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Federico Nardari, Bochen Wu, Qi Zeng

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Idiosyncratic Skewness Co-movement and Aggregate Stock Returns*

Federico Nardari[a], Bochen Wu[a], and Qi Zeng[†a]

[a]Department of Finance, University of Melbourne

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Abstract

We find a strong co-movement pattern in firm idiosyncratic skewness. We, then, show that the common component in idiosyncratic skewness (CIS) is a powerful predictor of future market excess returns and it outperforms a battery of popular equity premium predictors, both in and out of sample. Further, CIS predictive power adds economic value out-of-sample to mean-variance investors for a wide range of relative risk aversion. Our results are robust across observation frequencies and out-of-sample evaluation periods. From a rational pricing perspective, we show that CIS predictive power stems from a discount rate channel.

Keywords: Asset Pricing, Equity Premium Predictability, Idiosyncratic Skewness.

JEL Classification: G11, G12, G41.

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†Email Addresses: federico.nardari@unimelb.edu.au (F.Nardari), bochenw@student.unimelb.edu.au (B.Wu), and qzeng@unimelb.edu.au (Q.Zeng).

1 Introduction

The predictability (or, lack thereof) of the equity risk premium has far-reaching implications for several fundamental areas of finance, ranging from capital budgeting to asset allocation. Despite a voluminous literature, researchers are still actively searching for statistically reliable and economically interpretable predictors. [1]

In this paper, we show that there is a strong non-linear relation between the common component of firms' idiosyncratic skewness (CIS, short for common idiosyncratic skewness) and future equity market excess returns. Similarly to Adrian et al. (2019), this predictive relation is not detected within a linear regression framework while it is well-captured by a quadratic specification. [2]

We, first, provide in-sample evidence that CIS positively (negatively) predicts the equity premium in the next month or quarter when it is low (high). The results are highly statistically significant, and do not appear to be driven by forward-looking biases. When CIS is low, a one-standard deviation increase in CIS translates into a 0.72% (1.89%) *increase* in market excess return in the next month (quarter). When CIS is high, a one-standard deviation increase in CIS leads to the market excess return to *decrease* by 0.35% (0.96%) in the next month (quarter). The in-sample adjusted R^2 is around 1.80% (3.10%) at the monthly (quarterly) frequency, which is much higher than for the majority of popular predictors in the literature. The predictive power of CIS remains after controlling for all those predictors.

Second, to guard against over-fitting, possibly exacerbated by the non-linear specification, we follow the large literature (e.g. Welch and Goyal (2008)) and examine the out-of-sample (OOS) performance of the CIS-based predictive model. The OOS results corroborate our in-sample evidence. At both monthly and quarterly horizons, the CIS

[1] Recent works include Pyun (2019), Atanasov et al. (2020), Huang et al. (2021) among many others.

[2] While the vast majority of the existing evidence relies on linear predictive relations, recent work emphasizes the presence of non-linear relations.For instance, Rossi and Timmermann (2010) and Adrian et al. (2019) document the non-linearity is driven by non-linear risk-return trade-off.

model generates positive and significant OOS R^2s which compare rather favorably with the OOS forecasting performance of the popular equity premium predictors proposed in the literature. The positive and significant OOS performance of CIS holds across several sample periods and it appears to get stronger in more recent times.

Next, we evaluate the economic significance of our predictability results by conducting a portfolio exercise for a mean-variance investor allocating between a market index and a riskless asset. We show that, across a wide rage of risk aversion levels, a strategy based on CIS as equity premium predictor generates substantive utility gains compared to strategies based on commonly used predictors as well as compared to a strategy based on a prevailing mean forecast. For instance, for the period between 1966 and 2019 an investor with a risk aversion coefficient of 3 (5) would have paid up to 232 (206) basis points per year in certainty equivalent terms to switch from a strategy based on the prevailing equity premium average to the CIS-based strategy: these utility gains are substantially larger than those generated by any of the commonly used predictors.

In the last part of the paper we investigate the sources of CIS predictive ability. We explore two possible channels. First, we show that, within a standard rational asset pricing framework (see, e.g., Cochrane (2011)), CIS anticipates future movements in discount rates, while it does not predict aggregate dividend growth. This evidence links the uncovered predictability by CIS to time-variation in expected returns. Second, motivated by recent literature pointing to biased growth expectations as likely sources of equity premium predictability [3], we explore the relation between CIS and two proxies for biased beliefs: earnings forecast error by analysts and GDP forecast error by professional forecasters. We find that CIS is not related to either, hence suggesting that mispricing induced by biased growth expectations is not a likely source of the predictability we uncover.

[3]Recent examples include Arif and Lee (2014), Huang et al. (2015) and Huang et al. (2021).

This study provides two main contributions. First, it adds to the literature on return predictability (equity premium predictability in particular). Following the challenges raised by Welch and Goyal (2008), who find that most predictors fail to pass out-of-sample tests, the literature is still debating whether return predictability even exists and whether further insights can be gained by exploring non-linear relations [4]. To the best of our knowledge, this is the first paper that document a strong non-linear relation between idiosyncratic skewness and market returns. More importantly, we provide out-of-sample verification that confirms that our non-linear relation is not due to overfitting. From an asset-allocation point of view, the trading strategy based on our return predictability results generates significant utility gain for a wide range of relative risk aversion parameters.

Second, we extend the literature that establishes a relationship between co-movements in firm characteristics and future returns on the stock market. For instance, while Lynch et al. (2014) find strong evidence of co-movement in daily shorting flows of individual stocks, Rapach et al. (2016) further show that average short interest is a powerful predictor of future market excess returns. Kelly and Jiang (2014) exploit common fluctuations in firm-level crash risk to measure aggregate tail risk, and find that their aggregate tail risk measure also has strong predictive power for subsequent market returns. Herskovic et al. (2016) show that there is a strong commonality in firm-level idiosyncratic volatility. Goyal and Santa-Clara (2003) find that average stock volatility, which is largely idiosyncratic, is able to predict future return on the market. Guo and Savickas (2008) and Guo and Savickas (2010) confirm and extend the evidence on the predictive power of idiosyncratic volatility, in conjunction with aggregate market

[4] Among papers that investigate non-linear equity premium predictability, our paper is closely related to Rossi and Timmermann (2010) and Adrian et al. (2019). Using boosted regression trees, Rossi and Timmermann (2010) document a strong non-linear relation between conditional market volatility and expected stock market return. Similarly, Adrian et al. (2019) document a statistically significant relation between VIX and future equity premium. However, the significant relation between VIX and market excess returns disappears when linear specification is used. Gu et al. (2020) find that, after allowing nonlinearity (as captured by neural networks), traditional equity premium predictors are able to beat the prevailing mean forecast benchmark in out-of-sample tests.

volatility. We contribute to this strand of literature by: a) demonstrating that there is also a strong co-movement pattern in firm idiosyncratic skewness, which motivates us to measure the common component of firms idiosyncratic skewness. We show that, on average, CIS explains about 40%(20%) variation of portfolio-level (firm-level) idiosyncratic skewness. Furthermore, at the firm level, more than 75% of all firms have significant loadings on CIS at the 5% level. b) providing empirical evidence that the skewness dimension of idiosyncratic risk is also related to the time-series of aggregate market returns.

The rest of this paper is structured as follows. Section 2 presents the strong co-movement pattern in firm idiosyncratic skewness. Section 3 reports return predictability results, both in-sample and out-of-sample. Section 4 examines the economic significance of our predictability result using an asset-allocation analysis. Section 5 investigates the origins of CIS predictive ability for future equity premium realizations. Section 6 concludes.

2 Commonality in Skewness

In this section, we show that there is a strong commonality in firm idiosyncratic skewness. We define idiosyncratic skewness as the standardized third moment of residual returns that are orthogonal to common risk factors. Namely, for each firm i, at the end of each month t, we regress the previous five-year firm excess returns (including month t) onto the corresponding Fama and French (1993) three factors [5] [6]

[5]For robustness, we also use other factor models, in addition to Fama and French (1993) three factor model, to estimate idiosyncratic skewness, and find that all our main results are confirmed. The Appendix contains these robustness checks.

[6]Following Boyer et al. (2010) and Bali et al. (2016), we use five-year monthly returns to estimate firm skewness because skewness is difficult to be measured empirically and a long time-series of returns is needed.

:

$$r_{i,t-59:t} - rf_{t-59:5} = \alpha_{i,t} + \beta_{1,i,t} MKT_{t-59:t} + \beta_{2,i,t} SMB_{t-59:t} + \beta_{3,i,t} HML_{t-59:t} + \epsilon_{i,t-59:t}.$$

We, then, compute firm i's idiosyncratic skewness in month t as the standardized third moment of residuals from the regression model above:

$$iskew_{i,t} = \frac{\frac{1}{60}\sum_{\tau=t-59}^{t} \epsilon_{i,\tau}^3}{\left(\frac{1}{60}\sum_{\tau=t-59}^{t} \epsilon_{i,\tau}^2\right)^{3/2}}.$$

[Insert Figure 1]

Following the idiosyncratic volatility co-movement literature (see, e.g., Herskovic et al. (2016) and van der Heijden et al. (2018)), we first use portfolios to show co-movement in idiosyncratic skewness. We assign firms into five size-sorted and five leverage-sorted portfolios. We follow, among many others, van der Heijden et al. (2018) to construct these 25 portfolios. Specifically, at the end of June of each year t, we form leverage quintile portfolios across all firms based on the leverage at last fiscal year end. The five size-sorted portfolios are formed based on the NYSE breakpoints. For each of these 25 portfolios, we define portfolio idiosyncratic skewness as the equally-weighted average idiosyncratic skewness across all firms in that portfolio. We then plot the time series of average idiosyncratic skewness for each portfolio. Panel A of figure 1 plots average idiosyncratic skewness for each of the five size portfolios where size 1 (5) represents the portfolio of the smallest (largest) firms. It is clear that idiosyncratic skewness of all size portfolios displays similar dynamics. The average pairwise correlation of idiosyncratic skewness across these five size-sorted portfolios is 0.71 whereas the maximum (minimum) correlation is 0.93 (0.29). The smallest and second small-

est firm portfolios display the highest correlation in idiosyncratic skewness whereas the smallest and largest firm portfolios show the lowest correlation. In addition, the largest firm portfolio exhibit the lowest idiosyncratic skewness and the lowest variation in idiosyncratic skewness. On the contrary, both idiosyncratic skewness and the volatility of idiosyncratic skewness for smallest firms are the largest. Both theoretical and empirical work shows that firms' idiosyncratic skewness is positively related to their growth opportunities (Barberis and Huang, 2008; Zhang, 2013; Trigeorgis and Lambertides, 2014; Del Viva et al., 2017). Therefore, the empirical observation that smaller firms have higher idiosyncratic skewness and larger variation in idiosyncratic skewness should be expected because growth opportunities represent a larger proportion of firm value for smaller firms than for larger firms. The results are similar in Panel B of figure 1, which plots average idiosyncratic skewness for the five leverage-sorted portfolios where leverage 1 (5) represents the portfolio consist of firms with lowest (highest) leverage. The average correlation across leverage quintile portfolios is 0.77 whereas the maximum (minimum) correlation is 0.89 (0.57). Furthermore, firms with higher leverage tend to have higher idiosyncratic skewness, especially after 1990. This is consistent with the theoretical developments in van der Heijden et al. (2018). Although the model proposed in van der Heijden et al. (2018) is aimed at explaining the commonality in firm's idiosyncratic volatility described in Herskovic et al. (2016), the economic intuition can also apply in our setting. Specifically, van der Heijden et al. (2018) model firms' capital structure within the framework of Goldstein et al. (2001): firms only update their capital structure once the leverage ratio hits a predetermined upper or lower threshold. In between these thresholds, the leverage ratio varies directly with changes in the asset values. Further, returns on unlevered firms' assets obey a standard CAPM. It follows that both the systematic and the idiosyncratic component of firms' equity returns vary directly with leverage. The results above confirm that firm's idiosyncratic skewness is an increasing function of firm leverage although this pattern is weaker in the first half of our sample.

As Herskovic et al. (2016) do for idiosyncratic volatility,, we use the equal-weighted average idiosyncratic skewness across all firms to summarize the commonality in idiosyncratic skewness:

$$CIS_t = \frac{\sum_{i=1}^{n} iskew_{i,t}}{n} \tag{1}$$

where n denotes the number of firms in month t. We, then, use CIS to explain portfolio- and firm-level idiosyncratic skewness. If co-movement in idiosyncratic skewness exists, we should observe that both portfolio and firm skewness significantly load on CIS, and that CIS explains a large proportion of variation in idiosyncratic skewness at both firm and portfolio level.

[Insert Table 1]

We, thus, regress portfolio idiosyncratic skewness on CIS for each of the 25 portfolios. Estimated coefficients, t-statistics, and adjusted R^2s are reported in Table 1. All the CIS loadings are highly statistically significant. In addition, the CIS factor explains a significant portion of idiosyncratic skewness variation at the portfolio level. On average, the CIS explains approximately 40% of variation in portfolio skewness. In an unreported test, we regress firm-level idiosyncratic skewness on CIS separately for each firm. The average adjusted r-squared is 22%. In firm-level time-series regressions, around 75% of firms have significant CIS loadings at 5% level. We thus confirm the co-movement in idiosyncratic skewness at both firm and portfolio level.

To sum up this section, we find a strong co-movement pattern in firm idiosyncratic skewness. In the next section, we will show that the common component of firm idiosyncratic skewness, CIS, is a powerful predictor of aggregate equity market excess returns.

3 Return Predictability

In this section, we investigate whether the common component of firm idiosyncratic skewness (CIS) can predict the equity premium. We first describe our sample and variable construction in 3.1. We then conduct in-sample examination of return predictability in Section 3.2. We report the out-sample performance of CIS in section 3.3.

3.1 Data

We use standard stock price data from CRSP. Our sample includes all common stocks (those with share codes 10, or 11) listed on NYSE, AMEX, and Nasdaq (those with exchange code 1, 2, or 3). We exclude firms with stock prices less than one dollar. Our sample starts from January 1926. As described in section 2, we use the first five years to estimate idiosyncratic skewness. As a result, for our equity premium predictability tests the sample starts from January 1931. We compare the predictive power of CIS with a battery of popular equity premium predictors in the literature. In particular, we rely on the 14 predictors from Goyal and Welch (2008), which we download from Amit Goyal's website [7] and that are defined as follows:

1. **Log dividend-price ratio (DP)**: the difference between the log of dividends and the log of prices where dividends are the 12-month moving sums of dividends paid on the S&P 500 index and prices refer to the S&P 500 index level.

2. **Log dividend yield (DY)**: the difference between the log of dividends and the log of *lagged* prices.

3. **Log earnings-price ratio (EP)**: the difference between the log of earnings and the log of prices where earnings are defined as the 12-month moving sums of earnings on the S&P 500 index.

[7] Please see: https://sites.google.com/view/agoyal145/?redirpath=

4. **Log dividend-payout ratio (DE)**: the difference between the log of dividends and the log of earnings.

5. **Stock variance (SVAR)**: computed as sum of squared daily returns on the S&P 500.

6. **Book-to-market ratio (BM)**: book-to-market value ratio for the Dow Jones Industrial Average. For the months from March to December, this is computed by dividing book value at the end of the previous year by the price at the end of the current month. For the months of January and February, this is computed by dividing book value at the end of two years ago by the price at the end of the current month.

7. **Net equity expansion (NTIS)**: the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks.

8. **Treasury bill rate (TBL)**: interest rate on a three-month Treasury bill.

9. **Long-term yield (LTY)**: long-term government bond yield.

10. **Long-term return (LTR)**: return on long-term government bonds.

11. **Term Spread (TMS)**: long-term yield minus the Treasury bill rate.

12. **Default yield spread (DFY)**: difference between Moody's BAA- and AAA-rated corporate bond yields.

13. **Default return Spread (DFR)**: long-term corporate bond return minus the long-term government bond return.

14. **Inflation (INFL)**: calculated from the Consumer Price Index (CPI) for all urban consumers.

In addition, we also control for average total skewness (**SKEW**), which is estimated using daily returns within a month (Jondeau et al., 2019). Summary statistics are

reported in Table 2.

[Insert Table 2]

[Insert Table 3]

Table 3 reports the Pearson correlation matrix, in which we observe that the correlations between CIS and other predictors are at most moderate. The highest correlation is between CIS and Long-term yield (LTY), which is 0.32. CIS is also moderately correlated with the Treasury bond rate (TBL) and net equity expansion (NTIS), with a correlation of 0.25. Note that the correlation between CIS and the market variance (SVAR) is only 0.02.

3.2 In-Sample Analysis

This subsection examines the in-sample predictive power of CIS for future market excess returns. We start with a simple linear predictive regression:

$$r_{m,t+1} = \alpha + \beta X_t + \epsilon_{t+1} \tag{2}$$

where $r_{m,t+1}$ is the market excess return in period $t+1$, which is proxied by the CRSP value-weighted index return (including dividends) in excess of the 30-day T-bill rate, and X_t is either set equal to CIS_t or to one of the 15 commonly used predictors listed above. Again, CIS_t is defined as the equally-weighted average idiosyncratic skewness across all firms in period t. We focus one-month and one-quarter ahead short-term predictability for the following two reasons. First, substantial empirical evidence has shown that return predictability is a short-horizon phenomenon that is magnified at longer horizons (e.g., Ang and Bekaert (2007) and Boudoukh et al.

(2008) among many others). Second, using monthly and quarterly non-overlapping returns circumvent the econometric issues associated with long-horizon regressions and overlapping observations (Hodrick, 1992).

Using regression (2), we do not find any statistically significant in-sample predictive power of CIS. However, the failure of a linear specification does not imply that there is no relation between CIS and market returns. Motivated by Adrian et al. (2019), we investigate whether a non-linear relation exists. [8] We use the following dummy variable specification to mimic a quadratic relationship [9] :

$$r_{m,t+1} = \alpha + \beta_1 CIS_t + \beta_2 CIS_{high,t} + \beta_3 CIS_t * CIS_{high,t} + \epsilon_{t+1} \tag{3}$$

where CIS_t is defined in equation (1), $CIS_{high,t}$ is a dummy variable equal to one if CIS_t is greater than or equal to its median and zero otherwise; and $CIS_t * CIS_{high,t}$ is the interaction between CIS_t and $CIS_{high,t}$. To eliminate forward-looking biases, for each period t we estimate the CIS median using the data from the beginning of our sample up to month t (inclusive).[10] We use the first 30-year data to estimate the first CIS median.[11] If there is a quadratic relationship between CIS and future market excess return, the estimated coefficient of CIS and the interaction term, $\hat{\beta}_1$ and $\hat{\beta}_3$, should both be statistically significant.

[Insert Table 4]

[8] Adrian et al. (2019) do not find any significant relation between VIX and future market returns. However, when a VIX polynomial (including a quadratic and a cubic term) is used to fit the data, they document a strong non-linear relation between VIX and future market returns.

[9] We intended to add a quadratic term into equation (2) to capture the non-linearity. However, CIS and CIS^2 are almost perfectly correlated, with Pearson correlation close to 1. This would cause severe multi-collinearity issues.

[10] As we will show below, using the CIS mean rather than the median generates very similar results.

[11] In unreported tests, we ran our tests using either 20 year sort 40 years of data to estimate the first CIS median and mean: the baseline results are very similar to the 30-year case.

Table 4 reports the results of predictive regression (3) estimated on monthly data. Newey and West (1987) adjusted t-statistics are reported in parentheses. The results show that there is a strong hump-shaped relationship between CIS and future market excess returns. When CIS is low, a one-standard-deviation increase in CIS translates into an 0.72% increase in next-month market excess return. On the contrary, when CIS is high, a one-standard-deviation increase in CIS leads to excess return on the market in the following month to decrease by 0.35%.[12] The monthly in-sample adjusted R^2 is 1.8%.

Table 4 also reports the in-sample performance of the popular equity premium predictors listed above: their performance is assessed using the linear specification in equation (2). The results indicate that some of these predictors have in-sample predictive power. For instance, a one-standard-deviation increase in stock market variance (SVAR) predicts a 0.42% decrease in the equity premium in the next month. A one-standard-deviation increase in the return on long-term government bond (LTR) leads to 0.48% increase in the next-months market excess return. In addition, the three-month Treasury bill rate (TBL), long-term government bond yield (LTY), and term spread (TMS) have statistically significant in-sample predictive power. Among all these predictive models, though,, our CIS measure generates the highest in-sample adjusted R^2.

In appendix A5, we report the results when using quarterly data. The results show that the predictive power of CIS also holds at the quarterly horizon. When CIS is low, a one-standard-deviation increase in CIS predicts a 1.89% increase in buy-and-hold market excess return in the next quarter. On the other hand, when CIS is high, a one-standard-deviation increase in CIS predicts a 0.96% decrease in the market excess return in the next quarter. Among the other predictors, TBL, LTR and TMS retain their

[12] When CIS is low (high), its standard deviation is 0.0725 (0.0519). Therefore, when CIS is low, a one-standard deviation increase in CIS predicts the next-month market excess return to increase 0.0725× 9.915 ≈ 0.72%. Similarly, when CIS is high, an one-standard deviation increase causes next-month market excess return to decrease 0.0519× (16.710-9.915) ≈ 0.35%.

significance, while SVAR and LTY, that were significant at the monthly frequency, are no longer so.

In the above comparisons CIS is given more flexibility, through the non-linear specification, than the other predictors, which are constrained to the linear relation. We, thus, rerun the in-sample regressions but with each of the other predictors having the same non-linear relation as CIS with subsequent market returns. The results are reported in table A4 and indicate that giving these predictors more flexibility does not increase their in-sample significance or predictive power. The only noticeable exception is inflation (INFL: its in-sample adjusted R_2 increases from 0.4% to 1.5%, which is comparable with our CIS model. For other predictors, the change is either trivial or even negative.

We next examine whether the in-sample predictive power of CIS can be absorbed by the other predictors. To do so, we first add each of the predictors into regression (3). We also use a "kitchen-sink" specification, with all the predictors added to regression (3) at once. Results are shown in Table 5.

[Insert Table 5]

Across all these specifications, the three CIS-related variables remain statistically significant. In addition, the estimated coefficients are largely on par with the results in Table 4, where there is no additional predictor. Even when the estimated spread between coefficients on CIS and CIS*CIS_{high} gets smaller than in other specifications, the magnitude of the relation is still economically significant. For instance, in model 8, after controlling for the short-term Treasury bill rate (TBL), a one-standard-deviation increase in CIS is associated with a 26-basis point decrease in equity premium in the following month when CIS is high.

As a final in-sample assessment, We fit a non-parametric model to explore and, hopefully, confirm the hump-shaped relationship between CIS and future returns. [13] Following, e.g., Tetlock (2007) we use LOWESS (Locally Weighted Scatterplot Smoothing) method to describe the relation non-parametrically. Essentially, LOWESS creates a smooth line through a scatter plot that depicts the relationship between CIS and future market excess returns. The LOWESS smoothing is plotted in Figure 2.

[Insert Figure 2]

The horizontal axis in Figure 2 represents CIS levels whereas the vertical axis represents future market excess returns. For each CIS value, the corresponding y-axis value is the local mean of next-month equity premium (fitted values). We show the results using different bandwidths. A smaller bandwidth indicates that the local mean is estimated using a relatively higher number of local neighbours. The opposite is true for larger bandwidths. Hence, the larger the bandwidth the smoother the fitted line will be. Regardless of the selected bandwidth, we observe a strong hump-shaped relation between CIS and next-month market excess return. We conclude that the non-parametric estimation confirms our OLS results in Table 4.

To sum up this subsection, we conclude that, CIS is a powerful in-sample predictor for equity premium at short-term horizons. Furthermore, the predictive power of CIS is not absorbed by other commonly used equity premium predictors.

3.3 Out-of-Sample Analysis

Results in the previous subsection show that CIS positively predicts future market returns when its level is low, but negatively predicts future market returns when its

[13] Notice that our purpose in fitting a non-parametric specification is not producing and assessing forecasts, as non-parametric approaches may suffer from over-fitting. Our purpose is to give an additional characterization of the relation between CIS and equity premium.

level is high. To guard against the possibility that we over-fit the data by introducing a non-linear relation between CIS and future market returns, and to further check the robustness of our empirical findings, we examine the out-of-sample performance of CIS and compare it with other popular equity premium predictors.

3.3.1 Out-of-Sample Performance

For each period t we estimate equation (2) for each of the 15 popular predictors and equation (3) for CIS. In each case, we use only predictors information available up to time t to estimate the regression coefficients and, hence, to generate an out-of-sample forecast for $r_{m,t+1}$. We run the out-of-sample analysis on both monthly and quarterly data and match the length of the forecast with the data frequency, thus generating one-month ahead and one-quarter ahead forecasts. Following Campbell and Thompson (2008) and Welch and Goyal (2008) among many others, the forecasting performance is evaluated through the out-of-sample R^2, calculated as follows:

$$R^2_{oos} = 1 - \frac{\sum_{\tau=1}^{T}(r_{m,\tau} - \hat{r}_{m,\tau})^2}{\sum_{\tau=1}^{T}(r_{m,\tau} - \bar{r}_{m,\tau})^2} \tag{4}$$

where $r_{m,\tau}$ is the realised market excess return, $\hat{r}_{m,\tau}$ is the predicted market excess return by a candidate model, and $\bar{r}_{m,\tau}$ is the historical average market excess return up to month τ. R^2_{oos} compares forecast errors of a candidate model with those of prevailing (or, historical) mean forecasts, which assumes no return predictability, i.e., a constant equity risk premium. If the model performs better than the historical mean forecast in predicting future market returns, R^2_{oos} is positive, otherwise it is negative. We follow Clark and West (2007) to examine the statistical significance of our R^2_{oos}s: formally, we test $H_0 : R^2_{oos} \leq 0$ against $H_A : R^2_{oos} > 0$. To mediate between the need for having enough observations for reliable parameter estimates in our initial estimation period and the goal of a sufficiently long series for out-of-sample evaluation, our first

estimation runs from January 1931 to December 1955 [14]. For robustness, we also analyze out-of-sample periods starting in 1966, 1976, 1986, and 1996.[15] In addition to considering unrestricted forecasts of $r_{m,t+1}$ based on the estimated coefficients, we follow Campbell and Thompson (2008) and restrict the predicted equity premium to be non-negative.

[Insert Table 6]

The out-of-sample results based on monthly forecasts are reported in Table 6. Panel A of Table 6 reports the results based on the unrestricted forecast. For the out-of-sample starting from 1956, the CIS model generates an R^2_{oos} of 0.40% which is statistically significant at conventional levels. Consistent with Welch and Goyal (2008), we find that most of the popular predictors do not generate statistically positive R^2_{oos}s. On the other hand, a few of those predictors do beat the prevailing mean forecast benchmark. Namely, short-term Treasury bill rate (TBL), the return on long-term government bond (LTR), term spread (TMS), default yield spread (DFY), and inflation (INFL) generate significant and positive R^2_{oos} that are comparable with CIS. However, for subsequent out-of-sample periods the predictive power of CIS appears to be substantially superior. For the period beginning in 1966, our CIS model generates a statistically significant R^2_{oos} of 1.06% . This R^2_{oos} increases to 1.49%, 1.94% and 2.56% (all statistically significant) when the out-of-sample starts from 1976,1986 and 1996, respectively. On the other hand, the R^2_{oos} of the other predictors is never significantly positive for any of the sub-periods starting in either 1976 or 1986 or 1996, with the only exception of LTR

[14]Starting the OOS analysis from January 1956 amounts to using the first 30% observations for our initial estimation. As pointed out by Hansen and Timmermann (2012), having a forecast evaluation period relatively large compared to the entire sample improves the size properties of the tests for predictive ability

[15]Welch and Goyal (2008) find that, the performance of popular predictors is heavily affected by the first Oil Shock recession of 1973-1975. No predictor seems to have performed consistently well since the Oil Shock recession. Accordingly, it is particularly relevant to examine more recent sub-samples that those starting in the 1950s and in the 1960s.

for the period starting in 1976, although LTR's R^2_{oos} (0.27%) is well below that of CIS (1.49%).

In panel B of Table 6, we report results for the cases where the predicted equity premium is restricted to be non-negative. With this economically motivated restriction, the out-of-sample results are slightly enhanced in terms of both significance and magnitudes which is consistent with Campbell and Thompson (2008). But the broad messages from the unrestricted case still obtain: CIS is the only predictor with a significantly positive R^2_{oos} in all sub-periods and the magnitude of its predictive power is reliably above that of the predictors that happen to have a significant R^2_{oos} in a given sample. The results in Panel B also imply that superior out-of-sample performance of CIS is not driven by negative equity premium forecasts.

In appendix Table A6, we report out-of-sample performances for the quarterly forecasting horizon and find results broadly consistent with those at the monthly frequency. For instance, with the non-negativity restriction on equity premium forecasts (Panel B), the R^2_{oos}s for CIS are -2.03%, 0.61%, 1.61%, 1.64%, and 2.11% for out-of-sample periods starting from 1956, 1966, 1976, 1986, and 1996, respectively. Although the R^2_{oos} is negative for the out-of-sample period starting from 1956, all the other R^2_{oos}s are positive, statistically significant and larger than those of all other predictors.

Finally, in appendix Table A7, we allow the classic predictors to forecast the equity premium at the monthly frequency through the same flexible non-linear specification we used for CIS. Table A7 shows that CIS is still the only predictor that generates a positive and significant (at the 1% or 5% level) R^2_{oos} in all considered sample periods. Confirming the evidence presented earlier, CIS predictive power appears to have improved over more recent times, having become particularly strong over the past 30-35 years relatively to the other predictors which, instead, seem to have become progressively weaker.

To summarize, the out-of-sample analysis indicates that the hump-shaped relation be-

tween CIS and future equity premium documented in our in-sample tests is, likely, not due to over-fitting. Instead, in out-of-sample examination, our CIS model can generate sizable and highly statistically significant R^2_{oos}s, while commonly used predictors fail to do so in a consistent manner.

3.3.2 Forecast Encompassing Test

Following, among others, Rapach et al. (2016), we use the encompassing test proposed by Harvey et al. (1998) to directly examine whether CIS adds information to existing predictors when making out-of-sample equity premium forecasts. Specifically, we form an optimal out-of-sample combination forecast as a convex combination of forecasts made by two predictors, i and j:

$$\hat{r}^*_{t+1} = (1-\lambda)\hat{r}^i_{t+1} + \lambda\hat{r}^j_{t+1}. \tag{5}$$

where $\hat{r}^*_{t+1}$ is the optimal combination forecasts, $\hat{r}^i_{t+1}$ ($\hat{r}^j_{t+1}$) is the forecasts made by predictor i (j), and $0 \leq \lambda \leq 1$. To estimate λ, we define forecasts errors e^i_{t+1} and e^j_{t+1} as follows:

$$e^i_{t+1} = r_{t+1} - \hat{r}^i_{t+1},$$
$$e^j_{t+1} = r_{t+1} - \hat{r}^j_{t+1}$$

where r_{t+1} is the realised market excess returns. Then, equation (5) can be re-written as:

$$e^i_{t+1} = \lambda(e^i_{t+1} - e^j_{t+1}).$$

We then regress e^i_{t+1} onto $(e^i_{t+1} - e^j_{t+1})$ to estimate λ. We follow Harvey et al. (1998) to estimate the statistical significance. Formally, we test $H_0 : \lambda = 0$ against $H_A : \lambda > 0$. If $\lambda = 0$, then the optimal forecast does not contain information from predictor j. We

say that predictor i encompasses predictor j. In other words, predictor j does not contain information that goes beyond the information in predictor i for predicting r_{t+1}. If $\lambda > 0$, on the other hand, then predictor j does contain useful information that goes beyond predictor i. Estimated λs are reported in Table 7. Column $\hat{\lambda}_1$ ($\hat{\lambda}_2$) represents the estimated λ that uses CIS as predictor j (predictor i). That is, if $\hat{\lambda}_1 > 0$, then CIS contains useful information beyond a particular predictor. On the other hand, if $\hat{\lambda}_2 > 0$, then a particular predictor contains information beyond CIS.

[Insert Table 7]

We find that the $\hat{\lambda}_1$s are all quite sizeable and significant in all the sub-samples, indicating that none of the forecasts based om the other predictors encompasses the CIS-based forecast. Importantly, while the $\hat{\lambda}_1$s are typically close to 1, the $\hat{\lambda}_1$s are close to 0, and are rarely statistically significant. These results indicate that CIS adds useful information beyond traditional predictors most of the time. These popular predictors, on the other hand, do not add information beyond CIS.[16]. The exceptions occurs in the sample starting in 1956 and, to a lesser extent. for the sample starting in 1966. But even for those periods, it is never the case that an alternative predictor subsumes the forecasting power of CIS.

4 Economic Significance

In this section, we examine the economic significance of our predictability results by conducting an out-of-sample asset allocation exercise. Following, among many others, Campbell and Thompson (2008) and Huang et al. (2015) we take the perspective of a mean-variance investor allocating wealth between riskless US Treasury bills and the

[16]In Table 7, for these popular predictors, we use simple linear regressions to make forecasts. In Appendix Table A8, we report results using the same non-linear specification as CIS, and the baseline messages remain unchanged.

aggregate US equity market. The investor rebalances her portfolio at the end of each month based on the one-month ahead forecasts of the market excess return and of its variance. Namely, for a mean-variance investor with coefficient of relative risk aversion γ, the optimal portfolio weight invested in the equity market at the end of month τ is:

$$w_\tau^X = \frac{1}{\gamma} \frac{\hat{r}_{m,\tau+1}^X}{\hat{\sigma}_{\tau+1}^2} \tag{6}$$

where $\hat{r}_{m,\tau+1}^X$ is the predicted excess return using a given predictor X and $\hat{\sigma}_{\tau+1}^2$ is the predicted variance of market excess returns.[17] As in Campbell and Thompson (2008), we use a five-year rolling window of past monthly returns to estimate $\hat{\sigma}_{\tau+1}^2$ and restrict w_τ^X to lie between 0 and 1.5, which imposes realistic portfolio constraints. The portfolio allocation decision is made using only the available information up to time τ and the *ex post* portfolio excess return at the end of month $\tau + 1$ is then:

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

where $r_{m,\tau+1}$ is the realised market excess return at time $\tau + 1$. Denoting the realized portfolio mean return by $\bar{r}_p^X$ and standard deviation by σ_p^X, we use two statistics to evaluate the performance of a trading strategy based on predictor X. The first one is the Sharpe ratio:

$$SR^X = \frac{\bar{r}_p^X}{\sigma_p^X} \tag{8}$$

The second is the certainty equivalent return (CER), defined as the risk-free rate that the investor would consider equivalent to investing in a risky trading strategy. For a

[17] When the predictor is CIS, the predicted market excess return is computed using equation (3). For each predictors other than CIS, the predicted return is calculated using the simple linear regression in (2) .

mean-variance investor with risk aversion γ the CER is computed as

$$CER^X = \bar{r}_p^X - 0.5\gamma(\sigma_p^X)^2 \tag{9}$$

We also compute the CER for an investor who uses the realized average market excess return up to month τ as her prediction for the excess return in month $\tau + 1$: such prediction is labeled as prevailing mean forecast. Finally, we compute the performance measures generated by a simple buy-and-hold strategy for the market index. We further define the utility gain as the difference in CERs generated, respectively, by the strategy that relies on predictor X and by the strategy that uses the prevailing mean forecast. We annualize the utility gain so that it can be interpreted as the annual management fee that an investor would be willing to pay to switch from a fund manager who relies on the prevailing mean forecast to a manager who allocates based on the forecast from predictor X. Consistent with the out-of-sample tests in Section 3.3, we examine out-of-sample asset allocation periods starting from January 1956, 1966, 1976, 1986, and 1996. We allow for three different values of γs: 3, 5, and 7, representing low, moderate and high levels of relative risk aversion.

[Insert Table 8]

Table 8 reports annualized utility gains and Sharpe ratios for each strategy. It is evident that, irrespective of the chosen level of risk aversion and sample period, the trading strategy based on CIS systematically outperforms the prevailing mean strategy, the strategies based on the other predictors and the passive buy-and-hold strategy, in terms of both CER and Sharpe ratio. Compared to the prevailing mean strategy, the CIS-based strategy delivers utility gains around 2% per year for investors with low ($\gamma = 3$) and moderate risk aversion ($\gamma = 5$) and around 1.2% for more risk averse investors ($\gamma = 7$). Those gains are fairly stable across sample periods although they

get substantially larger over the more recent 1996-2019 stretch. Compared to the buy-and-hold strategy, CIS adds roughly 100 – 130 basis points per year for investors with low gammas, and over 200 basis points for more risk averse investors. Looking at the performances generated by the commonly used predictors, we observe that that some of them do generate positive utility gains despite generating negative R^2_{oos} in predictive regressions. This is consistent with Rapach and Zhou (2013), in which the authors find 10 out of 14 economic variables have positive annualized utility gains despite their negative R^2_{oos}s. Noticeably though, the performance of any of the alternative predictors is rather inconsistent across sub-periods and it appears to steadily deteriorate over time, except for the earnings-to-price ratio (EP) and for the default return spread (DFR). More importantly, CIS dominates most of the standard predictors across all considered sample periods. As an example, consider a rather successful predictor such as the long-term government bond return (LTR): CIS delivers between 40 and 60 additional basis point per year over the entire OOS period (1956-2019), growing to about 150 basis points in the 1986-2019 period. There are, on the other hand, a handful of cases where CIS is outperformed. However, this occurs for only three predictors (EP, TBL and TMS) and not consistently across time or risk-aversion levels. [18]

To sum up this section, we conclude that the predictive power of CIS for future market returns appears to add significant economic value for a mean-variance investor relatively to what could be generated by previously proposed predictors, including the historical average risk-premium. These baseline conclusions hold for a wide range of investors' risk aversion and across several out-of-sample evaluation periods.

[18] In the Appendix Table A9, we allow the classical predictors to have the same flexibility as CIS. The results are basically unchanged. For instance, we find that INFL can generate similar utility gain and Sharpe ratio as CIS for low risk aversion. However, when relative risk aversion is high, CIS performs much better than INFL.

5 Sources of Predictability

Why CIS can predict aggregate market returns? In this section, we try to understand the underlying economic mechanism. We, first, look at the issue from a standard valuation framework as in, e.g., Campbell and Shiller (1988) where a log linearization of stock return generates, as shown in Cochrane (2011), the following approximate identity

$$r_{m,t+1} = k + D/P_t - \rho D/P_{t+1} + DG_{t+1} \tag{10}$$

where $r_{m,t+1}$ is the aggregate stock market return from t to $t+1$, DG_{t+1} is the log aggregate dividend-growth rate, D/P_t is the log aggregate dividend-price ratio, and ρ is a positive log-linearization constant. From (10), one can see that if CIS (or, any other variable) predicts next period market return beyond the information contained in D/P_t,it must predict either DG_{t+1} (the cash flow component) or D/P_{t+1} (the discount rate component) or both. As a consequence, testing whether CIS_t is significantly related to future DP or future DG can shed light on whether CIS predictive power for returns is due to its ability to capture movements in future discount rates or in future expected cash flows. We, therefore, estimate the following specification

$$Y_{t+1} = \alpha + \beta_1 CIS_t + \beta_2 CIS_{high,t}, \beta_3 CIS_t * CIS_{high,t} + \beta_4 Y_t + \epsilon_{t+1}$$

where Y_{t+1} is set to either DG_{t+1} or to DP_{t+1} and the CIS-related variables are defined as in previous sections. Following Cochrane (2011), DG and DP are estimated using CRSP value-weighted returns with and without dividends; and the regressions are run at the annual frequency over the period 1961-2019. The results are reported in Table 9. The coefficients of the CIS variables on DG are not significant. On the other hand, CIS is significantly related to future DPs, Importantly, the non-linear relation between CIS and DP is conceptually consistent with the hump-shaped predictive power of

CIS for future returns. As the coefficients in the DP column of Table 9 suggest, an increase in CIS when CIS is low is associated with lower future discount rates and, hence, higher future market returns; whereas an increase in CIS when it is at high levels (relatively to its mean) is followed by higher discount rates, i.e., lower market returns. The above evidence indicates that, within the standard valuation framework, the predictive ability of CIS for the equity premium is related its ability to capture movements in future discount rates rather than in future cash flows.

As a second line of exploration, we build on the literature that points to mispricing induced by biased expectations about future growth as a source of return predictability. [19] In this framework, biased expectations (or, beliefs) lead to temporary overvaluation or undervaluation of the aggregate equity market. If CIS captures this type of market mispricing, then it should be related to future surprises (or, shocks) in realized growth measures.

To test this mechanism, we use earnings forecast errors and GDP growth forecast errors as proxies for investors' beliefs and run the following regression:

$$Error_t = \alpha + \beta_1 CIS_t + \beta_2 Sentiment + \beta_3 Error_{t-1} + \epsilon_t.$$

where $Error_t$ the average forecast errors in period t. We control for sentiment because Hribar and McInnis (2012) find that analyst forecast errors are positively related to sentiment.[20] We also control for lagged forecast errors because there is ample evidence showing that analyst forecast errors are positively auto-correlated (Linnainmaa et al. (2016) among many others). Following Hribar and McInnis (2012), at the end of each month t, for each firm i, we calculate the EPS forecast error ($Error_{i,t}$) as:

$$EError_{i,t} = \frac{EForecast_{i,t} - EActual_{i,t,fy+1}}{|EForecast_{i,t}|}$$

[19] Recent examples include Arif and Lee (2014), Huang et al. (2015) and Huang et al. (2021).

[20] We use the Baker and Wurgler (2006) investor sentiment index and the data is downloaded form Jeffrey Wurgler's website: http://people.stern.nyu.edu/jwurgler/.

where $EForecast_{i,t}$ is the consensus EPS forecast from IBES for the most recent fiscal year, $EActual_{i,t,fy+1}$ is the actual announced EPS, and $|EForecast_{i,t}|$ is the absolute value of the consensus EPS forecast. [21] Then we compute the average forecast errors ($EError_{i,t}$) across all firms in month t as the aggregate-level forecast errors ($Error_{i,t}$).

Similarly, the GDP forecast error ($GError_{i,t}$) is defined as:

$$GError_{i,t} = \frac{GForecast_{i,t} - GActual_t}{|GForecast_{i,t}|}$$

where $GForecast_{i,t}$ is the GDP growth forecast for the current quarter by professional forecaster i in quarter t, and $GActual_t$ is the realised GDP growth (i.e., the latest estimate of GDP growth) in quarter t. Then $Error_t$ is defined as the average $GError_{i,t}$ across all professional forecasters in quarter t. GDP growth forecasts and realised GDP growth data are downloaded from Philadelphia Reserve website. [22]

[Insert Table 10]

The results are reported in Table 10. We find that CIS is not associated in any significant manner to either earnings forecast error or GDP growth forecast error. This finding holds whether we test a linear (Models 1 and 2) or a non-linear (Models 3 and 4) relation and whether or not we control for market sentiment.

6 Conclusion

In this study, we find that firm's idiosyncratic skewness exhibits a strong co-movement pattern. The common component in idiosyncratic skewness captures up to 40% of

[21] We use the mean forecast as our measure for the consensus forecast. In unreported tests, we use the median forecast to measure the consensus forecast and find no appreciable difference in the findings.

[22] https://www.philadelphiafed.org/surveys-and-data/rgdp.

idiosyncratic skewness at the portfolio level. We, then, show that common idiosyncratic skewness, CIS, is a powerful predictor of the equity risk premium, both in and out of sample, at monthly and quarterly forecast horizons. CIS's predicting power is not absorbed by other popular equity premium predictors and, in facts, it compares rather favorably with those produced by many previously proposed predictors. In economic terms, CIS-induced predictability delivers sizeable out-of-sample utility gains in asset allocation to mean-variance investors. We explore plausible economic mechanisms behind the uncovered predictability: We find that that. within a standard asset pricing framework, CIS predicts market excess returns through the discount rate channel. On the other hand, we find no empirical support for a mis-pricing channel where investors have biased expectations about future growth.

Overall, our analysis suggests that idiosyncratic skewness has important implications not only or the cross-section of equity returns, as previously established in the literature, but also at the aggregate market level.

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7 Figures and Tables

Figure 1 Idiosyncratic Skewness by Size and Leverage

This figure plots portfolio level idiosyncratic skewness, which is defined as the equally-weighted average idiosyncratic skewness across all firms within a specific portfolio. The upper (lower) panel shows portfolio average idiosyncratic skewness for five size-sorted (leverage-sorted) portfolios. We re-balance each portfolio at the beginning of each. In the upper panel, Size 1 (5) represents average idiosyncratic skewness of the smallest-firm (largest-firm) portfolio. In the lower panel, Leverage (1) plots average idiosyncratic skewness of firms in the lowest (highest) leverage quintile. The sample period is from July 1965 to December 2019.

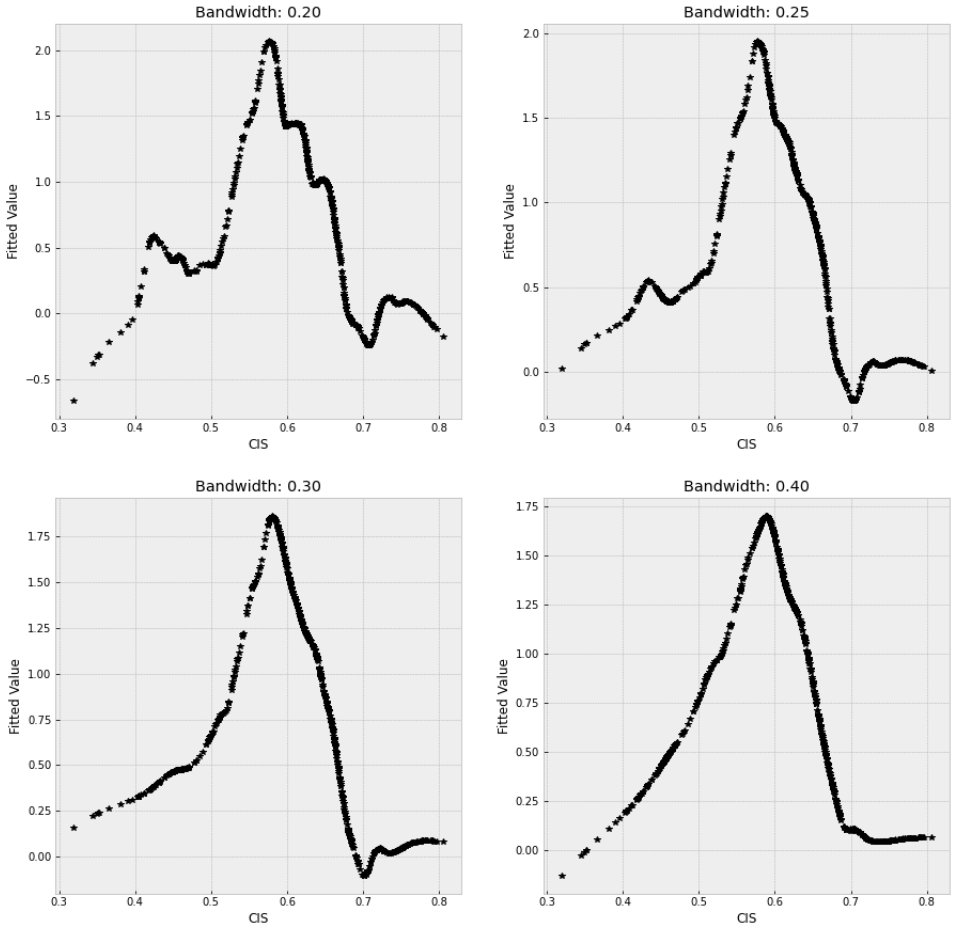

Figure 2 Non-Parametric Estimation

This figure plots the non-parametric relationship between CIS and market excess returns in the next month where CIS is the average idiosyncratic skewness across all firms in month t. The horizontal axes are CIS whereas the vertical axes represents fitted value using LOWESS (Locally Weighted Scatterplot Smoothing). The upper panels plot the results using bandwidth of 0.20 and 0.25, respectively. The lower panels plot the results using bandwidth of 0.30 and 0.40, respectively. The sample period is from January 1961 to December 2019.

Table 1 Idiosyncratic Skewness Co-Movement

This table presents contemporaneous regressions of the form, separately for each portfolio p:

$$iskew_{p,t} = \alpha + \beta CIS_t + \epsilon_t$$

where $iskew_{p,t}$ is the equal-weighted average idiosyncratic skewness for portfolio p at month t and CIS_t is the equal-weighted average idiosyncratic skewness across all firms in month t. We divide firms into 5-by-5 size-leverage portfolios. To construct these 25 portfolios, at the end of June of each year t, We form leverage quintile portfolios across all firms based on the leverage of last fiscal year end. The five size-sorted portfolios are formed in the same way but based on the NYSE breakpoints. S1 (S5) represents smallest (largest) firms portfolio. Similarly, L1 (L5) represents the lowest (highest) leverage firms portfolio. The sample period is from July 1965 to December 2019.

	CIS Loadings					t-statistics				
	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
L1	0.9914	0.9155	0.9556	0.4801	0.2068	24.4586	18.2329	18.0035	13.368	6.2644
L2	0.9051	0.8134	0.6982	0.6157	0.6273	26.0017	16.6134	16.0428	13.6038	15.0169
L3	1.1554	0.8288	0.7443	0.7376	0.4071	30.2486	17.3976	15.3862	16.4866	11.1605
L4	1.0534	1.0402	0.7506	0.9773	1.1395	30.9154	24.8249	17.9761	19.6358	19.9137
L5	1.4059	1.2404	1.4956	1.0048	1.3596	28.5635	21.4611	24.7946	12.8618	17.664

	$Adj.R^2$				
	S1	S2	S3	S4	S5
L1	0.5069	0.3632	0.3574	0.2342	0.0618
L2	0.5375	0.3213	0.3062	0.2406	0.2787
L3	0.6114	0.3418	0.2886	0.3179	0.1754
L4	0.6217	0.5143	0.3567	0.3983	0.4051
L5	0.5838	0.4417	0.5137	0.2206	0.3487

Table 2 Summary Statistics

This table reports summary statistics of variables used in this study. $\mathbf{r_m}$ is the return on CRSP value-weighted index including dividends, displayed in percentage points. **CIS** is the average idiosyncratic skewness across all firms in a specific month. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **LTR** is the return on long-term government bonds. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. The sample period is from January 1931 to December 2019.

	mean	std	min	25%	50%	75%	max
$r_m(\%)$	0.945	5.264	-29.173	-1.799	1.285	3.855	39.414
CIS	0.608	0.104	0.319	0.524	0.617	0.682	0.855
DP	-3.395	0.471	-4.524	-3.800	-3.375	-3.033	-1.873
DY	-3.390	0.469	-4.531	-3.795	-3.366	-3.027	-1.913
EP	-2.745	0.424	-4.836	-2.965	-2.806	-2.462	-1.775
DE	-0.650	0.330	-1.244	-0.870	-0.646	-0.516	1.380
SVAR	0.003	0.005	0.000	0.001	0.001	0.002	0.071
BM	0.571	0.269	0.121	0.334	0.550	0.753	2.028
NTIS	0.013	0.019	-0.056	0.004	0.016	0.026	0.114
TBL	0.034	0.031	0.000	0.004	0.028	0.052	0.163
LTY	0.051	0.028	0.016	0.028	0.043	0.069	0.148
LTR	0.005	0.025	-0.112	-0.007	0.003	0.017	0.152
TMS	0.018	0.013	-0.036	0.009	0.018	0.026	0.045
DFY	0.011	0.007	0.003	0.007	0.009	0.013	0.056
DFR	0.000	0.014	-0.098	-0.005	0.001	0.006	0.074
INFL	0.003	0.005	-0.021	0.000	0.002	0.005	0.059
SKEW	0.031	0.047	-0.361	0.010	0.035	0.059	0.426

Table 3 Pearson Correlation Matrix

This table reports the correlation matrix of variables used in this study. $\mathbf{r_m}$ is the return on CRSP value-weighted index including dividends, displayed in percentage points. **CIS** is the average idiosyncratic skewness across all firms in a specific month. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **LTR** is the return on long-term government bonds. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. The sample period is from January 1931 to December 2019.

index	$r_m(\%)$	CIS	DP	DY	EP	DE	SVAR	BM	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL	SKEW
$r_m(\%)$	1.00																
CIS	-0.05	1.00															
DP	0.06	0.08	1.00														
DY	0.07	0.07	0.99	1.00													
EP	0.07	0.09	0.73	0.73	1.00												
DE	0.00	-0.01	0.49	0.48	-0.24	1.00											
SVAR	0.00	0.02	0.20	0.18	-0.09	0.41	1.00										
BM	0.09	0.09	0.88	0.87	0.73	0.32	0.22	1.00									
NTIS	-0.05	0.25	0.23	0.22	0.20	0.07	-0.18	0.16	1.00								
TBL	-0.02	0.25	0.00	0.00	0.26	-0.33	-0.16	0.18	0.03	1.00							
LTY	-0.00	0.32	-0.04	-0.04	0.15	-0.25	-0.10	0.14	-0.01	0.92	1.00						
LTR	0.07	-0.01	-0.02	-0.02	-0.00	-0.03	0.07	-0.01	-0.08	0.05	0.05	1.00					
TMS	0.03	0.09	-0.10	-0.09	-0.30	0.25	0.19	-0.15	-0.11	-0.43	-0.04	-0.01	1.00				
DFY	0.06	0.19	0.41	0.41	0.04	0.54	0.60	0.47	-0.26	-0.07	0.06	0.07	0.30	1.00			
DFR	0.03	0.02	-0.01	0.01	-0.08	0.09	-0.06	-0.01	0.03	-0.04	-0.01	-0.46	0.09	0.02	1.00		
INFL	-0.04	0.11	0.01	0.01	0.17	-0.20	-0.22	0.08	0.07	0.27	0.22	-0.10	-0.18	-0.24	0.03	1.00	
SKEW	0.04	0.08	0.02	0.07	-0.03	0.07	0.05	0.06	0.01	0.15	0.14	0.01	-0.05	0.13	0.02	-0.08	1.00

Table 4 In-Sample Predictive Regressions

This table reports the in-sample performance of CIS and other popular predictors. **CIS** is the average idiosyncratic skewness across all firms in a specific month. $\mathbf{CIS_{high}}$ is a dummy variable equal to 1 if CIS is higher than the CIS historical median up to month t and 0 otherwise, and $\mathbf{CIS{*}CIS_{high}}$ is the interaction term between **CIS** and $\mathbf{CIS_{high}}$. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **LTR** is the return on long-term government bonds. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. For CIS, we use the predictive regression as specified in equation (3). For predictors other than CIS, we use the univariate predictive regression. Newey and West (1987) t-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample covers the period from January 1931 to December 2019. We use first 30 years data to estimate first CIS median. As a result, the estimation period is from January 1961 to December 2019.

Predictor	$\hat{\beta}$	$Adj.R^2$	Predictor	$\hat{\beta}$	$Adj.R^2$	Predictor	$\hat{\beta}$	$Adj.R^2$
CIS	9.915***	0.018	DE	0.368	-0.001	LTR	16.273***	0.010
	(2.62)			(0.96)			(3.75)	
CIS_{high}	9.159***		$SVAR$	-97.127***	0.008	TMS	20.407**	0.003
	(2.60)			(-3.40)			(1.98)	
$CIS * CIS_{high}$	-16.710***		BM	0.142	-0.001	DFY	51.403	0.001
	(-2.95)			(0.29)			(1.21)	
DP	0.443	0.000	$NTIS$	-6.870	-0.000	DFR	16.684	0.002
	(1.34)			(-0.59)			(1.40)	
DY	0.515	0.001	TBL	-9.118***	0.003	$INFL$	-91.313	0.004
	(1.50)			(-2.58)			(-1.53)	
EP	0.191	-0.001	LTY	-6.466*	0.000	$SKEW$	0.196	-0.001
	(0.50)			(-1.75)			(0.05)	

Table 5 In-Sample Predictive Regression with Control Variables

This table reports results of in-sample predictive regression with control variables. **CIS** is the average idiosyncratic skewness across all firms in a specific month. $\mathbf{CIS_{high}}$ is a dummy variable equal to 1 if CIS is higher than the CIS historical median up to month t and 0 otherwise, and $\mathbf{CIS{*}CIS_{high}}$ is the interaction term between **CIS** and $\mathbf{CIS_{high}}$. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **LTR** is the return on long-term government bonds. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. Newey and West (1987) t-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample covers the period from January 1931 to December 2019. We use the first 30 years data to estimate the first CIS median. As a result, the estimation period is from January 1961 to December 2019.

Predictor	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
$const$	-1.397	-1.179	-2.940	-4.197*	-3.313**	-4.935**	-4.715**	-4.403**	-4.394**	-4.352**	-4.238*	-5.610**	-4.152**	-4.141*	-4.272**	6.482
	(-0.60)	(-0.52)	(-0.91)	(-1.84)	(-2.10)	(-2.10)	(-2.30)	(-2.15)	(-2.15)	(-1.98)	(-1.89)	(-2.06)	(-2.08)	(-1.88)	(-1.99)	(1.13)
CIS	10.235**	10.150**	9.621**	10.577**	8.405***	10.328**	10.807***	10.632***	10.677***	9.856**	9.426**	10.781**	9.657***	9.930***	9.835***	12.779***
	(2.42)	(2.40)	(2.44)	(2.35)	(3.04)	(2.55)	(3.02)	(2.88)	(2.80)	(2.53)	(2.32)	(2.26)	(2.74)	(2.61)	(2.63)	(3.20)
CIS_{high}	10.598***	10.612***	9.554***	9.605**	8.567***	10.806***	9.560***	7.979**	8.896**	8.697**	7.724*	11.445***	9.029***	8.254**	9.198***	9.497**
	(2.77)	(2.77)	(2.89)	(2.42)	(2.62)	(2.82)	(2.78)	(2.15)	(2.55)	(2.40)	(1.89)	(2.93)	(2.59)	(2.09)	(2.59)	(2.27)
$CIS * CIS_{high}$	-19.022***	-19.025***	-17.317***	-17.467***	-15.519***	-19.348***	-17.358***	-14.961**	-16.347***	-16.006***	-14.520**	-20.258***	-16.457***	-15.274**	-16.767***	-17.172**
	(-3.09)	(-3.09)	(-3.29)	(-2.72)	(-3.05)	(-3.14)	(-3.16)	(-2.52)	(-2.93)	(-2.75)	(-2.20)	(-3.19)	(-2.96)	(-2.38)	(-2.93)	(-2.55)
DP	0.832***															5.788**
	(2.72)															(2.00)
DY		0.881***														-5.976
		(2.75)														(-1.43)
EP			0.404													3.294**
			(0.85)													(2.06)
DE				0.594												2.494*
				(1.32)												(1.74)
$SVAR$					-81.125***											-140.022***
					(-3.37)											(-3.49)
BM						0.994										-2.049
						(1.59)										(-1.47)
$NTIS$							-8.868									-2.860
							(-0.95)									(-0.38)
TBL								-7.112								-14.487**
								(-1.59)								(-2.02)
LTY									-5.412							-19.828***
									(-0.93)							(-3.39)
LTR										15.602***						22.854***
										(3.54)						(3.43)
TMS											12.241					-5.342
											(1.16)					(-0.85)
DFY												86.654**				133.284***
												(2.27)				(3.68)
DFR													14.686			30.254*
													(1.31)			(1.88)
$INFL$														-62.987		-37.109
														(-1.10)		(-0.63)
$SKEW$															1.220	2.494
															(0.29)	(0.53)
$Adj.R^2$	0.022	0.022	0.018	0.018	0.022	0.019	0.018	0.018	0.017	0.027	0.018	0.023	0.019	0.019	0.016	0.060

Table 6 Out-of-Sample Performance

This table reports out-of-sample R^2 of each predictor. **CIS** is the average idiosyncratic skewness across all firms in a specific month. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **LTR** is the return on long-term government bonds. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. For CIS, we use equation (3) to predict future returns. For predictors other than CIS, we use the simple linear predictive regression in (2). Panel A reports the results without any prediction restrictions, whereas Panel B reports the results with non-negative equity premium predictions following Campbell and Thompson (2008). Clark and West (2007) p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1931 to December 2019.

Panel A: No Restriction

Out of Sample Starts: 1956						Out of Sample Starts: 1966					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0040**	*BM*	-0.0285	*TMS*	0.0024**	*CIS*	0.0106***	*BM*	-0.0269	*TMS*	0.0011**
	(0.0166)		(0.8740)		(0.0291)		(0.0057)		(0.7781)		(0.0448)
DP	-0.0005	*NTIS*	-0.0123	*DFY*	0.0044*	*DP*	0.0002**	*NTIS*	-0.0167	*DFY*	0.0041*
	(0.9690)		(0.8662)		(0.0661)		(0.0492)		(0.7901)		(0.0959)
DY	-0.0039	*TBL*	0.0013**	*DFR*	-0.0022	*DY*	-0.0015	*TBL*	0.0013**	*DFR*	-0.0021
	(0.9802)		(0.0209)		(0.5914)		(0.9636)		(0.0363)		(0.5662)
EP	-0.0064	*LTY*	-0.0034	*INFL*	0.0038*	*EP*	-0.0066	*LTY*	-0.0033	*INFL*	0.0045*
	(0.7820)		(0.9326)		(0.0723)		(0.7312)		(0.9176)		(0.0664)
DE	-0.0048	*LTR*	0.0055**	*SKEW*	-0.0035	*DE*	-0.0037	*LTR*	0.0066**	*SKEW*	-0.0039
	(0.9746)		(0.0151)		(0.7580)		(0.9443)		(0.0132)		(0.8308)

Out of Sample Starts: 1976						Out of Sample Starts: 1986					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0149***	*BM*	-0.0374	*TMS*	-0.0102	*CIS*	0.0194***	*BM*	-0.0331	*TMS*	-0.0160
	(0.0062)		(0.6305)		(0.7490)		(0.0047)		(0.6177)		(0.6408)
DP	-0.0105	*NTIS*	-0.0242	*DFY*	-0.0013	*DP*	-0.0157	*NTIS*	-0.0359	*DFY*	-0.0044
	(0.7549)		(0.6405)		(0.6063)		(0.6954)		(0.7277)		(0.6096)
DY	-0.0155	*TBL*	-0.0116	*DFR*	-0.0018	*DY*	-0.0224	*TBL*	-0.0022	*DFR*	-0.0014
	(0.7710)		(0.7409)		(0.5371)		(0.7131)		(0.6150)		(0.5158)
EP	-0.0113	*LTY*	-0.0119	*INFL*	0.0009	*EP*	-0.0082	*LTY*	0.0003	*INFL*	-0.0006
	(0.6291)		(0.6304)		(0.2374)		(0.6688)		(0.3183)		(0.6263)
DE	-0.0024	*LTR*	0.0027**	*SKEW*	-0.0040	*DE*	-0.0030	*LTR*	-0.0021	*SKEW*	-0.0036
	(0.7911)		(0.0413)		(0.8054)		(0.8098)		(0.8105)		(0.7524)

Out of Sample Starts: 1996					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0256***	*BM*	-0.0258	*TMS*	-0.0109
	(0.0055)		(0.5727)		(0.5985)
DP	-0.0176	*NTIS*	-0.0394	*DFY*	-0.0071
	(0.6383)		(0.9085)		(0.6895)
DY	-0.0248	*TBL*	-0.0004	*DFR*	-0.0023
	(0.6567)		(0.6758)		(0.5033)
EP	-0.0123	*LTY*	0.0023	*INFL*	-0.0049
	(0.5965)		(0.1361)		(0.6150)
DE	-0.0034	*LTR*	-0.0014	*SKEW*	-0.0019
	(0.7583)		(0.7618)		(0.6046)

Panel B: Non-Negative Prediction

Out of Sample Starts: 1956						Out of Sample Starts: 1966					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0047**	*BM*	-0.0178	*TMS*	0.0029**	*CIS*	0.0113***	*BM*	-0.0172	*TMS*	0.0017*
	(0.0165)		(0.8508)		(0.0340)		(0.0044)		(0.7724)		(0.0539)
DP	0.0026**	*NTIS*	-0.0115	*DFY*	0.0044*	*DP*	0.0036**	*NTIS*	-0.0156	*DFY*	0.0041*
	(0.0183)		(0.8558)		(0.0661)		(0.0295)		(0.7770)		(0.0959)
DY	0.0017**	*TBL*	0.0050**	*DFR*	-0.0022	*DY*	0.0045**	*TBL*	0.0053**	*DFR*	-0.0021
	(0.0118)		(0.0161)		(0.6136)		(0.0187)		(0.0322)		(0.5859)
EP	-0.0000*	*LTY*	0.0048**	*INFL*	0.0039*	*EP*	0.0005	*LTY*	0.0058**	*INFL*	0.0046*
	(0.0912)		(0.0226)		(0.0694)		(0.1239)		(0.0294)		(0.0637)
DE	-0.0048	*LTR*	0.0060**	*SKEW*	-0.0036	*DE*	-0.0037	*LTR*	0.0071**	*SKEW*	-0.0039
	(0.9746)		(0.0169)		(0.7630)		(0.9443)		(0.0147)		(0.8357)

Out of Sample Starts: 1976						Out of Sample Starts: 1986					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0152***	*BM*	-0.0245	*TMS*	-0.0092	*CIS*	0.0197***	*BM*	-0.0163	*TMS*	-0.0160
	(0.0038)		(0.6219)		(0.6984)		(0.0029)		(0.6119)		(0.6406)
DP	-0.0061	*NTIS*	-0.0235	*DFY*	-0.0013	*DP*	-0.0100	*NTIS*	-0.0351	*DFY*	-0.0044
	(0.7762)		(0.6400)		(0.6063)		(0.7069)		(0.7299)		(0.6096)
DY	-0.0075	*TBL*	-0.0051	*DFR*	-0.0019	*DY*	-0.0120	*TBL*	-0.0022	*DFR*	-0.0015
	(0.7754)		(0.6635)		(0.5559)		(0.6958)		(0.6150)		(0.5041)
EP	-0.0022	*LTY*	-0.0031	*INFL*	0.0010	*EP*	0.0036	*LTY*	0.0003	*INFL*	-0.0006
	(0.7974)		(0.6991)		(0.2339)		(0.1331)		(0.3183)		(0.6263)
DE	-0.0024	*LTR*	0.0034**	*SKEW*	-0.0040	*DE*	-0.0030	*LTR*	-0.0028	*SKEW*	-0.0036
	(0.7911)		(0.0469)		(0.8113)		(0.8098)		(0.7695)		(0.7602)

Out of Sample Starts: 1996					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0259***	*BM*	-0.0121	*TMS*	-0.0109
	(0.0031)		(0.6480)		(0.5981)
DP	-0.0103	*NTIS*	-0.0394	*DFY*	-0.0071
	(0.6545)		(0.9085)		(0.6895)
DY	-0.0110	*TBL*	-0.0004	*DFR*	-0.0024
	(0.6735)		(0.6758)		(0.5178)
EP	0.0038	*LTY*	0.0023	*INFL*	-0.0049
	(0.1867)		(0.1361)		(0.6150)
DE	-0.0034	*LTR*	-0.0024	*SKEW*	-0.0019
	(0.7583)		(0.7061)		(0.6046)

Table 7 Out-of-Sample Encompassing Test

This table reports results of out-of-sample encompassing tests. $\hat{\lambda}_1$ is the estimated weight on forecasts based on our CIS model, equation (3), in a combination forecast, which is a convex combination of forecasts based on CIS and another popular predictor. Similarly, $\hat{\lambda}_2$ is the estimated weight on forecasts based on a popular predictor in a combination forecast, which is a convex combination of forecasts based on CIS and another popular predictor. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **LTR** is the return on long-term government bonds. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. p-values based on Harvey et al. (1998) statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1931 to December 2019.

	Out of Sample Starts: 1956		Out of Sample Starts: 1966		Out of Sample Starts: 1976		Out of Sample Starts: 1986		Out of Sample Starts: 1996	
Predictor	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_1$	$\hat{\lambda}_2$
DP	0.5482***	0.4518***	0.6381***	0.3619**	0.7990***	0.2010	0.9311***	0.0689	1.0000***	0.0000
DY	0.5654***	0.4346***	0.6333***	0.3667**	0.7946***	0.2054	0.9098***	0.0902	0.9987***	0.0013
EP	0.6346***	0.3654**	0.7656***	0.2344	0.8569***	0.1431	1.0000***	0.0000	1.0000***	0.0000
DE	0.7475***	0.2525	0.9081***	0.0919	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
SVAR	0.8438***	0.1562	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
BM	0.6948***	0.3052**	0.7839***	0.2161*	0.8294***	0.1706	0.9445***	0.0555	1.0000***	0.0000
NTIS	0.6827***	0.3173**	0.8235***	0.1765	0.9666***	0.0334	1.0000***	0.0000	1.0000***	0.0000
TBL	0.5339***	0.4661**	0.6572***	0.3428	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
LTY	0.5972***	0.4028**	0.7202***	0.2798	1.0000***	0.0000	1.0000***	0.0000	1.0000**	0.0000
LTR	0.4763**	0.5237***	0.5659***	0.4341**	0.6893***	0.3107	0.9749***	0.0251	1.0000***	0.0000
TMS	0.5290***	0.4710**	0.6868***	0.3132	0.9631***	0.0369	1.0000***	0.0000	1.0000***	0.0000
DFY	0.4926**	0.5074**	0.6518**	0.3482	0.8577***	0.1423	1.0000***	0.0000	1.0000***	0.0000
DFR	0.6641**	0.3359	0.8605***	0.1395	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
INFL	0.5050**	0.4950**	0.6809**	0.3191	0.9600***	0.0400	1.0000***	0.0000	1.0000***	0.0000
SKEW	0.6889***	0.3111	0.8751***	0.1249	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000

Table 8 Utility Gain and Sharpe Ratio

This table reports out-of-sample annualized certainty equivalent return (CER) gain (in percentage), relative to prevailing mean forecasts, for a mean-variance investor with relative risk aversion coefficient of γ. Annualized Sharpe ratio is also reported. The mean-variance investor allocates between stock and risk-free bonds using a predictive regression excess return forecast based on the predictor variable shown in the first column. We require the proportion of wealth invested in the stock market to lie between 0 and 1.5. For robustness purpose, we consider initial in-sample estimation periods of 10, 20, and 30 years. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **LTR** is the return on long-term government bonds. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. The sample period is from January 1931 to December 2019.

	Out of Sample Starts: 1956				Out of Sample Starts: 1966				Out of Sample Starts: 1976				Out of Sample Starts: 1986				Out of Sample Starts: 1996			
Predictor	$\gamma = 3$	$\gamma = 5$	$\gamma = 7$	SR	$\gamma = 3$	$\gamma = 5$	$\gamma = 7$	SR	$\gamma = 3$	$\gamma = 5$	$\gamma = 7$	SR	$\gamma = 3$	$\gamma = 5$	$\gamma = 7$	SR	$\gamma = 3$	$\gamma = 5$	$\gamma = 7$	SR
CIS	1.96%	1.79%	1.16%	0.47	2.32%	2.06%	1.47%	0.42	2.09%	1.86%	1.15%	0.54	2.34%	2.12%	1.29%	0.57	3.29%	3.52%	1.92%	0.55
DP	-0.73%	0.63%	0.96%	0.28	-0.24%	1.07%	1.09%	0.23	-1.71%	-0.30%	0.00%	0.30	-2.41%	-0.38%	0.01%	0.28	-2.45%	0.29%	0.61%	0.19
DY	-0.50%	0.79%	1.08%	0.30	0.52%	1.55%	1.43%	0.28	-1.65%	-0.23%	0.05%	0.31	-2.32%	-0.33%	0.05%	0.32	-1.93%	0.60%	0.84%	0.26
EP	0.82%	0.68%	0.92%	0.35	1.42%	1.21%	1.09%	0.31	1.79%	1.40%	1.09%	0.49	2.36%	2.44%	2.02%	0.73	2.72%	3.32%	2.78%	0.68
DE	-0.22%	-0.22%	-0.43%	0.31	-0.26%	-0.33%	-0.38%	0.23	-0.35%	-0.32%	-0.22%	0.37	-0.45%	-0.41%	-0.28%	0.38	-0.61%	-0.45%	-0.29%	0.32
$SVAR$	-0.12%	-0.42%	-0.50%	0.28	-0.14%	-0.26%	-0.59%	0.23	-0.26%	-0.72%	-1.21%	0.31	-0.51%	-1.03%	-1.64%	0.31	-0.56%	-0.95%	-1.71%	0.28
BM	-1.87%	-1.19%	-1.11%	0.16	-1.03%	-0.77%	-1.13%	0.15	-1.82%	-1.02%	-1.08%	0.24	-2.46%	-0.41%	-0.01%	0.48	-1.37%	0.94%	1.08%	0.55
$NTIS$	1.55%	0.36%	0.01%	0.44	1.61%	0.06%	-0.63%	0.38	0.50%	-0.67%	-1.35%	0.45	-0.39%	-1.38%	-2.17%	0.41	-0.04%	-0.66%	-2.05%	0.35
TBL	1.57%	1.36%	0.93%	0.35	2.35%	1.73%	0.91%	0.32	0.26%	-0.21%	-0.74%	0.34	1.00%	0.13%	-0.67%	0.38	1.35%	0.34%	-0.83%	0.36
LTY	1.05%	1.05%	0.97%	0.35	1.74%	1.55%	1.09%	0.32	-0.13%	-0.21%	-0.36%	0.36	0.51%	0.14%	-0.17%	0.41	0.64%	0.29%	-0.17%	0.39
LTR	1.57%	1.15%	0.71%	0.45	1.85%	1.40%	0.86%	0.42	1.28%	1.02%	0.51%	0.50	0.59%	0.42%	-0.01%	0.46	-0.54%	0.04%	-0.38%	0.39
TMS	2.28%	1.46%	0.69%	0.43	2.80%	1.77%	0.56%	0.38	1.21%	0.02%	-1.06%	0.40	0.09%	-1.12%	-2.17%	0.34	-0.10%	-0.66%	-1.44%	0.30
DFY	0.67%	0.05%	-0.08%	0.30	0.81%	0.22%	-0.27%	0.24	0.16%	-0.66%	-1.15%	0.30	-0.08%	-1.01%	-1.59%	0.26	-0.00%	-1.10%	-2.02%	0.19
DFR	0.38%	0.37%	0.23%	0.36	0.45%	0.45%	0.32%	0.30	0.70%	0.71%	0.50%	0.45	1.04%	1.07%	0.77%	0.48	1.19%	1.44%	1.04%	0.44
$INFL$	1.33%	0.84%	0.12%	0.37	1.57%	0.99%	0.17%	0.31	1.09%	0.41%	-0.45%	0.39	0.88%	0.20%	-0.81%	0.39	0.43%	-0.33%	-1.59%	0.32
$SKEW$	-0.30%	0.03%	0.08%	0.36	-0.49%	-0.18%	-0.13%	0.27	-0.74%	-0.25%	-0.06%	0.40	-0.88%	-0.21%	0.00%	0.41	-0.86%	0.39%	0.48%	0.39
buy-and-hold	1.10%	0.81%	-0.87%	0.43	1.62%	0.86%	-1.42%	0.39	0.93%	0.81%	-0.92%	0.51	0.86%	1.09%	-0.60%	0.52	1.09%	1.71%	-0.21%	0.50
prevailing mean	0.00%	0.00%	0.00%	0.35	0.00%	0.00%	0.00%	0.28	0.00%	0.00%	0.00%	0.41	0.00%	0.00%	0.00%	0.42	0.00%	0.00%	0.00%	0.37

Table 9 Forecasting Discount Rates and Cash Flows Using CIS

This table reports results of predictive regressions of the form:

$$Y_{t+1} = \alpha + \beta_1 CIS_t + \beta_2 CIS_{high,t}, \beta_3 CIS_t \cdot CIS_{high,t} + \beta_4 Y_t + \epsilon_{t+1}$$

where Y_{t+1} is a proxy for economic activities, CIS_t is the average idiosyncratic skewness across all firms in month t. $CIS_{high,t}$ is a dummy variable equal to 1 if CIS in month t is higher than the CIS historical median up to month t and 0 otherwise, and $CIS_t * CIS_{high,t}$ is the interaction term between CIS_t and $CIS_{high,t}$. Newey and West (1987) t-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The second and third rows report the results for Y_{t+1} being equal to log dividend growth (DG) and log dividend-price ratio (DP), respectively. Following Cochrane (2011), DG and DP are estimated using CRSP value-weighted returns with and without dividends; and the regressions are run at the annual frequency. We use the first 30 years data to estimate the first CIS sample median. As a result, the sample period is from January 1961 to December 2019.

	$const$	CIS	CIS_{high}	$CIS \cdot CIS_{high}$	y_t	$Adj.R^2$
DG_{t+1}	0.262	-0.029	0.079	-0.155	0.048	-0.044
	(1.491)	(-0.150)	(0.380)	(-0.484)	(1.297)	
DP_{t+1}	0.038	-0.641**	-0.401	0.783**	0.923***	0.887
	(0.161)	(-2.195)	(-1.589)	(1.987)	(23.153)	

Table 10 CIS and Forecast Errors

This table reports the estimated coefficients of the following regression:

$$Error_t = \alpha + \beta_1 CIS + \beta_2 Sentiment_2 + \beta_3 Error_{t-1} + \epsilon_t$$

where $Error_t$ can be earnings forecast errors or GDP growth forecast errors in period t. We calculate earnings forecast errors as follows. For each firm i in each month t, the earnings forecast error is defined as $EError_{i,t} = \frac{EForecast_{i,t} - EActual_{i,t,fy+1}}{|EForecast_{i,t}|}$ where $EForecast_{i,t}$ is the consensus EPS forecast for the most recent fiscal year end for firm i and published in month t; and $EActual_{i,t,fy+1}$ is the actual announced EPS. Sentiment is the sentiment index proposed by Baker and Wurgler (2006). Similarly, GDP growth forecast errors are defined as $GError = \frac{GForecast_{i,t} - GActual_t}{|GForecast_{i,t}|}$ where $GForecast_{i,t}$ is the current quarter GDP growth forecast produced by professional forecaster i in quarter t, and $GActual_t$ is the latest GDP growth estimates for quarter t. Then, $Error_t$ is computed as the average forecast error (earnings forecast or GDP growth forecast error) in period t. Panel A (B) reports the results for earnings forecast errors (GDP growth forecast errors). Newey and West (1987) t-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1976 to December 2019 for earnings forecasts.

	Panel A: EPS Forecast				Panel B: GDP Forecast			
Indep. Var.	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
$const$	-0.0117	-0.0084	-0.0236	-0.0219	-4.1241	-4.9405	-8.9250	-9.7757
	(-1.101)	(-0.792)	(-1.448)	(-1.202)	(-0.817)	(-0.891)	(-0.936)	(-0.981)
CIS	0.0255	0.0208	0.0508*	0.0483	0.756	7.0943	15.2084	16.6170
	(1.492)	(1.234)	(1.709)	(1.459)	(0.756)	(0.841)	(0.924)	(0.968)
CIS_{high}	-	-	-0.0032	0.0061	-	-	8.9011	8.6808
	-	-	(-0.104)	(0.205)	-	-	(0.891)	(0.881)
$CIS * CIS_{high}$	-	-	-0.0046	-0.0179	-	-	-15.7032	-15.4214
	-	-	(-0.093)	(-0.369)	-	-	(-0.923)	(-0.917)
$Sentiment$	-	0.0046	-	0.0044	-	-0.4027	-	-0.4046
	-	(1.644)	-	(1.620)	-	(-1.316)	-	(-1.300)
$Error_{t-1}$	0.9384***	0.9244***	0.9382***	0.9246***	-0.0365	-0.0406	-0.0474	-0.0516
	(67.256)	(61.878)	(69.125)	(63.541)	(-1.451)	(-1.469)	(-1.292)	(-1.327)
$Adj.R^2$	0.892	0.893	0.892	0.893	-0.000	-0.001	-0.001	-0.003

Appendix

Alternative Factor Models

In this section, we provide further robustness check of our main results using alternative factor models to estimate idiosyncratic skewness. Harvey and Siddique (2000) use the following model to estimate firms' co-skewness with the market:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i} MKT_t + \beta_{2,i} MKT_t^2 + \epsilon_{i,t}$$

where $r_{i,t}$ is firm i's return in month t, $r_{f,t}$ is the risk free rate in month t, and MKT_t is the market excess return in month t. $\beta_{t,i}$ is firm i's co-skewness with the market. Hence, we interpret the skewness of $\epsilon_{i,t}$ as firm i's idiosyncratic skewness. Again, we use five-year rolling window to estimate idiosyncratic skewness. We then re-run the main analysis and report the results in Table A1. Both co-movement and predictability results are qualitatively the same as the main results.

Next, we use Fama and French (2015) five factor model to estimate idiosyncratic skewness. The results in Table A2 are again largely on par with the main analysis. Note that these factors are available from July 1963 and we adjust the sample period accordingly.

Lastly, we use a pure statistical factor model to estimate firms' idiosyncratic skewness. We extract the first five principal components of firm returns to capture the common movement in firm returns. We project firm returns onto these five principal components and idiosyncratic skewness is computed as the skewness of residual returns. Results reported in Table A3 indicate that the main results are also robust to this pure statistical model.

Table A1 Robustness Check using Harvey and Siddique (2000) Model

This table report results using the following model to estimate to estimate firm idiosyncratic skewness:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i} MKT_t + \beta_{2,i} MKT_t^2 + \epsilon_{i,t}$$

where $r_{i,t}$ is firm i's return in month t, $r_{f,t}$ is the risk free rate in month t, and MKT_t is the market excess return in month t. Panel A presents contemporaneous regressions of the form, separately for each portfolio p:

$$iskew_{p,t} = \alpha + \beta CIS_t + \epsilon_t$$

where $iskew_{p,t}$ is the equal-weighted average idiosyncratic skewness for portfolio p at month t and CIS_t is the equal-weighted average idiosyncratic skewness across all firms in month t. We divide firms into 5-by-5 size-leverage portfolios. To construct these 25 portfolios, at the end of June of each year t, we form leverage quintile portfolios across all firms based on the leverage of last fiscal year end. The five size-sorted portfolios are formed in the same way but based on the NYSE breakpoints. S1 (S5) represents smallest (largest) firms portfolio. Similarly, L1 (L5) represents the lowest (highest) leverage firms portfolio. The sample period is from July 1965 to December 2019. Panel B reports predictability results. The first four columns report in-sample estimation and the last column reports the out-of-sample R^2 with out-of-sample period starting from January 1966. For in-sample estimations, Newey and West (1987) t-values are reported in parentheses. For Out-of-sample R^2s, Clark and West (2007) p-values are reported in parentheses.

Panel A: Co-movement in Idiosyncratic skewness

	CIS Loadings					t-statistics				
	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
L1	0.9827	1.0059	0.7507	0.4767	0.487	32.5455	23.073	17.3942	12.9183	16.7406
L2	0.9554	0.9583	0.7339	0.617	0.5184	41.5135	27.4423	20.6645	15.7574	17.3402
L3	0.8522	0.9162	0.5162	0.8556	0.464	44.8728	20.1426	12.9828	20.9947	15.9551
L4	0.9343	0.7449	0.5883	0.6666	0.9053	33.0297	19.9207	13.934	13.6835	20.8337
L5	1.1606	0.6254	0.6903	0.8185	0.6996	33.8377	11.1357	13.6442	11.6913	8.4885

	$Adj.R^2$				
	S1	S2	S3	S4	S5
L1	0.6184	0.4486	0.3159	0.2026	0.2995
L2	0.7251	0.5353	0.3948	0.2747	0.3146
L3	0.755	0.3826	0.2042	0.4024	0.2797
L4	0.6253	0.3774	0.2283	0.2219	0.3987
L5	0.6366	0.1585	0.2209	0.172	0.0981

Panel B: Predictability Results

	CIS	CIS_{high}	$CIS * CIS_{high}$	$Adj.R^2$	R^2_{oos}
Coef.	4.691*	10.443**	-15.755***	0.014	0.0075***
	(1.71)	(2.43)	(-2.71)		(0.0092)

Table A2 Robustness Check using Five Factor Model

This table report results using Fama and French (2015) five factor model estimate firm idiosyncratic skewness. Panel A presents contemporaneous regressions of the form, separately for each portfolio p:

$$iskew_{p,t} = \alpha + \beta CIS_t + \epsilon_t$$

where $iskew_{p,t}$ is the equal-weighted average idiosyncratic skewness for portfolio p at month t and CIS_t is the equal-weighted average idiosyncratic skewness across all firms in month t. We divide firms into 5-by-5 size-leverage portfolios. To construct these 25 portfolios, at the end of June of each year t, we form leverage quintile portfolios across all firms based on the leverage of last fiscal year end. The five size-sorted portfolios are formed in the same way but based on the NYSE breakpoints. S1 (S5) represents smallest (largest) firms portfolio. Similarly, L1 (L5) represents the lowest (highest) leverage firms portfolio. The sample period is from July 1965 to December 2019. Panel B reports predictability results. The first four columns report in-sample estimation and the last column reports the out-of-sample R^2 with out-of-sample period starting from January 1986. For in-sample estimations, Newey and West (1987) t-values are reported in parentheses. For out-of-sample R^2s, Clark and West (2007) p-values are reported in parentheses.

Panel A: Co-movement in Idiosyncratic skewness

	CIS Loadings					t-statistics				
	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
L1	0.9982	0.8831	0.6584	0.4161	0.4707	34.7865	18.7904	14.9075	12.02	16.0345
L2	1.0084	0.8755	0.8026	0.6485	0.5634	43.8159	21.6826	21.5843	17.6558	15.8423
L3	0.8785	0.8586	0.6164	0.9252	0.3611	41.3735	17.3695	16.0097	21.4098	10.0678
L4	0.8701	0.7195	0.5624	0.4946	0.7227	32.5942	18.153	12.7049	9.951	16.5077
L5	1.0122	0.5281	0.6657	0.9323	0.6817	29.0201	8.9059	11.3281	12.5818	7.9842

	$Adj.R^2$				
	S1	S2	S3	S4	S5
L1	0.6493	0.3503	0.2531	0.1801	0.2817
L2	0.7461	0.4181	0.4159	0.3224	0.2768
L3	0.7237	0.3153	0.2811	0.4119	0.1332
L4	0.6191	0.3347	0.1972	0.1305	0.2937
L5	0.563	0.1071	0.1632	0.1941	0.0877

Panel B: Predictability Results

	CIS	CIS_{high}	$CIS * CIS_{high}$	$Adj.R^2$	R^2_{oos}
Coef.	10.018*	25.978**	-45.534**	0.040	0.0139***
	(1.93)	(1.97)	(-2.20)		(0.0056)

Table A3 Robustness Check using Statistical Factor Model

This table report results using five principal components to estimate firm idiosyncratic skewness. Panel A presents contemporaneous regressions of the form, separately for each portfolio p:

$$iskew_{p,t} = \alpha + \beta CIS_t + \epsilon_t$$

where $iskew_{p,t}$ is the equal-weighted average idiosyncratic skewness for portfolio p at month t and CIS_t is the equal-weighted average idiosyncratic skewness across all firms in month t. We divide firms into 5-by-5 size-leverage portfolios. To construct these 25 portfolios, at the end of June of each year t, we form leverage quintile portfolios across all firms based on the leverage of last fiscal year end. The five size-sorted portfolios are formed in the same way but based on the NYSE breakpoints. S1 (S5) represents smallest (largest) firms portfolio. Similarly, L1 (L5) represents the lowest (highest) leverage firms portfolio. The sample period is from July 1965 to December 2019. Panel B reports predictability results. The first four columns report in-sample estimation and the last column reports the out-of-sample R^2 with out-of-sample period starting from January 1966. For in-sample estimations, Newey and West (1987) t-values are reported in parentheses. For Out-of-sample R^2s, Clark and West (2007) p-values are reported in parentheses.

Panel A: Co-movement in Idiosyncratic skewness

	CIS Loadings					t-statistics				
	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
L1	0.9914	0.9155	0.9556	0.4801	0.2068	24.4586	18.2329	18.0035	13.368	6.2644
L2	0.9051	0.8134	0.6982	0.6157	0.6273	26.0017	16.6134	16.0428	13.6038	15.0169
L3	1.1554	0.8288	0.7443	0.7376	0.4071	30.2486	17.3976	15.3862	16.4866	11.1605
L4	1.0534	1.0402	0.7506	0.9773	1.1395	30.9154	24.8249	17.9761	19.6358	19.9137
L5	1.4059	1.2404	1.4956	1.0048	1.3596	28.5635	21.4611	24.7946	12.8618	17.664

	$Adj.R^2$				
	S1	S2	S3	S4	S5
L1	0.5069	0.3632	0.3574	0.2342	0.0618
L2	0.5375	0.3213	0.3062	0.2406	0.2787
L3	0.6114	0.3418	0.2886	0.3179	0.1754
L4	0.6217	0.5143	0.3567	0.3983	0.4051
L5	0.5838	0.4417	0.5137	0.2206	0.3487

Panel B: Predictability Results

	CIS	CIS_{high}	$CIS * CIS_{high}$	$Adj.R^2$	R^2_{oos}
Coef.	10.838**	10.684***	-21.059***	0.013	0.0053**
	(2.30)	(3.06)	(-3.23)		(0.0336)

Additional Tables

Table A4 In-Sample Results (Flexible Control Variables)

This table reports results of in-sample comparisons with other popular predictors having the same flexibility as **CIS**. **CIS** is the average idiosyncratic skewness across all firms in a specific month. $\mathbf{CIS_{high}}$ is a dummy variable equal to 1 if CIS is higher than the CIS sample mean and 0 otherwise, and $\mathbf{CIS{*}CIS_{high}}$ is the interaction term between **CIS** and $\mathbf{CIS_{high}}$. X is a vector of control variables which are described as follows. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **LTR** is the return on long-term government bonds. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. Newey and West (1987) t-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample covers the period from January 1931 to December 2019. We use the first 30 years data to estimate the first CIS median. As a result, the estimation period is from January 1961 to December 2019.

Predictor	$\hat{\beta}$	$Adj.R^2$	Predictor	$\hat{\beta}$	$Adj.R^2$	Predictor	$\hat{\beta}$	$Adj.R^2$
CIS	9.915***	0.018	BM	0.566	0.003	TMS	46.905**	0.005
	(2.62)			(0.50)			(2.36)	
CIS_{high}	9.159***		BM_{high}	-4.477*		TMS_{high}	1.506**	
	(2.60)			(-1.95)			(2.50)	
$CIS * CIS_{high}$	-16.710***		$BM * BM_{high}$	4.419*		$TMS * TMS_{high}$	-70.590**	
	(-2.95)			(1.66)			(-2.34)	
DP	0.356	0.002	$NTIS$	8.801	0.002	DFY	-28.959	-0.001
	(0.74)			(0.50)			(-0.20)	
DP_{high}	25.496		$NTIS_{high}$	0.618		DFY_{high}	-0.735	
	(1.44)			(0.51)			(-0.81)	
$DP * DP_{high}$	8.481		$NTIS * NTIS_{high}$	-47.811		$DFY * DFY_{high}$	91.404	
	(1.44)			(-1.23)			(0.68)	
DY	0.271	-0.001	TBL	-59.780**	0.006	DFR	36.736	0.006
	(0.48)			(-2.35)			(1.64)	
DY_{high}	9.468		TBL_{high}	0.154		DFR_{high}	0.394	
	(0.58)			(0.48)			(0.69)	
$DY * DY_{high}$	3.022		$TBL * TBL_{high}$	45.683*		$DFR * DFR_{high}$	-60.635***	
	(0.55)			(1.79)			(-2.80)	
EP	0.192	-0.004	LTY	-73.215***	0.002	$INFL$	201.588**	0.015
	(0.21)			(-2.60)			(2.34)	
EP_{high}	-0.788		LTY_{high}	-2.357***		$INFL_{high}$	-0.287	
	(-0.23)			(-2.60)			(-0.83)	
$EP * EP_{high}$	-0.352		$LTY * LTY_{high}$	69.158**		$INFL * INFL_{high}$	-318.911***	
	(-0.24)			(2.46)			(-3.30)	
DE	-0.789	0.001	LTR	21.908	0.008	$SKEW$	-7.720	-0.001
	(-0.91)			(1.62)			(-1.04)	
DE_{high}	1.315		LTR_{high}	0.117		$SKEW_{high}$	0.407	
	(1.31)			(0.33)			(0.68)	
$DE * DE_{high}$	2.368***		$LTR * LTR_{high}$	-11.461		$SKEW * SKEW_{high}$	5.353	
	(2.75)			(-0.70)			(0.44)	
$SVAR$	-73.881	0.007						
	(-0.20)							
$SVAR_{high}$	0.461							
	(1.27)							
$SVAR * SVAR_{high}$	-40.751							
	(-0.11)							

Table A5 In-Sample Results (Quarterly Horizon with Non-Overlapping Returns)

This table reports in-sample results of quarterly horizon with non-overlapping returns. **CIS** is the average idiosyncratic skewness across all firms in a specific month. $\mathbf{CIS_{high}}$ is a dummy variable equal to 1 if CIS is higher than the CIS sample mean and 0 otherwise, and $\mathbf{CIS*CIS_{high}}$ is the interaction term between **CIS** and $\mathbf{CIS_{high}}$. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **LTR** is the return on long-term government bonds. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. Newey and West (1987) t-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample covers the period from January 1931 to December 2019. We use the first 30 years data to estimate the first CIS median. As a result, the estimation period is from Q1 1961 to Q4 2019.

Predictor	$\hat{\beta}$	$Adj.R^2$	Predictor	$\hat{\beta}$	$Adj.R^2$	Predictor	$\hat{\beta}$	$Adj.R^2$
CIS	26.062**	0.031	DE	1.684	-0.000	LTR	50.357***	0.020
	(2.52)			(1.45)			(4.38)	
CIS_{high}	24.164**		$SVAR$	70.902	-0.004	TMS	59.340**	0.006
	(2.55)			(0.22)			(1.99)	
$CIS * CIS_{high}$	-44.315***		BM	0.868	-0.004	DFY	162.945	0.003
	(-2.92)			(0.59)			(1.32)	
DP	1.676*	0.002	$NTIS$	-22.937	-0.001	DFR	22.857	-0.002
	(1.65)			(-0.70)			(0.73)	
DY	1.748*	0.003	TBL	-23.252**	0.004	$INFL$	-145.516	-0.000
	(1.67)			(-2.28)			(-1.02)	
EP	0.510	-0.004	LTY	-14.496	-0.002	$SKEW$	14.758	-0.001
	(0.41)			(-1.25)			(0.83)	

Table A6 Out-of-Sample Performance (Quarterly Horizon with Non-Overlapping Returns)

This table reports out-of-sample R^2 of each predictor with quarterly horizon and non-overlapping returns. **CIS** is the average idiosyncratic skewness across all firms in a specific month. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **LTR** is the return on long-term government bonds. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. For CIS, we use equation (3) to predict future returns. For predictors other than CIS, we use univariate predictive regression. Panel A reports the results without any prediction restrictions, whereas Panel B reports the results with non-negative equity premium predictions following Campbell and Thompson (2008). Clark and West (2007) p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from Q1 1931 to Q4 2019.

Panel A: No Restriction

Out of Sample Starts: 1956						Out of Sample Starts: 1966					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	-0.0224	*BM*	-0.0223	*TMS*	-0.0102	*CIS*	0.0038**	*BM*	-0.0246	*TMS*	-0.0099
	(0.8894)		(0.9321)		(0.8877)		(0.0429)		(0.9151)		(0.8417)
DP	-0.0008	*NTIS*	-0.0130	*DFY*	-0.0178	*DP*	0.0003**	*NTIS*	-0.0133	*DFY*	-0.0180
	(0.9747)		(0.8769)		(0.5713)		(0.0203)		(0.8785)		(0.7654)
DY	-0.0069	*TBL*	-0.0093	*DFR*	-0.0021	*DY*	-0.0032	*TBL*	-0.0076	*DFR*	-0.0020
	(0.9759)		(0.9366)		(0.6315)		(0.9880)		(0.9526)		(0.6077)
EP	-0.0132	*LTY*	-0.0075	*INFL*	0.0022	*EP*	-0.0024	*LTY*	-0.0027	*INFL*	0.0034*
	(0.8311)		(0.8845)		(0.1059)		(0.9287)		(0.9376)		(0.0670)
DE	-0.0040	*LTR*	0.0033**	*SKEW*	-0.0223	*DE*	-0.0028	*LTR*	0.0032**	*SKEW*	-0.0105
	(0.8291)		(0.0193)		(0.9506)		(0.7121)		(0.0247)		(0.8317)

Out of Sample Starts: 1976						Out of Sample Starts: 1986					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0138**	*BM*	-0.0258	*TMS*	-0.0024	*CIS*	0.0179*	*BM*	-0.0299	*TMS*	-0.0030
	(0.0411)		(0.9064)		(0.9532)		(0.0618)		(0.8639)		(0.9283)
DP	0.0014**	*NTIS*	-0.0144	*DFY*	-0.0009	*DP*	-0.0001	*NTIS*	-0.0169	*DFY*	-0.0024
	(0.0163)		(0.8614)		(0.8390)		(0.9758)		(0.7905)		(0.6697)
DY	-0.0016	*TBL*	-0.0069	*DFR*	-0.0021	*DY*	-0.0038	*TBL*	-0.0072	*DFR*	-0.0020
	(0.9908)		(0.9591)		(0.6045)		(0.9853)		(0.9494)		(0.5898)
EP	-0.0047	*LTY*	-0.0040	*INFL*	0.0035*	*EP*	-0.0029	*LTY*	-0.0028	*INFL*	0.0035*
	(0.8930)		(0.9255)		(0.0682)		(0.8933)		(0.9376)		(0.0742)
DE	-0.0039	*LTR*	0.0030**	*SKEW*	-0.0061	*DE*	-0.0027	*LTR*	0.0046**	*SKEW*	-0.0043
	(0.8590)		(0.0270)		(0.6572)		(0.7719)		(0.0179)		(0.6806)

Out of Sample Starts: 1996					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0231*	*BM*	-0.0322	*TMS*	0.0020**
	(0.0680)		(0.8363)		(0.0305)
DP	-0.0025	*NTIS*	-0.0126	*DFY*	0.0020
	(0.9556)		(0.8609)		(0.1298)
DY	-0.0070	*TBL*	-0.0001	*DFR*	-0.0020
	(0.9686)		(0.9772)		(0.5832)
EP	-0.0060	*LTY*	-0.0036	*INFL*	0.0040*
	(0.7927)		(0.9307)		(0.0630)
DE	-0.0038	*LTR*	0.0048**	*SKEW*	-0.0028
	(0.9167)		(0.0174)		(0.5506)

Panel B: Non-Negative Prediction

Out of Sample Starts: 1956						Out of Sample Starts: 1966					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	-0.0203	*BM*	-0.0127	*TMS*	-0.0051	*CIS*	0.0061*	*BM*	-0.0142	*TMS*	-0.0064
	(0.8285)		(0.9207)		(0.8846)		(0.0650)		(0.9047)		(0.8527)
DP	0.0017**	*NTIS*	-0.0125	*DFY*	-0.0056	*DP*	0.0030**	*NTIS*	-0.0128	*DFY*	-0.0072
	(0.0155)		(0.8477)		(0.6449)		(0.0114)		(0.8493)		(0.5211)
DY	-0.0022	*TBL*	-0.0044	*DFR*	-0.0021	*DY*	0.0018***	*TBL*	-0.0023	*DFR*	-0.0021
	(0.9827)		(0.9147)		(0.6573)		(0.0068)		(0.9468)		(0.6314)
EP	-0.0081	*LTY*	-0.0010	*INFL*	0.0023	*EP*	0.0030**	*LTY*	0.0044**	*INFL*	0.0035*
	(0.9054)		(0.9163)		(0.1008)		(0.0187)		(0.0201)		(0.0633)
DE	-0.0040	*LTR*	0.0037**	*SKEW*	-0.0089	*DE*	-0.0028	*LTR*	0.0036**	*SKEW*	-0.0065
	(0.8291)		(0.0222)		(0.8021)		(0.7121)		(0.0280)		(0.7875)

Out of Sample Starts: 1976						Out of Sample Starts: 1986					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0161**	*BM*	-0.0152	*TMS*	-0.0000**	*CIS*	0.0164*	*BM*	-0.0187	*TMS*	-0.0015
	(0.0402)		(0.8921)		(0.0460)		(0.0671)		(0.8440)		(0.9219)
DP	0.0041***	*NTIS*	-0.0139	*DFY*	-0.0003	*DP*	0.0028**	*NTIS*	-0.0158	*DFY*	-0.0024
	(0.0086)		(0.8280)		(0.8459)		(0.0138)		(0.7799)		(0.6704)
DY	0.0035**	*TBL*	-0.0014	*DFR*	-0.0021	*DY*	0.0016***	*TBL*	-0.0023	*DFR*	-0.0021
	(0.0047)		(0.9577)		(0.6279)		(0.0082)		(0.9418)		(0.6118)
EP	0.0010**	*LTY*	0.0034**	*INFL*	0.0036*	*EP*	0.0031**	*LTY*	0.0050**	*INFL*	0.0036*
	(0.0343)		(0.0289)		(0.0644)		(0.0286)		(0.0194)		(0.0713)
DE	-0.0039	*LTR*	0.0035**	*SKEW*	-0.0053	*DE*	-0.0027	*LTR*	0.0051**	*SKEW*	-0.0044
	(0.8590)		(0.0307)		(0.7372)		(0.7719)		(0.0201)		(0.7756)

Out of Sample Starts: 1996					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0211*	*BM*	-0.0206	*TMS*	0.0025**
	(0.0741)		(0.8088)		(0.0358)
DP	0.0005**	*NTIS*	-0.0118	*DFY*	0.0020
	(0.0291)		(0.8501)		(0.1298)
DY	-0.0014	*TBL*	0.0034**	*DFR*	-0.0021
	(0.9781)		(0.0197)		(0.6046)
EP	0.0002*	*LTY*	0.0044**	*INFL*	0.0041*
	(0.0837)		(0.0241)		(0.0603)
DE	-0.0038	*LTR*	0.0053**	*SKEW*	-0.0033
	(0.9167)		(0.0195)		(0.6740)

Table A7 Out-of-Sample Performance (More Flexibility for Popular Predictors)

This table reports out-of-sample R^2s of each predictor. For a predict **X**, we use the following predictive regression to make forecasts:

$$r_{m,t+1} = \alpha + \beta_1 X_t + \beta_2 X_{high,t} + \beta_3 X_t * X_{high,t} + \epsilon_{t+1}.$$

CIS is the average idiosyncratic skewness across all firms in a specific month. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. Clark and West (2007) p-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1931 to December 2019. Panel A reports the out-of-sample performance without any restrictions whereas Panel B reports the results with non-negative equity premium prediction (Campbell et al., 2008).

Panel A: No Restriction

Out of Sample Starts: 1956						Out of Sample Starts: 1966					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0040**	*BM*	-0.0150	*TMS*	0.0047**	*CIS*	0.0106***	*BM*	-0.0144	*TMS*	0.0040**
	(0.0166)		(0.8277)		(0.0191)		(0.0057)		(0.7265)		(0.0308)
DP	-0.0084	*NTIS*	-0.0345	*DFY*	-0.0048	*DP*	-0.0088	*NTIS*	-0.0370	*DFY*	0.0001
	(0.7768)		(0.7240)		(0.6760)		(0.7587)		(0.7055)		(0.1898)
DY	-0.0084	*TBL*	-0.0025	*DFR*	-0.0041	*DY*	-0.0068	*TBL*	-0.0001	*DFR*	-0.0017
	(0.8335)		(0.9862)		(0.7216)		(0.8695)		(0.9656)		(0.7642)
EP	-0.0219	*LTY*	-0.0094	*INFL*	0.0100***	*EP*	-0.0192	*LTY*	-0.0042	*INFL*	0.0141***
	(0.6696)		(0.9477)		(0.0020)		(0.6530)		(0.8999)		(0.0012)
DE	-0.0109	*LTR*	0.0014**	*SKEW*	-0.0101	*DE*	-0.0086	*LTR*	0.0024**	*SKEW*	-0.0070
	(0.5525)		(0.0423)		(0.7496)		(0.5037)		(0.0361)		(0.7410)

Out of Sample Starts: 1976						Out of Sample Starts: 1986					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0149***	*BM*	-0.0230	*TMS*	-0.0061	*CIS*	0.0194***	*BM*	-0.0123	*TMS*	-0.0072
	(0.0062)		(0.5165)		(0.7841)		(0.0047)		(0.7247)		(0.5317)
DP	-0.0185	*NTIS*	-0.0475	*DFY*	-0.0049	*DP*	-0.0255	*NTIS*	-0.0516	*DFY*	-0.0116
	(0.5463)		(0.6415)		(0.5893)		(0.6232)		(0.7648)		(0.7231)
DY	-0.0175	*TBL*	-0.0100	*DFR*	0.0006	*DY*	-0.0231	*TBL*	0.0008	*DFR*	0.0031
	(0.5473)		(0.7427)		(0.2349)		(0.5295)		(0.1942)		(0.2166)
EP	-0.0215	*LTY*	-0.0100	*INFL*	0.0129***	*EP*	-0.0216	*LTY*	0.0008	*INFL*	0.0116**
	(0.6535)		(0.6077)		(0.0032)		(0.6851)		(0.1865)		(0.0109)
DE	-0.0102	*LTR*	-0.0031	*SKEW*	-0.0141	*DE*	-0.0112	*LTR*	-0.0031	*SKEW*	-0.0169
	(0.6583)		(0.9014)		(0.5815)		(0.8043)		(0.8046)		(0.7220)

Out of Sample Starts: 1996					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0256***	*BM*	-0.0085	*TMS*	-0.0046
	(0.0055)		(0.7782)		(0.6177)
DP	-0.0265	*NTIS*	-0.0544	*DFY*	-0.0157
	(0.7384)		(0.9491)		(0.8187)
DY	-0.0285	*TBL*	0.0045	*DFR*	0.0063
	(0.7689)		(0.1210)		(0.2148)
EP	-0.0281	*LTY*	0.0050*	*INFL*	0.0076*
	(0.5476)		(0.0961)		(0.0605)
DE	-0.0149	*LTR*	-0.0065	*SKEW*	-0.0113
	(0.8800)		(0.6674)		(0.5655)

Panel B: Non-Negative Prediction

Out of Sample Starts: 1956						Out of Sample Starts: 1966					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0047**	*BM*	-0.0145	*TMS*	0.0069**	*CIS*	0.0113***	*BM*	-0.0143	*TMS*	0.0064**
	(0.0165)		(0.8177)		(0.0147)		(0.0044)		(0.7280)		(0.0252)
DP	-0.0003	*NTIS*	-0.0336	*DFY*	-0.0035	*DP*	0.0002	*NTIS*	-0.0362	*DFY*	0.0003
	(0.9041)		(0.7313)		(0.7027)		(0.1028)		(0.7145)		(0.1875)
DY	-0.0016	*TBL*	0.0062***	*DFR*	-0.0011	*DY*	0.0008*	*TBL*	0.0071**	*DFR*	0.0012
	(0.9001)		(0.0064)		(0.7735)		(0.0696)		(0.0162)		(0.1580)
EP	-0.0069	*LTY*	0.0033**	*INFL*	0.0112***	*EP*	-0.0031	*LTY*	0.0052**	*INFL*	0.0152***
	(0.8250)		(0.0177)		(0.0013)		(0.8303)		(0.0301)		(0.0007)
DE	-0.0065	*LTR*	0.0019*	*SKEW*	-0.0085	*DE*	-0.0037	*LTR*	0.0030*	*SKEW*	-0.0056
	(0.5360)		(0.0707)		(0.7762)		(0.6317)		(0.0577)		(0.7673)

Out of Sample Starts: 1976						Out of Sample Starts: 1986					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0152***	*BM*	-0.0229	*TMS*	-0.0028	*CIS*	0.0197***	*BM*	-0.0121	*TMS*	-0.0069
	(0.0038)		(0.5143)		(0.7918)		(0.0029)		(0.7208)		(0.5326)
DP	-0.0069	*NTIS*	-0.0470	*DFY*	-0.0048	*DP*	-0.0106	*NTIS*	-0.0515	*DFY*	-0.0116
	(0.6437)		(0.6468)		(0.5921)		(0.5614)		(0.7636)		(0.7231)
DY	-0.0073	*TBL*	-0.0027	*DFR*	0.0015	*DY*	-0.0106	*TBL*	0.0008	*DFR*	0.0039
	(0.6681)		(0.7969)		(0.1711)		(0.5749)		(0.1942)		(0.1314)
EP	-0.0008	*LTY*	-0.0035	*INFL*	0.0135***	*EP*	0.0052*	*LTY*	0.0008	*INFL*	0.0120**
	(0.8555)		(0.7385)		(0.0028)		(0.0855)		(0.1865)		(0.0105)
DE	-0.0054	*LTR*	-0.0010	*SKEW*	-0.0118	*DE*	-0.0069	*LTR*	-0.0051	*SKEW*	-0.0157
	(0.5307)		(0.8511)		(0.5193)		(0.7217)		(0.6322)		(0.7042)

Out of Sample Starts: 1996					
Predictor	R^2_{oos}	Predictor	R^2_{oos}	Predictor	R^2_{oos}
CIS	0.0259***	*BM*	-0.0085	*TMS*	-0.0041
	(0.0031)		(0.7782)		(0.6206)
DP	-0.0142	*NTIS*	-0.0544	*DFY*	-0.0157
	(0.6085)		(0.9491)		(0.8187)
DY	-0.0152	*TBL*	0.0045	*DFR*	0.0069
	(0.6209)		(0.1210)		(0.1151)
EP	0.0004	*LTY*	0.0050*	*INFL*	0.0082*
	(0.2149)		(0.0961)		(0.0580)
DE	-0.0090	*LTR*	-0.0072	*SKEW*	-0.0102
	(0.8656)		(0.5154)		(0.5379)

Table A8 Out-of-Sample Encompassing Test (Flexible Control Variables)

This table reports results of out-of-sample encompassing tests. $\hat{\lambda}_1$ is the estimated weight on forecasts based on our CIS model, equation (3), in a combination forecast, which is a convex combination of forecasts based on CIS and another popular predictor. Similarly, $\hat{\lambda}_2$ is the estimated weight on forecasts based on a popular predictor in a combination forecast, which is a convex combination of forecasts based on CIS and another popular predictor. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **LTR** is the return on long-term government bonds. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. p-values based on Harvey et al. (1998) statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1931 to December 2019.

	Out of Sample Starts: 1956		Out of Sample Starts: 1966		Out of Sample Starts: 1976		Out of Sample Starts: 1986		Out of Sample Starts: 1996	
Predictor	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_1$	$\hat{\lambda}_2$
DP	0.6575***	0.3425**	0.7698***	0.2302	0.9225***	0.0775	1.0000***	0.0000	1.0000***	0.0000
DY	0.6636***	0.3364**	0.7359***	0.2641*	0.9083***	0.0917	1.0000***	0.0000	1.0000***	0.0000
EP	0.7664***	0.2336	0.8556***	0.1444	0.8935***	0.1065	1.0000***	0.0000	1.0000***	0.0000
DE	0.8112***	0.1888	0.8824***	0.1176	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
SVAR	0.9553***	0.0447	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
BM	0.6538***	0.3462**	0.7579***	0.2421	0.8412***	0.1588	1.0000***	0.0000	1.0000***	0.0000
NTIS	0.8324***	0.1676	0.9272***	0.0728	0.9888***	0.0112	1.0000***	0.0000	1.0000***	0.0000
TBL	0.5645***	0.4355***	0.6714***	0.3286	1.0000***	0.0000	1.0000***	0.0000	1.0000**	0.0000
LTY	0.6131***	0.3869***	0.7036***	0.2964	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
LTR	0.5427***	0.4573**	0.6364***	0.3636*	0.7899***	0.2101	0.9397***	0.0603	1.0000***	0.0000
TMS	0.4862**	0.5138**	0.6621**	0.3379	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
DFY	0.6674***	0.3326*	0.7106***	0.2894	0.8843***	0.1157	1.0000***	0.0000	1.0000***	0.0000
DFR	0.6497***	0.3503*	0.7385***	0.2615	0.7807**	0.2193	0.8314**	0.1686	0.8387*	0.1613
INFL	0.3967**	0.6033***	0.4378**	0.5622**	0.5363**	0.4637**	0.6453**	0.3547	0.8425**	0.1575
SKEW	0.7019***	0.2981*	0.8092***	0.1908	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000

Table A9 Utility Gain and Sharpe Ratio (Flexible Control Variables)

This table reports out-of-sample annualized certainty equivalent return (CER) gain (in percentage), relative to prevailing mean forecasts, for a mean-variance investor with relative risk aversion coefficient of γ. Annualized Sharpe ratio is also reported. The mean-variance investor allocates between stock and risk-free bonds using a predictive regression excess return forecast based on the predictor variable shown in the first column. We require the proportion of wealth invested in the stock market to lie between 0 and 1.5. For robustness purpose, we consider initial in-sample estimation periods of 10, 20, and 30 years. **DP** is the log dividend-price ratio, calculated as the difference between the log of dividends and the log of prices. **DY** is the log dividend yield, calculated as the difference between the log of dividends and the log of *lagged* prices. **EP** is the log earnings-price ratio, calculated as the difference between the log of earnings and the log of the prices. **DE** is the log dividend-payout ratio, calculated as the difference between the log of dividends and the log of earnings. **SVAR** is the stock variance, computed as the sum of squared daily returns on the S&P 500. **BM** is the book-to-market ratio of the Dow Jones Industrial Average. **NTIS** is the net equity expansion, calculated as the ratio of 12-month moving sums of net issues by NYSE listed stocks divided by the total end-of-year market capitalization of NYSE stocks. **TBL** is the interest rate on a three-month Treasury bill. **LTY** is the long-term government bond yield. **LTR** is the return on long-term government bonds. **TMS** is the term spread, calculated as the long-term yield minus the Treasury bill rate. **DFY** is the default yield spread, computed as the difference between Moddy's BAA- and AAA-rated corporate bond yields. **DFR** is the default return spread, calculated as the difference between long-term corporate bond return and the long-term government bond return. **INFL** is the inflation. **SKEW** is the average total skewness calculated using daily return within a month. The sample period is from January 1931 to December 2019.

	Out of Sample Starts: 1956				Out of Sample Starts: 1966				Out of Sample Starts: 1976				Out of Sample Starts: 1986				Out of Sample Starts: 1996			
Predictor	$\gamma = 3$	$\gamma = 5$	$\gamma = 7$	SR	$\gamma = 3$	$\gamma = 5$	$\gamma = 7$	SR	$\gamma = 3$	$\gamma = 5$	$\gamma = 7$	SR	$\gamma = 3$	$\gamma = 5$	$\gamma = 7$	SR	$\gamma = 3$	$\gamma = 5$	$\gamma = 7$	SR
CIS	1.96%	1.79%	1.16%	0.47	2.32%	2.06%	1.47%	0.42	2.09%	1.86%	1.15%	0.54	2.34%	2.12%	1.29%	0.57	3.29%	3.52%	1.92%	0.55
DP	-1.13%	0.02%	0.49%	0.24	-1.08%	0.36%	0.58%	0.17	-2.17%	-0.55%	-0.18%	0.27	-2.85%	-0.76%	-0.26%	0.21	-3.54%	-0.52%	0.04%	0.10
DY	-0.51%	0.63%	0.71%	0.28	-0.33%	1.04%	1.08%	0.23	-1.79%	-0.29%	0.01%	0.30	-2.66%	-0.61%	-0.16%	0.23	-3.44%	-0.41%	0.11%	0.11
EP	0.48%	0.51%	0.49%	0.32	1.01%	0.94%	0.82%	0.30	1.46%	1.62%	1.28%	0.52	2.13%	2.70%	2.27%	0.76	1.54%	2.70%	2.33%	0.64
DE	0.55%	-0.05%	-0.51%	0.32	0.65%	-0.15%	-0.51%	0.22	-0.53%	-0.69%	-0.64%	0.32	-0.77%	-0.94%	-0.87%	0.33	-0.90%	-1.08%	-0.97%	0.25
$SVAR$	-0.30%	-0.61%	-0.91%	0.26	-0.34%	-0.59%	-0.91%	0.20	-0.44%	-0.84%	-1.28%	0.30	-0.49%	-1.04%	-1.62%	0.31	-0.61%	-0.97%	-1.70%	0.28
BM	-1.42%	-1.09%	-1.32%	0.22	-0.74%	-0.78%	-1.48%	0.21	-1.37%	-1.23%	-1.68%	0.29	-1.78%	-0.60%	-0.69%	0.27	-1.07%	0.26%	-0.18%	0.29
$NTIS$	-0.32%	-0.80%	-0.99%	0.35	0.25%	-0.53%	-1.08%	0.33	-0.07%	-0.79%	-1.63%	0.42	-0.31%	-1.27%	-2.24%	0.38	0.07%	-0.74%	-2.22%	0.30
TBL	1.52%	1.34%	1.25%	0.38	2.44%	1.76%	1.29%	0.35	0.39%	-0.16%	-0.26%	0.38	1.16%	0.20%	-0.05%	0.43	1.78%	0.61%	0.18%	0.43
LTY	0.34%	1.15%	1.30%	0.37	1.44%	1.82%	1.56%	0.35	-0.38%	0.22%	0.30%	0.40	0.37%	0.81%	0.76%	0.46	0.97%	1.66%	1.46%	0.48
LTR	1.17%	0.81%	0.39%	0.40	1.45%	1.10%	0.57%	0.36	0.83%	0.59%	0.11%	0.45	0.07%	0.03%	-0.36%	0.42	-1.19%	-0.53%	-0.99%	0.34
TMS	1.90%	1.35%	1.10%	0.43	2.34%	1.61%	1.05%	0.39	0.62%	-0.14%	-0.41%	0.42	-0.56%	-1.15%	-1.22%	0.36	-0.89%	-0.47%	-0.43%	0.33
DFY	-0.09%	-0.28%	-0.53%	0.29	0.16%	-0.04%	-0.21%	0.22	-0.82%	-0.90%	-0.92%	0.30	-1.57%	-1.55%	-1.47%	0.25	-2.42%	-2.21%	-2.08%	0.18
DFR	1.06%	1.24%	0.93%	0.41	1.47%	1.71%	1.30%	0.38	1.30%	1.77%	1.35%	0.54	1.72%	2.36%	1.80%	0.58	2.63%	3.38%	2.56%	0.57
$INFL$	3.04%	2.22%	0.91%	0.50	3.53%	2.44%	0.97%	0.45	2.92%	1.99%	0.55%	0.53	2.78%	1.82%	0.17%	0.54	1.99%	1.20%	-0.90%	0.45
$SKEW$	0.04%	-0.19%	-0.20%	0.29	0.36%	-0.04%	-0.17%	0.24	-1.30%	-1.66%	-1.32%	0.29	-1.81%	-2.35%	-1.90%	0.26	-0.37%	-0.00%	-0.22%	0.34
buy-and-hold	1.10%	0.81%	-0.87%	0.43	1.62%	0.86%	-1.42%	0.39	0.93%	0.81%	-0.92%	0.51	0.86%	1.09%	-0.60%	0.52	1.09%	1.71%	-0.21%	0.50
prevailing mean	0.00%	0.00%	0.00%	0.35	0.00%	0.00%	0.00%	0.28	0.00%	0.00%	0.00%	0.41	0.00%	0.00%	0.00%	0.42	0.00%	0.00%	0.00%	0.37

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