

Uncertainty and Real Estate Return Predictability: Evidence from U.S. REITs

Yawen Zheng (Durham) Damian Daminov (Durham) Sam Pybis (MMU)

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- Real estate investment trusts (REITs) play a vital role in asset allocation.
- We examine whether uncertainty can predict REIT returns.
- Our contribution focuses on novel uncertainty measures.

- The issue of whether REITs are forecastable remains contentious in academic literature.
- A considerable amount of in-sample evidence of predictability, but out-of-sample explorations are still needed from the literature.
- The role of uncertainty in asset pricing remains understudied in the context of REITs.

- This paper contributes to the literature by assessing a range of uncertainty variables when forecasting a number of real estate indices.
- Financial uncertainty carries substantial predictive content for asset returns.
- The evidence suggests that behavioral responses to uncertainty, rather than changes in risk premia, are the key drivers of returns.
- Our analysis also points towards economic significance in forecasting returns.

- Our analysis shows that increased economic uncertainty significantly improves forecasting accuracy for REIT returns.
- We find that financial uncertainty measures (e.g., VIX) have a stronger predictive power than traditional risk factors.
- This suggests that investor sentiment and macroeconomic uncertainty play a crucial role in shaping market behavior.

- We find robust evidence that uncertainty factors provide valuable information for predicting REIT returns.
- The paper highlights the importance of incorporating economic uncertainty into asset pricing models.
- Future research could explore the effect of geopolitical risks and macroeconomic shocks on REIT performance.

- We use predictive regressions to assess whether lagged uncertainty variables forecast subsequent returns.

Key Findings

- The highest level of predictability exists when utilizing lagged industry information to forecast stocks within the bottom 30% category.
- Predictability diminishes as we progress to forecasting stocks within the top 30%.
- Results are robust when defining the size portfolios as quintiles and deciles.

- Observing the predictive capabilities inherent in many industry portfolios for small-cap portfolios, we utilize the scaled Principal Component Analysis (sPCA) method of [Huang et al. \(2022\)](#).
- This approach aggregates data from key industries, providing market agents with an efficient mechanism to integrate signals from the set of industry portfolios.

- Ever since the seminal work of [Welch and Goyal \(2008\)](#), out-of-sample tests have become a staple in validating predictive models.
- We provide evidence supporting the predictability of the small-capitalization index out-of-sample, with lower forecast errors compared to the historical average forecast.
- Findings reveal positive out-of-sample R^2 statistics, surpassing 3% for certain industries, confirming the predictive relationship between industry portfolios and the small-cap index.

Why Industry Portfolios Forecast Small-Cap Returns

- Industry portfolios' ability to forecast small-cap returns can be attributed to the slower diffusion of information in small-cap stocks.
- Small-cap firms generally receive limited attention from analysts and investors, reacting more gradually to new information compared to large-cap firms as noted by Brennan et al. (1993), Mola et al. (2013) and Hou and Moskowitz (2005).
- This links to the research of Hong et al. (2000), who document that stocks with more analyst coverage adjust more quickly to value-relevant information.

- Substantial research has focused on the lead-lag relationships between small-cap and larger-cap stocks.
- [Lo and MacKinlay \(1990\)](#) discovered that "aggregate shocks to the economy are transmitted from large capitalization companies to small ones."
- This finding complements our study, where information appears to diffuse from industry portfolios to the small-cap index with a lag.

- Monthly returns for 49 value-weighted industry portfolios, the broad stock market (Mkt), and size-based portfolios (bottom 30%, middle 40%, top 30%).
- Data sources: Kenneth French Data Library, CRSP, Ibbotson Associates (risk-free rate).
- All returns measured in excess of the one-month Treasury bill rate.
- Robustness checks with market portfolios split into quintiles and deciles.
- Predictability assessment using [Fama and French \(2015\)](#) five factors: Mkt, SMB, HML, RMW, CMA.

Macroeconomic Predictors

- Comparison with 14 macroeconomic predictors from [Welch and Goyal \(2008\)](#):
 - DP: Log dividend-price ratio
 - DY: Log dividend yield
 - EP: Log earnings-price ratio
 - DE: Log dividends earnings ratio
 - RVOL: Stock return volatility
 - BM: Book-to-market ratio
 - NTIS: Net equity expansion
 - TBL: Treasury bill rate
 - LTY: Long-term yield
 - LTR: Long-term return
 - TMS: Term spread
 - DFY: Default yield spread
 - DFR: Default return spread
 - INF: Inflation
- Data period: 1963:07 - 2021:12

Summary Statistics: Industry Portfolios

Variable	Mean	Std	AR-1	Variable	Mean	Std	AR-1
Agric	0.57	6.36	0.02	Mines	0.74	7.09	0.08
Food	0.72	4.19	0.02	Coal	0.76	9.92	0.05
Beer	0.74	4.92	0.02	Oil	0.70	5.72	0.02
Smoke	0.97	5.82	0.01	Util	0.59	3.83	0.00
Toys	0.69	7.30	0.10	Telcm	0.57	4.38	0.03
Fun	1.01	7.31	0.09	PerSv	0.52	6.51	0.06
Books	0.72	5.88	0.10	BusSv	0.71	5.30	0.06
Hshld	0.68	4.58	0.02	Hardw	0.89	6.82	0.02
Clths	0.72	6.06	0.08	Chips	0.90	7.21	0.05
MedEq	0.85	5.38	0.03	LabEq	0.93	6.56	0.05
Drugs	0.84	4.95	0.00	Paper	0.65	5.60	0.05
Chems	0.64	5.43	0.04	Boxes	0.72	5.36	0.02
Rubbr	0.84	5.84	0.08	Trans	0.67	5.65	0.06
Txtls	0.63	6.99	0.13	Whlsl	0.68	5.42	0.09
BldMt	0.75	5.90	0.07	Rtail	0.78	5.08	0.02
Cnstr	0.73	6.99	0.13	Meals	0.87	5.90	0.08
Steel	0.51	7.24	0.08	Banks	0.73	5.71	0.06
Mach	0.74	5.94	0.06	Insur	0.69	5.58	0.04
ElcEq	0.89	6.14	0.04	RIEst	0.57	7.42	0.14
Autos	0.80	7.01	0.10	Fin	0.82	5.92	0.06
Aero	0.88	6.73	0.10	Other	0.40	6.55	0.09
Ships	0.69	6.81	0.08				

Summary Statistics: Other Portfolios and Macroeconomic Predictors

Variable	Mean	Std	AR-1	Variable	Mean	Std	AR-1
Mkt	0.66	4.31	0.03	SMB	0.23	3.03	0.07
Lo 30	1.16	6.19	0.16	HML	0.27	2.90	0.17
Med 40	1.12	5.37	0.11	RMW	0.28	2.21	0.16
Hi 30	0.94	4.28	0.02	CMA	0.27	1.98	0.11
Lo 20	1.15	6.34	0.18	DP	-3.56	0.42	0.99
Qnt 2	1.16	5.92	0.12	DY	-3.55	0.42	0.99
Qnt 3	1.12	5.41	0.11	EP	-2.82	0.42	0.99
Qnt 4	1.10	5.06	0.08	DE	-0.73	0.29	0.99
Hi 20	0.93	4.24	0.02	RVOL	0.14	0.05	0.96
Lo 10	1.16	6.37	0.23	BM	0.50	0.25	0.99
Dc 2	1.14	6.4	0.13	NTIS	0.01	0.02	0.98
Dc 3	1.19	6.07	0.12	TBL	4.10	3.10	0.99
Dc 4	1.14	5.84	0.12	LTY	5.76	2.85	1.00
Dc 5	1.17	5.64	0.11	LTR	0.53	2.77	0.05
Dc 6	1.09	5.29	0.11	TMS	1.66	1.38	0.96
Dc 7	1.10	5.22	0.09	DFY	0.96	0.43	0.97
Dc 8	1.09	5.00	0.07	DFR	0.03	1.44	-0.06
Dc 9	1.02	4.61	0.07	INFL	0.29	0.36	0.55
Hi 10	0.91	4.22	0.00				

Drawing from established literature, univariate predictive regressions have been a common framework for evaluating stock return predictability.

Consistent with these studies, we also utilize a univariate framework to assess predictability.

$$r_{t+1} = \alpha + \beta x_t + u_{t+1} \quad (1)$$

where r_{t+1} is the return on a portfolio of interest, and x_t is a lagged predictor variable.

- The dependent variable r_{t+1} represents the future return of the portfolio being analyzed.
- The independent variable x_t represents the lagged value of the predictor variable.
- The error term u_{t+1} captures the unexplained variation in the portfolio return.

In-sample results

Portfolio	Number of Significant Industries			Average R^2
	10%	5%	1%	$R^2\%$
Low 30	41	40	39	2.005
Med 40	36	24	9	0.698
High 30	3	1	0	0.112

In-sample results: quintiles and deciles

Portfolio	Number of Significant Industries			Average R^2
	10%	5%	1%	$R^2\%$
Low 20	41	41	40	2.557
Quintile 2	39	39	25	1.146
Quintile 3	35	25	9	0.700
Quintile 4	14	8	2	0.393
High 20	3	0	0	0.098
Low 10	42	42	41	3.525
Decile 02	40	39	38	1.641
Decile 03	39	39	25	1.152
Decile 04	39	38	24	1.121
Decile 05	37	29	15	0.775
Decile 06	33	23	6	0.635
Decile 07	24	16	5	0.520
Decile 08	9	7	1	0.312
Decile 09	10	6	1	0.258
High 10	0	0	0	0.080

Goyal and Welch (2008) - predictive regression models would not have helped a market agent time the market

- We assess out-of-sample forecasts in the following manner,

$$\hat{r}_{i,t} = \hat{\gamma}_i + \hat{\lambda}_i x_{i,t-1} \quad (2)$$

$$\hat{r}_t^{HA} = \frac{1}{t} \sum_{j=1}^t r_j \quad (3)$$

- We produce forecasts in an expanding window manner, with the initial forecast using 181 months.

The comparison between the predictive regression forecast and the historical average can be summarised using the out-of-sample R_{OS}^2 statistic. Following the framework provided in [Campbell and Thompson \(2008\)](#),

$$R_{OS}^2 = 1 - \frac{\sum (r_t - \hat{r}_{i,t})^2}{\sum (r_t - \hat{r}_t^{HA})^2} \quad (4)$$

[Neely et al. \(2014\)](#) found that only three out of the fourteen predictors produce [Campbell and Thompson \(2008\)](#), out-of-sample R^2 statistics that are statistically superior when compared to the historical average forecast

Out-of-sample results

Portfolio	Number of Significant - R^2_{OOS}			Average R^2_{OOS}
	10%	5%	1%	R^2_{OOS}
Low 30	39	37	22	1.211
Med 40	21	5	0	0.153
High 30	0	0	0	-0.29

Out-of-sample results: quintiles and deciles

Portfolio	Number of Significant - R_{OOS}^2			Average R_{OOS}^2
	10%	5%	1%	R_{OOS}^2
Low 20	41	38	31	1.793
Quintile 2	33	25	4	0.489
Quintile 3	20	3	0	0.12
Quintile 4	5	2	0	0.007
High 20	0	0	0	-0.312
Low 10	41	41	37	2.732
Decile 02	38	34	13	1.082
Decile 03	32	24	5	0.464
Decile 04	33	24	3	0.497
Decile 05	23	9	2	0.23
Decile 06	17	3	0	0.026
Decile 07	8	3	0	0.041
Decile 08	4	1	0	-0.036
Decile 09	2	0	0	-0.117
High 10	0	0	0	-0.343

Introduction to Scaled Principal Component Analysis (sPCA)

Overview

- Introduced by [Huang et al. \(2022, Management Science\)](#).
- Advances traditional PCA by using a scale based on each predictor's predictive slope related to the forecast target.
- Integrates multiple predictors' information to avoid over-fitting.

Methodology of sPCA

- Calculate each predictor's predictive slope on the target variable.
- Use scaled predictors in conventional PCA to derive Principal Components.
- sPCA diffusion indexes (K-vector) where $K < N$, based on adjusted R^2 .
- Estimate future values: $r_{t+1} = \alpha + \sum_{k=1}^K \beta_k F_t^{sPCA} + u_{t+1}$.
- sPCA assigns weight based on forecasting capabilities.

Scaled Principal Components Analysis

In-sample							
	$k=\text{Adjusted } R^2$					$k = 1$	
	β_1	β_2	β_3	k	R^2	β_1	R^2
Lo 30	0.214***	0.065	-0.267	3	3.452	0.214***	3.165
Med 40	0.106***	0.147	-0.207	3	1.391	0.106***	1.039
Hi 30	0.023	0.102	-0.203	3	0.503	0.0229	0.075
Lo 20	0.248***	0.022	-0.300	3	4.374	0.248***	4.052
Hi 20	0.019	0.100	-0.204	3	0.488	0.0188	0.052
Lo 10	0.293***	-0.099	-0.318	3	6.003	0.293***	5.602
Hi 10	0.012	0.104	-0.209	3	0.485	0.0117	0.020

Scaled Principal Components Analysis - Out-of-Sample

Out-of-Sample							
	$k=\text{Adjusted } R^2$					$k = 1$	
	β_1	β_2	β_3	k	R^2	β_1	R^2
Lo 30	0.185***	0.054	-0.242	3	2.951	0.185***	2.764
Med 40	0.092***	0.125	-0.186	3	1.237	0.092***	0.926
Hi 30	0.020	0.089	-0.178	3	0.442	0.020	0.066
Lo 20	0.217***	0.019	-0.263	3	3.777	0.217***	3.492
Hi 20	0.017	0.090	-0.183	3	0.421	0.017	0.045
Lo 10	0.257***	-0.087	-0.279	3	5.182	0.257***	4.837
Hi 10	0.011	0.092	-0.185	3	0.419	0.011	0.018

Our findings support a slower diffusion of industry information into small-cap share prices.

- **Information diffusion:** Smaller firms incorporate news more slowly (Mola et al., 2013; Hong and Stein, 1999).
- **Analyst coverage:** Heavily followed stocks respond to information sooner (Hong et al., 2000).
- **Specialised coverage:** Analysts' limited attention can delay industry-wide price adjustment (Menzly and Ozbas, 2010).
- **Lead-lag relationships:** Shocks tend to travel from large to small firms (Lo and MacKinlay, 1990).
- **Robustness:** Predictive results persist across size sorts and both in-sample and out-of-sample tests.
- **Scaled PCA:** Aggregating industry signals generates further forecasting improvements (Huang et al., 2022).

Thank you. Questions?