

Can financial uncertainty forecast aggregate stock market returns?

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US monthly evidence, 1978–2021

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The main finding

Changes in financial uncertainty predict lower subsequent excess returns.

6.825%

In-sample R^2 for ΔU_F

Robust IVX-Wald inference also rejects no predictability.

7.485%

Out-of-sample R^2 for ΔU_F

One-month forecasts, with 264 observations in the initial estimation window.

The change measure outperforms short interest and all fourteen conventional predictors at the monthly horizon in the reported comparisons.

Source: manuscript, Tables 3 and 6. Out-of-sample R^2 is relative to the historical mean, not a portfolio return.

The forecasting question

Does financial uncertainty contain information beyond established predictors?

- Return predictability often weakens outside the estimation sample (Welch and Goyal, 2008).
- Short interest provides a demanding benchmark (Rapach et al., 2016).
- Financial uncertainty measures the unpredictability of a broad set of financial series (Ludvigson et al., 2021).

We examine both the **level** of uncertainty and its **log change**, using robust in-sample inference and expanding-window forecasts.

Data and comparison set

Outcome	Monthly value-weighted S&P 500 log return in excess of the one-month Treasury bill rate.
Main sample	January 1978 to December 2021.
Uncertainty	Financial uncertainty index (U_F) and its log change (ΔU_F); December 2021 data vintage.
Comparators	Fourteen Welch–Goyal predictors, aggregate short interest (SI), and S&P 500 constituent short interest (SI^{500}).

Sources reported in the manuscript: Amit Goyal; Sydney Ludvigson; CRSP and Compustat. Main sample follows the data section and Tables 1–4.

Measuring financial uncertainty

A broad measure of unpredictability in financial markets

The index draws on **147 financial time series**, including valuation ratios, bond yields and spreads, and equity portfolio returns.

The level, U_F

How elevated is financial uncertainty?

It may remain high even as market conditions begin to improve.

The log change, ΔU_F

Is uncertainty rising or falling?

It can capture a turning point before the level returns to normal.

Ludvigson et al. (2021); manuscript, Data and Out-of-sample analysis.

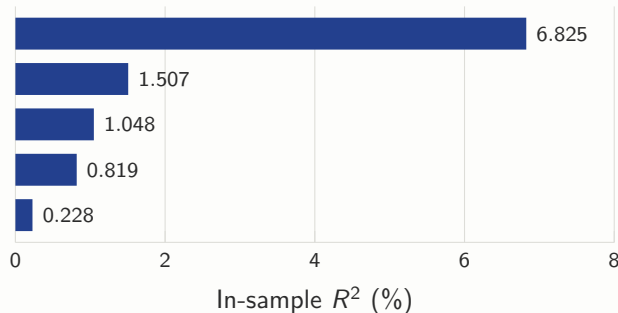
Predictive regressions and robust inference

$$r_t = \alpha_i + \beta_i X_{i,t-1} + e_{it}, \quad H_0 : \beta_i = 0.$$

- Estimate a separate univariate regression for each of the 18 predictors.
- Report OLS estimates and in-sample explanatory power.
- Use IVX-Wald inference to address persistent predictors and correlation between predictor and return shocks.

Stambaugh (1999); Kostakis et al. (2015, 2023). Forecasts use lagged predictors; the manuscript's precise uncertainty-change dating requires reconciliation.

The change measure has the strongest in-sample fit



Both uncertainty coefficients are negative.

ΔU_F has the largest R^2 among all 18 predictors.

DFR is the strongest of the 14 conventional predictors by full-sample R^2 .

Source: manuscript, Table 3. Sample: 1978:01–2021:12. DFR: default return spread.

The monthly result survives IVX-Wald inference

Predictor	OLS $\hat{\beta}$	OLS p	IVX-Wald	IVX p
DFR	0.003	0.037	4.267	0.039
SI	-0.005	0.018	5.807	0.016
SI^{500}	-0.211	0.263	0.632	0.427
U_F	-0.032	0.005	8.329	0.004
ΔU_F	-0.335	< 0.001	36.656	< 0.001

Only DFR among the fourteen conventional predictors is significant at 5% under both methods in the full sample.

Source: manuscript, Table 3. Printed $p = 0.000$ values are displayed as $p < 0.001$. Coefficient magnitudes depend on predictor units.

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Subsample evidence is strongest for the change measure

Period	Predictor	OLS R^2 (%)	IVX p
1978:01–2000:01	U_F	0.583	0.252
	ΔU_F	5.636	< 0.001
2000:01–2021:12	U_F	2.321	0.066
	ΔU_F	8.215	< 0.001

The change measure remains significant in both reported subsamples. Evidence for the uncertainty level is weaker.

Source: manuscript, Table 4. Period labels and significance follow the table rather than the conflicting prose.

Out-of-sample evaluation

Expanding estimation window

Fit the model using observations through month t , then forecast the next return:

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

Re-estimate as each new observation becomes available.

Initial windows: 100, 200, 264 or 300 observations.

Campbell and Thompson (2008); Clark and West (2007). The manuscript uses a December 2021 uncertainty vintage; a real-time vintage exercise is not documented.

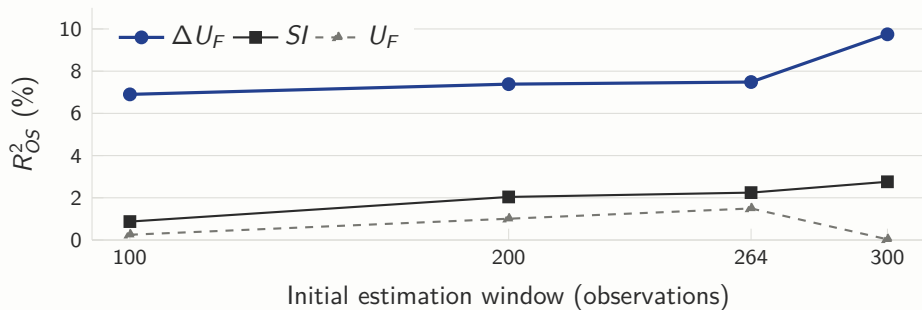
Historical-mean benchmark

Compare forecast errors with those from the expanding historical average:

$$R_{OS}^2 = 1 - \frac{\sum (r_t - \hat{r}_t)^2}{\sum (r_t - \tilde{r}_t)^2}.$$

$R_{OS}^2 > 0$ means lower squared forecast error.
Use the one-sided Clark–West test.

Monthly forecast gains persist across initial windows



Source: manuscript, Table 6. One-month forecasts; historical-average benchmark. Different initial windows imply different evaluation periods.

The level and change have different forecast evidence

Predictor	R_{OS}^2 (%)	CW p	Interpretation
ΔU_F	7.485	0.001	Largest reported gain
SI	2.246	0.005	Significant improvement
U_F	1.495	0.115	Positive, not significant at 5%
RVOL	0.208	0.196	Best conventional R_{OS}^2
SI^{500}	-2.020	0.600	Below historical mean

For ΔU_F , forecast-error reductions are significant across all four initial windows. For U_F , none is significant at 5%.

Source: manuscript, Table 6. Initial estimation window: 264 observations. CW: one-sided Clark–West test.

Predictability weakens at longer horizons

IVX-Wald p -values for cumulative-return regressions

Horizon (months)	1	3	6	12	24	48
ΔU_F	< .001	< .001	.003	.041	.218	.182
U_F	.004	.090	.368	.518	.502	.241
SI	.016	.013	.015	.038	.193	.357

ΔU_F remains significant at 5% through 12 months in-sample.

Reported out-of-sample tests for ΔU_F are significant through six months, but not at 12, 24 or 48 months.

Sources: manuscript, Tables 5 and 7. Blue marks $p < 0.05$. Table 7 contains inconsistent R^2 entries and window labels; only its reported test significance is summarised here.

Financial uncertainty adds information beyond short interest

$$\hat{e}_{t,i} = \mu + \theta z_{t-1} + \eta_t$$

Auxiliary regressions test whether another predictor explains the residuals of a univariate return regression.

Residuals from	Added predictor	Reported IVX p
SI model	U_F	0.002
SI model	ΔU_F	< 0.001
U_F model	SI	0.341
ΔU_F model	SI	0.352

The reported tests favour adding uncertainty to the short-interest model; they do not favour adding short interest to the uncertainty models.

The change measure is weakly correlated with rivals

Conventional predictors

0.256

Largest absolute correlation of ΔU_F with the fourteen conventional predictors or the two short-interest measures.

Correlation with SI : 0.108.

Correlation with SI^{500} : 0.013.

Other uncertainty measures

0.412

Largest reported absolute correlation with the alternative uncertainty measures considered: the change in macroeconomic uncertainty.

Low correlation is consistent with different information, but does not by itself establish forecasting value.

Source: manuscript, Table 2 and discussion of alternative uncertainty measures.

An economic interpretation

Rising uncertainty may reduce investors' willingness to hold equities.

- Both uncertainty measures have negative coefficients in the full-sample equity-return regressions.
- The manuscript also reports positive predictive coefficients for Treasury bill yields.
- This is consistent with changes in participation or portfolio demand during periods of heightened uncertainty.

These predictive associations do not identify investor flows or a causal mechanism.

Manuscript, Introduction and In-sample analysis; proposed interpretation draws on Bali et al. (2017).

Conclusion

The clearest evidence is for changes in financial uncertainty.

- Stronger monthly in-sample fit than all other predictors in the comparison set, with robust IVX-Wald significance.
- Significant monthly forecast gains over the historical mean across all four initial estimation windows.
- Additional information beyond short interest; weaker evidence at longer horizons and for the uncertainty level.

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Appendix: monthly forecast results

R^2_{OS} (%); Clark–West p -values in parentheses

Initial window	100	200	264	300
ΔU_F	6.900 ($< .001$)	7.385 ($< .001$)	7.485 (.001)	9.746 (.001)
U_F	0.250 (.152)	1.009 (.116)	1.495 (.115)	0.033 (.223)
SI	0.874 (.014)	2.041 (.004)	2.246 (.005)	2.759 (.006)
SI^{500}	-1.351 (.550)	-1.554 (.440)	-2.020 (.600)	-1.172 (.540)

Appendix: the fourteen conventional predictors

DP	Log dividend-price ratio	TBL	Treasury bill rate
DY	Log dividend yield	LTY	Long-term government yield
EP	Log earnings-price ratio	LTR	Long-term government return
DE	Log dividend-earnings ratio	TMS	Term spread
RVOL	Excess return volatility	DFY	Default yield spread
BM	Book-to-market ratio	DFR	Default return spread
NTIS	Net equity expansion	INF	Inflation

Source: manuscript, Data and Appendix A; Welch and Goyal (2008).

Appendix: construction of short interest

- Compute shares held short relative to shares outstanding, using CRSP and Compustat.
- Exclude stocks priced below \$5 and stocks below the fifth NYSE size percentile.
- Construct an aggregate measure and a separate measure restricted to S&P 500 constituents.
- Detrend log equal-weighted short interest using a linear time trend; use the residual as the predictor.

$$\log(EWSI_t) = a + bt + u_t, \quad SI_t = u_t.$$

Manuscript, Data; follows Rapach et al. (2016).

Selected references

- Welch and Goyal (2008). A comprehensive look at the empirical performance of equity premium prediction.
- Ludvigson, Ma and Ng (2021). Uncertainty and business cycles: exogenous impulse or endogenous response?
- Rapach, Ringgenberg and Zhou (2016). Short interest and aggregate stock returns.
- Kostakis, Magdalinos and Stamatogiannis (2015). Robust econometric inference for stock return predictability.
- Campbell and Thompson (2008). Predicting excess stock returns out of sample: can anything beat the historical average?
- Clark and West (2007). Approximately normal tests for equal predictive accuracy in nested models.