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Can financial uncertainty forecast aggregate stock market returns?

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Abstract

We investigate the role of financial uncertainty in forecasting aggregate stock market returns. Our results suggest that financial uncertainty, along with its change, are more powerful predictors of excess US monthly stock market returns than 14 macroeconomic predictors commonly used in the literature. Financial uncertainty is shown to outperform short interest, which has been suggested to be the strongest known predictor of the equity risk premium. These results persist using robust econometric methods in-sample, and when forecasting out-of-sample.

KEYWORDS
equity risk premium, financial uncertainty, predictive regression, return predictability

JEL CLASSIFICATION
C53, C58, G11, G17

1 | INTRODUCTION

The efficient market hypothesis dictates that stock returns should not be forecastable using publicly available information. However, certain variables from valuation ratios, to the output gap, appear to be able to predict future returns[1]. A critique of much of the previous literature is the lack of out-of-sample predictability that stems from such predictor variables (Goyal & Welch, 2008). Despite this, there are a small number of exceptions, for example, Rapach et al. (2016), find that short interest can forecast the returns of the S&P 500 over the period 1978–2014, both in- and out-of-sample[2].

In this paper, we uncover two powerful new predictors of monthly stock market returns in the United States, financial uncertainty and its change. We show that financial uncertainty and its change are powerful predictors of the equity risk premium, outperforming a host of previously suggested predictor variables when using in-sample and out-of-sample tests and at short and long horizons. Our results suggest that the change in financial uncertainty is arguably the strongest known predictor variables to date.

Our analysis proceeds as follows. We begin with a predictive regression framework which relates measures of uncertainty to monthly excess returns of the S&P 500 over a period 1973:01 to 2021:12. To measure uncertainty, we utilise the financial uncertainty index provided by Ludvigson et al. (2021)[3]. Following the conventional view that predictability increases with the horizon[4], we also assess these relationships with long-horizon predictive regressions. In order to alleviate any econometric concerns that are common in predictive regressions and exacerbated further as the horizon increases, our in-sample analysis utilises the IVX-Wald approach developed by Kostakis et al. (2015, 2023). This estimation procedure is robust to the time-series properties of the predictor variables and accounts for the well-known Stambaugh (1999) bias. Our in-sample results show that, when using both measures of uncertainty as a predictor of the equity risk premium, we reject the null of no predictability at the 5% level or better, using both least-squares and the IVX-Wald estimation procedure.

In order to account for the critique that suggests predictive regressions perform poorly out-of-sample, we extend our analysis with out-of-sample tests and provide evidence of out-of-sample R^2 statistics of over 5%, far greater than current known predictors of the stock market. To the best of our knowledge, we are first to document positive out-of-sample tests when forecasting aggregate stock market returns with a financial uncertainty index. Bali et al. (2017) investigate the role of economic uncertainty in the cross-section, finding that stocks with low uncertainty betas generate up to 6% annualised risk-adjusted return. Gao et al. (2019) extend the cross-sectional research to the UK market, again finding that economic uncertainty has significant power in the cross-sectional pricing of returns. Other authors who have considered economic uncertainty when forecasting stock market returns tend to favour economic policy uncertainty, see Brogaard and Detzel (2015) and Phan et al. (2018). Compared with economic policy uncertainty, our uncertainty measures appear to be much stronger predictors out-of-sample, we also document predictability at the longer-horizons. Previous research, for example, Megaritis et al. (2021) has highlighted the usefulness of macroeconomic uncertainty of Jurado et al. (2015) and financial uncertainty of Ludvigson et al. (2021) both in- an out-of-sample when forecasting stock market volatility.

We present evidence that suggests that the information about future stock returns impounded in financial uncertainty differs from that contained in the short interest data. While the residuals from the short interest predictive regressions can be explained by the financial uncertainty variables, the converse is not the case. This difference is important for agents seeking to make predictive inference about future returns.

In addition, we also compare the uncertainty predictor variables against the set of 14 macroeconomic variables used in Goyal and Welch (2008). At the 1-month horizon, in no part of our analysis do any of these variables outperform either of the uncertainty measures in terms of in-sample and out-of-sample tests. We obtain larger t-statistics and R^2's in-sample and larger out-of-sample R^2 statistics when comparing the forecasting performance of the variables against the historical average. It is also the case that the uncertainty predictor variables are not strongly correlated to any of the Goyal and Welch (2008) predictor variables or short interest, signalling some 'new' information.

Why does financial uncertainty forecast aggregate stock market returns? Throughout our analysis, we find that the uncertainty measures are negatively related to future stock market returns. It may be the case that our results are driven by an agent's risk preferences driving transfers of wealth in periods of high uncertainty away from stocks to less risky assets. Bali et al. (2017) suggest if an investor's preferences are dispersed in periods of high uncertainty, this heterogeneity may lead pessimistic investors who have a relatively high risk aversion against uncertainty to 'cease or reduce participation in the stock market'. We provide further support for this mechanism by showing that the uncertainty indices are positively related to government treasury bills[5]. In addition, Rapach and Zhou (2013) suggest that, theoretically, asset returns are functions of state variables of the real economy and state variables that track economic conditions should help to forecast returns. Several studies have shown that aggregate uncertainty is a relevant state variable[6]. In periods of heightened uncertainty, economic agents are more likely to be conservative in their investment and reduce their future consumption. This suggests that time-varying shocks to economic uncertainty are linked to real activity and asset prices (Bloom, 2009; Jurado et al., 2015). In this regard, several studies have shown the significance of economic uncertainty on asset pricing in cross-sectional stock returns (see, e.g., Ozoguz, 2009; Anderson et al., 2009; Bali et al., 2017). Analysing the effect of uncertainty on aggregate stock market returns, however, appears to have been overlooked by the previous literature.

In sum, the evidence supports the view that the measures of financial uncertainty are important predictors of future stock market returns both in and out-of-sample. Our out-of-sample tests are careful to only use information available to researchers at the time of the forecast, therefore these results not only provide an interesting empirical finding, but are also useful for market agents who forecast excess stock market returns. The transferability of stock return predictability across the literature suggests that improved return forecasts are also important for various applications, from improving asset pricing models to economic modelling.

The rest of the paper is organised as follows: Section 2 describes the data; the third section reports the methodology and results; the forth a comparison of uncertainty and short interest as predictors of stock market returns; in the penultimate section, we compare financial uncertainty to alternative measures; the fifth section concludes the paper.

2 | DATA

Continuously compounded monthly returns for the US S&P 500 (r_t) and 14 stock market predictors were collected from Amit Goyal's website[7]. The 14 variables are as follows: log dividend-price ratio (DP), log dividend yield (DY), log earnings price ratio (EP), log dividend earnings ratio (DE), excess return volatility (RVOL), book-to-market ratio (BM), net equity expansion (NTIS), treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR) and inflation (INF).

The financial uncertainty index of Ludvigson et al. (2021) was collected from Sydney Ludvigson's website. Jurado et al. (2015), *inter alia*, find volatility in financial markets can vary over time possibly due to changes in leverage and/or risk aversion/sentiment. In similar fashion, the cross-section of company's profits, sales and productivity tends to fluctuate over the business cycle due to heterogeneity in the business activity of firms. To allow for fluctuations that are not driven by the business cycle, we employ the financial uncertainty index introduced by Ludvigson et al. (2021). The dataset primarily contains 147 financial time series such as: valuation ratios such as the dividend-price ratio and earnings-price ratio, growth rates of aggregate dividends and prices, default and term spreads, yields on corporate bonds of different rating grades, yields on treasuries and yield spreads and a broad cross-section of industry, size, book-market and momentum portfolio equity returns[8]. Financial uncertainty (U_F) is measured using the level of the respective uncertainty index. The change in financial uncertainty (ΔU_F) is measured as ($\log(U_{F,t+1}/U_{F,t})$)[9]. Consistent with the previous literature, we attempt to forecast the value-weighted log-returns of the S&P 500 index in excess of the 1-month treasury bill rate. Table 1 provides summary statistics for our 16 predictor variables and the excess log-returns of the S&P 500. All data are collected for the period 1978:01 to 2021:12.

Rapach et al. (2016) suggest that short interest (SI) is arguably the strongest known predictor of aggregate stock market returns to date. We update their measure of short interest that finishes in 2014:12. However, short interest data are only available from 1978:01 and we collect all data to match this sample period[10]. Following directly from Rapach et al. (2016), using data from Compustat and CRSP, we calculate a ratio of short interest, which is the number of shares held short divided by the number of shares outstanding. To alleviate any liquidity concerns, stocks with a share price of less than \$5 per share are excluded along with stocks below the fifth percentile on the NYSE, data on this are provided on Kenneth French's data library. In addition to this, we also construct a short interest measure which only uses data from S&P 500 constituents, (SI^{500}). The construction is of a similar fashion to the SI variable. Rapach et al. (2016) discuss the trending nature of these short interest variables and suggest the use of detrended measures, which we follow in this paper[11].

TABLE 1 Summary statistics.

Predictor	Mean	Median	Max	Min	Std.
DP	−3.719	−3.862	−2.753	−4.524	0.429
DY	−3.711	−3.851	−2.751	−4.531	0.429
EP	−2.925	−2.950	−1.899	−4.836	0.468
DE	−0.794	−0.850	1.380	−1.244	0.341
RVOL	0.146	0.140	0.317	0.055	0.051
BM	0.415	0.320	1.207	0.121	0.261
NTIS	0.004	0.007	0.046	−0.056	0.020
TBL	4.250	4.310	16.300	0.010	3.647
LTY	6.298	5.935	14.820	0.620	3.224
LTR	0.711	0.665	15.230	−11.240	3.198
TMS	2.048	2.105	4.550	−3.650	1.465
DFY	1.070	0.940	3.380	0.550	0.449
DFR	0.015	0.050	7.370	−9.760	1.574
INF	0.286	0.273	1.521	−1.915	0.367
SI	0.000	0.120	2.738	−3.000	1.000
SI^{500}	0.000	−0.175	5.219	−2.190	1.000
U_F	0.903	0.880	1.546	0.637	0.165
ΔU_F	0.000	−0.001	0.154	−0.141	0.034
r	0.006	0.010	0.122	−0.248	0.044

Note: This table reports the summary statistics for the 14 Goyal and Welch (2008) predictors, short interest and an updated measure of short interest which only includes S&P 500 constituents, the two uncertainty measures that we consider in this study, see Ludvigson et al. (2021) and the excess log-returns of the S&P 500 (r) over a period 1978:01 to 2021:12. Data come for the macroeconomic variables come from Amit Goyal's website, for the short interest variables COMPUSTAT and CRSP and the uncertainty measures from Sydney Ludvigson's website.

Rapach et al. (2016) argue that if a predictor contains a significant amount of new information, it should not be highly correlated with any other predictors. This is evident with the change of the financial uncertainty index, where no correlation in excess of 0.256 is found. While there are larger correlations with the level of the financial uncertainty index, the largest (in magnitude) is 0.693 between the financial uncertainty index and RVOL. Table 2 shows the correlations between the uncertainty variables (17–18), the 14 stock market predictors (1–14) and the short interest variables (15–16) (see Figure 1).

3 | METHODOLOGY AND RESULTS

3.1 | In-sample analysis

We estimate the following univariate predictive regression[12] for each of the stock market predictors, which is the standard framework in a stock return predictability setting,

$$r_t = \alpha_i + \beta_i X_{i,t-1} + e_{it} \tag{1}$$

TABLE 2 Pairwise correlation.

Predictor	U_F	ΔU_F
DP	−0.043	−0.019
DY	−0.064	−0.052
EP	−0.289	0.068
DE	0.341	−0.117
RVOL	0.693	−0.256
BM	0.010	−0.008
NTIS	−0.137	−0.076
TBL	−0.020	0.070
LTY	−0.043	0.028
LTR	0.067	0.003
TMS	−0.047	−0.113
DFY	0.413	−0.132
DFR	−0.065	−0.242
INF	−0.027	0.093
SI	0.192	0.108
SI^{500}	0.430	0.013
U_F	–	0.107
ΔU_F	0.107	–

Note: This table displays the Pearson correlation coefficients for the 14 Goyal and Welch (2008) predictors and two short interest variables against the uncertainty four uncertainty measures.

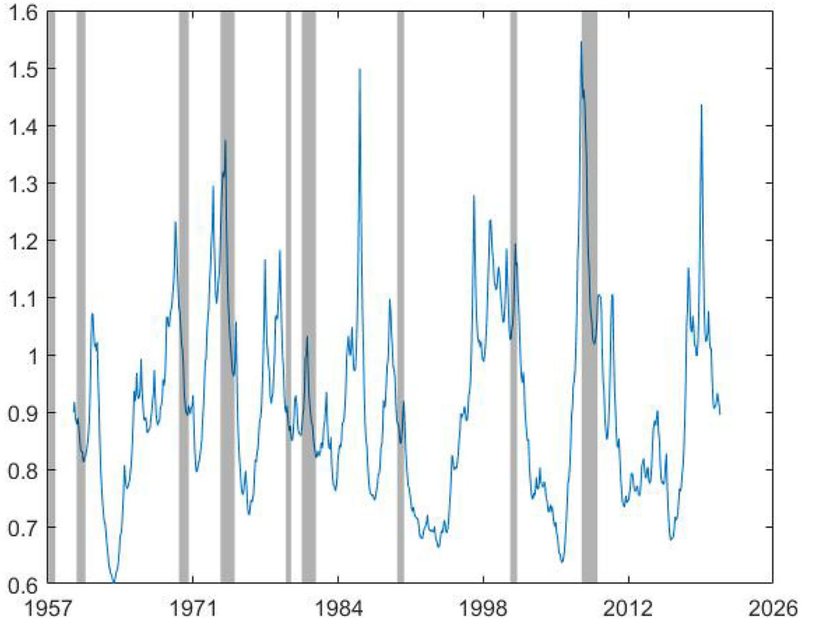

FIGURE 1 The figure shows the time series of fianncial uncertainty. The two largest peaks being 'Black Monday' and the '2008 Global Financial Crisis'. Shaded areas are NBER recessions, data spans 1960:08 to 2021:12. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Univariate predictive regressions, in-sample.

Predictor	$\beta_{i,LS}$	$t_{i,LS}$	p-value	$\beta_{i,IVX}$	IVX-Wald	p-value	R^2_{LS}
Period: 1978:01 to 2021:12							
DP	0.004	(0.938)	[0.348]	0.008	(0.829)	[0.363]	0.167
DY	0.005	(1.016)	[0.310]	0.008	(1.122)	[0.289]	0.196
EP	0.003	(0.622)	[0.534]	0.005	(1.192)	[0.275]	0.074
DE	0.002	(0.324)	[0.746]	0.001	(0.054)	[0.816]	0.020
RVOL	0.055	(1.476)	[0.140]	0.052	(1.830)	[0.176]	0.413
BM	0.002	(0.315)	[0.753]	0.009	(0.327)	[0.567]	0.019
NTIS	0.002	(0.021)	[0.984]	0.034	(0.113)	[0.736]	0.000
TBL	−0.001	(−1.375)	[0.169]	−0.001	(1.720)	[0.190]	0.359
LTY	−0.001	(−1.283)	[0.199]	−0.001	(1.648)	[0.199]	0.313
LTR	0.001	(1.189)	[0.234]	0.001	(1.252)	[0.263]	0.269
TMS	0.001	(0.600)	[0.549]	0.001	(0.2000)	[0.654]	0.068
DFY	−0.001	(−0.137)	[0.891]	−0.001	(0.095)	[0.758]	0.004
DFR	0.003	(2.082)	[0.037]	0.003	(4.267)	[0.039]	0.819
INF	0.004	(0.748)	[0.455]	0.005	(0.747)	[0.388]	0.106
SI	−0.005	(−2.358)	[0.018]	−0.005	(5.807)	[0.016]	1.048
SI^{500}	−0.211	(−1.12)	[0.263]	−0.200	(0.632)	[0.427]	0.228
U_F	−0.032	(−2.834)	[0.005]	−0.033	(8.329)	[0.004]	1.507
ΔU_F	−0.335	(−6.201)	[0.000]	−0.329	(36.656)	[0.000]	6.825

Note: This table shows the in-sample results from estimating Equation (1), univariate predictive regressions, $r_t = \alpha_i + \beta_i X_{i,t-1} + e_{it}$, for each of the 14 Goyal and Welch (2008) predictors, the short interest variables and the uncertainty measures of Ludvigson et al. (2021). We report, β_{LS} coefficients, (t-stats) and [p-values] for least-squares estimation and β_{IVX}, (Wald-stats) and [p-values] for the robust procedure as in Kostakis et al. (2015, 2023), testing the null hypothesis that $\beta_i = 0$ against the alternative, $\beta_i \neq 0$.

where, r_t is the excess return to the S&P 500 and X_i are each of the 18 predictor variables, the 14 Goyal and Welch (2008) predictors, two short interest predictors, see Rapach et al. (2016), (SI and SI^{500}), the financial uncertainty index and the log change (U_F, ΔU_F). We, therefore, estimate (1) on 18 occasions using OLS. The resulting coefficient estimate, $\widehat{\beta}_i$, indicates the direction that a given the predictor variable leads stock market returns.

It is well known (see Nelson & Kim, 1993, and Stambaugh, 1999, *inter alia*) that statistical inference can be complex in the predictive framework displayed in Equation (1). This complexity increases with persistent X_i variables and when return shocks are correlated with predictor variable shocks. Accordingly, we also report estimates obtained using the robust IVX-Wald estimation procedure of Kostakis et al. (2015, 2023). This procedure is robust to the degree of persistence of the regressors and guards against the well-known Stambaugh (1999) bias.

Table 3 reports the results of in-sample tests over the period 1978:01 to 2021:12 reporting the least-squares β estimate and its corresponding t-statistic and the p-values associated with the hypothesis test that $H_0 : \beta = 0$ against the alternative that $H_A : \beta \neq 0$. We also report the corresponding estimate and Wald-statistic and p-value from the IVX-Wald procedure. At the monthly horizon, one variable of the 14 Goyal and Welch (2008) variables are significant at the 10% level or better when we estimate using either least squares or IVX-Wald. Short interest (SI) is significant at 5% level regardless of the estimation procedure whilst the less informative measure, SI^{500} is never found to be significant. The uncertainty variables (U_F, ΔU_F), are both significant 5% level or better regardless of the estimation procedure. We also consider two additional sub-samples, 1990–2018 and 2000–2018, to address the view that predictability has lessened in later periods and to assess the robustness of the uncertainty measures overtime. These results are reported in Table 4. The coefficients related to the uncertainty variables are negative throughout and remain statistically significant at the 5% level or better regardless of the sample period considered. The in-sample R^2 statistics displayed across Tables 3 and 4 are comparable to those of the previous literature, being relatively small, but as is pointed out by Campbell and Thompson (2008) statistics as low as 0.5% can still produce economically meaningful results. Rapach and Zhou (2013) argue that excess predictability in the sense of large R^2 suggests that either existing asset pricing models are grossly incorrect or the market is highly inefficient. For the uncertainty variables, we see larger R^2 statistics compared to the 14 Goyal and Welch (2008) variables, with the change in financial uncertainty producing the largest in-sample R^2 statistic of 6.825%. Both of the uncertainty measures produce R^2's well above the 0.5% threshold suggested by Campbell and Thompson (2008), and are larger than the R^2's associated with each of the 14 Goyal and Welch (2008) predictors. We note also that the R^2's associated with the uncertainty measures exceed those obtained for the short interest measures in each and every sample period considered.

The negative coefficients on the uncertainty variables remain regardless of the sample period chosen, which is consistent with the view that investors may transfer wealth away from stocks in periods of heightened uncertainty. With the same rationale, we also find that the uncertainty indices are positively related to future treasury bill yields, often touted as one of the most secure assets in the world[13].

We also consider the usefulness of uncertainty as a predictor at longer horizons, that is, we adapt our dependent variable to be a cumulative sum of returns, $r_t(h) = \sum_{i=1}^{h} r_{t+i}$, with h the horizon,

$$r_t(h) = \mu_i + \lambda_i X_{i,t-1} + \eta_{it} \tag{2}$$

The long-horizon coefficients, λ_i, from Equation (2) are estimated using the IVX-Wald procedure. Long-horizon results are reported in Table 5, we see the uncertainty variables remain largely significant across the horizons, but to a lessening degree[14]. We only report results from IVX-Wald in this instance since standard methods have been shown to be grossly oversized, as is demonstrated in Kostakis et al. (2015, 2023)[15].

3.2 | Out-of-sample analysis

To address the critique by Goyal and Welch (2008), among others, that in-sample results are often not useful to an investor seeking to time the market we also test for out-of-sample predictability. We report the results of the out-of-sample R^2 of Campbell and Thompson (2008). Following the previous literature, see, for example, Rapach and Zhou (2013), for each predictor variable, we compute a predictive regression forecast of the form,

$$\hat{r}_{t+1} = \hat{\alpha}_{it} + \hat{\beta}_{it} X_{i,t}, \tag{3}$$

where, $\hat{\alpha}_i$ and $\hat{\beta}_i$, are the least-squares estimates obtained for each of the i predictors as described above. Equation 3 is re-estimated in an expanding window framework, from the beginning of the sample to month t. This forecast is compared to the historical average forecast at each point in time.

$$\tilde{r}_{t+1} = \hat{\alpha}_t = \frac{1}{T} \sum_{t=1}^{T} r_t \tag{4}$$

This comparison is standard in the stock return predictability literature. The sum of mean squared forecast errors are compared using the approach of Campbell and Thompson (2008),

$$R^2_{OS} = 1 - \frac{\sum (r_i - \hat{r}_i)^2}{\sum (r_i - \tilde{r}_i)^2} \tag{5}$$

TABLE 4 Sub-period results univaraite predictive regressions, in-sample.

Predictor	$\beta_{i,LS}$	$t_{i,LS}$	*p*-value	$\beta_{i,IVX}$	IVX-Wald	*p*-value	R^2_{LS}
Period: 1978:01 to 2000:01							
DP	−0.003	(−0.513)	[0.608]	−0.001	(0.01)	[0.922]	0.101
DY	−0.004	(−0.524)	[0.600]	−0.001	(0.025)	[0.874]	0.105
EP	−0.001	(−0.188)	[0.851]	0.003	(0.089)	[0.765]	0.014
DE	−0.01	(−0.701)	[0.484]	−0.014	(0.84)	[0.360]	0.188
RVOL	0.052	(0.845)	[0.398]	0.046	(0.544)	[0.461]	0.273
BM	−0.005	(−0.567)	[0.571]	0.000	(0.000)	[0.995]	0.123
NTIS	−0.196	(−1.373)	[0.170]	−0.172	(1.361)	[0.243]	0.717
TBL	−0.002	(−1.893)	[0.058]	−0.002	(3.281)	[0.070]	1.355
LTY	−0.002	(−1.653)	[0.098]	−0.002	(2.665)	[0.103]	1.036
LTR	0.001	(0.978)	[0.328]	0.001	(0.687)	[0.407]	0.365
TMS	0.002	(1.148)	[0.251]	0.002	(0.959)	[0.328]	0.502
DFY	0.001	(0.187)	[0.852]	0.001	(0.019)	[0.890]	0.013
DFR	0.006	(2.389)	[0.017]	0.006	(5.710)	[0.017]	2.140
INF	−0.006	(−0.695)	[0.487]	−0.005	(0.342)	[0.559]	0.185
SI	0.000	(−0.088)	[0.930]	−0.004	(0.476)	[0.490]	0.003
SI^{500}	0.100	(−0.343)	[0.732]	−0.002	−1.077	[0.299]	0.052
U_F	−0.025	(−1.237)	[0.216]	−0.023	(1.310)	[0.252]	0.583
ΔU_F	−0.306	(−3.948)	[0.000]	−0.293	(14.015)	[0.000]	5.636
Predictor	$\beta_{i,LS}$	$t_{i,LS}$	*p*-value	$\beta_{i,IVX}$	**IVX-Wald**	*p*-value	R^2_{LS}
Period: 2000:01 - 2021:12							
DP	0.031	(2.284)	[0.022]	0.008	(0.074)	[0.786]	1.952
DY	0.035	(2.534)	[0.011]	0.015	(0.376)	[0.540]	2.393
EP	0.004	(0.567)	[0.571]	0.001	(0.023)	[0.880]	0.123
DE	0.003	(0.516)	[0.606]	0.000	(0.003)	[0.958]	0.101
RVOL	0.057	(1.209)	[0.227]	0.059	(1.545)	[0.214]	0.555
BM	0.079	(1.943)	[0.052]	0.021	(0.161)	[0.688]	1.420
NTIS	0.149	(0.984)	[0.325]	0.309	(3.704)	[0.054]	0.368
TBL	−0.004	(−2.760)	[0.006]	−0.003	(1.595)	[0.207]	2.826
LTY	−0.007	(−3.626)	[0.000]	−0.008	(6.348)	[0.012]	4.778
LTR	0.001	(0.658)	[0.511]	0.000	(0.056)	[0.814]	0.165
TMS	−0.001	(−0.245)	[0.806]	−0.001	(0.491)	[0.484]	0.023
DFY	−0.003	(−0.527)	[0.598]	−0.009	(1.559)	[0.212]	0.106
DFR	0.002	(1.116)	[0.265]	0.002	(1.549)	[0.213]	0.473
INF	0.010	(1.348)	[0.178]	0.009	(1.532)	[0.216]	0.689
SI	−0.005	(−2.476)	[0.013]	−0.006	(7.544)	[0.006]	2.287
SI^{500}	−0.100	(−0.534)	[0.593]	−0.1000	(−0.433)	[0.510]	0.083
U_F	−0.035	(−2.495)	[0.013]	−0.028	(3.372)	[0.066]	2.321
ΔU_F	−0.365	(−4.842)	[0.000]	−0.298	(14.541)	[0.000]	8.215

(Continues)

TABLE 4 (Continued)

Note: This table shows the in-sample results from estimating Equation (1), univariate predictive regressions, $r_t = \alpha_i + \beta_i X_{i,t-1} + e_{it}$, for each of the 14 Goyal and Welch (2008) predictors, the short interest variables and the uncertainty measures of Ludvigson et al. (2021). We report, β_{LS} coefficients, (t-stats) and [p-values] for least-squares estimation and β_{IVX}, (Wald-stats) and [p-values] for the robust procedure as in Kostakis et al. (2015, 2023), testing the null hypothesis that $\beta_i = 0$ against the alternative, $\beta_i \neq 0$, over two sample periods, the first 1978:01 to 2000:01 and the second, 2000:01 to 2021:12.

A positive value of R^2_{OS} indicates that the sum of mean-squared forecast errors is less than the sum of the errors from the historical average forecast. The statistical significance of this test is measured using the Clark and West (2007) method. The null hypothesis of the test is $R^2_{OS} \leq 0$ while the alternative hypothesis is, $R^2_{OS} > 0$. These results are displayed in Table 6. To ensure that our results are not dependent on a single estimation window we employ different initial estimation windows of 100, 200, 264 (half of the full sample) and 300, respectively. Rapach et al. (2016) argue that approximately 200 observations is a reasonably long initial window to yield accurately estimated parameters. The superior results with larger initial windows are in line with the research of Cochrane (2008) who suggests that in-sample tests are more powerful because they exploit more information, leading to more efficient estimates.

The evidence in Table 6 suggests that the out-of-sample $R^2_{OS}(\%)$ statistics remain positive for both of the uncertainty variables. When considering the out-of-sample forecasts across the horizons, the performance of the uncertainty measures as predictors deteriorates as the horizon increases, the results for the R^2_{OS} across various horizons are reported in Table 7.

The results in Table 7 highlight the superior out-of-sample forecasting performance of ΔU_F in comparison to all other predictors considered. A plausible reason of why the change in financial uncertainty is a stronger predictor of the market is that it may be a better measure of overall market risk. To provide an example, if we consider the financial uncertainty index, a peak of the data occurs during the 2008 financial crisis (2008:11), uncertainty remains high in the level past this point, but the change in financial uncertainty would capture a falling of uncertainty and start to provide investors with a signal that market conditions are improving.

Ludvigson et al. (2021) provide a number of arguments as to why financial uncertainty differs to alternative types of uncertainty such as macroeconomic uncertainty and Jurado et al. (2015), and economic policy uncertainty of Baker et al. (2016). Ludvigson et al. (2021) show that positive shocks to financial uncertainty cause a sharp and persistent decline in real activity, lending support to the idea that heightened financial uncertainty is an exogenous impulse and creates economic downturns. Whereas the same does not appear to be true for macroeconomic uncertainty and economic policy uncertainty and where positive shocks to these do not appear to cause lower economic activity. Therefore, it appears than financial uncertainty empirically contains different information to alternative uncertainty measures.

We compare financial uncertainty to alternative measures of uncertainty (macroeconomic uncertainty (U_M) of Jurado et al. (2015), economic policy uncertainty (EPU), news-based economic policy uncertainty, (nEPU) of Baker et al. (2016), and US monetary policy uncertainty (MPU) of and Husted et al. (2017) and the respective changes in the measures, by computing their correlations. The largest correlation in magnitude is between ΔU_F and ΔU_M, with a correlation coefficient of 0.412. The low correlation coefficient suggests that ΔU_F contains information that is distinct from alternative uncertainty measures as is suggested in Ludvigson et al. (2021)[16].

4 | A COMPARISON OF UNCERTAINTY AND SHORT INTEREST AS PREDICTORS OF EXCESS STOCK RETURNS

Rapach et al. (2016) indicate that short interest (SI) is arguably the strongest known predictor of stock market returns. In the above analysis, we provide two rivals which in certain circumstances appear to outperform short interest both

TABLE 5 Long-horizon univariate predictive regressions, in-sample.

	$\lambda_{i,IVX}$, (Wald), [*p*-values]		
Predictor/Horizon	**1**	**3**	**6**
DP	0.008	0.009	0.009
	(0.829) [0.363],	(0.889) [0.346],	(0.869) [0.351]
DY	0.008	0.008	0.008
	(1.122) [0.289],	(1.015) [0.314],	(1.022) [0.312]
EP	0.005	0.004	0.003
	(1.192) [0.275],	(0.637) [0.425],	(0.369) [0.544]
DE	0.001	0.004	0.005
	(0.054) [0.816],	(0.384) [0.536],	(0.712) [0.399]
RVOL	0.052	0.044	0.032
	(1.83) [0.176],	(1.268) [0.26],	(0.613) [0.434]
BM	0.009	0.01	0.011
	(0.327) [0.567],	(0.438) [0.508],	(0.487) [0.485]
NTIS	0.034	0.07	0.07
	(0.113) [0.736],	(0.471) [0.493],	(0.434) [0.51]
TBL	−0.001	−0.001	−0.001
	(1.72) [0.19],	(1.100) [0.294],	(0.975) [0.323]
LTY	−0.001	−0.001	−0.001
	(1.648) [0.199],	(1.058) [0.304],	(0.824) [0.364]
LTR	0.001	0.001	0.003
	(1.252) [0.263],	(0.96) [0.327],	(4.246) [0.039]
TMS	0.001	0.001	0.001
	(0.200) [0.654],	(0.128) [0.721],	(0.203) [0.652]
DFY	−0.001	−0.001	0.001
	(0.095) [0.758],	(0.074) [0.786],	(0.074) [0.786]
DFR	0.003	0.001	0.004
	(4.267) [0.039],	(0.266) [0.606],	(2.007) [0.157]
INF	0.005	−0.002	−0.012
	(0.747) [0.388],	(0.115) [0.734],	(1.86) [0.173]
SI	−0.005	−0.005	−0.005
	(5.807) [0.016],	(6.208) [0.013],	(5.946) [0.015]
SI^{500}	−0.002	−0.002	−0.006
	(0.632) [0.427]	(1.269) [0.260]	(1.736) [0.188]
U_F	−0.033	−0.02	−0.011
	(8.329) [0.004],	(2.875) [0.09],	(0.81) [0.368]
ΔU_F	−0.329	−0.357	−0.337
	(36.656) [0.000],	(24.404) [0.00],	(8.79) [0.003]

(Continues)

TABLE 5 (Continued)

	$\lambda_{i,IVX}$, (Wald), [*p*-values]		
Predictor/Horizon	**12**	**24**	**48**
DP	0.009	0.009	0.009
	(0.932) [0.334],	(0.826) [0.364],	(0.727) [0.394]
DY	0.009	0.009	0.009
	(1.12) [0.29],	(0.979) [0.322],	(0.877) [0.349]
EP	0.004	0.003	0.003
	(0.585) [0.444],	(0.241) [0.623],	(0.232) [0.63]
DE	0.006	0.016	0.064
	(0.678) [0.41],	(1.742) [0.187],	(3.792) [0.052]
RVOL	0.015	0.002	−0.05
	(0.104) [0.748],	(0.001) [0.976],	(0.137) [0.711]
BM	0.011	0.007	0.006
	(0.475) [0.491],	(0.16) [0.689],	(0.124) [0.725]
NTIS	0.064	0.059	0.059
	(0.301) [0.583],	(0.155) [0.693],	(0.091) [0.763]
TBL	−0.001	−0.001	−0.001
	(0.867) [0.352],	(0.77) [0.38],	(0.545) [0.46]
LTY	0	0	0
	(0.336) [0.562],	(0.057) [0.812],	(0.000) [0.991]
LTR	0.004	0.004	0.004
	(3.959) [0.047],	(0.904) [0.342],	(0.607) [0.436]
TMS	0.002	0.003	0.01
	(0.926) [0.336],	(2.557) [0.11],	(4.998) [0.025]
DFY	0.002	0.002	0.004
	(0.112) [0.738],	(0.085) [0.771],	(0.278) [0.598]
DFR	0.004	0.011	0.021
	(0.618) [0.432],	(2.235) [0.135],	(4.508) [0.034]
INF	−0.016	−0.014	−0.013
	(2.98) [0.084],	(1.905) [0.168],	(1.542) [0.214]
SI	−0.005	−0.003	−0.003
	(4.301) [0.038],	(1.694) [0.193],	(0.85) [0.357]
SI^{500}	−0.002	0.000	0.000
	(0.686) [0.407]	(0.001) [0.974]	(0.001) [0.971]
U_F	−0.009	−0.012	−0.042
	(0.418) [0.518],	(0.451) [0.502],	(1.374) [0.241]
ΔU_F	−0.391	−0.394	−0.949
	(4.158) [0.041],	(1.516) [0.218],	(1.783) [0.182]

(Continues)

TABLE 5 (Continued)

Note: This table shows the in-sample results from estimating Equation (2), univariate predictive regressions, $r_t(h) = \mu_i + \lambda_i X_{i,t-1} + \eta_{it}$, for each of the 14 Goyal and Welch (2008) predictors, the short interest variables and the uncertainty measures of Ludvigson et al. (2021). We report, β_{IVX} coefficients, (Wald-stats) and [*p*-values] for the robust procedure as in Kostakis et al. (2015, 2023) and testing the null hypothesis that $\lambda_i = 0$ against the alternative, $\lambda_i \neq 0$.

in- and out-of-sample. In this section, we attempt to compare the variables in terms of their performance across a number of measures more thoroughly.

To examine whether the short interest and the uncertainty measures explain stock returns in a heterogenous manner, we estimate several auxiliary regressions. First we regress each of the variables on stock market returns as in Equation (1), storing the residuals from these regression which we label, $\hat{e}_{tU_F}$, $\hat{e}_{t\Delta\, U_F}$, $\hat{e}_{tSI}$,. From here, we run a series of further regressions to see if the short interest variables can explain the residuals from the uncertainty regressions and whether the uncertainty variables can explain the residuals from the short interest regressions, results of this are found in Table 8.

$$\hat{e}_{ti} = \mu + \theta\, z_{it-1} + \eta_t \tag{6}$$

With $\hat{e}_{ti}$, being the estimated residuals from the univariate predictive regressions (1) and z_i being one of the short interest or uncertainty predictors. The results from the auxiliary regressions are reported in Table 8. Significant coefficients from the auxiliary regressions suggest that the uncertainty measures contain different information when compared with the short interest measures.

Effectively, Equation (6) represents a test for the addition of an omitted and significant variable in the various variants of Equation (1) estimated. On the basis of the significance of the estimates of θ reported in Table 8, it is clear that the forecast from the *SI* regressions could be improved using the various measures of uncertainty. The converse is not true for the forecast from the financial uncertainty regressions. A Lagrange Multiplier Test for the significance of θ in Equation (6) and may be constructed as $T.R^2$ where T is the number of observations (in this case 551) and R^2 is the coefficient of determination in Equation (6). Rejection of the null hypothesis of $H_0 : \theta = 0$ implies that z_{it-1} should be added to Equation (1). This test is distributed as χ^2 with one degree of freedom. The implication of a significant additional variable is that z_{it-1} carries additional information useful in forecasting stock returns over and above the original explanatory variable, $X_{i,t-1}$, in Equation (1). The evidence strongly suggests that $U_{F,t-1}$ and $\Delta U_{F,t-1}$ contain significant information about $\hat{e}_{tSI^{500}}$, and $\hat{e}_{tSI}$, at the 5% level of confidence or better. In contrast, the null hypothesis of $H_0 : \theta = 0$ is satisfied for the addition of *SI* or SI^{500} to the regressions using both of the financial uncertainty variables.

In sum, these results suggest that the uncertainty measures contain new and important information over that contained in the Short Interest measures considered by Rapach et al. (2016).

5 | CONCLUSION

In this paper, we find that measures of financial uncertainty are statistically significant predictors of future stock market returns over the sample period 1978:01 to 2021:12. Following the previous work of Rapach et al. (2016), who suggest that 'short interest' is arguably the strongest known predictor, we provide two rivals. In-sample, we show that both variables are statistically significant predictors of one-step ahead returns, these results are robust to the time-series properties of the data, with the relationships persisting when using the IVX-Wald estimation method which guards against the well-known Stambaugh bias. In-sample, both of our uncertainty measures display stronger performance when compared with 14 commonly used predictor variables from across the literature. Similar to short interest, the change in financial uncertainty is not highly correlated to the other predictors, signaling some 'new' information.

TABLE 6 Out-of-sample tests, univariate forecast versus historical average, short-horizon.

	100	200	264	300
Window	**R^2_{OS}, (*CW*-stats), [*p*-value's], initial window as above.**			
DP	−1.288	−0.803	−0.161	−0.799
	(−1.332) [0.908]	(−0.861) [0.805]	(0.141) [0.444]	(−1.02) [0.846]
DY	−1.49	−0.806	−0.126	−0.713
	(−1.291) [0.901]	(−0.787) [0.784]	(0.214) [0.415]	(−0.759) [0.776]
EP	−1.164	−0.648	−0.537	−1.655
	(−0.555) [0.71]	(−0.097) [0.539]	(0.041) [0.484]	(−0.447) [0.672]
DE	−1.708	−1.327	−1.728	−1.719
	(−0.703) [0.759]	(−0.444) [0.671]	(−0.516) [0.697]	(−0.321) [0.626]
RVOL	−0.132	0.196	0.208	0.784
	(0.479) [0.316]	(0.952) [0.171]	(0.855) [0.196]	(1.801) [0.036]
BM	−0.813	−0.293	−0.293	−0.211
	(−1.815) [0.965]	(−1.05) [0.853]	(−1.223) [0.889]	(−0.849) [0.802]
NTIS	−1.403	−1.306	−1.276	−1.403
	(−0.34) [0.633]	(−1.88) [0.97]	(−1.693) [0.954]	(−1.557) [0.94]
TBL	−1.525	−0.463	−1.154	0.35
	(−0.102) [0.54]	(−0.021) [0.508]	(−1.105) [0.865]	(1.031) [0.151]
LTY	−0.731	−0.299	−0.999	0.323
	(0.063) [0.475]	(0.229) [0.409]	(−1.178) [0.88]	(0.938) [0.174]
LTR	−0.475	−0.244	−0.247	−0.099
	(−0.321) [0.626]	(0.08) [0.468]	(0.062) [0.475]	(0.272) [0.393]
TMS	−1.123	−0.765	−0.655	−0.372
	(−0.672) [0.749]	(−0.942) [0.827]	(−0.617) [0.731]	(−0.266) [0.605]
DFY	−0.626	−0.842	−0.558	−0.678
	(−0.927) [0.823]	(−1.316) [0.906]	(−0.739) [0.77]	(−0.685) [0.753]
DFR	−0.771	−2.068	−2.501	−1.304
	(0.632) [0.264]	(0.152) [0.439]	(0.084) [0.467]	(0.366) [0.357]
INF	−0.29	−0.268	−0.498	−0.216
	(−0.415) [0.661]	(−0.236) [0.593]	(−0.579) [0.718]	(−0.06) [0.524]
SI	0.874	2.041	2.246	2.759
	(2.217) [0.014]	(2.699) [0.004]	(2.555) [0.005]	(2.503) [0.006]
SI^{500}	−1.351	−1.554	−2.020	−1.172
	(−0.12) [0.55]	(0.15) [0.44]	(−0.26) [0.60]	(−0.09) [0.54]
U_F	0.25	1.009	1.495	0.033
	(1.029) [0.152]	(1.195) [0.116]	(1.201) [0.115]	(0.761) [0.223]
ΔU_F	6.9	7.385	7.485	9.746
	(3.772) [0.000]	(3.397) [0.000]	(3.104) [0.001]	(3.088) [0.001]

Note: The table reports the R^2_{OS} of Campbell and Thompson (2008), using each predictor at the short horizon, $h = 1$. We also complete the Clark and West (2007) test of the null hypothesis that $H_0 : R^2_{OS} \leq 0$, versus the alternative, $H_A : R^2_{OS} > 0$. Test statistics are in parentheses and the associated p-value in square brackets. Forecasts are produced in an expanding window manner, with the initial window shown above. A positive value indicates that the predictor variable produces a lower mean squared error when compared to the historical average forecast.

TABLE 7 Out-of-sample tests, univariate forecast versus historical average, long horizon.

Predictor/Horizon	1	3	6
	R^2_{OS}, (*CW*-stats), [*p*-value's], initial window 264.		
DP	0.141	0.274	−0.374
	(0.141) [0.444]	(0.274) [0.392]	(−0.374) [0.646]
DY	0.214	0.129	−0.469
	(0.214) [0.415]	(0.129) [0.449]	(−0.469) [0.68]
EP	0.041	−0.29	−0.614
	(0.041) [0.484]	(−0.29) [0.614]	(−0.614) [0.73]
DE	−0.516	−1.317	−2.157
	(−0.516) [0.697]	(−1.317) [0.906]	(−2.157) [0.984]
RVOL	0.855	0.53	−0.63
	(0.855) [0.196]	(0.53) [0.298]	(−0.63) [0.736]
BM	−1.223	−1.174	−1.53
	(−1.223) [0.889]	(−1.174) [0.88]	(−1.53) [0.937]
NTIS	−1.693	−2.416	−2.577
	(−1.693) [0.954]	(−2.416) [0.992]	(−2.577) [0.995]
TBL	−1.105	−1.466	−1.552
	(−1.105) [0.865]	(−1.466) [0.928]	(−1.552) [0.939]
LTY	−1.178	−1.538	−1.784
	(−1.178) [0.88]	(−1.538) [0.938]	(−1.784) [0.962]
LTR	0.062	−0.681	0.23
	(0.062) [0.475]	(−0.681) [0.752]	(0.23) [0.409]
TMS	−0.617	−0.694	−0.595
	(−0.617) [0.731]	(−0.694) [0.756]	(−0.595) [0.724]
DFY	−0.739	−1.308	−2.029
	(−0.739) [0.77]	(−1.308) [0.904]	(−2.029) [0.978]
DFR	0.084	−1.145	−0.164
	(0.084) [0.467]	(−1.145) [0.874]	(−0.164) [0.565]
INF	−0.579	−1.644	0.523
	(−0.579) [0.718]	(−1.644) [0.95]	(0.523) [0.301]
SI	2.555	3.275	3.202
	(2.555) [0.005]	(3.275) [0.001]	(3.202) [0.001]
SI^{500}	−2.020	−5.50	−10.68
	(−0.26) [0.60]	(0−0.28) [0.61]	(−0.48) [0.68]
U_F	1.201	0.537	−0.094
	(1.201) [0.115]	(0.537) [0.296]	(−0.094) [0.538]
ΔU_F	3.104	3.331	2.048
	(3.104) [0.001]	(3.331) [0]	(2.048) [0.021]

(Continues)

TABLE 7 (Continued)

Predictor/Horizon	12	24	48
	R^2_{OS}, (*CW*-stats), [*p*-value's], initial window 275.		
DP	−1.05	−1.115	−0.741
	(−1.05) [0.853]	(−1.115) [0.867]	(−0.741) [0.77]
DY	−1.087	−1.132	−0.76
	(−1.087) [0.861]	(−1.132) [0.871]	(−0.76) [0.776]
EP	−1.033	−1.751	−1.396
	(−1.033) [0.849]	(−1.751) [0.96]	(−1.396) [0.918]
DE	−0.753	0.442	1.125
	(−0.753) [0.774]	(0.442) [0.329]	(1.125) [0.13]
RVOL	−1.171	−1.268	−1.734
	(−1.171) [0.879]	(−1.268) [0.897]	(−1.734) [0.958]
BM	−1.737	−1.239	−1.01
	(−1.737) [0.958]	(−1.239) [0.892]	(−1.01) [0.843]
NTIS	−2.569	−1.497	−0.223
	(−2.569) [0.995]	(−1.497) [0.933]	(−0.223) [0.588]
TBL	−1.018	−0.238	−1.288
	(−1.018) [0.846]	(−0.238) [0.594]	(−1.288) [0.901]
LTY	−2.194	−1.55	−0.96
	(−2.194) [0.986]	(−1.55) [0.939]	(−0.96) [0.831]
LTR	−0.259	−0.382	0.339
	(−0.259) [0.602]	(−0.382) [0.649]	(0.339) [0.367]
TMS	0.32	1.63	2.297
	(0.32) [0.375]	(1.63) [0.052]	(2.297) [0.011]
DFY	−1.221	−1.217	0.079
	(−1.221) [0.889]	(−1.217) [0.888]	(0.079) [0.469]
DFR	−1.74	−0.629	0.483
	(−1.74) [0.959]	(−0.629) [0.735]	(0.483) [0.315]
INF	0.068	−0.287	0.012
	(0.068) [0.473]	(−0.287) [0.613]	(0.012) [0.495]
SI	2.811	1.484	1.971
	(2.811) [0.003]	(1.484) [0.069]	(1.971) [0.025]
SI^{500}	−17.64	−15.01	−40.34
	(−1.170) [0.880]	(−1.270) [0.900]	(−1.690) [0.950]
U_F	−0.248	−0.527	−0.765
	(−0.248) [0.598]	(−0.527) [0.701]	(−0.765) [0.778]
δU_F	0.775	−0.416	0.714
	(0.775) [0.219]	(−0.416) [0.661]	(0.714) [0.238]

Note: The table reports the R^2_{OS} of Campbell and Thompson (2008), using each predictor at the long horizon, *h* between 1 and 60. We also complete the Clark and West (2007) test of the null hypothesis that $H_0 : R^2_{OS} \leq 0$, versus the alternative, $H_A : R^2_{OS} > 0$. Test statistics are in parentheses and the associated *p*-value in square brackets. Forecasts are produced in an expanding window manner, with the initial window of 275. A positive value indicates that the predictor variable produces a lower mean squared error when compared to the historical average forecast.

TABLE 8 Auxiliary regressions.

Panel A: Least-squares estimation, coefficient, (*t*-stat), [*p*-value]				
	SI	SI^{500}	U_F	ΔU_F
$\hat{e}_{tSI}$			−0.034	−0.327
			(−3.12)	(−5.764)
			[0.000]	[0.000]
$\hat{e}_{tSI^{500}}$			−0.037	−0.334
			(−3.446)	(−5.886)
			[0.001]	[0.000]
$\hat{e}_{tU_F}$	−0.002	0.002		
	(−1.086)	−1.085		
	[0.277]	[0.278]		
$\hat{e}_{t\Delta U_F}$	−0.002	0.001		
	(−1.253)	−0.592		
	[0.210]	[0.554]		
Panel B: IVX-Wald estimation, coefficient, (IVX-Wald), [*p*-value]				
	SI	SI^{500}	U_F	ΔU_F
$\hat{e}_{tSI}$			−0.033	−0.306
			(−9.202)	(−27.615)
			[0.002]	[0.000]
$\hat{e}_{tSI^{500}}$			−0.037	−0.316
			(−11.602)	(−29.469)
			[0.001]	[0.000]
$\hat{e}_{tU_F}$	−0.002	0.002		
	(−0.907)	(−1.241)		
	[0.341]	[0.265]		
$\hat{e}_{t\Delta U_F}$	−0.002	0.001		
	(−0.867)	(−0.503)		
	[0.352]	[0.478]		
Panel C: LR test, R^2, (LR-stat), [*p*-value]				
	SI	SI^{500}	U_F	ΔU_F
$\hat{e}_{tSI}$			1.748	5.716
			(9.649)	(31.552)
			[0.001]	[0.000]
$\hat{e}_{tSI^{500}}$			2.12	5.946
			(11.702)	(32.822)
			[0.000]	[0.000]
$\hat{e}_{tU_F}$	0.215	0.214		
	(1.187)	(1.181)		
	[0.202]	[0.203]		

(Continues)

TABLE 8 (Continued)

Panel C: LR test, R^2, (LR-stat), [p-value]				
	SI	SI^{500}	U_F	ΔU_F
$\hat{e}_{t\Delta U_F}$	0.286	0.064		
	(1.57)	(0.353)		
	[0.144]	[0.563]		

Note: Panel A reports least-squares, coefficients θ, (t-stats) and [p-values], Panel B, IVX-Wald coefficients, (Wald-stats) and [p-values] from the auxiliary regressions, as in Equation (6). Panel C reports, R^2, (LR-statistics) and [p-values] from the LR test as above. The variables in the left-hand column represent the dependent variables whilst the variables across columns (2)–(7) are the explanatory variables.

Our evidence strongly suggests that the financial uncertainty measures contain new and important information about future returns over that in the short interest measures.

Out-of-sample tests document statistically significant forecasts, particularly for ΔU_F, when compared with the historical average, which is the standard benchmark in the stock return predictability literature. The results in terms of out-of-sample R^2 are particularly important following the Goyal and Welch (2008) critique that suggests despite in-sample predictability, predictors of stock market returns often fail out-of-sample.

Our results provide insight into the rationale of market agents during periods of high uncertainty. Our uncertainty measures are negatively related to future stock market returns, but positively related to treasury bill yields often seen as a 'safe haven asset'. These result suggests a transfer of wealth in periods of high uncertainty. The perceived risk disparity between stocks and alternative assets in periods of heightened uncertainty appears to lead to a fall in value in the higher risk assets (see Tables B.1 and B.2).

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ENDNOTES

[1] See, for example, Cowles (1933), Rozeff (1984), Kothari and Shanken (1997), Campbell and Shiller (1988), Rapach and Wohar (2005), Ang and Bekaert (2007), Hong et al. (2007), Cochrane (2008), Driesprong et al. (2008), Cooper and Priestley (2009), McMillan (2014), *inter alia*. Rapach and Zhou (2013) and Damodaran (2009) provide an overview of the literature. Other sections of the literature also assess equity premium crashes, see, for example, Lleo and Ziemba (2017).

[2] These results were particularly surprising as return predictability has appeared to decline in later periods (Campbell & Yogo, 2006).

[3] The financial uncertainty index utilises the same approach as in Jurado et al. (2015) who construct a broad measure of macroeconomic uncertainty. Preliminary analysis suggests that using macoreconomic uncertainty for prediction yields poorer results in- and out-of-sample when forecasting excess stock market returns.

[4] See, among others, Cochrane (1997) and Campbell et al. (1997).

[5] Existing studies, for example, Cao et al. (2005), along with, Epstein and Schneider (2010), provide similar rationale.

[6] See, for example, Bloom (2009). It is also addressed in Ludvigson et al. (2021) that the uncertainty measures closely track falls and rises in financial activity, thereby providing further evidence that these are state variables.

[7] The US return data along with the risk-free rate is originally collected from CRSP, the 14 predictor variables have been previous suggested by the literature, further details are found in Goyal and Welch (2008) and the appendix of this paper.

[8] See Sydney Ludvigson's website for a detailed description of the series used (https://www.sydneyludvigson.com/) – Version 2021:12 collected.

[9] Unexpected changes in uncertainty concerns investors about their future investment and consumption, affecting the indirect utility of real wealth and equity prices. Therefore, the use of changes in financial uncertainty is consistent with the literature. For more details, see, for example, Merton (1973), Chen et al. (1986) and Bali et al. (2020).

[10] Similar results are produced over the longer sample period 1960:08 to 2022:12, these are shown in Appendix B.

[11] Due to the trending nature of equal weighted short interest (EWSI), to detrend, the residuals are stored from a linear regression in the following form, $\log(EWSI_t) = a + b.t + u_t$, and u_t is the detrended measure of short interest (SI). Further details of the construction are provided in Rapach et al. (2016).

[12] Whilst the univariate predictive regression is the standard in the stock return predictability literature, see Rapach and Zhou (2013, p. 338), we experiment with a general-to-specific procedure, starting with all 18 variables in a multivariate regression and removing the variable with the largest p-value from the IVX-Wald procedure until all predictors have a p-value less than 5%. Financial uncertainty and its change remains in the final set of predictors, these results are available upon request.

[13] We run two regressions in the following form, $tbill_t = \alpha + \phi X_{t-1,i} + v_t$, where X_i is equal to U_F and ΔU_F, the relevant ϕ_i coefficients and (t-stats) along with significance levels denotes by ***,**,* 1%, 5% and 10%, when testing the null $H_0 : \phi = 0$ versus the alternative $H_0 : \phi \neq 0$, are as follows, 0.219 (3.040***) and 0.078 (1.99**).

[14] If stock returns can be predicted, the frequency of returns becomes important, the approach by Lioui and Poncet (2019) shows that predictability can significantly benefit investors, especially at longer horizons.

[15] Ordinary least squares estimates and relevant statistics corresponding to Table 5 are available upon request.

[16] Preliminary analysis also suggests that each measure of uncertainty fails to outperform ΔU_F in in-sample and out-of-sample predictive regression analysis. These results are available upon request.

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APPENDIX A: VARIABLE DEFINITIONS

1. Log dividend-price ratio (DP): log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of stock prices (S&P 500 index).
2. Log dividend yield (DY): log of a 12-month moving sum of dividends minus the log of lagged stock prices.
3. Log earnings-price ratio (EP): log of a 12-month moving sum of earnings on the S&P 500 index minus the log of stock prices.
4. Log dividends earnings ratio (DE): log of a 12-month moving sum of dividends minus the log of lagged stock prices.
5. Excess return volatility (RVOL): calculated by squaring daily returns and summing per month.

6. Book-to-market ratio (BM): book-to-market value ratio for the DJIA.
7. Net equity expansion (NTIS): ratio of a 12-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalisation of NYSE stocks.
8. Treasury bill rate (TBL): interest rate on a 3-month Treasury bill (secondary market).
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 BAA- and AAA-rated corporate bond yields.
13. Default return spread (DFR): difference between the long-term corporate bond return and the long-term government bond return.
14. Inflation (INF): consumer price index of United States urban consumers.

APPENDIX B: ADDITIONAL RESULTS 1960:08 TO 2018:12

TABLE B.1 Univaraite predictive regressions, in-sample.

Predictor	$\beta_{i,LS}$	$t_{i,LS}$	*p*-value	$\beta_{i,IVX}$	IVX-Wald	*p*-value	R^2_{LS}
Period: 1960:08 to 2021:12							
DP	0.002	(0.500)	[0.617]	0.003	(0.476)	[0.490]	0.034
DY	0.002	(0.626)	[0.531]	0.004	(0.705)	[0.401]	0.053
EP	0.001	(0.146)	[0.884]	0.001	(0.021)	[0.885]	0.003
DE	0.002	(0.451)	[0.652]	0.004	(0.492)	[0.483]	0.028
RVOL	0.076	(2.479)	[0.013]	0.070	(5.121)	[0.024]	0.830
BM	−0.002	(−0.295)	[0.768]	−0.001	(0.049)	[0.824]	0.012
NTIS	−0.072	(−0.895)	[0.371]	−0.044	(0.289)	[0.591]	0.109
TBL	−0.001	(−2.143)	[0.032]	−0.001	(4.857)	[0.028]	0.622
LTY	−0.001	(−1.581)	[0.114]	−0.001	(3.179)	[0.075]	0.340
LTR	0.001	(2.208)	[0.027]	0.001	(4.211)	[0.040]	0.660
TMS	0.002	(1.644)	[0.100]	0.002	(2.034)	[0.154]	0.367
DFY	0.004	(1.011)	[0.312]	0.002	(0.436)	[0.509]	0.139
DFR	0.002	(1.468)	[0.142]	0.002	(2.881)	[0.090]	0.293
INF	−0.001	(−0.33)	[0.741]	−0.002	(0.284)	[0.594]	0.015
U_F	−0.030	(−3.176)	[0.001]	−0.031	(10.408)	[0.001]	1.356
ΔU_F	−0.338	(−7.365)	[0.000]	−0.33	(51.194)	[0.000]	6.882

Note: This table shows the in-sample results from estimating Equation (1), univariate predictive regressions, $r_t = \alpha_i + \beta_i X_{i,t-1} + e_{it}$, for each of the 14 Goyal and Welch (2008) predictors, the short interest variables and the uncertainty measures of Ludvigson et al. (2021). We report, β_{LS} coefficients, (*t*-stats) and [*p*-values] for least-squares estimation and β_{IVX}, (Wald-stats) and [*p*-values] for the robust procedure as in Kostakis et al. (2015, 2023), testing the null hypothesis that $\beta_i = 0$ against the alternative, $\beta_i \neq 0$.

TABLE B.2 Out-of-sample tests, univariate forecast versus historical average, short-horizon, 1960:08 to 2021:12.

	R^2_{OS}	(*CW*-stats)	[*p*-value's]
Period: 1960:08 to 2021:12, Window 264			
DP	−0.564	(−0.243)	[0.596]
DY	−0.596	(−0.114)	[0.545]
EP	−0.501	(−0.394)	[0.653]
DE	−1.145	(−1.064)	[0.856]
RVOL	0.200	(1.414)	[0.079]
BM	−0.372	(−1.209)	[0.886]
NTIS	−0.462	(1.025)	[0.153]
TBL	−0.303	(0.257)	[0.399]
LTY	−0.353	(−0.498)	[0.691]
LTR	−0.24	(0.992)	[0.161]
TMS	−0.525	(0.696)	[0.243]
DFY	−0.268	(0.166)	[0.434]
DFR	−0.408	(−0.044)	[0.518]
INF	−0.512	(−0.745)	[0.772]
U_F	1.164	(1.435)	[0.076]
ΔU_F	6.424	(3.342)	[0.000]

Note: The table reports the R^2_{OS} of Campbell and Thompson (2008), using each predictor at the short horizon, $h = 1$. We also complete the Clark and West (2007) test of the null hypothesis that $H_0 : R^2_{OS} \leq 0$, versus the alternative, $H_A : R^2_{OS} > 0$. Test statistics are in parentheses and the associated *p*-value in square brackets. Forecasts are produced in an expanding window manner, with the initial window shown above. A positive value indicates that the predictor variable produces a lower mean squared error when compared to the historical average forecast.

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