Idiosyncratic Volatility and Stock Return Predictability: Evidence from the Korean Stock Market

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Abstract

Constructing a newly proposed measure of idiosyncratic volatility by Garcia *et al*. (2014), we investigate the relation between idiosyncratic volatility and future market returns in Korea. From monthly predictive regressions, we find that our idiosyncratic volatility proxy has a significantly positive relation with the future market excess return. Moreover, we find that the predictive power of idiosyncratic volatility does exist at the daily frequency data. The predictive power of idiosyncratic volatility is robust to several considerations including weighting schemes, sample periods, and trading exchanges. Overall, our empirical results indicate that idiosyncratic volatility plays an important role in predicting future stock returns in the Korean stock market.

JEL Classification: G12

Keywords: Idiosyncratic volatility; Stock return predictability; Cross-sectional variance

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1. Introduction

Understanding the inter-temporal relation between risk and return has long been a central research question in financial economics. Starting with Merton's (1973) ICAPM, most asset pricing models predict that expected return from a stock portfolio has a positive relation with risk estimated as the variance or standard deviation of the portfolio's return. However, the empirical findings on the relation between risk and expected return in aggregate stock market have been inconclusive and mixed (Campbell 1987; French, Schwert, and Stambaugh 1987; Pindyck 1984; Whitelaw 1994).

Contrary to the standard asset pricing theories, some previous works have theoretically developed models incorporating the effect of idiosyncratic volatility on asset returns.[3] For example, Levy (1978) and Malkiel and Xu (2002) show that idiosyncratic volatility is positively related to expected stock returns since investors hold undiversified portfolios. Introducing a non-traded human capital, Mayers (1976) also derives similar relation between idiosyncratic volatility and stock returns. Given these economic theories, there have been efforts to identify the importance of idiosyncratic volatility in predicting stock returns in the U.S. stock market (Goyal and Santa-Clara 2003; Bali *et al*. 2005; Wei and Zhang 2005).

One big concern in conducting empirical experiment is the estimation of idiosyncratic volatility measure because it is not observable. The literature commonly uses the individual firm residuals of the CAPM and Fama-French three-factor model to estimate the idiosyncratic risk. As an alternative, a recent paper by Garcia *et al*. (2014) suggests a new approach: They estimate aggregate idiosyncratic risk as cross-sectional variance (CSV) of stock returns. The measure has some advantages. First, it has theoretical background. Garcia *et al.* (2014) show that cross-sectional variance of stock returns is a consistent and asymptotically efficient estimator for

[3] In this study, "volatility" refers to variance and standard deviation of a stock returns.

aggregate idiosyncratic volatility. Second, since calculation of the CSV measure does not require standard asset pricing models such as the CAPM or Fama-French three-factor model, it is model-free. Finally, the CSV measure enables us to estimate aggregate idiosyncratic volatility at any frequency, while previous measures have relied on monthly model-based measures constructed from daily data.

Constructing this newly proposed measure of idiosyncratic volatility by Garcia *et al*. (2014), we investigate the relation between idiosyncratic volatility and future market returns in Korea. We are particularly interested in the effect of idiosyncratic risk on future market returns in one emerging market, Korea, for the following reasons. First, little is known about the inter-temporal relation between idiosyncratic volatility and future stock returns in Korea. Although some studies have paid attention to idiosyncratic volatility in the Korean stock market, they focus on the cross-sectional relation between idiosyncratic risk and stock returns (Eom *et al*., 2014; Kang *et al*., 2014; Kim and Byun, 2011). Rather, we study the time-series relation between idiosyncratic risk and stock returns. Thus, our work provides out-of-sample evidence as to whether there exists an inter-temporal relation between idiosyncratic risk and stock returns in emerging markets. Second, the Korean stock market has experienced rapid growth among emerging markets. According to the World Bank, the market capitalization of listed companies in Korea increased from $172 billion in 2000 to $1180 billion in 2012.

Our empirical findings are summarized as follows. From monthly predictive regressions, we find that our idiosyncratic volatility proxy, CSV measure, has a significantly positive relation with the future market excess returns. Moreover, the explanatory power of idiosyncratic risk is striking compared to that found in the U.S. market. Garcia *et al*. (2014) document that for any univariate regression, the adjusted R^2 is no more than 1.37% in the U.S. market. On the other hand, we find that the adjusted R^2 values are in the range of 1.41%-3.69% when the CSV volatility measure is employed as an independent variable. From daily predictive regressions, we show that the predictive power of idiosyncratic volatility does exist at the high frequency data. Given that previous studies have been confined to the investigation of stock return predictability using low frequency monthly measure, our finding on a daily basis provide new evidence on stock return predictability literature.

The predictive power of idiosyncratic volatility is robust to several considerations. Robustness tests are particularly important in our study because in the U.S. market, empirical findings on the relation between idiosyncratic volatility and future market return have been different in terms of (1) weighting schemes in constructing market excess return and aggregate idiosyncratic risk, (2) sample periods, and (3) trading exchanges. In their seminal paper, Goyal and Santa-Clara (2003) find that the equal-weighted idiosyncratic risk has a striking forecasting power for the value-weighted market excess returns during the period of August 1963 to December 1999. Wei and Zhang (2005) criticize the empirical specification of Goyal and Santa-Clara (2003) because they use mismatched weighting schemes. Bali *et al*. (2005) and Wei and Zhang (2005) do not find the positive relation between future market return and idiosyncratic volatility for extended sample periods. In addition, Bali *et al*. (2005) show that the empirical evidence from Goyal and Santa-Clara (2003) is driven by small stocks traded on the NASDAQ.

First, the forecasting power of idiosyncratic volatility is present regardless of weighting scheme in the Korean stock market. Unlike the finding of Goyal and Santa-Clara (2003), we find positive linkage between non-mismatched weighting schemes, equal-weighted market excess return and equal-weighted idiosyncratic volatility, and value-weighted market excess return and value-weighted idiosyncratic volatility. Second, our sub-sample period results show that the positive relation between future market return and idiosyncratic volatility is largely retained in extended sample periods. Except for the pre-Asian financial crisis period, the estimated slope coefficients on CSV are positively significant regardless of the weighting scheme. Finally, by performing predictive regressions with stocks traded on the KOSPI, we find that the positive relation between idiosyncratic risk and future market excess return is not due to small stocks traded on the KOSDAQ.

What drives our empirical results? One possible explanation for our finding is related with the fact that investors hold undiversified portfolios among financial assets. Levy (1978), Merton (1987), and Malkiel and Xu (2002) show that a market-wide measure of idiosyncratic risk explains future returns if investors, for some exogenous reason, hold undiversified portfolios. Previous studies document that the levels of individual ownership and trading are unusually high in Korea and a significant fraction of individual investors hold undiversified portfolios. Barber *et al*. (2006) report that the Korean stock markets have high individual ownership and trading activity. By examining stock holdings of 660,000 customers, one large security company in Korea, Samsung securities, reports that 40% of individual investors hold just one stock in their portfolios as of February 2013. Therefore, it is not surprising that idiosyncratic volatility plays an important role in predicting future market returns in the Korean stock market.

Our study is linked to a growing body of research on idiosyncratic volatility in the Korean stock market. Kim and Byun (2011) find that portfolios with high idiosyncratic volatility have significantly lower return than portfolios with low idiosyncratic volatility. Eom *et al*. (2014) report that stocks with high idiosyncratic volatility have negative returns in down market, inducing the idiosyncratic volatility puzzle in the Korean stock markets. Kang *et al*. (2014) provide empirical evidence that idiosyncratic puzzle is due to overpricing caused by noise traders. Our study differs with theirs, however, in that we focus on the time-series relation between idiosyncratic risk and stock returns, whereas they investigate whether level of idiosyncratic risk can explain the cross-section of stock returns.

The remainder of this paper is organized as follows. Section 2 presents the data and idiosyncratic volatility measures. Section 3 presents forecasting power of idiosyncratic volatility on market excess return. Section 4 summarizes and concludes the paper.

2. Data and Idiosyncratic Volatility Measures

2.1 Data

We investigate stocks traded on the KOSPI and KOSDAQ over the period from August 1991 to April 2015.[4] A total of 1,795 stocks are included during this period. For each stock, stock price, number of shares outstanding, market capitalization, and accounting data come from the FnGuide database. Since we examine stock return predictability on daily and monthly frequencies, we calculate returns for the two cases. Stock returns at each frequency are adjusted to reflect stock splits and the stock and cash dividends. To calculate value-weighted returns using individual stock returns, we include observations with positive market capitalization. After all, we have a sample of 511,575 firm-month observations and 11,167,528 firm-day observations.

We perform time-series regressions to test whether each idiosyncratic risk measure predicts future market excess returns. Market excess returns, dependent variables in predictive regressions, are calculated by the difference between equal-weighted or value-weighted average returns and the risk-free rate. Following prior studies, we employ the 91-day CD as our risk-free asset (Lee *et al*., 2015).

The independent variables in predictive regressions are various aggregate idiosyncratic risk measures including our main proxy, CSV measure. For some specifications, aggregate idiosyncratic risk measures are estimated using the CAPM or Fama-French three-factor model. Following Fama and French (1993), we construct the returns of the Fama-French factors, MKT, SMB, and HML. MKT is defined as the difference between the KOSPI value-weighted returns and the 91-day CD rate. SMB is defined as the difference of average returns of small and large stock groups, and HML is computed as the difference between returns on high book-to-market stock groups and low book-to-market stock groups.

2.2 Aggregate idiosyncratic risk measures

[4] Due to issues around availability of the 91-day CD rate, the proxy for the risk-free rate, the data begin at August 1991.

In the literature, aggregate idiosyncratic risk is commonly defined as a weighted average of individual idiosyncratic risks. Specifically, on month *t*, the aggregate idiosyncratic risk, as denoted by AIR_t, can be written as:

$$AIR_t = \sum_{i=1}^{N} \omega_{i,t} V_{i,t}, \tag{1}$$

where $V_{i,t}$ is the idiosyncratic risk of firm *i* on month *t*. The ways to proxy the individual idiosyncratic risk are different among researchers. Although we are particularly interested in the CSV measure, we employ the four proxies for the individual idiosyncratic risk to compare the forecasting power of CSV measure with other measures suggested in the literature. As summarized in Table 1, we adopt the approach suggested by Garcia *et al*. (2014), Goyal and Santa-Clara (2003), and Bekaert *et al*. (2012). Also, we calculate both equal- and value-weighted aggregate idiosyncratic risk for each specification in Table 1.

As displayed in Table 1, each measure is unique in that it estimates individual idiosyncratic risk, $V_{i,t}$. Our main measure for this study is the aggregate idiosyncratic volatility proposed by Garcia *et al.* (2014). They calculate aggregate idiosyncratic risk as cross-sectional variance (CSV) of stock returns using both equal-weights and value-weights. Following their approach, for each month *t*, we use monthly returns of each stock to obtain idiosyncratic risk for firm *i* on month *t*, $V_{i,t} = \left(r_{i,t} - \overline{r_t}\right)^2$ and average them with both equal-weights and value-weights to create CSV^{EW} and CSV^{VW}. We choose CSV measure as our main interest for the following reasons. First, it has concrete theoretical background. Garcia *et al.* (2014) show that cross-sectional variance of stock returns is a consistent and asymptotically efficient estimator for aggregate idiosyncratic volatility. Given that one big concern in this literature is the measurement of idiosyncratic volatility, it is natural to use a measure with theoretical justification. Second, since calculation of the CSV measure does not require standard asset pricing models such as the CAPM and Fama-French three-factor model, it is model-free. Finally, the CSV measure enables us to estimate aggregate idiosyncratic volatility at any frequency, while previous measures have relied on monthly model-based measures constructed from daily data. Exploiting this property, we include daily measure of Garcia *et al.* (2014) into our analysis to provide whether the idiosyncratic volatility has forecasting power for future market excess return at daily frequency.

To compare the forecasting power of the CSV measure with those suggested in previous studies, we obtain idiosyncratic measures of Goyal and Santa-Clara (2003) and Bekaert *et al*. (2012). First, to obtain monthly version of aggregate idiosyncratic risk suggested by Goyal and Santa-Clara (2003), we compute idiosyncratic risk for firm *i* on month *t* as follows:

$$V_{i,t} = \sum_{d=1}^{D} r_{i,d}^2 + 2\sum_{d=2}^{D} r_{i,d} r_{i,d-1}, \tag{2}$$

where *D* denotes the number of daily observations on each month.[5] As Goyal and Santa-Clara (2003) point out, $V_{i,t}$ can be occasionally negative when negative autocorrelation dominates the squared return in equation (2). Following Goyal and Santa-Clara (2003), we use only the first term in equation (2) for such cases. We also exclude a firm with returns less than five days in a month. We calculate aggregate idiosyncratic volatility measures using both equal-weight and value-weight, and they are denoted by GS^{EW} and GS^{VW}, respectively.

Second, as in Bekaert *et al*. (2012), we employ the CAPM and Fama-French three-factor model to estimate idiosyncratic risk. Specifically, for each month, we run daily regressions of each firm's excess returns on the factors and obtain residuals of the regressions. The time-series sample variances of the residuals, $\sigma^2(\varepsilon_{i,t}^{CAPM})$ and $\sigma^2(\varepsilon_{i,t}^{FF})$, are used for the idiosyncratic variances of firm *i* on month *t*.[6] With variances of residuals, $\sigma^2(\varepsilon_{i,t}^{CAPM})$, we compute equal-

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[5] Since French *et al*. (1987) adopt this definition, many subsequent studies including Goyal and Santa-Clara (2003) have used equation (2) in calculating idiosyncratic risk.

[6] Previous studies have used standard deviation for this calculation. However, we use variance instead of the standard deviation to compare the measure of Bekaert *et al*. (2012) with other measures investigated. Note that the GS and CSV measures are the weighted averages of variances. We also estimate idiosyncratic risk measures based on CAPM and Fama and French three-factor model using the standard deviation. The (unreported) result shows that our conclusion remains unchanged.

weighted and value-weighted aggregate idiosyncratic volatility, $CAPM^{EW}$ and $CAPM^{VW}$. Also, using variances of residuals, $\sigma^2(\varepsilon_{i,t}^{FF})$, we calculate equal-weighted and value-weighted aggregate idiosyncratic volatility, FF^{EW} and FF^{VW}.[7]

2.3 Weighting scheme

In this paper, we explore the linkage between aggregate idiosyncratic risk and the future market excess return. To this end, we run the following time-series regression.

$$R_{t+1} = \alpha + \beta' AIR_t + \gamma' X_t + \varepsilon_{t+1}, \quad (3)$$

where R_t is the market excess return, measured by the difference between the market return and the risk-free rate, AIR_t is a vector of aggregate idiosyncratic risk, and X_t is a vector of control variables.

One concern in implementing equation (3) is the choice of weighting scheme in constructing market excess return and aggregate idiosyncratic risk since different weighting schemes have been employed in the analysis of previous studies. For example, Goyal and Santa-Clara (2003) investigate the relationship between the equal-weighted idiosyncratic risk, AIR_t^{EW}, and the value-weighted market excess returns, R_{t+1}^{VW}. On the other hand, Bali *et al*. (2005) argue that investigating the relation with matched weighting schemes, $(R_{t+1}^{EW}, AIR_t^{EW})$, or $(R_{t+1}^{VW}, AIR_t^{VW})$ is more natural. In addition, Wei and Zhang (2005) criticize the empirical specification of Goyal and Santa-Clara (2003) because Goyal and Santa-Clara (2003) use mismatched weighting schemes. To provide a complete picture, Wei and Zhang (2005) investigate three pairs where $(R_{t+1}, AIR_t) = (R_{t+1}^{VW}, AIR_t^{EW})$, $(R_{t+1}^{EW}, AIR_t^{EW})$, or $(R_{t+1}^{VW}, AIR_t^{VW})$. Following Wei and Zhang (2005), Garcia *et al.* (2014) also use the same three specifications. In this study, we employ the aforementioned three weighting schemes for the following reasons. First, since it appears that

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[7] Given that the CAPM and Fama-French three-factor model cannot explain the cross-section of stock returns in Korea (Yun *et al*., 2009; Jung *et al*., 2009; Jang *et al*., 2012), idiosyncratic risk estimated from those models may include some systematic risk.

the choice of weighting scheme makes empirical evidence inconclusive and mixed, we provide more complete empirical evidence by presenting the results with the three specifications. Second, we use the three weighting schemes to compare the empirical evidence from the Korean stock market with that from the U.S. stock market.

3. Empirical Results

3.1 Descriptive statistics

Panels A and B of Figure 1 display the monthly time-series behavior of equal-weighted and value-weighted aggregate idiosyncratic risk measures, respectively. Consistent with the evidence from the developed markets, the Korean market shows no time-trend in aggregate idiosyncratic risk over our sample period.[8] Rather, the AIR measures (regardless of the methodology of the measurement) exhibit huge spikes following several significant (domestic and global) episodes. For example, all measures soar during the period of IMF crisis (currency crisis in Korea, November 1997 to December 1998) and in the time of the recent global financial crisis after Lehman Brothers' bankruptcy (August 2008). Especially, the increases in the equal-weighted CSV measure in Panel A of Figure 1 are noticeable during the two significant episodes in the financial markets. As will be shown later, the forecasting power of the equal-weighted CSV for market returns is especially pronounced. It appears that the strong predictability is attributable to the nature that the movement of equal-weighted CSV well-matches to market-wide episodes.

[Insert Figure 1 about here]

Table 2 presents the summary statistics of market returns and aggregate idiosyncratic risk measures. In Panel A, the means and standard deviations of CSV measures are higher than other

[8] In the U.S. market, Campbell *et al*. (2001) argue that the increase in idiosyncratic risk during 1990s was a time-trend, but Brandt *et al*. (2010), covering an extended sample period, show that the time-trend reverses to the low level of pre-1990s and conclude that the increase was not a time-trend but an episode concentrated on some companies. Examining 23 developed equity markets, Bekaert *et al.* (2012) also find no evidence of upward trends.

idiosyncratic volatility measures. To gauge the importance of idiosyncratic volatility in the Korean stock market, we examine the portion of idiosyncratic risk in the total risk following Goyal and Santa-Clara (2003). Given the descriptive statistics in Table 2, we see that the equal-weighted portfolio of stocks has (annualized) mean and standard deviation of 20 and 33 percent, respectively while the (annualized) standard deviation of idiosyncratic innovations is 66 percent.[9] As explained by Goyal and Santa-Clara (2003), we decompose the GS measure into the systematic risk and idiosyncratic risk parts as 124 and 363, respectively.

From this calculation, we see that the portion of diversifiable risk within the total risk is, on average, 75 (=363/487) percent in Korea. This result gives us two important implications. First, a significant amount of risk is attributed to idiosyncratic risk in Korea. Thus, if investors in Korea hold a couple of assets in their portfolios, they take sizable idiosyncratic risk and would like to be compensated for bearing the diversifiable risk. This implies the positive relation between average idiosyncratic risk and market returns in an aggregate sense. Second, Compare to the results of the U.S. market reported by Goyal and Santa-Clara (2003), the GS measure might not be a good measure to test the idiosyncratic risk-return relation at least in the Korean market. As shown in Goyal and Santa-Clara (2003), 89 percent of the GS measure comes from the idiosyncratic risk in the U.S. market. The authors argue that such a large portion of idiosyncratic risk justifies the reason of being a good estimator measuring aggregate idiosyncratic volatility. In the case of Korea, however, our calculation shows that idiosyncratic risk accounts for a relatively low percentage (75 percent) of the GS measure. This lead to a possibility that the GS measure may not fully capture the variation in idiosyncratic risk. One reason for introducing and focusing on a newly devised measure or CSV is partly attributed to such a possibility in Korea.

Panel B represents the correlation coefficients among idiosyncratic volatility measures. Correlation coefficients between CSV measures and other idiosyncratic volatility measures are in

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[9] The average standard deviation of idiosyncratic innovations is not reported in Table 2.

the range of 55%~71%. Correlation coefficients among other idiosyncratic measures are higher, in the range of 91%~99%. One reason is that the CSV measures are estimated from cross-sectional data, while other volatility measures are estimated from time-series data. Therefore, results of correlation coefficients indicate that the choice of estimating method is important in constructing idiosyncratic volatility.

[Insert Table 2 about here]

3.2 Monthly evidence

In this subsection, we investigate a monthly time-series relationship between market excess return and lagged aggregate idiosyncratic risk measures without control variables, then in Section 3.4.1, we examine whether the empirical results remain the same in the presence of control variables. Panels A, B, and C of Table 3 display one-month-ahead predictive regressions of the market excess returns on aggregate idiosyncratic risk with $(R_{t+1}, AIR_t) = (R^{VW}_{t+1}, AIR^{EW}_t)$, $(R^{EW}_{t+1}, AIR^{EW}_t)$, and $(R^{VW}_{t+1}, AIR^{VW}_t)$, respectively. For each Panel, each column represents one regression result. Specifically, we reports the ordinary least squares (OLS) coefficient estimates in the first row, the Newey–West (1987) corrected t-statistics with twelve lags in parentheses, and the adjusted R^2.

[Insert Table 3 about here]

Panel A of Table 3 reports the relationship between value-weighted market returns and equal-weighted aggregate idiosyncratic risk measures. We include this specification following Goyal and Santa-Clara (2003). Several features are worth highlighting. First, in univariate regressions, the positive relationship between value-weighted market returns and equal-weighted volatility measure is especially pronounced when CSV measure is employed as volatility measure. For CSV^{EW}, the estimated slope coefficient is 0.08 and the Newey-West (1987) adjusted *t*-statistics is

2.47. In addition, the adjusted R^2 is 3.69% which is substantially higher than those from other volatility measures. Second, the forecasting power of CSV measure remains in the presence of competing volatility measures, while the magnitude of estimated slope coefficients and significance on other volatility measure actually decrease when the CSV measure is added in the predictive regressions.

Panel B of Table 3 presents the results of predictive regressions between equal-weighted market excess returns and equal-weighted aggregated idiosyncratic risk measures. Consistent with the results in Panel A, the forecasting power of CSV measure is positively significant: The estimated slope coefficient on CSV^{EW} is 0.06 (adjusted *t*-statistic of 2.24), and the regression produces an adjusted R^2 of 2.30%. In addition, the positive relationship between equal-weighted market excess returns and CSV^{EW} is largely retained in the presence of other idiosyncratic risk measures. On the other hand, the forecasting power of other explanatory variables is quite weak: For GS^{EW}, $CAPM^{EW}$, and FF^{EW} volatility measures, the estimated slope coefficients and the Newey-West (1987) adjusted *t*-statistics in parentheses are 0.07 (1.04), 0.08 (0.94), and 0.08 (0.82), respectively.

Panel C of Table 3 reports the results of predictive regressions when the dependent variable is value-weighted market excess return and the independent variable is value-weighted aggregate idiosyncratic risk measure. Unlike the U.S. evidence documented by Bali *et al*. (2005), Wei and Zhang (2005), and Garcia *et al*. (2014), we find that value-weighted volatility measures are positively significant in predicting value-weighted market excess returns in the Korean stock market. In univariate regressions, the estimated slopes for CSV^{VW} and GS^{VW} are 0.08 (adjusted *t*-statistic of 1.69) and 0.21 (adjusted *t*-statistic of 2.23).

Overall, we find that our main idiosyncratic volatility proxy, CSV has a striking forecasting power for future market excess returns. In addition, our empirical findings imply that compared with the U.S evidence, the importance of idiosyncratic risk is more pronounced in the Korean stock market for the following reasons. First, adjusted R^2 in predictive regressions are higher in the Korean market than in the U.S. market indicating that variations in market excess return is better captured by variations in lagged idiosyncratic volatility in the Korean stock market. For example, Garcia *et al*. (2014) document that for any univariate regression, the adjusted R^2 is no more than 1.37% in the U.S. market. In addition, in most cases, the adjusted R^2 is less than 1.00%. On the other hand, we find that the adjusted R^2 values are in the range of 1.41%-3.69% when the CSV volatility measure is employed as an independent variable. Second, the forecasting power of idiosyncratic volatility is present regardless of weighting scheme in the Korean stock market. While Goyal and Santa-Clara (2003) report a significantly positive relationship only between mismatched weighting scheme of $(R_{t+1}^{VW}, AIR_t^{EW})$, we additionally find positive linkage between non-mismatched weighting schemes, $(R_{t+1}^{EW}, AIR_t^{EW})$, and $(R_{t+1}^{VW}, AIR_t^{VW})$.

What drives our empirical results? One possible explanation for our finding is related with the fact that investors hold undiversified portfolios among financial assets. Levy (1978), Merton (1987), and Malkiel and Xu (2002) show that a market-wide measure of idiosyncratic risk explains future returns if investors, for some exogenous reason, hold undiversified portfolios. Early work of Bark (1991) shows that the CAPM does not explain stock returns in Korea, indicating that investors in Korea hold highly undiversified portfolios. In addition, previous studies document that the levels of individual ownership and trading are unusually high in Korea and a significant fraction of individual investors hold undiversified portfolios. For example, Barber *et al*. (2006) report that Korean stock market have high individual ownership and trading activity. By examining stock holdings of 660,000 customers, one large security company in Korea, Samsung securities, reports that 40% of individual investors hold just one stock in their portfolios as of February 2013. Therefore, it is not surprising that idiosyncratic volatility plays an important role in predicting future market returns in the Korean stock market.

Another possible explanation behind our empirical results is the effect of non-traded assets documented by Goyal and Santa-Clara (2003). Given that investors hold non-traded assets, they argue that if the risk of non-traded asset increases, high expected return from market portfolio of traded assets is required to attract investors. As a result, we observe the relation between market return and idiosyncratic risk as long as the riskiness of the non-traded assets is linked to the total risk of individual stocks. Statistics Korea in 2013 reports that Korea is one of the few countries with an unusually high percentage of real assets out of total household assets: the ratio of real assets in total is 73.3% and especially, real estate asset ratio is 67.8%. For comparison, the ratio of real assets in total is 31.5%, 40.9%, and 50.1% in U.S., Japan, and U.K. as of 2012. Real estate assets have characteristic of non-traded assets since transactions of real estate assets entail high cost. Thus, we are likely to observe the relation between market return and idiosyncratic risk in the Korean stock market.

3.3 Daily Evidence

Previous studies have been confined to the investigation of stock return predictability using low frequency monthly measure. The CSV measure of Garcia *et al.* (2014), however, overcomes this limitation since it allows us to examine whether idiosyncratic volatility has a forecasting power over very short horizon, daily frequency. Our study on a daily basis is meaningful for the following reasons. First, to our best knowledge, we are the first to investigate stock return predictability at daily frequency. Therefore, our work sheds light on short horizon predictability of stock returns with idiosyncratic volatility. Second, our study is related to the argument of Pontiff (2006), who demonstrates that idiosyncratic risk is the largest cost faced by arbitrageurs in their pursuit of mispricing opportunities. If mispricing opportunities disappear in the long run, we may observe relationship between idiosyncratic volatility and future stock returns over very short horizons.

[Insert Table 4 about here]

Panel A of Table 4 displays one-day-ahead predictive regressions of the market excess returns on CSV measure with $(R_{t+1}, CSV_t) = (R_{t+1}^{VW}, CSV_t^{EW})$, $(R_{t+1}^{EW}, CSV_t^{EW})$, and $(R_{t+1}^{VW}, CSV_t^{VW})$, respectively. Since the original estimates are too small, all estimates have been multiplied by 100, and the Newey-West t-statistics with 30 lags are reported. We find that the relation is statistically positive for the weighting schemes of $(R_{t+1}^{EW}, CSV_t^{EW})$ and $(R_{t+1}^{VW}, CSV_t^{VW})$. Therefore, we show that the predictive power of idiosyncratic volatility does exist at the daily frequency.

3.4 Robustness

3.4.1 Controlling for business cycle

Next, we investigate whether the predictive power of idiosyncratic risk remains in the presence of common business cycle variables. Building on the time-series predictability literature, we use dividend yield (DIV), short-term interest rate (RF), term spread (TERM), and default spread (DEF), which are known for their predictive power.[10] Dividend yield is computed as the sum of dividends of the KOSPI value-weighted portfolio over the preceding 12 months, divided by the level of the index. The short-term interest rate is the CD 91-day yield. The term spread is the difference between a five-year treasury yield and a CD 91-day yield. The default spread is the difference between the yields on AA^{-} corporate bonds and a five-year treasury yield. Since yields on five-year treasury are available from May 1995, we perform regressions during full sample period and over the period May 1995-April 2015.

[Insert Table 5 about here]

Table 5 shows the predictive regression results during the entire sample period when the dividend yield and short-term interest rate are included in equation (3). Panels A, B, and C display one-month-ahead predictive regressions of the market excess returns on aggregate idiosyncratic risk with $(R_{t+1}, AIR_t) = (R_{t+1}^{VW}, AIR_t^{EW})$, $(R_{t+1}^{EW}, AIR_t^{EW})$, and $(R_{t+1}^{VW}, AIR_t^{VW})$ with conditioning variables, DIV and RF. Looking at the results of CSV volatility measure, the

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10 See,for example,Fama and French(1988) for the dividend yield, Fama and French (1989) for the term spread, Keim and Stambaugh (1986) for the default spread, and Ferson (1989) for the short-term interest rate.

magnitude of estimated slope coefficients and significance actually increase when the two predictive variables are included. For example, when we add the two business cycle variables, the estimated slope coefficient on CSV in Panel A increases from 0.08 (Newey-West *t*-statistic of 2.47) to 0.09 (Newey-West *t*-statistic of 2.80). In addition, for every specification, the slope on CSV is positive and statistically significant. Therefore, the information contained in the CSV regarding the future market excess returns is independent of the information contained in the business cycle variables. However, Table 5 shows that some of the estimates on DIV and RF are statistically significant, and the adjusted R^2 is increased when the two variables are added. This means that CSV volatility measure does not contain all the information revealed by the business cycle variables commonly used in the literature. For the other idiosyncratic volatility measures, the estimated slope coefficients and significance are largely retained in the presence of the business cycle variables.

[Insert Table 6 about here]

Table 6 reports the regression results from May 1995 to April 2015 when the four business cycle variables are contained in equation (3). During this sub-sample period, the CSV volatility measure is positively significant in univariate regressions for weighting schemes, $(R_{t+1}^{VW}, AIR_t^{EW})$ and $(R_{t+1}^{EW}, AIR_t^{EW})$. The magnitude of estimated slope coefficients and significance remain unchanged when the four business cycle variables are added. Again, Table 6 shows that the predictive power of term spread is especially pronounced during this sample period, and the adjusted R^2 of the regression generally increases significantly when we add the four variables.

In sum, Tables 5 and 6 indicate that the forecasting power of CSV volatility measure is still present in the presence of common business cycle variables even though CSV volatility measure does not contain all the information revealed by the business cycle variables.

3.4.2 Predictive regressions with stocks on KOSPI

Goyal and Santa-Clara (2003) document a significantly positive relation between idiosyncratic volatility and future market excess returns for the period of August 1963 to December 1999 in the U.S. stock market. However, Bali *et al*. (2005) show that the empirical evidence from Goyal and Santa-Clara (2003) is driven by small stocks traded on the NASDAQ. Up to now, we have reported our empirical results from the Korean stock market based on the KOSPI and KOSDAQ common stocks. Therefore, one may argue that our finding from the Korean stock market come from the stocks traded on the KOSDAQ.[11] To see whether this is indeed the case, we replicate Table 3 with stocks traded on the KOSPI, and represent the results in Table 7.

[Insert Table 7 about here]

Focusing on the CSV measures, two features are worth mentioning. First, in univariate regressions, the magnitude of estimated slope coefficients increases for all weighting schemes, and statistical significance increases two out of the three specifications. Second, for weighting schemes, $(R_{t+1}^{VW}, AIR_t^{EW})$ and $(R_{t+1}^{EW}, AIR_t^{EW})$, the forecasting power of CSV measure remains in the presence of other volatility measures. Overall, our empirical finding from the stocks traded on the KOSPI indicates that a positive relation between idiosyncratic risk and future market excess return is not due to small stocks traded on the KOSDAQ.

3.4.3 Sub-sample period results

Since the pioneering work of Goyal and Santa-Clara (2003), subsequent studies have re-examined the relation between idiosyncratic volatility and future market excess return in extended sample period. Researchers have documented that the finding of Goyal and Santa-Clara does not

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[11] In the Korean stock market, stocks traded on the KOSPI market are essentially all issued by sound and reliable companies. Extremely small stocks and/or stocks issued by small and/or venture companies (which therefore, contain substantial credit risk and are less liquid) are listed on a separate market, the KOSDAQ market.

hold in extended sample periods. For example, Bali *et al*. (2005) and Wei and Zhang (2005) do not find the positive relation between future market return and idiosyncratic volatility for the period of August 1963 to December 2001, and August 1963 to December 2002, respectively. In this subsection, we examine the role of idiosyncratic risk in predicting future market return in different sample period for the case of the Korean stock market.

Figure 1 shows large fluctuations in idiosyncratic risk during these periods. Therefore, one natural experiment is to study the role of idiosyncratic risk on future market return in extended sample periods where each of the two financial crises is breakpoint. Specifically, following Baek *et al*. (2004), we define the Asian financial crisis period as between November 1997 and December 1998. In addition, following Dooley and Hutchison (2009), we define the credit crisis period as between January 2007 and December 2008.

[Insert Table 8 about here]

Table 8 represents predictive regression results in extended sample periods. Again, we report the empirical results with the three weighting schemes. Since we focus on the CSV measure, we only report the results when the independent variable is the CSV measure. Except for the pre-Asian financial crisis period, the estimated slope coefficients on CSV are positively significant regardless of the weighting scheme. On the average, the adjusted R^2 and statistical significance are stronger when the equal-weighted CSV measure is employed. Overall, our empirical result of positive relation between future market return and idiosyncratic volatility is confirmed in extended sample periods.

4. Conclusion

Although recent studies have paid considerable attention to the forecasting power of idiosyncratic volatility on stock returns, little is known about the inter-temporal relation between idiosyncratic volatility and future stock returns in Korea. To fill this gap, we investigate the relation between idiosyncratic volatility and future market returns in Korea by constructing a newly proposed measure of idiosyncratic volatility by Garcia *et al*. (2014). The measure has some advantages. First, Garcia *et al.* (2014) show that the new measure is a consistent and asymptotically efficient estimator for aggregate idiosyncratic volatility. Second, since calculation of the new measure does not require standard asset pricing models such as the CAPM or Fama-French three-factor model, it is model-free. Finally, the measure enables us to estimate aggregate idiosyncratic volatility at any frequency, while previous measures have relied on monthly model-based measures constructed from daily data.

From monthly predictive regressions, we find that our idiosyncratic volatility proxy has a significantly positive relation with the future market excess returns. Moreover, the explanatory power of idiosyncratic risk is striking compared to that found in the U.S. market. From daily predictive regressions, we show that the predictive power of idiosyncratic volatility does exist at the high frequency data. Given that previous studies have been confined to the investigation of stock return predictability using low frequency monthly measure, our finding on a daily basis provide new evidence on stock return predictability literature. The predictive power of idiosyncratic volatility is robust to several considerations including weighting schemes in constructing market excess return and aggregate idiosyncratic risk, sample periods, and trading exchanges.

Our work sheds light on the relation between idiosyncratic volatility and expected return in aggregate stock market. Thus, a successful model that predicts the market excess return should consider aggregate idiosyncratic volatility in the Korean stock market. One possible explanation behind our empirical finding is related with theoretical frameworks stating that market-wide measure of idiosyncratic risk explains future returns if investors, for some exogenous reason, hold undiversified portfolios (Levy, 1978; Merton, 1987; Malkiel and Xu, 2002). We leave for future research an exhaustive analysis of possible explanations for our empirical evidence.

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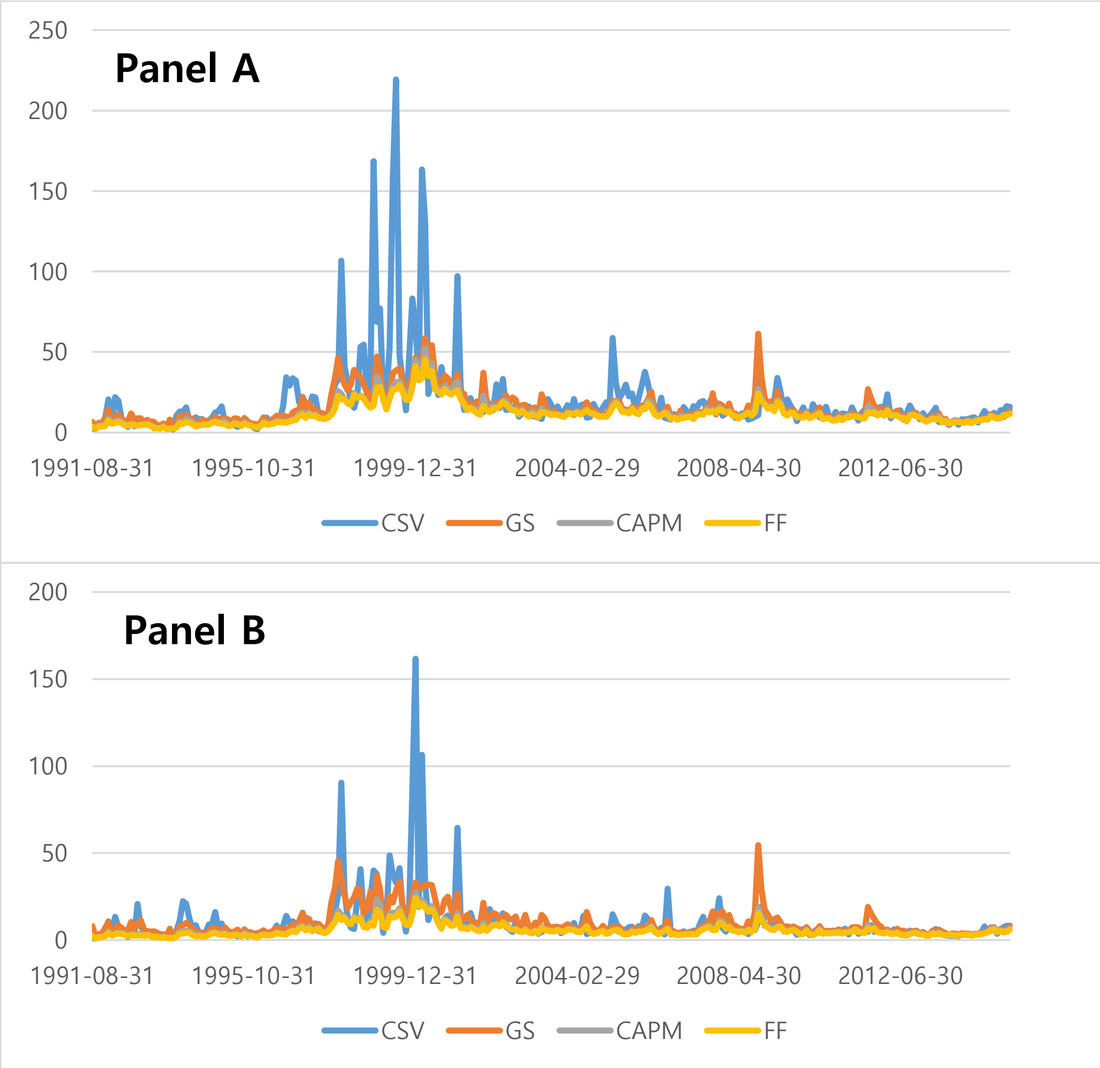

Figure 1. Time-Series of Monthly Aggregate Idiosyncratic Risk Measures

This graph plots monthly time-series of the following AIR measures with equal-weight (Panel A) and value-weight (Panel B) schemes: CSV by Garcia *et al*. (2014) GS by Goyal and Santa-Clara (2003), CAPM and FF, the average variances of residuals with respect to the CAPM and Fama-French 3 factor model, respectively. For comparison purpose, the CSV and GS measures are divided by 20, the average number of trading days per month.

Table 1. Summary of Proxies for the Individual Idiosyncratic Risk

This table summarizes idiosyncratic volatility measures suggested in the previous studies. "CSV" and "GS" represent idiosyncratic measure proposed by Garcia *et al*. (2014), and Goyal and Santa-Clara (2003), respectively. "CAPM" and "FF" are the idiosyncratic measures estimated from the individual firm residuals of the CAPM and Fama-French three-factor model. For each idiosyncratic risk measure, both equal- and value-weighted aggregate idiosyncratic risk are calculated in this study.

Authors	Abbreviation	$V_{i,t}$
Garcia, Mantilla-García, and Martellini (2014)	CSV^{EW}, CSV^{VW}	$\left(r_{i,t} - \overline{r_t}\right)^2$
Goyal and Santa-Clara (2003)	GS^{EW}, GS^{VW}	$\sum_{d=1}^{D} r_{i,d}^2 + 2\sum_{d=2}^{D} r_{i,d} r_{i,d-1}$
Bekaert, Hodrick, and Zhang (2012)	$CAPM^{EW}, CAPM^{VW}$	$\sigma\left(\varepsilon_{i,t}^{CAPM}\right)$
Bekaert, Hodrick, and Zhang (2012)	FF^{EW}, FF^{VW}	$\sigma\left(\varepsilon_{i,t}^{FF}\right)$

Table 2. Summary Statistics

This table contains the summary statistics of market returns and aggregate idiosyncratic risk measures (monthly). All statistics are calculated with monthly percent returns. Panel A presents the mean, median, standard deviation, minimum, maximum, skewness, and kurtosis of each variable. Panel B shows correlations. The sample period is from August 1991 to April 2015. For comparison, the CSV and GS measures are divided by 20, the average number of trading days per month.

Panel A: Univariate Statistics

	r^{EW}	r^{VW}	CSV^{EW}	GS^{EW}	$CAPM^{EW}$	FF^{EW}	CSV^{VW}	GS^{VW}	$CAPM^{VW}$	FF^{VW}
Mean	1.69	2.29	19.27	15.35	12.44	11.62	9.78	9.91	6.06	5.52
Med	1.79	1.86	13.61	11.99	10.77	10.40	5.88	7.09	4.84	4.50
Std	9.48	9.34	24.48	9.96	7.68	6.88	14.90	7.91	4.13	3.62
Min	-30.69	-27.02	1.87	3.26	2.12	2.10	0.80	1.91	0.93	0.86
Max	37.95	63.92	219.43	61.37	52.36	45.38	161.71	54.46	27.35	24.22
Skew	0.32	1.35	4.90	1.89	1.89	1.69	6.17	2.22	2.23	2.07
Kurt	2.17	7.20	29.01	3.89	4.81	3.97	48.87	5.77	5.89	5.20

Panel B: Correlations

r^{EW}	1									
r^{VW}	0.77	1								
CSV^{EW}	0.49	0.40	1							
GS^{EW}	-0.03	0.08	0.62	1						
$CAPM^{EW}$	0.07	0.14	0.65	0.94	1					
FF^{EW}	0.07	0.14	0.64	0.93	0.99	1				
CSV^{VW}	0.30	0.50	0.66	0.57	0.61	0.60	1			
GS^{VW}	-0.05	0.14	0.55	0.94	0.83	0.81	0.60	1		
$CAPM^{VW}$	0.07	0.21	0.64	0.92	0.93	0.92	0.71	0.92	1	
FF^{VW}	0.06	0.19	0.63	0.92	0.93	0.93	0.70	0.91	0.99	1

Table 3. Monthly Predictive Regressions of Market Returns

This table reports the result of predictive regressions of market returns. Panels A, B, and C display one-month-ahead predictive regressions of the market excess returns on aggregate idiosyncratic risk with (R_{t+1}, AIR_t) = (R_{t+1}^{VW}, AIR_t^{EW}), (R_{t+1}^{EW}, AIR_t^{EW}), and (R_{t+1}^{VW}, AIR_t^{VW}), respectively. The Newey-West t-statistics with 12 lags for estimates are given in parentheses. The sample period is August 1991 to April 2015 (a total of 285 monthly observations). ***, **, and * correspond to the 1%, 5%, and 10% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A: Value-weighted market return				
CONST	0.83	0.13	0.62	0.65	0.39	1.17	1.24
	(1.44)	(0.11)	(0.49)	(0.51)	(0.31)	(0.94)	(1.02)
CSV^{EW}	0.08**				0.07*	0.08***	0.09***
	(2.47)				(1.93)	(2.71)	(2.94)
GS^{EW}		0.14*			0.04		
		(1.79)			(0.48)		
$CAPM^{EW}$			0.14			-0.04	
			(1.29)			(-0.40)	
FF^{EW}				0.14			-0.05
				(1.24)			(-0.49)
Adj.R^2	3.69%	1.94%	0.90%	0.76%	3.47%	3.42%	3.43%
			Panel B: Equal-weighted market return				
CONST	0.51	0.65	0.69	0.79	0.93	1.21	1.35
	(0.86)	(0.67)	(0.65)	(0.73)	(0.90)	(1.17)	(1.33)
CSV^{EW}	0.06**				0.07***	0.08***	0.08***
	(2.24)				(2.82)	(3.22)	(3.48)
GS^{EW}		0.07			-0.04		
		(1.04)			(-0.58)		
$CAPM^{EW}$			0.08			-0.08	
			(0.94)			(-1.06)	
FF^{EW}				0.08			-0.10
				(0.82)			(-1.28)
Adj.R^2	2.30%	0.19%	0.10%	-0.01%	2.06%	2.21%	2.28%
			Panel C: Value-weighted market return				
CONST	1.50**	0.20	0.71	0.93	0.23	1.07	1.42
	(2.36)	(0.19)	(0.67)	(0.91)	(0.22)	(1.00)	(1.37)
CSV^{VW}	0.08*				0.02	0.06	0.08*
	(1.69)				(0.76)	(1.42)	(1.68)
GS^{VW}		0.21**			0.19*		
		(2.23)			(1.83)		
$CAPM^{VW}$			0.26			0.10	
			(1.60)			(0.62)	
FF^{VW}				0.25			0.02
				(1.40)			(0.11)
Adj.R^2	1.41%	2.91%	1.02%	0.59%	2.67%	1.17%	1.06%

Table 4. Daily Predictive Regressions of Market Returns

This table represents the result of predictive regressions of daily market excess returns. The dependent variable of each predictive regression is daily market excess returns over the 91day-CDS rate. We use the value of market capitalization at the end of each month for value-weighting. The predictors are one-day lagged AIR measures. We run univariate regressions using a market excess return as the dependent variable and a one-day lagged CSV measure as the predictor. Each column corresponds to the results of univariate regressions using (VW, EW), (EW, EW) and (VW,VW) as the weighting schemes of market excess return and CSV or $(R_{t+1},\ CSV_t\ )$. The Newey-West t-statistics with 30 lags are reported in parentheses. The sample period is August 1, 1991 to April 30, 2015 (a total of 6,218 daily observations). ***, **, and * correspond to the 1%, 5%, and 10% significance levels, respectively.

	(VW, EW)	(EW, EW)	(VW, VW)
CONST	-0.04	0.01	-0.01
	(-0.98)	(0.23)	(-0.13)
CSV	1.14***	0.45	1.57**
	(2.95)	(1.07)	(2.37)
R^2	0.29%	0.06%	0.27%

Table 5. Monthly Regressions of Market Returns with Control Variables

This table reports the result of predictive regressions of monthly market returns. The dependent variable of each predictive regression is the market excess returns over the 91day-CD rate. The predictors are one-month lagged AIR measures. Panels A, B, and C display one-month-ahead predictive regressions of the market excess returns on aggregate idiosyncratic risk with (R_{t+1}, AIR_t) = (R_{t+1}^{VW}, AIR_t^{EW}) , (R_{t+1}^{EW}, AIR_t^{EW}), and (R_{t+1}^{VW}, AIR_t^{VW}), respectively. We use the value of market capitalization at the end of each month for the value-weight. The control variables are DIV and RF, denoting aggregate dividend yield and risk-free rate (CD91). The Newey-West t-statistics with 12 lags for estimates are given in parentheses. The sample period is August 1991 to April 2015 (a total of 285 monthly observations). ***, **, and * correspond to the 1%, 5%, and 10% significance levels, respectively.

	CSV		GS		CAPM		FF	
Panel A: Value-weighted market return and equal-weighted AIR measures								
CONST	0.83	-2.44	0.13	-1.33	0.62	-1.61	0.65	-1.56
	(1.44)	(-1.00)	(0.11)	(-0.49)	(0.49)	(-0.55)	(0.51)	(-0.54)
AIR^{EW}	0.08**	0.09***	0.14*	0.15*	0.14	0.14	0.14	0.15
	(2.47)	(2.80)	(1.79)	(1.81)	(1.29)	(1.36)	(1.24)	(1.28)
DIV		2.46**		1.42		1.75		1.74
		(1.98)		(0.99)		(1.17)		(1.15)
RF		-0.15		-0.16		-0.10		-0.10
		(-1.37)		(-1.57)		(-0.98)		(-0.95)
Adj.R^2	3.69%	4.98%	1.94%	2.30%	0.90%	1.23%	0.76%	1.07%
Panel B: Equal-weighted market return and equal-weighted AIR measures								
CONST	0.51	-0.67	0.65	0.53	0.69	0.25	0.79	0.34
	(0.86)	(-0.34)	(0.67)	(0.24)	(0.65)	(0.11)	(0.73)	(0.15)
AIR^{EW}	0.06**	0.07***	0.07	0.10	0.08	0.10	0.08	0.10
	(2.24)	(2.72)	(1.04)	(1.22)	(0.94)	(1.08)	(0.82)	(0.94)
DIV		1.61		0.81		1.01		1.01
		(1.31)		(0.52)		(0.68)		(0.67)
RF		-0.27**		-0.26**		-0.23**		-0.23**
		(-2.32)		(-2.14)		(-2.08)		(-2.07)
Adj.R^2	2.30%	3.76%	0.19%	1.08%	0.10%	0.79%	-0.01%	0.64%
Panel C: Value-weighted market return and value-weighted AIR measures								
CONST	1.50**	-1.59	0.20	-0.95	0.71	-1.84	0.93	-1.55
	(2.36)	(-0.56)	(0.19)	(-0.38)	(0.67)	(-0.63)	(0.91)	(-0.54)
AIR^{VW}	0.08*	0.10**	0.21**	0.24**	0.26	0.31*	0.25	0.29*
	(1.69)	(2.02)	(2.23)	(2.23)	(1.60)	(1.93)	(1.40)	(1.69)
DIV		2.33		1.34		1.95		1.89
		(1.58)		(1.03)		(1.38)		(1.28)
RF		-0.14		-0.22**		-0.15		-0.13
		(-1.35)		(-2.10)		(-1.46)		(-1.30)
Adj.R^2	1.41%	2.46%	2.91%	3.69%	1.02%	1.72%	0.59%	1.16%

Table 6. Monthly Predictive Regressions with Control Variables 2

This table reports the result of predictive regressions of equal-weighted market returns with control variables. The predictors are one-month lagged AIR measures. Panels A, B, and C display one-month-ahead predictive regressions of the market excess returns on aggregate idiosyncratic risk with (R_{t+1}, AIR_t) = (R_{t+1}^{VW}, AIR_t^{EW}), (R_{t+1}^{EW}, AIR_t^{EW}), and (R_{t+1}^{VW}, AIR_t^{VW}), respectively. The control variables are one lagged values of DIV, RF, TERM, and DEF, denoting aggregate dividend yield, risk-free rate (CD91), term premium (five-year treasury yield over CD91), and default premium (corporate yield of AA$^-$ over five-year treasury yield), respectively. The Newey-West t-statistics with 12 lags for estimates are given in parentheses. The sample period is May 1995 to April 2015 (a total of 240 monthly observations). ***, **, and * correspond to the 1%, 5%, and 10% significance levels, respectively.

	CSV		GS		CAPM		FF	
Panel A: Value-weighted market return and equal-weighted AIR measures								
CONST	0.54	-0.25	-0.45	0.78	-0.11	0.71	-0.14	0.76
	(0.89)	(-0.11)	(-0.33)	(0.34)	(-0.07)	(0.30)	(-0.09)	(0.32)
AIR^{EW}	0.08***	0.07***	0.16*	0.06	0.17	0.04	0.19	0.03
	(2.65)	(2.63)	(1.89)	(0.91)	(1.38)	(0.44)	(1.35)	(0.27)
DIV		0.46		-0.40		-0.35		-0.36
		(0.33)		(-0.24)		(-0.20)		(-0.21)
RF		-0.36		-0.26		-0.22		-0.21
		(-1.37)		(-0.95)		(-0.74)		(-0.72)
TERM		3.52*		3.84*		4.05*		4.11*
		(1.81)		(1.76)		(1.88)		(1.88)
DEF		0.40		0.74		0.87		0.94
		(0.53)		(0.80)		(0.86)		(0.92)
Adj.R^2	4.55%	11.90%	2.58%	8.72%	1.48%	8.52%	1.31%	8.48%
Panel B: Equal-weighted market return and equal-weighted AIR measures								
CONST	0.25	1.35	0.26	2.37	0.13	2.18	0.23	2.25
	(0.37)	(0.47)	(0.22)	(0.78)	(0.09)	(0.71)	(0.15)	(0.73)
AIR^{EW}	0.07**	0.07***	0.09	0.06	0.11	0.07	0.11	0.05
	(2.39)	(2.85)	(1.19)	(0.68)	(1.08)	(0.70)	(0.97)	(0.47)
DIV		0.4		-0.44		-0.38		-0.40
		(0.21)		(-0.21)		(-0.18)		(-0.19)
RF		-0.52*		-0.41		-0.40		-0.38
		(-1.85)		(-1.51)		(-1.34)		(-1.31)
TERM		2.00		2.35		2.40		2.49
		(1.41)		(1.40)		(1.52)		(1.57)
DEF		-0.14		0.23		0.21		0.30
		(-0.20)		(0.28)		(0.24)		(0.35)
Adj.R^2	2.78%	5.92%	0.36%	2.92%	0.35%	2.89%	0.18%	2.79%
Panel C: Value-weighted market return and value-weighted AIR measures								
CONST	1.45**	0.56	-0.08	0.88	0.28	0.66	0.48	0.87
	(2.05)	(0.24)	(-0.07)	(0.38)	(0.22)	(0.28)	(0.39)	(0.36)
AIR^{VW}	0.08	0.05	0.22**	0.10	0.30*	0.08	0.30	0.01
	(1.65)	(1.56)	(2.23)	(1.47)	(1.66)	(0.65)	(1.50)	(0.06)
DIV		0.02		-0.30		-0.26		-0.35
		(0.01)		(-0.18)		(-0.15)		(-0.20)
RF		-0.26		-0.29		-0.22		-0.18
		(-0.91)		(-1.04)		(-0.77)		(-0.64)
TERM		3.88*		3.68*		4.03*		4.20*
		(1.86)		(1.69)		(1.85)		(1.91)
DEF		0.79		0.72		0.89		1.04
		(0.87)		(0.84)		(0.89)		(1.02)

Adj.R^2	1.42%	8.97%	3.34%	8.84%	1.39%	8.53%	0.89%	8.45%

Table 7. Monthly Regression of Market Return with KOSPI Companies Only

This table reports the result of predictive regressions of market returns with KOSPI companies only. We exclude KOSDAQ-listed companies in this analysis. The number of KOSPI-listed companies is 729. All variables are calculated using the data on the 729 KOSPI companies. The dependent variable of each predictive regression is the equal-weighted market excess returns over the 91day-CD rate. The predictors are one-month lagged AIR measures. Panels A, B, and C display one-month-ahead predictive regressions of the market excess returns on aggregate idiosyncratic risk with $(R_{t+1}, AIR_t) = (R^{VW}_{t+1}, AIR^{EW}_t)$, $(R^{EW}_{t+1}, AIR^{EW}_t)$, and $(R^{VW}_{t+1}, AIR^{VW}_t)$, respectively. The Newey-West t-statistics with 12 lags for estimates are given in parentheses. The sample period is August 1991 to April 2015 (a total of 285 monthly observations). ***, **, and * correspond to the 1%, 5%, and 10% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Value-weighted market return and equal-weighted AIR measures							
CONST	0.61	0.36	0.91	1.11	0.11	0.77	1.00
	(1.02)	(0.33)	(0.73)	(0.89)	(0.1)	(0.69)	(0.91)
CSV^{EW}	0.11***				0.09*	0.12***	0.13***
	(2.81)				(1.93)	(3.31)	(4.02)
GS^{EW}		0.13*			0.06		
		(1.71)			(0.73)		
$CAPM^{EW}$			0.12			-0.02	
			(0.96)			(-0.23)	
FF^{EW}				0.11			-0.06
				(0.79)			(-0.56)
Adj.R^2	2.63%	1.57%	0.40%	0.15%	2.56%	2.31%	2.40%
Panel B: Equal-weighted market return and equal-weighted AIR measures							
CONST	0.45	1.10	1.36	1.51	0.83	1.22	1.41
	(0.71)	(1.18)	(1.22)	(1.33)	(0.90)	(1.25)	(1.42)
CSV^{EW}	0.08*				0.1***	0.11***	0.12***
	(1.88)				(2.62)	(3.70)	(4.36)
GS^{EW}		0.03			-0.05		
		(0.46)			(-0.63)		
$CAPM^{EW}$			0.02			-0.11	
			(0.17)			(-1.26)	
FF^{EW}				0.00			-0.15
				(0.04)			(-1.50)
Adj.R^2	1.13%	-0.24%	-0.34%	-0.35%	0.93%	1.24%	1.42%
Panel C: Value-weighted market return and value-weighted AIR measures							
CONST	0.88	0.17	0.71	1.00	0.13	1.00	1.36
	(1.40)	(0.16)	(0.65)	(0.94)	(0.12)	(0.95)	(1.33)
CSV^{VW}	0.16***				0.09*	0.17***	0.2***
	(2.77)				(1.79)	(3.24)	(3.85)
GS^{VW}		0.21**			0.14		
		(2.06)			(1.30)		
$CAPM^{VW}$			0.26			-0.04	
			(1.39)			(-0.18)	
FF^{VW}				0.23			-0.15
				(1.12)			(-0.77)
Adj.R^2	2.30%	2.71%	0.76%	0.31%	2.79%	1.97%	2.11%

Table 8. Results of Sub-Sample Periods

This table reports the result of predictive regressions in extended sample periods. Panels A, B, and C display one-month-ahead predictive regressions of the market excess returns on the CSV measure with $(R_{t+1},\ CSV_t\ ) = (R_{t+1}^{VW},\ CSV_t^{EW}),\ (R_{t+1}^{EW},\ CSV_t^{EW})$, and $(R_{t+1}^{VW},\ CSV_t^{VW})$, respectively. The estimated slope coefficients are presented in the first row, and the Newey-West t-statistics with 12 lags for estimates are given in parentheses. ***, **, and * correspond to the 1%, 5%, and 10% significance levels, respectively.

	Panel A: (R^{VW}, CSV^{EW})			Panel B: (R^{EW}, CSV^{EW})			Panel C: (R^{VW}, CSV^{VW})		
Sample Period	CONST	CSV	R^2	CONST	CSV	R^2	CONST	CSV	R^2
1991.8~1997.10	2.14	-0.11	1.24%	1.18	0.00	0.00%	-0.26	0.20	1.44%
	(1.54)	(-1.47)		(0.98)	(-0.01)		(-0.24)	(1.32)	
1991.8~1998.12	-0.11	0.13***	6.46%	-0.24	0.10**	4.67%	-0.48	0.26***	7.27%
	(-0.09)	(4.57)		(-0.21)	(2.49)		(-0.45)	(5.32)	
1991.8~2006.12	0.84	0.07**	4.14%	0.37	0.06**	2.94%	1.56*	0.08	1.80%
	(1.11)	(2.36)		(0.46)	(2.22)		(1.75)	(1.63)	
1991.8~2008.12	0.78	0.08**	4.16%	0.19	0.07**	3.04%	1.51*	0.08	1.78%
	(1.07)	(2.45)		(0.23)	(2.33)		(1.77)	(1.65)	
1991.8~2015.4	0.83	0.08**	4.03%	0.51	0.06**	2.64%	1.5**	0.08*	1.76%
	(1.44)	(2.47)		(0.86)	(2.24)		(2.36)	(1.69)	