Idiosyncratic Skewness Co-movement and Aggregate Stock Returns

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 non-linear predictor of future market excess returns and it outperforms a battery of existing 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. Within a standard valuation framework, we show that CIS predictive power stems from the discount rate channel.

Keywords: Asset Pricing, Equity Premium Predictability, Idiosyncratic Skewness, Non-linear models

JEL Classification: G11, G12, G17, G41.

1 Introduction

The predictability 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 economically interpretable and statistically reliable predictors.[1]

Theoretical as well as empirical contributions illustrate the importance of idiosyncratic risk for subsequent returns.[2] While the literature on the predictive power of idiosyncratic volatility has investigated both the cross-section of individual asset returns and the time-series of aggregate equity returns, the research on idiosyncratic skewness has focused exclusively on cross-sectional predictability.[3] Given the conceptual motivations and the scope of the extant empirical literature, it seems natural to analyze whether idiosyncratic skewness is related to future returns at the market level.

In this paper, we show empirically 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. This predictive relation is not detected within a linear regression framework while it is well-captured by a quadratic specification.[4]

We, first, provide in-sample evidences 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 or by finite sample biases.[5] When CIS is low, a one-standard deviation increase

[1]Recent work includes Jondeau et al. (2019), Pyun (2019), Atanasov et al. (2020), Chang et al. (2021), Huang et al. (2021) among others.

[2]Barberis and Huang (2001) theoretically motivate why idiosyncratic risk affects investors with loss aversion utility. Mitton and Vorkink (2007), in a rational model where investors have heterogeneous preferences for skewness, predict lower expected returns for assets with larger idiosyncratic skewness.

[3]See Boyer et al. (2010), Conrad et al. (2013), Boyer and Vorkink (2014) and Amaya et al. (2015) for the cross-section of individual stock returns, Bali and Murray (2013) and Byun and Kim (2016) for individual option returns.

[4]Similarly, Adrian et al. (2019) find that the VIX predicts market returns through a quadratic relation but not within a linear one.

[5]As detailed in the empirical sections and in the Appendix: Bootstrap Procedure, we use extensive

in CIS translates into a 0.86% (2.22%) *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 0.28% (0.75%) in the next month (quarter). The in-sample adjusted R^2 is around 1.80% (3.10%) at the monthly (quarterly) frequency, which is substantially higher than for a host of predictors previously proposed in the literature. The predictive power of CIS remains after controlling for 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 monthly, quarterly, and semi-annual horizons, the CIS model generates positive and significant OOS R^2s which compare rather favorably with the forecasting performance of the 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 range 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) and rebalancing monthly 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 consistently larger across out-of-sample periods than those generated by other predictors, with sporadic exceptions. Strategies based on CIS forecasts generate similar or lower transaction costs, compared to other strategies with

bootstrap simulations to correct biases in OLS estimates (see, e.g., Stambaugh (1999)) and make statistical inferences.

similar performance.

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 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,[6] 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.

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 non-spurious and robust return predictability exists. In particular, we add to the literature that links idiosyncratic risk and subsequent returns, as well as to the literature that documents non-linear predictive relations.[7] As mentioned earlier, a large literature examines the predictive power of idiosyncratic skewness for the cross-section of individual returns. Recently, Jondeau et al. (2019) show that average *total* skewness is a powerful linear predictor of market-level returns but do not consider idiosyncratic skewness. To the best of our knowledge, our paper is the first that documents a strong and non-linear predictive relation between

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

[7]Among papers that investigate non-linear equity premium predictability, our paper is 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.

idiosyncratic skewness and market returns. We show that the predictive ability of CIS holds, in and out-of-sample, after controlling for the average total skewness measure of Jondeau et al. (2019) and several alternative idiosyncratic risk proxies. The out-of-sample verification suggests that the significance of the non-linear relation is not due to overfitting. From an asset-allocation perspective, the trading strategy based on CIS forecasts generates out-of-sample utility gains that are hardly matched by those produced by a host of alternative predictors.

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 volatility. On the other hand, Bali et al. (2005) object that the predictability is not robust to either sample construction or chosen time period. Maio (2016) shows that cross-sectional return dispersion provides useful information about future excess stock returns both at the aggregate and at the portfolio level. 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. c) showing that CIS is a stronger time-series predictor, statistically as well as from an investor's perspective, than the aggregate idiosyncratic risk measures mentioned above.

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 (i.e., firm returns that are orthogonal to common risk factors). Following Boyer et al. (2010) and Bali et al. (2016), 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[8,9]:

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

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

[9]Boyer et al. (2010) and Bali et al. (2016) advocate the use of a relatively long estimation window. For robustness, we also compute firm-level skewness using rolling windows of four and six years: we find that our baseline results are only marginally affected.

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]

To investigate the existence of co-movements in idiosyncratic skewness, we closely follow the approach adopted by Herskovic et al. (2016) for the analysis of idiosyncratic volatility co-movements. First, we assign firms into five size-sorted and five leverage-sorted portfolios.[10] 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 smallest 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 varia-

[10]Herskovic et al. (2016) focus on size-sorted portfolios. Following van der Heijden et al. (2018) we also consider for leverage sorted portfolios. For robustness, we also sort by Book-to-Market and by industry and confirm the co-movement patterns found with the size sorted and leverage sorted portfolios. The results with the additional sorts are available upon request.

tion 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 the 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, in and out-of-sample. We first describe our sample and variable construction in 3.1. In section 3.2, we present in-sample predictive regressions. We report the out-sample analysis 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 start with the 14 predictors from Welch and Goyal (2008), which we download from Amit Goyal's website[11] and they 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.

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

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

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.
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.

Given the widespread use of these 14 variables in the predictability literature before and, especially, after the Welch and Goyal (2008) study, we label them as *classical* predictors.

Rapach et al. (2010) and Rapach and Zhou (2013) show that the simple equal-weighted average of the above 14 predictors work better than individual ones because of model uncertainty and instability. Following Jondeau et al. (2019), we combine these popular predictors using their first principal component (**ECON$_{\mathbf{PC}}$**) and their equal-weighted average (**ECON$_{\mathbf{AVG}}$**) of these predictors, and compare the predictive power of these variables with that of CIS. 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 0.52. CIS is also moderately correlated with Treasury bond rate (TBL), net equity expansion (NTIS), and the average of the 14 economic variables (ECON$_{AVG}$) with a correlation of around 0.47, 0.38, and 0.33, respectively. Note that the correlation between CIS and the market variance (SVAR) is only -0.14.

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:

$$r_{m,t+h} = \alpha + \beta X_t + \epsilon_{t+1} \quad (2)$$

where $r_{m,t+h}$ is the buy-and-hold CRSP value-weighted index return (including dividends) in excess of the 30-day T-bill rate from the end of period t to period $t+h$, and X_t is either set equal to CIS_t or one of the 16 predictors listed above.

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.[12] We use the following dummy variable specification to mimic a quadratic relationship[13] :

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

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).[14] We use the first 30-year data to estimate the first CIS median.[15] 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 and with opposite signs.

For all our analysis, we use non-overlapping returns to circumvent the econometric issues associated with long-horizon regressions and overlapping observations (Hodrick, 1992). Econometric concerns also arise when predictors' innovations are correlated with those of the dependent variable. Namely, estimated betas are biased and the corresponding t-statistics are oversized (Stambaugh, 1999). This lagged-endogenous regressors bias is more pronounced when the predictor is highly persistent. Since CIS is persistent and its shocks are, indeed, contemporaneously correlated with those to market returns, we make corrections to the OLS estimates and associated standard errors via a bootstrap procedure. We follow Chen et al. (2018) as a recent and compre-

[12] Adrian et al. (2019) do not find any significant linear 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.

[13] 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.

[14] Using the CIS mean rather than the median generates very similar results and conclusions. Those results are available upon request.

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

hensive implementation of the procedure, which is detailed in the Appendix: Bootstrap Procedure.

[Insert Table 4]

Table 4 reports the biased-corrected beta estimates for the predictive regression (3) and, in parentheses, two-sided bootstrapped p-values. 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 0.86% 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 0.28%.[16] For comparison, consider the only two other predictors that turns out to be significant over the entire sample at the monthly horizon: market variance (SVAR) and returns on long-term government bond (LTR). One standard deviation increase in SVAR predicts the market excess return to drop by 0.49%. One standard deviation increase in LTR leads to a 0.41% drop in the market excess return. In terms of adjusted R^2, the CIS model performs much better than SVAR and LTR. The monthly adjusted R^2 of the CIS model is 1.8% whereas the adjusted R^2s for SVAR and LTR are 0.8% and 1.0%, respectively. In the Internet Appendix Table IA4, we report OLS parameter estimates and p-values based on asymptotic Newey and West (1987) HAC standard errors. The biases in the estimated βs are noticeable, as well as the differences between asymptotic and bootstrapped p-values, indicating the importance of making small corrections.

The hump-shaped relation between CIS and equity premium also holds at both quarterly and semi-annual forecast horizons. In quarterly data, when CIS is low, one

[16]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 $0.0725\times 11.486 \approx 0.86\%$. Similarly, when CIS is high, an one-standard deviation increase causes next-month market excess return to decrease $0.0519\times (16.919\text{-}11.486) \approx 0.28\%$.

standard deviation increase in CIS leads to an 2.22% increase in the market excess return in the next quarter. When CIS is high, one standard deviation increase in CIS causes the market excess return to decrease 0.75% in the next quarter. Again, the magnitudes are economically meaningful. The in-sample adjusted R^2 increases to 3.1% from the monthly 1.8%. For the classical predictors, after correcting OLS biases, only LTR keeps exhibiting statistically significant in-sample predictive power, and its adjusted R^2 is 2%. At the semi-annual horizon, CIS becomes marginally insignificant and the other two CIS-related variables are still statistically significant. The predictive power of LTR remains at the semi-annual horizon, and its adjusted R^2 is higher than that of the CIS model. In addition to LTR, term spread (TMS) has a significant bias-corrected beta.[17] In the remainder of the paper, we focus on the monthly results and comment on quarterly and semi-annual results when relevant. The quarterly and semi-annual results are contained in the Internet Appendix.

[Insert Table 5]

3.2.1 Controlling for Other Predictors

It is be possible that our CIS is just a proxy for some of the existing predictors. To address this concern, we first add each of the classical predictors to the CIS regression in equation (3). We, then, use a "kitchen-sink" specification, with all the predictors added to the CIS regression. Results at the monthly frequency are reported in Table 5. Across all specifications, CIS-related variables are always statistically significant at least at the 5% level. The strong non-linear predictive ability of CIS is, thus, confirmed after controlling for the classical predictors and their combination.

One may argue that the predictability literature has progressed and identified new and,

[17]In unreported tests, at the annual horizon, CIS no longer has a statistically significant predictive power.

possibly, more powerful predictors than those listed earlier in section 3.1. As noted by Jondeau et al. (2019), these additional predictors generally capture various aspects of either aggregate or idiosyncratic risk. Therefore, we aim to control for these recently proposed variables and label them as *newer* predictors. Namely:

- **Average Correlation (AC)**: proposed by Pollet and Wilson (2010), available from January 1961 to December 2016.
- **Aggregate Short Interest (SII)**: proposed by Rapach et al. (2016), available from January 1973 to December 2014.
- **Tail Risk (TR)**: proposed by Kelly and Jiang (2014), available from January 1960 to December 2016.
- **Variance Risk Premium (VRP)** and **Tail Risk Premium (TRP)**: proposed by Bollerslev et al. (2015), available from January 1996 to August 2013.
- **Equal-Weighted Average Total Skewness (Skew) and Value-Weighted Average Total Skewness (Skvw)**: proposed by Jondeau et al. (2019), available from January 1961 to December 2016.

In addition, we include variables that have been used as controls when assessing the predictive ability of the newer predictors above. Specifically:

- **Market Variance (Vm)**: estimated using daily market returns within a month.
- **Market Skewness (Skm)**: estimated using daily market returns within a month.
- **Equal-Weighted Average Variance (Vew)**: equally weighted average firm variance, which is estimated using daily returns within a month.
- **Value-Weighted Average Variance (Vvw)**: value-weighted average firm variance, which is estimated using daily returns within a month.
- **Implied Volatility Index (VIX)**: volatility implied by S&P 500 index options.

- **Expected Illiquidity (ILLIQ^{E})**: the expected component of aggregate-level illiquidity.

All these variables are available from January 1960 to December 2016 except the VIX and ILLIQ^{E}, which is from January 1990 to December 2015 and February 1960 to December 2016, repsectively. All the series for the *newer* predictors and control variables are downloaded from Eric Jondeau's website.[18]

Given the evidence in Goyal and Santa-Clara (2003), Guo and Savickas (2008) and Guo and Savickas (2010), we also control for average **idiosyncratic volatility (IVOL)**, calculated as the equally-weighted average idiosyncratic volatility across all firms in a specific month.[19]

Lastly, we control for option-implied skewness, given the evidence in Bali and Murray (2013) for the cross-section of option returns and given the relation, pointed out by Dew-Becker (2021), between risk-neutral skewness and the business cycle. We rely on the following three measures, all downloaded from Ian Dew-Becker's website[20]:

- **ISF**: value-weighted average option-implied firm total skewness, available from January 1980 to December 2019.
- **ISM**: option-implied market skewness, available from March 1983 to December 2019.
- **ISI**: value-weighted average option-implied idiosyncratic skewness, available from March 1983 to December 2019.

Before proceeding to the regression results, we compare CIS with the other skewness measures. Table 6 reports pairwise correlations among the measures computed at

[18] `https://people.unil.ch/ericjondeau/research/`. See Jondeau et al. (2019) for details on those variables.

[19] Firm-level idiosyncratic volatility is downloaded from the Open Source Asset Pricing project by Chen and Zimmermann (forthcoming) and is available over our entire sample period. Please see `https://www.openassetpricing.com/`

[20] `http://www.dew-becker.org/`. Please, see Dew-Becker (2021) for details on the measures.

the monthly frequency. CIS is essentially uncorrelated with market skewness (*Skm*) and only weakly correlated with firm average total skewness, with coefficients of 0.23 for equally-weighted firm skewness and 0.14 for the value-weighted measure. Interestingly, the risk-neutral skewness measures also have low correlations with physical market skewness as well as with physical average firm skewness. More apparent are the correlations between CIS and option-implied firm skewness (ISF), as well as option-implied market skewness (ISM), with a Pearson correlation of 0.47 and 0.44, respectively, over the 1983-2019 period. CIS is also more similar to the option-implied measures in terms of time-series persistence[21]: while the total skewness measures display fairly low auto-correlation, with AR(1) coefficients between 0.08 (for *Skm*) and 0.22 (for *Skew*), option-implied skewness and CIS are much more persistent, with AR(1) coefficients around 0.93 for *ISF* and *ISN*, and around 0.98 for CIS.

[Insert Table 6]

[Insert Table 7]

The monthly predictive regression results for the *newer* predictors and additional control variables are reported in Table 7. Again, none of these variables absorbs the strong predictive power of CIS. Quarterly and semi-annual results confirm this baseline message (see Internet Appendix Table IA7 and Table IA8). We, thus, find robust evidence that CIS provides additional predictive power for market returns relatively to the more recently proposed predictors, including various measures of idiosyncratic risk and, in particular, of asset return skewness.

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. One might argue that this is not a fair comparison. We address this concern by showing

[21] We compute serial correlation statistics for all the measure but do not report them.

that, even when we give all these variables the same level of flexibility, all the main findings above still hold. The results in Internet Appendix Table IA5 and Table IA6 indicate that most variables do not have predictive power for the equity premium even we use the same dummy variable regression as we do for CIS. One noticeable exception is inflation (INFL). Its in-sample adjusted R^2 increases from 0.4% (linear specification) to 1.5% (quadratic specification). We also find that tail risk premium (TRP) has significant betas under the quadratic specification. However, in terms of adjusted R^2, the improvement from the linear to the quadratic specification is limited. For all the other predictors, we do not find any significant quadratic predictive relation. As a result, we conclude that, even with the same non-linear specification for each of the predictors, CIS is still the best in-sample performer.

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.[22] 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 next-month 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 smaller number of local neighbours. The opposite is true

[22]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.

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 non-linear in-sample predictor for the equity premium at horizons ranging from one to six months. Furthermore, the predictive power of CIS is not absorbed by any of the classical and of the more recent predictors. CIS continues to outperform even when the same non-linear specification is accommodated for each of the other 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 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 classical and more recent equity premium predictors.

3.3.1 Out-of-Sample Performance

For each period t we estimate equation (2) for each of the predictors described above 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 monthly, quarterly, and semi-annual data.[23] For brevity, we report monthly results in our main text and quarterly and semi-annual results in the Internet Appendix. Following Campbell and Thompson (2008) and Welch and Goyal (2008) among many others, the forecasting

[23]To be consistent with our in-sample tests, our out-of-sample analysis also uses non-overlapping data for quarterly and semi-annual forecast horizons.

performance is evaluated through the out-of-sample R^2, calculated as follows:

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

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.[24] 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.[25] For robustness, we also analyze out-of-sample periods starting in 1966, 1976, 1986, and 1996.[26] 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 8]

[24]The historical average market excess return is estimated using data from the start of our sample (January 1931) to time τ.

[25]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.

[26]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 than those starting in the 1950s and in the 1960s.

The out-of-sample results based on monthly forecasts are reported in Table 8. R^2_{oos} in Table 8 reports the results based on the unrestricted forecast whereas $R^2_{oos}(+)$ reports non-negative forecasts. 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 for the period starting in 1976, although LTR's R^2_{oos} (0.27%) is well below that of CIS (1.49%).

As for the newer predictors [27], we find that the value-weighted average total skewness (Skvw) generates positive and significant R^2_{oos}s for the sub-periods starting in 1966, 1986, and 1996 with R^2_{oos}s of 0.09%, 0.53%, and 0.61%, respectively. Equal-weighted average skewness (Skew) beat the historical mean forecasts for the sub-period starting in 1986. In addition, tail risk (TR) has a significant R^2_{oos} of 0.53% in the sub-period starting in 1966. Short interest (SII) outperforms the prevailing mean forecasts by 0.88% for the sub-period starting in 1996. Overall, compared with the newer predictors, our CIS substantially outperforms in terms of both magnitude and consistency of predictive

[27] As some of the newer predictors have shorter data coverage, we require that they have at least five years of data for initial estimation before each out-of-sample start date. As a result, for those predictors the OOS performance is not computed for all sub-periods.

ability.[28]

With the economically motivated non-negative restriction ($R^2_{oos}(+)$), 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 for $R^2_{oos}(+)$ also imply that the superior out-of-sample performance of CIS is not driven by negative equity premium forecasts.

In Internet Appendix Table IA9, 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 ($R^2_{oos}(+)$), 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} of CIS is negative for the out-of-sample period starting from 1956, the R^2_{oos}s for all other sample periods are positive, statistically significant, and larger than those of the vast majority of other predictors. For semi-annual results reported in Table IA10, CIS generates negative R^2_{oos} in the sub-period starting in 1956 and 1966. For all the sub-periods starting in 1976, 1986, and 1996, CIS generates the highest R^2_{oos} although the R^2_{oos} starting in 1996 is marginally insignificant. Among all the predictors, with or without the non-negativity forecast restriction, CIS generates much higher R^2_{oos} than all the others after 1976.

Finally, in Internet Appendix Table IA11, we allow the other predictors to forecast the equity premium at the monthly frequency through the same flexible non-linear specification we used for CIS. Table IA11 shows that CIS is the best performer as

[28]We do not include the option-implied skewness measures in our OOS analysis, since they turn out to be insignificant in our in-sample tests, as illustrated in section 3.2.1. Further, they have not been used as predictors of aggregate equity returns by previous literature.

it 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 between 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 the classical and the newer 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 9. 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 9]

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 on the other predictors encompasses the CIS-based forecasts. Importantly, while the $\hat{\lambda}_1$s are typically close to 1, the $\hat{\lambda}_2$s are close to 0, and are rarely statistically significant. These results indicate that CIS always adds useful information beyond classical as well as newer predictors. All these predictors, on the other hand, do not add information beyond CIS.[29] The exceptions to the latter occur 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

[29]In Table 9 we use simple linear regressions to make forecasts. In Internet Appendix Table IA14, we report results using the same non-linear specification as CIS, and the baseline messages remain unchanged.

the forecasting power of CIS. In all sub-periods after 1976, no predictor contains information beyond CIS. For quarterly data (see Internet Appendix Table IA12) the same baseline conclusions hold. At the semi-annual frequency (Internet Appendix Table IA13), the results become slightly weaker: nonetheless, CIS still adds information beyond the vast majority of the predictors considered in our paper over the longer OOS samples and beyond all of them for the samples starting in 1976, 1986 and 1996.

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 aggregate US equity market. The investor rebalances her portfolio at the end of each holding period based on the one-period 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 each holding period 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.[30] As in Campbell and Thompson (2008), we use a five-year rolling window 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

[30]When the predictor is CIS, the predicted market excess return is computed using equation (3). The rebalancing frequency is consistent with the forecasting horizon. Again, we run the analysis for monthly, quarterly, and semi-annual forecasting horizons. For each predictors other than CIS, the predicted return is calculated using the simple linear regression in (2) .

return at the end of period $\tau + 1$ is then:

$$r^X_{p,\tau+1} = w^X_\tau r_{m,\tau+1} \tag{7}$$

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

$$SR^X = \frac{\bar{r}^X_p}{\sigma^X_p}. \tag{8}$$

To test whether the Sharpe ratio of predictor X is statistically different from the Sharpe ratio generated by prevailing mean forecasts, following e.g. DeMiguel et al. (2009), we use the method suggested by Jobson and Korkie (1981) after making the correction proposed by Memmel (2003).[31] The second performance measure we rely on 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 mean-variance investor with risk aversion γ the CER is computed as

$$CER^X = \bar{r}^X_p - 0.5\gamma(\sigma^X_p)^2. \tag{9}$$

We also compute the CER for an investor who uses the realized average market excess return up to time τ as her prediction for the excess return in the next period, $\tau + 1$: 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

[31] The test statistic can be found in footnote 16 in DeMiguel et al. (2009).

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. Lastly, we compute the annualized transaction fee generated by each considered strategy. Following Jondeau et al. (2019), the annualized transaction fees is calculated as:

$$Fee^X = \frac{nf}{T_{oos}} \sum_{t=s_0}^{T} |w_{t+1}^X - w_t^X| \tag{10}$$

where n is equal to 12/4/2 if the rebalancing frequency is monthly/quarterly/semi-annual, f is the fee per dollar, s_0 is the out-of-sample starting period, and w_t^X is the portfolio weight invested in the stock market based on X's forecasts. 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. For brevity, when calculating Sharpe ratio and transaction fees, we use asset allocation strategies generated by the moderate level ($\gamma = 5$) of relative risk aversion.

[Insert Table 10]

Table 10 reports annualized utility gains, Sharpe ratios, and transaction fees for each strategy with monthly rebalancing. 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 classical and newer 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 all 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.[32]

Furthermore, strategies based on CIS forecasts have high Sharpe ratio and low transaction fees. To be specific, for all the OOS sub-periods, asset allocation strategies based on CIS have higher Sharpe ratios than strategies based on prevailing mean forecasts. These differences are statistically significant at least at the 5% level. Compared to other strategies including a buy-and-hold passive strategy, CIS also outperforms. CIS gener-

[32]In the Internet Appendix Table IA17, 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. Compared with more recent predictors, CIS also outperforms. In terms of utility gains, the only predictor that seems to beat CIS is the short interest index (SII). SII generates an additional 40 to 150 bps on top of CIS, depending on different gammas and OOS sub-periods. For all the other predictors, CIS has superior performance most of the time.

ates the highest Sharpe ratio among all the predictors we considered. EP is the only predictor that can generate higher Sharpe ratio than CIS. However, this superior performance only exists in the OOS sub-periods starting in 1986 and 1996. One the other hand, CIS is consistently one of the best performers across all the OOS sub-periods. Importantly, the superior performance of CIS strategies is not achieved through relatively higher turnover. Transaction fees of CIS-based strategies are fairly reasonable and stable. For instance, in OOS sub-periods starting in 1956 and 1966, LTR has similar Sharpe ratios as CIS. However, the transaction fees generated by LTR strategies are roughly 5 times higher than those required by the CIS strategies. Two strategies that can generate significantly higher Sharpe ratio than the prevailing mean strategy are those based on TMS and INFL. Annualized transaction fees generated by TMS and INFL are approximately 11 bps and 16 bps. Compared to CIS's 8 bps, transaction fees based on TMS and INFL are 38% and 100% higher, respectively.

Quarterly and semi-annual results are reported in Internet Appendix Table IA15 and Table IA16. These results are slightly weaker but largely on par with our monthly results. In terms of utility gains, CIS strategies are consistently top performers, although with quarterly rebalancing CIS strategies produce negative utility gains when gamma is high. In addition, Sharpe ratios of CIS strategies are consistently higher than the prevailing mean strategy. Furthermore, consistent with monthly results, with quarterly and semi-annual rebalancing, CIS strategies have an advantage in terms of transaction fees.

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. CIS strategies generate substantially lower transaction fees than most strategies with similar performance.

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, for instance, Campbell and Shiller (1988) where a log linearization of stock return generates, as shown in Cochrane (2011), the following approximate identity

$$r_{m,t+1} = k + D/P_t - \rho D/P_{t+1} + DG_{t+1} \tag{11}$$

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 equation (11), 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 11. 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 11 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.[33] 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.[34] 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

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

[34]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/.

month t, for each firm i, we calculate the EPS forecast error ($Error_{i,t}$) as:

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

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.[35] Then, we compute the aggregate-level forecast errors ($Error_{i,t}$) as the average forecast errors ($EError_{i,t}$) across all firms in month 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 the Philadelphia FED's website.[36]

[Insert Table 12]

The results are reported in Table 12. 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.

[35] 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.

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

6 Conclusion

In this study, we find that firm's idiosyncratic skewness exhibits a strong co-movement pattern. 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, quarterly, and semi-annual 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 and in particular, with those generated by alternative measures of skewness and of idiosyncratic risk. In economic terms, CIS-induced predictability delivers sizeable out-of-sample utility gains in asset allocation to mean-variance investors. In terms of both forecasting ability and economic value added, differently from a host of alternative equity premium predictors, CIS performance is remarkably robust across out-of-sample periods and appears to become stronger over more recent decades. 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.

References

Adrian, T., Crump, R. K., and Vogt, E. (2019). Nonlinearity and flight-to-safety in the risk-return trade-off for stocks and bonds. *The Journal of Finance*, 74(4):1931–1973.

Amaya, D., Christoffersen, P., Jacobs, K., and Vasquez, A. (2015). Does realized skewness predict the cross-section of equity returns? *Journal of Financial Economics*, 118(1):135–167.

Arif, S. and Lee, C. M. (2014). Aggregate investment and investor sentiment. *The Review of Financial Studies*, 27(11):3241–3279.

Atanasov, V., Møller, S. V., and Priestley, R. (2020). Consumption fluctuations and expected returns. *The Journal of Finance*, 75(3):1677–1713.

Baker, M. and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61(4):1645–1680.

Bali, T., Cakici, N., Yan, X., and Zhang, Z. (2005). Does idiosyncratic risk really matter? *Journal of Finance*, 60:905–929.

Bali, T. and Murray, S. (2013). Does risk-neutral skewness predict the cross-section of equity option returns. *Journal of Financial and Quantitative Analysis*, 48:1141–1171.

Bali, T. G., Engle, R. F., and Murray, S. (2016). *Empirical Asset Pricing: The Cross Section of Stock Returns*. John Wiley & Sons.

Barberis, N. and Huang, M. (2001). Mental accounting, loss aversion, and individual stock returns. *The Journal of Finance*, 56:1247 – 1292.

Barberis, N. and Huang, M. (2008). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review*, 98(5):2066–2100.

Bollerslev, T., Todorov, V., and Xu, L. (2015). Tail risk premia and return predictability. *Journal of Financial Economics*, 118(1):113–134.

Boyer, B., Mitton, T., and Vorkink, K. (2010). Expected idiosyncratic skewness. *Review of Financial Studies*, 23(1):170–202.

Boyer, B. H. and Vorkink, K. (2014). Stock options as lotteries. *Journal of Finance*, 69(4):1485–1527.

Byun, S.-J. and Kim, D.-H. (2016). Gambling preference and individual equity option returns. *Journal of Financial Economics*, 122(1):155–174.

Campbell, J. Y. and Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. *The Review of Financial Studies*, 1(3):195–228.

Campbell, J. Y. and Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *The Review of Financial Studies*, 21(4):1509–1531.

Chang, R., Chu, L., Jun, T., Zhang, B., and Zhou, G. (2021). Esg and the market return. *Working Paper*.

Chen, A. Y. and Zimmermann, T. (Forthcoming). Open source cross sectional asset pricing. *Critical Finance Review*.

Chen, Y., Eaton, G. W., and Paye, B. S. (2018). Micro (structure) before macro? the predictive power of aggregate illiquidity for stock returns and economic activity. *Journal of Financial Economics*, 130(1):48–73.

Clark, T. E. and West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of econometrics*, 138(1):291–311.

Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of finance*, 66(4):1047–1108.

Conrad, J., Dittmar, R. F., and Ghysels, E. (2013). Ex ante skewness and expected stock returns. *The Journal of Finance*, 68(1):85–124.

Del Viva, L., Kasanen, E., and Trigeorgis, L. (2017). Real options, idiosyncratic skewness, and diversification. *Journal of Financial and Quantitative Analysis*, 52(1):215–241.

DeMiguel, V., Garlappi, L., and Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/n portfolio strategy? *The Review of Financial Studies*, 22(5):1915–1953.

Dew-Becker, I. (2021). Real-time forward-looking skewness over the business cycle. *Working Paper*.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*.

Goldstein, R., Ju, N., and Leland, H. (2001). An ebit-based model of dynamic capital structure. *The Journal of Business*, 74(4):483–512.

Goyal, A. and Santa-Clara, P. (2003). Idiosyncratic risk matters! *The Journal of Finance*, 58(3):975–1007.

Granger, C. W. and Joyeux, R. (1980). An introduction to long-memory time series models and fractional differencing. *Journal of Time Series Analysis*, 1(1):15–29.

Gu, S., Kelly, B., and Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies*, 33(5):2223–2273.

Guo, H. and Savickas, R. (2008). Average idiosyncratic volatility in g7 countries. *The Review of Financial Studies*, 21:1259–1296.

Guo, H. and Savickas, R. (2010). Relation between time-series and cross-sectional effects of idiosyncratic variance on stock returns. *Journal of Banking and Finance*, 34:1637–1649.

Hansen, P. and Timmermann, A. (2012). Choice of sample split in out-of-sample forecast evaluation. *Working Paper*.

Harvey, D. I., Leybourne, S. J., and Newbold, P. (1998). Tests for forecast encompassing. *Journal of Business & Economic Statistics*, 16(2):254–259.

Herskovic, B., Kelly, B., Lustig, H., and Van Nieuwerburgh, S. (2016). The common factor in idiosyncratic volatility: Quantitative asset pricing implications. *Journal of Financial Economics*, 119(2):249–283.

Hodrick, R. J. (1992). Dividend yields and expected stock returns: Alternative procedures for inference and measurement. *The Review of Financial Studies*, 5(3):357–386.

Hosking, J. R. (1981). Fractional differencing. *Biometrika*, 68:165–176.

Hribar, P. and McInnis, J. (2012). Investor sentiment and analysts' earnings forecast errors. *Management Science*, 58(2):293–307.

Huang, D., Jiang, F., Tu, J., and Zhou, G. (2015). Investor sentiment aligned: A powerful predictor of stock returns. *The Review of Financial Studies*, 28(3):791–837.

Huang, D., Li, J., and Wang, L. (2021). Are disagreements agreeable? evidence from information aggregation. *Journal of Financial Economics*.

Jobson, J. D. and Korkie, B. M. (1981). Performance hypothesis testing with the sharpe and treynor measures. *The Journal of Finance*, pages 889–908.

Jondeau, E., Zhang, Q., and Zhu, X. (2019). Average skewness matters. *Journal of Financial Economics*, 134(1):29–47.

Kelly, B. and Jiang, H. (2014). Tail risk and asset prices. *The Review of Financial Studies*, 27(10):2841–2871.

Linnainmaa, J. T., Torous, W., and Yae, J. (2016). Reading the tea leaves: Model uncertainty, robust forecasts, and the autocorrelation of analysts forecast errors. *Journal of Financial Economics*, 122(1):42–64.

Lynch, A., Nikolic, B., Yan, X. S., and Yu, H. (2014). Aggregate short selling, commonality, and stock market returns. *Journal of Financial Markets*, 17:199–229.

Maio, P. (2016). Cross-sectional return dispersion and the equity premium. *Journal of Financial Markets*, 29:87–109.

Memmel, C. (2003). Performance hypothesis testing with the sharpe ratio. *Finance Letters*, 22:21–23.

Mitton, T. and Vorkink, K. (2007). Equilibrium underdiversification and the preference for skewness. *Review of Financial Studies*, 20(4):1255–1288.

Newey, W. K. and West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(2):703–708.

Pollet, J. M. and Wilson, M. (2010). Average correlation and stock market returns. *Journal of Financial Economics*, 96(3):364–380.

Pyun, S. (2019). Variance risk in aggregate stock returns and time-varying return predictability. *Journal of Financial Economics*, 132(1):150–174.

Rapach, D. and Zhou, G. (2013). Forecasting stock returns. In *Handbook of economic forecasting*, volume 2, pages 328–383. Elsevier.

Rapach, D. E., Ringgenberg, M. C., and Zhou, G. (2016). Short interest and aggregate stock returns. *Journal of Financial Economics*, 121(1):46–65.

Rapach, D. E., Strauss, J. K., and Zhou, G. (2010). Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *The Review of Financial Studies*, 23(2):821–862.

Rossi, A. G. and Timmermann, A. (2010). What is the shape of the risk-return relation? In *AFA 2010 Atlanta Meetings Paper*.

Stambaugh, R. F. (1999). Predictive regressions. *Journal of Financial Economics*, 54(3):375–421.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, 62(3):1139–1168.

Trigeorgis, L. and Lambertides, N. (2014). The role of growth options in explaining stock returns. *Journal of Financial and Quantitative Analysis*, pages 749–771.

van der Heijden, T., Zeng, Q., and Zhu, Y. (2018). A multi-factor model of idiosyncratic volatility. In *31st Australasian Finance and Banking Conference*.

Welch, I. and Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, 21(4):1455–1508.

Zhang, X.-J. (2013). Book-to-market ratio and skewness of stock returns. *The Accounting Review*, 88(6):2213–2240.

7 Figures and Tables

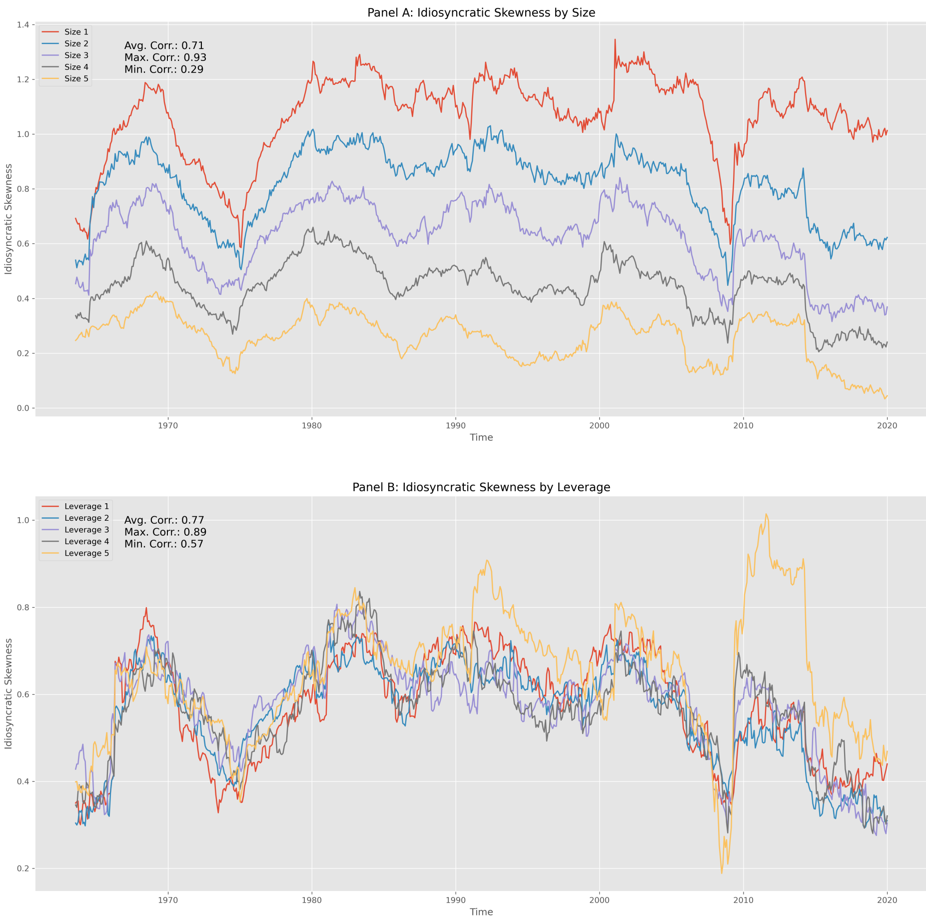

Figure 1 Idiosyncratic Skewness by Size and Leverage

This figure plots firm idiosyncratic skewness at the portfolio level, 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 end of each month. 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 1963 to December 2019.

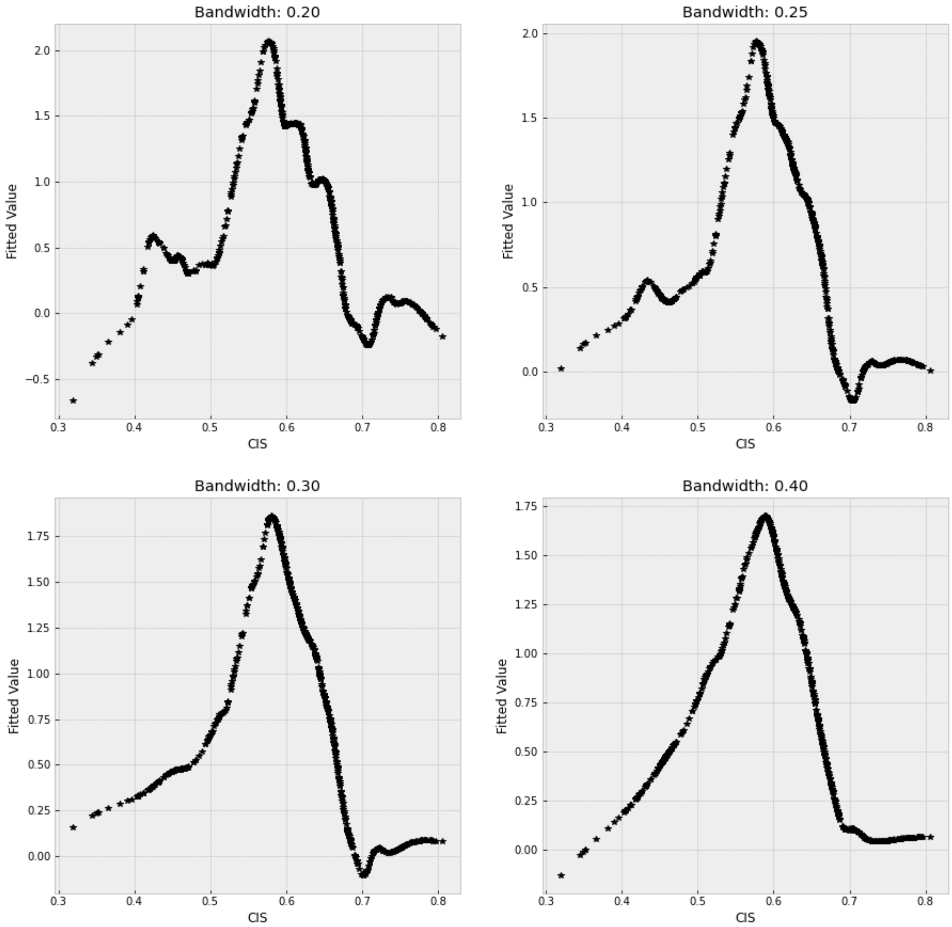

Figure 2 Non-Parametric Estimation

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 1963 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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. The sample period is from January 1961 to December 2019.

	mean	std	min	25%	50%	75%	max
$r_m(\%)$	0.900	4.361	-22.536	-1.648	1.252	3.728	16.558
CIS	0.608	0.103	0.319	0.536	0.621	0.677	0.806
DP	-3.611	0.395	-4.524	-3.943	-3.536	-3.348	-2.753
DY	-3.605	0.395	-4.531	-3.935	-3.529	-3.342	-2.751
EP	-2.854	0.425	-4.836	-3.085	-2.884	-2.666	-1.899
DE	-0.757	0.306	-1.244	-0.919	-0.792	-0.603	1.380
$SVAR$	0.002	0.004	0.000	0.001	0.001	0.002	0.071
BM	0.489	0.258	0.121	0.286	0.431	0.643	1.207
$NTIS$	0.010	0.020	-0.056	-0.002	0.013	0.024	0.051
TBL	0.046	0.032	0.000	0.023	0.047	0.061	0.163
LTY	0.064	0.027	0.016	0.042	0.060	0.080	0.148
LTR	0.006	0.029	-0.112	-0.011	0.004	0.023	0.152
TMS	0.018	0.015	-0.036	0.007	0.018	0.030	0.045
DFY	0.010	0.004	0.003	0.007	0.009	0.012	0.034
DFR	0.000	0.015	-0.098	-0.005	0.001	0.006	0.074
$INFL$	0.003	0.004	-0.019	0.001	0.003	0.005	0.018
$ECON_{AVG}$	-0.088	0.426	-0.811	-0.461	-0.145	0.182	1.221
$ECON_{PC}$	-0.825	1.720	-4.114	-2.297	-0.761	0.222	3.426

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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. The sample period is from January 1961 to December 2019.

	r_m(%)	CIS	DP	DY	EP	DE	$SVAR$	BM	$NTIS$	TBL	LTY	LTR	TMS	DFY	DFR	$INFL$	$ECON_{AVG}$	$ECON_{PC}$
r_m(%)	1.00																	
CIS	0.04	1.00																
DP	-0.03	0.18	1.00															
DY	0.08	0.18	0.99	1.00														
EP	-0.03	0.27	0.72	0.72	1.00													
DE	0.01	-0.15	0.28	0.28	-0.46	1.00												
$SVAR$	-0.33	-0.14	-0.03	-0.07	-0.16	0.18	1.00											
BM	-0.03	0.23	0.91	0.90	0.81	0.05	-0.07	1.00										
$NTIS$	-0.03	0.38	0.18	0.18	0.15	0.03	-0.19	0.26	1.00									
TBL	-0.02	0.47	0.66	0.65	0.67	-0.08	-0.07	0.68	0.19	1.00								
LTY	-0.00	0.52	0.67	0.67	0.61	0.02	-0.02	0.65	0.20	0.89	1.00							
LTR	0.09	-0.02	0.02	0.03	0.03	-0.01	0.14	0.01	-0.06	0.02	0.01	1.00						
TMS	0.05	-0.03	-0.17	-0.17	-0.31	0.21	0.13	-0.26	-0.04	-0.50	-0.05	-0.02	1.00					
DFY	0.05	0.05	0.38	0.38	0.14	0.30	0.31	0.39	-0.29	0.26	0.42	0.12	0.22	1.00				
DFR	0.25	0.02	0.00	0.03	-0.08	0.12	-0.15	-0.00	0.01	-0.05	-0.01	-0.46	0.08	0.07	1.00			
$INFL$	-0.07	0.24	0.37	0.36	0.43	-0.12	-0.17	0.46	0.16	0.47	0.40	-0.15	-0.28	0.05	-0.01	1.00		
$ECON_{AVG}$	0.02	0.33	0.90	0.90	0.65	0.26	0.10	0.86	0.27	0.72	0.82	0.14	-0.00	0.55	0.08	0.41	1.00	
$ECON_{PC}$	-0.02	0.21	0.98	0.98	0.75	0.23	0.03	0.95	0.20	0.70	0.71	0.05	-0.19	0.47	-0.01	0.39	0.93	1.00

Table 4 Bias-Corrected In-Sample Results

This table reports the in-sample performance of CIS and other popular predictors with biased-corrected beta estimates. **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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. For CIS, we use the predictive regression as specified in equation (3). For predictors other than CIS, we use the univariate predictive regression. Bootstrapped 2-sided p-values are reported in parentheses. The results are based on 5,000 simulations. *, **, 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.

	$h=1$		$h=3$		$h=6$	
Predictor	$\hat{\beta}$	$Adj.R^2$	$\hat{\beta}$	$Adj.R^2$	$\hat{\beta}$	$Adj.R^2$
CIS	11.486**	0.018	30.617*	0.031	45.894	0.032
	(0.032)		(0.051)		(0.118)	
CIS_{high}	9.081**		23.952**		40.772*	
	(0.017)		(0.030)		(0.067)	
$CIS*CIS_{high}$	-16.919***		-44.927**		-74.369**	
	(0.008)		(0.013)		(0.038)	
DP	-0.104	0.000	0.033	0.002	0.137	0.005
	(0.474)		(0.378)		(0.330)	
DY	0.472	0.001	1.615	0.003	3.200	0.005
	(0.278)		(0.250)		(0.230)	
EP	-0.173	-0.001	-0.580	-0.004	-0.397	-0.004
	(0.773)		(0.791)		(0.589)	
DE	0.324	-0.001	1.554	-0.000	1.923	-0.005
	(0.629)		(0.359)		(0.468)	
$SVAR$	-98.753**	0.008	70.066	-0.004	593.905	0.004
	(0.044)		(0.872)		(0.231)	
BM	-0.448	-0.001	-0.906	-0.004	-0.139	-0.003
	(0.864)		(0.738)		(0.484)	
$NTIS$	-7.037	-0.000	-23.461	-0.001	-50.153	-0.002
	(0.584)		(0.555)		(0.531)	
TBL	-9.714	0.003	-25.167	0.004	-43.623	0.003
	(0.103)		(0.152)		(0.134)	
LTY	-7.934	0.000	-18.922	-0.002	-29.070	-0.006
	(0.311)		(0.421)		(0.486)	
LTR	16.357***	0.010	51.038***	0.020	95.100**	0.034
	(0.003)		(0.009)		(0.019)	
TMS	20.571	0.003	59.746	0.006	111.179*	0.011
	(0.113)		(0.134)		(0.081)	
DFY	46.823	0.001	148.114	0.003	300.190	0.009
	(0.395)		(0.346)		(0.191)	
DFR	16.393	0.002	22.159	-0.002	-41.813	-0.006
	(0.298)		(0.598)		(0.679)	
$INFL$	-91.639	0.004	-146.222	-0.000	-400.905	0.008
	(0.128)		(0.357)		(0.143)	
$ECON_{AVG}$	0.146	-0.001	1.019	0.001	1.588	-0.000
	(0.500)		(0.283)		(0.300)	
$ECON_{PC}$	-0.029	-0.001	0.027	-0.000	0.164	0.003
	(0.617)		(0.441)		(0.333)	

Table 5 In-Sample Results 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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. Two sided p-values based on Newey and West (1987) t-statistics 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	Model 17
$const$	-1.398	-1.180	-2.945	-4.200*	-3.316*	-4.939**	-4.718**	-4.407*	-4.397*	-4.355*	-4.241*	-5.615**	-4.155*	-4.144*	-3.960	-4.273*	-7.145
	(0.646)	(0.693)	(0.338)	(0.086)	(0.094)	(0.039)	(0.045)	(0.065)	(0.067)	(0.070)	(0.083)	(0.020)	(0.065)	(0.090)	(0.109)	(0.076)	(0.484)
CIS	10.242**	10.156**	9.627**	10.585**	8.411**	10.335**	10.813***	10.638**	10.683**	9.863**	9.432**	10.788**	9.663**	9.936**	9.560**	10.274**	12.857***
	(0.017)	(0.017)	(0.023)	(0.015)	(0.018)	(0.014)	(0.010)	(0.015)	(0.022)	(0.021)	(0.037)	(0.016)	(0.016)	(0.022)	(0.029)	(0.016)	(0.003)
CIS_{high}	10.601***	10.615***	9.556***	9.608***	8.568**	10.810***	9.562***	7.981**	8.898**	8.700**	7.726*	11.449***	9.031**	8.257**	10.141***	10.825***	9.471**
	(0.004)	(0.004)	(0.010)	(0.010)	(0.013)	(0.004)	(0.008)	(0.033)	(0.013)	(0.018)	(0.078)	(0.002)	(0.012)	(0.036)	(0.006)	(0.003)	(0.015)
$CIS * CIS_{high}$	-19.028***	-19.031***	-17.321***	-17.474***	-15.523***	-19.354***	-17.362***	-14.966**	-16.352***	-16.010***	-14.525**	-20.265***	-16.461***	-15.280**	-18.276***	-19.372***	-17.120***
	(0.001)	(0.001)	(0.004)	(0.004)	(0.005)	(0.002)	(0.003)	(0.013)	(0.005)	(0.008)	(0.041)	(0.001)	(0.005)	(0.017)	(0.002)	(0.001)	(0.006)
DP	0.833*																3.583
	(0.063)																(0.288)
DY		0.882**															-6.685
		(0.048)															(0.170)
EP			0.403														1.980
			(0.503)														(0.285)
DE				0.595													1.603
				(0.354)													(0.325)
$SVAR$					-81.154**												-141.162***
					(0.033)												(0.000)
BM						0.995											-4.535
						(0.202)											(0.187)
$NTIS$							-8.867										0.938
							(0.375)										(0.921)
TBL								-7.110									-16.008***
								(0.256)									(0.009)
LTY									-5.411								-1.803
									(0.479)								(0.894)
LTR										15.603***							34.508***
										(0.005)							(0.000)
TMS											12.236						14.205
											(0.382)						(0.294)
DFY												86.705*					90.669***
												(0.099)					(0.000)
DFR													14.704				52.616**
													(0.311)				(0.039)
$INFL$														-62.917			23.305
														(0.261)			(0.296)
$ECON_{AVG}$															0.671		-4.177*
															(0.133)		(0.074)
$ECON_{PC}$																0.176	2.095
																(0.105)	(0.134)
$Adj.R^2$	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	0.020	0.021	0.061

Table 6 Pairwise Correlations for Different Skewness Measures

This table reports pairwise correlations for different skewness measures. **CIS** is the average idiosyncratic skewness across all firms in a specific month (January 1931 to December 2019). **Skm** is the market skewness (from January 1960 to December 2016). **Skew** and **Skvw** are equal-weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). **ISF** is the value-weighted average option-implied skewness (from January 1980 to December 2019). **ISM** is the option-implied market skewness (from March 1983 to December 2019). **ISI** is the value-weighted average option-implied idiosyncratic skewness (from March 1983 to December 2019). To be consistent with in-sample regression results, all the pairwise correlations are estimated using available data between January 1961 to December 2019.

	CIS	Skm	$Skew$	$Skvw$	ISF	ISM	ISI
CIS	1.00						
Skm	-0.00	1.00					
$Skew$	0.23	0.26	1.00				
$Skvw$	0.14	0.48	0.78	1.00			
ISF	0.47	-0.06	0.25	0.17	1.00		
ISM	0.44	0.14	0.25	0.15	0.65	1.00	
ISI	0.26	-0.13	0.14	0.06	0.89	0.39	1.00

Table 7 In-Sample Results with Additional 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 $\mathbf{CIS_{high}}$. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^E}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to December 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **VRP** and **TRP** (Bollerslev et al., 2015) are the variance risk premium, and the tail risk premium, respectively (from January 1996 to August 2013). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. **ISF** is the value-weighted average option-implied skewness (from January 1980 to December 2019). **ISM** is the option-implied market skewness (from March 1983 to December 2019). **ISI** is the value-weighted average option-implied idiosyncratic skewness (from March 1983 to December 2019). Two-sided p-values based on Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

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	Model 17	Model 18
$const$	-4.408*	-5.566*	-4.712*	-5.319**	-5.303*	-5.415*	-1.219	-6.577**	-6.947*	-11.937***	-7.144**	-13.961***	-12.388**	-4.341*	-6.243*	-5.100	-6.202**	0.007
	(0.075)	(0.050)	(0.065)	(0.045)	(0.061)	(0.054)	(0.750)	(0.018)	(0.075)	(0.001)	(0.018)	(0.000)	(0.012)	(0.055)	(0.050)	(0.182)	(0.037)	(0.999)
CIS	10.292**	12.143**	11.061**	11.897**	12.621**	12.242**	13.005***	12.973***	14.478**	21.158***	11.459**	25.522***	23.183***	9.815**	12.744**	11.079*	13.077**	31.419***
	(0.018)	(0.016)	(0.015)	(0.012)	(0.011)	(0.013)	(0.007)	(0.010)	(0.031)	(0.001)	(0.019)	(0.000)	(0.006)	(0.032)	(0.017)	(0.061)	(0.012)	(0.002)
CIS_{high}	9.543**	10.444***	9.440**	10.268***	9.889**	10.004**	10.334***	10.292**	12.365**	29.884***	8.768**	33.181***	32.250***	9.059**	11.375**	18.061***	19.645***	37.718***
	(0.011)	(0.009)	(0.012)	(0.008)	(0.014)	(0.012)	(0.009)	(0.011)	(0.019)	(0.001)	(0.037)	(0.000)	(0.001)	(0.021)	(0.033)	(0.008)	(0.005)	(0.005)
$CIS*CIS_{high}$	-17.251***	-18.940***	-17.205***	-18.628***	-18.101***	-18.209***	-18.900***	-18.811***	-22.146***	-49.547***	-16.382**	-54.984***	-53.194***	-16.553***	-20.492**	-30.590***	-33.377***	-62.017***
	(0.004)	(0.004)	(0.005)	(0.003)	(0.006)	(0.005)	(0.003)	(0.005)	(0.009)	(0.000)	(0.016)	(0.000)	(0.000)	(0.010)	(0.015)	(0.004)	(0.002)	(0.003)
Vm	-1653.998*																	-14008.393***
	(0.084)																	(0.008)
Skm		-0.017																0.271
		(0.955)																(0.614)
Vvw			-35.090*															116.626
			(0.095)															(0.329)
Vew				-5.748														57.247
				(0.674)														(0.130)
$Skew$					-10.430*													-12.164
					(0.077)													(0.520)
$Skvw$						-7.628*												0.376
						(0.061)												(0.977)
$ILLIQ^E$							0.297*											0.759
							(0.061)											(0.225)
AC								2.168										7.905*
								(0.136)										(0.089)
SII									0.428**									-0.591
									(0.017)									(0.142)
VIX										0.220*								0.135
										(0.054)								(0.708)
TR											4.612							-1.097
											(0.117)							(0.901)
VRP												8.384***						4.639
												(0.000)						(0.243)
TRP													14.140*					56.719**
													(0.092)					(0.025)
$IVOL$														-4.697				155.263
														(0.851)				(0.179)
ISF															-0.873			5.299
															(0.125)			(0.123)
ISM																-0.168		1.533
																(0.602)		(0.198)
ISI																	-0.642**	-2.156
																	(0.046)	(0.114)
$Adj.R^2$	0.024	0.020	0.024	0.020	0.024	0.025	0.024	0.023	0.035	0.070	0.023	0.118	0.076	0.016	0.030	0.033	0.042	0.119

TABLE 8 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. **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. **$\mathbf{ECON_{AVG}}$** is the equally weighted average of the above classical 14 predictors. **$\mathbf{ECON_{PC}}$** is the first principal component extracted from the above 14 classical predictors. In addition, we also compare our CIS with the following recent predictors. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). **$\mathbf{ILLIQ^E}$** is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to December 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. For CIS, we use equation (3) to predict future returns. For predictors other than CIS, we use the simple linear predictive regression in (2). R^2_{OOS} is the out-of-sample R^2 without any restriction, whereas $R^2_{OOS}(+)$ are the out-of-sample R^2 with non-negative equity premium predictions following Campbell and Thompson (2008). One-sided 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.

	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	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$
CIS	0.0040**	0.0047**	0.0106***	0.0113***	0.0149***	0.0152***	0.0194***	0.0197***	0.0256***	0.0259***
	(0.0166)	(0.0165)	(0.0057)	(0.0044)	(0.0062)	(0.0038)	(0.0047)	(0.0029)	(0.0055)	(0.0031)
DP	-0.0005	0.0026**	0.0002**	0.0036**	-0.0105	-0.0061	-0.0157	-0.0100	-0.0175	-0.0103
	(0.9691)	(0.0183)	(0.0491)	(0.0295)	(0.7552)	(0.7764)	(0.6957)	(0.7073)	(0.6387)	(0.6549)
DY	-0.0039	0.0017**	-0.0015	0.0046**	-0.0155	-0.0074	-0.0224	-0.0120	-0.0248	-0.0110
	(0.9802)	(0.0118)	(0.9637)	(0.0187)	(0.7713)	(0.7757)	(0.7134)	(0.6962)	(0.6571)	(0.6739)
EP	-0.0064	-0.0000*	-0.0066	0.0005	-0.0113	-0.0022	-0.0082	0.0036	-0.0123	0.0039
	(0.7818)	(0.0911)	(0.7311)	(0.1238)	(0.6289)	(0.7975)	(0.6686)	(0.1330)	(0.5964)	(0.1866)
DE	-0.0048	-0.0048	-0.0037	-0.0037	-0.0024	-0.0024	-0.0030	-0.0030	-0.0034	-0.0034
	(0.9743)	(0.9743)	(0.9438)	(0.9438)	(0.7902)	(0.7902)	(0.8088)	(0.8088)	(0.7572)	(0.7572)
$SVAR$	-0.0121	-0.0121	-0.0132	-0.0132	-0.0203	-0.0203	-0.0274	-0.0274	-0.0145	-0.0145
	(0.8100)	(0.8100)	(0.8291)	(0.8291)	(0.9002)	(0.9002)	(0.9194)	(0.9194)	(0.8518)	(0.8518)
BM	-0.0285	-0.0178	-0.0269	-0.0172	-0.0374	-0.0245	-0.0330	-0.0163	-0.0258	-0.0121
	(0.8740)	(0.8509)	(0.7782)	(0.7726)	(0.6307)	(0.6222)	(0.6179)	(0.6122)	(0.5731)	(0.6483)
$NTIS$	-0.0123	-0.0115	-0.0167	-0.0156	-0.0242	-0.0235	-0.0359	-0.0351	-0.0394	-0.0394
	(0.8660)	(0.8556)	(0.7899)	(0.7768)	(0.6403)	(0.6398)	(0.7278)	(0.7300)	(0.9085)	(0.9085)
TBL	0.0013**	0.0050**	0.0013**	0.0053**	-0.0116	-0.0051	-0.0022	-0.0022	-0.0004	-0.0004
	(0.0209)	(0.0161)	(0.0363)	(0.0323)	(0.7408)	(0.6633)	(0.6147)	(0.6147)	(0.6753)	(0.6753)
LTY	-0.0034	0.0048**	-0.0033	0.0058**	-0.0119	-0.0031	0.0003	0.0003	0.0023	0.0023
	(0.9326)	(0.0226)	(0.9176)	(0.0294)	(0.6304)	(0.6990)	(0.3186)	(0.3186)	(0.1366)	(0.1366)
LTR	0.0055**	0.0059**	0.0066**	0.0071**	0.0027**	0.0034**	-0.0021	-0.0028	-0.0014	-0.0024
	(0.0151)	(0.0169)	(0.0132)	(0.0147)	(0.0413)	(0.0470)	(0.8104)	(0.7694)	(0.7616)	(0.7060)
TMS	0.0024**	0.0029**	0.0011**	0.0017*	-0.0102	-0.0092	-0.0160	-0.0160	-0.0109	-0.0109
	(0.0291)	(0.0340)	(0.0448)	(0.0539)	(0.7489)	(0.6983)	(0.6409)	(0.6407)	(0.5986)	(0.5982)
DFY	0.0044*	0.0044*	0.0041*	0.0041*	-0.0013	-0.0013	-0.0044	-0.0044	-0.0071	-0.0071
	(0.0660)	(0.0660)	(0.0959)	(0.0959)	(0.6066)	(0.6066)	(0.6090)	(0.6090)	(0.6890)	(0.6890)
DFR	-0.0022	-0.0022	-0.0021	-0.0021	-0.0018	-0.0019	-0.0014	-0.0015	-0.0023	-0.0024
	(0.5911)	(0.6136)	(0.5659)	(0.5858)	(0.5369)	(0.5559)	(0.5159)	(0.5040)	(0.5031)	(0.5179)
$INFL$	0.0038*	0.0039*	0.0045*	0.0046*	0.0009	0.0010	-0.0006	-0.0006	-0.0049	-0.0049
	(0.0725)	(0.0696)	(0.0666)	(0.0639)	(0.2380)	(0.2345)	(0.6256)	(0.6256)	(0.6156)	(0.6156)
$ECON_{AVG}$	-0.0028	-0.0028	-0.0032	-0.0032	-0.0082	-0.0082	-0.0064	-0.0064	-0.0072	-0.0072
	(0.9027)	(0.9025)	(0.8419)	(0.8415)	(0.6966)	(0.6957)	(0.6635)	(0.6624)	(0.6770)	(0.6759)
$ECON_{PC}$	-0.0077	-0.0032	-0.0052	-0.0006	-0.0186	-0.0127	-0.0232	-0.0156	-0.0225	-0.0138
	(0.9594)	(0.9666)	(0.9298)	(0.9446)	(0.6889)	(0.6620)	(0.6447)	(0.6038)	(0.6169)	(0.6051)
$IVOL$	-0.0022	-0.0022	-0.0036	-0.0036	-0.0059	-0.0059	-0.0099	-0.0099	-0.0150	-0.0150
	(0.6838)	(0.6838)	(0.5769)	(0.5769)	(0.5029)	(0.5029)	(0.6044)	(0.6044)	(0.7902)	(0.7902)
Vm	-	-	-0.0058	-0.0031	-0.0063	-0.0094	-0.0059	-0.0099	0.0041	-0.0027
	-	-	(0.7296)	(0.6465)	(0.7027)	(0.6727)	(0.7045)	(0.6984)	(0.2064)	(0.5572)
Skm	-	-	-0.0051	-0.0053	-0.0068	-0.0066	-0.0061	-0.0058	-0.0020	-0.0020
	-	-	(0.5532)	(0.5203)	(0.6674)	(0.6557)	(0.6983)	(0.6843)	(0.5146)	(0.5146)
Vvw	-	-	-0.0026	0.0047*	-0.0014	-0.0021	0.0026	0.0006	0.0057	0.0053
	-	-	(0.8493)	(0.0826)	(0.7618)	(0.6713)	(0.2118)	(0.2935)	(0.2090)	(0.2170)
Vew	-	-	-0.0100	-0.0051	-0.0132	-0.0124	-0.0151	-0.0140	-0.0090	-0.0076
	-	-	(0.5818)	(0.6189)	(0.7412)	(0.7801)	(0.7638)	(0.8130)	(0.5635)	(0.5931)
$Skew$	-	-	0.0014	0.0025*	0.0007	0.0006	0.0040*	0.0036	0.0042	0.0037
	-	-	(0.1205)	(0.0875)	(0.1416)	(0.1483)	(0.0942)	(0.1038)	(0.1120)	(0.1243)
$Skvw$	-	-	0.0009*	0.0014*	0.0008	0.0011	0.0053*	0.0050*	0.0061*	0.0051*
	-	-	(0.0920)	(0.0893)	(0.1129)	(0.1136)	(0.0512)	(0.0606)	(0.0591)	(0.0787)
$ILLIQ^E$	-	-	-0.0027	0.0026**	-0.0105	-0.0029	-0.0147	-0.0054	-0.0201	-0.0071
	-	-	(0.9638)	(0.0357)	(0.8670)	(0.8599)	(0.7247)	(0.7604)	(0.7035)	(0.7420)
AC	-	-	-0.0026	-0.0011	-0.0050	-0.0050	-0.0079	-0.0079	-0.0027	-0.0027
	-	-	(0.6744)	(0.7457)	(0.5495)	(0.5495)	(0.5750)	(0.5750)	(0.5794)	(0.5794)
TR	-	-	0.0053*	0.0051*	-0.0002	-0.0006	0.0003	-0.0003	-0.0007	-0.0014
	-	-	(0.0620)	(0.0594)	(0.7298)	(0.7076)	(0.2790)	(0.6972)	(0.6712)	(0.6404)
SII	-	-	-	-	-	-	-0.0028	-0.0008	0.0088*	0.0047*
	-	-	-	-	-	-	(0.8380)	(0.8471)	(0.0832)	(0.0945)
VIX	-	-	-	-	-	-	-	-	-0.0231	-0.0179
	-	-	-	-	-	-	-	-	(0.7881)	(0.7555)

Table 9 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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^E}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to December 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. For CIS, we use equation (3) to predict future returns. For predictors other than CIS, we use the simple linear predictive regression in (2). *, **, 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	0.9309***	0.0691	1.0000***	0.0000
DY	0.5653***	0.4347***	0.6332***	0.3668**	0.7945***	0.2055	0.9096***	0.0904	0.9985***	0.0015
EP	0.6346***	0.3654**	0.7657***	0.2343	0.8571***	0.1429	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
$SVAR$	0.8440***	0.1560	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	0.9444***	0.0556	1.0000***	0.0000
$NTIS$	0.6828***	0.3172**	0.8236***	0.1764	0.9668***	0.0332	1.0000***	0.0000	1.0000***	0.0000
TBL	0.5339***	0.4661**	0.6573***	0.3427	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
LTY	0.5973***	0.4027**	0.7203***	0.2797	1.0000***	0.0000	1.0000***	0.0000	1.0000**	0.0000
LTR	0.4763**	0.5237***	0.5660***	0.4340**	0.6894***	0.3106	0.9751***	0.0249	1.0000***	0.0000
TMS	0.5291***	0.4709**	0.6869***	0.3131	0.9632***	0.0368	1.0000***	0.0000	1.0000***	0.0000
DFY	0.4926**	0.5074**	0.6518**	0.3482	0.8576***	0.1424	1.0000***	0.0000	1.0000***	0.0000
DFR	0.6642**	0.3358	0.8605***	0.1395	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
$INFL$	0.5053**	0.4947**	0.6812**	0.3188	0.9603***	0.0397	1.0000***	0.0000	1.0000***	0.0000
$ECON_{AVG}$	0.5812***	0.4188**	0.7007***	0.2993*	0.7902***	0.2098	1.0000***	0.0000	1.0000***	0.0000
$ECON_{PC}$	0.5976***	0.4024***	0.6741***	0.3259**	0.8144***	0.1856	0.9517***	0.0483	1.0000***	0.0000
$IVOL$	0.6246***	0.3754*	0.8376***	0.1624	0.9838***	0.0162	1.0000***	0.0000	1.0000***	0.0000
Vm	-	-	0.8089***	0.1911	0.9334***	0.0666	0.9901***	0.0099	0.8982**	0.1018
Skm	-	-	0.9151***	0.0849	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
Vvw	-	-	0.7288**	0.2712	0.9309***	0.0691	0.9354***	0.0646	1.0000**	0.0000
Vew	-	-	0.9233***	0.0767	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
$Skew$	-	-	0.7456***	0.2544	0.9400***	0.0600	1.0000***	0.0000	1.0000***	0.0000
$Skvw$	-	-	0.7372***	0.2628	0.8842***	0.1158	0.9131***	0.0869	1.0000***	0.0000
$ILLIQ^E$	-	-	0.7428***	0.2572	0.9067***	0.0933	0.9724***	0.0276	1.0000***	0.0000
AC	-	-	0.8709***	0.1291	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
TR	-	-	0.6858**	0.3142	0.9836***	0.0164	1.0000***	0.0000	1.0000***	0.0000
SII	-	-	-	-	-	-	0.8894***	0.1106	1.0000***	0.0000
VIX	-	-	-	-	-	-	-	-	1.0000***	0.0000

Table 10 Utility Gain, Sharpe Ratio, and Transaction Fees

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 (SR) and transaction fees (Fee) are 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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^E}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to December 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. For CIS, we use equation (3) to predict future returns.For CIS, we use equation (3) to predict future returns. For predictors other than CIS, we use the simple linear predictive regression in (2). 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	Fee	$\gamma=3$	$\gamma=5$	$\gamma=7$	SR	Fee	$\gamma=3$	$\gamma=5$	$\gamma=7$	SR	Fee	$\gamma=3$	$\gamma=5$	$\gamma=7$	SR	Fee	$\gamma=3$	$\gamma=5$	$\gamma=7$	SR	Fee
CIS	1.96%	1.79%	1.15%	0.48^{**}	0.07%	2.32%	2.06%	1.47%	0.42^{**}	0.08%	2.09%	1.86%	1.15%	0.56^{**}	0.08%	2.34%	2.12%	1.29%	0.58^{**}	0.09%	3.30%	3.52%	1.92%	0.60^{***}	0.09%
DP	-0.73%	0.64%	0.97%	0.28	0.04%	-0.23%	1.07%	1.09%	0.23	0.03%	-1.70%	-0.30%	0.00%	0.30	0.03%	-2.40%	-0.38%	0.01%	0.28	0.02%	-2.44%	0.30%	0.62%	0.19	0.02%
DY	-0.50%	0.79%	1.08%	0.30	0.05%	0.52%	1.55%	1.43%	0.28	0.05%	-1.64%	-0.22%	0.05%	0.31	0.04%	-2.31%	-0.32%	0.05%	0.32	0.03%	-1.92%	0.61%	0.84%	0.26	0.03%
EP	0.83%	0.69%	0.92%	0.35	0.05%	1.43%	1.21%	1.09%	0.32	0.05%	1.80%	1.40%	1.09%	0.51	0.04%	2.36%	2.44%	2.02%	0.73^{***}	0.04%	2.72%	3.32%	2.78%	0.67^{**}	0.04%
DE	-0.22%	-0.22%	-0.42%	0.34	0.03%	-0.26%	-0.33%	-0.38%	0.25	0.03%	-0.35%	-0.32%	-0.22%	0.38	0.03%	-0.44%	-0.41%	-0.28%	0.39	0.04%	-0.61%	-0.45%	-0.29%	0.34	0.04%
$SVAR$	-0.12%	-0.42%	-0.51%	0.32	0.06%	-0.14%	-0.26%	-0.59%	0.26	0.06%	-0.27%	-0.72%	-1.21%	0.36	0.06%	-0.51%	-1.04%	-1.64%	0.36	0.06%	-0.56%	-0.95%	-1.71%	0.33	0.05%
BM	-1.87%	-1.19%	-1.10%	0.17	0.04%	-1.03%	-0.76%	-1.13%	0.16	0.04%	-1.81%	-1.01%	-1.08%	0.26	0.02%	-2.45%	-0.41%	-0.01%	0.48	0.01%	-1.36%	0.95%	1.08%	0.55	0.01%
$NTIS$	1.55%	0.35%	0.01%	0.43	0.08%	1.61%	0.05%	-0.64%	0.37	0.07%	0.50%	-0.67%	-1.36%	0.45	0.07%	-0.39%	-1.38%	-2.18%	0.41	0.06%	-0.04%	-0.67%	-2.06%	0.38	0.06%
TBL	1.57%	1.36%	0.93%	0.40	0.05%	2.35%	1.73%	0.91%	0.37	0.03%	0.26%	-0.22%	-0.74%	0.39	0.03%	1.00%	0.13%	-0.67%	0.44	0.03%	1.35%	0.33%	-0.83%	0.43	0.03%
LTY	1.05%	1.05%	0.97%	0.37	0.04%	1.74%	1.55%	1.09%	0.34	0.03%	-0.13%	-0.21%	-0.36%	0.38	0.03%	0.51%	0.14%	-0.17%	0.44	0.03%	0.64%	0.29%	-0.17%	0.42^{**}	0.03%
LTR	1.57%	1.15%	0.71%	0.46^{**}	0.41%	1.85%	1.40%	0.86%	0.41^{**}	0.48%	1.28%	1.02%	0.50%	0.51	0.49%	0.59%	0.42%	-0.02%	0.47	0.46%	-0.54%	0.04%	-0.38%	0.40	0.45%
TMS	2.28%	1.46%	0.69%	0.47^{*}	0.10%	2.80%	1.77%	0.56%	0.43^{**}	0.11%	1.21%	0.01%	-1.06%	0.46	0.10%	0.09%	-1.12%	-2.18%	0.40	0.09%	-0.10%	-0.66%	-1.45%	0.35	0.08%
DFY	0.67%	0.05%	-0.08%	0.35	0.05%	0.81%	0.21%	-0.26%	0.29	0.05%	0.16%	-0.67%	-1.15%	0.37	0.05%	-0.08%	-1.01%	-1.59%	0.34	0.05%	-0.00%	-1.11%	-2.01%	0.29	0.05%
DFR	0.38%	0.37%	0.23%	0.38	0.13%	0.45%	0.45%	0.32%	0.31	0.15%	0.70%	0.71%	0.50%	0.46	0.13%	1.04%	1.08%	0.77%	0.49	0.16%	1.19%	1.44%	1.04%	0.45	0.19%
$INFL$	1.33%	0.84%	0.12%	0.42^{**}	0.14%	1.57%	0.99%	0.17%	0.35^{**}	0.16%	1.09%	0.40%	-0.45%	0.45	0.16%	0.88%	0.20%	-0.81%	0.45	0.17%	0.43%	-0.34%	-1.59%	0.38	0.18%
$ECON_{AVG}$	-0.27%	0.00%	0.49%	0.30	0.14%	0.14%	0.22%	0.45%	0.25	0.13%	0.02%	-0.04%	0.18%	0.37	0.11%	-0.18%	0.55%	0.67%	0.42	0.11%	-0.39%	1.22%	1.27%	0.36	0.11%
$ECON_{PC}$	-1.64%	-0.24%	0.34%	0.20	0.04%	-0.73%	0.39%	0.60%	0.19	0.04%	-2.42%	-1.16%	-0.61%	0.22	0.03%	-3.36%	-0.95%	-0.40%	0.14	0.02%	-3.09%	-0.09%	0.34%	0.11	0.02%
$IVOL$	-0.48%	-0.81%	-0.66%	0.34	0.06%	-0.56%	-0.97%	-1.06%	0.28	0.06%	-0.59%	-1.20%	-1.37%	0.38	0.05%	-1.17%	-1.80%	-1.95%	0.37	0.05%	-1.90%	-3.00%	-3.32%	0.25	0.06%
Vm	-	-	-	-	-	0.50%	1.14%	1.00%	0.20	0.12%	-0.58%	0.28%	0.31%	0.33	0.11%	-0.37%	0.61%	0.58%	0.35	0.14%	0.42%	2.01%	1.77%	0.34	0.16%
Skm	-	-	-	-	-	-0.03%	0.37%	0.23%	0.16	0.15%	-1.21%	-0.42%	-0.17%	0.26	0.11%	-1.14%	-0.29%	-0.02%	0.28	0.11%	-0.54%	0.52%	0.65%	0.25	0.12%
Vvw	-	-	-	-	-	1.88%	2.20%	1.89%	0.31	0.15%	0.76%	1.08%	0.97%	0.43	0.14%	1.47%	1.71%	1.48%	0.48^{*}	0.16%	2.60%	3.07%	2.59%	0.46^{**}	0.18%
Vew	-	-	-	-	-	0.21%	0.81%	0.63%	0.20	0.10%	-0.79%	-0.21%	-0.28%	0.30	0.07%	-0.70%	-0.07%	-0.22%	0.32	0.08%	-0.24%	0.95%	0.71%	0.31	0.09%
$Skew$	-	-	-	-	-	1.39%	0.99%	0.60%	0.25	0.24%	0.63%	0.18%	-0.02%	0.36	0.24%	1.27%	0.50%	0.16%	0.39	0.28%	1.21%	0.46%	0.06%	0.32	0.33%
$Skvw$	-	-	-	-	-	1.10%	0.72%	0.10%	0.22	0.32%	0.78%	0.36%	-0.32%	0.37	0.32%	1.60%	0.82%	-0.18%	0.42	0.39%	1.35%	0.85%	-0.51%	0.34	0.45%
$ILLIQ^E$	-	-	-	-	-	0.27%	1.53%	1.40%	0.21	0.13%	-0.60%	0.61%	0.62%	0.39	0.11%	-1.13%	0.60%	0.67%	0.34	0.12%	-2.30%	0.72%	0.89%	0.08	0.07%
AC	-	-	-	-	-	0.19%	-0.15%	-0.51%	0.20	0.24%	-0.19%	-0.96%	-1.42%	0.29	0.24%	-0.48%	-1.40%	-1.97%	0.29	0.26%	1.30%	0.12%	-1.34%	0.32	0.26%
TR	-	-	-	-	-	1.76%	2.27%	1.89%	0.35^{**}	0.22%	0.69%	1.27%	1.05%	0.45^{*}	0.22%	0.51%	1.43%	1.21%	0.45	0.23%	0.59%	1.80%	1.56%	0.34	0.25%
SII	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2.36%	2.72%	2.24%	0.54^{**}	0.07%	4.00%	4.55%	3.70%	0.54^{***}	0.07%
VIX	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-2.22%	-1.84%	-3.14%	0.18	0.06%
buy-and-hold	1.10%	0.82%	-0.88%	0.43^{*}	-	1.63%	0.86%	-1.42%	0.39^{**}	-	0.94%	0.81%	-0.92%	0.51^{*}	-	0.86%	1.09%	-0.61%	0.52^{*}	-	1.10%	1.71%	-0.21%	0.50^{*}	-
prevailing mean	-	-	-	0.36	0.02%	-	-	-	0.28	0.02%	-	-	-	0.41	0.02%	-	-	-	0.43	0.02%	-	-	-	0.37	0.02%

Table 11 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 $CIS_t c\dot{C}IS_{high,t}$ 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 12 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: Bootstrap Procedure

Firstly, we examine whether CIS has a long memory component (captured by an ARFIMA(p,d,q) process) and estimate the following predictive system under the null:

$$
\begin{aligned}
r_t &= \mu_{r,t} + \epsilon_{r,t}, \\
(1 - \sum_{i=1}^{p} \phi_i L^i)(1-L)^d x_t &= (1 + \sum_{i=1}^{q} \theta_i L^i)\epsilon_{x,t}, \\
\epsilon_t \equiv (\epsilon_{r,t}, \epsilon_{x,t})' &\sim \text{i.i.d. } N(0, \Sigma),
\end{aligned} \tag{12}
$$

where r_t is the market excess return, which is assumed to be non-predictable, x_t is any return predictor (in this case it is CIS), L is the backshift operator, d is the fractional differencing parameter, and Σ is the covariance matrix. We first confirm that, although CIS is highly persistent, it is indeed stationary. CIS is well characterized by an Autoregressive Fractionally Integrated Moving Average process, ARFIMA(1,d,0), with the Autorgressive and fractional differencing coefficients estimated to be 0.97 and 0.25, respectively.[37] We then generate a bootstrapped sample by drawing with replacement from estimated $\hat{\epsilon}_t$. With these bootstrapped shocks, we simulate both r_t and CIS_t using equation (12) and the estimated parameters. This bootstrapping procedure preserves the long-memory structure of the predictor and the contemporaneous correlation between the shocks of returns and the shocks of the predictor. The length of each bootstrapped sample equals to 500 burn-in draws plus the length of our sample (from January 1931 to December 2019). We then create $CIS_{high,t}$ and the interaction term $CIS_t * CIS_{high,t}$ in the same way as described above. Finally, we run the predictive regression (3) using OLS and keep recording $\hat{\beta}_i$ for the i-th bootstrapped sample. We repeat the bootstrapping procedure for $B = 5000$ times. Since we simulate the system under the null, $(1/B)\sum_{i=1}^{B} \hat{\beta}_i$ captures the biases when we use OLS to estimate regres-

[37] Granger and Joyeux (1980) and Hosking (1981) show that when the absolute value of the fractional difference parameter, d, is smaller than 0.5, the process is a stationary long-memory time series.

sion (3). As a result, the bias-corrected OLS estimate is defined as $\hat{\beta} - (1/B)\sum_{i=1}^{B}\hat{\beta}_i$ where $\hat{\beta}$ is the OLS estimates for the predictive regression 3. In addition, we compute two-sided empirical p-values for OLS beta estimates by comparing the t-statistics computed from the actual sample with the empirical distribution of t-statistics.[38] We repeat the above procedure for each of the alternative predictors listed in the Data section.[39]

[38]For the t-statistics in the actual sample we use HAC Newey-West t-statistics with lag-length selected via the Newey-West automatic bandwidth procedure.

[39]For CIS, TBL, and $ECON_{AVG}$, we simulate using an ARFIMA(1,d,0) process. For all the other variables, an AR(1) process turns out to be sufficient.

Internet Appendix for:

Idiosyncratic Skewness Co-movement and Aggregate Stock Returns

1 Alternative Factor Models

In this section we provide robustness checks 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 IA1. 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 IA2 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 IA3 indicate that the main results are also robust to this pure statistical model.

TABLE IA1 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 IA2 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 IA3 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)

2 Additional Tables

Table IA4 In-Sample Predictive Regressions (OLS results)

This table reports the in-sample performance of CIS and other popular predictors with OLS beta estimates. **CIS** is the average idiosyncratic skewness across all firms in a specific month. $\textbf{CIS}_{\textbf{high}}$ is a dummy variable equal to 1 if CIS is higher than the CIS historical median up to month t and 0 otherwise, and $\textbf{CIS*CIS}_{\textbf{high}}$ is the interaction term between **CIS** and $\textbf{CIS}_{\textbf{high}}$. **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. $\textbf{ECON}_{\textbf{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\textbf{ECON}_{\textbf{PC}}$ is the first principal component extracted from the above 14 classical predictors. For CIS, we use the predictive regression as specified in equation (3). For predictors other than CIS, we use the univariate predictive regression. Two-sided p-values based on Newey and West (1987) t-statistics 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.

	$h=1$		$h=3$		$h=6$	
Predictor	$\hat{\beta}$	$Adj.R^2$	$\hat{\beta}$	$Adj.R^2$	$\hat{\beta}$	$Adj.R^2$
CIS	9.922**	0.018	26.079**	0.031	37.216*	0.032
	(0.019)		(0.024)		(0.056)	
CIS_{high}	9.161**		24.170**		41.432**	
	(0.013)		(0.017)		(0.032)	
$CIS*CIS_{high}$	-16.715***		-44.327***		-73.560**	
	(0.005)		(0.006)		(0.014)	
DP	0.443	0.000	1.678	0.002	3.438	0.005
	(0.330)		(0.229)		(0.174)	
DY	0.516	0.001	1.750	0.003	3.474	0.005
	(0.258)		(0.215)		(0.173)	
EP	0.191	-0.001	0.509	-0.004	1.789	-0.004
	(0.739)		(0.756)		(0.513)	
DE	0.369	-0.001	1.688	-0.000	2.185	-0.005
	(0.618)		(0.332)		(0.427)	
$SVAR$	-97.171**	0.008	71.154	-0.004	598.101	0.004
	(0.025)		(0.853)		(0.135)	
BM	0.143	-0.001	0.870	-0.004	3.416	-0.003
	(0.848)		(0.690)		(0.393)	
$NTIS$	-6.864	-0.000	-22.926	-0.001	-49.122	-0.002
	(0.565)		(0.524)		(0.483)	
TBL	-9.115*	0.003	-23.241	0.004	-39.564*	0.003
	(0.093)		(0.125)		(0.096)	
LTY	-6.461	0.000	-14.485	-0.002	-20.190	-0.006
	(0.295)		(0.395)		(0.446)	
LTR	16.274***	0.010	50.384***	0.020	94.383***	0.034
	(0.003)		(0.005)		(0.007)	
TMS	20.404*	0.003	59.328	0.006	109.648**	0.011
	(0.097)		(0.104)		(0.050)	
DFY	51.445	0.001	163.125	0.003	330.397	0.009
	(0.364)		(0.292)		(0.131)	
DFR	16.703	0.002	22.832	-0.002	-40.050	-0.006
	(0.271)		(0.572)		(0.649)	
$INFL$	-91.245	0.004	-145.466	-0.000	-397.306*	0.008
	(0.118)		(0.329)		(0.099)	
$ECON_{AVG}$	0.295	-0.001	1.447	0.001	2.502	-0.000
	(0.482)		(0.254)		(0.255)	
$ECON_{PC}$	0.064	-0.001	0.308	-0.000	0.728	0.003
	(0.547)		(0.345)		(0.221)	

Table IA5 In-Sample Results (Flexible Control Variables)

This table reports results of in-sample comparisons with other popular predictors having the same flexibility as **CIS**. For a predict **X**, we use the following predictive regression to make forecasts:

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

X is a vector of control variables which are described as follows. **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. **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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. Two-sided p-values based on Newey and West (1987) t-statistics 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 median of X. 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	9.922**	0.018	BM	0.567	0.003	DFY	-28.908	-0.001
	(0.019)			(0.654)			(0.849)	
CIS_{high}	9.161**		BM_{high}	-4.477*		DFY_{high}	-0.736	
	(0.013)			(0.090)			(0.571)	
$CIS * CIS_{high}$	-16.715***		$BM * BM_{high}$	4.418		$DFY * DFY_{high}$	91.411	
	(0.005)			(0.162)			(0.586)	
DP	0.356	0.002	$NTIS$	8.808	0.002	DFR	36.780	0.006
	(0.521)			(0.624)			(0.300)	
DP_{high}	25.488		$NTIS_{high}$	0.618		DFR_{high}	0.394	
	(0.212)			(0.629)			(0.391)	
$DP * DP_{high}$	8.479		$NTIS * NTIS_{high}$	-47.822		$DFR * DFR_{high}$	-60.678	
	(0.209)			(0.251)			(0.201)	
DY	0.271	-0.001	TBL	-59.795**	0.006	$INFL$	201.707**	0.015
	(0.638)			(0.017)			(0.041)	
DY_{high}	9.454		TBL_{high}	0.155		$INFL_{high}$	-0.286	
	(0.603)			(0.786)			(0.500)	
$DY * DY_{high}$	3.017		$TBL * TBL_{high}$	45.698*		$INFL * INFL_{high}$	-319.020***	
	(0.618)			(0.081)			(0.007)	
EP	0.191	-0.004	LTY	-73.235*	0.002	$ECON_{AVG}$	-0.526	-0.002
	(0.855)			(0.087)			(0.522)	
EP_{high}	-0.786		LTY_{high}	-2.357*		$ECON_{AVG,high}$	0.452	
	(0.872)			(0.070)			(0.610)	
$EP * EP_{high}$	-0.351		$LTY * LTY_{high}$	69.178		$ECON_{AVG} * ECON_{AVG,high}$	0.831	
	(0.856)			(0.112)			(0.653)	
DE	-0.788	0.001	LTR	21.902	0.008	$ECON_{PC}$	0.099	0.004
	(0.426)			(0.120)			(0.496)	
DE_{high}	1.316		LTR_{high}	0.117		$ECON_{PC,high}$	-2.945	
	(0.234)			(0.797)			(0.109)	
$DE * DE_{high}$	2.371*		$LTR * LTR_{high}$	-11.449		$ECON_{PC} * ECON_{PC,high}$	1.285	
	(0.063)			(0.536)			(0.179)	
$SVAR$	-74.085	0.007	TMS	46.893*	0.005			
	(0.894)			(0.056)				
$SVAR_{high}$	0.461		TMS_{high}	1.506*				
	(0.354)			(0.068)				
$SVAR * SVAR_{high}$	-40.610		$TMS * TMS_{high}$	-70.579*				
	(0.942)			(0.060)				

Table IA6 In-Sample Results (Flexible Additional Control Variables)

This table reports OLS esimates of in-sample comparisons with additional predictors having the same flexibility as **CIS**. For a predict **X**, we use the following predictive regression to make forecasts:

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

X is a vector of variables which are described as follows. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). **ILLIQ^E** is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to Decmber 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. **ISF** is the value-weighted average option-implied skewness (from January 1980 to December 2019). **ISM** is the option-implied market skewness (from March 1983 to December 2019). **ISI** is the value-weighted average option-implied idiosyncratic skewness (from March 1983 to December 2019). Two-sided p-values based on Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Predictor	$\hat{\beta}$	$Adj.R^2$	Predictor	$\hat{\beta}$	$Adj.R^2$	Predictor	$\hat{\beta}$	$Adj.R^2$
Vm	-1526.939	0.005	$ILLIQ$	0.217	-0.001	VRP	8.032*	0.026
	(0.814)			(0.197)			(0.079)	
Vm_{high}	0.171		$ILLIQ_{high}$	6.824		VRP_{high}	1.884	
	(0.627)			(0.710)			(0.114)	
$Vm * Vm_{high}$	-858.250		$ILLIQ * ILLIQ_{high}$	0.436		$VRP * VRP_{high}$	-7.697	
	(0.896)			(0.712)			(0.319)	
Skm	0.402	-0.002	AC	5.211	0.004	TRP	32.461**	0.007
	(0.330)			(0.123)			(0.017)	
Skm_{high}	-0.387		AC_{high}	-0.505		TRP_{high}	1.918**	
	(0.398)			(0.590)			(0.049)	
$Skm * Skm_{high}$	-0.659		$AC * AC_{high}$	-1.509		$TRP * TRP_{high}$	-44.313***	
	(0.457)			(0.728)			(0.006)	
Vvw	-65.688	0.004	SII	0.524*	0.006	ISF	-0.685	0.005
	(0.508)			(0.086)			(0.175)	
Vvw_{high}	-0.063		SII_{high}	0.374		ISF_{high}	-17.085***	
	(0.910)			(0.464)			(0.006)	
$Vvw * Vvw_{high}$	14.807		$SII * SII_{high}$	-0.385		$ISF * ISF_{high}$	-44.955***	
	(0.885)			(0.378)			(0.009)	
Vew	-6.145	-0.001	VIX	0.380***	0.009	ISM	-0.057	0.013
	(0.916)			(0.007)			(0.804)	
Vew_{high}	0.546		VIX_{high}	0.501		ISM_{high}	5.614*	
	(0.528)			(0.858)			(0.098)	
$Vew * Vew_{high}$	-11.766		$VIX * VIX_{high}$	-0.307		$ISM * ISM_{high}$	5.841**	
	(0.848)			(0.449)			(0.032)	
$Skew$	-7.649	0.003	TR	7.141*	0.011	ISI	-0.363	-0.003
	(0.261)			(0.099)			(0.310)	
$Skew_{high}$	-0.933		TR_{high}	-5.338		ISI_{high}	-0.051	
	(0.578)			(0.130)			(0.942)	
$Skew * Skew_{high}$	5.776		$TR * TR_{high}$	10.398		$ISI * ISI_{high}$	1.143	
	(0.793)			(0.185)			(0.323)	
$Skvw$	-3.633	0.005						
	(0.505)							
$Skvw_{high}$	0.020							
	(0.981)							
$Skvw * Skvw_{high}$	-9.484							
	(0.473)							

Table IA7 In-Sample Results with Additional Control Variables (Quarterly Reuslts)

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 $\mathbf{CIS_{high}}$. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^{E}}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to Decmber 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **VRP** and **TRP** (Bollerslev et al., 2015) are the variance risk premiu, and the tail risk premium, respectively (from January 1996 to August 2013). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. **ISF** is the value-weighted average option-implied skewness (from January 1980 to December 2019). **ISM** is the option-implied market skewness (from March 1983 to December 2019). **ISI** is the value-weighted average option-implied idiosyncratic skewness (from March 1983 to December 2019). Two-sided p-values based on Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

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	Model 17	Model 18
$const$	-17.858**	-14.356*	-14.511*	-15.077*	-14.435*	-14.324*	0.632	-22.035**	-16.830*	-38.175***	-15.983**	-39.030***	-38.939***	-11.510*	-18.429**	-14.194	-18.058**	-6.670
	(0.020)	(0.056)	(0.057)	(0.056)	(0.056)	(0.053)	(0.953)	(0.010)	(0.081)	(0.000)	(0.041)	(0.000)	(0.000)	(0.082)	(0.029)	(0.159)	(0.029)	(0.796)
CIS	37.757***	32.243**	32.303**	32.834**	33.332**	32.055**	34.814***	39.944***	36.709**	63.395***	31.071**	71.553***	65.597***	25.177**	37.260***	31.201**	37.743***	76.160***
	(0.004)	(0.014)	(0.014)	(0.015)	(0.014)	(0.012)	(0.006)	(0.006)	(0.026)	(0.000)	(0.017)	(0.000)	(0.000)	(0.043)	(0.008)	(0.044)	(0.009)	(0.005)
CIS_{high}	30.921***	26.929**	27.839**	28.104***	27.316**	27.591**	27.485**	28.535**	30.070**	75.157***	25.438**	74.168***	77.599***	23.177**	22.185	41.933**	44.198**	78.703***
	(0.004)	(0.013)	(0.010)	(0.010)	(0.012)	(0.010)	(0.011)	(0.012)	(0.027)	(0.001)	(0.029)	(0.000)	(0.000)	(0.031)	(0.157)	(0.013)	(0.013)	(0.003)
$CIS * CIS_{high}$	-56.250***	-49.609***	-50.755***	-51.254***	-50.082***	-50.333***	-50.510***	-52.550***	-55.059**	-127.259***	-47.031**	-125.975***	-129.259***	-42.770**	-43.184*	-72.796***	-77.447***	-132.296***
	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)	(0.012)	(0.000)	(0.012)	(0.000)	(0.000)	(0.014)	(0.078)	(0.006)	(0.006)	(0.002)
Vm	5031.874																	-21398.354**
	(0.461)																	(0.015)
Skm		0.871																0.667
		(0.378)																(0.817)
Vvw			9.009															132.420
			(0.937)															(0.709)
Vew				18.066														-122.549
				(0.727)														(0.533)
$Skew$					-10.311													6.624
					(0.639)													(0.928)
$Skvw$						0.342												-6.830
						(0.981)												(0.884)
$ILLIQ^{E}$							1.016*											0.529
							(0.055)											(0.737)
AC								12.591***										15.190
								(0.006)										(0.200)
SII									1.119**									-0.210
									(0.026)									(0.876)
VIX										1.124***								0.992*
										(0.000)								(0.096)
TR											5.226							-35.735
											(0.513)							(0.185)
VRP												21.373***						-0.488
												(0.001)						(0.960)
TRP													158.888***					350.122***
													(0.000)					(0.000)
$IVOL$														-45.646				227.765
														(0.525)				(0.376)
ISF															-2.948**			28.521***
															(0.037)			(0.000)
ISM																-0.506		4.179
																(0.553)		(0.228)
ISI																	-2.243***	-9.986***
																	(0.001)	(0.001)
$Adj.R^2$	0.039	0.037	0.034	0.034	0.034	0.034	0.047	0.066	0.058	0.170	0.035	0.191	0.243	0.028	0.057	0.058	0.094	0.313

Table IA8 In-Sample Results with Additional Control Variables (Semi-Annual Reuslts)

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 $\mathbf{CIS_{high}}$. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^{E}}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to Decmber 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **VRP** and **TRP** (Bollerslev et al., 2015) are the variance risk premiu, and the tail risk premium, respectively (from January 1996 to August 2013). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. **ISF** is the value-weighted average option-implied skewness (from January 1980 to December 2019). **ISM** is the option-implied market skewness (from March 1983 to December 2019). **ISI** is the value-weighted average option-implied idiosyncratic skewness (from March 1983 to December 2019). Two-sided p-values based on Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

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	Model 17	Model 18
$const$	-27.535*	-17.897	-19.432	-19.785	-19.917*	-19.666*	7.847	-30.295**	-21.649	-46.399**	-24.494**	-71.329***	-52.844***	-15.228	-27.053*	-21.515	-24.992*	-76.874
	(0.089)	(0.125)	(0.119)	(0.108)	(0.095)	(0.086)	(0.652)	(0.034)	(0.125)	(0.012)	(0.045)	(0.000)	(0.000)	(0.168)	(0.066)	(0.193)	(0.099)	(0.124)
CIS	58.142**	43.369**	45.979**	46.387**	46.289**	44.923**	50.981***	55.606**	49.866**	82.343***	42.801**	126.677***	90.729***	36.333*	55.255**	47.729*	53.404**	89.026*
	(0.034)	(0.030)	(0.026)	(0.022)	(0.043)	(0.026)	(0.008)	(0.020)	(0.041)	(0.002)	(0.035)	(0.000)	(0.000)	(0.058)	(0.022)	(0.055)	(0.039)	(0.079)
CIS_{high}	52.421**	40.536**	46.136**	46.647**	46.702**	45.525**	45.254**	43.292**	47.085**	167.926***	40.023*	227.907***	202.253***	40.485**	50.550**	104.240***	108.717***	191.596***
	(0.019)	(0.049)	(0.024)	(0.020)	(0.020)	(0.028)	(0.027)	(0.027)	(0.034)	(0.000)	(0.071)	(0.000)	(0.000)	(0.042)	(0.042)	(0.001)	(0.000)	(0.000)
$CIS * CIS_{high}$	-93.102***	-74.163**	-81.830**	-82.709***	-82.775***	-80.923**	-81.333***	-78.138**	-84.310**	-269.176***	-72.452**	-360.701***	-316.625***	-72.056**	-89.344**	-171.130***	-178.578***	-308.356***
	(0.009)	(0.020)	(0.010)	(0.008)	(0.009)	(0.011)	(0.009)	(0.012)	(0.016)	(0.000)	(0.034)	(0.000)	(0.000)	(0.020)	(0.021)	(0.000)	(0.000)	(0.000)
Vm	14965.072*																	-11681.897
	(0.097)																	(0.777)
Skm		3.420**																19.744***
		(0.048)																(0.000)
Vvw			-34.746															-1487.544*
			(0.888)															(0.083)
Vew				-5.417														-76.680
				(0.953)														(0.818)
$Skew$					1.248													219.610***
					(0.979)													(0.001)
$Skvw$						17.790												-251.593***
						(0.539)												(0.000)
$ILLIQ^{E}$							1.864*											-7.599***
							(0.057)											(0.000)
AC								19.398***										33.648
								(0.001)										(0.259)
SII									2.554**									8.720***
									(0.018)									(0.000)
VIX										1.032								-0.708
										(0.247)								(0.753)
TR											15.472							-202.321***
											(0.305)							(0.006)
VRP												37.264***						82.432***
												(0.002)						(0.000)
TRP													188.245*					178.831
													(0.052)					(0.510)
$IVOL$														-42.843				-565.171
														(0.747)				(0.379)
ISF															-4.693*			16.007
															(0.059)			(0.437)
ISM																-0.875		12.082**
																(0.532)		(0.031)
ISI																	-3.244**	5.375
																	(0.019)	(0.668)
$Adj.R^2$	0.049	0.056	0.033	0.033	0.033	0.035	0.055	0.072	0.083	0.255	0.038	0.458	0.405	0.025	0.083	0.135	0.186	0.546

Table IA9 Out-of-Sample Performance (Quarterly Results)

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. **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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. In addition, we also compare our CIS with the following recent predictors. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^E}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to Decmber 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. For CIS, we use equation (3) to predict future returns. For predictors other than CIS, we use the simple linear predictive regression in equation (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.

	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	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$
CIS	-0.0224	-0.0203	0.0038**	0.0061*	0.0138**	0.0161**	0.0179*	0.0164*	0.0231*	0.0211*
	(0.8893)	(0.8285)	(0.0429)	(0.0650)	(0.0412)	(0.0402)	(0.0619)	(0.0672)	(0.0681)	(0.0742)
DP	-0.0244	0.0071***	-0.0118	0.0162***	-0.0658	-0.0254	-0.0878	-0.0369	-0.0931	-0.0326
	(0.9903)	(0.0062)	(0.9803)	(0.0094)	(0.8067)	(0.7998)	(0.7617)	(0.7310)	(0.6947)	(0.6944)
DY	-0.0403	0.0056***	-0.0180	0.0157**	-0.0770	-0.0268	-0.0994	-0.0362	-0.1053	-0.0315
	(0.9903)	(0.0071)	(0.9805)	(0.0104)	(0.8066)	(0.7956)	(0.7746)	(0.7446)	(0.7059)	(0.7121)
EP	-0.0317	-0.0009	-0.0337	0.0002*	-0.0662	-0.0195	-0.0501	0.0087	-0.0685	0.0047
	(0.8176)	(0.9391)	(0.7546)	(0.0914)	(0.5790)	(0.7723)	(0.6360)	(0.1287)	(0.5429)	(0.2118)
DE	-0.0019	-0.0019	-0.0006	-0.0006	-0.0023	-0.0023	-0.0051	-0.0051	-0.0020	-0.0020
	(0.6310)	(0.6310)	(0.6726)	(0.6726)	(0.6442)	(0.6442)	(0.5680)	(0.5680)	(0.6248)	(0.6248)
$SVAR$	-0.0039	-0.0039	-0.0063	-0.0063	-0.0324	-0.0324	-0.0504	-0.0504	-0.0593	-0.0593
	(0.7138)	(0.7138)	(0.6463)	(0.6463)	(0.5549)	(0.5549)	(0.6305)	(0.6305)	(0.6178)	(0.6178)
BM	-0.1865	-0.0822	-0.1688	-0.0848	-0.2508	-0.1315	-0.2066	-0.0564	-0.1563	-0.0477
	(0.9372)	(0.8724)	(0.8612)	(0.8131)	(0.6650)	(0.5968)	(0.6821)	(0.6252)	(0.6147)	(0.6298)
$NTIS$	-0.0989	-0.0940	-0.1138	-0.1086	-0.1557	-0.1520	-0.1900	-0.1852	-0.1782	-0.1782
	(0.8048)	(0.7556)	(0.7516)	(0.6948)	(0.6226)	(0.6047)	(0.7037)	(0.7224)	(0.8602)	(0.8602)
TBL	0.0001*	0.0131**	-0.0000*	0.0144*	-0.0269	-0.0102	-0.0042	-0.0042	0.0002	0.0002
	(0.0708)	(0.0435)	(0.0834)	(0.0555)	(0.7456)	(0.7107)	(0.6211)	(0.6211)	(0.3301)	(0.3301)
LTY	-0.0131	0.0120*	-0.0125	0.0155**	-0.0277	-0.0070	0.0018	0.0018	0.0055	0.0055
	(0.8302)	(0.0540)	(0.8348)	(0.0493)	(0.6304)	(0.7404)	(0.2720)	(0.2720)	(0.1296)	(0.1296)
LTR	0.0029**	0.0007*	0.0077**	0.0053*	0.0174**	0.0125*	0.0152*	0.0132*	0.0159	0.0125
	(0.0470)	(0.0622)	(0.0423)	(0.0570)	(0.0355)	(0.0505)	(0.0619)	(0.0729)	(0.1089)	(0.1276)
TMS	0.0018*	0.0034*	-0.0004	0.0013	-0.0273	-0.0229	-0.0392	-0.0392	-0.0233	-0.0233
	(0.0810)	(0.0929)	(0.9002)	(0.1154)	(0.6872)	(0.6514)	(0.6685)	(0.6685)	(0.5725)	(0.5725)
DFY	0.0152**	0.0152**	0.0141*	0.0141*	-0.0097	-0.0097	-0.0110	-0.0110	-0.0175	-0.0175
	(0.0445)	(0.0445)	(0.0840)	(0.0840)	(0.6311)	(0.6311)	(0.5582)	(0.5582)	(0.5387)	(0.5387)
DFR	-0.0867	-0.0713	-0.0701	-0.0610	-0.0523	-0.0510	-0.0561	-0.0556	-0.0541	-0.0541
	(0.8759)	(0.8421)	(0.8270)	(0.8027)	(0.8743)	(0.8705)	(0.8652)	(0.8651)	(0.8192)	(0.8192)
$INFL$	0.0043	0.0054	0.0055	0.0067	-0.0064	-0.0050	-0.0027	-0.0027	-0.0143	-0.0143
	(0.1690)	(0.1497)	(0.1627)	(0.1435)	(0.5843)	(0.6161)	(0.6170)	(0.6170)	(0.6406)	(0.6406)
$ECON_{AVG}$	-0.0161	-0.0124	-0.0144	-0.0122	-0.0438	-0.0403	-0.0236	-0.0193	-0.0340	-0.0295
	(0.9674)	(0.9575)	(0.9296)	(0.9104)	(0.7982)	(0.7458)	(0.8463)	(0.8014)	(0.8079)	(0.7408)
$ECON_{PC}$	-0.0681	-0.0094	-0.0427	-0.0012	-0.1136	-0.0527	-0.1275	-0.0509	-0.1236	-0.0454
	(0.9863)	(0.9809)	(0.9702)	(0.9690)	(0.7688)	(0.6742)	(0.7628)	(0.6610)	(0.7002)	(0.6422)
$IVOL$	-0.0064	-0.0064	-0.0111	-0.0111	-0.0254	-0.0254	-0.0365	-0.0365	-0.0455	-0.0455
	(0.7662)	(0.7662)	(0.6610)	(0.6610)	(0.5032)	(0.5032)	(0.5656)	(0.5656)	(0.7160)	(0.7160)
Vm	-	-	-0.0685	-0.0596	-0.1072	-0.0947	-0.1548	-0.1388	-0.1862	-0.1647
	-	-	(0.6324)	(0.5926)	(0.7326)	(0.6960)	(0.8388)	(0.8089)	(0.8242)	(0.7922)
Skm	-	-	-0.0094	-0.0059	-0.0170	-0.0161	-0.0122	-0.0111	-0.0073	-0.0073
	-	-	(0.6809)	(0.7183)	(0.5272)	(0.5239)	(0.5133)	(0.5177)	(0.5077)	(0.5077)
Vvw	-	-	-0.0380	-0.0146	-0.0431	-0.0339	-0.0559	-0.0442	-0.0662	-0.0504
	-	-	(0.5190)	(0.6898)	(0.6074)	(0.5286)	(0.6933)	(0.6258)	(0.6778)	(0.6045)
Vew	-	-	-0.0420	-0.0275	-0.0469	-0.0412	-0.0615	-0.0543	-0.0815	-0.0718
	-	-	(0.5637)	(0.7220)	(0.5893)	(0.6477)	(0.5208)	(0.5403)	(0.5522)	(0.5099)
$Skew$	-	-	-0.0186	-0.0097	-0.0265	-0.0195	-0.0171	-0.0171	-0.0108	-0.0108
	-	-	(0.5985)	(0.6642)	(0.6244)	(0.5650)	(0.6942)	(0.6942)	(0.6481)	(0.6481)
$Skvw$	-	-	-0.0114	-0.0016	-0.0330	-0.0220	-0.0267	-0.0261	-0.0127	-0.0127
	-	-	(0.6841)	(0.7835)	(0.7203)	(0.6074)	(0.8625)	(0.8623)	(0.6671)	(0.6671)
$ILLIQ^E$	-	-	-0.0119	0.0181**	-0.0439	-0.0000*	-0.0475	-0.0067	-0.0699	-0.0149
	-	-	(0.9755)	(0.0168)	(0.8737)	(0.0794)	(0.7726)	(0.8475)	(0.7137)	(0.7919)
AC	-	-	0.0066*	0.0056*	0.0015	0.0000	-0.0384	-0.0389	-0.0033	-0.0048
	-	-	(0.0580)	(0.0685)	(0.1088)	(0.1250)	(0.6778)	(0.6537)	(0.7872)	(0.7756)
TR	-	-	0.0004	0.0021	-0.0110	-0.0104	-0.0063	-0.0055	-0.0075	-0.0064
	-	-	(0.2326)	(0.2106)	(0.5432)	(0.5328)	(0.5432)	(0.5551)	(0.5451)	(0.5572)
SII	-	-	-	-	-	-	-0.0043	0.0030	0.0191	0.0167
	-	-	-	-	-	-	(0.7621)	(0.1775)	(0.1295)	(0.1321)
VIX	-	-	-	-	-	-	-	-	-0.0386	-0.0359
	-	-	-	-	-	-	-	-	(0.6344)	(0.6403)

Table IA10 Out-of-Sample Performance (Semi-Annual Results)

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. **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. **$ECON_{AVG}$** is the equally weighted average of the above 14 classical predictors. **$ECON_{PC}$** is the first principal component extracted from the above 14 classical predictors. In addition, we also compare our CIS with the following recent predictors. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). **$ILLIQ^E$** is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to Decmber 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. For CIS, we use equation (3) to predict future returns. For predictors other than CIS, we use the simple linear predictive regression in equation (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.

	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	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$
CIS	-0.0625	-0.0519	-0.0176	-0.0054	0.0245*	0.0312*	0.0374*	0.0368*	0.0387	0.0378
	(0.6891)	(0.6805)	(0.8445)	(0.8582)	(0.0630)	(0.0545)	(0.0694)	(0.0705)	(0.1155)	(0.1177)
DP	0.0070**	0.0325***	0.0093**	0.0385**	-0.0836	-0.0378	-0.1271	-0.0656	-0.1482	-0.0652
	(0.0119)	(0.0064)	(0.0216)	(0.0117)	(0.8206)	(0.8333)	(0.7729)	(0.7748)	(0.7128)	(0.7182)
DY	-0.0037	0.0277***	0.0060**	0.0412**	-0.0941	-0.0384	-0.1451	-0.0702	-0.1610	-0.0675
	(0.9876)	(0.0071)	(0.0218)	(0.0116)	(0.8198)	(0.8343)	(0.7663)	(0.7664)	(0.7225)	(0.7176)
EP	-0.0304	0.0186**	-0.0392	0.0170*	-0.1140	-0.0261	-0.0930	0.0250	-0.1461	0.0154
	(0.8836)	(0.0352)	(0.8334)	(0.0571)	(0.6522)	(0.8205)	(0.6994)	(0.1073)	(0.5879)	(0.1967)
DE	-0.0195	-0.0195	-0.0149	-0.0149	-0.0044	-0.0044	-0.0062	-0.0062	-0.0032	-0.0032
	(0.9195)	(0.9195)	(0.8447)	(0.8447)	(0.5143)	(0.5143)	(0.5327)	(0.5327)	(0.5423)	(0.5423)
$SVAR$	0.0013	0.0013	0.0033*	0.0033*	0.0039	0.0039	0.0035	0.0035	0.0045	0.0045
	(0.2525)	(0.2525)	(0.0752)	(0.0752)	(0.1228)	(0.1228)	(0.1832)	(0.1832)	(0.1690)	(0.1690)
BM	-0.1319	-0.0574	-0.1388	-0.0609	-0.3042	-0.1774	-0.2900	-0.1196	-0.2262	-0.1013
	(0.9617)	(0.9452)	(0.9160)	(0.9001)	(0.7400)	(0.6818)	(0.7336)	(0.6725)	(0.7004)	(0.6734)
$NTIS$	-0.0725	-0.0680	-0.0879	-0.0829	-0.1590	-0.1576	-0.2630	-0.2611	-0.2956	-0.2956
	(0.7501)	(0.7552)	(0.7180)	(0.7231)	(0.5985)	(0.5923)	(0.7258)	(0.7328)	(0.8407)	(0.8407)
TBL	-0.0339	0.0219**	-0.0253	0.0286**	-0.0824	-0.0289	-0.0136	-0.0136	0.0030	0.0030
	(0.9573)	(0.0159)	(0.9079)	(0.0446)	(0.7103)	(0.6931)	(0.6257)	(0.6257)	(0.2741)	(0.2741)
LTY	-0.0418	0.0211**	-0.0462	0.0259*	-0.0838	-0.0231	-0.0029	-0.0029	0.0120	0.0120
	(0.8360)	(0.0432)	(0.8100)	(0.0558)	(0.5663)	(0.6810)	(0.6414)	(0.6414)	(0.1407)	(0.1407)
LTR	-0.0638	-0.0472	-0.0673	-0.0648	-0.1831	-0.1789	-0.2113	-0.2037	-0.0793	-0.0685
	(0.9967)	(0.9946)	(0.9910)	(0.9800)	(0.8585)	(0.7681)	(0.5259)	(0.5015)	(0.7357)	(0.7270)
TMS	-0.0016	-0.0084	-0.0097	-0.0195	-0.0772	-0.0752	-0.0809	-0.0809	-0.0591	-0.0591
	(0.9597)	(0.9307)	(0.9206)	(0.8538)	(0.7641)	(0.6226)	(0.5549)	(0.5549)	(0.5244)	(0.5244)
DFY	0.0175**	0.0175**	0.0174*	0.0174*	0.0061	0.0061	0.0053	0.0053	0.0042	0.0042
	(0.0394)	(0.0394)	(0.0584)	(0.0584)	(0.2458)	(0.2458)	(0.2212)	(0.2212)	(0.2719)	(0.2719)
DFR	-0.0359	-0.0351	-0.0264	-0.0255	-0.0286	-0.0272	-0.0755	-0.0737	-0.0692	-0.0665
	(0.7878)	(0.7855)	(0.6608)	(0.6571)	(0.6221)	(0.6179)	(0.9116)	(0.9110)	(0.8601)	(0.8588)
$INFL$	0.0096	0.0096	0.0101	0.0101	0.0067	0.0067	0.0141	0.0141	0.0055	0.0055
	(0.1440)	(0.1440)	(0.1588)	(0.1588)	(0.2411)	(0.2411)	(0.1868)	(0.1868)	(0.3200)	(0.3200)
$ECON_{AVG}$	0.0056*	0.0056*	-0.0030	-0.0030	-0.0512	-0.0512	-0.0172	-0.0172	-0.0232	-0.0232
	(0.0530)	(0.0530)	(0.8944)	(0.8944)	(0.7056)	(0.7056)	(0.8073)	(0.8073)	(0.7954)	(0.7954)
$ECON_{PC}$	0.0001**	0.0215**	0.0020**	0.0266**	-0.0920	-0.0536	-0.1199	-0.0683	-0.1246	-0.0650
	(0.0168)	(0.0116)	(0.0326)	(0.0233)	(0.7948)	(0.7961)	(0.7761)	(0.7789)	(0.7332)	(0.7303)
$IVOL$	-0.0015	-0.0015	-0.0047	-0.0047	-0.0145	-0.0145	-0.0226	-0.0226	-0.0371	-0.0371
	(0.6355)	(0.6355)	(0.5462)	(0.5462)	(0.5987)	(0.5987)	(0.6448)	(0.6448)	(0.7828)	(0.7828)
Vm	-	-	-0.0544	-0.0532	-0.0537	-0.0519	-0.0758	-0.0733	-0.0981	-0.0944
	-	-	(0.5607)	(0.5569)	(0.5262)	(0.5209)	(0.7175)	(0.7118)	(0.8367)	(0.8314)
Skm	-	-	0.0102*	0.0201**	0.0016*	0.0173*	-0.0214	-0.0010	-0.0332	-0.0183
	-	-	(0.0539)	(0.0444)	(0.0763)	(0.0608)	(0.8067)	(0.8372)	(0.6389)	(0.6740)
Vvw	-	-	-0.0859	-0.0734	-0.0564	-0.0540	-0.0682	-0.0649	-0.0868	-0.0819
	-	-	(0.7860)	(0.7358)	(0.5570)	(0.5498)	(0.6421)	(0.6343)	(0.6757)	(0.6673)
Vew	-	-	-0.1282	-0.1164	-0.0677	-0.0670	-0.0777	-0.0768	-0.1138	-0.1125
	-	-	(0.8483)	(0.8130)	(0.5912)	(0.5933)	(0.5572)	(0.5597)	(0.5060)	(0.5087)
$Skew$	-	-	-0.0494	-0.0377	-0.0623	-0.0462	-0.0487	-0.0317	-0.0483	-0.0252
	-	-	(0.5390)	(0.5248)	(0.5705)	(0.5094)	(0.5890)	(0.5002)	(0.5953)	(0.5003)
$Skvw$	-	-	-0.0396	0.0012	-0.0864	-0.0365	-0.0336	-0.0238	-0.0222	-0.0083
	-	-	(0.7587)	(0.1167)	(0.5371)	(0.6433)	(0.6078)	(0.6546)	(0.6147)	(0.6680)
$ILLIQ^E$	-	-	-0.0186	0.0456**	-0.1186	-0.0090	-0.1592	-0.0267	-0.2238	-0.0296
	-	-	(0.9739)	(0.0185)	(0.8717)	(0.8829)	(0.7147)	(0.7974)	(0.7066)	(0.7955)
AC	-	-	0.0024*	0.0017*	0.0207*	0.0195*	-0.0102	-0.0114	0.0199	0.0198
	-	-	(0.0705)	(0.0740)	(0.0528)	(0.0559)	(0.8577)	(0.8514)	(0.1350)	(0.1352)
TR	-	-	0.0011	0.0073	-0.0184	-0.0138	-0.0137	-0.0074	-0.0128	-0.0035
	-	-	(0.2619)	(0.2181)	(0.5456)	(0.5809)	(0.5809)	(0.6196)	(0.6030)	(0.6426)
SII	-	-	-	-	-	-	0.0016	0.0144*	0.0564	0.0490
	-	-	-	-	-	-	(0.1305)	(0.0994)	(0.1016)	(0.1027)
VIX	-	-	-	-	-	-	-	-	-0.0916	-0.0632
	-	-	-	-	-	-	-	-	(0.6477)	(0.6014)

Table IA11 Out-of-Sample Performance (Flexible Control Variables)

This table reports out-of-sample R^2s of each predictor. For a predictor **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. **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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. In addition, we also compare our CIS with the following recent predictors. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^E}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to Decmber 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. R^2_{OOS} is the out-of-sample R^2 without any restriction, whereas $R^2_{OOS}(+)$ are the out-of-sample R^2 with non-negative equity premium predictions following Campbell and Thompson (2008). One-sided 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.

	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	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$	R^2_{oos}	$R^2_{oos}(+)$
CIS	0.0040**	0.0047**	0.0106***	0.0113***	0.0149***	0.0152***	0.0194***	0.0197***	0.0256***	0.0259***
	(0.0166)	(0.0165)	(0.0057)	(0.0044)	(0.0062)	(0.0038)	(0.0047)	(0.0029)	(0.0055)	(0.0031)
DP	-0.0084	-0.0003	-0.0088	0.0003	-0.0185	-0.0069	-0.0255	-0.0105	-0.0264	-0.0142
	(0.7770)	(0.9043)	(0.7590)	(0.1026)	(0.5459)	(0.6441)	(0.6228)	(0.5619)	(0.7380)	(0.6078)
DY	-0.0084	-0.0015	-0.0067	0.0008*	-0.0175	-0.0073	-0.0231	-0.0106	-0.0284	-0.0151
	(0.8337)	(0.9002)	(0.8696)	(0.0695)	(0.5477)	(0.6685)	(0.5291)	(0.5754)	(0.7685)	(0.6202)
EP	-0.0219	-0.0069	-0.0192	-0.0031	-0.0215	-0.0008	-0.0216	0.0052*	-0.0281	0.0005
	(0.6695)	(0.8251)	(0.6529)	(0.8304)	(0.6534)	(0.8556)	(0.6849)	(0.0854)	(0.5476)	(0.2147)
DE	-0.0109	-0.0065	-0.0086	-0.0037	-0.0102	-0.0054	-0.0112	-0.0069	-0.0149	-0.0090
	(0.5524)	(0.5361)	(0.5038)	(0.6318)	(0.6582)	(0.5309)	(0.8040)	(0.7213)	(0.8798)	(0.8651)
$SVAR$	-0.0165	-0.0165	-0.0170	-0.0170	-0.0229	-0.0229	-0.0291	-0.0291	-0.0150	-0.0150
	(0.9080)	(0.9080)	(0.8949)	(0.8949)	(0.9191)	(0.9191)	(0.9195)	(0.9195)	(0.8440)	(0.8440)
BM	-0.0150	-0.0145	-0.0144	-0.0143	-0.0230	-0.0229	-0.0123	-0.0121	-0.0085	-0.0085
	(0.8277)	(0.8177)	(0.7266)	(0.7280)	(0.5164)	(0.5142)	(0.7245)	(0.7207)	(0.7778)	(0.7778)
$NTIS$	-0.0345	-0.0336	-0.0370	-0.0362	-0.0475	-0.0470	-0.0516	-0.0514	-0.0543	-0.0543
	(0.7238)	(0.7311)	(0.7053)	(0.7143)	(0.6413)	(0.6465)	(0.7649)	(0.7637)	(0.9490)	(0.9490)
TBL	-0.0025	0.0062***	-0.0001	0.0071**	-0.0100	-0.0027	0.0008	0.0008	0.0045	0.0045
	(0.9862)	(0.0064)	(0.9656)	(0.0163)	(0.7427)	(0.7968)	(0.1944)	(0.1944)	(0.1213)	(0.1213)
LTY	-0.0094	0.0033**	-0.0042	0.0052**	-0.0100	-0.0035	0.0008	0.0008	0.0049*	0.0049*
	(0.9477)	(0.0177)	(0.8998)	(0.0301)	(0.6076)	(0.7383)	(0.1868)	(0.1868)	(0.0964)	(0.0964)
LTR	0.0014**	0.0019*	0.0024**	0.0030*	-0.0031	-0.0010	-0.0031	-0.0051	-0.0065	-0.0072
	(0.0423)	(0.0708)	(0.0361)	(0.0578)	(0.9013)	(0.8509)	(0.8044)	(0.6318)	(0.6672)	(0.5157)
TMS	0.0047**	0.0069**	0.0040**	0.0064**	-0.0061	-0.0028	-0.0072	-0.0069	-0.0046	-0.0041
	(0.0191)	(0.0147)	(0.0308)	(0.0253)	(0.7840)	(0.7917)	(0.5315)	(0.5324)	(0.6174)	(0.6203)
DFY	-0.0048	-0.0035	0.0001	0.0003	-0.0049	-0.0048	-0.0116	-0.0116	-0.0157	-0.0157
	(0.6762)	(0.7029)	(0.1897)	(0.1874)	(0.5895)	(0.5923)	(0.7227)	(0.7227)	(0.8183)	(0.8183)
DFR	-0.0041	-0.0011	-0.0016	0.0012	0.0006	0.0015	0.0031	0.0039	0.0063	0.0069
	(0.7215)	(0.7735)	(0.7641)	(0.1580)	(0.2350)	(0.1712)	(0.2168)	(0.1315)	(0.2149)	(0.1152)
$INFL$	0.0100***	0.0112***	0.0141***	0.0152***	0.0129***	0.0135***	0.0116**	0.0120**	0.0076*	0.0082*
	(0.0020)	(0.0013)	(0.0012)	(0.0007)	(0.0032)	(0.0028)	(0.0110)	(0.0106)	(0.0607)	(0.0583)
$ECON_{AVG}$	-0.0212	-0.0190	-0.0215	-0.0188	-0.0269	-0.0242	-0.0286	-0.0250	-0.0142	-0.0141
	(0.5922)	(0.5434)	(0.5734)	(0.5160)	(0.6719)	(0.6230)	(0.9826)	(0.9760)	(0.8304)	(0.8301)
$ECON_{PC}$	-0.0028	0.0014*	-0.0012	0.0034*	-0.0100	-0.0037	-0.0162	-0.0077	-0.0181	-0.0135
	(0.9008)	(0.0757)	(0.9281)	(0.0522)	(0.7390)	(0.7882)	(0.5363)	(0.6138)	(0.7046)	(0.6445)
$IVOL$	-0.0015	-0.0004	0.0018*	0.0029*	-0.0078	-0.0063	-0.0111	-0.0094	-0.0211	-0.0188
	(0.8925)	(0.9062)	(0.0751)	(0.0648)	(0.6652)	(0.6917)	(0.5082)	(0.5460)	(0.7355)	(0.7024)
Vm	-	-	-0.0151	-0.0119	-0.0132	-0.0159	-0.0113	-0.0154	0.0039	-0.0028
	-	-	(0.5783)	(0.7125)	(0.6089)	(0.8370)	(0.6504)	(0.8170)	(0.2032)	(0.5433)
Skm	-	-	-0.0205	-0.0159	-0.0188	-0.0142	-0.0126	-0.0102	-0.0054	-0.0049
	-	-	(0.8175)	(0.7986)	(0.9265)	(0.8990)	(0.8956)	(0.8519)	(0.6588)	(0.6464)
Vvw	-	-	-0.0124	-0.0015	-0.0108	-0.0100	-0.0086	-0.0083	0.0036	0.0028
	-	-	(0.6933)	(0.7748)	(0.5835)	(0.6167)	(0.6137)	(0.5985)	(0.2255)	(0.2775)
Vew	-	-	-0.0172	-0.0098	-0.0177	-0.0167	-0.0213	-0.0197	-0.0078	-0.0056
	-	-	(0.5243)	(0.5153)	(0.6561)	(0.7582)	(0.7105)	(0.8051)	(0.5862)	(0.5464)
$Skew$	-	-	-0.0056	0.0002	-0.0076	-0.0046	0.0019	0.0019	0.0041	0.0040
	-	-	(0.7110)	(0.1418)	(0.5611)	(0.6115)	(0.1334)	(0.1392)	(0.1116)	(0.1171)
$Skvw$	-	-	-0.0049	-0.0030	-0.0054	-0.0035	0.0012*	0.0010*	0.0012	0.0010
	-	-	(0.7840)	(0.8409)	(0.7611)	(0.8255)	(0.0796)	(0.0849)	(0.1005)	(0.1079)
$ILLIQ^E$	-	-	-0.0098	0.0003*	-0.0119	-0.0007	-0.0149	-0.0018	-0.0235	-0.0049
	-	-	(0.9242)	(0.0678)	(0.8610)	(0.8797)	(0.7221)	(0.8165)	(0.6676)	(0.7598)
AC	-	-	-0.0134	-0.0113	-0.0122	-0.0128	-0.0210	-0.0206	-0.0144	-0.0142
	-	-	(0.5052)	(0.5069)	(0.5085)	(0.5362)	(0.7236)	(0.7245)	(0.5946)	(0.5921)
TR	-	-	-0.0023	-0.0001	-0.0038	-0.0028	-0.0017	-0.0001	0.0021	0.0027
	-	-	(0.8886)	(0.9010)	(0.7906)	(0.8058)	(0.7781)	(0.8115)	(0.1905)	(0.1812)
SII	-	-	-	-	-	-	-0.0023	-0.0011	0.0062	-0.0005
	-	-	-	-	-	-	(0.8553)	(0.7749)	(0.1466)	(0.7483)
VIX	-	-	-	-	-	-	-	-	-0.0415	-0.0304
	-	-	-	-	-	-	-	-	(0.8253)	(0.7693)

Table IA12 Out-of-Sample Encompassing Test (Quarterly Results)

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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^E}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to Decmber 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. For CIS, we use equation (3) to predict future returns. For predictors other than CIS, we use the simple linear predictive regression in equation (2). *, **, 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	0.5045***	0.4955***	0.5500***	0.4500***	0.7120***	0.2880*	0.7987***	0.2013	0.8433***	0.1567
DY	0.5345***	0.4655***	0.5642***	0.4358***	0.7221***	0.2779*	0.7992***	0.2008	0.8431***	0.1569
EP	0.5292***	0.4708***	0.6461***	0.3539**	0.7564***	0.2436	0.8528**	0.1472	0.9601**	0.0399
DE	0.3413*	0.6587***	0.5392**	0.4608*	0.6675**	0.3325	0.8182**	0.1818	0.8230*	0.1770
$SVAR$	0.3991*	0.6009**	0.5804*	0.4196	0.8465*	0.1535	1.0000*	0.0000	1.0000*	0.0000
BM	0.6875***	0.3125***	0.7539***	0.2461**	0.8045***	0.1955**	0.8646***	0.1354	0.8910***	0.1090
$NTIS$	0.6883***	0.3117**	0.8119***	0.1881	0.9259***	0.0741	1.0000***	0.0000	1.0000***	0.0000
TBL	0.3666*	0.6334**	0.5301*	0.4699	0.9912***	0.0088	0.8316**	0.1684	0.9069*	0.0931
LTY	0.4446*	0.5554**	0.6182**	0.3818	1.0000***	0.0000	0.8014*	0.1986	0.8998	0.1002
LTR	0.3821**	0.6179***	0.4793**	0.5207**	0.4787**	0.5213**	0.5208*	0.4792*	0.5565*	0.4435
TMS	0.3482*	0.6518***	0.5313**	0.4687*	0.7972***	0.2028	1.0000***	0.0000	0.9947**	0.0053
DFY	0.3104*	0.6896***	0.4277*	0.5723**	0.6482**	0.3518	0.8455**	0.1545	0.9677**	0.0323
DFR	0.7895***	0.2105	0.8873***	0.1127	1.0000***	0.0000	1.0000**	0.0000	1.0000**	0.0000
$INFL$	0.2703	0.7297***	0.4827*	0.5173*	0.7676**	0.2324	0.9029*	0.0971	1.0000**	0.0000
$ECON_{AVG}$	0.4837***	0.5163***	0.5634***	0.4366***	0.6576***	0.3424**	0.6917***	0.3083	0.7259***	0.2741
$ECON_{PC}$	0.5753***	0.4247***	0.6128***	0.3872***	0.7449***	0.2551**	0.8190***	0.1810	0.8520***	0.1480
$IVOL$	0.4129**	0.5871***	0.6082**	0.3918*	0.7742***	0.2258	0.9776**	0.0224	1.0000**	0.0000
Vm	-	-	0.8886**	0.1114	1.0000**	0.0000	1.0000**	0.0000	1.0000**	0.0000
Skm	-	-	0.6166**	0.3834*	0.8145***	0.1855	0.8614**	0.1386	0.9421**	0.0579
Vvw	-	-	0.7535**	0.2465	0.8748**	0.1252	1.0000**	0.0000	1.0000*	0.0000
Vew	-	-	0.7726***	0.2274	0.8422***	0.1578	0.9800**	0.0200	1.0000**	0.0000
$Skew$	-	-	0.6711***	0.3289	0.8967***	0.1033	0.9868**	0.0132	1.0000**	0.0000
$Skvw$	-	-	0.6199**	0.3801*	0.9339***	0.0661	1.0000***	0.0000	1.0000**	0.0000
$ILLIQ^E$	-	-	0.5970***	0.4030**	0.7957***	0.2043	0.7924***	0.2076	0.8453***	0.1547
AC	-	-	0.4921**	0.5079**	0.5912**	0.4088*	0.9152***	0.0848	0.7252*	0.2748
TR	-	-	0.5526*	0.4474*	0.8045**	0.1955	0.9102**	0.0898	0.9708*	0.0292
SII	-	-	-	-	-	-	0.7353**	0.2647	0.6387	0.3613
VIX	-	-	-	-	-	-	-	-	0.8582**	0.1418

Table IA13 Out-of-Sample Encompassing Test (Semi-Annual Results)

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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^E}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to Decmber 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. For CIS, we use equation (3) to predict future returns. For predictors other than CIS, we use the simple linear predictive regression in equation (2). *, **, 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	0.3795**	0.6205***	0.4425**	0.5575***	0.6743***	0.3257*	0.7659***	0.2341	0.7829***	0.2171
DY	0.4073***	0.5927***	0.4516**	0.5484***	0.6820***	0.3180*	0.7752***	0.2248	0.7804***	0.2196
EP	0.4382**	0.5618***	0.5468**	0.4532**	0.7284**	0.2716	0.7986*	0.2014	0.8739*	0.1261
DE	0.2641	0.7359**	0.4848*	0.5152*	0.6629**	0.3371	0.8418**	0.1582	0.7782*	0.2218
$SVAR$	0.1559	0.8441***	0.3771	0.6229*	0.6203*	0.3797	0.8160*	0.1840	0.7725	0.2275
BM	0.5644***	0.4356***	0.6325***	0.3675**	0.7565***	0.2435*	0.8212***	0.1788	0.8002***	0.1998
$NTIS$	0.5234**	0.4766**	0.6707***	0.3293	0.8816***	0.1184	1.0000***	0.0000	1.0000**	0.0000
TBL	0.4431***	0.5569***	0.5287**	0.4713*	0.9990***	0.0010	0.8205**	0.1795	0.7464*	0.2536
LTY	0.4361*	0.5639**	0.6145**	0.3855	1.0000**	0.0000	0.8292*	0.1708	0.7469	0.2531
LTR	0.5015***	0.4985***	0.5658***	0.4342***	0.7933***	0.2067	0.9572***	0.0428	0.7563***	0.2437
TMS	0.3336*	0.6664***	0.4706**	0.5294**	0.7876***	0.2124	0.9589***	0.0411	0.8666**	0.1334
DFY	0.1345	0.8655***	0.3160	0.6840**	0.5861*	0.4139	0.7531*	0.2469	0.7333*	0.2667
DFR	0.3892*	0.6108**	0.5394*	0.4606*	0.7488**	0.2512	1.0000***	0.0000	1.0000**	0.0000
$INFL$	0.0880	0.9120***	0.3224	0.6776**	0.6169	0.3831	0.7097	0.2903	0.7505	0.2495
$ECON_{AVG}$	0.3440*	0.6560***	0.4601**	0.5399**	0.6507***	0.3493*	0.6663**	0.3337	0.6492**	0.3508
$ECON_{PC}$	0.3969**	0.6031***	0.4600**	0.5400***	0.6745***	0.3255*	0.7583***	0.2417	0.7571***	0.2429
$IVOL$	0.2145	0.7855**	0.4293	0.5707*	0.7049**	0.2951	0.9528*	0.0472	0.9698*	0.0302
Vm	-	-	0.6740**	0.3260	0.8425**	0.1575	1.0000**	0.0000	1.0000**	0.0000
Skm	-	-	0.4090*	0.5910**	0.5833**	0.4167*	0.6927**	0.3073	0.7741**	0.2259
Vvw	-	-	0.7834**	0.2166	0.8236**	0.1764	0.9687**	0.0313	1.0000*	0.0000
Vew	-	-	0.9048***	0.0952	0.8436**	0.1564	0.9448**	0.0552	0.9797**	0.0203
$Skew$	-	-	0.6445**	0.3555	0.8662**	0.1338	0.9082**	0.0918	0.9257*	0.0743
$Skvw$	-	-	0.5853**	0.4147*	0.8650**	0.1350	0.8018**	0.1982	0.7786*	0.2214
$ILLIQ^E$	-	-	0.5078**	0.4922**	0.8031***	0.1969	0.8403***	0.1597	0.8352***	0.1648
AC	-	-	0.4085*	0.5915**	0.5394**	0.4606*	0.7562**	0.2438	0.6430*	0.3570
TR	-	-	0.4041	0.5959*	0.7513**	0.2487	0.8434*	0.1566	0.7912*	0.2088
SII	-	-	-	-	-	-	0.6554*	0.3446	0.4823	0.5177
VIX	-	-	-	-	-	-	-	-	1.0000**	0.0000

Table IA14 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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. In addition, we also compare our CIS with the following recent predictors. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^E}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to Decmber 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. *, **, 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	0.9224***	0.0776	1.0000***	0.0000	1.0000***	0.0000
DY	0.6636***	0.3364**	0.7358***	0.2642*	0.9082***	0.0918	1.0000***	0.0000	1.0000***	0.0000
EP	0.7665***	0.2335	0.8557***	0.1443	0.8935***	0.1065	1.0000***	0.0000	1.0000***	0.0000
DE	0.8113***	0.1887	0.8825***	0.1175	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
$SVAR$	0.9554***	0.0446	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
BM	0.6538***	0.3462**	0.7580***	0.2420	0.8413***	0.1587	1.0000***	0.0000	1.0000***	0.0000
$NTIS$	0.8325***	0.1675	0.9273***	0.0727	0.9890***	0.0110	1.0000***	0.0000	1.0000***	0.0000
TBL	0.5645***	0.4355***	0.6715***	0.3285	1.0000***	0.0000	1.0000***	0.0000	1.0000**	0.0000
LTY	0.6132***	0.3868***	0.7037***	0.2963	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
LTR	0.5428***	0.4572**	0.6365***	0.3635*	0.7900***	0.2100	0.9399***	0.0601	1.0000***	0.0000
TMS	0.4863**	0.5137**	0.6623**	0.3377	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
DFY	0.6674***	0.3326*	0.7106***	0.2894	0.8842***	0.1158	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
$INFL$	0.3969**	0.6031***	0.4380**	0.5620**	0.5367**	0.4633**	0.6458**	0.3542	0.8430**	0.1570
$ECON_{AVG}$	0.7675***	0.2325	0.8377***	0.1623	0.9097***	0.0903	1.0000***	0.0000	1.0000***	0.0000
$ECON_{PC}$	0.5934***	0.4066**	0.6660***	0.3340*	0.8132***	0.1868	1.0000***	0.0000	1.0000***	0.0000
$IVOL$	0.6051**	0.3949*	0.6932**	0.3068	0.9817***	0.0183	1.0000***	0.0000	1.0000***	0.0000
Vm	-	-	0.9397***	0.0603	1.0000***	0.0000	1.0000***	0.0000	0.8922**	0.1078
Skm	-	-	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
Vvw	-	-	0.8875***	0.1125	1.0000***	0.0000	1.0000***	0.0000	1.0000**	0.0000
Vew	-	-	0.9978***	0.0022	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
$Skew$	-	-	0.8557***	0.1443	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
$Skvw$	-	-	0.8315***	0.1685	0.9691***	0.0309	0.9480***	0.0520	1.0000***	0.0000
$ILLIQ^E$	-	-	0.8400***	0.1600	0.9160***	0.0840	0.9769***	0.0231	1.0000***	0.0000
AC	-	-	0.9879***	0.0121	1.0000***	0.0000	1.0000***	0.0000	1.0000***	0.0000
TR	-	-	0.7848***	0.2152	0.9351***	0.0649	1.0000***	0.0000	1.0000***	0.0000
SII	-	-	-	-	-	-	0.8126***	0.1874	0.9240**	0.0760
VIX	-	-	-	-	-	-	-	-	1.0000***	0.0000

Table IA15 Utility Gain, Sharpe Ratio, and Transaction Fees (Quarterly Results)

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 (SR) and transaction fees (Fee) are 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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^E}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to Decmber 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. 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*	*Annual Fee*	$\gamma=3$	$\gamma=5$	$\gamma=7$	*SR*	*Annual Fee*	$\gamma=3$	$\gamma=5$	$\gamma=7$	*SR*	*Annual Fee*	$\gamma=3$	$\gamma=5$	$\gamma=7$	*SR*	*Annual Fee*	$\gamma=3$	$\gamma=5$	$\gamma=7$	*SR*	*Annual Fee*
CIS	1.54%	1.35%	-0.06%	0.38^{***}	0.04%	1.97%	1.55%	0.47%	0.34^{***}	0.04%	2.03%	1.25%	-0.02%	0.46^{***}	0.04%	2.13%	1.00%	-0.46%	0.48^{***}	0.04%	3.22%	1.72%	-0.51%	0.45^{***}	0.05%
DP	-0.03%	1.61%	1.77%	0.22	0.02%	1.16%	2.10%	1.98%	0.23	0.02%	-1.22%	-0.01%	0.45%	0.23	0.02%	-1.78%	0.29%	0.86%	0.24	0.01%	-0.93%	1.56%	2.09%	0.21	0.01%
DY	0.21%	1.75%	1.87%	0.23	0.02%	1.56%	2.34%	2.15%	0.25	0.02%	-0.89%	0.19%	0.59%	0.25	0.02%	-1.36%	0.54%	1.04%	0.35	0.01%	-0.30%	1.94%	2.35%	0.32	0.01%
EP	1.21%	1.77%	1.35%	0.33	0.04%	1.90%	2.04%	1.31%	0.31^{*}	0.04%	2.36%	1.84%	1.00%	0.46^{*}	0.03%	2.68%	2.81%	2.34%	0.61^{***}	0.03%	3.10%	3.73%	3.19%	0.53^{***}	0.03%
DE	-0.05%	-0.08%	-0.00%	0.28	0.03%	-0.06%	-0.09%	0.02%	0.22	0.03%	-0.46%	-0.37%	-0.16%	0.33	0.03%	-0.41%	-0.67%	-0.34%	0.35	0.03%	-0.35%	-0.72%	-0.27%	0.31	0.03%
SVAR	0.16%	0.84%	0.04%	0.30	0.05%	0.60%	0.75%	-0.38%	0.27^{*}	0.05%	-0.00%	-0.52%	-1.63%	0.34	0.05%	-0.36%	-1.21%	-2.49%	0.33	0.05%	0.16%	-1.14%	-3.08%	0.32	0.06%
BM	-2.16%	-0.86%	-0.68%	0.12	0.02%	-1.45%	-0.88%	-0.96%	0.11	0.02%	-1.70%	-0.35%	-0.64%	0.22	0.01%	-2.63%	-0.22%	0.49%	0.27	0.00%	-1.53%	1.20%	1.83%	0.32	0.00%
NTIS	1.21%	0.11%	-0.48%	0.38^{**}	0.07%	1.68%	-0.32%	-1.20%	0.35^{***}	0.05%	0.95%	-0.95%	-1.89%	0.43^{**}	0.05%	-0.12%	-2.22%	-2.92%	0.38	0.05%	0.58%	-1.01%	-2.32%	0.35	0.04%
TBL	1.43%	1.88%	1.22%	0.35^{*}	0.03%	2.31%	2.15%	1.25%	0.32^{**}	0.03%	0.39%	0.15%	-0.38%	0.36	0.02%	0.84%	0.09%	-0.56%	0.40	0.03%	1.16%	0.22%	-0.68%	0.38^{***}	0.02%
LTY	1.24%	1.58%	1.22%	0.33	0.03%	1.86%	1.92%	1.42%	0.30^{*}	0.02%	-0.01%	-0.01%	-0.08%	0.34	0.02%	0.48%	-0.02%	-0.11%	0.38	0.02%	0.63%	0.06%	-0.06%	0.36^{***}	0.02%
LTR	1.72%	1.42%	0.44%	0.40^{***}	0.18%	1.81%	1.35%	0.59%	0.36^{***}	0.18%	2.26%	1.40%	0.72%	0.48^{***}	0.16%	2.58%	1.40%	0.80%	0.50^{***}	0.15%	1.97%	0.79%	0.22%	0.40^{**}	0.14%
TMS	1.86%	1.30%	0.59%	0.39^{***}	0.06%	2.46%	1.49%	0.55%	0.36^{***}	0.07%	1.16%	-0.22%	-0.91%	0.41^{*}	0.06%	0.25%	-1.18%	-1.80%	0.36	0.05%	0.06%	-0.63%	-1.53%	0.32	0.04%
DFY	0.48%	0.85%	-0.22%	0.31	0.04%	1.05%	0.78%	-0.68%	0.29^{**}	0.04%	0.23%	-0.56%	-2.05%	0.34	0.04%	0.09%	-0.44%	-1.66%	0.34	0.04%	0.63%	-0.14%	-1.97%	0.31	0.04%
DFR	-0.57%	-0.86%	-1.89%	0.28	0.11%	-0.37%	-0.84%	-1.69%	0.23	0.10%	-0.07%	-0.18%	-1.01%	0.36	0.08%	-0.26%	-0.57%	-1.53%	0.36	0.06%	0.40%	-0.21%	-1.76%	0.34	0.06%
INFL	0.53%	0.66%	0.02%	0.33^{**}	0.07%	0.66%	0.92%	0.13%	0.29^{***}	0.08%	0.15%	0.16%	-0.54%	0.38	0.08%	0.67%	0.20%	-0.71%	0.41^{**}	0.09%	0.14%	-0.29%	-1.42%	0.34	0.09%
$ECON_{AVG}$	-0.06%	1.09%	0.92%	0.24	0.05%	0.57%	1.11%	0.70%	0.22	0.05%	0.16%	0.46%	0.08%	0.32	0.04%	-0.23%	0.94%	1.28%	0.36	0.04%	-0.26%	1.57%	2.03%	0.21	0.03%
$ECON_{PC}$	-0.83%	1.00%	0.88%	0.17	0.02%	0.29%	1.43%	0.96%	0.18	0.02%	-1.90%	-0.60%	-0.64%	0.18	0.02%	-2.80%	-0.32%	0.42%	0.07	0.01%	-2.05%	0.89%	1.61%	0.04	0.01%
IVOL	-0.69%	-0.58%	-0.83%	0.29	0.04%	-0.80%	-1.05%	-1.50%	0.26	0.03%	-0.92%	-1.56%	-2.07%	0.34	0.03%	-1.28%	-2.13%	-2.77%	0.35	0.03%	-1.90%	-3.53%	-4.41%	0.24	0.03%
Vm	-	-	-	-	-	-0.66%	-0.09%	-1.42%	0.17	0.09%	-1.23%	-1.29%	-2.71%	0.24	0.08%	-2.45%	-2.68%	-4.27%	0.19	0.08%	-1.31%	-2.50%	-5.20%	0.19	0.07%
Skm	-	-	-	-	-	-0.76%	1.04%	1.09%	0.14	0.08%	-1.56%	0.10%	0.41%	0.26	0.07%	-1.29%	0.26%	0.64%	0.30	0.07%	-0.88%	1.09%	1.50%	0.25	0.05%
Vvw	-	-	-	-	-	0.99%	2.02%	1.26%	0.25^{**}	0.05%	0.24%	1.02%	0.43%	0.36	0.05%	0.41%	1.10%	0.39%	0.38	0.05%	1.26%	2.17%	1.04%	0.36^{***}	0.04%
Vew	-	-	-	-	-	0.38%	1.37%	0.79%	0.22	0.07%	-0.23%	0.46%	0.04%	0.33	0.06%	-0.60%	0.11%	-0.30%	0.33	0.05%	-1.38%	-0.12%	-0.62%	0.25	0.03%
Skew	-	-	-	-	-	0.39%	1.18%	0.89%	0.17	0.06%	-0.86%	-0.16%	-0.04%	0.24	0.06%	-0.55%	-0.21%	-0.06%	0.27	0.05%	0.10%	0.39%	0.47%	0.23	0.05%
Skvw	-	-	-	-	-	0.12%	0.99%	0.99%	0.16	0.07%	-1.59%	-0.63%	-0.19%	0.21	0.06%	-1.87%	-1.03%	-0.39%	0.22	0.05%	-0.30%	0.13%	0.66%	0.21	0.04%
$ILLIQ^E$	-	-	-	-	-	0.91%	2.27%	1.99%	0.22	0.06%	0.29%	1.60%	1.46%	0.39	0.05%	0.04%	1.57%	1.54%	0.38	0.05%	-0.97%	1.81%	1.97%	0.13	0.03%
AC	-	-	-	-	-	1.56%	0.54%	-0.59%	0.29^{***}	0.15%	2.20%	0.30%	-1.16%	0.40^{***}	0.14%	0.50%	-1.55%	-2.95%	0.33	0.14%	3.85%	1.34%	-1.74%	0.43^{***}	0.14%
TR	-	-	-	-	-	1.09%	2.63%	2.21%	0.28^{***}	0.05%	0.20%	1.51%	1.35%	0.38^{***}	0.04%	0.67%	1.91%	1.73%	0.43^{***}	0.05%	0.91%	2.86%	2.62%	0.36^{***}	0.04%
SII	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2.43%	3.10%	2.71%	0.49^{***}	0.04%	4.27%	5.21%	4.54%	0.50^{***}	0.04%
VIX	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-1.55%	-2.73%	-5.25%	0.17	0.07%
buy-and-hold	1.56%	1.31%	-1.13%	0.41^{***}	-	2.01%	0.98%	-1.92%	0.37^{***}	-	1.52%	1.21%	-0.83%	0.49^{***}	-	1.42%	1.18%	-0.76%	0.50^{***}	-	1.91%	1.82%	-0.41%	0.46^{***}	-
prevailing mean	-	-	-	0.30	0.02%	-	-	-	0.24	0.02%	-	-	-	0.36	0.02%	-	-	-	0.39	0.02%	-	-	-	0.34	0.02%

Table IA16 Utility Gain, Sharpe Ratio, and Transaction Fees (Semi-Annual Results)

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 (SR) and transaction fees (Fee) are 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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^E}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to Decmber 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. 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*	*Annual Fee*	$\gamma=3$	$\gamma=5$	$\gamma=7$	*SR*	*Annual Fee*	$\gamma=3$	$\gamma=5$	$\gamma=7$	*SR*	*Annual Fee*	$\gamma=3$	$\gamma=5$	$\gamma=7$	*SR*	*Annual Fee*	$\gamma=3$	$\gamma=5$	$\gamma=7$	*SR*	*Annual Fee*
CIS	1.86%	2.50%	0.90%	0.40***	0.03%	2.14%	3.30%	2.12%	0.38***	0.03%	1.85%	2.58%	1.39%	0.48***	0.03%	1.69%	2.04%	0.46%	0.51***	0.03%	2.68%	2.98%	0.71%	0.48***	0.04%
DP	-0.26%	1.91%	1.63%	0.22	0.02%	0.02%	2.01%	1.68%	0.20	0.02%	-1.41%	0.48%	0.45%	0.23	0.02%	-1.99%	0.90%	1.51%	0.28	0.01%	-1.21%	2.35%	2.92%	0.25	0.01%
DY	0.29%	2.24%	1.94%	0.24	0.02%	0.83%	2.49%	2.10%	0.23	0.02%	-0.96%	0.74%	0.75%	0.24	0.02%	-1.43%	1.23%	1.75%	0.38	0.01%	-0.32%	2.88%	3.30%	0.35	0.01%
EP	1.04%	2.45%	1.85%	0.33**	0.03%	1.32%	2.65%	1.93%	0.32***	0.03%	2.02%	2.54%	1.68%	0.44***	0.03%	2.06%	3.27%	3.01%	0.60***	0.03%	2.63%	4.54%	4.20%	0.54***	0.02%
DE	-0.25%	-0.07%	-0.25%	0.26	0.02%	-0.35%	-0.12%	-0.14%	0.22	0.02%	-0.33%	-0.05%	0.03%	0.33	0.02%	-0.35%	-0.21%	-0.24%	0.37	0.02%	-0.42%	-0.22%	-0.29%	0.32	0.02%
SVAR	0.01%	0.02%	-0.05%	0.27	0.02%	0.01%	0.05%	-0.01%	0.24	0.02%	0.01%	0.02%	-0.04%	0.34	0.02%	0.03%	-0.02%	-0.14%	0.38	0.02%	0.03%	-0.03%	-0.20%	0.33	0.02%
BM	-1.87%	0.34%	0.36%	0.17	0.02%	-1.78%	0.21%	0.21%	0.16	0.02%	-1.67%	0.36%	0.15%	0.21	0.01%	-2.71%	0.43%	1.17%	0.46*	0.00%	-1.42%	2.18%	2.80%	0.53***	0.00%
NTIS	0.71%	1.59%	0.22%	0.40***	0.04%	1.07%	1.55%	-0.05%	0.39***	0.04%	0.90%	0.48%	-1.34%	0.45***	0.04%	0.32%	0.01%	-1.66%	0.45***	0.03%	1.26%	0.68%	-2.01%	0.40***	0.03%
TBL	1.25%	2.33%	1.37%	0.32*	0.02%	2.06%	2.66%	1.48%	0.32***	0.02%	0.22%	0.76%	-0.15%	0.35	0.02%	0.37%	0.15%	-1.23%	0.40	0.02%	0.85%	0.53%	-1.47%	0.38***	0.02%
LTY	0.96%	2.21%	1.80%	0.31*	0.02%	1.65%	2.48%	1.95%	0.30**	0.02%	-0.04%	0.68%	0.54%	0.33	0.02%	0.10%	0.09%	-0.30%	0.38	0.02%	0.47%	0.44%	-0.18%	0.36***	0.02%
LTR	2.27%	2.99%	1.45%	0.45***	0.11%	1.78%	2.32%	0.72%	0.40***	0.10%	0.73%	1.00%	-0.24%	0.42***	0.10%	-0.76%	-0.58%	-1.91%	0.38	0.09%	-0.44%	-0.22%	-2.18%	0.31	0.09%
TMS	1.81%	2.15%	0.60%	0.39***	0.05%	2.66%	2.49%	0.59%	0.39***	0.05%	1.00%	0.52%	-1.29%	0.42***	0.05%	0.36%	-0.31%	-2.28%	0.41**	0.04%	0.63%	-0.16%	-2.97%	0.36**	0.04%
DFY	0.13%	0.20%	-0.30%	0.28	0.02%	0.31%	0.22%	-0.43%	0.25**	0.02%	0.14%	-0.07%	-0.82%	0.34	0.02%	0.05%	0.03%	-0.48%	0.38	0.02%	0.04%	0.14%	-0.62%	0.34**	0.02%
DFR	-0.52%	-0.16%	-1.09%	0.28	0.03%	-0.46%	-0.13%	-1.02%	0.26**	0.03%	-0.18%	0.12%	-0.85%	0.37***	0.03%	-0.32%	-0.17%	-1.54%	0.38	0.03%	-0.29%	-0.21%	-2.22%	0.32	0.03%
INFL	0.15%	1.07%	1.09%	0.30***	0.03%	0.21%	1.33%	1.29%	0.28***	0.03%	0.12%	1.26%	1.29%	0.39***	0.03%	0.33%	1.66%	1.29%	0.47***	0.03%	0.14%	2.10%	1.72%	0.42***	0.03%
$ECON_{AVG}$	0.20%	1.50%	1.20%	0.26	0.03%	0.34%	1.39%	1.07%	0.22	0.03%	-0.03%	0.99%	0.61%	0.31	0.03%	-0.34%	1.46%	1.85%	0.37	0.04%	-0.11%	2.38%	2.86%	0.27	0.04%
$ECON_{PC}$	-0.43%	1.80%	1.39%	0.22	0.02%	-0.14%	1.90%	1.40%	0.20	0.02%	-0.96%	0.74%	0.40%	0.24	0.02%	-1.52%	1.15%	1.69%	0.36	0.01%	-0.44%	2.77%	3.22%	0.33	0.01%
IVOL	-0.09%	0.07%	0.11%	0.28*	0.02%	-0.00%	-0.01%	-0.02%	0.25***	0.02%	0.06%	-0.05%	-0.08%	0.35**	0.02%	0.04%	-0.09%	-0.18%	0.39*	0.02%	-0.24%	-0.46%	-0.42%	0.31	0.02%
Vm	-	-	-	-	-	-0.85%	0.89%	0.95%	0.14	0.04%	-0.71%	0.88%	0.84%	0.27	0.03%	-1.09%	0.25%	0.09%	0.29	0.03%	-1.09%	0.73%	0.41%	0.24	0.03%
Skm	-	-	-	-	-	0.80%	2.73%	2.49%	0.26***	0.08%	0.50%	2.56%	2.39%	0.40***	0.08%	0.20%	2.12%	1.80%	0.41***	0.09%	0.35%	3.16%	2.62%	0.34***	0.09%
Vvw	-	-	-	-	-	-0.47%	1.02%	1.15%	0.16	0.04%	-0.26%	1.45%	1.44%	0.32	0.03%	-0.27%	1.37%	1.18%	0.37***	0.03%	-0.08%	2.28%	1.95%	0.33***	0.03%
Vew	-	-	-	-	-	-1.03%	1.15%	1.25%	0.15	0.04%	-0.58%	1.51%	1.64%	0.32	0.03%	-0.44%	1.36%	1.26%	0.37***	0.03%	-0.69%	1.90%	1.80%	0.30***	0.03%
Skew	-	-	-	-	-	-1.09%	1.61%	1.71%	0.13	0.04%	-1.19%	1.38%	1.55%	0.27	0.03%	-0.43%	1.57%	1.41%	0.36	0.03%	0.10%	2.84%	2.47%	0.33***	0.03%
Skvw	-	-	-	-	-	-0.42%	2.50%	2.38%	0.18	0.05%	-0.91%	1.83%	1.87%	0.31	0.05%	-0.32%	2.05%	1.73%	0.40***	0.05%	0.50%	3.70%	3.07%	0.38***	0.06%
$ILLIQ^E$	-	-	-	-	-	1.87%	4.17%	3.86%	0.35***	0.03%	0.66%	2.99%	3.04%	0.48***	0.03%	0.19%	2.56%	2.55%	0.48***	0.03%	0.10%	3.51%	3.56%	0.31	0.02%
AC	-	-	-	-	-	0.99%	1.85%	0.97%	0.27***	0.07%	1.77%	2.24%	0.97%	0.42***	0.06%	1.22%	1.45%	-0.21%	0.43***	0.07%	2.59%	2.65%	0.09%	0.43***	0.07%
TR	-	-	-	-	-	1.19%	3.28%	3.05%	0.31***	0.04%	0.21%	2.26%	2.35%	0.39***	0.04%	0.39%	2.48%	2.28%	0.45***	0.04%	0.63%	3.72%	3.41%	0.38***	0.04%
SII	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2.49%	4.24%	3.68%	0.54***	0.03%	4.63%	7.00%	6.04%	0.56***	0.03%
VIX	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.79%	2.34%	1.78%	0.23**	0.03%
buy-and-hold	1.61%	2.11%	-0.28%	0.41***	-	1.73%	1.90%	-0.62%	0.37***	-	1.85%	2.96%	1.53%	0.52***	-	1.48%	2.68%	1.36%	0.54***	-	2.25%	3.98%	2.57%	0.52***	-
prevailing mean	-	-	-	0.27	0.02%	-	-	-	0.24	0.02%	-	-	-	0.34	0.02%	-	-	-	0.38	0.02%	-	-	-	0.33	0.02%

Table IA17 Utility Gain, Sharpe Ratio, and Transaction Fees (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 (SR) and transaction fees (Fee) are 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. $\mathbf{ECON_{AVG}}$ is the equally weighted average of the above 14 classical predictors. $\mathbf{ECON_{PC}}$ is the first principal component extracted from the above 14 classical predictors. **Vm** and **Skm** are market variance and skewness, respectively (from January 1960 to December 2016). **Vew** and **Vvw** are equally weighted and value-weighted average variance, respectively (from January 1960 to December 2016). **Skew** and **Skvw** are equally weighted and value-weighted average total skewness, respectively (from January 1960 to December 2016). $\mathbf{ILLIQ^E}$ is the expected market illiquidity (from February 1960 to December 2016). AC (Pollet and Wilson, 2010) is the average correlation (from January 1960 to December 2016). **SII** (Rapach et al., 2016) is the aggregate short interest index (from January 1973 to December 2014). **VIX** is the implied volatility index (from January 1990 to Decmber 2015). **TR** (Kelly and Jiang, 2014) is the tail risk measure (from January 1960 to December 2016). **IVOL** is the equal-weighted average idiosyncratic skewness, estimated using Fama and French (1993) three-factor model. 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*	*Annual Fee*	$\gamma=3$	$\gamma=5$	$\gamma=7$	*SR*	*Annual Fee*	$\gamma=3$	$\gamma=5$	$\gamma=7$	*SR*	*Annual Fee*	$\gamma=3$	$\gamma=5$	$\gamma=7$	*SR*	*Annual Fee*	$\gamma=3$	$\gamma=5$	$\gamma=7$	*SR*	*Annual Fee*
CIS	1.96%	1.79%	1.15%	0.48^{**}	0.07%	2.32%	2.06%	1.47%	0.42^{**}	0.08%	2.09%	1.86%	1.15%	0.56^{**}	0.08%	2.34%	2.12%	1.29%	0.58^{**}	0.09%	3.30%	3.52%	1.92%	0.60^{***}	0.09%
DP	-1.13%	0.02%	0.49%	0.25	0.07%	-1.08%	0.37%	0.58%	0.17	0.07%	-2.17%	-0.55%	-0.18%	0.27	0.06%	-2.84%	-0.75%	-0.26%	0.21	0.04%	-3.53%	-0.51%	0.04%	0.10	0.04%
DY	-0.50%	0.63%	0.71%	0.31	0.10%	-0.33%	1.05%	1.08%	0.23	0.11%	-1.78%	-0.29%	0.01%	0.30	0.08%	-2.65%	-0.61%	-0.15%	0.23	0.06%	-3.43%	-0.40%	0.12%	0.11	0.06%
EP	0.49%	0.51%	0.49%	0.34	0.10%	1.02%	0.94%	0.82%	0.31	0.09%	1.46%	1.62%	1.28%	0.53	0.08%	2.13%	2.71%	2.27%	0.76^{**}	0.08%	1.54%	2.70%	2.33%	0.64^{*}	0.06%
DE	0.55%	-0.05%	-0.51%	0.35	0.04%	0.65%	-0.15%	-0.51%	0.26	0.05%	-0.53%	-0.69%	-0.64%	0.35	0.06%	-0.77%	-0.95%	-0.87%	0.36	0.07%	-0.90%	-1.08%	-0.97%	0.28	0.06%
SVAR	-0.30%	-0.61%	-0.91%	0.31	0.11%	-0.34%	-0.60%	-0.91%	0.24	0.10%	-0.44%	-0.84%	-1.28%	0.35	0.09%	-0.49%	-1.04%	-1.63%	0.36	0.09%	-0.61%	-0.98%	-1.71%	0.34	0.09%
BM	-1.42%	-1.09%	-1.32%	0.24	0.07%	-0.74%	-0.78%	-1.48%	0.23	0.07%	-1.36%	-1.23%	-1.68%	0.33	0.06%	-1.78%	-0.60%	-0.69%	0.31	0.05%	-1.07%	0.26%	-0.18%	0.33	0.05%
NTIS	-0.32%	-0.81%	-1.00%	0.35	0.14%	0.25%	-0.53%	-1.08%	0.32	0.12%	-0.07%	-0.80%	-1.64%	0.43	0.09%	-0.31%	-1.28%	-2.24%	0.40	0.08%	0.06%	-0.74%	-2.23%	0.36	0.07%
TBL	1.52%	1.34%	1.25%	0.40	0.04%	2.44%	1.76%	1.29%	0.37	0.04%	0.39%	-0.16%	-0.26%	0.39	0.04%	1.16%	0.20%	-0.05%	0.45	0.05%	1.78%	0.61%	0.18%	0.45	0.05%
LTY	0.34%	1.15%	1.30%	0.36	0.06%	1.44%	1.82%	1.56%	0.34	0.06%	-0.38%	0.22%	0.30%	0.39	0.05%	0.37%	0.81%	0.76%	0.46	0.06%	0.97%	1.66%	1.45%	0.46^{*}	0.07%
LTR	1.17%	0.81%	0.39%	0.43	0.41%	1.45%	1.10%	0.57%	0.38^{*}	0.46%	0.83%	0.58%	0.10%	0.47	0.48%	0.07%	0.03%	-0.36%	0.44	0.46%	-1.18%	-0.53%	-0.99%	0.35	0.47%
TMS	1.90%	1.35%	1.09%	0.44	0.12%	2.34%	1.61%	1.05%	0.40^{*}	0.11%	0.62%	-0.14%	-0.41%	0.43	0.10%	-0.56%	-1.15%	-1.22%	0.37	0.10%	-0.89%	-0.48%	-0.43%	0.31	0.10%
DFY	-0.09%	-0.28%	-0.53%	0.32	0.10%	0.16%	-0.04%	-0.21%	0.24	0.11%	-0.82%	-0.90%	-0.92%	0.33	0.10%	-1.57%	-1.55%	-1.47%	0.29	0.08%	-2.42%	-2.21%	-2.08%	0.22	0.09%
DFR	1.06%	1.24%	0.93%	0.43	0.34%	1.48%	1.71%	1.30%	0.38^{*}	0.36%	1.30%	1.77%	1.35%	0.55^{**}	0.33%	1.72%	2.36%	1.80%	0.59^{**}	0.36%	2.63%	3.38%	2.56%	0.59^{**}	0.40%
INFL	3.04%	2.22%	0.91%	0.53^{***}	0.37%	3.53%	2.44%	0.96%	0.48^{***}	0.39%	2.92%	1.99%	0.54%	0.58^{**}	0.42%	2.78%	1.81%	0.17%	0.58^{**}	0.44%	1.99%	1.20%	-0.91%	0.50^{*}	0.42%
$ECON_{AVG}$	-1.13%	-1.09%	-1.58%	0.30	0.20%	-1.02%	-0.89%	-1.58%	0.24	0.20%	-2.10%	-1.49%	-1.84%	0.31	0.15%	-2.94%	-1.48%	-1.53%	0.26	0.12%	-1.48%	-0.12%	-0.51%	0.31	0.11%
$ECON_{PC}$	-0.42%	0.05%	0.30%	0.30	0.08%	-0.47%	0.31%	0.52%	0.22	0.09%	-1.78%	-0.48%	-0.16%	0.30	0.07%	-2.81%	-0.69%	-0.22%	0.23	0.05%	-4.03%	-0.75%	-0.13%	0.10	0.06%
IVOL	0.66%	0.75%	0.19%	0.39	0.14%	1.39%	1.43%	0.70%	0.38	0.14%	0.08%	0.21%	-0.42%	0.44	0.12%	-0.10%	0.15%	-0.62%	0.47	0.13%	-1.35%	-1.15%	-2.02%	0.35	0.14%
Vm	-	-	-	-	-	-0.19%	0.18%	0.09%	0.13	0.21%	-0.90%	-0.30%	-0.19%	0.27	0.18%	-0.47%	0.04%	0.06%	0.30	0.19%	0.93%	1.58%	1.45%	0.32	0.20%
Skm	-	-	-	-	-	-1.33%	-0.74%	-0.63%	0.08	0.30%	-2.42%	-1.25%	-0.75%	0.18	0.20%	-1.99%	-0.92%	-0.47%	0.22	0.18%	-1.25%	0.04%	0.32%	0.21	0.16%
Vvw	-	-	-	-	-	1.39%	1.62%	1.29%	0.24	0.19%	0.08%	0.40%	0.26%	0.34	0.17%	0.86%	0.98%	0.67%	0.39	0.18%	2.31%	2.66%	2.13%	0.41^{*}	0.19%
Vew	-	-	-	-	-	0.78%	0.95%	0.41%	0.23	0.24%	-0.10%	0.29%	-0.18%	0.36	0.23%	0.08%	0.51%	-0.15%	0.38	0.26%	0.47%	1.27%	0.42%	0.35	0.28%
Skew	-	-	-	-	-	0.69%	0.63%	0.28%	0.23	0.34%	-0.41%	-0.34%	-0.55%	0.31	0.30%	0.75%	0.33%	-0.17%	0.37	0.31%	1.45%	0.65%	-0.16%	0.32	0.32%
Skvw	-	-	-	-	-	0.70%	0.18%	-0.57%	0.19	0.35%	0.08%	-0.27%	-0.90%	0.32	0.35%	1.17%	0.28%	-0.73%	0.37	0.41%	1.39%	0.55%	-0.98%	0.32	0.45%
$ILLIQ^E$	-	-	-	-	-	0.36%	1.37%	1.25%	0.20	0.16%	0.18%	1.17%	1.03%	0.47	0.13%	-0.04%	1.38%	1.25%	0.45	0.13%	-0.76%	1.64%	1.56%	0.26	0.07%
AC	-	-	-	-	-	0.09%	-0.72%	-1.25%	0.17	0.35%	-0.44%	-1.29%	-1.71%	0.27	0.32%	-1.35%	-2.23%	-2.64%	0.24	0.34%	-0.39%	-0.67%	-1.81%	0.25	0.32%
TR	-	-	-	-	-	1.69%	2.42%	1.96%	0.36^{*}	0.34%	1.07%	1.89%	1.56%	0.51^{**}	0.32%	0.16%	1.85%	1.73%	0.49^{*}	0.33%	1.07%	2.88%	2.62%	0.44^{*}	0.31%
SII	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2.28%	2.80%	1.68%	0.55^{***}	0.09%	2.68%	3.69%	2.14%	0.48^{***}	0.07%
VIX	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-1.42%	-1.19%	-2.66%	0.22	0.20%
buy-and-hold	1.10%	0.82%	-0.88%	0.43^{*}	-	1.63%	0.86%	-1.42%	0.39^{**}	-	0.94%	0.81%	-0.92%	0.51^{*}	-	0.86%	1.09%	-0.61%	0.52^{*}	-	1.10%	1.71%	-0.21%	0.50^{*}	-
prevailing mean	-	-	-	0.36	0.02%	-	-	-	0.28	0.02%	-	-	-	0.41	0.02%	-	-	-	0.43	0.02%	-	-	-	0.37	0.02%

References

Bollerslev, T., Todorov, V., and Xu, L. (2015). Tail risk premia and return predictability. *Journal of Financial Economics*, 118(1):113–134.

Campbell, J. Y. and Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *The Review of Financial Studies*, 21(4):1509–1531.

Clark, T. E. and West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of econometrics*, 138(1):291–311.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Harvey, C. R. and Siddique, A. (2000). Conditional skewness in asset pricing tests. *The Journal of Finance*, 55(3):1263–1295.

Kelly, B. and Jiang, H. (2014). Tail risk and asset prices. *The Review of Financial Studies*, 27(10):2841–2871.

Newey, W. K. and West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(2):703–708.

Pollet, J. M. and Wilson, M. (2010). Average correlation and stock market returns. *Journal of Financial Economics*, 96(3):364–380.

Rapach, D. E., Ringgenberg, M. C., and Zhou, G. (2016). Short interest and aggregate stock returns. *Journal of Financial Economics*, 121(1):46–65.