TAA2	-22.66%	17.31%	0.340%	3.620%	0.602
KOSPI200	-22.549%	17.129%	0.122%	3.574%	0.115

Panel B: Risk Adjusted Performance of TAA1, TAA2 and KOSPI200

		a	b1	b2	b3	b4
TAA1	Estimate	0.0021	0.5271	0.2364	-0.2896	-0.0063
	p-value	0.0314	0	0.0099	0.0231	0.8819
TAA2	Estimate	0.00144	1.005	-0.0188	0.0260	-0.0104
	p-value	0	0	0.220	0.224	0.147

Motivated with the results in TABLE 3, we suggest three tactical-asset allocations (TAA) as follows.

TAA1: This strategy is a balanced portfolio between market portfolio and cash with signals generated from sentiments.

TAA2: This strategy is an enhanced market portfolio by adding zero-cost size and value premiums to market portfolio according to the sentiment signals.

TAA3: The third possible strategy is a mixed portfolio of TAA1 and TAA2.

The performances of the three strategies are: TAA1 generates 0.21% weekly alpha (11.54% per annum); TAA2 generates 0.144% weekly alpha (7.78% per annum); TAA3 generates 0.354% per week (19.32% per annum). Those performances are excess performance after the standard risk factors (market, size, value and momentum premiums) and transaction costs are controlled.

Hereafter, we will describe the three tactical-asset allocations and their results in detail. Figure 3 and Table 4 show TAA1. It clearly enhances the performance of asset allocation between market portfolio and cash (call loan) to consider investor sentiment. We generate sentiment signal and conduct asset allocation between market portfolio and call loan in accordance to Table 3. Table 4 evaluates the performance of our portfolio with risk-adjustment returns and Sharpe Ratio. Sentiment signal is generated as follows. First, we select six out of nine proxies to generate 84 possible indexes (${}_9C_6$ = 84) at each time x using prior data $t = 0, 1 \ldots x\text{-}1$. We consider only six proxies because in the early data period we do not have many prior observations. Lack of prior data can cause severe estimation errors in principal component analysis, especially in the course of estimating a correlation matrix. Second, we choose one index out of 84 combinations with the maximum virtual hits at every period. To explain virtual hit, let $PRED_{i,t}$ = sign ($\Delta market_t$)*sign ($\Delta index_{i,t-1}$) for i=1,2,3,...84, and let $HIT_{i,t}$ =1 if $PRED_{i,t} = -1$ (i.e. when $\Delta index_{i,t-1}$ correctly (negatively) predicts $\Delta market_t$) and $HIT_{i,t}$ =0 otherwise (i.e. when $\Delta index_{i,t-1}$ incorrectly predicts $\Delta market_t$). The virtual hit of k-th index out of 84 at time t is defined as the summation of $HIT_{k,t-j}$ through j=0 to 9 (i.e. historical performances of predicting $\Delta market_t$). Among 84 indices (i.e. for all i of $\Delta index$), we choose the index which attains the maximum virtual hits and call the index value as sentiment at time t. Third, we compute the percentile of sentiment change[5] ($\Delta sentiment_t$) at time t for $i = 2 \ldots$ t. Let us call the percentile as PCT. Fourth, we invest (1-PCT)% in KOSPI200 and PCT% in call loan. We consider transaction cost to compute our portfolio's performance: 10 bp per unit (brokerage fee + implied costs) whenever buying KOSPI200 and 40 bp per unit (brokerage fee + implied costs + transaction tax) whenever selling KOSPI200. In Korea, transaction tax (30 bp per unit) is imposed on sellers only. We intentionally consider only crude allocation strategies to render our results simple and robust to more sophisticated allocation strategies. More sophisticated tactics may increase the portfolio performance further.

Panel A shows the distribution of the weekly portfolio and KOSPI200 returns. We rebalance the portfolio weekly. Panel B shows risk and excess return of our tactical portfolio. We regress the excess return of our tactical portfolio over weekly risk free rate (call rate) on Fama-French three factors and momentum factor as follows:

$$\textit{Portfolio Ret} - \textit{Risk Free rate} = a + b_1{*}\textit{KOSPI200 Ret} + b_2{*}\,\textit{SMB Ret} + b_3{*}\,\textit{HML Ret} + b_4{*}\textit{MOM Ret} + \textit{error}. \quad (4)$$

R^2 is 0.5748. Intercept, i.e. weekly alpha (a), is estimated as 0.21% per week, equivalent to 11.54% per annum. Our tactical allocation is significantly exposed to market, size and value premiums, while unexposed to momentum premium. Figure 3 graphically compares the performances of TAA1 and market.

[5] More specifically, we choose the best predictor (maximum virtual hit) out of 84 combinations at time t. Then, the predictor becomes the value of sentiment at time t in our strategy. This value of sentiment is different from those described in Table 3 which describes the sentiment for the whole period. Next, we compute again the percentage change between t-1 and t of the constructed sentiment at time t. We develop trading strategies with this percentage change.

Table 5. Time-series Regression of Portfolio Returns

We regress the returns of long-short portfolios (i.e. SMB, HML, MOM and VOL) on lagged sentiments and each other. Table 6 present regression coefficients (p-values in parenthesis). We constructed long-short portfolios regarding size (SMB), book-to-market value (HML), 12-month momentum (MOM) and 1-week volatility (VOL) exactly same as the previous analysis in Table 4. VOL portfolio is constructed by buying upper 30% of high volatility stocks and shorting bottom 30% of bottom volatility stocks. SMB, HML and MOM are defined as same. In the unconditional model, the portfolios returns are regressed on sentiment index of previous week. In the conditional model, the portfolio returns are regressed on the conditioning variables of market premium, SMB, HML, and MOM. When SMB (HML or MOM) are dependent variables, SMB (HML or MOM) are omitted from conditioning variables.

Long-short portfolios	Conditioning only on Sentiment (t-1)	Conditioning with SMB + HML + MOM
SMB	-0.011 (0.163)	0.001 (0.647)
HML	-0.013 (0.066)	-0.001 (0.641)
MOM	0.005 (0.367)	0.004 (0.483)
VOL	-0.014 (0.01)	-0.01 (0.042)

The second part of Table 4 shows TAA2; We can surely improve the performance by exploiting the component of cross sectional variations that investor sentiment can explain. Table 4 evaluates the performance of tactical portfolio that takes into account cross sectional variations of stock returns after adjusting risks (TAA2). Similar to the previous case, we invest (1-PCT)% of initial wealth in size and value premium (SMB+HML) in addition to the base allocation in market portfolio. Both SMB and HML are zero-cost portfolios. SMB+HML take long positions on small and value stocks and short positions on large and growth stocks. We consider transaction cost to compute our portfolio's performance as well: 25 bp per unit (brokerage fee + implied costs + transaction tax/2) whenever buying SMB+HML and 25 bp per unit (brokerage fee + implied costs + transaction tax/2) whenever selling SMB+HML. We rebalanced the portfolio weekly. Panel A shows the distribution of the weekly portfolio and KOSPI200 returns. Panel B shows risk and excess return of our tactical portfolio. We regress the excess return of our tactical portfolio over weekly risk free rate (call rate) on Fama-French three factors and momentum factor. R^2 is 0.9953. Intercept, i.e. weekly alpha, is estimated as 0.144% per week, equivalent to 7.78% per annum. Our tactical allocation is significantly exposed to market risk, but unexposed to size, value and momentum premium. Thus, this allocation can benefit active fund managers whose benchmark is a market portfolio since it can produce a high information ratio for fund managers.

We can obtain best performance by using both TAA1 and TAA2, which we call TAA3[6]. The beauty of our tactical-asset allocation schemes lies in its practicality. It is easy to invest in either SMB or HML portfolio in Korea because there are KOSPI futures (large firms), KOSDAQ futures (small firms), and exchange traded funds for value and growth stocks.

Additionally, we regress the returns of long-short portfolios (i.e. SMB, HML, MOM and VOL) on lagged sentiments and each other[7]. Table 5 present regression coefficients (p-values in

[6] Appendix (Figure 4) shows their performances.

[7] We appreciate an anonymous reviewer for suggesting this analysis.

parenthesis). We constructed long-short portfolios regarding size (SMB), book-to-market value (HML), 12-month momentum (MOM) and 1-week volatility (VOL) exactly same as the previous analysis. VOL portfolio is constructed by buying upper 30% of high volatility stocks and shorting bottom 30% of bottom volatility stocks. SMB, HML and MOM are defined as same. In the unconditional model, the portfolios returns are regressed on sentiment index of previous week. In the conditional model, the portfolio returns are regressed on the conditioning variables of market premium, SMB, HML, and MOM. When SMB (HML or MOM) are dependent variables, SMB (HML or MOM) are omitted from conditioning variables.

We find that sentiment has marginal predicting power for HML in unconditional model, but the predictive power disappears with conditional variables. However, we should note that the prior VAR analysis (Table 3) offers more informative results considering the correlation structure in error terms. For VOL, sentiment index has significant predictive power both in unconditional and conditional models. This suggests that our sentiment index can be useful to trade derivatives as well as volatility index such as VIX in the US market or VKOSPI in the Korean market.

IV. *Conclusion*

Investor sentiment is a significant subject, with various indexes published by financial institutes and hedge funds that attempt exploiting sentiment to generate excess returns. Baker and Wurgler [2006, 2007] offer a comprehensive review and show that macro-level investor sentiment indexes can predict cross sectional stock returns. Baker and Wurgler argue that the extent of subjective valuation and arbitrage constraints generate such cross sectional variations. Nevertheless, few articles illustrate how to apply investor sentiment in order to generate excess performance with active portfolio allocation.

The Korean stock market is an ideal experimental site to test Baker and Wurgler's intuition on portfolio management. First, it is smaller than other developed markets, but important enough to have practical implications. Thus, subjective valuation may matter more for Korean stocks than U.S. stocks. Second, the Korean stock market has various regulations that restrict arbitrage trading. This can sustain trading opportunities arising from investors' sentiment. Tactical asset allocation is our tool to conduct this experiment because it attempts rebalancing a portfolio based on short-term market predictions such as the fleeting dynamics of investor sentiment.

Our results find that the impact of investor sentiment is material enough: tactical asset allocation upon investor sentiment can generate excess returns after adjusting risks through a standard risk model and transaction costs. In addition, the asset allocation generates extra performance whether we use valuation fluctuation of a market portfolio or cross sectional valuation fluctuation of individual stocks. It is certain that it will generate enhanced performance to combine allocation strategies about both time series and cross section variations of stocks.

Many extensions of our paper are possible. We consider only very crude asset allocation strategies for robustness and simplicity. More sophisticated strategies may generate even larger excess returns. In fact, we have tried other complicated schemes in tactical asset allocation and are actually making money. It is not difficult to produce excess returns greater than those presented in this paper. Future literature can systematically study such possibilities. In addition, while we conducted our experiment only in the South Korean stock market, other financial markets or asset classes can provide academic and practical opportunities.

Appendix

Robustness Check and Discussion

This section discusses MOM (momentum), FORE (foreign investor behavior) and ETF (discount rate of ETF) because they are newly added in this paper in comparison to BW.

MOM

It is arguable to justify momentum effect as a proxy of investor sentiment. For example, Vayanos and Woolley (2013) provide a convincing explanation of momentum effect based on institutional aspects. We just wrote that MOM was suggested by some practitioners and do not provide any economic explanation that relates Mom variable to investor sentiments.

Therefore, we exclude MOM in constructing sentiment and reproduce the tactical asset allocation. TABLE 7 shows the results and validates our previous ones. R2 is 0.5748 and intercept, i.e. weekly alpha is estimated as 0.21% per week, equivalent to 11.54% per annum. Thus, our results become even stronger after excluding momentum effects. This makes our trading strategy more profitable and easily implementable. This also contrasts the common sense of the Korean professionals in the financial sectors.

Table 6. Investor Sentiment (Without Momentum Effects) and Tactical Asset Allocation Among Stocks

We evaluate the performance of the tactical portfolio that takes into account cross sectional variations of stock returns (TAA2) after adjusting risks, but except momentum risk. See Table 4 for the analysis with momentum risks and further details on this regression analysis.

Panel A

	Min	Max	Average	STD	MDD
Portfolio	-3.87 %	11.68 %	0.225%	1.325%	-8.606%
KOSPI200	-22.549%	17.129%	0.122%	3.574%	-52.093%

Panel B

	a	b1	b2	b3	b4
Estimate	0.0023	-0.107	-0.0597	0.2139	-0.0833
p-value	0.005	0.011	0.4462	0.05114	0.0247

FORE

As a robustness check, we dropped Fore in constructing sentiment index. This does not change our results. We did not report its similar result from the same methods. In addition, in intuitive explanation as follows.

In the Korean Market, the investor categories defined by the Korea Exchange (KRX) are: individual, institutional and Foreigner. The foreigner category is not clearly defined because their purpose of investment activities is not reported. The KRX classifies the accounts in securities companies registered as foreigners as the foreigner category. Therefore, it is difficult to analyze their behaviors in the market. However, most of individual and institutional investors in Korea closely monitor the behavior of the foreigners such as trading volume and arbitrage trading between futures and index baskets. The Korean media follows the investment activities of foreigners very closely too. In addition, foreigners tend to swing their exposures very quickly and widely compared to other investor groups. Therefore, many Korean experts believe that this combination of attention, media coverage and foreigner behaviors affects the sentiment of the Korean market.

ETF

The closed-end fund discount puzzle was one of the major focuses in early behavioral finance literature. However, there is no research that relates the open-end fund discount to the investor sentiment. As a robustness check, we dropped ETF. However, this does not change our results. We did not report its similar result from the same methods. In addition, the reason that we put ETF variable for the analysis is as follows.

The Korean ETF market is big, but premature in the market at least at time we started the analysis. Liquidity providers and individual investors of ETFs were not very well-trained. Thus, the discrepancy rate between underlying asset or value of PDF (Portfolio Deposit File: the constituents and their weights in an ETF) and market price of the ETFs were large. We believe this gap contains valuable information about market sentiment. Of course, the information from close-end mutual funds would be more preferable. However, unfortunately, there is no close-end mutual funds listed in the Korean market. In addition, institutional investors rarely trade ETFs since it is much cheaper for them to trade index baskets. Therefore, individual investors who want to invest on equity indices usually go for ETF. Those individual traders are the drivers of market sentiments.

Figure 4 graphically compares their performances. We can obtain best performance by using both TAA1 and TAA2, which we call TAA3. The beauty of our tactical-asset allocation schemes lies in its practicality. It is easy to invest in either SMB or HML portfolio in Korea because there are KOSPI futures (large firms), KOSDAQ futures (small firms), and exchange traded funds for value and growth stocks.

FIGURE 4. PERFORMANCES OF TAA1, TAA2 AND MARKET PORTFOLIO (KOSPI200)

Solid line is for KOSPI200, dashed-line is for TAA1 and dashed-line overlaid with "o" is TAA2. For the further details, see Figure 3 and Table 4.

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