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Average skewness matters☆

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ABSTRACT

Average skewness, which is the average of monthly skewness values across firms, performs well at predicting future market returns. This prediction still holds after controlling for the size or liquidity of the firms or for current business cycle conditions. Also, average skewness compares favorably with other economic and financial predictors of subsequent market returns. The asset allocation exercise based on predictive regressions also shows that average skewness generates superior performance.

1. Introduction

This paper investigates the ability of the average asymmetry in individual stock returns to predict subsequent market returns. The role of the asymmetry of a distribution (or skewness) can be interpreted according to two complementary views. On the one hand, a negative skewness measures the risk of large negative realizations and can be viewed as a source of tail risk (Kelly and Jiang, 2014; Bollerslev et al., 2015) or crash risk (Kozhan et al., 2012). On the other hand, preference for skewness captures the gambling nature of investors (Barberis and Huang, 2008; Bordalo et al., 2012). For both of these reasons, investor decisions are likely to be highly sensitive to the level of skewness (Mitton and Vorkink, 2007; Kumar, 2009).

The importance of skewness in investor preferences was introduced as an extension to the standard capital asset pricing model (CAPM). Acknowledging that investors have a preference for positively skewed securities, the three-moment CAPM provides the equilibrium implications of the preference for skewness. Because idiosyncratic, or firm-specific, risk can be diversified away, only the systematic component of skewness (i.e., the co-skewness of a firm's

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return with the market portfolio return) should be rewarded and explain the cross-sectional dispersion of expected returns across firms (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000).

An enormous literature emphasizes the ability of idiosyncratic risks to predict subsequent returns. On the theoretical side, previous studies suggest that investors with loss aversion utility are concerned by idiosyncratic risk (Barberis and Huang, 2001), which would explain why investors hold under-diversified portfolios. This line of argument is used to explain the role of idiosyncratic volatility (Merton, 1987) and, more recently, the role of idiosyncratic skewness (Barberis and Huang, 2008; Kumar, 2009; Boyer et al., 2010). Mitton and Vorkink (2007) show that investors with a preference for skewness under-diversify their portfolio to invest more in assets with positive idiosyncratic skewness. As a consequence, at equilibrium, stocks with high idiosyncratic skewness pay a premium.

The importance of skewness has been confirmed at the individual level in a number of empirical studies. It has a substantial predictive power with respect to future individual stock returns and equity option returns (Boyer et al., 2010; Bali and Murray, 2013; Conrad et al., 2013; Boyer and Vorkink, 2014; Amaya et al., 2015; Byun and Kim, 2016). So far, no paper has reported on the ability of market skewness or average skewness to predict subsequent market returns. Although the three-moment CAPM implies that market skewness should be a predictor of market return, this implication is not supported by the data (Chang et al., 2011). Also, to date, no paper has investigated the ability of average individual skewness to predict subsequent market returns.

In this paper, we assess the importance of average skewness at the market level. We provide both theoretical foundations and empirical evidence that average stock skewness, i.e., asymmetry in the stock return distribution, helps to predict subsequent market excess return. In a model in which investors have preference for systematic or individual skewness, we show theoretically that average skewness should predict future movements in market return. We extend empirically the work on average volatility by Goyal and Santa-Clara (2003) and Bali et al. (2005) and use the same data and methodology to study realized skewness (i.e., the physical measure of skewness). We find a significant negative relation between the average stock skewness and future market return. This relation holds for equal-weighted and value-weighted skewness. It holds for our extended sample (1963–2016), which includes the 2007–2009 financial crisis, as well as for subsamples. It also holds after controlling for the usual economic and financial variables known to predict market returns and after excluding firms with small price, small size, and low liquidity. Even when a measure of market illiquidity is introduced into the regression, the effect of average stock skewness remains significant. In our baseline regression with average skewness alone, a one standard deviation increase in average monthly skewness results, on average, in a 0.52% decrease in the subsequent monthly market return.

We also evaluate the out-of-sample performance of average skewness as a predictor of future market excess returns. We compute out-of-sample one-month-ahead forecasts with several combinations of predictors, including market excess return, market variance and skewness, average variance and skewness, and several economic and financial variables. We find evidence that the predictive power of the average skewness dominates that of the other predictors. We design an allocation strategy based on predictive regressions following Goyal and Welch (2008) and Ferreira and Santa-Clara (2011). We obtain that the average skewness dominates other predictors both in terms of Sharpe ratio and certainty equivalent. These results confirm that average skewness is an important driver of the subsequent market return.

The remainder of the paper proceeds as follows. In Section 2, we provide theoretical arguments rationalizing the relation between the asymmetry in the stock return distribution and the future market return. Section 3 describes the construction of the variables used in the paper and presents a preliminary analysis. Section 4 offers empirical evidence that average skewness negatively predicts subsequent market excess return. It compares favorably with other economic and financial predictors of market return. In Section 5, we evaluate the out-of-sample performance of average skewness as a predictor of future market return in out-of-sample prediction and allocation exercises. Section 6 concludes this paper. The Technical Appendix provides additional investigation.

2. Sources of predictability in average skewness

The ability of average skewness to predict future market returns can be rationalized as follows: Investors have a preference for skewness and for holding securities with positive skewness rather than securities with negative skewness. Therefore, positively skewed securities tend to be overpriced and have negative expected returns. At the aggregate level, an increase in the average skewness in a given month tends to be followed by a lower market return in the next month.

Several theories provide explanations for why investors prefer to hold positively skewed securities. Scott and Horvath (1980) show that a risk-averse investor with consistent moment preferences exhibits a positive preference for skewness. In expected utility theory, preference for skewness is associated with prudence (Kimball, 1990; Ebert and Wiesen, 2011). An important consequence of the investor's preference for skewness is that, in equilibrium, positively skewed securities tend to be overpriced and command a negative return premium. Early papers on the role of skewness in asset pricing 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; Dittmar, 2002). The first-order condition for an investor's portfolio choice problem is the Euler equation: $E_t[(1+R_{i,t+1})m_{t+1}]=1$ for all i, where $R_{i,t+1}$ denotes the return of firm i and m_{t+1} denotes the intertemporal marginal rate of substitution between t and $t+1$, which also represents the pricing kernel for risky assets. In the three-moment CAPM, the pricing kernel is quadratic in the market return (Harvey and Siddique, 2000; Dittmar, 2002).

The three-moment CAPM has received empirical support based on the ability of the co-skewness of an asset with the market portfolio to explain the cross-sectional variation of expected returns across assets (Harvey and Siddique, 2000). However, the evidence of the ability of market skewness to predict future market return is very weak (Chang et al., 2011). As we demonstrate in Section 4.1, market volatility and market skewness are weak predictors of subsequent market return. Therefore, systematic skewness is not the main channel by which investor's preference for skewness affects future market return.

An explanation for the failure of market skewness to predict future market return could be that investors do not hold well-diversified portfolios (Mitton and Vorkink, 2007; Kumar, 2009). Several theories are consistent with this empirical feature. Cumulative prospect theory (Tversky and Kahneman, 1992) has stimulated a large strand of literature demonstrating that gambling preference, characterized by the preference for individual stock skewness, significantly affects investment decisions and asset prices. As found by Simkowitz and Beedles (1978) and Conine and Tamarkin (1981), investors with a preference for skewness hold under-diversified portfolios to benefit from the upside potential of positively skewed assets. In a model in which the preference for skewness is heterogeneous across agents, Mitton and Vorkink (2007) find that not only will the systematic skewness be priced, but the idiosyncratic skewness will also be relevant for asset pricing. Assets with high idiosyncratic skewness command a negative return premium. In a similar context, Barberis and Huang (2008) construct a model in which investors incorrectly measure probability weights, such that they invest more in positively skewed securities. Other theories have drawn similar conclusions. Brunnermeier and Parker (2005) and Brunnermeier et al. (2007) show that investors choose to have distorted beliefs about the probabilities of future states to maximize their expected utility. They tend to under-diversify their portfolio by investing in positively skewed assets. Bordalo et al. (2012) develop a theory in which investors overweight the salient payoffs relative to their objective probabilities. This thinking leads to a preference for assets with the possibility of high, salient payoffs, such as right-skewed assets.[1] In Bordalo et al. (2013), assets with large upsides (positive skewness) are overpriced, and assets with large downsides (negative skewness) are underpriced.

Recent papers have also argued that the relation between firms' idiosyncratic skewness and subsequent return could be related to growth options. In Trigeorgis and Lambertides (2014) and Del Viva et al. (2017), growth options are significant determinants of idiosyncratic skewness because of 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 options, firms with growth options are generally associated with low expected returns.[2]

When investors have a preference both for systematic and individual skewness, the pricing kernel depends on all sources of risk, including individual innovations. A typical approach consists in writing the pricing kernel as linear in the underlying sources of risk (Aït-Sahalia and Lo, 1998; Bates, 2008; Christoffersen et al., 2012). In our context with quadratic terms, the expected market return would be driven by the following equation:

$$E_t[R_{m,t+1}] - R_{f,t} = \lambda_{m,t}\ V_{m,t} + \psi_{m,t}\ Sk_{m,t} + \lambda_{I,t}\ V_{w,t} + \psi_{I,t}\ Sk_{w,t}, \tag{1}$$

where $R_{m,t+1}$ and $R_{f,t}$ denote the market return and the risk-free rate, $V_{m,t} = V_t[R_{m,t+1}]$ and $Sk_{m,t} = Sk_t[R_{m,t+1}]$ denote the market variance and market skewness at time $t+1$ conditional on the information available at time t, $V_{w,t} = \sum_{i=1}^{N} w_{i,t}\ V_t[\varepsilon_{i,t+1}]$ and $Sk_{w,t} = \sum_{i=1}^{N} w_{i,t}\ Sk_t[\varepsilon_{i,t+1}]$ denote the average variance and skewness, and $w_{i,\ t}$ is the relative market capitalization of firm i. The first two terms of the expression correspond to the three-moment CAPM of Kraus and Litzenberger (1976). The last two terms correspond to the contribution of the average firm-specific expected variance and skewness to the aggregate expected return. The magnitude and significance of the parameters associated with these various predictors in principle depend on investors' preferences. Additional details on the model behind the predictive regression implied from Eq. (1) can be found in Technical Appendix Section A.1.

Driven by the theoretical motivation that individual or idiosyncratic volatility and skewness should be priced, several papers have investigated the ability of these variables to predict the subsequent individual stock return in cross-section regressions.[3] To our knowledge, the ability of the average skewness to predict subsequent market return implied by Eq. (1) has not been evaluated. A few previous papers have estimated related time series regressions, with mixed results. Using Standard & Poor's (S&P) index options, Chang et al. (2011) find a negative and weakly significant effect of physical market skewness on the future monthly return (between 1996 and 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-sectional distribution of monthly returns to predict the future market returns based on Center for Research in Securities Prices (CRSP) data (between 1963 and 2006). They find that the skewness parameter is insignificant when predicting the monthly value-weighted market return. Stöckl and Kaiser (2016) find that the

[1] A preference for skewness has been found in other fields such as horse race bets (Golec and Tamarkin, 1998) and casino gambling (Barberis, 2012).

[2] Cao et al. (2008) and Grullon et al. (2012) provide evidence that real options are important drivers of idiosyncratic volatility and can explain the positive relation between stock returns and volatility shown by Duffee (1995). The convexity generated by real options also qualifies them as likely drivers of return asymmetry and, therefore, of idiosyncratic skewness. Xu (2007) notes that short sale restrictions lead to convexity in payoffs and, therefore, to return skewness.

[3] Such cross-section regressions have been estimated, for instance, in Boyer et al. (2010), Xing et al. (2010), Bali and Murray (2013), Conrad et al. (2013), Boyer and Vorkink (2014), and Amaya et al. (2015). Most of these papers find a negative relation between skewness and the subsequent individual stock returns.

cross-sectional skewness of the Fama-French portfolios adds to the predictive power of cross-sectional volatility (between 1963 and 2015), although only for short horizons.

3. Data and preliminary analysis

Market excess return is calculated as the aggregate stock return minus the short-term interest rate. Aggregate stock return is the simple return on the value-weighted CRSP index including dividends, and the short-term interest rate is the one-month Treasury bill rate. 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 $r_{m,t} = R_{m,t} - R_{f,t-1}$ the excess market return in month t. We also denote by $r_{i,d}$ and $r_{m,d}$, $d = 1, \ldots, D_t$, the daily excess 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 with share codes 10 or 11 from the CRSP data set, including those listed on the NYSE, AMEX, and Nasdaq.[4] 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 August 1963 to December 2016, extending the sample of Bali et al. (2005) by 15 years.

When daily data are available, a common way of calculating the monthly variance of stock i in month t is

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

where $\bar{r}_{i,t}$ is the average daily excess return of stock i in month t. 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). We use two approaches to calculate the average of monthly variances across firms. 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, notably adopted by Bali et al. (2005), is based on 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.

Measuring skewness is an admittedly difficult task, in particular because raising all observations to the third power renders the skewness sensitive to outliers.[5] The monthly (standardized) skewness of stock i is defined as

$$Sk_{i,t} = \sum_{d=1}^{D_t} \tilde{r}_{i,d}^3, \qquad (3)$$

where $\tilde{r}_{i,d} = (r_{i,d} - \bar{r}_{i,t})/\sigma_{i,t}$ with $\sigma_{i,t}^2 = \sum_{d=1}^{D_t} (r_{i,d} - \bar{r}_{i,t})^2$. 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, $Sk_{vw,t} = \sum_{i=1}^{N_t} w_{i,t}\ Sk_{i,t}$.[6]

As Fig. 1 illustrates, the market variance and the average stock variance have similar dynamic properties. Most large increases in the market variance coincide with National Bureau of Economic Research (NBER) – dated recessions (with the exception of the 1987 market crash). The 2007–2009 subprime crisis has the most pronounced and long-lasting impact on market variance. The largest increase in the average stock variance corresponds to the dotcom boom and burst between 1998 and 2003. In addition, the subprime crisis results in a very pronounced increase in the average variance. In contrast, the recent period (2015–2016) is associated with an increase in the equal-weighted average stock variance, although market variance remains at a relatively low level.

Fig. 2 shows that the market skewness and average stock skewness have different patterns and are, in general, asynchronous. The market skewness is negative on average and lies within a relatively wide range of values (between −1 and 1). The average skewness is generally positive, with values between 0 and 0.1. This evidence, confirmed in Table 1 (Panel A), suggests that periods exist when the average skewness and the market skewness are of opposite signs. For instance, the most positive market skewness value (in 1985) is accompanied by a moderate level of average skewness. Periods with persistently positive average skewess (1963–1974 and 1992–2001) were accompanied by a predominantly negative market skewness. Albuquerque (2012) proposes a theoretical explanation for the different signs of skewness at firm and market levels. That is, positive skewness in individual stock returns is due to the positive correlation between expected returns and volatility (risk-return trade-off), and negative market skewness arises from cross-sectional heterogeneity in firms' earnings announcement events.

Because the market return, average variance, and average skewness are constructed as cross-sectional moments of daily returns, they are likely to exhibit contemporaneous correlation. Table 1 (Panel B) reveals that the relation between the market return and average variance and skewness are very different. The average variance is negatively correlated with the market return (−22.8% and −10.1% for the value-weighted and equal-weighted variance, respectively), and the contemporaneous correlation between

[4] Monthly market excess return is directly extracted from Kenneth French's website, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. CRSP data on individual firms consist of daily returns on common stocks, corrected for corporate actions and dividend payments.

[5] To circumvent this issue, several measures have been proposed based on option prices (Bakshi et al., 2003; Conrad et al., 2013), high-frequency data (Neuberger, 2012; Amaya et al., 2015), cross-sectional moments (Kapadia, 2012; Stöckl and Kaiser, 2016), or quantiles of the return distribution (Garcia et al., 2014; Ghysels et al., 2016).

[6] Because average variance and skewness are based on daily returns, whether returns are demeaned should have limited impact. However, it can affect the correlation between these measures and the market return itself. In Technical Appendix Section B.1, we provide additional details on the measurement of average volatility and skewness and discuss an alternative way to construct average skewness, in which we demean daily returns in Eq. (3) using market returns. We find no material difference in the main results. Furthermore, standardizing the skewness using the standard definition of the variance or the corrected version given by Eq. (2) has no substantial impact on the results.

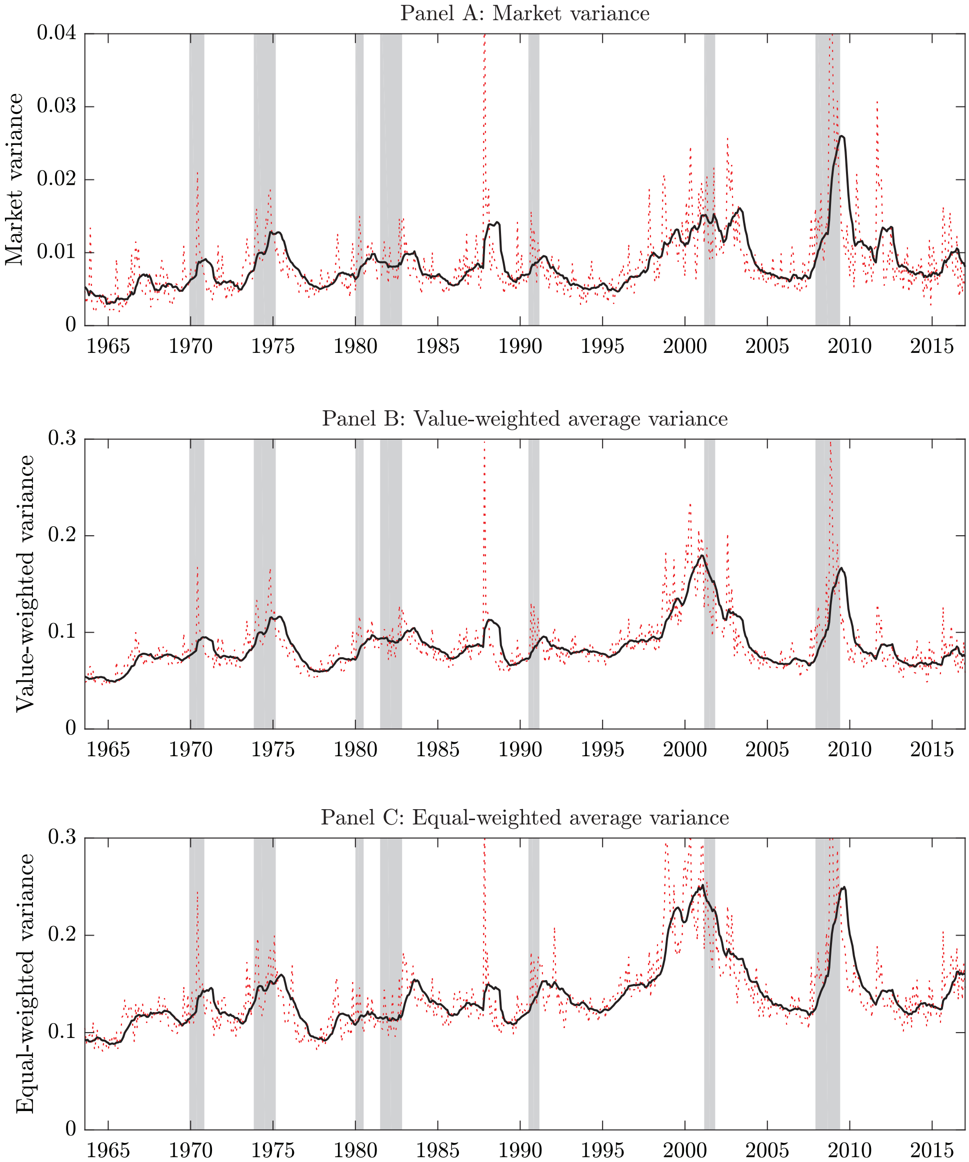

Fig. 1. Market and average stock variance. This figure presents the 12-month moving-average values (in solid line) and raw data series (in dotted line) for the square root of the market variance, the square root of the value-weighted variance, and the square root of the equal-weighted variance. The sample period is August 1963 to December 2016. National Bureau of Economic Research recessions are represented by shaded bars.

the market return and average skewness is positive (9.3% and 14.4% for the value-weighted and equal-weighted skewness, respectively). This positive contemporaneous correlation between the cross-sectional mean and the cross-sectional skewness of a variable has to be expected in finite samples when the cross-sectional distribution of the variable is non-normal (see Bryan and Cecchetti, 1999). This high correlation exists even with no time dependence in the data and therefore provides no indication of a correlation between the market return and lagged skewness.

The correlation between the market 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 market return with lagged average variance is negative (−9.1% and −3.9% for the value-weighted and equal-weighted variance, respectively). In contrast to the contemporaneous case, the correlation with lagged average skewness is negative (−11.6% and −9.7% for the value-weighted and equal-weighted skewness, respectively), suggesting that average skewness can negatively predict market return.

The table also reveals that the correlation between the market skewness and average skewness is relatively low (50.2% and 26.7% 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 Fig. 2. Market skewness is mainly driven by coskewness terms, which reflect nonlinear dependencies between firms' returns and

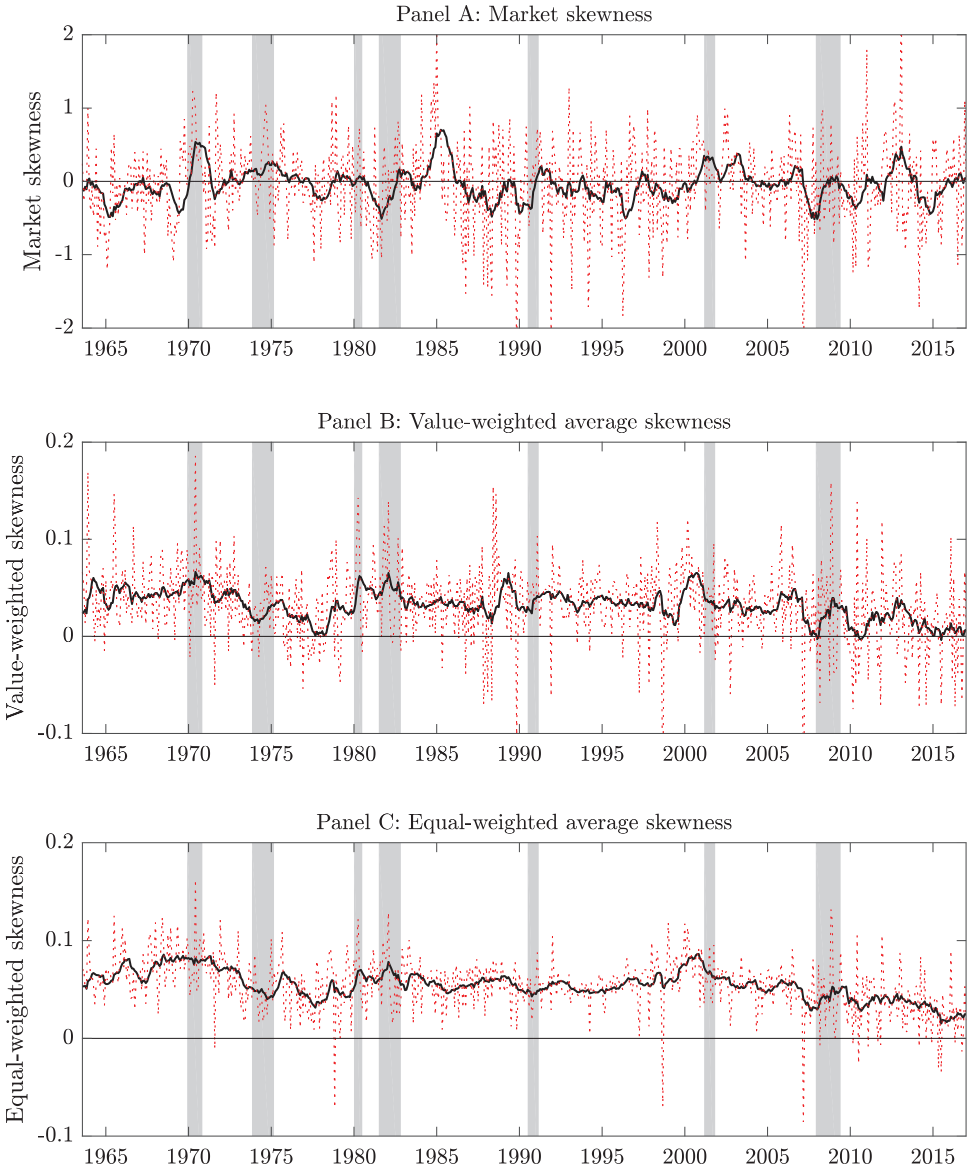

Fig. 2. Market and average stock skewness. This figure presents the 12-month moving-average values (in solid line) and raw data series (in dotted line) for market skewness, value-weighted skewness, and equal-weighted skewness. The sample period is August 1963 to December 2016. National Bureau of Economic Research recessions are represented by shaded bars.

does not depend on average skewness when the number of firms is large (see Technical Appendix Section A.2 for details).

4. Empirical results

We now evaluate the ability of market variance and skewness and average variance and skewness to predict the subsequent market excess return in a regression corresponding to the theoretical expression (1).

4.1. Baseline regressions

The baseline regression can be written as follows, with the definitions of average variance and skewness based on value and equal weights, respectively:

$$r_{m,t+1} = a + b\ V_{m,t} + c\ Sk_{m,t} + d\ V_{vw,t} + e\ Sk_{vw,t} + e_{m,t+1} \tag{4}$$

and

$$r_{m,t+1} = a + b\ V_{m,t} + c\ Sk_{m,t} + d\ V_{ew,t} + e\ Sk_{ew,t} + e_{m,t+1}. \tag{5}$$

Eq. (4) is the preferred regression because average variance and skewness are defined consistently with the value-weighted definition of the market excess return.

In Table 2, we consider each of the variables in Eqs. (4) and (5) introduced separately. Panel A reports the results of the regressions for the 1963–2016 sample. The

Table 1
Summary statistics and correlation matrix.
This table provides summary statistics and the correlation matrix for the following variables: value-weighted Center for Research in Security Prices market excess return $r_{m,t}$, market variance $V_{m,t}$, market skewness $Sk_{m,t}$, value-weighted average variance $V_{vw,\,t}$, equal-weighted average variance $V_{ew,\,t}$, value-weighted average skewness $Sk_{vw,\,t}$, and equal-weighted average skewness $Sk_{ew,\,t}$. The sample period is August 1963 to December 2016.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Summary statistics							
Variable	Mean	Minimum	Median	Maximum	Standard deviation	AR_1	
$r_{m,t}$	0.005	−0.232	0.008	0.161	0.044	0.073	
$V_{m,t} \times 100$	0.010	0.000	0.005	0.249	0.019	0.567	
$Sk_{m,t}$	−0.042	−2.844	−0.035	2.585	0.584	0.090	
$V_{vw,\,t}$	0.009	0.002	0.006	0.090	0.008	0.621	
$V_{ew,\,t}$	0.021	0.007	0.017	0.142	0.015	0.754	
$Sk_{vw,\,t}$	0.032	−0.229	0.033	0.186	0.041	0.053	
$Sk_{ew,\,t}$	0.054	−0.086	0.056	0.163	0.028	0.250	
Panel B: Correlation							
Variable	$r_{m,t+1}$	$r_{m,t}$	$V_{m,t}$	$Sk_{m,t}$	$V_{vw,\,t}$	$V_{ew,\,t}$	$Sk_{vw,\,t}$
$r_{m,t}$	0.073						
$V_{m,t}$	−0.093	−0.324					
$Sk_{m,t}$	−0.024	0.092	−0.002				
$V_{vw,\,t}$	−0.091	−0.228	0.840	0.048			
$V_{ew,\,t}$	−0.039	−0.101	0.723	0.046	0.902		
$Sk_{vw,\,t}$	−0.116	0.093	−0.009	0.502	0.085	0.050	
$Sk_{ew,\,t}$	−0.097	0.144	0.044	0.267	0.171	0.151	0.766

market variance is weakly significant with a p-value equal to 4% and an adjusted R^2 equal to 0.71%. As discussed in Section 2, market skewness does not predict future market return. The value-weighted average variance has some predictive power for future market returns with a relatively low adjusted R^2, and the equal-weighted average variance fails to predict market return. The coefficient of the average skewness is highly significant and has a negative value of −0.1259. That is, as the standard deviation of the value-weighted average skewness is equal to 0.041, a one standard deviation increase in monthly average skewness results in a 0.52% ($= 0.1259 \times 0.041$) decrease in the future monthly market return. For the value-weighted average skewness, the p-value is the lowest (equal to 0.2%) and the adjusted R^2 is the highest (equal to 1.18%).

Table 3 reports combinations of the variables introduced in Eqs. (4) and (5). In Section 2, we argue that the three-moment CAPM provides a good description of the cross-sectional variation of expected returns across firms (Harvey and Siddique, 2000) but that market skewness has limited predictive power for the subsequent monthly market excess return. To confirm this argument, we report the predictive regressions with market moments (Column 1). The parameters of the market variance and market skewness are weakly significant, and the adjusted R^2 is low (0.61%), which suggests that the contribution of market variance and skewness to the prediction of the subsequent market excess return is weak at best. Columns 2 and 3 report predictive regressions with value-weighted and equal-weighted average moments, respectively. As in Table 2, only the value-weighted average skewness is highly significant, with a parameter estimate equal to −0.118 and a p-value of 0.6%. The equal-weighted average skewness is also significant with a relatively higher p-value (equal to 1.6%) and a lower adjusted R^2. In Columns 4 and 5, we report the predictive regressions with market moments and average moments, which correspond to Eq. (1). Again, market variance and skewness have no predictive ability for the value-weighting scheme. The only significant predictor is the value-weighted average skewness. Columns 6 and 7 correspond to the same regressions with the current market return as a control variable. It has a positive parameter, with a p-value close to 15%. It slightly increases the adjusted R^2 to 1.91% in the value-weighting scheme.

Finally, Columns 8 and 9 report regressions with market return and average skewness only. Market return has a positive and significant coefficient, with a p-value equal to 4.4% and 3.1% with value-weighted and equal-weighted average skewness, respectively. The average skewness has a negative and highly significant coefficient. The p-value is equal to 0.1% and the adjusted R^2 is equal to 1.73% in the value-weighting scheme. The p-value is equal to 0.2% and the adjusted R^2 is equal to 1.4% in the equal-weighting scheme.

In Panel B of Tables 2 and 3, we report estimates based on the second half of the sample (1990–2016). In the recent period, the effect of value-weighted average skewness is slightly reduced. When variables are introduced alone, in the recent period, the value-weighted average skewness is again the variable with the lowest p-value (equal to 2.9%), with an adjusted R^2 equal to 1.02%. The adjusted R^2 increases to 1.46% when market return is added.

If we focus on the regression with average skewness and excess market returns as regressors (Table 3, Panel A, Column 8), the effect of average skewness can be quantified as follows. A one standard deviation increase in the average monthly skewness results, on average, in a 0.55% ($= 0.1344 \times 0.041$) decrease in the subsequent monthly

Table 2
Predictive regressions of market return – individual variables.
This table reports results of the one-month-ahead predictive regressions of the value-weighted Center for Research in Security Prices market excess return $r_{m,t+1}$. $V_{m,t}$ and $Sk_{m,t}$ are market variance and skewness. $V_{vw,\,t}$ 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. 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 August 1963 to December 2016 (Panel A) and January 1990 to December 2016 (Panel B).

Predictor	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 1963–2016						
Constant	0.0072	0.0050	0.0093	0.0091	0.0075	0.0135
	(0.000)	(0.008)	(0.000)	(0.000)	(0.025)	(0.000)
$V_{m,t}$	−21.7320	–	–	–	–	–
	(0.040)					
$Sk_{m,t}$	–	−0.0018	–	–	–	–
		(0.560)				
$V_{vw,\,t}$	–	–	−0.5044	–	–	–
			(0.023)			
$Sk_{vw,\,t}$	–	–	–	−0.1259	–	–
				(0.002)		
$V_{ew,\,t}$	–	–	–	–	−0.1156	–
					(0.487)	
$Sk_{ew,\,t}$	–	–	–	–	–	−0.1559
						(0.008)
Adj. R^2	0.709%	−0.100%	0.676%	1.179%	−0.008%	0.792%
Panel B: 1990–2016						
Constant	0.0097	0.0063	0.0121	0.0097	0.0116	0.0134
	(0.000)	(0.013)	(0.000)	(0.002)	(0.007)	(0.002)
$V_{m,t}$	−25.3780	–	–	–	–	–
	(0.074)					
$Sk_{m,t}$	–	−0.0030	–	–	–	–
		(0.465)				
$V_{vw,\,t}$	–	–	−0.5690	–	–	–
			(0.038)			
$Sk_{vw,\,t}$	–	–	–	−0.1168	–	–
				(0.029)		
$V_{ew,\,t}$	–	–	–	–	−0.1966	–
					(0.310)	
$Sk_{ew,\,t}$	–	–	–	–	–	−0.1432
						(0.055)
Adj. R^2	1.374%	−0.139%	1.293%	1.016%	0.339%	0.527%

market excess return. This contribution is slightly larger than that of a one standard deviation decrease in the lagged market excess return ($0.37\% = 0.0839 \times 0.044$). The result suggests that the predictability of the future market excess return is driven by the combination of market excess return and average skewness. When the market excess return is low and average skewness is high in a given month, the model predicts a low market excess return for the next month.

To confirm this prediction, we compute in our data the average market excess return for the months following a month with a market excess return above its mean and an average skewness below its mean, which represent 27.1% of our sample. We obtain an average excess return equal to 1.14% over these months. The average market excess return for months following a month with a market excess return below its mean and an average skewness above its mean (21.3% of our sample) is equal to −0.19%.[7] This empirical evidence is also close to the time series momentum identified by Moskowitz et al. (2012), who show that most financial markets exhibit persistence in returns for horizons up to 12 months. This phenomenon is consistent with predictions made by theoretical asset pricing models, such as Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999).[8]

In summary, our estimates show that average skewness is a strong predictor of future market returns when introduced in combination with current market return or not. Market variance, market skewness, and the average stock variance do not help predict future market returns. In the rest of Section 4, we consider several modifications of the benchmark model and several macroeconomic and financial alternative predictive variables and show that this main result still holds. The significance of average skewness is not driven by some specific categories of firms and is robust to alternative definitions of average skewness or to adding other predictive variables. From now on, we

[7] On average, periods with high market excess return and low average skewness correspond to periods of economic expansion and relatively liquid market conditions. See Technical Appendix Section B.2 for additional details.

[8] Time series momentum should not be confused with cross-section momentum, described by Jegadeesh and Titman (1993) and recently analyzed by Jacobs et al. (2015) and Daniel and Moskowitz (2016).

Table 3
Predictive regressions of market return – combination of variables.
This table reports results of the one-month-ahead predictive regressions of the value-weighted Center for Research in Security Prices market excess return $r_{m,t+1}$. $V_{m,t}$ and $Sk_{m,t}$ are market variance and skewness. $V_{vw,\,t}$ 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. 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 August 1963 to December 2016 (Panel A) and January 1990 to December 2016 (Panel B).

Predictor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: 1963–2016									
Constant	0.0071	0.0127	0.0147	0.0124	0.0122	0.0120	0.0127	0.0089	0.0142
	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.000)	(0.006)	(0.000)	(0.000)
$r_{m,t}$	–	–	–	–	–	0.0580	0.0564	0.0839	0.0883
						(0.148)	(0.151)	(0.044)	(0.031)
$V_{m,t}$	−21.7431	–	–	−20.2642	−35.1707	−14.4452	−28.4858	–	–
	(0.039)			(0.380)	(0.016)	(0.540)	(0.068)		
$Sk_{m,t}$	−0.0018	–	–	0.0035	0.0000	0.0032	−0.0002	–	–
	(0.562)			(0.314)	(0.992)	(0.345)	(0.941)		
$V_{vw,\,t}$	–	−0.4535	–	−0.0488	–	−0.0890	–	–	–
		(0.044)		(0.925)		(0.862)			
$Sk_{vw,\,t}$	–	−0.1183	–	−0.1512	–	−0.1542	–	−0.1344	–
		(0.006)		(0.001)		(0.001)		(0.001)	
$V_{ew,\,t}$	–	–	−0.0731	–	0.2577	–	0.2161	–	–
			(0.663)		(0.234)		(0.303)		
$Sk_{ew,\,t}$	–	–	−0.1500	–	−0.1660	–	−0.1765	–	−0.1764
			(0.016)		(0.008)		(0.005)		(0.002)
Adj. R^2	0.611%	1.694%	0.694%	1.764%	1.460%	1.908%	1.574%	1.726%	1.404%
Panel B: 1990–2016									
Constant	0.0096	0.0139	0.0154	0.0136	0.0132	0.0130	0.0134	0.0094	0.0139
	(0.000)	(0.000)	(0.001)	(0.000)	(0.015)	(0.001)	(0.012)	(0.002)	(0.001)
$r_{m,t}$	–	–	–	–	–	0.0472	0.0450	0.0864	0.0894
						(0.433)	(0.440)	(0.146)	(0.133)
$V_{m,t}$	−25.0056	–	–	−20.1932	−33.4304	−16.2925	−28.7637	–	–
	(0.080)			(0.444)	(0.102)	(0.548)	(0.192)		
$Sk_{m,t}$	−0.0025	–	–	0.0024	0.0000	0.0020	−0.0003	–	–
	(0.548)			(0.624)	(0.995)	(0.671)	(0.952)		
$V_{vw,\,t}$	–	−0.4832	–	−0.1045	–	−0.1192	–	–	–
		(0.094)		(0.849)		(0.825)			
$Sk_{vw,\,t}$	–	−0.0945	–	−0.1219	–	−0.1254	–	−0.1263	–
		(0.135)		(0.075)		(0.068)		(0.018)	
$V_{ew,\,t}$	–	–	−0.1332	–	0.1848	–	0.1610	–	–
			(0.545)		(0.510)		(0.555)		
$Sk_{ew,\,t}$	–	–	−0.1122	–	−0.1515	–	−0.1593	–	−0.1653
			(0.242)		(0.129)		(0.113)		(0.022)
Adj. R^2	1.185%	1.819%	0.476%	1.653%	1.259%	1.537%	1.116%	1.457%	1.010%

report results with the value-weighted average skewness (with and without market return) for the full sample and the recent subsample.

In Technical Appendix B, we provide additional regression results based on alternative definitions of the variables. To avoid possible lead-lag effects in the aggregation of stock returns, we also use the monthly return from S&P 500 index futures contracts (Technical Appendix Section B.3). Our main results are based on the use of variance itself as a regressor. We also report the results of regressions when the square root and the log of the variance are used instead, with similar significance of the average skewness parameter (Technical Appendix Section B.4). We also investigate alternative measures of skewness, based on the median instead of the average and based on the cross section of monthly stock returns instead of daily returns (Technical Appendix Sections B.5 and B.6). In all these cases, the results are consistent with those reported here.

We also control for several firm's characteristics, such as the firm's size, the liquidity of the stocks, or the price of the shares. Evidence reported in Technical Appendix Section C.1 confirms that the significance of the average skewness is not due to small and illiquid firms. We test whether our results are robust to economic recessions (expansions), as identified by the NBER and find that economic downturns and booms do not affect the predictive power of average skewness (Technical Appendix Section C.2). Finally, we investigate the ability of average skewness to predict subsequent market excess return above one month. In Technical Appendix Section C.3, we report results for forecast horizons from one to six months. We find that predictability usually improves up to the three-month horizon.

4.2. Controlling for the business cycle and other predictors

The significance of average skewness could be due to the fact that it is a proxy for more fundamental business cycle factors. Goyal and Santa-Clara (2003) investigate the relation between market return and average stock variance when certain macro variables are used as controls for business cycle fluctuations. We consider the same set of control variables: 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 ten-year Treasury bond yield (*DEF*); the term spread, calculated as the difference between the ten-year Treasury bond yield and three-month Treasury bill rate (*TERM*); and the relative three-month Treasury bill rate, calculated as the difference between the current Treasury 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.[9]

Table 4 reports the results of the regressions including all of the business cycle variables with average skewness (Columns 1 and 2). Note that, even if some of these variables are significant when they are introduced alone as shown in previous literature (see, among others, Bali et al., 2005), they have a limited contribution when they are introduced together. This evidence suggests that once the current average skewness is introduced, business cycle variables do not contribute significantly to the predictability of the subsequent market return. The parameter of the average skewness is essentially unaffected by the introduction of these variables. Over the 1963–2016 sample (Panel A, Column 1), its parameter estimate is equal to −0.12 (with a *p*-value of 0.3%) and the adjusted R^2 is equal to 1.8%. For the 1990–2016 sample, we obtain similar estimates, with a parameter equal to −0.119 (with a *p*-value of 2.6%) and an adjusted R^2 equal to 1.92%. When business cycle variables are introduced in the regression, lagged market return does not help predict subsequent market return, with a *p*-value above 12%. Furthermore, Columns 3 and 4 reveal that expected illiquidity has an insignificant estimated coefficient and does not alter the predictive ability of average skewness.

Rapach et al. (2009) and Rapach and Zhou (2013) argue that the failure of previous papers to find significant out-of-sample gains in forecasting market return could be due to model uncertainty and instability. They recommend combining individual forecasts and provide evidence that a simple equal-weighted combination of 14 standard economic variables works well in predicting the monthly market return.[10] 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 1963–2016 sample period, Table 5 demonstrates that average skewness performs better than the first principal component, ECON_{PC}. The adjusted R^2 is equal to 1.18% with average skewness but negative for ECON_{PC}.

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 value-weighted Center for Research in Security Prices market excess 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 August 1963 to December 2016 (Panel A) and January 1990 to December 2016 (Panel B).

Predictor	(1)	(2)	(3)	(4)
Panel A: 1963–2016				
Constant	0.0302	0.0289	0.0505	0.0491
	(0.095)	(0.088)	(0.081)	(0.077)
$r_{m,t}$	–	0.0694	–	0.0692
		(0.127)		(0.131)
$Sk_{vw,\,t}$	−0.1199	−0.1277	−0.1219	−0.1297
	(0.003)	(0.002)	(0.003)	(0.002)
DP_t	0.0072	0.0069	0.0037	0.0034
	(0.118)	(0.115)	(0.597)	(0.606)
DEF_t	0.1154	0.1206	0.1859	0.1904
	(0.729)	(0.698)	(0.605)	(0.570)
$TERM_t$	0.1365	0.1264	0.1375	0.1274
	(0.363)	(0.376)	(0.362)	(0.375)
$RREL_t$	−0.2637	−0.2208	−0.2240	−0.1815
	(0.236)	(0.302)	(0.332)	(0.409)
$ILLIQ_t^E$	–	–	0.0021	0.0021
			(0.426)	(0.405)
Adj. R^2	1.805%	2.119%	1.744%	2.057%
Panel B: 1990–2016				
Constant	0.0862	0.0817	0.1060	0.1012
	(0.029)	(0.032)	(0.018)	(0.020)
$r_{m,t}$	–	0.0683	–	0.0678
		(0.237)		(0.238)
$Sk_{vw,\,t}$	−0.1186	−0.1258	−0.1256	−0.1326
	(0.026)	(0.018)	(0.015)	(0.011)
DP_t	0.0187	0.0177	0.0109	0.0101
	(0.061)	(0.065)	(0.405)	(0.416)
DEF_t	−0.1114	−0.0740	−0.0697	−0.0334
	(0.824)	(0.872)	(0.890)	(0.943)
$TERM_t$	−0.0281	−0.0349	−0.0070	−0.0141
	(0.889)	(0.855)	(0.972)	(0.941)
$RREL_t$	0.6014	0.5694	0.7079	0.6741
	(0.081)	(0.077)	(0.048)	(0.044)
$ILLIQ_t^E$	–	–	0.0030	0.0030
			(0.340)	(0.327)
Adj. R^2	1.917%	2.071%	1.784%	1.931%

[9] 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. 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): $\log(ILLIQ_{t+1}) = -0.727(-3.9) + 0.956(83.7)\log(ILLIQ_t) + \text{residual}$, with the adjusted R^2 equal to 91.6%. The expected illiquidity, denoted by $ILLIQ^E$, is defined by the first two terms on the right-hand side.

[10] The 14 economic variables are: 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.

Table 5
Comparison with economic variables.
This table reports results of the one-month-ahead predictive regressions of the value-weighted Center for Research in Security Prices market excess return $r_{m,t+1}$. $Sk_{vw,\,t}$ is the value-weighted average skewness. The other predictors, represented by X_t, are the first principal component $ECON_{PC,t}$ (Columns 2–4) and the equal-weighted average $ECON_{AVG,t}$ (Columns 5–7) of 14 economic predictors (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 August 1963 to December 2016 (Panel A) and January 1990 to December 2016 (Panel B).

		$ECON_{PC,t}$			$ECON_{AVG,t}$		
Predictor	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: 1963–2016							
Constant	0.0091	0.0050	0.0091	0.0090	0.0166	0.0233	0.0241
	(0.000)	(0.007)	(0.000)	(0.000)	(0.217)	(0.088)	(0.057)
$r_{m,t}$	–	–	–	0.0854	–	–	0.0859
				(0.041)			(0.040)
$Sk_{vw,\,t}$	−0.1259	–	−0.1282	−0.1375	–	−0.1296	−0.1386
	(0.002)		(0.002)	(0.001)		(0.002)	(0.001)
X_t	–	0.0002	0.0008	0.0010	0.0159	0.0195	0.0209
		(0.904)	(0.687)	(0.580)	(0.379)	(0.281)	(0.215)
Adj. R^2	1.179%	−0.154%	1.059%	1.628%	−0.008%	1.246%	1.826%
Panel B: 1990–2016							
Constant	0.0097	0.0128	0.0172	0.0171	0.0603	0.0629	0.0630
	(0.002)	(0.005)	(0.000)	(0.000)	(0.063)	(0.053)	(0.037)
$r_{m,t}$	–	–	–	0.0890	–	–	0.0873
				(0.128)			(0.156)
$Sk_{vw,\,t}$	−0.1168	–	−0.1272	−0.1372	–	−0.1158	−0.1254
	(0.029)		(0.019)	(0.011)		(0.032)	(0.020)
X_t	–	0.0081	0.0093	0.0095	0.0667	0.0659	0.0665
		(0.157)	(0.104)	(0.075)	(0.093)	(0.094)	(0.068)
Adj. R^2	1.016%	0.499%	1.751%	2.241%	0.766%	1.764%	2.225%

Average skewness also performs better than the average of the 14 economic variables $ECON_{AVG}$, which has an adjusted R^2 equal to −0.01%. When the variables are introduced together in the regression, the p-value of the average skewness coefficient is equal to 0.2%, and the p-values of $ECON_{PC}$ and $ECON_{AVG}$ are equal to 69% and 28%, respectively. When current market return is added, average skewness still performs better than the economic factors. For the 1990–2016 period, we find a similar result, although the predictive ability of $ECON_{PC}$ and $ECON_{AVG}$ slightly increases.

Finally, we compare the predictability of average skewness to six predictors that capture various aspects of aggregate risk or fragility in financial market: (1) the average correlation across stocks (*AC*) is interpreted as a measure of aggregate market risk (Pollet and Wilson, 2010) or as a measure of the degree of disagreement between investors (Buraschi et al., 2014). (2) The aggregate short interest index (*SII*) across firms is a measure of market pessimism (Rapach et al., 2016). (3) *VIX* is a measure of the stock market's expectation of volatility implied by S&P 500 index options. This is often referred to as the fear index. (4) The tail risk measure (*TR*) is a cross-sectional measure of extreme risk (Kelly and Jiang, 2014). (5) The variance risk premium (*VRP*) is also often viewed as an indicator of fear in financial markets (Bollerslev et al., 2009; 2015). (6) The tail risk premium (*TRP*) is defined as the difference between the actual and risk-neutral expectations of the forward aggregate market variation (Bollerslev et al., 2015).[11]

Table 6 reports the results of respective predictive regressions with sample periods defined according to the availability of the data. For all long subsamples that we consider, average skewness is highly significant. Among its competitors, the short interest index (*SII*) and the tail risk measure (*TR*) are found to be significant predictors of market excess return. When *SII* is introduced alone (over the 1973–2014 sample period), it is associated with an adjusted R^2 similar to that of average skewness (1.06%

[11] We construct average correlation *AC* following (Pollet and Wilson, 2010): For a given month, we compute the correlation between two stocks using daily returns. Then, we compute the average correlation on that month as the value-weighted average over all pairs. It is available from August 1963 to December 2016. The aggregate *SII* is constructed following (Rapach et al., 2016): The raw short interest is the number of shares that are held short in a given firm. Then, it is normalized by dividing the level of short interest by each firm's shares outstanding. It is filtered to exclude assets with a stock price below $5 per share and assets that are below the fifth percentile breakpoint of NYSE market capitalization. The series is multiplied by −1 to obtain a positive parameter. The aggregate series is available from January 1973 through December 2014. The *VIX* is the implied option volatility of the S&P 500 index. It is available from January 1990 to December 2015. *TR* is the common time-varying component of return tails, estimated monthly by applying the (Hill, 1975) power law estimator to the set of daily return observations for all stocks in month t. It is available from August 1963 to December 2011 from Kelly and Jiang (2014). We have updated the series through December 2016. *VRP* is defined by Bollerslev et al. (2015) as the difference (normalized by horizon) between the quadratic variation of market return evaluated under the objective and risk-neutral probability measures and *TRP* is defined as the difference (normalized by horizon) between the left jump tail variation of market return evaluated under the objective and risk-neutral probability measures. Actual realized variation measures are based on high-frequency S&P 500 futures prices. Risk-neutral measures are based on closing bid and ask quotes for all options traded on the Chicago Board of Options Exchange (CBOE). *VRP* and *TRP* are available from January 1996 to August 2013 from Bollerslev et al. (2015).

Table 6
Comparison with financial variables.
This table reports results of the one-month-ahead predictive regressions of the value-weighted Center for Research in Security Prices market excess return $r_{m,t+1}$. $Sk_{vw,\,t}$ is the value-weighted average skewness. The other predictors, represented by X_t, are the average correlation, *AC* (Pollet and Wilson, 2010), the aggregate short interest index, *SII* (Rapach et al., 2016), the volatility index, *VIX*, the tail risk measure, *TR* (Kelly and Jiang, 2014), the variance risk premium, *VRP*, and the tail risk premium, *TRP* (Bollerslev et al., 2015). 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. Sample periods are as noted.

Predictor	(1)	(2)	(3)	(4)
Panel A: AC (1963–2016)				
Constant	0.0091	−0.0006	0.0048	0.0026
	(0.000)	(0.890)	(0.257)	(0.509)
$r_{m,t}$	–	–	–	0.0981
				(0.016)
$Sk_{vw,\,t}$	−0.1259	–	−0.1179	−0.1240
	(0.002)		(0.003)	(0.002)
X_t	–	0.0225	0.0160	0.0238
		(0.213)	(0.362)	(0.126)
Adj. R^2	1.179%	0.231%	1.216%	1.975%
Panel B: SII (1973–2014)				
Constant	0.0090	0.0053	0.0091	0.0090
	(0.000)	(0.013)	(0.000)	(0.000)
$r_{m,t}$	–	–	–	0.0762
				(0.095)
$Sk_{vw,\,t}$	−0.1257	–	−0.1290	−0.1391
	(0.004)		(0.005)	(0.003)
X_t	–	0.0052	0.0052	0.0048
		(0.011)	(0.012)	(0.011)
Adj. R^2	1.078%	1.058%	2.148%	2.522%
Panel C: VIX (1990–2016)				
Constant	0.0097	0.0035	0.0077	0.0027
	(0.002)	(0.714)	(0.372)	(0.744)
$r_{m,t}$	–	–	–	0.1090
				(0.067)
$Sk_{vw,\,t}$	−0.1168	–	−0.1120	−0.1212
	(0.029)		(0.040)	(0.027)
X_t	–	0.0005	0.0003	0.0011
		(0.814)	(0.876)	(0.506)
Adj. R^2	1.016%	−0.271%	0.555%	1.258%
Panel D: TR (1963–2016)				
Constant	0.0091	−0.0258	−0.0210	−0.0139
	(0.000)	(0.061)	(0.129)	(0.330)
$r_{m,t}$	–	–	–	0.0609
				(0.182)
$Sk_{vw,\,t}$	−0.1259	–	−0.1239	−0.1306
	(0.002)		(0.002)	(0.001)
X_t	–	0.0723	0.0704	0.0534
		(0.019)	(0.022)	(0.100)
Adj. R^2	1.179%	0.648%	1.788%	1.958%
Panel E: VRP (1996–2013)				
Constant	0.0080	0.0000	0.0025	0.0025
	(0.058)	(0.997)	(0.611)	(0.589)
$r_{m,t}$	–	–	–	0.1152
				(0.079)
$Sk_{vw,\,t}$	−0.1010	–	−0.0729	−0.0869
	(0.105)		(0.234)	(0.160)
X_t	–	0.0561	0.0516	0.0491
		(0.088)	(0.117)	(0.123)
Adj. R^2	0.471%	2.109%	2.118%	2.969%
Panel F: TRP (1996–2013)				
Constant	0.0080	0.0040	0.0067	0.0048
	(0.058)	(0.348)	(0.103)	(0.257)
$r_{m,t}$	–	–	–	0.1405
				(0.058)
$Sk_{vw,\,t}$	−0.1010	–	−0.1020	−0.1186
	(0.105)		(0.099)	(0.055)
X_t	–	0.0328	0.0371	0.0834
		(0.785)	(0.733)	(0.377)
Adj. R^2	0.471%	−0.414%	0.075%	1.439%

instead of 1.08%). When both *SII* and average skewness are introduced in the regression, no matter with or without controlling for market return, average skewness has a lower *p*-value than this competitor. Over the 1963–2016 period, the tail risk measure predicts subsequent market return with a *p*-value equal to 1.9% and an adjusted R^2 equal to 0.65%. When they are introduced together, the average skewness and *TR* are significant and the R^2 increases to 1.79%. The *p*-value of average skewness is again lower than the *p*-value of *TR*.

Regarding the variance and tail risk premia, the relations are estimated over a short sample period, 1996–2013, which makes these empirical results less relevant. Average skewness and *VRP* are found to be weakly significant when introduced alone, with a *p*-value close to 10%. In combination with average skewness, none of the predictors is significant. Also, *TRP* is not found to be a significant predictor of next-month market returns.[12]

5. Out-of-sample evaluation

In-sample analysis provides a clear indication that average skewness predicts subsequent market return. We now investigate its performance in terms of out-of-sample prediction and asset allocation.

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

$$r_{m,t+1} = \mu + \vartheta' \, X_t + \eta_{t+1}, \qquad t = 1, \dots, s, \tag{6}$$

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 excess return forecasts based on the information available up to time s:

$$\hat{\mu}^{\{X\}}_{m,s} = E[r_{m,s+1}|X_s] = \hat{\mu} + \hat{\vartheta}' \, X_s, \qquad s = s_0, \dots, T-1. \tag{7}$$

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. The out-of-sample R^2 compares the predictive power of the regression with the historical sample mean. It is defined as $R^{\{X\}2}_{OOS} = 1 - MSE^{\{X\}}_P / MSE_N$, where $MSE^{\{X\}}_P = (1/T_{OOS}) \sum_{t=s_0}^{T-1} (r_{m,t+1} - \hat{\mu}^{\{X\}}_{m,t})^2$ is the mean square error of the out-of-sample predictions based on the model and $MSE_N = (1/T_{OOS}) \sum_{t=s_0}^{T-1} (r_{m,t+1} - \bar{r}_{m,t})^2$ is the mean square error based on the sample mean (assuming no predictability). The adjusted R^2_{OOS} is defined as $\bar{R}^{\{X\}2}_{OOS} = R^{\{X\}2}_{OOS} - (k/(T_{OOS} - k - 1))(1 - R^{\{X\}2}_{OOS})$, where k is the number of

12 *VRP* and *TRP* improve as predictors of market returns when we consider longer forecast horizons, as noted by Bollerslev et al. (2015). *VRP* is significant for the three-month horizon and above and *TRP* is significant for the six-month horizon. In combination with average skewness, both variables are highly significant for these horizons.

regressors. The out-of-sample $\bar{R}^{\{X\}2}_{OOS}$ 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), defined as

$$ENC^{\{X\}} = \frac{T_{OOS} - k + 1}{T_{OOS}} \times \frac{\sum_{t=s_0}^{T-1} \left[(r_{m,t+1} - \bar{r}_{m,t})^2 - (r_{m,t+1} - \bar{r}_{m,t})(r_{m,t+1} - \hat{\mu}^{\{X\}}_{m,t}) \right]}{MSE_P^{\{X\}}}. \quad (8)$$

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 future market 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 stock market and the risk-free asset (one-month Treasury bill) (Ferreira and Santa-Clara, 2011). For each period, predictions of market excess returns are used to calculate the Markowitz optimal weight on the stock market:

$$w^{\{X\}}_{m,s} = \frac{\hat{\mu}^{\{X\}}_{m,s}}{\lambda\ \hat{V}^{\{X\}}_{m,s}}, \quad (9)$$

where λ is the risk aversion and $\hat{V}^{\{X\}}_{m,s}$ is the corresponding sample variance of market return.[13] Portfolio decisions can be made in real time with data available when decisions are made. The ex post portfolio excess return is then calculated at the end of month $s+1$ as

$$r^{\{X\}}_{p,s+1} = w^{\{X\}}_{m,s}\ r_{m,s+1}. \quad (10)$$

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 $\bar{r}^{\{X\}}_p$ the sample mean and by $\sigma^{\{X\}2}_p$ the sample variance of the portfolio return, we define two statistics to evaluate the performance of the trading strategies: the Sharpe ratio, $\mathrm{SR}^{\{X\}} = \bar{r}^{\{X\}}_p/\sigma^{\{X\}}_p$, which measures the risk-adjusted performance of the strategy, and the certainty equivalent return, $\mathrm{CE}^{\{X\}} = \bar{r}^{\{X\}}_p - (\lambda/2)\sigma^{\{X\}2}_p$, 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.[14] Finally, we compute the annual transaction fee generated by each strategy as $Fee^{\{X\}} = \frac{12f}{T_{OOS}} \sum_{t=s_0}^{T-1} |w^{\{X\}}_{m,t+1} - w^{\{X\}}_{m,t+}|$, where f is the fee per dollar and $w^{\{X\}}_{m,t+}$ denotes the market weight just before rebalancing at $t+1$.

Table 7 reports the results for the out-of-sample predictions based on the variance and skewness measures introduced in Section 2 and the financial predictors introduced in Section 4.2. We consider the August 1983–December 2016 sample to compute the performance of these alternative predictors.[15] Consistent with individual regressions reported in Table 2, the variance and skewness measures with the highest out-of-sample R^2 are the value-weighted and equal-weighted average skewness, with $\bar{R}^2_{OOS}$ equal to 0.93% and 0.75%, respectively.[16] The encompassing test *ENC* confirms that these variables are statistically significant as unique predictors of market returns at the 5% significance level. Among financial variables, the short interest index (*SII*), the tail risk (*TR*), and the variance risk premium (*VRP*) also generate a large out-of-sample R^2 and a significant *ENC* statistic. *AC* and *VIX* have no predictive power with a negative out-of-sample R^2 and an insignificant *ENC* statistic. The *TRP* produces a large out-of-sample R^2 but a negative *ENC* statistic.

When the market return is introduced as an additional predictor, we find that the out-of-sample R^2 slightly increases for the pairs $(r_{m,t}, Sk_{vw,\,t})$ and $(r_{m,t}, Sk_{ew,\,t})$, which also pass the encompassing test. *AC* and *SII* are the only additional variables that pass the encompassing test at the 5% significance level.

Figs. 3 and 4 allow us to visualize the evolution of the out-of-sample performance of some of the (combinations of) variables 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 $OOS^{\{X\}}_s = \sum_{t=1}^{s}(r_{m,t+1} - \bar{r}_{m,t})^2 - \sum_{t=1}^{s}(r_{m,t+1} - \hat{\mu}^{\{X\}}_{m,t})^2$, $s = s_0, \ldots, T-1$, where the mean $\bar{r}_{m,t}$ and the prediction $\hat{\mu}^{\{X\}}_{m,t}$ are calculated over the period from s_0 to t. An increase in the line indicates that the model provides a better prediction than

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

[14] 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). To test the null hypothesis that $\mathrm{CE}^{\{X\}} = \mathrm{CE}_0$, we use the statistic for the test of equal CE given in their footnote 18.

[15] Given data availability, we use information from August 1963 to July 1983 as a burning period ($s_0 = 20$ years) for variance and skewness measures, *AC*, and *TR* and from January 1973 to July 1983 ($s_0 = 10.5$ years) for *SII*. For *VIX*, we use information from January 1990 to December 1994 as the burning period ($s_0 = 5$ years). For *VRP* and *TRP*, we use information from January 1996 to December 1998 as the burning period ($s_0 = 3$ years). For *SII*, the out-of-sample period ends in December 2014. To save space, we do not report the results for the economic factors (ECON_{PC} and ECON_{Avg}) because their performances are very low compared with those obtained with financial predictors. For all predictors, the tests of equal SR and CE are based on consistent samples. We compute the mean and variance of the strategy based on the historical mean of market excess return over the same sample used for the strategy based on the predictor.

[16] The $\bar{R}^2_{OOS}$ can be higher than the in-sample adjusted R^2 reported in Tables 2–6 because the samples are different.

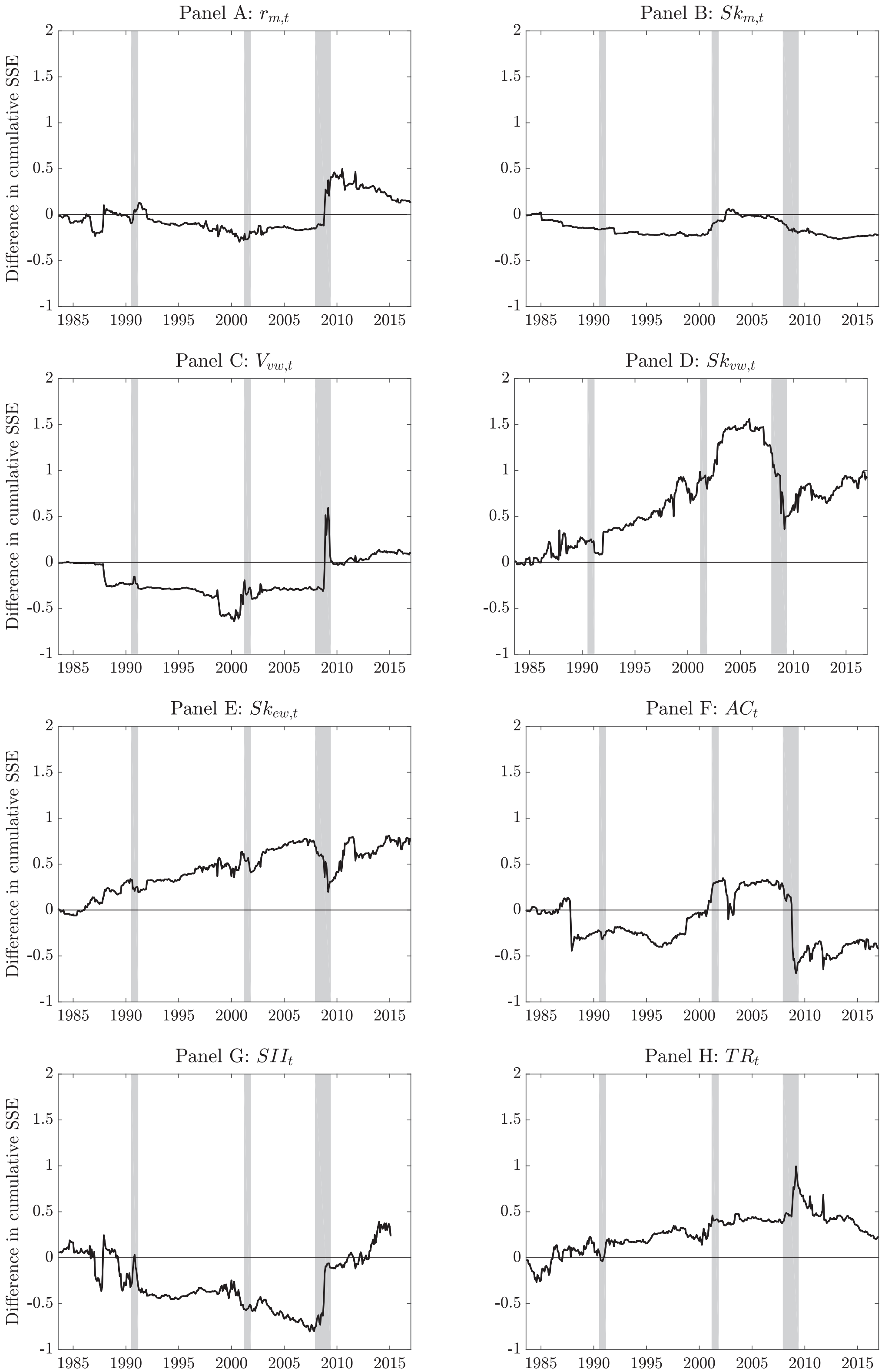

Fig. 3. Monthly out-of-sample performance of various predictors – one variable case. This figure presents the out-of-sample predictive performance of the alternative models. The performance is measured by the difference between the cumulative sum of squared errors (SSE) generated by the prevailing sample mean minus the cumulative SSE generated by a given variable. The out-of-sample evaluation period is August 1983 to December 2016. National Bureau of Economic Research recessions are represented by shaded bars.

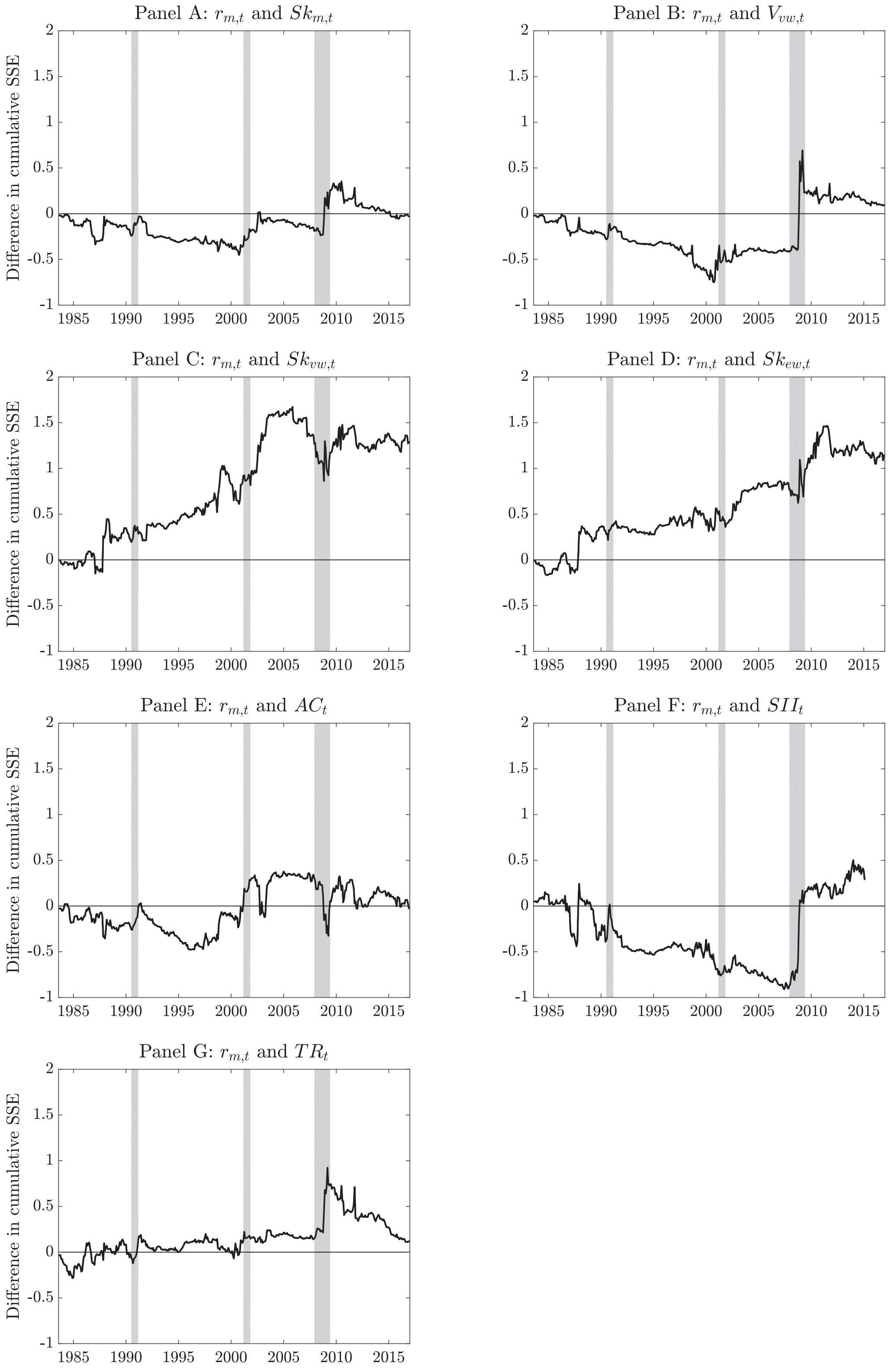

Fig. 4. Monthly out-of-sample performance of various predictors – multi-variable case. This figure presents the out-of-sample predictive performance of the alternative models. The performance is measured by the difference between the cumulative sum of squared errors (SSE) generated by the prevailing sample mean and the cumulative SSE generated by a given set of variables. The out-of-sample evaluation period is August 1983 to December 2016. National Bureau of Economic Research recessions are represented by shaded bars.

Table 7
Out-of-sample performances based on predictive regressions of market return.
This table reports the out-of-sample performance of the following variables: the value-weighted Center for Research in Security Prices market excess return ($r_{m,t}$), the market variance ($V_{m,t}$) and skewness ($Sk_{m,t}$), the value-weighted ($V_{vw,\,t}$) and equal-weighted ($V_{ew,\,t}$) average variance, the value-weighted ($Sk_{vw,\,t}$) and equal-weighted ($Sk_{ew,\,t}$) average skewness, the average correlation, *AC*, the short-sell interests, *SII*, the volatility index, *VIX*, the tail risk measure, *TR*, the variance risk premium, *VRP*, and the tail risk premium, *TRP*. Performance measures are the adjusted out-of-sample R^2, $\bar{R}^2_{OOS}$; the encompassing test statistics *ENC*; the average market weight, $\bar{w}_m$; the annualized average return, volatility, and skewness of the portfolio; the annualized Sharpe ratio (SR); the annualized certainty equivalent (CE); and the annual transaction fee, obtained by assuming an $f = 10$ basis point fee. The risk-aversion parameter λ is equal to 2. Critical values for the encompassing test statistics are from (Clark and McCracken, 2001, Table 1). The asymptotic distribution for the test of the null hypothesis that the SR (CE) of a given strategy is equal to the SR (CE) of the strategy based on the historical mean of the market return is given in DeMiguel et al. (2009). * denotes significance at the 5% significance level. The out-of-sample period is from August 1983 to December 2016 (from August 1983 to December 2014 for *SII*, from January 1995 to December 2015 for *VIX*, and from January 1999 to August 2013 for *VRP* and *TRP*).

Predictor	$\bar{R}^2_{OOS}$ (percent) (1)	*ENC* (2)	Market weight ($\bar{w}_m$) (3)	Annualized return (percent) (4)	Annualized volatility (percent) (5)	Skew-ness (6)	Annualized SR (7)	Annualized CE (percent) (8)	Annual fee (percent) (9)
Historical mean	–	–	1.19	9.60	19.83	−1.48	0.38	3.70	0.08
Buy-and-hold strategy	–	–	1.00	10.50	15.23	−0.82	0.50	5.22	0.00
$r_{m,t}$	−0.07	1.28	1.16	10.95	18.15	−0.72	0.47	5.15	0.66
$V_{m,t}$	−2.44	−0.31	1.10	9.21	17.37	−1.69	0.39	3.75	0.25
$Sk_{m,t}$	−0.54	−0.41	1.13	9.31	19.37	−1.58	0.37	3.50	0.27
$V_{vw,\,t}$	−0.12	1.85	1.13	11.25	16.96	−1.21	0.50	5.65	0.23
$V_{ew,\,t}$	−1.89	−1.95	1.19	9.54	19.57	−1.12	0.38	3.64	0.14
$Sk_{vw,\,t}$	0.93	6.16*	1.13	15.80	21.62	−0.82	0.62*	8.82*	0.91
$Sk_{ew,\,t}$	0.75	3.93*	1.27	14.55	21.88	−1.01	0.57*	7.69*	0.63
AC_t	−0.79	0.44	1.26	11.50	24.16	−1.38	0.43	4.57	0.50
SII_t	3.62	3.51*	0.92	12.84	18.06	−0.60	0.59	7.38	0.15
VIX_t	−0.58	−1.33	1.45	6.44	25.55	−1.05	0.29	0.94	0.15
TR_t	0.05	2.20	1.25	11.30	20.68	−1.18	0.45	5.07	0.46
VRP_t	8.37	1.59	1.13	3.52	22.38	−0.42	0.20	−0.44	0.46
TRP_t	4.42	−1.13	0.94	1.54	18.58	−0.78	0.08	−2.01	0.43
($r_{m,t}$; $V_{m,t}$)	−3.16	−0.88	1.13	9.54	17.41	−1.14	0.40	4.01	0.58
($r_{m,t}$; $Sk_{m,t}$)	−0.54	1.08	1.14	10.63	18.35	−0.88	0.45	4.83	0.69
($r_{m,\,t}$; $V_{vw,\,t}$)	−0.37	2.51	1.16	11.58	16.75	−0.71	0.52	5.94	0.57
($r_{m,\,t}$; $V_{ew,\,t}$)	−1.80	−0.42	1.20	10.16	18.77	−1.01	0.42	4.34	0.62
($r_{m,\,t}$; $Sk_{vw,\,t}$)	1.16	8.44*	1.19	14.80	20.97	−0.90	0.60*	8.08*	0.89
($r_{m,\,t}$; $Sk_{ew,\,t}$)	0.98	6.67*	1.30	13.69	20.68	−0.74	0.55	7.14	0.79
($r_{m,t}$; AC_t)	−0.53	3.04*	1.31	11.38	23.12	−1.50	0.43	4.70	0.69
($r_{m,t}$; SII_t)	3.43	4.05*	0.94	13.25	17.74	−0.53	0.62	7.82	0.30
($r_{m,t}$; VIX_t)	−0.89	−0.66	1.45	7.10	25.86	−1.01	0.32	1.50	0.42
($r_{m,t}$; TR_t)	−0.34	2.33	1.24	11.38	20.26	−1.15	0.46	5.20	0.63
($r_{m,t}$; VRP_t)	7.76	2.33	1.16	1.59	21.83	−0.61	0.10	−2.60	0.63
($r_{m,t}$; TRP_t)	4.74	−0.05	1.05	4.69	19.53	−0.21	0.27	1.50	0.76

the prevailing mean. We have selected the most relevant predictors in the figures. Two results are worth emphasizing. First, as Fig. 3 illustrates, the out-of-sample measures involving the market return, market variance, *SII*, and *TR* jump up during the subprime crisis, reflecting some instability in the relation between these predictors and the subsequent market return. The out-of-sample performance of market return, market skewness, average variance, *AC*, and *SII* are even negative for relatively long periods of time. For the (value-weighted and equal-weighted) average skewness, the out-of-sample measure increases in a smooth way (approximately, from 1983 to 2006), which reflects the stable relation between this variable and the subsequent market return. For both predictors, the subprime crisis results in a lower out-of-sample performance. Second, in the two-variable case (Fig. 4), adding the market return improves the out-of-sample performance of the two average skewness measures. Market return and value-weighted average skewness are clearly the best pair of predictors, with an almost continuously increasing out-of-sample performance. For the market variance and skewness, the *SII*, and *TR*, adding the market return does not improve the out-of-sample performance.

Table 7 also reports summary statistics on the performance of the trading strategies, including the annualized return, the annualized volatility, and the skewness (Columns 4–6). The average return is low and the volatility is high for the strategies based on the *VIX, VRP*, and *TRP* because they are implemented over the recent period in which the subprime crisis contributes the most. All strategies are associated with negative skewness, which reflects the fact that the average weight of the market portfolio is relatively close to one (between 0.92 and 1.45).

The table also reports performance measures of the trading strategies, i.e., the SR and CE (Columns 7 and 8). The annualized SR of the strategy based on the historical mean is equal to 0.38. The SR is increased to 0.47 and 0.62 for the strategies based on market return only and on value-weighted average skewness only. The SR also improves for strategies based on *SII* and *TR* (to 0.59 and 0.45, respectively). The increase in SR relative to the strategy based on the historical mean is statistically significant only

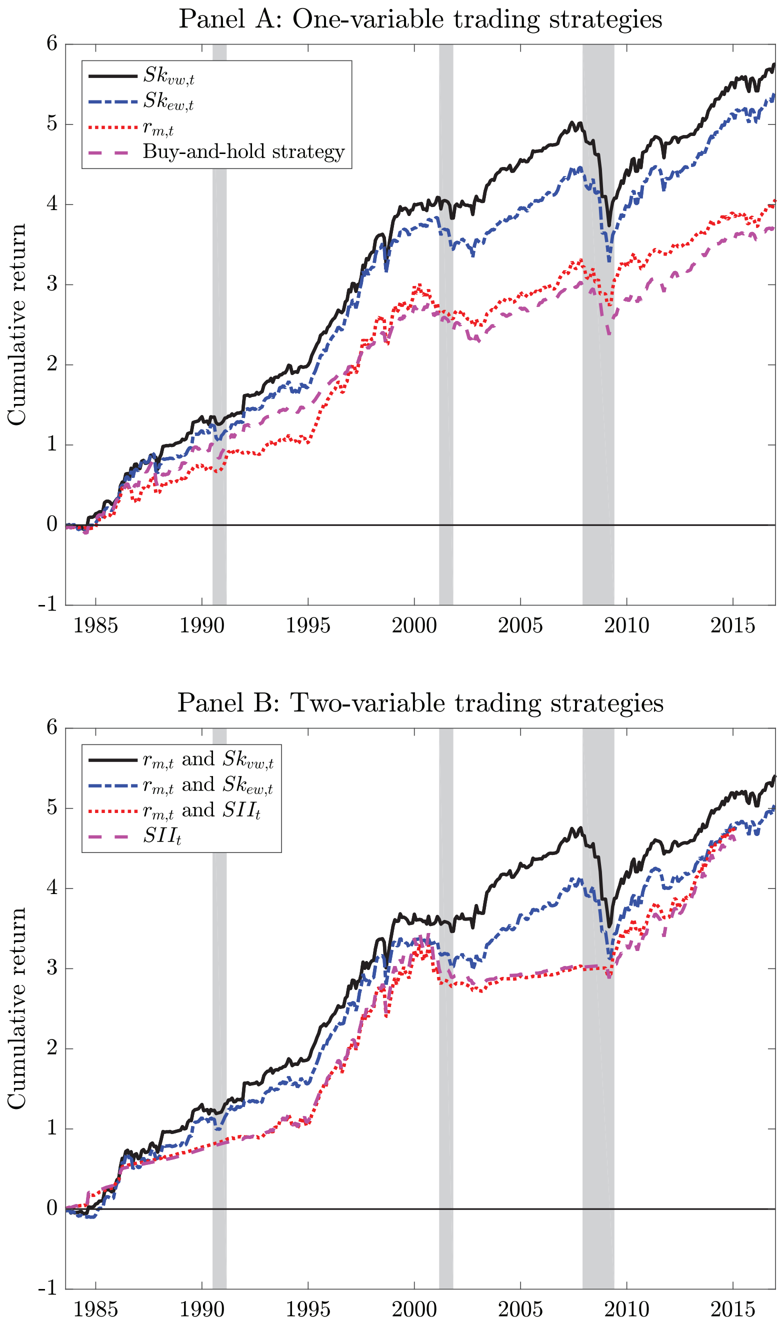

Fig. 5. Cumulative return of out-of-sample forecasting. This figure presents the cumulative return generated by implementing various trading strategies. Trading strategies are formed from predictive regressions using the value-weighted Center for Research in Security Prices market excess return ($r_{m,t}$), the value-weighted average skewness ($Sk_{vw,\,t}$), the equal-weighted average skewness ($Sk_{ew,\,t}$), and the short interest index (SII_t). Optimal weights are determined assuming a risk aversion of $\lambda = 2$. The out-of-sample evaluation period is August 1983 to December 2016. National Bureau of Economic Research recessions are represented by shaded bars.

for strategies based on average skewness (with or without market return).[17]

Most of the annualized CE values of the strategy based on one predictor are in the range [3%; 9%], and they are close to 7–9% for the strategies based on average skewness

[17] 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 value-weighted average skewness. The SR of this strategy is equal to 0.5, which represents an insignificant increase relative to the strategy based on the historical mean. The difference between the SR of the strategy based on value-weighted skewness and the SR of the buy-and-hold strategy is sizable (0.62 versus 0.5), although not statistically different from zero. The difference in CE (8.8% versus 5.2%) is statistically positive at the usual 5% significance level.

and *SII*. The gain relative to the strategy based on the historical mean is statistically significant only for the strategies based on the average skewness. Strategies with two predictors generate CE values that are in the similar range as the strategies with single predictor.

Finally, the annual fee that an investor would have to pay for the various strategies is moderate, between 0.14% and 0.91% of the value of the portfolio per year (Column 9). Strategies based on average skewness generate relatively large annual fees because they imply more rebalancing every month. 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 and CE values relative to other competing predictors.

Fig. 5 displays the cumulative return of some of the representative models. In Panel A, we compare strategies based on average skewness with the strategy based on market return only and the buy-and-hold strategy. The strategy with value-weighted average skewness clearly dominates the other strategies in terms of cumulative performance. The strategy based on lagged market return slightly outperforms the buy-and-hold strategy although its SR is lower. Panel B displays the cumulative return of the strategies involving average skewness or *SII*. Between 2001 and 2009, *SII* predicts a negative market return. As short sales are excluded, strategies based on *SII* are invested in the risk-free asset during most of this period. As the market trend was positive during the period, this result explains the poor out-of-sample performance of *SII* as a predictor of market return (Fig. 3) and the poor performance of the strategies based on *SII*. These strategies perform well in the recent period (since 2009), although not sufficiently to catch up strategies based on average skewness.

6. Conclusion

In this paper, we investigate the ability of the average skewness of a firm's returns to predict future market return. We find that the value-weighted average of (standardized) stock skewness is the best predictor of next-month market returns. The impact of the monthly average skewness on the subsequent market excess return is substantial. A one standard deviation increase in the average skewness results, on average, in a 0.52% decrease in the market excess return the next month. Moreover, in the case of a market excess return above its mean and an average skewness below its mean, the subsequent market excess return is equal to 1.14% on average. In the case of a market excess return below its mean and an average skewness above its mean, the subsequent market excess return is equal to −0.19% on average. These results are robust to the alternative specifications, controls, and definitions that we consider.

The predictability of average skewness is also statistically and economically significant out of sample. When the next-month market return is predicted out of sample using a recursive window, we find that value-weighted average skewness (in combination with market excess return or not) has the highest predictive power among the macroeconomic and financial variables that we consider. Implementing a strategy based on the predictive regression including the value-weighted average skewness allows the investor to generate better performance compared with a strategy that is based on other predictors. The annualized returns are equal to 15.8% and 14.6% for the strategies based on the value-weighted and equal-weighted average skewness, respectively, and the buy-and-hold strategy and the strategy based on the historical mean produce annualized returns equal to 10.5% and 9.6%, respectively. Annualized Sharpe ratios are equal to 0.62, 0.57, 0.50, and 0.38, respectively.

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