Skewness and Index Futures Return [*]

Qunzi Zhang[a,*], Eric Jondeau [b,c], Xuewu Wang[d], Zhipeng Yan[e]

January 2019

[a] School of Economics, Shandong University, Shandong, P. R. China.

[b] University of Lausanne, Faculty of Business and Economics, 1015 Lausanne, Switzerland

[c] Swiss Finance Institute, Boulevard du Pont-d'Arve 40, 1205 Genève, Switzerland

[d] Division of Finance, Michael F. Price College of Business, University of Oklahoma, Norman, Oklahoma.

[e] Martin Tuchman School of Management, New Jersey Institute of Technology, Newark, New Jersey.

Abstract

In this paper, we show that the individual skewness, defined as the average of monthly skewness across firms, performs very well at predicting the return of S&P 500 index futures. This result holds after controlling for the liquidity risk or for the current business cycle conditions. We also find that individual skewness performs very well at predicting index futures returns out-of-sample.

1 Introduction

For decades, a substantial literature has explored the dynamics between U.S. equity index market and the index futures market. The common finding is that the futures market is an important dominant of the equity index market. And there is scant evidence that the equity market performs well in predicting the index futures market. Additionally, predicting index futures market based on equity market remains a challenging task. However, theoretically the equity market should provide valuable forecasting indicators as the prices of index futures contract are supposed to reflect the expected value of the equity market index.

In this paper, we fill this gap by providing a new finding that the cross-firm average skewness in the equity market plays a prominent role in predicting the S&P 500 index futures market return. Specifically, we find that average skewness significantly predicts index futures return, i.e. a one-standard-deviation increase in monthly average skewness predicts a 0.59% decrease in the monthly index futures return. Additionally, we find this significant negative relation between average stock skewness and index futures return holds over the subsample periods. It also holds after controlling for usual variables known to predict market returns such as market illiquidity measures and business conditions. We also find that average skewness outperforms other economic variables proposed by Goyal and Welch (2008) in predicting index futures returns.

Additionally, we evaluate the out-of-sample performance of the average skewness as a predictor for index futures return. For this purpose, we perform out-of-sample one-month ahead forecasts with several predictors, including the equity index return, the average variance, the average skewness, and economic variables proposed by Goyal and Welch (2008). We find evidence that the predictive power of the average skewness dominates that of the other predictors. Additionally, we show that an investor forms his strategy based on timing average skewness can not only make positive investment profit but also enjoy significant economic gains. All these results confirm that the average (individual) skewness is an important predictor of subsequent index futures returns.

In fact, the potential relation between individual skewness and the future asset returns has been investigated in a long standing literature. Several theories have been proposed to explain why high (individual or idiosyncratic) skewness determines expected returns. First, the role of

idiosyncratic skewness has also been put forward to explain why investors actually hold under-diversified portfolios (Simkowitz and Beedles, 1978; Conine and Tamarkin, 1981; Mitton and Vorkink, 2007; Kumar, 2009). That is, investors with preference for skewness may hold under-diversified portfolios in order to benefit from the upside potential of positively skewed assets. Mitton and Vorkink (2007) argue that investors with preference for skewness underdiversify their portfolio to invest more in assets with positive idiosyncratic skewness. At the equilibrium, stocks with high idiosyncratic skewness will pay a premium. This finding contrasts to the traditional view that individual or idiosyncratic skewness risk should not be priced since it can be diversified away.

Second, investors beliefs and preferences on skewness influence future asset returns. Brunnermeier et al. (2007) show that investors choose to have distorted beliefs about the probabilities of future states to maximize their expected utility. They will tend to under-diversify their portfolio by investing in positively skewed assets. In the context of cumulative prospect theory (Kahneman and Tversky, 1979), Barberis and Huang (2008) construct a model in which investors wrongly measure probability weights. This results in an overpricing of positively skewed securities, which earn a negative average excess return at the equilibrium. See also Kumar (2009) and Bali et al. (2011). Bordalo et al. (2013) develop a theory in which investors overweight the salient payoffs relative to their objective probabilities. In this approach, assets with large upside (positive skewness) are overpriced, whereas assets with large downsides (negative skewness) are under-priced.

Third, the potential growth of firms is also related to skewness which in turn affect firm's stock return. Trigeorgis and Lambertides (2014) and Del Viva et al. (2017) argue that growth options are significant determinants of idiosyncratic skewness. This relation is due to the convexity of the payoff of real options. As investors are willing to pay a premium to benefit from the upside potential of the real option, firms with growth options are generally associated with a negative return premium.[1]

However, to date, the literature on the relation between the average skewness and the subsequent equity index return is very scarce and provides mixed results. Using S&P index

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[1]Cao et al. (2008) and Grullon et al. (2012) provide evidence that real options are important drivers of idiosyncratic volatility and may explain the positive relation between stock return and volatility documented by Duffee (1995).

options to estimate skewness, Chang et al. (2011) find a negative and weakly significant effect of the physical market skewness on the future monthly return for the period 1996–2005. Garcia et al. (2014) investigate the ability of cross-sectional variance and a robust measure of skewness, based on the quantiles of the cross-section distribution of monthly returns, to predict the future market return based on CRSP data between 1963 and 2006. The empirical estimate that they find for the skewness parameter is insignificant when predicting the monthly value-weighted market return. In contrast, Stöckl and Kaiser (2016) find that cross-sectional skewness adds to the predictive power of cross-sectional volatility in the short run.

A recent study by Jondeau et al. (2018) find a significant negative relation between average skewness and future stock market returns. More negatively skewed returns are associated with subsequent higher returns. So far, no paper has investigated the ability of the average (individual) skewness to predict subsequent index futures return. We do this by extending the work of Goyal and Santa-Clara (2003), Bali et al. (2005), and Jondeau et al. (2018). We use the same data and methodology and perform a similar robustness analysis. We note that our measure is different from the ones from Jondeau et al. (2018). Their monthly individual firm's skewness is calculated with demeaned individual return, where the mean is the average of individual firm return within each month; however, we use the average of equity market index return within each month as the mean to demean the individual firm return. In this way, we eliminate the effect from the equity market return, and we find that average skewness calculated based on this procedure is an effective predictor for index futures returns.

The rest of this paper is organized as follows. Section 2 conducts literature review. Section 3 describes the data and the construction of the variables used in the paper. Section 4 presents empirical evidence that the average skewness negatively predicts subsequent market return. We show that this result is robust to several alterations of the baseline specification. In Section 5, we evaluate the out-of-sample performance of the average skewness as a predictor of future market return. We also find that average skewness generates superior economic performance compared to alternative predictors. Section 6 concludes.

4

2 Literature

Given the premise that a typical investor would have a preference for skewness (Scott and Horvath, 1980), earlier studies propose that the systematic component of higher moments should be rewarded and explain the cross-sectional dispersion of expected returns across firms (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000).[2] These papers on the importance of skewness for asset pricing have considered the case of investors with a fully diversified portfolio. In this context, the coskewness of an asset with the market portfolio (systematic risk) should be priced (Kraus and Litzenberger, 1976, Barone-Adesi, 1985, Harvey and Siddique, 2000). In particular, Harvey and Siddique (2000) find that systematic skewness commends a risk premium of 3.6% per year on average. Different these studies, we focus on individual skewness and explore the predictability of index futures returns.

The other group of literature has investigated the empirical relation between individual or idiosyncratic skewness and future stock return, in a typical cross-section regression, such as Fama MacBeth regression (Fama and MacBeth (1973)). For instance, Boyer et al. (2010) first measure the expected idiosyncratic skewness based on lagged idiosyncratic volatility and skewness. Then using monthly data (1987–2005), they find a strong negative impact of expected idiosyncratic skewness on portfolios' returns. Amaya et al. (2015) report that realized skewness of individual equities have a strong negative impact on next week's stock return. A few papers have used options data to construct a measure of skewness from the risk-neutral density of option prices. Xing et al. (2010) find a negative relation between skewness and future individual stock returns. They measure skewness as the difference between the implied volatilities of out-of-the-money puts and at-the-money calls. Using the approach developed by Bakshi et al. (2003), Conrad et al. (2013) construct model-free implied variance and skewness and evaluate the predictive ability of these risk-neutral measures. Again, the paper reports a negative relation between skewness and the subsequent stock return. Instead, we focus on the predictive relation between average skewness and index futures return.

As mentioned in the previous section, the existing literature documents that futures market is the main source of market wide information for cash market. For example, studies have

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[2]In usual utility functions, such as CARA or CRRA function, the third-order derivative with respect to wealth is positive, indicating that investors prefer more than less skewness.

documented that futures market leads cash market in terms of price (Kawaller et al., 1987; Wahab and Lashgari, 1993), return (Chan, 1992; Hasbrouck, 2003), and volatility (Koutmos and Tucker, 1996). MacKinlay and Ramaswamy (1988) documents that the excess variability in the futures markets induce the autocorrelation in the equity market. Based on intraday data, researchers also find there is close relation between equity market and the futures market. And the consensus finding is that futures market leads the movement of equity market. Stoll and Whaley (1990) find the the intraday futures returns tend to lead the stock market returns by five minutes, and the reverse effect also exists but is rather mild. Harris et al. (1994) investigates the role of program trading in influencing intraday changes in the futures prices and the equity index. Chol and Subrahmanyam (1994) examines the effect of index futures on the returns and volatility of the underlying equity index using intraday data. Researchers also investigate the relation between cash and futures market while introducing other market such as options (Fleming et al., 1996; Ryu, 2015) and SPDRs (Chu et al., 1999).

To date, the literature on predicting index futures return based on different indicators is still growing. Stoll and Whaley (1990) find mild evidence on using lagged equity market returns to forecast index futures returns. Another group of literature finds that proxies of investor sentiment can also predict index futures returns. For instance, Simon and Wiggins III (2001) constructed market based sentiment indicators such as the volatility index, the put-call ratio, and the trading index to predict subsequent returns on the S&P 500 futures contract. Gao and Yang (2017) considers investor sentiment with mixed frequencies when predict index futures return. Wang et al. (2018) uses search volume index to predict short-term return reversal in the index futures market.

3   Data and Measuring Risk

The monthly S&P 500 Futures Index return is calculated as the simple return on the S&P 500 Futures Index level. The monthly futures index return is the cumulative product of all the daily simple returns within each month. S&P 500 Futures Index data are directly downloaded from Datastream. From now on, we denote by $r_{i,t} = R_{i,t} - R_{f,t-1}$ the excess return of stock i in month t and by $r_{m,t}$ the index futures return in month t. We also denote by $r_{i,d}$ and $r_{m,d}$, $d = 1, \cdots, D_t$, the daily returns on day d, where D_t is the number of days in month t.

For measuring average variance and skewness, we use daily firm-level returns for all common stocks from the CRSP data set, including those listed on the NYSE, AMEX, and Nasdaq.[3] For a given month, we use all stocks that have at least ten valid return observations for that month. We exclude the least liquid stocks (firms with an illiquidity measure in the highest 0.1% percentile) and the lowest-priced stocks (stocks with a price less than \$1). The sample period ranges from June 1982 to December 2016 due to the availability of S&P 500 index futures contract.[4] The variance of a stock has long been used as the measure of risk. When daily data are available, a common way of calculating the monthly variance of stock i in month t is:

$$V_{i,t} = \sum_{d=1}^{D_t} (r_{i,d} - \bar{r}_{m,t})^2 + 2 \sum_{d=2}^{D_t} (r_{i,d} - \bar{r}_{m,t}) (r_{i,d} - \bar{r}_{m,t}), \tag{1}$$

where D_t is the number of days in month t and $r_{i,d} = R_{i,d} - R_{f,d-1}$ is the excess return of stock i on day d. $\bar{r}_{m,t}$ is the mean value of market return within month t, that is $\bar{r}_{m,t} = 1/T_m \sum_d^{T_m} r_{m,d}$ The second term on the right-hand side corresponds to the adjustment for the first-order autocorrelation in daily returns (see French et al., 1987).

The average of monthly variances across firms can be computed in two common ways. The first measure, used by Goyal and Santa-Clara (2003), is based on equal weights: $V_{ew,t} = \frac{1}{N_t} \sum_{i=1}^{N_t} V_{i,t}$, where N_t is the number of firms available in month t. The second measure, adopted by Bali et al. (2005), is based on market capitalization (or value) weights: $V_{vw,t} = \sum_{i=1}^{N_t} w_{i,t} V_{i,t}$, where $w_{i,t}$ is the relative market capitalization of stock i in month t.

In this paper, we define the monthly (standardized) skewness of stock i is defined as:

$$Sk_{i,t} = \frac{1}{V_{i,t}^{3/2}} \sum_{d=1}^{D_t} (r_{i,d} - \bar{r}_{m,t})^3, \tag{2}$$

Using the standardized measure allows the skewness to be compared across firms with different variances. As for the average variance, the average of the monthly skewness is computed as the equal-weighted measure, $Sk_{ew,t} = \frac{1}{N_t} \sum_{i=1}^{N_t} Sk_{i,t}$, or the value-weighted measure, $Sk_{vw,t} = \sum_{i=1}^{N_t} w_{i,t} Sk_{i,t}$.

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[3]CRSP data on individual firms consist of daily returns on common stocks, corrected for corporate actions and dividend payments.

[4]We also investigate the predictability of the E-mini S&P index futures return. We find similar results as that of the S&P 500 index futures contract.

4   Empirical results

Figure 1 shows that the dynamics of market variance is different from the dynamics of the average stock variance. As most large increases in the market variance coincide with NBER-dated recession periods (with the exception of the 1987 market crash). The subprime crisis has the most influential effect on the market variance. But the average stock variance do not necessarily increases during recessions. The largest jumps of value-weighted average stock variance appear in 1983, 1986, and 2010, which are not years associated with recessions. Additionally, the value-weighted and equal-weighted average variances do not increase significanlty during subprime crisis period. However, during the recent period: 2010–2012, there is a large increase in both value-weighted and equal-weighted average stock variances, although the market variance stays at a relatively low level.

As illustrated in Figure 2, the market skewness and the average stock skewness have different dynamic properties. Most of the time the market skewness remains between -0.5 and 0.5. In contrast, the (value-weighted or equal-weighted) average skewness is in general positive (mostly between -0.03 and 0.05). This evidence suggests that there are periods when the average skewness and the market skewness are apart from each other or even have opposite signs. For instance, the most positive market skewness (in 1984) was accompanied by a moderate level of average skewness.

[Insert Table 1 and Figures 1 and 2 here]

The correlation between various variables are reported in Table 1 (Panel B). It reveals that the current index futures return exhibits a weak and negative correlation with both average variance and skewness. The correlation between average variance and the index futures return is negative and weak (-0.8% and -5.6% for the value-weighted and equal-weighted variance, respectively), and the contemporaneous correlation between the index futures return and average skewness is also negative (-3.5% and -14.9% for the value-weighted and equal-weighted skewness, respectively).

The correlation between the index futures return in month $t + 1$ and the average variance or skewness in month t is of a different nature because it involves the time dependence in the return process. The table shows that, as in the contemporaneous case, the correlation of

the subsequent index futures return with the current average variance is still negative (-5.5% and -2.0% for the value-weighted and equal-weighted variance, respectively). The correlation with current average skewness is also negative (-13.4% and -3.3% for the value-weighted and equal-weighted skewness, respectively), suggesting that average variance and average skewness may negatively predict market return.

The table also reveals that the correlation between the market skewness and average skewness is relatively low (46.1% and 17.4% for the value-weighted and equal-weighted measures, respectively). These numbers confirm that the market skewness and average skewness convey different types of information, as illustrated in Figure 2.

4.1   Baseline Regressions

We now evaluate the ability of market variance and skewness and average variance and skewness, to predict the subsequent S&P 500 index futures return in a regression. Given the definitions of average variance and skewness based on value and equal weights, the regression can be written respectively as below:

$$R_{m,t+1} \;=\; a + b\,V_{vw,t} + c\,Sk_{vw,t} + d\,V_{m,t} + e\,Sk_{m,t} + e_{m,t+1}, \tag{3}$$

$$R_{m,t+1} \;=\; a + b\,V_{ew,t} + c\,Sk_{ew,t} + d\,V_{m,t} + e\,Sk_{m,t} + e_{m,t+1}. \tag{4}$$

In Table 2, we consider each of the variables in Equations (3) and (4) introduced separately. Panel A reports the results of the regressions for the 1982–2016 sample. The current index futures return fails to predict the subsequent index futures return with a p-value equal to 78% and an adjusted R^2 equal to -0.21%. Consistent with previous literature discussed in Section 2, market skewness does not significantly predict index futures return. Although the market variance has strong predictive power for index futures returns with a low p-value, its predictive ability is not robust in subsample periods as shown later in Table 3. The average variance also fails to predict index futures return with a high p-value (31.3% for value-weighted variance and 66.4% for equal-weighted variance) and a low adjusted R^2 (0.06% for value-weighted variance and -0.21% for equal-weighted variance). In contrast, the coefficient of the average skewness is

highly significant and with a negative value of -0.1425. That is, as the standard deviation of the value-weighted average skewness is equal to 0.042, a one-standard-deviation increase in monthly average skewness results in a 0.59% $(= -0.1425 \times 0.042)$ decrease in the monthly index futures return. For the value-weighted average skewness, the p-value is the low (equal to 0.8%) and the adjusted R^2 is high (equal to 1.547%). However, we notice that the equal-weighted skewness fails to predict the index futures return. The reason maybe that implementing equal-weighting scheme to calculate average skewness treats large and small firm equally. The small firm returns are more likely to experience extreme movements and exhibit high volatility. Measuring skewness is admittedly a challenging work as it raises everything to the third power which makes skewness sensitive to outliers. Therefore, the failure of the equal-weighted skewness in predicting index futures return maybe due to its sensitivity to outliers.

[Insert Table 2 here]

4.2   Control business cycle and market liquidity risk

Is the significant predictive power of average skewness due to the fact that it is just representing the fundamental business cycle variables? To answer this question, we follow Goyal and Santa-Clara (2003) and investigate the relationship between the index futures return and average stock skewness when a set of macroeconomic factors are used as controls for business cycle conditions. The control variables are: the dividend-price ratio, calculated as the difference between the log of the last 12-month dividends and the log of the current level of the market index (DP); the default spread, calculated as the difference between a Moody's Baa corporate bond yield and the 10-year Treasury bond yield (DEF); the term spread, calculated as the difference between the 10-year Treasury bond yield and 3-month T-bill rate ($TERM$); and the relative 3-month T-bill rate, calculated as the difference between the current T-bill rate and its 12-month backward-moving average ($RREL$). We also introduce the market illiquidity measure proposed by Amihud (2002), which has been found to have some predictive power for future market returns. Bali et al. (2005) show that the predictive power of the equal-weighted variance is partly explained by a liquidity premium, as small stocks dominate the equal-weighted

variance.[5]

Table 4 Panel A reports the regression results when all of the business cycle factors are considered with average skewness. First, the results imply that, even if some of these variables are significant as documented in the previous studies (see among others, Bali et al., 2005), their contribution to the predictability of subsequent index futures remains limited when they are introduced together. Second, the significance of the average skewness coefficient is essentially not affected by the introduction of these business cycle variables. Over the 1982–2016 sample, its coefficient estimate is equal to -0.1626 (with a p-value of 0.5%) and the adjusted R^2 is equal to 3.691%. When the current index futures return is introduced as additional control variable, we also obtain similar estimates, with a coefficient equal to -0.1633 (with a p-value of 0.5%) and an adjusted R^2 equal to 3.48%. We also note that, no matter the business cycle factors are introduced in the regression or not, the current index futures return does not help predict subsequent index futures return, with a p-value above 15%. Furthermore, Columns II and V report that expected illiquidity has an insignificant estimated coefficient and does not alter the predictive ability of average skewness. When both the expected illiquidity and unexpected illiquidity are introduced, Columns III and VI reveal that both illiquidity variables have significant estimated coefficients and the predictability of average skewness remains highly significant. As documented in Panel B, for sample period 2000 to 2016, although less significant, we find similar predictive performance of average skewness when macro variables and illiquidity measures are considered.

We also note that, it seems that the illiquidity risk works well at predicting index futures return. However it is not an appropriate predictor since the estimation of both expected and illiquidity risk requires the data in the whole sample period, which makes its predictive power suffers from the look-ahead bias.

[Insert Table 4 here]

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[5]The illiquidity of a given stock i in month t is defined as $ILLIQ_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|r_{i,d}|}{Vol_{i,d}}$, where $Vol_{i,d}$ is the dollar trading volume of firm i on day d. Then, the aggregate illiquidity is the average across all stocks available in month t: $ILLIQ_t = \sum_{i=1}^{N_t} w_{i,t} \, ILLIQ_{i,t}$. The expected component of the aggregate illiquidity measure is obtained by the following regression (t-statistics in parentheses): $\log(ILLIQ_{t+1}) = -0.727(-1.81) + 0.54(2.14) \log(ILLIQ_t) + \text{residual}$, with the adjusted R^2 equal to 23.1%. The expected illiquidity, denoted by $ILLIQ^E$, is defined by the first two terms on the right-hand side.

4.3　Comparison with economic variables-14 economic variables

Rapach et al. (2009) and Rapach and Zhou (2013) argue that model uncertainty and instability may cause the failure of previous papers to find significant out-of-sample gains in forecasting market return. They recommend combining individual predictors and find that a simple equal-weighted combination of 14 standard economic variables succeeds in predicting the monthly market return.[6] We combine these economic variables using the first principal component (denoted by ECON_{PC}) and their equal-weighted average (denoted by ECON_{AVG}) and compare the predictive ability of these variables with that of average skewness.

For the 1982–2016 sample period, Table 5 Panel A reveals that value-weighted average skewness outperforms the first principal component, ECON_{PC}. The adjusted R^2 is equal to 1.55% with average skewness but only 0.76% for ECON_{PC}. Average skewness also outperforms the average of the 14 economic variables ECON_{AVG}, which has an adjusted R^2 equal to 1.04%. Also, the predictability of value-weighted skewness is not essentially affected when the economic variables are considered. That is when the variables are introduced together in the regression, the p-value of the average skewness coefficient is equal to 0.3% and 0.2%, when ECON_{PC} and ECON_{AVG} are introduced respectively. When the current index futures return is added into the regression, average skewness still outperforms the economic factors. For sample period from 2000 to 2016, we find similar result as in Panel A. The average skewness continues to perform better than the economic variables in predicting index futures return.

[Insert Table 5 here]

In-sample analysis provides a very clear indication that average skewness predicts subsequent index futures return. In the next section, we investigate its performance in terms of out-of-sample prediction and asset allocation.

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[6]The 14 economic variables are the following: the dividend-price ratio, the dividend yield, the earnings-price ratio, the dividend-payout ratio, the stock variance, the book-to-market ratio, the net equity expansion, the Treasury bill rate, the long-term yield, the long-term return, the term spread, the default yield spread, the default return spread, and the inflation rate.

5 Out-of-sample evaluation

Following Goyal and Welch (2008) and Ferreira and Santa-Clara (2011), we predict the index futures return using a sequence of expanding windows. For the first window, we use the first s_0 observations, $t = 1, \cdots, s_0$. Then, for the sample ending in month $s = s_0, \cdots, T-1$, we run the following predictive regression:

$$r_{m,t+1} = \mu + \vartheta' X_t + \eta_{t+1}, \qquad t = 1, \cdots, s,$$

where X_t denotes a set of predictive variables. By increasing the sample size s from s_0 to $T-1$, we generate a sequence of $T_{OOS} = T - s_0$ out-of-sample index futures return forecasts based on the information available up to time s:

$$\hat{\mu}_{m,s}^{\{X\}} = E[r_{m,s+1}|X_s] = \hat{\mu} + \hat{\vartheta}' X_s, \qquad s = s_0, \cdots, T-1.$$

This process mimics the way in which a sequence of forecasts is achieved in practice. We also denote by $\bar{r}_{m,s} = \frac{1}{s}\sum_{t=1}^{s} r_{m,t}$ the historical mean of market excess return up to time s.

We evaluate the performance of the competing indicators in the forecasting exercise using several statistics. First, the out-of-sample R^2 compares the predictive power of the regression with the historical sample mean. It is defined as $R_{OOS}^{\{X\}2} = 1 - MSE_P^{\{X\}}/MSE_N$, where $MSE_P^{\{X\}} = (1/T_{OOS})\sum_{t=s_0}^{T-1}(r_{m,t+1} - \hat{\mu}_{m,t}^{\{X\}})^2$ is the mean square error of the out-of-sample predictions based on the model, $MSE_N = (1/T_{OOS})\sum_{t=s_0}^{T-1}(r_{m,t+1} - \bar{r}_{m,t})^2$ is the mean square error based on the sample mean (assuming no predictability). The out-of-sample $R_{OOS}^{\{X\}2}$ takes positive (negative) values when the model predicts returns with higher (lower) accuracy than the historical mean. We also use the encompassing ENC test statistic proposed by Harvey et al. (1998) and Clark and McCracken (2001) and defined as

$$ENC^{\{X\}} = \frac{T_{OOS} - k + 1}{T_{OOS}}\frac{\sum_{t=s_0}^{T-1}\left[(r_{m,t+1} - \bar{r}_{m,t})^2 - (r_{m,t+1} - \bar{r}_{m,t})(r_{m,t+1} - \hat{\mu}_{m,t}^{\{X\}})\right]}{MSE_P^{\{X\}}}. \tag{5}$$

Under the null hypothesis, the forecasts based on the historical mean encompass the forecasts based on the model, meaning that the model does not help to predict index futures returns. Because the test statistic has a nonstandard distribution under the null hypothesis in the case

of nested models, we rely on the critical values computed by Clark and McCracken (2001).

The performances of the competing predictors are also compared using an out-of-sample trading strategy based on predictive regressions, which combines the index futures and the risk-free asset (1-month T-bill) (Ferreira and Santa-Clara, 2011). For each period, predictions of market excess returns are used to calculate the Markowitz optimal weight on the index futures:

$$w_{m,s}^{\{X\}} = \frac{\hat{\mu}_{m,s}^{\{X\}}}{\lambda\, \hat{V}_{m,s}^{\{X\}}}, \tag{6}$$

where λ is the risk aversion and $\hat{V}_{m,s}^{\{X\}}$ is the corresponding sample variance of market return.[7] Portfolio decisions can be made in real time with data available at the time of the decision. The ex post portfolio excess return is then calculated at the end of month $s + 1$ as follows:

$$r_{p,s+1}^{\{X\}} = w_{m,s}^{\{X\}}\, r_{m,s+1}. \tag{7}$$

After iterating this process until the end of the sample $(T - 1)$, we obtain a time series of ex post excess returns for each optimal portfolio. Denoting by $\bar{r}_p^{\{X\}}$ the sample mean and by $\sigma_p^{\{X\}2}$ the sample variance of the portfolio return, we define two statistics to evaluate the performance of the trading strategies: the Sharpe ratio, $\mathrm{SR}^{\{X\}} = \bar{r}_p^{\{X\}}/\sigma_p^{\{X\}}$, which measures the risk-adjusted performance of the strategy, and the certainty equivalent return, $\mathrm{CE}^{\{X\}} = \bar{r}_p^{\{X\}} - (\lambda/2)\sigma_p^{\{X\}2}$, which is the risk-free return that a mean-variance investor (with risk aversion λ) would consider equivalent to investing in the strategy. To test whether the SR of the strategy based on predictor X is equal to the SR of the strategy based on the historical mean of market return, denoted by SR_0, we follow the approach of Jobson and Korkie (1981) and DeMiguel et al. (2009). We proceed in a similar way to test whether the CE of the strategy based on X is equal to the CE of the strategy based on the historical mean of market excess return, denoted by CE_0.[8] Finally, we compute the annual transaction fee generated by each strategy as $Fee^{\{X\}} = \frac{12f}{T_{OOS}} \sum_{t=s_0}^{T-1} |w_{m,t+1}^{\{X\}} - w_{m,t+}^{\{X\}}|$, where f is the fee per dollar and $w_{m,t+}^{\{X\}}$ denotes the

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[7]Following Campbell and Thompson (2008), we impose realistic portfolio constraint: $w_{m,s}^{\{X\}}$ lies between 0 and 2 to exclude short sales and to allow for at most 100% leverage. We also use five-year rolling windows of past monthly returns to estimate $\hat{V}_{m,s}^{\{X\}}$.

[8]To test the null hypothesis that $\mathrm{SR}^{\{X\}} = \mathrm{SR}_0$, we use the statistic given in footnote 16 of DeMiguel et al. (2009). Similarly, to test the null hypothesis that $\mathrm{CE}^{\{X\}} = \mathrm{CE}_0$, we use the statistic for the test of equal CE is given in their footnote 18.

market weight just before rebalancing at $t+1$.

Table 6 reports the results for the out-of-sample predictions based on the variance and skewness measures introduced in Section 3 and the economic predictors introduced in Section 4.3. We consider the June 1983–December 2016 sample to compute the performance of these alternative predictors. Consistently with individual regressions reported in Table 2, the variance and skewness measures with the highest out-of-sample R^2 is the value-weighted average skewness, with R^2_{OOS} equal to 2.78% The encompassing test ENC confirms that the value-weighted average skewness is statistically significant as unique predictors of market returns at the 5% significance level. Although the other predictors also generate positive R^2_{OOS}, such as 1.54% for the simple average of 14 economic variables, their predictability fails to pass the encompassing test.

Figure 3 makes it possible for us to visualize the evolution of the out-of-sample performance of the predictors over time. The performance is measured by the difference between the cumulative sum of squared errors (SSE) generated by the sample mean and the cumulative SSE generated by a given set of variables. The out-of-sample performance is measured by $OOS_s^{\{X\}} = \sum_{t=1}^{s}(r_{m,t+1} - \bar{r}_{m,t})^2 - \sum_{t=1}^{s}(r_{m,t+1} - \hat{\mu}_{m,t}^{\{X\}})^2$, $s = s_0, \cdots, T-1$, where the mean $\bar{r}_{m,t}$ and the prediction $\hat{\mu}_{m,t}^{\{X\}}$ are calculated over the period from s_0 to t. An increase in the line indicates that the model provides a better prediction than the prevailing mean. Several results are worth emphasizing. First, as Figure 3 demonstrates, the OOS measures involving the index futures return, the average variance, and market variance jump up during the subprime crisis, reflecting some instability in the relation between these predictors and the subsequent index futures return. The out-of-sample performance of the index futures return and the average variance are even negative for relatively long periods of time. In contrast, for the value-weighted average skewness, the OOS measure increases in a smooth way, which reflects the stable relation between this variable and the subsequent index futures return. Especially during the subprime crisis, the value-weighted average skewness results in a higher out-of-sample performance. Based on the evolution of predictive performance, the value-weighted average skewness is clearly the best predictor, with an almost continuously increasing out-of-sample performance.

[Insert Table 6 and Figure 3 here]

The table also reports performance measures of the trading strategies, i.e., the SR, CE,

the SR gain, the CE gain, and the annualized return. The annualized SR of the strategy based on the historical mean is equal to -0.2. The SR is increased to 0.24 and 0.47 for the strategies based on market return only and on value-weighted average skewness only. However, the increase in SR relative to the strategy based on the historical mean is statistically significant only for strategies based on average skewness. We also consider a simple Buy-and-Hold strategy, with a constant weight computed to produce the same volatility of the portfolio return as the strategy based on market return and average skewness. The SR of this strategy is equal to 0.24. The difference between the SR of the strategy based on value-weighted skewness and the SR of the Buy-and-Hold strategy is sizable (0.47 vs. 0.24), although not statistically different from 0. However, the difference in CE (2.82% vs. 6.73%) is statistically larger than 0 at the usual 5% significance level.

Most of the annualized CE values of the strategy based on one predictor are in the range $[-3\%; 7\%]$, and the highest CE value is generated by strategy based on value-weighted average skewness with CE value of 6.73%. The CE gain relative to the strategy based on the historical mean is statistically significant only for the strategies based on the value-weigthed average skewness.

Finally, the annual fee that an investor would have to pay for the various strategies is moderate, between 0.04% and 0.75% of the value of the portfolio per year. Strategies based on the value-weighted average skewness generate relatively large annual fee because they imply more rebalancing every month. But, we also realize that the annual return of the strategy based on value-weighted skewness is also the highest with a value of 9.76%. This result suggests that, although transaction costs should not be neglected, they are unlikely to substantially reduce the relative performance of the trading strategies. To summarize, strategies with value-weighted skewness generate superior economic performance in terms of SR, CE values and annual returns relative to other competing predictors.

6   Conclusion

In this paper, we investigate the ability of the average skewness of the firm's returns to predict S&P 500 index futures returns. We find that the value-weighted average of (standardized) stock

skewness is by far the best predictor of monthly index futures returns. The magnitude of the effect of the monthly average skewness on the subsequent index futures return is sizable, as a one standard deviation increase in the average skewness implies, on average, a 0.59% decrease in the index futures return next month. This result is robust to the alternative sample periods or controls that we consider.

The predictability of the average skewness is also economically significant: An investor implementing a mean-variance strategy based on market return forecasts would obtain a higher Sharpe ratio if she predicts the future market return with the current value-weighted average skewness. The annualized returns are equal to 9.76%, with annualized Sharpe ratio and certainty equivalent equal to 0.47 and 6.73%, respectively.

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Table 1: Summary Statistics and Correlation Matrix

This table provides summary statistics and the correlation matrix for the following variables: the subsequent S&P 500 Futures Index return $r_{m,t+1}$, the current S&P 500 Futures Index return $r_{m,t}$, market variance $V_{m,t}$, market skewness $Sk_{m,t}$, value-weighted individual variance $V_{vw,t}$, equal-weighted individual variance $V_{ew,t}$, value-weighted individual skewness $Sk_{vw,t}$, and equal-weighted individual skewness $Sk_{ew,t}$. Sample period: June 1982 to December 2016.

Panel A: Summary statistics

	Mean	Min	Med	Max	Std	AR_1
$r_{m,t}$	0.0070	-0.2230	0.0110	0.1530	0.0450	0.0170
$V_{m,t}$	0.0140	0.0010	0.0070	0.7090	0.0410	0.2140
$Sk_{m,t}$	-0.0190	-2.9970	0.0000	3.5210	0.6930	-0.0160
$V_{vw,t}$	0.0190	0.0030	0.0120	0.5100	0.0320	0.1570
$V_{ew,t}$	0.0410	0.0090	0.0280	0.6960	0.0520	0.0900
$Sk_{vw,t}$	0.0180	-0.1470	0.0210	0.1450	0.0420	0.1450
$Sk_{ew,t}$	0.0260	-0.0970	0.0270	0.1500	0.0400	0.3620

Panel B: Correlation

	$r_{m,t+1}$	$r_{m,t}$	$V_{m,t}$	$Sk_{m,t}$	$V_{vw,t}$	$V_{ew,t}$	$Sk_{vw,t}$	$Sk_{ew,t}$
$r_{m,t+1}$	1							
$r_{m,t}$	0.0180	1						
$V_{m,t}$	-0.1360	-0.3860	1					
$Sk_{m,t}$	-0.0880	0.2010	-0.0430	1				
$V_{vw,t}$	-0.0550	-0.0080	0.2770	-0.0220	1			
$V_{ew,t}$	-0.0200	-0.0560	0.1910	0.0920	0.2710	1		
$Sk_{vw,t}$	-0.1340	-0.0350	-0.0330	0.4610	-0.1060	0.0600	1	
$Sk_{ew,t}$	-0.0330	-0.1490	0.0130	0.1740	-0.0150	0.0640	0.5270	1

Table 2: Predictive Regressions of S&P 500 Futures Index Return – Baseline Case

This table reports results of the one-month-ahead predictive regressions of the S&P 500 Futures Index return $r_{m,t+1}$. $V_{vw,t}$ and $Sk_{vw,t}$ are the value-weighted average variance and skewness. $V_{ew,t}$ and $Sk_{ew,t}$ are the equal-weighted average variance and skewness. $V_{m,t}$ and $Sk_{m,t}$ are market variance and skewness. Rows without brackets show the parameter estimates. Rows with brackets show the two-sided p-values based on Newey-West adjusted t-statistics. The last row presents the adjusted R^2 values. Sample period: June 1982 to December 2016.

	I	II	III	IV	V	VI
Constant	0.0067	0.0083	0.0093	0.0092	0.0113	0.0126
	(0.005)	(0)	(0)	(0)	(0)	(0)
$r_{m,t}$	0.0177			0.0131	0.0123	-0.0388
	(0.78)			(0.852)	(0.856)	(0.532)
$V_{vw,t}$		-0.077			-0.0977	-0.0405
		(0.313)			(0.205)	(0.515)
$Sk_{vw,t}$			-0.1425	-0.142	-0.15	-0.1389
			(0.008)	(0.013)	(0.008)	(0.018)
$V_{m,t}$						-0.1609
						(0.005)
$Sk_{m,t}$						-0.0018
						(0.564)
Adjusted R^2	-0.211%	0.064%	1.547%	1.325%	1.575%	2.916%
Constant	0.0067	0.0075	0.0077	0.0076	0.0082	0.0092
	(0.005)	(0.002)	(0.001)	(0.005)	(0.006)	(0.002)
$r_{m,t}$	0.0177			0.0132	0.0124	-0.0256
	(0.78)			(0.852)	(0.86)	(0.679)
$V_{ew,t}$		-0.0166			-0.0144	0.015
		(0.664)			(0.72)	(0.696)
$Sk_{ew,t}$			-0.0365	-0.0343	-0.0332	-0.0226
			(0.483)	(0.513)	(0.525)	(0.652)
$V_{m,t}$						-0.1656
						(0.004)
$Sk_{m,t}$						-0.0057
						(0.057)
Adjusted R^2	-0.211%	-0.205%	-0.136%	-0.362%	-0.579%	1.645%

Table 3: Predictive Regressions of S&P 500 Futures Index Return – Subsamples

This table reports results of the one-month-ahead predictive regressions of the S&P 500 Futures Index return $r_{m,t+1}$. $V_{vw,t}$ and $Sk_{vw,t}$ are the value-weighted average variance and skewness. $V_{ew,t}$ and $Sk_{ew,t}$ are the equal-weighted average variance and skewness. $V_{m,t}$ and $Sk_{m,t}$ are market variance and skewness. Rows without brackets show the parameter estimates. Rows with brackets show the two-sided p-values based on Newey-West adjusted t-statistics. The last row presents the adjusted R^2 values. Sample periods are from January 1990 to December 2016 (Columns I to VI) and from January 2000 to December 2016 (Columns VII to XII).

	1990–2016 sample						2000–2016 sample					
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Panel A: Value-weighted variance and skewness												
Constant	0.0058	0.0069	0.0084	0.0084	0.0097	0.0106	0.0031	0.0044	0.0055	0.0055	0.0071	0.0085
	(0.026)	(0.004)	(0)	(0.002)	(0)	(0.001)	(0.358)	(0.173)	(0.055)	(0.097)	(0.021)	(0.025)
$r_{m,t}$	0.0235			0.0017	0.0029	-0.0219	0.0446			-0.0026	-0.0016	-0.0364
	(0.745)			(0.983)	(0.971)	(0.755)	(0.616)			(0.979)	(0.987)	(0.678)
$V_{vw,t}$		-0.0475			-0.0619	-0.032		-0.0499			-0.0658	-0.036
		(0.473)			(0.365)	(0.577)		(0.475)			(0.341)	(0.546)
$Sk_{vw,t}$			-0.1592	-0.1589	-0.1627	-0.1474			-0.2147	-0.2154	-0.2197	-0.2112
			(0.012)	(0.013)	(0.011)	(0.013)			(0.003)	(0.004)	(0.003)	(0.004)
$eV_{m,t}$						-0.1245						-0.1277
						(0.552)						(0.555)
$Sk_{m,t}$						-0.0004						0.0016
						(0.893)						(0.71)
Adjusted R^2	-0.255%	-0.161%	1.976%	1.67%	1.618%	1.395%	-0.298%	-0.285%	3.579%	3.098%	2.982%	2.489%
Panel B: Equal-weighted variance and skewness												
Constant	0.0058	0.0077	0.0075	0.0074	0.0089	0.0092	0.0031	0.0052	0.0061	0.0062	0.0068	0.0064
	(0.026)	(0.005)	(0.002)	(0.014)	(0.006)	(0.015)	(0.358)	(0.254)	(0.038)	(0.081)	(0.14)	(0.236)
$r_{m,t}$	0.0235			0.0084	0.0052	-0.0107	0.0446			-0.0126	-0.0143	-0.0506
	(0.745)			(0.921)	(0.95)	(0.881)	(0.616)			(0.906)	(0.888)	(0.588)
$V_{ew,t}$		-0.0428			-0.0372	-0.0087		-0.0488			-0.0157	0.0691
		(0.287)			(0.404)	(0.864)		(0.592)			(0.879)	(0.6)
$Sk_{ew,t}$			-0.0639	-0.0616	-0.0585	-0.0399			-0.1615	-0.1663	-0.1648	-0.1457
			(0.274)	(0.295)	(0.318)	(0.489)			(0.02)	(0.02)	(0.023)	(0.051)
$V_{m,t}$						-0.1554						-0.218
						(0.463)						(0.33)
$Sk_{m,t}$						-0.004						-0.0026
						(0.237)						(0.529)
Adjusted R^2	-0.255%	-0.112%	0.054%	-0.252%	-0.417%	0.027%	-0.298%	-0.368%	1.879%	1.403%	0.92%	1.479%

Table 4: Predictive regressions of market return — business cycle and market liquidity

This table reports results of the one-month-ahead predictive regressions of the S&P 500 Futures Index return $r_{m,t+1}$. $Sk_{vw,t}$ is the value-weighted average skewness. DP_t is the dividend yield of the Standard & Poor's 500 index. DEF_t represents the default spreads, calculated as the difference between Moodys Baa corporate bond yields and ten-year Treasury bond yields. $TERM_t$ is the term spread, calculated as the difference between ten-year Treasury bond yields and three-month Treasury bill rates. $RREL_t$ is the relative three-month Treasury bill rate, calculated as the difference between current Treasury bill rate and its 12-month backward-moving average. $ILLIQ_t^E$ is the expected market illiquidity, as described in Section 4.2. Presented are the parameter estimates. The two-sided p-values based on Newey-West adjusted t-statistics are in parentheses. Also reported are the adjusted R^2 values. The sample periods are June 1982 to December 2016 (Panel A) and January 2000 to December 2016 (Panel B).

	I	II	III	IV	V	VI
Panel A: 1982-2016						
Constant	0.0782	0.0238	0.0012	0.0798	0.0219	-0.0053
	(0.019)	(0.609)	(0.98)	(0.016)	(0.646)	(0.912)
$R_{m,t}$				-0.0179	-0.0363	-0.0858
				(0.793)	(0.596)	(0.186)
$V_{vw,t}$	-0.0782	-0.0683	-0.0479	-0.0778	-0.0668	-0.0425
	(0.263)	(0.315)	(0.422)	(0.28)	(0.355)	(0.524)
$Sk_{vw,t}$	-0.1626	-0.1538	-0.1342	-0.1633	-0.1546	-0.1345
	(0.005)	(0.006)	(0.011)	(0.005)	(0.007)	(0.013)
DP_t	1.6446	2.7603	3.7163	1.6783	2.9348	4.2063
	(0.017)	(0.01)	(0.001)	(0.016)	(0.007)	(0)
DEF_t	0.3258	0.3717	0.4701	0.3215	0.3673	0.4678
	(0.744)	(0.705)	(0.622)	(0.748)	(0.711)	(0.63)
$TERM_t$	-0.3126	-0.3621	-0.4288	-0.3186	-0.3789	-0.474
	(0.078)	(0.047)	(0.017)	(0.068)	(0.035)	(0.009)
$RREL_t$	-0.7193	-0.6706	-0.6152	-0.7343	-0.6961	-0.6711
	(0.02)	(0.024)	(0.027)	(0.016)	(0.018)	(0.017)
$ILLIQ_t^E$		-0.0063	-0.01		-0.0069	-0.0117
		(0.136)	(0.018)		(0.11)	(0.007)
$ILLIQ_t^U$			-0.0258			-0.0279
			(0)			(0)
Adjusted R^2	3.691%	4.073%	8.433%	3.479%	3.955%	8.866%
Panel B: 2000-2016						
Constant	0.2228	0.4039	0.256	0.2393	0.4122	0.248
	(0.014)	(0.046)	(0.245)	(0.016)	(0.048)	(0.263)
$R_{m,t}$				-0.0633	-0.0588	-0.1003
				(0.524)	(0.552)	(0.287)
$Sk_{vw,t}$	-0.134	-0.1308	-0.1231	-0.144	-0.1402	-0.1381
	(0.12)	(0.129)	(0.14)	(0.08)	(0.088)	(0.087)
DP_t	4.9216	5.6002	4.9358	5.2833	5.9103	5.365
	(0.019)	(0.014)	(0.032)	(0.022)	(0.017)	(0.029)
DEF_t	-1.1494	-2.0359	-1.2971	-1.2814	-2.1246	-1.3378
	(0.465)	(0.265)	(0.48)	(0.419)	(0.25)	(0.469)
$TERM_t$	-0.2877	-0.2688	-0.2838	-0.294	-0.2753	-0.2972
	(0.212)	(0.245)	(0.202)	(0.207)	(0.238)	(0.189)
$RREL_t$	-1.191	-1.3328	-1.1454	-1.2466	-1.379	-1.1962
	(0.037)	(0.015)	(0.021)	(0.025)	(0.01)	(0.016)
$ILLIQ_t^E$		0.009	0.002		0.0087	0.0004
		(0.278)	(0.827)		(0.301)	(0.968)
$ILLIQ_t^U$			-0.0184			-0.0211
			(0.027)			(0.005)
Adjusted R^2	7.006%	7.163%	8.891%	6.875%	6.981%	9.278%

Table 5: Comparison with Economic Variables

This table reports results of the one-month-ahead predictive regressions of the S&P 500 Futures Index return $r_{m,t+1}$. $Sk_{vw,t}$ is the value-weighted average skewness. The other predictors include $\text{ECON}_{PC,t}$: the first principle component and $\text{ECON}_{AVG,t}$: the equal-weighted average of 14 economic predictors described in Section 4.3). Rows without brackets show the parameter estimates. Rows with brackets show the two-sided p-values based on Newey-West adjusted t-statistics. The last row presents the adjusted R^2 values. The sample periods are June 1982 to December 2016 (Panel A) and January 2000 to December 2016 (Panel B).

|	I	II	III	IV	V	VI	VII	VIII	IX	X
Panel A: 1982-2016										
Constant	0.0093	0.012	0.0157	0.0479	0.0574	0.0092	0.0118	0.0156	0.0477	0.0572
	(0)	(0.001)	(0)	(0.005)	(0.001)	(0)	(0.003)	(0)	(0.007)	(0.002)
$r_{m,t}$						0.0131	0.0168	0.0115	0.0131	0.0072
						(0.852)	(0.816)	(0.873)	(0.854)	(0.919)
$Sk_{vw,t}$	-0.1425		-0.158		-0.1595	-0.142		-0.1576		-0.1591
	(0.008)		(0.003)		(0.002)	(0.013)		(0.005)		(0.005)
$ECON_{PC,t}$		0.006	0.0071				0.006	0.0071		
		(0.051)	(0.021)				(0.057)	(0.026)		
$ECON_{AVG,t}$				0.0534	0.0619				0.0532	0.0618
				(0.015)	(0.005)				(0.018)	(0.007)
Adjusted R^2	1.547%	0.765%	2.697%	1.045%	3.019%	1.325%	0.552%	2.473%	0.822%	2.787%
Panel B: 2000-2016										
Constant	0.0055	0.0204	0.0196	0.163	0.1347	0.0055	0.0204	0.0196	0.1614	0.1347
	(0.055)	(0.3)	(0.269)	(0.045)	(0.103)	(0.097)	(0.284)	(0.292)	(0.068)	(0.139)
$R_{m,t}$						-0.0026	0.0481	0.0035	0.0357	-0.0022
						(0.979)	(0.656)	(0.971)	(0.744)	(0.982)
$Sk_{vw,t}$	-0.2147		-0.2021		-0.1801	-0.2154		-0.2012		-0.1806
	(0.003)		(0.014)		(0.033)	(0.004)		(0.012)		(0.025)
$ECON_{PC,t}$		-0.0137	-0.0113				-0.0138	-0.0113		
		(0.332)	(0.384)				(0.313)	(0.404)		
$ECON_{AVG,t}$				0.1929	0.1565				0.1912	0.1565
				(0.045)	(0.112)				(0.068)	(0.15)
Adjusted R^2	3.579%	1.073%	4.161%	3.102%	5.371%	3.098%	0.812%	3.681%	2.746%	4.896%

Table 6: Out-of-Sample Performances based on Predictive Regressions of Market Return

This table reports the following results: the in-sample regression result, the out-of-sample R^2_{OOS}, the ENC statistics, which is the encompassing test of Harvey et al. (1998) and Clark and McCracken (2001) defined as ENC. The annualized Sharpe ratio and the annualized certainty equivalence for index futures return forecasts at monthly frequency from predictive regressions with an expanding window. The Sharpe ration (SR) is the Sharpe ratio gain of a trading strategy based on different return forecasts relative to that obtained with the historical mean return. The certainty equivalent (CE) gain is the portfolio gain of a trading strategy based on different return forecasts relative to that obtained with the historical mean return. It also reports T-statistics for SR and CE, and the Gains of SR and CE. The annual transaction fee, obtained by assuming an $f = 10$ basis point fee, and the annualized return of each strategy are also reported. The predicted variable is the one-month-ahead S&P 500 Future Index return. The risk-aversion parameter λ is equal to 2. The evaluation out-of-sample period is from January 2000 to December 2016. Estimation period for variance is 5 years. Critical values for the encompassing test statistics are from Clark and McCracken (2001) (Table 1).

|	β	P-Val	Adj. R^2 (%)	R^2_{OOS} (%)	ENC	SR	SR-T	CE (%)	CE-T	SRGain	SR Gain-T	CEGain (%)	CE Gain-T	Fee	Annual Ret.(%)
Buy-Hold						0.24	-0.13	2.82	-0.18	0.44	1.52	8.66	2.69	0.00	5.53
$r_{m,t}$	0.04	0.62	-0.30	-1.27	-1.06	-0.10	-2.99	-3.28	-2.86	0.11	0.79	2.55	0.96	0.24	-0.18
$Sk_{vw,t}$	-0.21	0.00	3.58	2.78	6.26	0.47	3.62	6.73	4.03	0.67	6.10	12.57	5.05	0.75	9.76
$Sk_{ew,t}$	-0.16	0.02	1.88	-0.98	-0.47	-0.07	-2.11	-3.54	-2.45	0.14	0.75	2.30	0.87	0.37	0.35
$V_{vw,t}$	-0.05	0.48	-0.29	-2.99	0.75	0.08	-1.02	0.71	-0.88	0.29	1.75	6.55	2.28	0.26	2.82
$V_{ew,t}$	-0.05	0.59	-0.37	-0.08	-0.06	-0.27	-2.40	-6.32	-2.42	-0.06	-1.21	-0.48	-0.42	0.06	-3.1
$V_{m,t}$	-20.50	0.19	1.29	0.82	1.97	-0.12	-3.40	-2.51	-2.96	0.09	0.00	3.33	0.85	0.17	-0.12
$Sk_{m,t}$	-0.01	0.11	0.28	0.63	1.17	0.09	-0.88	0.31	-1.26	0.30	1.73	6.14	2.20	0.56	3.23
ECON_{PC}	0.03	0.05	1.68	0.70	1.11	-0.07	-2.15	-2.81	-1.51	0.13	0.87	3.03	4.21	0.04	0.35
ECON_{Avg}	0.19	0.05	3.10	1.54	2.08	-0.10	-2.51	-3.06	-1.62	0.11	0.53	2.77	3.67	0.05	0.00

Figure 1: Market and Average Stock Variance

This figure presents the 12-month moving-average values (in solid-black line) and raw data series (in dotted-red line) for the squared root of the market variance, the squared root of the value-weighted variance, and the squared root of the equal-weighted variance. Sample: 1963 August–2016 December. NBER recessions are represented by shaded bars.
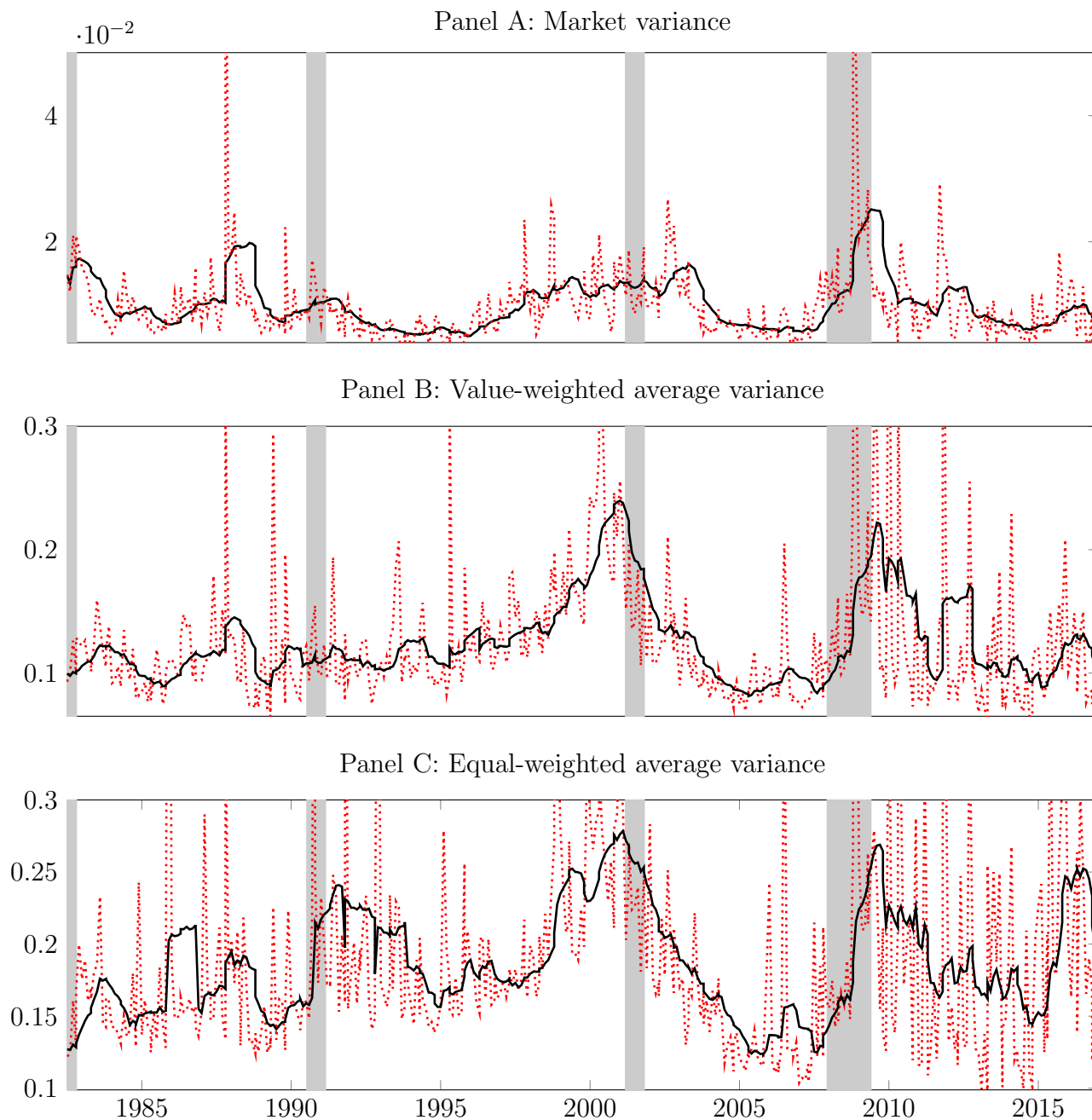
Figure 2: Market and Average Stock Skewness

This figure presents the 12-month moving-average values (in solid-black line) and raw data series (in dotted-red line) for market skewness, value-weighted skewness, and equal-weighted skewness. Sample: 1963 August–2016 December. NBER recessions are represented by shaded bars.

Panel A: Market skewness

Panel B: Value-weighted average skewness

Panel C: Equal-weighted average skewness
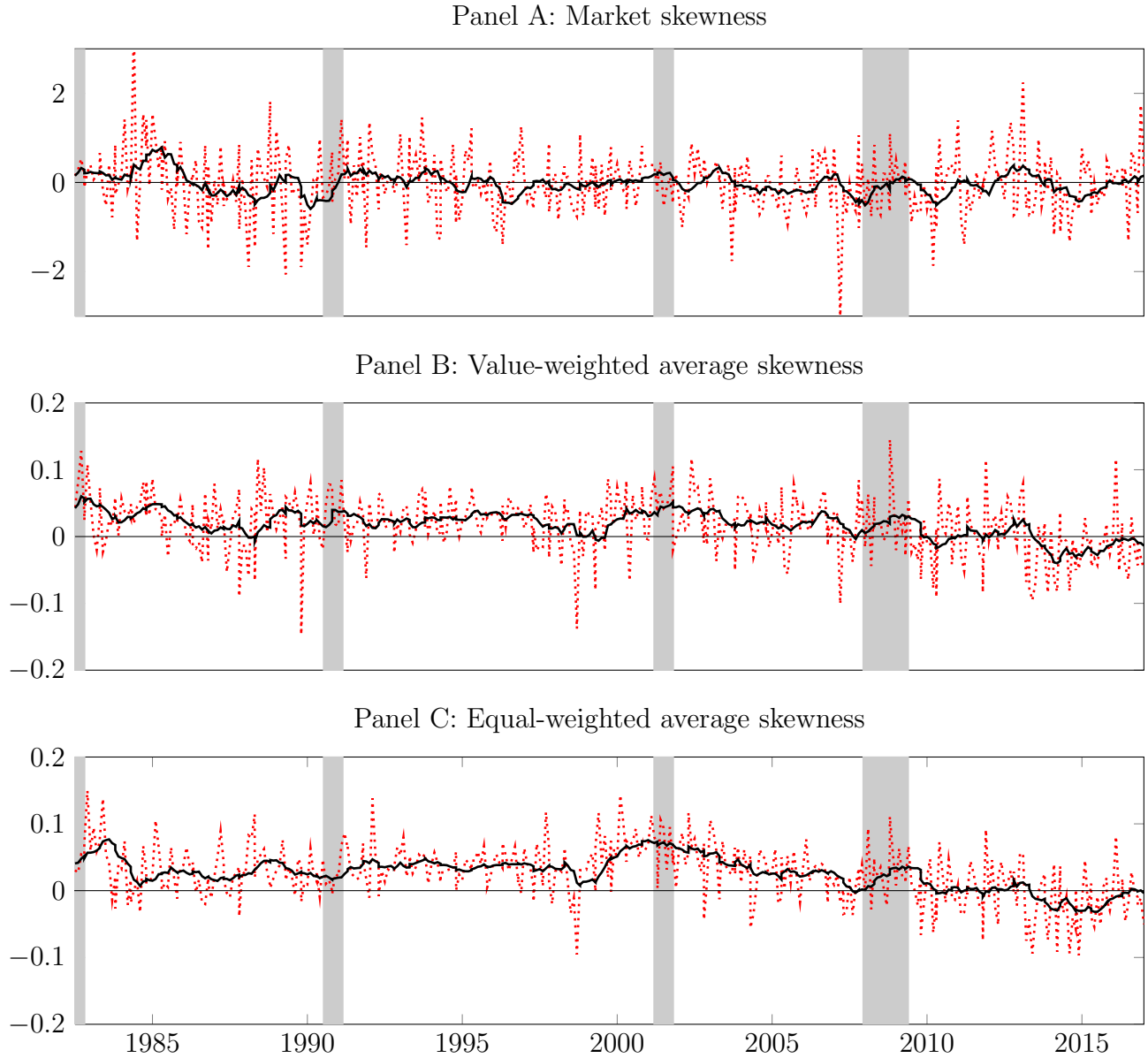
Figure 3: Dynamics of OOS

This figure presents the in-sample and out-of-sample predictive performance of the alternative models. The performance is measured by the difference between the cumulative sum of squared errors (SEE) generated by the prevailing sample mean and the cumulative SEE generated by a given set of variables. Out-of-sample forecasts begins from 2000. Sample: 2000–2016. NBER recessions are represented by shaded bars.