

Dynamics of Subjective Risk Premia ^{*}

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April 5, 2023

Abstract

We examine subjective risk premia implied by return expectations of individual investors and professionals for aggregate portfolios of stocks, bonds, currencies, and commodity futures. While in-sample predictive regressions with realized excess returns suggest that objective risk premia vary countercyclically with business cycle variables and aggregate asset valuation measures, subjective risk premia extracted from survey data do not comove much with these variables. A similar lack of cyclicity appears in out-of-sample forecasts of excess returns, which suggests that investors' learning of forecasting relationships in real time may explain much of the cyclicity gap.

^{*}We are grateful for comments and suggestions to Klaus Adam, Nick Barberis, Johannes Beutel, Ching-Tse Chen, Hui Chen, Ken French, Niels Gormsen, Ralph Koijen, Sydney Ludvigson, Ian Martin, Monika Piazzesi, Nick Roussanov, Steve Sharpe, seminar participants at Boston College, Federal Reserve Board, Frankfurt School, Harvard/MIT, National Bank of Belgium, University of Chicago, HKU, Luxembourg, Southern California, Trier, Utah, and conference participants at the BFI, EFA meetings, NBER Behavioral Finance and Asset Pricing Meetings. Nagel gratefully acknowledges financial support from the Fama-Miller Center at the University of Chicago Booth School of Business. Xu gratefully acknowledges financial support from the Research Grants Council of Hong Kong SAR, China (Project No. 21504421).

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1 Introduction

Explaining the empirically observed time-variation of risk premia in asset markets has been one of the main challenges in asset pricing research in recent decades. Evidence from in-sample predictive regressions shows that excess returns of aggregate portfolios of equities, bonds, currencies, and commodity futures are predictable with slow-moving predictors such as the dividend-price ratio, yield spreads, or the futures basis. Broadly speaking, the in-sample predicted excess returns in these regressions—which we refer to as *objective* risk premia—are countercyclical, i.e., higher in recessions than in booms.

These findings sparked a large literature of rational expectations (RE) asset pricing models in which time-varying risk premia are generated via time-varying risk or time-varying risk aversion (see [Cochrane \(2017\)](#) for a review). In these models, investors are endowed with perfect knowledge of the underlying stochastic processes that generate payoffs. As a consequence, the objective law of motion of returns that generates the data observable to the econometrician ex post is the same as the law of motion that investors perceive in real time.

Yet, if investors are not endowed with such perfect knowledge, the dynamics of *subjective* risk premia they perceive in real time may differ systematically from the dynamics of the objective risk premia that an econometrician’s predictive regressions extract from the data ex post. For example, if investors are learning about stochastic process parameters, there is a wedge between their real-time posterior beliefs about risk premia and the objective risk premia estimated by an econometrician from return data ex post with in-sample regressions. Fading memory, behavioral biases, and other imperfections can further magnify this wedge. In the presence of these wedges, one cannot infer perceived risks and risk aversion from objective risk premia estimates; subjective beliefs data is required.

In this paper, we present a pervasive stylized fact about subjective risk premia dynamics that holds true for different surveys, for expectations of individuals and professionals, for aggregate portfolios in different asset classes (stock market, Treasury bonds, currencies, commodity futures), and for a variety of state variables that have appeared in the literature to

capture the general business cycles and asset-class specific valuation cycles: Subjective risk premia are substantially less cyclical than objective risk premia inferred from in-sample predictive regressions. This calls into question the common practice of equating time-variation in objective risk premia with time-varying risk or time-varying risk aversion. Subjectively perceived risk or risk aversion appears to be substantially less sensitive to cyclical state variables than is assumed in RE models calibrated to match time-variation in objective risk premia.

We use survey data from a variety of different sources to construct monthly or quarterly subjective return expectations. For stock market return expectations, we use data on individuals, CFOs, and professional forecasters. For bonds, currencies, and commodity futures, we have professionals' expectations only. To study the dynamics of subjective risk premia, we focus on expected returns in excess of Treasury yields over a one-year forecast horizon in all asset classes. We then project these subjective expected excess returns on state variables. By projecting realized excess returns on the same state variables in predictive regressions, we can then compare the cyclicalities of subjective and objective risk premia.

In the first part of our analysis for each asset class, we focus on state variables that the prior literature has found to be good predictors of excess returns, for example, the dividend-price ratio for stock market returns, interest-rate cycle variables for bonds, interest rate spreads for currencies, and the futures basis for commodity futures. In virtually all combinations of state variables and different types of surveys, we find that projections of subjective risk premia on state variables yield coefficients that are substantially smaller in magnitude than projections of realized excess returns on the same state variables. In some cases, the point estimate for subjective risk premia has the opposite sign as for objective risk premia, but the overarching main regularity is that subjective risk premia vary a lot less with the state variables than future realized excess returns do in in-sample predictive regressions.

The state variables in this first part are asset-class specific, chosen based on earlier research that emphasized their role as significant excess return predictor for the specific asset class. On the other hand, many macro-finance models generate time-varying risk premia for different

asset classes that are all tied to the state of the business cycle (Cochrane 2017). Could there be better alignment between subjective and objective risk premia if we focus on projections of subjective expected excess returns and realized excess returns for the different asset classes on a common set of business cycle variables? Perhaps the misalignment is due to factors idiosyncratic to the asset classes, not due to the common business-cycle component?

We find that this is not the case. We consider a number of commonly used business cycle state variables, including term and default spreads, industrial production growth, a volatility index, and a real activity factor extracted from a large number of macroeconomic time series. Consistent with prior literature, these cyclical variables forecast excess returns in predictive regressions in several asset classes. But for these business cycle variables, too, we find that their association with subjective expected excess returns is much weaker than in the in-sample predictive regressions using empirically realized returns.

Overall, combining the evidence from asset-specific predictors and the common cyclical predictors and across all asset classes and surveys, we find that the average magnitude by which a one standard deviation change in a predictor moves the subjective expected excess return is only about one fifth of the average magnitude by which it moves the objective expected excess return according to in-sample predictive regressions using realized excess returns. This pervasive lack of cyclical movements in subjective risk premia casts doubt on the time-varying risk or risk aversion mechanisms that have been used in many macro-finance models to explain cyclical fluctuations in asset prices.

Does the lack of cyclicity evident in subjective excess return expectations indicate gross mistakes on the part of investors and forecasters, or is there a plausible belief formation mechanism that does not imply easily detectable prediction errors that could be exploited by sophisticated investors? To shed light on this, we examine the cyclicity of out-of-sample (OOS) excess return forecasts. At every point in time, these OOS forecasts are constructed based on regression coefficients that are estimated using only past data. Moreover, at every point in time, the forecaster evaluates which linear combination of the predictive regression

forecast and a simple trailing mean of excess returns would have done best in the past in forecasting OOS. The OOS forecast of excess returns is then based on this optimal linear combination. We find that these OOS forecasts are substantially less cyclical than in-sample forecasts. Moreover, if we construct the OOS forecasts with exponential weighting of past data to reflect fading memory as in Nagel and Xu (2022), or as combination forecasts of single-predictor forecasts as in Rapach et al. (2010), much of the cyclicity gap to the subjective risk premia in survey data disappears. Thus, while it is not our goal in this paper to provide evidence on a specific belief-formation mechanism, the OOS forecast evidence shows that the lack of cyclicity in subjective risk premia does not mean that the subjective forecasts are unreasonable or unsophisticated. Models in which investors have to learn about the data-generating process may be able to explain much of the cyclicity gap.

That subjective risk premia are largely unrelated to standard business cycle indicators and standard return predictors does not necessarily imply that subjective risk premia are constant. Indeed, we find that time-varying subjective risk perceptions appear to have some explanatory power for time-variation in subjective risk premia. This is in stark contrast to the literature on time-varying objective risk premia where researchers have not had much success linking them to time-varying risk. Due to data availability constraints, in this analysis we focus only on stock market expectations. For all three groups of market participants (individuals, CFOs, and professional forecasters) we find a positive link between the level of subjective risk premia and the stock market risk perceived by respondents in the CFO survey. In other words, in terms of subjective beliefs, there is a positive risk-return tradeoff.

Our work connects to a number of areas in the literature. Our findings are most closely related to earlier work by Piazzesi et al. (2015) who show that subjective bond risk premia of professional forecasters are less cyclical than predictive regression forecasts.¹ We show

¹ Other papers provide evidence that is related, but does not quite pin down the empirical time-variation in the subjective risk premium for aggregate asset classes. Bacchetta et al. (2009) show that at country level, professional forecasters' subjective expectations errors for currency excess returns are predictable with the interest-rate differential, with the same sign and often similar magnitude as realized excess returns. However, from these country-level results it is not clear how objective and subjective risk premia for the aggregate currency portfolio would vary over time because the country-level results could be driven by country-specific

that this relative lack of cyclicity result holds for a much broader range of state variables, not only for bonds but also for return expectations in stock market, for currencies, and for commodity futures, and in surveys of individual investors and CFOs. We further show OOS forecasts of excess return exhibit a similar lack of cyclicity.

Much of the earlier literature on subjective return expectations has focused on whether the sign of subjective return forecasts lines up with the sign of predictive regression forecasts. For example, for stock market return expectations, [Amromin and Sharpe \(2014\)](#) and [Greenwood and Shleifer \(2014\)](#) emphasize the procyclicality of individual investor return expectations. In contrast, [Wu \(2018\)](#) and [Wang \(2021\)](#) find that professional forecasters and asset managers issue countercyclical forecasts. Our results show that these differences between surveys are overshadowed by an economically much bigger common regularity: the general lack of sensitivity of subjective risk premia to variables that forecast excess returns in predictive regressions (and in rational expectations models built to match the predictive regression evidence). In contrast, [Dahlquist and Ibert \(2022\)](#) find a close alignment of objective and subjective risk premia for 10-year return expectations of asset managers. However, their findings are based on a very short sample, with little data before 2010, which makes it difficult to pin down the relationship with highly persistent cyclical variables such as the dividend-price ratio.

The lack of cyclical movements in subjective risk premia is consistent with models that generate volatile asset prices through time-varying subjective expectations of fundamentals growth rather than time-varying risk aversion or time-varying perceptions of risk. Examples include models of perpetual learning ([Collin-Dufresne et al. \(2017\)](#), [Nagel and Xu \(2022\)](#)) or diagnostic expectations ([Bordalo et al. \(2021\)](#)). In a similar vein, our evidence supports

components of the interest-rate differential and currency excess returns. From the viewpoint of macro-finance modeling, the properties of risk premia for aggregate strategy are arguably the most relevant. [De La O and Myers \(2021\)](#) find a small positive covariance between the price-dividend ratio and total return expectations from several surveys, but since the risk-free rate is correlated with the price-dividend ratio, their results are not directly informative about comovement of the price-dividend ratio with the subjective risk premium. Consistent with our empirical findings, [Beutel and Weber \(2022\)](#) provide experimental evidence that individuals' stock return expectations are positively related to recent returns, but not sensitive to valuation ratios.

models that generate bond price and exchange rate variation through subjective beliefs about future interest rates, as in Piazzesi et al. (2015) and Gourinchas and Tornell (2004), respectively, and commodity futures price variation through subjective beliefs about future spot prices.

Price-growth extrapolation mechanisms as in Adam et al. (2017) and Jin and Sui (2022) are not consistent with a complete lack of comovement between state variables that predict realized excess returns and subjective risk premia. In these models, a positive correlation between past returns and future subjectively expected returns is sustained in equilibrium by a subjective risk premium that is increasing in past price growth. As a consequence, the price level, as captured, say, by the price-dividend ratio, is positively related to the subjective equity premium. However, as Jin and Sui (2022) show, this positive relationship can be quite weak in a calibrated version of their model, which could be broadly consistent with the lack of cyclicity in subjective risk premia that we find in this paper. With such a weak link between past price growth and subjective risk premia, asset price movements largely reflect changing expectations about future fundamentals growth, similar to models that directly target time-varying subjective expectations of fundamentals growth.

Finally, our finding that allowing for real-time learning helps explain the dynamics of subjective excess return expectations relates to recent work by Farmer et al. (2023). They show that a model in which agents are learning in real time about long-run dynamics helps explain macroeconomic forecasting anomalies in professional forecasts data.

The paper is organized as follows. Section 2 introduces the data. Section 3 presents the main results on the cyclicity of subjective and objective risk premia. Section 4 compares the cyclicity of subjective risk premia and OOS forecasts. Section 5 looks at the subjective risk-return tradeoff. Section 6 concludes.

2 Data

In this section we describe the survey data and how we construct subjective return expectations in each asset market. We also describe the return predictors and business cycle variables. Appendix A provides more detailed information on the data sources and the exact timing assumptions that we use to match data on returns, predictor variables, and survey data.

2.1 Subjective expectations and returns data

Table 1 below reports the sample periods and moments of subjective return expectations in excess of risk-free rates. For comparison, we also report the moments of realized excess returns for the full sample period. Figure 1 plots the subjective excess return expectations in each asset market. We construct these measures as follows.

2.1.1 Stock market

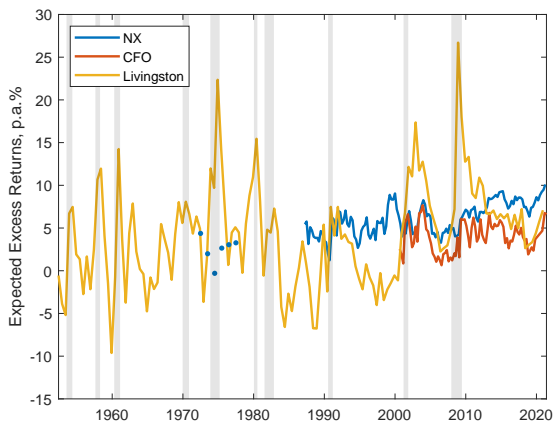
For aggregate stock market return expectations we use a series of individual investor expectations, CFO expectations, and a series of professional forecaster expectations. The individual investor series is from Nagel and Xu (2022) (NX). It covers several surveys in the period 1972 to 1977 and has continuous quarterly coverage from 1987 onward. The series is constructed by combining information from the UBS/Gallup survey, the Conference Board survey, and the Michigan Survey of Consumers, plus several smaller surveys of brokerage and investment firm customers. The second source of stock return expectations is the Graham-Harvey CFO survey (Ben-David et al. 2013) which asks about the expectations of annual S&P 500 returns. The series is available from 2000Q3 at quarterly frequency (with gaps) and we use the mean of respondents' expected return each period.² The third source is the Livingston Survey maintained by the Federal Reserve Bank of Philadelphia. The series provides semi-annual forecasts starting in June 1952. From June 1992 onward, we use the ratio of twelve-month to zero-month mean level forecasts of the S&P500 stock index (or its predecessors) to measure

² Survey forecasts in 2001Q3, 2019Q1, and 2020Q1-3 are not available.

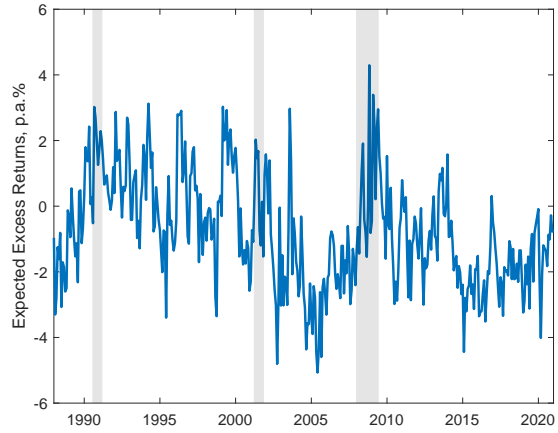
TABLE 1
Moments of Excess Returns and Excess Return Expectations

This table reports the frequencies, sample periods, means (%), and standard deviations (%) of realized one-year excess returns and survey-implied excess return expectations in each asset market. For stock market, we report the excess returns on the aggregate stock market. For Treasury bonds, we report the equal-weighted average excess returns on bonds with maturities of two, five, seven, and ten years. For foreign exchange, we report the average excess returns on a basket of developed market currencies. For commodities, we report the buy-and-hold excess returns on metals and crude oil, respectively.

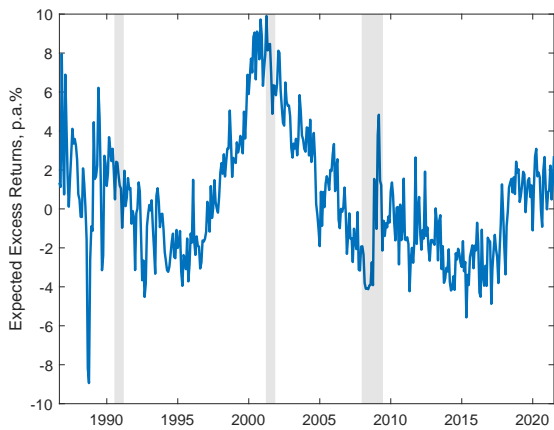
	Frequency	Sample Period	Mean	S.D.
A. Stock				
Realized	Monthly	1926/12–2020/12	8.15	21.15
NX	Quarterly	1972Q3–2021Q2	5.95	1.98
CFO	Quarterly	2000Q3–2021Q2	3.98	1.75
Livingston	Semi-annually	1952Q2–2020Q4	4.09	5.86
B. Treasury bond				
Realized	Monthly	1952/03–2020/12	1.32	5.08
BCFF	Monthly	1988/01–2020/12	-0.76	1.70
C. Foreign exchange				
Realized	Monthly	1984/10–2021/06	1.78	9.76
CE & FX4casts	Monthly	1986/08–2021/06	0.50	3.16
D. Commodity				
Realized, Metals	Monthly	1978/09–2021/06	1.53	25.54
CE, Metals	Monthly	1995/08–2021/06	0.70	5.67
Realized, Oil	Monthly	1984/12–2021/06	8.49	33.68
CE, Oil	Monthly	1995/08–2021/06	2.46	9.70



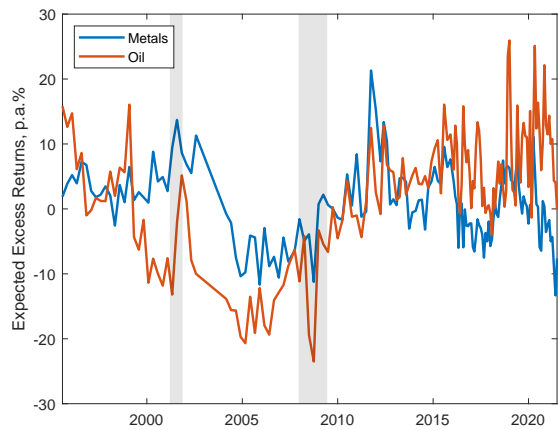
(A) Stock market



(B) Treasury bond market



(C) FX market



(D) Commodity market

FIGURE 1
Subjective Excess Return Expectations

Each panel plots the subjective excess return expectations implied by surveys. The grey-shaded areas indicate NBER recessions.

price growth expectations. In earlier periods, where the zero-month nowcast is not available, we use the annualized ratio of twelve-month to six-month forecasts. We adjust these price growth expectations with the dividend yield to arrive at return expectations.³

For each subjective one-year expected stock return series, $\tilde{\mathbb{E}}_t R_{t+1}$, we then construct the subjective risk premium by subtracting the one-year Treasury yield $R_{f,t}$ that prevailed at the time of the survey,

$$\tilde{\mathbb{E}}_t R_{t+1}^e = \tilde{\mathbb{E}}_t R_{t+1} - R_{f,t}. \quad (1)$$

For comparison, we also examine realized returns on the CRSP value-weighted index over the one-year forecast period. Realized returns are also expressed as excess returns over and above the one-year Treasury yield.

2.1.2 Treasury bond market

For bond return expectations of professional forecasters, we use the Blue Chip Financial Forecasts (BCFF) survey. Par yield forecasts are available for 6-month, 1-year, 2-year, 5-year, and 10-year bond maturities starting from January 1988. We take the average across forecasters in each survey month. Survey participants forecast the quarterly average of yields of a particular maturity for the current quarter, next quarter, and up to several quarters ahead. We follow [Kim and Orphanides \(2012\)](#) and treat these forecasts as approximately equal to a mid-quarter forecast. We interpolate linearly between these mid-quarter forecasts to obtain forecasts at a one-year horizon. To estimate a full expected par yield curve, we fit a Nelson-Siegel model to these forecasts period-by-period, as in [Diebold and Li \(2006\)](#). We then bootstrap zero-coupon yield forecasts from these par yield forecasts. The final step for each

³ We use the decomposition $\tilde{\mathbb{E}}_t R_{t+1} = \tilde{\mathbb{E}}_t(P_{t+1}/P_t) + (D_t/P_t)\tilde{\mathbb{E}}_t(D_{t+1}/D_t) - 1$. Similar to [Adam et al. \(2017\)](#), we set the expected dividend growth $\tilde{\mathbb{E}}_t(D_{t+1}/D_t)$ equal to the sample average of S&P annual dividend growth over the post-WWII sample period 1946–2020, which is 1.064. The dividend-price ratio is calculated using the S&P500 Index from CRSP.

maturity is then to construct implied return expectations by relying on the approximation

$$\tilde{\mathbb{E}}_t R_{t+1}^n \equiv \tilde{\mathbb{E}}_t \left[\frac{(1 + Y_t^n)^n}{(1 + Y_{t+1}^{n-1})^{n-1}} - 1 \right] \approx \frac{(1 + Y_t^n)^n}{\left(1 + \tilde{\mathbb{E}}_t Y_{t+1}^{n-1}\right)^{n-1}} - 1. \quad (2)$$

Given the time- t one-year ahead forecast of the $(n-1)$ -year zero-coupon yield $\tilde{\mathbb{E}}_t Y_{t+1}^{n-1}$ and the current n -year zero-coupon yield, we can then calculate $\tilde{\mathbb{E}}_t R_{t+1}^n$ for $n \in \{2, 5, 7, 10\}$. We aggregate to a bond portfolio return forecast $\tilde{\mathbb{E}}_t R_{t+1}$ by taking an equal-weighted average across maturities. Finally, we construct subjective expected excess returns, $\tilde{\mathbb{E}}_t R_{t+1}^e$, by subtracting the one-year Treasury yield from $\tilde{\mathbb{E}}_t R_{t+1}$.

To compare the subjective risk premium with predictive regression forecasts of realized excess returns, we use CRSP Treasury Index returns for maturities $n \in \{2, 5, 7, 10\}$. As for the subjective expectations, we form an equal-weighted average of these returns and subtract the one-year Treasury yield to obtain excess returns.

2.1.3 Foreign exchange market

In our analysis of currencies, we focus on the expected returns on a portfolio of developed market currencies from the perspective of a US investor. We use professional forecasts of exchange rates from FX4casts and Consensus Economics (CE) to construct subjective expected returns on this currency portfolio. We primarily use CE forecasts and supplement with FX4casts when CE forecasts are unavailable. Consensus forecasts in CE are arithmetic averages of individual forecasts; FX4casts uses a geometric average. With the time- t mean forecast $\tilde{\mathbb{E}}_t S_{t+1}^i$ of the one-year ahead spot exchange rate S_{t+1}^i of country i (in units of foreign currency per dollar), we approximate the subjective expected excess return on a US investor's position in an individual country's currency i as

$$\tilde{\mathbb{E}}_t R_{t+1}^{i,e} \equiv \tilde{\mathbb{E}}_t \left[\frac{F_t^i}{S_{t+1}^i} - 1 \right] \approx \frac{F_t^i}{\tilde{\mathbb{E}}_t S_{t+1}^i} - 1, \quad (3)$$

where F_t^i is the one-year forward rate at time t . Developed market currencies in our sample include Australia, Canada, Denmark, Germany (replaced by the Euro from 1999 onward), Japan, New Zealand, Norway, Sweden, Switzerland, and United Kingdom. To avoid a shift in sample composition at the Euro introduction in 1999, we use the German Mark as the only representative from the Eurozone currencies prior to Euro introduction. We calculate the expected excess return on the developed market currency portfolio as an equal-weighted average of the individual currencies' $\tilde{\mathbb{E}}_t R_{t+1}^{i,e}$.

The realized excess returns that we compare with subjective risk premia are constructed in similar fashion from forward and spot rates as $R_{t+1}^{i,e} = F_t^i / S_{t+1}^i - 1$.

2.1.4 Commodity futures market

We use commodity spot price forecasts to compute subjective expected returns on buy-and-hold futures positions. We obtain consensus spot price forecasts from CE that cover major commodities in metals and energy. The publication was quarterly before 2012, bi-monthly until 2015, and switched to a monthly release cycle since February 2016.⁴ We use the set of commodities with the longest history and highest coverage in CE: WTI crude oil and several metals (aluminum, copper, gold, and silver). These commodities cover the major components of the S&P GSCI index.⁵ Since CE commodity forecasts are also for quarterly average, we use the same linear interpolation as earlier for bonds to obtain one-year forecasts.

Using these spot price forecasts, we then calculate the expected excess return from entering a one-year futures position at time t at the one-year futures price F_t and holding it until it gets settled at maturity at $t + 1$ at the spot price S_{t+1} (or a futures price very close to the spot price shortly before maturity):

$$\tilde{\mathbb{E}}_t R_{t,t+1}^e \equiv \frac{\tilde{\mathbb{E}}_t S_{t+1}}{F_t} - 1. \quad (4)$$

⁴ During the period of August 2002 to March 2004, and the third quarter of 2007, there are no forecasts available as no surveys were undertaken by the previous owners of the publication.

⁵ Based on the 2021 reference percentage dollar weights, WTI crude oil accounts for 40.4% of the energy sector and the four metals we include account for 84.4% of the metals sector.

We obtain spot price and futures data from Datastream and Bloomberg. When spot price data is not available for a commodity, we follow [Kojien et al. \(2018\)](#) and extrapolate spot prices from Bloomberg generic futures data. We construct a sector-level subjective risk premium series for metals by taking an equal-weighted average of the subjective expected excess returns across metals.

We construct realized excess returns along similar lines as $R_{t+1}^e = S_{t+1}/F_t - 1$, with equal-weighted average within the metals sector.

2.2 Return Predictors and Cyclical Indicators

In this section, we introduce the main return predictors and cyclical indicators that we use in our analysis. For each asset class, we examine several asset class-specific return predictors that have appeared in the prior literature. We also examine a common set of business cycle indicators. [Table 2](#) reports the correlations of return predictors and cyclical indicators.

2.2.1 Asset-class specific predictors

The stock market return predictors are the log consumption-wealth ratio (CAY, quarterly, starting in 1951Q1) from [Lettau and Ludvigson \(2001\)](#), the repurchase-adjusted log dividend-price ratio of the CRSP value-weighted index (D/P, monthly, starting end of 1926) and a long-run exponential average of past per-capita real aggregate dividend growth (EXPD, quarterly, starting end of 1926) from [Nagel and Xu \(2022\)](#), as well as net equity expansion (NTIS, monthly, starting from end of 1926) from [Welch and Goyal \(2008\)](#), calculated as the ratio of twelve-month moving sums of net issues by NYSE-listed stocks divided by the total market capitalization of NYSE stocks at the end of the twelve-month window.

For Treasury bonds, we use two asset-class specific predictors. The first predictor is the macro factor from [Ludvigson and Ng \(2009\)](#) (LN). It is constructed as the fitted value from regressing equal-weighted bond portfolio excess returns on lagged principal components of a broad set of macro variables. We use the six-factor version of their model. The second

TABLE 2
Correlations of Return Predictors and Cyclical Indicators

This table reports the unconditional correlations of asset-class specific predictors and business-cycle indicators. For countercyclical business-cycle indicators, N-IP is the negative of the 12-month log change in the U.S. industrial production index; TERM is the spread between long interest rates from Robert Shiller's website and 3-month Treasury yields; DEFAULT is the spread between Moody's Seasoned Baa and Aaa Corporate Bond yields; F1 is the real factor from Ludvigson and Ng (2009); VIX² is the square of the CBOE volatility index; CAY is the aggregate log consumption-wealth ratio from Lettau and Ludvigson (2001); D/P and EXPD are the repurchase-adjusted log dividend-price ratio and the experienced payout growth from Nagel and Xu (2022), respectively; NTIS is the net equity expansion from Welch and Goyal (2008); LN is the macro factor from Ludvigson and Ng (2009); CYCLE is the cycle factor from Cieslak and Povala (2015); FD is the average forward discount on the basket of developed market currencies; BASIS is the percentage difference between futures and spot prices and OI is futures open interest growth for metals (M) and oil (E), respectively.

	N-IP	TERM	DEFAULT	F1	VIX ²	CAY	D/P	EXPD	NTIS	LN	CYCLE	FD	BASIS (M)	OI (M)	BASIS (E)	OI (E)
N-IP	1.00															
TERM	0.05	1.00														
DEFAULT	0.26	0.20	1.00													
F1	0.63	0.15	0.51	1.00												
VIX ²	0.08	-0.00	0.31	0.31	1.00											
CAY	-0.17	0.22	-0.05	0.08	-0.04	1.00										
D/P	0.17	0.10	0.50	0.31	0.15	-0.04	1.00									
EXPD	0.15	-0.39	-0.13	-0.05	0.06	-0.11	-0.04	1.00								
NTIS	0.01	-0.16	-0.18	-0.29	-0.02	0.02	-0.14	0.04	1.00							
LN	0.48	0.54	0.21	0.50	0.18					1.00						
CYCLE	-0.19	0.50	-0.13	-0.02	-0.01					0.18	1.00					
FD	0.22	0.43	0.12	0.29	0.02							1.00				
BASIS (M)	0.02	-0.31	0.47	-0.00	-0.10								1.00			
OI (M)	-0.03	0.17	-0.14	-0.16	-0.17								-0.14	1.00		
BASIS (E)	0.25	-0.04	0.28	0.20	0.28								-0.03	0.00	1.00	
OI (E)	-0.30	0.04	-0.19	-0.31	-0.20								-0.00	0.34	-0.43	1.00

predictor is the cycle factor from [Cieslak and Povala \(2015\)](#) (CYCLE). To construct this factor, we first regress zero-coupon yields of maturities between one to fifteen years from [Liu and Wu \(2021\)](#) on trend inflation to obtain the short-maturity cycle and the average longer-maturity cycles. The fitted value from regressing equal-weighted bond portfolio excess returns on these two cycle components then represents the cycle factor.

In our analysis of foreign exchange, we consider a US investor’s position in a portfolio of developed market currencies as in [Lustig et al. \(2014\)](#). Following their analysis of excess return predictability, we use the average one-year forward discount as predictor. For each currency i we construct the forward discount,

$$FD_t^i \equiv \frac{F_t^i}{S_t^i} - 1, \quad (5)$$

from one-year forward rates F_t^i and spot rates S_t^i . We then average these currency-level forward discounts across all currencies in the portfolio (FD).

Finally, for commodities we use two asset-class specific predictors. The first predictor, as in [Hong and Yogo \(2012\)](#), is the one-year futures basis defined as

$$Basis_t \equiv \frac{F_t}{S_t} - 1, \quad (6)$$

where F_t is the one-year futures price and S_t is the spot price (approximated by extrapolating from generic futures if not available, as discussed above). We average the commodity-specific bases within metals futures (BASIS). The second predictor is open interest growth following [Hong and Yogo \(2012\)](#). Using CFTC Commitments of Traders data, we multiply open interest in terms of number of outstanding contracts by the number of units per contract and the spot price per unit to get dollar open interest.⁶ We then sum up dollar open interests within each sector. As a final step, we calculate percentage growth rates over one-year periods (OI).

⁶ For Aluminum, we use open interest data from London Metal Exchange instead given the limited coverage of Aluminum in CFTC Commitments of Traders data.

2.2.2 Business-cycle indicators

The first business-cycle indicator is industrial production growth constructed as the year-over-year log growth using data from FRED database at the Federal Reserve Bank of St. Louis. For ease of interpretation, we take the negative of industrial production growth (N-IP) so that the series is countercyclical. The second indicator is the term spread (TERM) between long- and short-maturity yields. For long-maturity yields, we use the long interest rates from Robert Shiller’s website. For short-maturity yields, we use the annualized three-month Treasury bill yields. The third indicator is the default spread (DEFAULT) between the Moody’s Seasoned Baa and Aaa yields, obtained from FRED. The fourth indicator is the real factor (F1) from Ludvigson and Ng (2009) which is the first principal component of a broad set of macroeconomic variables. The last indicator we use is the square of CBOE Volatility Index (VIX^2).⁷ Given its relatively short history, we supplement the series with the news-implied volatility index (NVIX) from Manela and Moreira (2017). We estimate the relation between VIX and NVIX in the overlapping samples and impute VIX before 1990 with the fitted coefficients from this regression.⁸ All cyclical indicators are available at a monthly frequency. We lag N-IP and F1 by one-month to account for publication lags.

3 Dynamics of Subjective and Objective Risk Premia

We now examine how much subjective and objective risk premia vary with asset-class specific predictors and the business-cycle indicators. We regress subjective expected excess returns from surveys on the predictor variables and compare the results to regressions in which future realized excess returns are the dependent variable. We run two separate regressions rather than just one that uses the wedge between survey expectations and realized returns

⁷ We use VIX^2 instead of VIX because asset pricing theories typically relate risk premium to variance, not standard deviation.

⁸ The regression uses monthly data from January 1990 to March 2016 and yields:

$$VIX = -2.940 + 0.919 \times NVIX,$$

with an R^2 of 0.59.

as dependent variable because we are interested not only in potential deviations from the rational expectations hypothesis, but also, in case there is a deviation, in characterizing the dynamics of subjective risk premia. Are they procyclical, countercyclical, or acyclical?

For ease of interpretation, we standardize all predictor variables to have unit standard deviations in the full sample that we use in the realized excess return regressions.⁹ With standardized predictors we can easily compare the amount of variation in objective and subjective risk premia associated with different predictors by comparing the magnitudes of slope coefficients. For parsimony, while all regressions include an intercept, we omit the intercept estimates from all tables.

The realized returns regressions are run with monthly or quarterly data depending on data availability for the predictor variable. To match with the one-year forecast horizon in our subjective expected return data, we use realized excess returns compounded over one-year periods as the dependent variable. We use a stationary block bootstrap to account for the autocorrelations in residuals induced by the overlapping return windows in the dependent variable. We also use the bootstrap to adjust coefficients for the predictive regression bias discussed in [Stambaugh \(1999\)](#). [Appendix B](#) provides more details of the bootstrap approach. In regressions where subjective expected returns are the dependent variable, we adjust p -values for heteroskedasticity and autocorrelation in regression residuals using the equal-weighted cosine (EWC) approach from [Lazarus et al. \(2018\)](#).

3.1 Stock market

To provide a basis for comparison, [Table 3](#) first reports the results for predicting future one-year realized excess returns. All asset-class specific predictors except NTIS are at least marginally significant ($p < 0.10$) when used as sole predictor variable. The magnitude of slope coefficient point estimates are similar and quite large for all of them. Based on bias-adjusted slope coefficient estimates, a one standard deviation move in the predictor variable is

⁹ If predictor data is available, the full sample start date is December 1925, and otherwise at the earliest date of predictor availability.

TABLE 3
Regressing Realized Stock Market Excess Returns on Predictors

Dependent variable is the one-year cumulative excess returns on the CRSP index. The full sample period is from December 1926 to December 2020. Column variables are described in Section 2.2. R_{past}^e denotes the past one-year excess return. All independent variables are standardized to have unit standard deviations in the full sample period. In each block, the first row reports the OLS estimates multiplied by 100; bootstrap bias-adjusted coefficients are reported in braces; bootstrapped p -values are reported in parentheses. We use a stationary bootstrap with an optimal block length determined as in Politis and White (2004).

	Asset-Class Specific								Business-Cycle									
	CAY		D/P		EXPD		NTIS		N-IP		TERM		DEFAULT		F1		VIX ²	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Coeff	4.78	5.34	6.40	6.68	-6.48	-7.29	-5.23	-5.23	1.74	1.53	4.13	4.30	3.32	3.24	4.24	3.92	1.49	1.22
{bias-adj.}	{3.24}	{3.71}	{6.01}	{5.83}	{-6.44}	{-7.19}	{-4.87}	{-4.93}	{1.55}	{1.26}	{4.40}	{4.62}	{2.84}	{2.51}	{4.54}	{4.16}	{1.82}	{1.48}
(p -value)	(0.08)	(0.10)	(0.00)	(0.00)	(0.03)	(0.04)	(0.16)	(0.16)	(0.51)	(0.49)	(0.00)	(0.01)	(0.12)	(0.13)	(0.00)	(0.04)	(0.31)	(0.39)
R_{past}^e		-3.52		0.87		-3.51		-1.25		-0.70		-1.28		-0.24		-1.07		-1.01
{bias-adj.}		{-3.32}		{0.36}		{-3.70}		{-1.47}		{-1.23}		{-1.39}		{-0.55}		{-0.65}		{-1.24}
(p -value)		(0.12)		(0.71)		(0.09)		(0.51)		(0.74)		(0.55)		(0.91)		(0.69)		(0.62)
Adj. R^2	0.03	0.06	0.09	0.09	0.08	0.11	0.06	0.06	0.01	0.01	0.04	0.04	0.02	0.02	0.06	0.06	0.00	0.00
N	272	272	1117	1117	377	373	1117	1117	1129	1117	1129	1117	1129	1117	717	717	1129	1117

associated with a substantial change in objective expected returns of 3.24 to 6.44 percentage points over a one-year forecast horizon.

For cyclical indicators, TERM and F1 are the only ones that are individually at least marginally significant. The magnitudes of point estimates are also much more mixed than for the asset-class specific predictors, ranging from 1.55 for N-IP to 4.54 for F1. However, without exception, for all predictors in both groups, the point estimates indicate a countercyclical pattern of objective risk premia: low following booms, high following downturns in asset prices or the business cycle.

When past one-year realized excess returns are included as an additional predictor in the regressions, past returns are never statistically significant except marginally so when used along with EXPD ($p = 0.09$).

Table 4 shows the results of regressing subjective excess return expectations from different surveys on the same predictor variables as in Table 3. Panel A presents the results for individual investor expectations. Results for CFO expectations are shown in Panel B. Looking across all regressions, a striking commonality is that the magnitude of slope coefficients is generally much smaller than in the realized excess return regressions in Table 3. For example, in the single-predictor regressions, the biggest coefficient in Table 4 is 1.12 for TERM in Panel B. In contrast, the largest coefficient estimate in absolute magnitude is 6.44 for EXPD in in Table 3 (for TERM it is 4.40). Therefore, subjective expected excess returns of individual investors and CFOs vary much less with these standard predictor variables than objective risk premia do.

With subjective expected excess returns from the Livingston survey in Panel C, the magnitudes of estimated slope coefficients for the asset-class specific predictors are also fairly small. Only for the cyclical indicators, we obtain coefficients (5.62 for N-IP, 4.18 for DE-FAULT) that are in the ballpark of the magnitudes that we obtained in the realized return regressions. However, for these two predictors, the coefficients in the realized returns regression in Table 3 are actually quite small (1.55 and 2.84, respectively), so there is not a great

TABLE 4
Regressing Survey Stock Market Excess Return Expectations on Predictors

Dependent variables are the one-year-ahead excess return expectations from Nagel and Xu (2022), the CFO survey, and the Livingston survey, respectively. Column variables are described in Section 2.2. R_{past}^e denotes the past one-year excess return. All predictors are standardized to have unit standard deviations in the full sample period. The first row in each block reports the OLS estimates multiplied by 100. EWC p -values following Lazarus et al. (2018) are reported in parentheses.

	Asset-Class Specific								Business-Cycle									
	CAY		D/P		EXPD		NTIS		N-IP		TERM		DEFAULT		F1	VIX ²		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
A. Individual (NX)																		
Coeff	-0.75	-0.75	-0.24	-0.00	0.17	0.20	-0.36	-0.55	0.98	1.57	0.44	0.46	-0.30	0.57	0.15	0.63	-0.01	0.27
(p -value)	(0.04)	(0.03)	(0.52)	(1.00)	(0.63)	(0.54)	(0.48)	(0.23)	(0.17)	(0.01)	(0.20)	(0.18)	(0.35)	(0.13)	(0.68)	(0.08)	(0.95)	(0.14)
R_{past}^e		0.87		0.87		0.88		0.98		1.16		0.88		1.07		1.13		1.13
(p -value)		(0.01)		(0.02)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.01)
Adj. R^2	0.21	0.33	0.00	0.11	0.00	0.12	0.01	0.16	0.04	0.23	0.04	0.16	-0.00	0.13	-0.00	0.16	-0.01	0.15
N	142	142	142	142	142	142	142	142	143	142	143	142	143	142	142	142	143	142
B. CFO																		
Coeff	-0.23	-0.15	-0.47	-0.41	-0.94	-0.92	0.74	0.67	0.32	1.64	1.12	1.15	-0.15	0.47	0.08	0.59	0.01	0.23
(p -value)	(0.64)	(0.76)	(0.32)	(0.31)	(0.01)	(0.02)	(0.01)	(0.03)	(0.55)	(0.02)	(0.00)	(0.00)	(0.60)	(0.18)	(0.68)	(0.07)	(0.92)	(0.16)
R_{past}^e		0.35		0.30		0.16		0.20		0.89		0.39		0.63		0.85		0.73
(p -value)		(0.18)		(0.29)		(0.60)		(0.48)		(0.01)		(0.08)		(0.08)		(0.03)		(0.05)
Adj. R^2	-0.00	0.01	0.04	0.05	0.35	0.34	0.08	0.07	-0.01	0.12	0.37	0.44	-0.01	0.03	-0.01	0.06	-0.01	0.04
N	77	77	77	77	77	77	77	77	79	77	79	77	79	77	77	77	79	77
C. Livingston																		
Coeff	-1.70	-1.42	1.01	0.42	-0.37	-0.59	-1.05	-0.88	5.62	5.08	1.06	1.03	4.18	3.41	2.67	2.23	1.65	1.23
(p -value)	(0.08)	(0.09)	(0.48)	(0.73)	(0.40)	(0.17)	(0.43)	(0.34)	(0.00)	(0.00)	(0.38)	(0.37)	(0.03)	(0.04)	(0.00)	(0.00)	(0.00)	(0.02)
R_{past}^e		-2.70		-2.78		-2.94		-2.83		-2.28		-2.87		-1.79		-1.67		-2.23
(p -value)		(0.02)		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)		(0.05)		(0.08)		(0.06)
Adj. R^2	0.06	0.17	0.01	0.13	-0.00	0.14	0.01	0.14	0.27	0.35	0.03	0.16	0.22	0.26	0.23	0.26	0.13	0.20
N	138	138	138	138	138	138	138	138	138	138	138	138	138	138	122	122	138	138

match between subjective and objective risk premia in these cases either.

Since evidence for extrapolation from recent past returns play an important role in earlier studies of return expectations data, e.g., [Greenwood and Shleifer \(2014\)](#), we also run versions of these regressions with past one-year excess returns as a regressor. Past returns often have substantial explanatory power, with positive effects on subjective risk premia of individuals and CFOs, indicating extrapolation, and negative effects for professionals in the Livingston survey, indicating a contrarian influence of past returns. Therefore, recent past returns are a potentially important influence on subjective return expectations that one should seek to understand. The heterogeneity in past returns' influence on expectations between individuals/CFOs on one hand and professional forecasters on the other hints that a model with heterogeneous beliefs may be needed to understand the asset pricing consequences of belief formation, perhaps as in [Barberis et al. \(2015\)](#) where extrapolators coexist with traders that are rationally contrarian (although predictions from this model would be difficult to square with the lack of predictability associated with past returns in the realized return regressions in [Table 3](#)). However, for our purposes, the important take-away from the table is that the inclusion of past returns does not have a substantial impact on the slope coefficient estimates for the slower-moving asset-class specific predictors and cyclical indicators that are the focus of our analysis. Whatever the mechanism that let past returns affect return expectations, this mechanism seems to be largely distinct from the predictor variables and the low-frequency valuation cycles that have been emphasized in macro-finance modeling of asset markets.

[Figure 2](#) provides a visual summary of our results on objective and subjective risk premia in the stock market. While our discussion above focused on estimates in single-predictor regressions, this figure shows the coefficient estimates when past returns are included in the regression along with the predictor. The blue bars show the coefficients from the realized return regressions in [Table 3](#). The other bars show the corresponding coefficients from [Table 4](#) for the same predictor with the survey expected excess returns as dependent variable. The figure clearly illustrates that subjective risk premia have much lower sensitivity to the

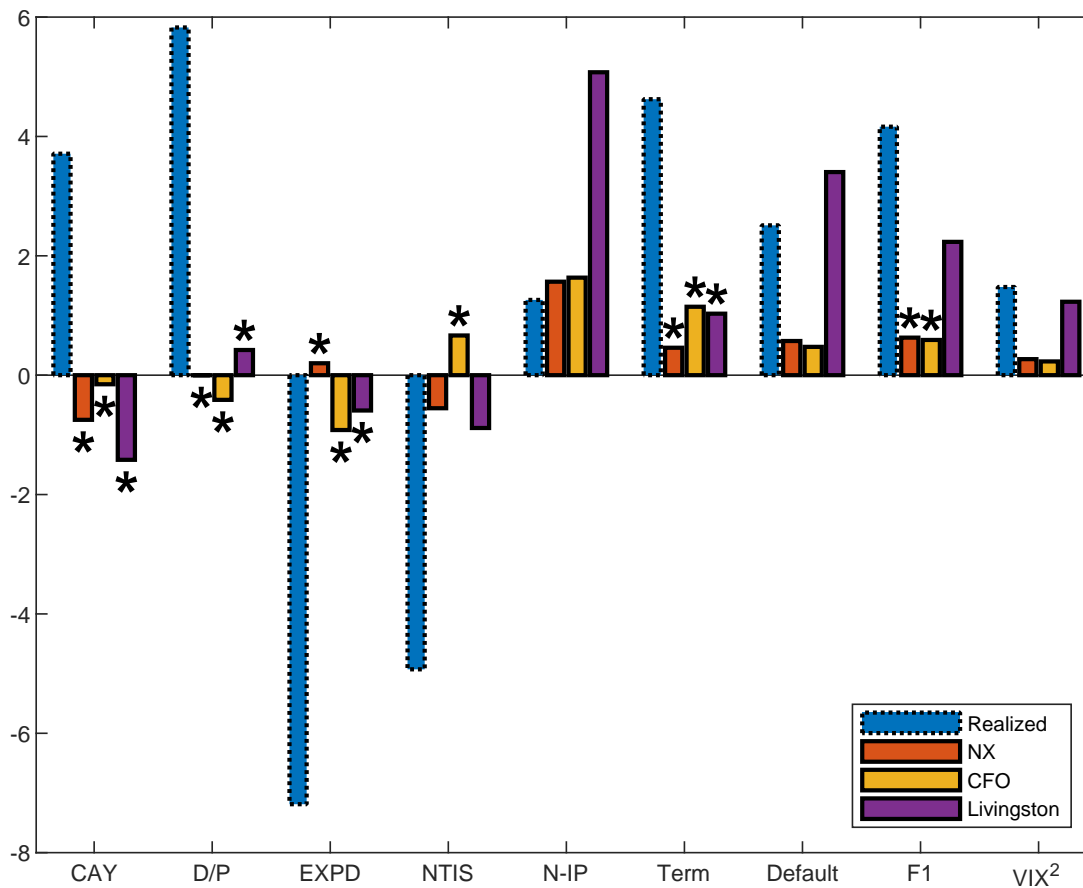


FIGURE 2
Coefficients from Regressing Stock Excess Returns on Predictors

The blue bars show the slope coefficients from regressing realized stock market excess returns on asset-class specific predictors and business-cycle indicators. The estimates are bootstrap bias-adjusted. The red, yellow, and purple bars use survey excess return expectations from Nagel and Xu (2022), the CFO survey, and the Livingston survey as dependent variable, respectively. All regressions control for past one-year realized excess returns. An asterisk indicates that the difference of the slope coefficients in the survey excess return regressions and realized excess return regressions is significantly different from zero at a 5% level.

predictor variables—with the exception of the Livingston survey for N-IP and DEFAULT—than the objective risk premia captured by the predictive regressions with realized returns.

Asterisks indicate that the difference in slope coefficients between the realized excess return and the survey expected excess return regression is statistically significant at a 5% level. The inference approach is a special case of the approach we develop in Appendix C to accommodate the different sample sizes and sampling frequencies of realized excess returns and survey data. While we will later focus on aggregate measures that summarize the differences in slope coefficients across surveys and asset classes, Figure 2 shows that many of the individual differences are also statistically significant, especially for predictors that produce a large slope coefficient in the realized excess return regression.

In stark contrast to the results in Figure 2, in a RE model of time-varying risk premia, the sensitivities of objective and subjective risk premia would be the same. Specific details of the results for particular predictors aside, the fact that subjective risk premia do not seem to move much with standard cyclical variables casts doubt on the empirical importance of time-varying risk or time-varying risk aversion as a major source of aggregate stock market price movements.

Price-growth extrapolation mechanisms as in Adam et al. (2017) and Jin and Sui (2022) produce pro-cyclical movements in subjective risk premia and hence, for example, a negative relationship between D/P and subjective risk premia. This relationship could be sufficiently weak to still be consistent with a largely acyclical subjective stock market risk premium. Jin and Sui (2022) report that a one standard deviation increase in their sentiment state variable pushes up annualized subjective expected stock market returns by about 0.60 percentage points. This would correspond roughly to a coefficient of -0.60 for CAY or D/P in our regressions in Table 4—which is in the ballpark of what we find for individual investor and CFO expectations in Panels A and B. Of course, most of these point estimates are statistically not significantly different from zero so we cannot say with much confidence whether these coefficients are truly different from zero.

TABLE 5
Regressing Treasury Bond Average Excess Returns on Predictors

In Panel A, dependent variable is the equal-weighted average of one-year excess returns on CRSP Treasury Indexes with maturities of two, five, seven, and ten years. The sample period is from March 1952 to December 2020. In Panel B, dependent variable is the equal-weighted average of one-year-ahead excess return expectations from BCFF with the same set of maturities as in Panel A. The sample period is from January 1988 to December 2020. Column variables are described in Section 2.2. R_{past}^e denotes the past one-year average excess returns. All independent variables are standardized to have unit standard deviations in the full sample period. The first row in each panel reports the OLS estimates multiplied by 100. In Panel A, bootstrap bias-adjusted coefficients are reported in braces; bootstrapped p -values are reported in parentheses. We use a stationary bootstrap with an optimal block length determined as in Politis and White (2004). In Panel B, EWC p -values following Lazarus et al. (2018) are reported in parentheses.

	Asset-Class Specific				Business-Cycle									
	LN		CYCLE		N-IP		TERM		DEFAULT		F1		VIX ²	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
A. Realized														
Coeff	1.94	2.33	2.85	2.85	0.57	0.66	1.50	1.88	1.20	1.26	1.00	1.07	0.31	0.32
{bias-adj.}	{1.94}	{2.32}	{2.29}	{2.38}	{0.75}	{0.85}	{1.48}	{1.92}	{1.36}	{1.35}	{1.08}	{1.13}	{0.30}	{0.33}
(p -value)	(0.00)	(0.00)	(0.01)	(0.02)	(0.61)	(0.60)	(0.00)	(0.00)	(0.12)	(0.13)	(0.04)	(0.07)	(0.22)	(0.20)
R_{past}^e		-0.90		-0.16		-0.13		-0.91		-0.22		-0.22		-0.09
{bias-adj.}		{-0.85}		{-0.37}		{-0.12}		{-0.94}		{-0.13}		{-0.10}		{0.02}
(p -value)		(0.20)		(0.79)		(0.84)		(0.08)		(0.73)		(0.77)		(0.88)
Adj. R^2	0.14	0.16	0.24	0.24	0.00	0.00	0.09	0.12	0.02	0.02	0.03	0.03	0.00	0.00
N	717	717	578	578	826	814	826	814	826	814	717	717	826	814
B. BCFF														
Coeff	0.37	0.50	0.83	0.83	0.54	0.67	0.30	0.33	0.30	0.41	0.57	0.75	0.17	0.22
(p -value)	(0.16)	(0.05)	(0.00)	(0.00)	(0.31)	(0.22)	(0.15)	(0.11)	(0.47)	(0.35)	(0.02)	(0.00)	(0.13)	(0.07)
R_{past}^e		-0.35		0.02		-0.25		-0.22		-0.24		-0.44		-0.28
(p -value)		(0.08)		(0.90)		(0.27)		(0.26)		(0.32)		(0.06)		(0.24)
Adj. R^2	0.03	0.05	0.23	0.22	0.02	0.03	0.03	0.04	0.01	0.02	0.07	0.11	0.02	0.04
N	397	397	397	397	397	397	397	397	397	397	397	397	397	397

3.2 Treasury bond market

Table 5 turns to the Treasury bond market. The dependent variable in Panel A is an equal-weighted average of one-year excess returns on CRSP Treasury Indexes with maturities of two, five, seven, and ten years. We observe realized returns at monthly frequency, hence as in the earlier stock market return regressions, the dependent variable is measured over overlapping annual windows and we use block-bootstrapped p -values to account for this overlap. In Panel B, the dependent variable is the subjective expected excess returns from the Blue Chip survey of professional forecasters. As in the case of realized returns, we use an equal-weighted average of subjective expected excess returns over two-, five-, seven-, and ten-year maturities.

In Panel A, for realized excess returns, the two asset-class specific predictors LN and CYCLE are statistically significant at conventional levels ($p < 0.01$ for LN; $p < 0.05$ for CYCLE). If used as single predictors, they get point estimates of 1.94 and 2.29, respectively. This means that a one standard deviation move in the predictor is associated with a roughly 2pp movement in objective expected excess returns. Among the cyclical indicators, TERM and F1 are also significant predictors at conventional levels, and DEFAULT marginally so. The magnitude of expected return variation associated with the cyclical indicators is generally smaller than for LN and CYCLE.

Interestingly, for all of these predictor variables, we again see much smaller coefficient estimates when subjective expected excess returns are the dependent variable in Panel B. Here we obtain the maximum coefficient with CYCLE, but at 0.83 the magnitude is still much smaller than in Panel A (2.29). Including excess returns over the past year as an additional predictor variable generally has very little effect, both in Panel A and B. Despite the generally smaller magnitude of slope coefficients in Panel B, those for LN and CYCLE are nevertheless statistically significant when past returns are included, and the one for VIX^2 is marginally so.¹⁰

¹⁰ Buraschi et al. (2022) find a stronger relationship of the subjective Treasury bond risk premium with

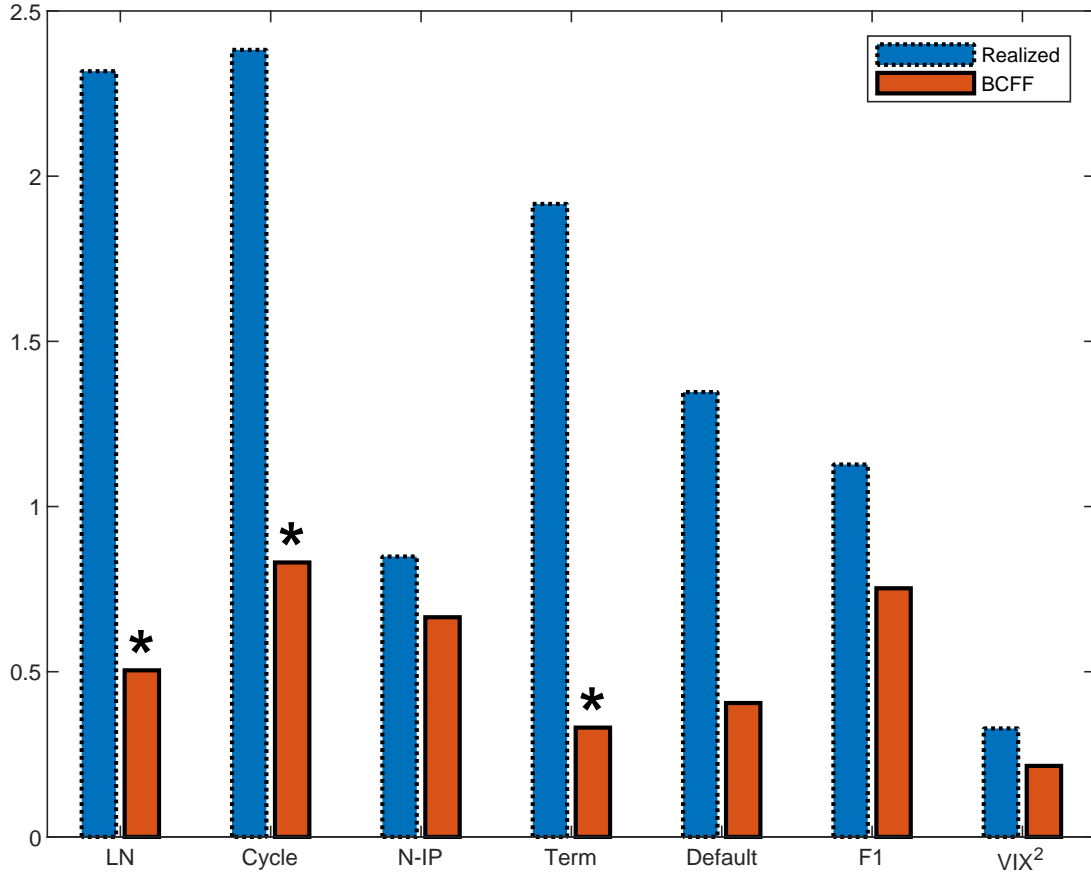


FIGURE 3

Coefficients from Regressing Treasury Bond Average Excess Returns on Predictors

The blue bars plot the slope coefficients from regressing the equal-weighted average of realized excess returns on CRSP Treasury Indexes on asset-class specific predictors and business-cycle indicators. The maturities include two, five, seven, and ten years. The coefficients are bias-adjusted using bootstrap. The red bars use the equal-weighted average of survey excess return expectations with the same set of maturities from BCFF as dependent variable. All regressions control for past one-year realized average excess returns. An asterisk indicates that the difference of the slope coefficients in the survey excess return regressions and realized excess return regressions is significantly different from zero at a 5% level.

Figure 3 summarizes the results, again focusing on coefficient estimates in regressions with past returns included as controls. The figure shows very clearly the different magnitudes of the slope coefficients in the regressions with realized excess returns, shown as blue bars, and regressions with subjective expected excess returns, shown as red bars. Thus, in the Treasury bond market, too, subjective risk premia are much less sensitive to cyclical predictor variables than objective risk premia are.

3.3 Foreign exchange market

Table 6 presents results for foreign exchange. The dependent variable in Panel A is the realized excess return on a portfolio of developed market currencies from the viewpoint of a US-based investor. The asset-class specific predictor is the average forward discount on the developed market currencies as in [Lustig et al. \(2014\)](#).

In Panel A, all predictors except TERM produce statistically significant or at least marginally significant coefficient estimates. The magnitudes are substantial. The one standard deviation change in the average forward discount is associated with a change of 3.75pp in predicted realized excess returns. Among the cyclical indicators, the strongest predictor is N-IP. A one standard deviation move in N-P is associated with a change of 6.66pp in the objective expected excess returns on a US investors' currency portfolio.

The estimates in Panel B for subjective expected excess returns show a sharp contrast to Panel A. Point estimates are generally much smaller and none of the coefficient estimates is significantly different from zero according to conventional levels.

As earlier in the case of bond excess returns, controlling for the past one-year return on the currency portfolio does not have much effect on the point estimates of the other predictors, neither for realized excess returns, nor for subjective expected excess returns.

Figure 4 visualizes the magnitude of the coefficients, focusing on the regressions that include past returns along with the predictor variable. The figure clearly shows the sharp risk-neutral Treasury bond volatility instead of the VIX.

TABLE 6
Regressing Foreign Exchange Average Excess Returns on Predictors

In Panel A, dependent variable is the average realized one-year excess returns on the basket of developed currencies. The sample period is from October 1984 to June 2021. In Panel B, dependent variable is the one-year-ahead average excess return expectations on the same basket of developed currencies from CE and FX4casts. The sample period is from August 1986 to June 2021. Column variables are described in Section 2.2. R_{past}^e denotes the past one-year excess returns. All independent variables are standardized to have unit standard deviations in the full sample period. The first row in each panel reports the OLS estimates multiplied by 100. In Panel A, bootstrap bias-adjusted coefficients are reported in braces; bootstrapped p -values are reported in parentheses. We use a stationary bootstrap with an optimal block length determined as in Politis and White (2004). In Panel B, EWC p -values following Lazarus et al. (2018) are reported in parentheses.

	Asset-Class Specific		Business-Cycle									
	FD		N-IP		TERM		DEFAULT		F1		VIX ²	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Realized												
Coeff	3.83	4.25	7.43	6.74	1.84	2.06	5.75	6.79	2.51	1.94	1.24	1.29
{bias-adj.}	{3.75}	{3.79}	{6.66}	{5.55}	{1.99}	{2.24}	{5.99}	{7.05}	{2.65}	{2.50}	{1.44}	{1.24}
(p -value)	(0.03)	(0.08)	(0.04)	(0.10)	(0.27)	(0.29)	(0.07)	(0.07)	(0.06)	(0.14)	(0.03)	(0.04)
R_{past}^e		-1.27		1.00		0.07		0.65		0.82		0.89
{bias-adj.}		{-1.23}		{1.03}		{-0.12}		{0.50}		{0.76}		{0.75}
(p -value)		(0.42)		(0.62)		(0.97)		(0.67)		(0.69)		(0.66)
Adj. R^2	0.15	0.13	0.10	0.07	0.03	0.04	0.11	0.15	0.04	0.02	0.03	0.04
N	442	430	442	430	442	430	442	430	442	430	442	430
B. CE & FX4casts												
Coeff	-0.19	0.01	0.27	0.10	-0.68	-0.62	0.27	0.23	0.06	-0.03	0.56	0.53
(p -value)	(0.75)	(0.99)	(0.74)	(0.91)	(0.24)	(0.25)	(0.69)	(0.77)	(0.89)	(0.94)	(0.10)	(0.13)
R_{past}^e		-0.41		-0.40		-0.20		-0.40		-0.43		-0.25
(p -value)		(0.54)		(0.57)		(0.76)		(0.57)		(0.54)		(0.71)
Adj. R^2	0.00	0.01	-0.00	0.01	0.04	0.04	-0.00	0.01	-0.00	0.01	0.07	0.07
N	419	419	419	419	419	419	419	419	414	414	419	419

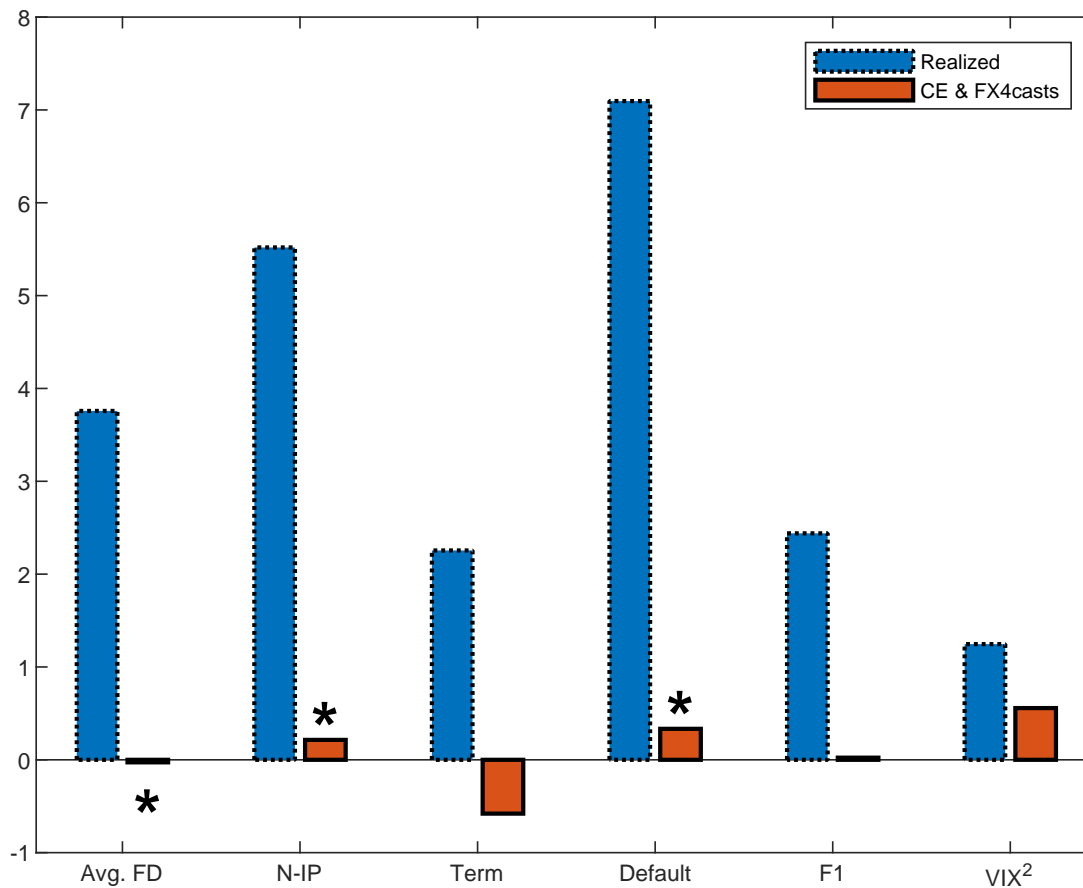


FIGURE 4

Coefficients from Regressing Foreign Exchange Average Excess Returns on Predictors

The blue bars the slope coefficients from regressing average realized one-year excess returns of developed currencies on asset-class specific predictors and business-cycle indicators. The coefficients are bootstrap bias-adjusted. The red bars use average survey excess return expectations on the same basket of currencies from CE and FX4casts as dependent variable. All regressions control for past one-year average realized excess returns. An asterisk indicates that the difference of the slope coefficients in the survey excess return regressions and realized excess return regressions is significantly different from zero at a 5% level.

contrast between the large coefficients obtained in realized excess return prediction regressions and the extremely small coefficients in the subjective expected excess return regressions. There is therefore little support for the notion that the objective return premia obtained in ex-post regressions with realized excess returns reflect ex-ante subjective risk premia from the viewpoint of the professional forecasters.

3.4 Commodity futures market

In our analysis of commodity futures risk premia, we look at the energy and metals sectors separately. The economic risks that the underlying commodities are exposed to could be quite different and the dynamics of risk premia could therefore be potentially different as well. Following [Hong and Yogo \(2012\)](#), the asset-class specific predictors for commodity futures are the futures basis and past one-year open interest growth.

3.4.1 Metals

The dependent variable in Panel A of [Table 7](#) is the average realized one-year buy-and-hold excess return on a portfolio of metals futures. As shown in columns (1) to (4), the futures basis and open interest growth are economically strong predictors, with one standard deviation change in the predictor associated with around 7pp change in the predicted excess returns. However, the commodity futures excess returns are so noisy and the sample sufficiently short that these estimates are not statistically significantly different from zero at conventional levels despite the large magnitude of the point estimates. With a p -value of 0.11, open interest growth, when used as a single predictor, is at least close to marginally significant. Among the cyclical indicators, only VIX^2 is marginally significant on its own ($p < 0.10$).

Panel B shows the corresponding regressions for subjective expected excess returns. Looking across all specifications, we again see the general pattern that the magnitudes of the slope coefficient estimates for the predictors are almost all lower than in Panel A (and often of different sign). [Figure 5](#) illustrates this graphically. There are no asterisks on any bars because

the individual wedges between the two types of regressions are not statistically significant at a 5% level. However, as we will show later, aggregated across predictors, the wedge is significant.

Interestingly, Panel B also shows that subjective risk premia of professional forecasters in the metals futures market seem to be strongly contrarian with respect to recent past excess returns on metals futures. A fairly large share of time-variation in subjective risk premia can be traced to this contrarian effect, even though the relationship of past returns to objective risk premia is, if anything, positive in Panel A.

3.4.2 The crude oil market

Table 8 presents the results for futures excess returns in the WTI crude oil market. The results for realized excess return prediction in Panel A show that there are no statistically significant predictors of excess returns. Some of the point estimates are large, though. For example, the point estimate for N-IP implies that a one standard deviation fall in industrial production growth is associated with a rise of predicted excess returns of 10.26pp. But the p -value of 0.21 indicates that there is a very large degree of uncertainty about the true magnitude of the effect.

Panel B presents the result for subjective expected excess returns. As in the case of metals futures, subjective risk premia are strongly contrarian with respect to recent past excess returns. Other than this past returns effect, there is little else in terms of a clear relationship to predictors. The basis in column (1) shows up with a statistically significant relationship on its own, but this goes away when past returns are controlled for. The DEFAULT variable in column (10) is a statistically significant predictor only when past returns are controlled for. Figure 6 shows that the overall picture of absolute coefficient magnitudes in the two panels is mixed, with no clear difference in magnitudes in the objective and subjective risk premia specifications. This is to be expected when none of the variables really has a strong relationship to objective or subjective risk premia.

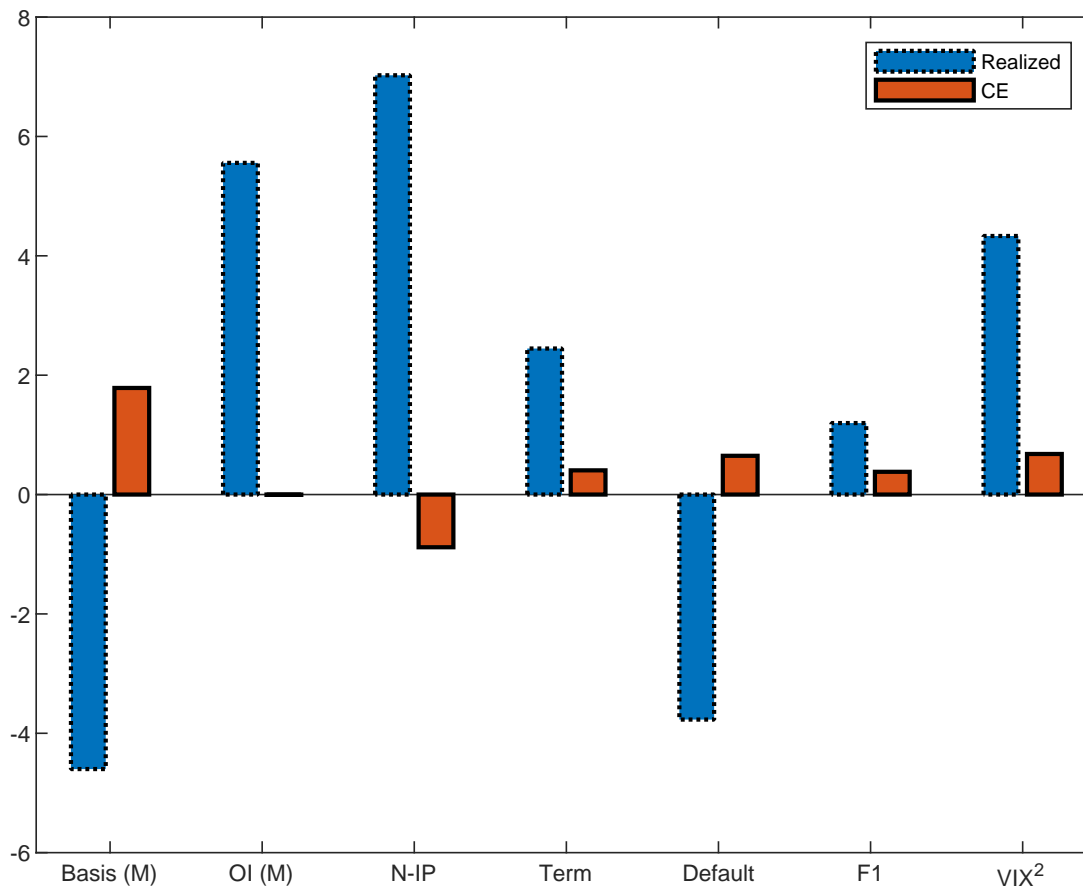


FIGURE 5
Coefficients from Regressing Metals Futures Excess Returns on Predictors

The blue bars plot the slope coefficients from regressing average realized one-year buy-and-hold excess returns of metals futures on asset-class specific predictors and business-cycle indicators. The coefficients are bootstrap bias-adjusted. The red bars use average survey excess return expectations from CE as dependent variable. All regressions control for past one-year average realized excess returns. An asterisk indicates that the difference of the slope coefficients in the survey excess return regressions and realized excess return regressions is significantly different from zero at a 5% level.

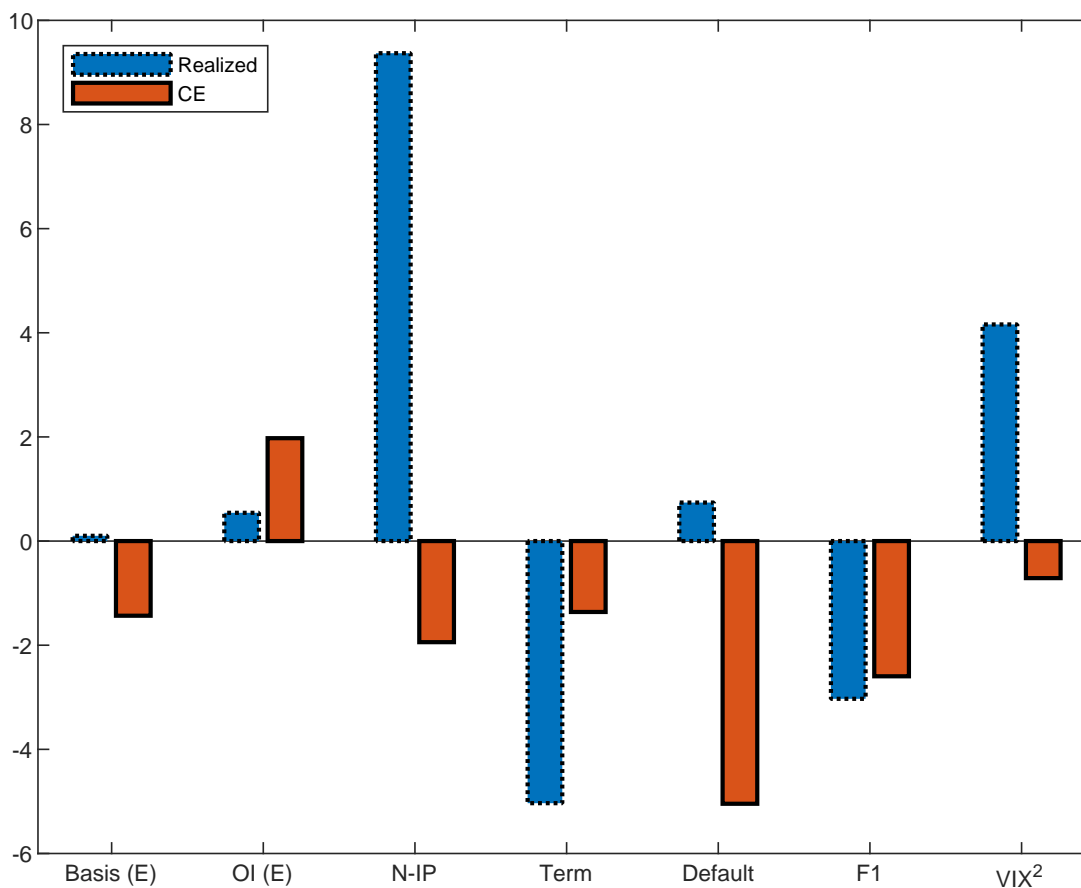


FIGURE 6
Coefficients from Regressing Crude Oil Futures Excess Returns on Predictors

The blue bars plot the slope coefficients from regressing realized one-year buy-and-hold excess returns of WTI crude oil futures on asset-class specific predictors and business-cycle indicators. The coefficients are bootstrap bias-adjusted. The red bars use survey excess return expectations from CE as dependent variable. All regressions control for past one-year realized excess returns. An asterisk indicates that the difference of the slope coefficients in the survey excess return regressions and realized excess return regressions is significantly different from zero at a 5% level.

TABLE 7
Regressing Metals Futures Excess Returns on Predictors

In Panel A, dependent variable is the average realized one-year buy-and-hold excess returns on metals. The sample period is from September 1978 to June 2021. In Panel B, dependent variable is the one-year-ahead average excess return expectations from CE. The sample period is from August 1995 to June 2021. Column variables are described in Section 2.2. R_{past}^e denotes the past one-year excess returns. All independent variables are standardized to have unit standard deviations in the full sample period. In Panel A, bootstrap bias-adjusted coefficients are reported in braces; bootstrapped p -values are reported in parentheses. We use a stationary bootstrap with an optimal block length determined as in Politis and White (2004). In Panel B, EWC p -values following Lazarus et al. (2018) are reported in parentheses.

	Asset-Class Specific				Business-Cycle									
	BASIS		OI		N-IP		TERM		DEFAULT		F1		VIX ²	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
A. Realized														
Coeff	-6.57	-6.69	6.38	5.72	5.84	7.80	1.51	1.98	-3.51	-1.61	-1.18	0.25	3.11	3.83
{bias-adj.}	{-5.86}	{-4.57}	{7.45}	{5.51}	{5.91}	{7.03}	{2.33}	{2.48}	{-5.19}	{-3.78}	{-0.88}	{1.24}	{3.80}	{4.31}
(p -value)	(0.20)	(0.31)	(0.11)	(0.19)	(0.55)	(0.43)	(0.75)	(0.64)	(0.69)	(0.86)	(0.80)	(0.96)	(0.06)	(0.03)
R_{past}^e		3.45		1.27		4.68		4.70		4.20		4.50		5.31
{bias-adj.}		{4.50}		{3.61}		{5.68}		{5.98}		{4.58}		{5.51}		{6.10}
(p -value)		(0.34)		(0.81)		(0.27)		(0.20)		(0.33)		(0.27)		(0.13)
Adj. R^2	0.06	0.09	0.09	0.09	0.01	0.04	0.00	0.03	0.00	0.02	-0.00	0.02	0.03	0.07
N	516	504	441	441	516	504	516	504	516	504	516	504	516	504
B. CE														
Coeff	7.27	1.79	-2.22	-0.01	-0.05	-0.89	0.47	0.41	2.28	0.65	1.24	0.38	1.09	0.68
(p -value)	(0.02)	(0.43)	(0.01)	(0.99)	(0.97)	(0.52)	(0.52)	(0.62)	(0.28)	(0.71)	(0.32)	(0.72)	(0.05)	(0.20)
R_{past}^e		-3.83		-4.12		-4.19		-4.12		-4.01		-3.83		-3.86
(p -value)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Adj. R^2	0.12	0.35	0.13	0.34	-0.01	0.35	-0.00	0.35	0.04	0.35	0.02	0.30	0.08	0.38
N	150	150	150	150	150	150	150	150	150	150	145	145	150	150

TABLE 8
Regressing Crude Oil Futures Excess Returns on Predictors

In Panel A, dependent variable is the realized one-year buy-and-hold excess returns on the WTI crude oil futures. The sample period is from December 1984 to June 2021. In Panel B, dependent variable is the one-year-ahead buy-and-hold excess return expectations from CE. The sample period is from August 1995 to June 2021. Column variables are described in Section 2.2. R_{past}^e denotes the past one-year excess returns. All independent variables are standardized to have unit standard deviations in the full sample period. In Panel A, bootstrap bias-adjusted coefficients are reported in braces; bootstrapped p -values are reported in parentheses. We use a stationary bootstrap with an optimal block length determined as in Politis and White (2004). In Panel B, EWC p -values following Lazarus et al. (2018) are reported in parentheses.

	Asset-Class Specific				Business-Cycle									
	BASIS		OI		N-IP		TERM		DEFAULT		F1		VIX ²	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
A. Realized														
Coeff	1.20	-0.71	0.36	5.14	9.89	7.82	-4.25	-4.33	2.43	2.03	-0.63	-2.35	3.88	3.64
{bias-adj.}	{1.74}	{0.24}	{-0.71}	{0.45}	{10.26}	{9.32}	{-4.46}	{-5.16}	{0.58}	{0.66}	{-0.47}	{-2.98}	{4.05}	{4.18}
(p -value)	(0.81)	(0.90)	(0.95)	(0.58)	(0.21)	(0.48)	(0.53)	(0.57)	(0.71)	(0.81)	(0.84)	(0.51)	(0.25)	(0.33)
R_{past}^e		-3.30		-6.39		-1.78		-3.10		-2.53		-3.34		-2.03
{bias-adj.}		{-1.38}		{-2.59}		{-0.66}		{-2.44}		{-2.19}		{-2.52}		{-0.51}
(p -value)		(0.67)		(0.55)		(0.77)		(0.57)		(0.67)		(0.55)		(0.75)
Adj. R^2	-0.00	-0.00	-0.00	0.00	0.01	0.01	0.01	0.02	-0.00	0.00	-0.00	0.00	0.03	0.02
N	439	427	426	426	439	427	439	427	439	427	439	427	439	427
B. CE														
Coeff	2.46	-1.43	-3.61	1.98	3.82	-1.94	-1.73	-1.36	0.19	-5.05	0.22	-2.60	0.52	-0.71
(p -value)	(0.04)	(0.36)	(0.13)	(0.38)	(0.23)	(0.55)	(0.35)	(0.41)	(0.95)	(0.00)	(0.92)	(0.19)	(0.52)	(0.29)
R_{past}^e		-6.47		-7.14		-5.93		-5.41		-6.60		-7.24		-5.83
(p -value)		(0.01)		(0.00)		(0.01)		(0.00)		(0.00)		(0.00)		(0.01)
Adj. R^2	0.07	0.33	0.14	0.33	0.03	0.32	0.01	0.32	-0.01	0.38	-0.01	0.43	0.00	0.32
N	150	150	150	150	150	150	150	150	150	150	145	145	150	150

3.5 Summary measures, variations, and statistical inference

We now construct summary measures that combine our findings across predictors and asset classes. This also allows us to compactly report the sensitivity of our results to a number of robustness checks. For each survey, we first calculate the following two ratios:

$$M_1 \equiv \frac{\sum_{k \in \mathbb{K}} \text{sgn}(\beta_k) \cdot \tilde{\beta}_k}{\sum_{k \in \mathbb{K}} \text{sgn}(\beta_k) \cdot \beta_k}, \quad (7)$$

and

$$M_2 \equiv \frac{\sum_{k \in \mathbb{K}} |\tilde{\beta}_k|}{\sum_{k \in \mathbb{K}} |\beta_k|}, \quad (8)$$

where $\tilde{\beta}_k$ is the slope coefficient on asset-class specific predictor or business-cycle indicator k in the regression with survey excess return expectations, β_k is the bias-adjusted coefficient in the regression with realized excess returns, and \mathbb{K} is the group of all asset-class specific predictors and cyclical indicators combined.

Because the sign of predictors can be arbitrary, we need to first align the signs before we can average coefficients across predictors. Multiplying with $\text{sgn}(\beta_k)$ in the numerator and denominator in (7) is like switching the signs of the predictor variables such that the coefficients in the realized return regressions are all positive, and hence the denominator of M_1 is always positive. Then, if subjective risk premia have the same variation with respect to predictors as objective risk premia do, M_1 will be about 1; if subjective risk premia have the exact opposite variation, M_1 will be about -1 .

It may also be of interest to simply compare the volatility of the predictor-related components in subjective and objective risk premia, without paying attention to the direction in which a predictor moves these premia. This is captured by ratio M_2 . This ratio uses the absolute values of coefficients.

The final summary measures are calculated by first taking the average of M_1 and M_2 within asset classes (if there are multiple surveys) then across asset classes.¹¹ Figure 7

¹¹ We treat metals and crude oil as in the same asset class. Treating them as separate asset classes does

presents the results.

To explore the robustness of our conclusions, we report results from several different specifications. First, we use coefficient point estimates obtained with (*Control*) or without (*Single*) controlling for past returns. Second, we re-run all of the analysis with a different definition of the realized excess return sample. In our baseline analysis above, we used the maximum sample length that was available given data availability constraints on the predictors and returns data. With this baseline approach, one might worry that the law of motion of objective risk premia has undergone structural change and may be different in the samples for which we have survey data coverage, which are often much shorter than the samples for which we have realized returns and predictor data. For this reason, we re-run all realized excess regressions with the realized returns sample restricted to the time periods for which we have survey data to construct subjective expected excess returns. In Figure 7, the results from our baseline analysis with the full sample are denoted with (*F*), those with the return sample matched to the survey sample are denoted with (*S*).

The four pairs of bars on the left-hand side of the figure show the results. The blue bars show the summary measure of the M_1 ratios, the red bars show the summary of the M_2 ratios. The baseline case in the left-most blue bar shows that a one percentage point move in the objective risk premium is associated, on average, only with 0.12 percentage point move in the same direction of the subjective risk premium. Based on the comparison of the first two blue bars, including or not including past returns has very little effect on the ratio of coefficients for objective and subjective premia. In both cases, we get a ratio of close to 0.15. Using the full sample for realized returns (first and second blue bar) or a shorter sample matched to the survey data set (third and fourth blue bar) does not have much effect on the results either, with a slight increase of about 0.05 in both *Control* and *Single* cases. Overall, subjective risk premia vary substantially less with the predictor variables than objective risk premia.

not quantitatively change the results.

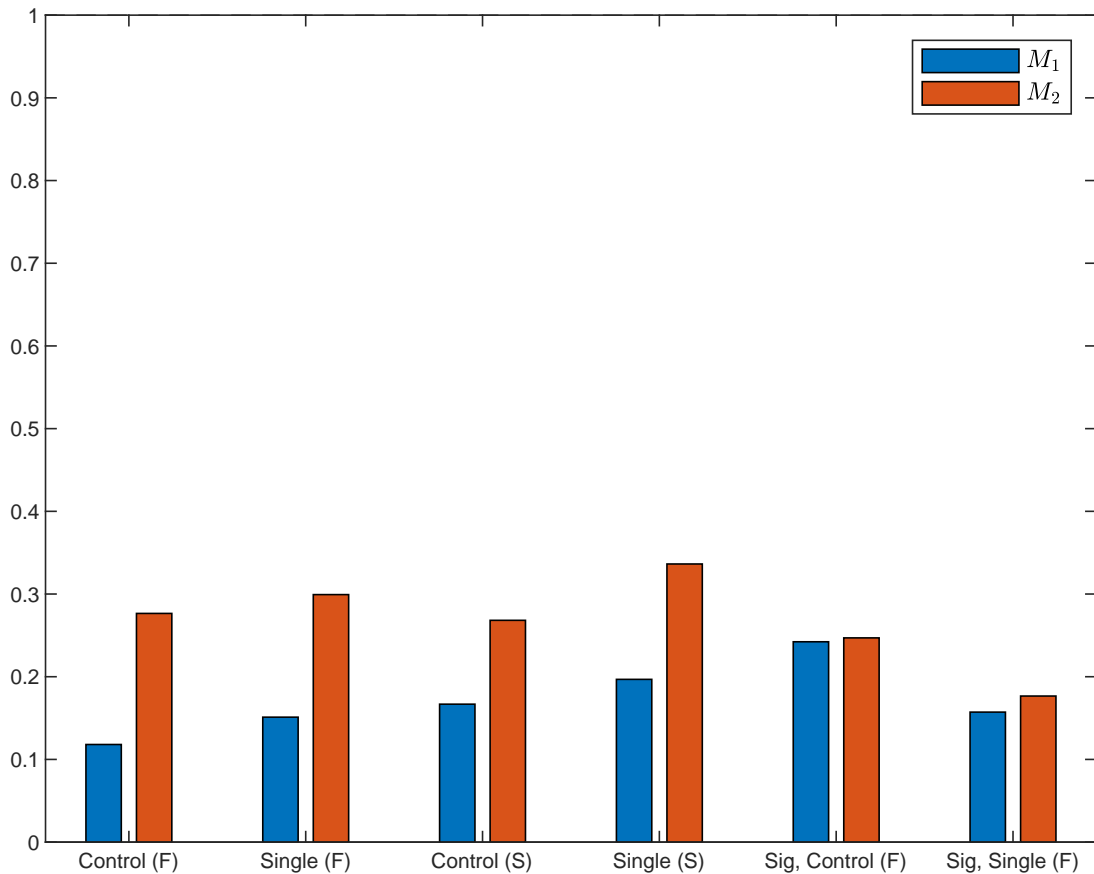


FIGURE 7

Comparing Magnitudes of Coefficients from Regressing Survey Expectations and Realized Returns

For each blue and red bar, we first calculate the following ratios for each survey:

$$M_1 \equiv \frac{\sum_{k \in \mathbb{K}} \text{sgn}(\beta_k) \cdot \tilde{\beta}_k}{\sum_{k \in \mathbb{K}} \text{sgn}(\beta_k) \cdot \beta_k}, \quad M_2 \equiv \frac{\sum_{k \in \mathbb{K}} |\tilde{\beta}_k|}{\sum_{k \in \mathbb{K}} |\beta_k|},$$

respectively, where $\tilde{\beta}_k$ is the slope coefficient on asset-class specific predictor or business-cycle indicator k in the regression with survey excess return expectations, β_k is the bias-adjusted coefficient in the regression with realized excess returns, and \mathbb{K} is the set of all predictors. We then take the average of M_1 and M_2 within each asset class if there are multiple surveys and finally across asset classes. *(F)* denotes estimates using the full return sample; *(S)* denotes estimates using the matched-to-survey return sample; *Control* and *Single* denote estimates with and without controlling for past excess returns, respectively; *Sig* denotes estimates only using predictors whose full-sample p-values are smaller than 0.05.

The red bars shows that the picture is quite similar if we ignore potential directional mismatch between the movements of subjective and objective risk premia and just look at the relative volatility of predictor-related components using the ratio M_2 . Even then, the ratio is far below one, indicating a much smaller volatility of the cyclical-variable component in subjective risk premia. Neither controlling for past returns nor using matched-to-survey samples has much effect on the summary measure of the M_2 ratios.

One potential concern about the analysis so far is that the set of predictors might include ones that are simply irrelevant for risk premia. If the predictor variable represents just irrelevant noise that is not truly related to risk premia, neither objective nor subjective, the true slope coefficients are zero. Due to estimation error, the slope coefficient estimates will be non-zero and they could have similar absolute magnitudes in the regressions with realized returns and subjective expectations. This would bias the M_2 ratio toward one and the M_1 ratio toward zero.

For this reason, the last two pairs of bars on the right-hand side include, within each asset class, only on predictor variables that are significant at conventional levels ($p \leq 0.05$) in predicting realized excess returns using the full available sample of realized return and predictor data. As the figure shows, for these variables, the relative magnitude of the subjective expected excess return regression coefficients is still small. Depending on whether we include past returns in the regression or not, we obtain ratios of slightly above or below 0.20 for both M_1 and M_2 ratios.

So far we have focused on point estimates in our summary measures. However, it would also be useful to assess the joint statistical significance of the cyclical wedges between subjective and objective risk premium dynamics. We develop an asymptotic inference approach in Appendix C. This is not straightforward as the regressions involve different predictors, sample periods, data sets, and measurement frequencies. Our approach treats all these regressions jointly as one big system of regression equations. We then construct a composite estimator that aggregates the differences between realized-return-based and survey-based co-

efficient estimates.

We first focus on one asset class at a time. We average all slope coefficients of asset-class specific predictors and business-cycle indicators from the realized excess return prediction regressions within each asset class, and then we subtract the average all corresponding slope coefficients from the survey-based regressions. This average wedge in slope coefficients represents the average wedge between realized excess returns and survey expectations associated with a one-standard-deviation change in the predictor variable. For the purposes of statistical inference, formulating this wedge as a difference is more tractable than the ratio that we used in our earlier summary measures in Figure 7. Since signs of regression coefficients matter for this calculation, we flip the signs of predictors if necessary such that they forecast future realized excess returns positively, as we did for the ratio M_1 earlier.

The top panel in Table 9 reports the results for individual asset classes. Focusing on the full-sample estimates in the first two columns, the point estimate for the aggregate wedge is between two to four times as big as the standard error, and hence statistically significant at conventional levels, for all asset classes except metals with past return control and oil.

To further aggregate across asset classes, we construct two composite measures. The first one equally weights all asset classes. The first two columns at the bottom panel in Table 9 show that this composite cyclical wedge is highly statistically significant with the point estimate more than five times as big as the standard error. To prevent asset classes with high return volatility from dominating, we construct a second composite measure that weights asset classes by the inverse of their realized excess return volatility. This point estimate for this second composite measure is smaller as it puts a higher weight on Treasury bonds, but the standard errors shrink to a similar degree, so that it remains highly statistically significant.

As a robustness check, we also repeat the analysis using the matched-to-survey sample, shown in the third and fourth column. All results hold except that the cyclical wedge narrows for Treasury bonds but widens for metals futures.

TABLE 9
Joint Statistical Significance of the Cyclicalities Wedges

This table reports the point estimates and standard errors of the following measure:

$$d = \mathbf{e}'_2 \mathbf{B} \mathbf{w},$$

where the $K \times J$ matrix \mathbf{B} horizontally concatenates the regression coefficient row vectors from J realized-return-based and survey-based regressions. The weight column vector \mathbf{w} is such that the elements that multiply coefficients from the predictive regressions with excess returns as dependent variable are positive, of equal magnitude, and sum to 1 across all regressions within an asset class, while those that multiply coefficients from the survey data regressions are negative and sum to -1 within an asset class; \mathbf{e}_2 is a vector with one as the second element and zeros otherwise to pick out the aggregated slope coefficient differences corresponding to asset-class specific predictors and business cycle indicators. The composite measure either equally weights the four asset classes or weights them in inverse proportion to the volatility of their realized excess returns σ . We multiply the point estimates d by 100. Standard errors calculated using the EWC estimator from Lazarus et al. (2018) are reported in parentheses (also multiplied by 100).

	Full-Sample		Survey-Sample	
	w/o R_{past}^e	with R_{past}^e	w/o R_{past}^e	with R_{past}^e
Stock Market	3.56 (0.96)	3.55 (1.01)	3.37 (1.16)	3.09 (1.36)
Treasury Bonds	0.90 (0.35)	0.95 (0.40)	0.40 (0.42)	0.62 (0.45)
Foreign Exchange	3.67 (0.92)	3.76 (1.00)	3.29 (0.93)	3.55 (0.97)
Commodities				
Metals	4.97 (2.27)	4.25 (2.40)	10.43 (2.22)	10.70 (2.46)
Oil	2.54 (1.86)	3.97 (2.64)	3.68 (2.49)	5.95 (3.45)
Composite				
Equal-weighted	2.97 (0.53)	3.09 (0.61)	3.53 (0.66)	3.90 (0.67)
σ^{-1} -weighted	2.23 (0.40)	2.31 (0.43)	2.04 (0.44)	2.29 (0.44)

4 Comparison with Out-of-Sample Forecasts

Our analysis so far compared the cyclicalities of subjective expected excess returns with the cyclicalities of forecasts implied by estimates of in-sample predictive regressions. For evaluating RE models, this is the appropriate comparison. In RE models, agents already know the underlying data-generating process, including the values of its parameters. In-sample predictive regressions are then the most efficient way for an econometrician to estimate what economic agents already know. Yet, the empirical evidence on the large gap in cyclicalities between subjective expectations and in-sample predictive regression forecasts is hard to square with RE models. This brings up the question whether non-RE belief-formation mechanisms that do not endow agents with so much knowledge of the data-generating process could explain the lack of cyclicalities in subjective expected excess returns.

One natural possibility is that, unlike in RE models, investors do not know the parameters of the data-generating process. Instead, they learn about these parameters from observed data in real time. If so, an OOS forecast, not the fitted value from an in-sample regression run ex post over the whole sample, should be close to their observed subjective expectations. For this reason, we now examine whether OOS forecasts of excess returns are closer to the subjective excess return expectations in terms of cyclicalities than the in-sample excess return predictions.

We first construct OOS forecasts at time t based on each individual predictor x_i by performing the following predictive regressions over expanding windows:

$$R_k^e = \alpha_{i,t} + \beta_{i,t} x_{i,k-1} + \varepsilon_{i,k}, \quad k = 2, \dots, t. \quad (9)$$

Given the negligible role of past excess returns in predicting future excess returns in our earlier analyses, we focus here on specifications with just a single predictor without including

past one-year excess returns. We assume that investors estimate $\alpha_{i,t}$ and $\beta_{i,t}$ as

$$(\hat{\alpha}_{i,t}, \hat{\beta}_{i,t}) \equiv \underset{\alpha, \beta}{\operatorname{argmin}} \sum_{k=2}^t \omega_{t,k} (R_k^e - \alpha - \beta x_{i,k-1})^2. \quad (10)$$

Our first set of analyses sets $\omega_{t,k} = 1$ and hence $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,t}$ are simply OLS estimates from recursively expanding windows.¹²

An OOS forecast of $t + 1$ excess returns based on $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,t}$ would, however, impose extreme confidence that the variable x_i is truly a predictor of excess returns. In practice, investors cannot be sure. If it's not, then a forecast that constrains $\beta_{i,t}$ to zero could perform better. For this reason, we assume that investors evaluate, based on the historical data that has accumulated until time t , whether the predictive regression forecast actually adds value, in terms of OOS forecasting, relative to simply setting the forecast equal to the historical mean of R_k^e

$$\bar{R}_t^e = \frac{\sum_{k=2}^t \omega_{t,k} R_k^e}{\sum_{k=2}^t \omega_{t,k}}. \quad (11)$$

More precisely, we assume that investors check in past data until period t which combination of \bar{R}_t^e and the predictive regression forecast $\hat{\alpha}_{i,t} + \hat{\beta}_{i,t} x_{i,t}$ produced the best OOS forecasts. Investors' forecast is then a weighted average:

$$\hat{\mathbb{E}}_{i,t} R_{t+1}^e \equiv s_{i,t} (\hat{\alpha}_{i,t} + \hat{\beta}_{i,t} x_{i,t}) + (1 - s_{i,t}) \bar{R}_t^e, \quad (12)$$

where the weight $s_{i,t}$ is chosen to maximize the historical OOS performance starting at t_{min}

¹² We have also experimented with adjusting $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,t}$ for finite-sample bias as in [Stambaugh \(1999\)](#). However, this has little effect on OOS forecast properties. The reason is that the effect of this bias-adjustment is a shrinkage of the forecast to the historical mean of excess returns. The shrinkage that we apply below is of the same form, and hence optimal choice of the degree of shrinkage already implicitly incorporates a bias-adjustment. As a consequence, a bias-adjustment of coefficients before this shrinkage step is rendered largely redundant.

after a burn-in period

$$s_{i,t} = \underset{s}{\operatorname{argmin}} \sum_{k=t_{min}}^t \omega_{t,k} u_k(s)^2, \quad (13)$$

$$u_k(s) \equiv R_k^e - s(\hat{\alpha}_{i,k-1} + \hat{\beta}_{i,k-1} x_{i,k-1}) - (1-s)\bar{R}_{k-1}^e. \quad (14)$$

In other words, we let investors look for the optimal degree of shrinkage of the predictive regression forecast toward the historical mean.

In our empirical implementation, we choose t_{min} of 10 years as burn-in period. For foreign exchange and commodity futures, we do not have enough data after the burn-in periods to have much statistical power. For this reason, we focus on stock and Treasury bond markets only in this analysis. For our cyclical tests, we then use the OOS forecast series starting from the dates when survey data becomes available (June 1952 for the stock market and January 1988 for the Treasury bond market). We regress the OOS forecasts $\hat{\mathbb{E}}_{i,t} R_{t+1}^e$ on $x_{i,t}$, just as we regress the subjective expected excess returns $\tilde{\mathbb{E}}_t R_{t+1}^e$ from the survey data on $x_{i,t}$.

Both of the asset-specific predictors for Treasury bond excess returns use look-ahead information in their construction that is not available to investors in real time: the bond excess return predictor of [Ludvigson and Ng \(2009\)](#) is constructed as a linear combination of macro factors with weights chosen to maximize in-sample bond excess return predictability subject to a model complexity penalty; the cycle factor of [Cieslak and Povala \(2015\)](#) is constructed by projecting in-sample bond yields on trend inflation and then bond excess returns on the residuals to construct the cycle factor. For the purpose of this OOS exercise, we therefore create real-time versions of these factors.¹³ [Appendix D.1](#) describes the details of their construction.

To parsimoniously present the results from this large number of regressions, we again use

¹³ The equity return predictor CAY and the business cycle variable F1 also use look-ahead information in their construction. For CAY, this involves estimation of a cointegration relationship over the full sample ex post; for F1 the estimation of principal components using full sample information. Therefore, these variables may also be contaminated with information that was not available to investors in real time, but the concern is perhaps less severe for CAY and F1 as their construction does not directly use realized excess returns.

the ratios introduced in (7) and (8), but now with numerators replaced with coefficients from using OOS forecasts:

$$M_1^* \equiv \frac{\sum_{k \in \mathbb{K}} \text{sgn}(\beta_k) \cdot \beta_k^{OOS}}{\sum_{k \in \mathbb{K}} \text{sgn}(\beta_k) \cdot \beta_k}, \quad M_2^* \equiv \frac{\sum_{k \in \mathbb{K}} |\beta_k^{OOS}|}{\sum_{k \in \mathbb{K}} |\beta_k|}. \quad (15)$$

We report the detailed individual coefficients from these regressions in Appendix D.2. If the OOS forecasts constructed in our exercise get close, in terms of cyclicity, to the subjective expected excess returns observed in the survey data, then we should see these ratios to be similar to the ones we reported in Figure 7 with coefficients from the subjective expected excess return regressions in the numerators.

As a baseline for comparison, the left-most blue bars in the two panels of Figure 8 therefore repeat the earlier estimates from Figure 7 in the *Single (F)* specification, i.e., without controlling for past excess returns, where the ratios were 0.16 for the stock market and 0.33 for the Treasury bond market. The neighboring blue bars to the right, labeled *Shrink (E)*, show the ratio (15) with coefficients from using OOS forecasts in the numerators. As the figure shows, that OOS forecasts differ from in-sample forecasts goes some way of explaining the cyclicity gap. If OOS forecasts were as cyclical as in-sample forecasts, the ratio would be about 1.0; if the OOS forecasts were as acyclical as subjective expected excess returns in the survey data, the ratio would be about equal to the ratio represented by the baseline bar. The actual estimate is somewhere inbetween, with 0.46 for the stock market and 0.51 for the Treasury bond market. Using absolute values of coefficients in calculating the measure has little effect, as can be seen from the red bars in the first two pairs.

That investors make use of the full historical record of asset return data in constructing their forecasts may overstate their reliance on historical data from the distant past. In Nagel and Xu (2022) we argued that a reasonable and empirically plausible way of representing investors' learning is to let memory of historical data slowly fade over time as observations recede into the distant past. This could reflect actually fading memory or investors' belief that parameter drift renders data from the distant past irrelevant for forecasting. In line with

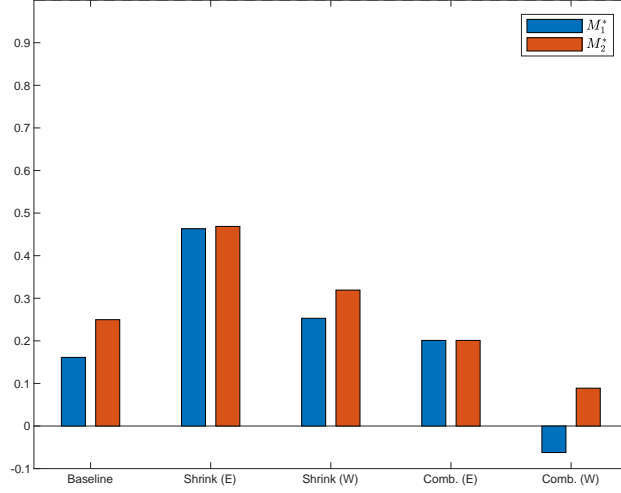
the learning model in Nagel and Xu (2022), we therefore construct an alternative series of OOS forecasts where investors downweight past data with exponential weights $\omega_{t,k} = \lambda^{t-k}$. We use the same value of $\lambda = 0.982$ as in Nagel and Xu (2022) for quarterly data (and its third root for monthly data). We then repeat our earlier exercise of regressing the OOS forecasts on each individual predictor and we compute the ratio in (15). The result is shown in Figure 8 in the third pair of bars from the left, labeled *Shrink (W)*. Especially for the stock market, where the M_1^* ratio drops by about half to 0.25, the exponential weighting approach brings the ratio substantially closer to the baseline column. For the Treasury bond market it also drops, albeit to a lesser extent, from 0.43 to 0.33. The red bars show a similar pattern.

Another potentially relevant consideration is that investors ex-ante may not know which one of the candidate predictor variables really is a useful OOS predictor. Rapach et al. (2010) show that combination forecasts constructed as average individual-predictor forecasts provide superior OOS performance. Such combination forecasts may therefore be an alternative way of representing how investors construct excess return predictions. We therefore use the individual-predictor OOS forecasts $\hat{\alpha}_{i,t} + \hat{\beta}_{i,t}x_{i,t}$ to construct combination OOS forecasts as a simple equal-weighted average across the N predictors:

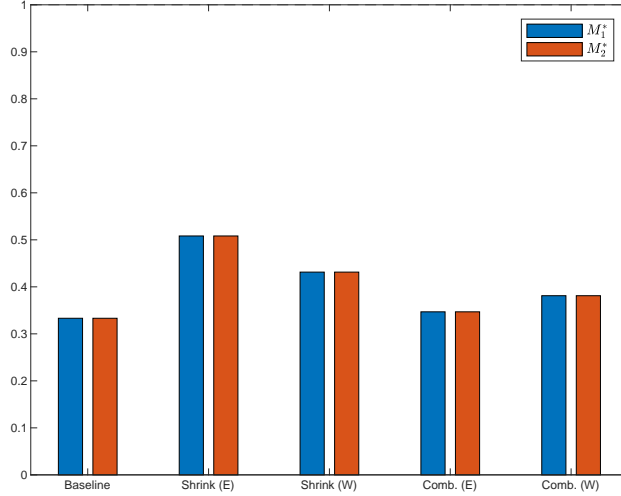
$$\hat{E}_t^C R_{t+1}^e = \frac{1}{N} \sum_{i=1}^N (\hat{\alpha}_{i,t} + \hat{\beta}_{i,t}x_{i,t}). \quad (16)$$

We then regress these combination forecasts on the individual predictors, one at a time, to construct the ratio in (15). The two right-most pairs of bars in the two panels of Figure 8 present the result, one with forecasts based on equally weighting historical data, labeled *Comb. (E)*, the other one based on exponential weighting, labeled *Comb. (W)*. These combination forecasts are very close, in terms of their weak cyclicity, to the subjective expected excess returns from survey data.

Finally, learning about predictive relationships may be particularly difficult for predictor variables that are highly persistent. If so, the cyclicity wedges between survey forecasts



(A) Stock market



(B) Treasury bond market

FIGURE 8

Comparing Magnitudes of Coefficients from Regressing OOS Forecasts and Realized Returns

The left-most pair of bars labeled *Baseline* repeats the estimates from Figure 7 in the *Single (F)* specification. The next four pairs of bars plot the following ratios, respectively,

$$M_1^* \equiv \frac{\sum_{k \in \mathbb{K}} \text{sgn}(\beta_k) \cdot \beta_k^{OOS}}{\sum_{k \in \mathbb{K}} \text{sgn}(\beta_k) \cdot \beta_k}, \quad M_2^* \equiv \frac{\sum_{k \in \mathbb{K}} |\beta_k^{OOS}|}{\sum_{k \in \mathbb{K}} |\beta_k|},$$

where β_k^{OOS} are the slope coefficients from regressing OOS excess return forecasts on predictor k ; \mathbb{K} is the set of all predictors. *Shrink* applies shrinkage to the predictive regression forecast toward the historical mean. *Comb.* uses combination forecasts as an equal-weighted average of individual-predictor forecasts. *(E)* denotes equal weighting historical data and *(W)* denotes exponential weighting of past data with a quarterly discount factor of 0.982 (and its third root for monthly data).

and in-sample regressions, and between OOS forecasts and in-sample regressions, should be particularly pronounced for high-persistence predictor variables. Appendix E provides evidence in support of this view. We group predictors by persistence and we find that the cyclical wedges are indeed biggest for the high-persistence predictors.

Overall, the results in this section show that simply moving away from the extreme assumption of RE models that investors know the data-generating process can go a long way of explaining why there is a gap between subjective risk premium dynamics in survey data and the dynamics of objective risk premia implied by in-sample predictive regressions. Based on these results, further exploration of learning models seems like a promising avenue for understanding the cyclical wedges.

5 Subjective Risk-Return Tradeoff

The evidence so far suggests that to the extent there is any substantial variation in subjective risk premia, standard predictor variables do not capture much of it. However, this does not imply that subjective risk premia are necessarily constant. They do seem to be largely acyclical with regards to typical proxies for business and asset-price cycles, but they could potentially vary systematically in a different way, unrelated to these standard proxies. As a final step in our analysis, we explore whether time-variation in subjective perceptions of risk could generate time-varying subjective risk premia. Due to data constraints, the analysis in this section focuses on the stock market only.

Standard asset-pricing models predict an approximately linear and positive relation between the conditional equity premium and the conditional equity return variance (Campbell and Cochrane 1999; Bansal and Yaron 2004). Empirically, however, evidence on the risk-return trade-off is mixed and inconclusive (see, e.g., Lettau and Ludvigson (2010) for a recent review). This existing evidence is based on measures of objective risk premia and objective measures of time-varying risk. Our analysis focuses on subjective risk premia and subjective perceptions of risk.

Following [Lochstoer and Muir \(2022\)](#), we construct a proxy of subjectively perceived stock market risk from the Graham-Harvey CFO survey. In this survey, respondents provide their assessment of the 10th and 90th percentile of the stock market return distribution at a one-year horizon. We use the square of the range between respondents' average 90th percentile and the average 10th percentile as a perceived risk proxy. If the perceived distribution was normal, this measure would be 2.56^2 times the perceived variance. For this reason, we refer to this measure as perceived variance. As we do not have a directly measured perceived risk measure in the other surveys for individuals and professional forecasters, we use the CFO perceived variance as subjective risk proxy for all three groups of participants.

Figure 9 provides a visual impression of the relationship between perceived risk and subjective excess return expectations from the CFO survey. The plot shows a clear positive relationship between the two series. In particular, the series both increase substantially in the early 2000s, following the technology crash and recession, in the wake of the financial crisis around 2008, and most recently during the COVID crisis in 2020.

Table 10 presents the results in regression form. Column (3) shows that, as suggested by Figure 9, there is a significant positive relationship between perceived variance and the subjective risk premium in the CFO survey. The standard deviation of the perceived variance measure is 0.62%, so a one-standard deviation increase in the perceived variance is associated with roughly a 1pp increase in the subjective risk premium. This is a slightly bigger effect than the effect of a one standard deviation increase in the one-year past excess return.

The strong link between perceived variance and subjective risk premium may seem surprising given that columns (17) and (18) in Table 4, Panel B show the loading of the CFO subjective risk premium on VIX^2 is neither statistically nor economically significant. This indicates that the CFO perceived variance contains information orthogonal to VIX^2 that is important for determining excess return expectations. One potential source of such an orthogonal component is highlighted in [Lochstoer and Muir \(2022\)](#). They find that the CFO perceived variance loads much more strongly on realized variance several months ago than

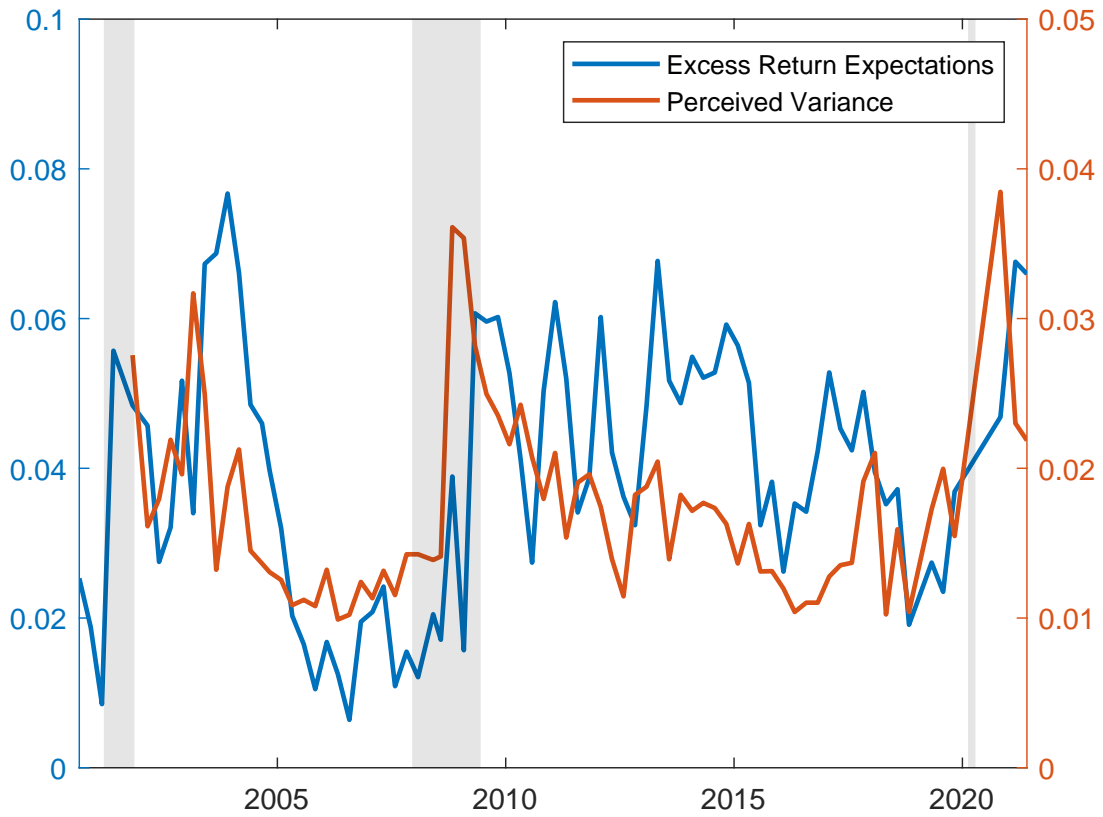


FIGURE 9
CFO Excess Return Expectations and Perceived Variance

The blue line plots the one-year excess return expectations from the CFO survey. The red line plots the square of the difference between the mean of respondents' 90th and 10th percentile of return forecasts from the CFO survey. The grey-shaded areas indicate NBER recessions.

TABLE 10
Subjective Excess Return Expectations and Perceived Variance

The dependent variable is the one-year-ahead excess return expectation from surveys. NX, CFO, and Livingston denote excess return expectations from Nagel and Xu (2022) of individual investors, the CFO survey, and the Livingston survey of professional forecasters, respectively. Perceived variance is calculated as the square of the difference between the 90th and the 10th percentile of return forecasts in the CFO survey. Fitted perceived variance is the fitted value from a projection of the perceived variance on lags of historical realized variance following Lochstoer and Muir (2022). R_{past}^e are one-year excess returns standardized to unit standard deviations in the full sample period. OLS estimates on R_{past}^e are multiplied by 100. EWC p -values following Lazarus et al. (2018) are reported in parentheses.

	NX		CFO		Livingston	
	(1)	(2)	(3)	(4)	(5)	(6)
Const	0.05	0.02	0.01	0.00	0.02	-0.06
(p -value)	(0.01)	(0.18)	(0.26)	(0.96)	(0.60)	(0.10)
Perceived variance	0.78		1.34		4.16	
(p -value)	(0.24)		(0.03)		(0.09)	
Fitted perceived variance		1.93		2.00		6.96
(p -value)		(0.02)		(0.02)		(0.01)
R_{past}^e	1.13	1.39	0.86	1.22	-2.61	-1.64
(p -value)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.11)
Adj. R^2	0.31	0.24	0.26	0.20	0.61	0.25
N	74	143	75	79	39	139

VIX² does.

In addition to the CFO series, we also examine the individual investor and Livingston survey series. Columns (1) and (5) show that individual investors' and professional forecasters' subjective risk premia are also positively related to CFOs' perceived variance, but the coefficient is only marginally statistically significant for the Livingston survey ($p = 0.09$) and not significant for the individual investor series ($p = 0.24$). Statistical power is weak here, especially for the Livingston survey which is available only semi-annually and hence has only 39 observations for which we also have observations of CFO perceived variance. For this reason, we only get marginal significance for the Livingston survey even though the point estimate is more than three times bigger than for the CFO survey.

To get more statistical power, we extend the perceived variance series backwards in time.

Lochstoer and Muir (2022) find that the CFO perceived variance series is captured well by a weighted average of lagged monthly realized variance. Following Lochstoer and Muir (2022), we use nonlinear least squares to estimate a , b , and ϕ in the following specification

$$\tilde{\sigma}_t^2 = a + b \sum_{j=0}^{12} \phi^j rv_{t-j} + \varepsilon_t, \quad (17)$$

where $\tilde{\sigma}_t^2$ denotes the quarterly CFO perceived variance observed in month t and rv_t denotes the realized variance in month t (calculated as within-month sum of daily squared returns of the CRSP value-weighted index). With quarterly observations of $\tilde{\sigma}_t^2$ from 2001 to 2021, we obtain estimates of $\phi = 0.88$, $a = 0.01$, and $b = 0.19$. We then construct monthly measure of fitted perceived variance based on these estimated parameter values that covers the entire sample period for which we have individual investor or professional forecaster survey data.

Columns (2), (4), and (6) show regressions in which we use the fitted perceived variance series to explain time-variation in subjective risk premia. For all three survey series, we get a strong and statistically significant relationship between fitted perceived variance and the subjective risk premium. The standard deviation of the fitted perceived variance series is about half the standard deviation of the original perceived variance series. Since the estimated coefficients are very roughly about twice as big as in columns (1), (3), and (5), this means that the effect of a one standard deviation change in the fitted variance is about the same as the effect of a one standard deviation change in the original perceived variance series. But the effect is now much more precisely estimated.

Overall, there is evidence for a positive risk-return tradeoff in subjective beliefs. Subjective risk premia are increasing with subjective perceptions of the quantity of risk. How can we reconcile this finding with the acyclicity of subjective risk premia with respect to the cyclical variables in our earlier analysis? There are two possibilities. Either the subjective quantity of risk is acyclical and the subjective price of risk is acyclical as well, or the subjective quantity of risk varies with the cyclical variables, but the price of risk varies in a counter-

vailing way to offset the cyclical nature of the subjective quantity of risk. In Table F.1 in the appendix we show that the data points to the first of these two possibilities. We extend the regressions in Table 10 to allow for a time-varying subjective price of risk and we find that it is acyclical.

This also means that the co-movement of subjective risk premia and the perceived quantity of risk cannot help explain asset price volatility, because the variation in the perceived quantity of risk is disconnected from the predictor variables that capture asset price cycles in Table 3.

An interesting question for future research is whether other systematic factors in addition to subjective risk perceptions and recent excess returns can help explain time-variation in subjective risk premia. The remaining variation is likely to contain measurement errors, but this is unlikely to be the full story. In Appendix G we show that the residuals in the regressions in Table 10 have substantial persistence, which is suggestive of yet-to-be-discovered persistent sources of variation in subjective risk premia.

6 Conclusion

Objective risk premia of major asset classes implied by in-sample predictive regressions of excess returns vary over time with cyclical state variables. In stark contrast, we find that subjective risk premia extracted from forecasts in surveys show very little movement with these cyclical variables. This lack of cyclical nature of subjective risk premia is pervasive: it holds for stocks, bonds, currencies, and commodity futures and for subjective beliefs of individuals, CFOs, and professional forecasters. While the properties of subjective expected excess return forecasts differ in some respects between groups of market participants and between asset classes—for example, whether they are extrapolative or contrarian with regards to recent realized returns—the pervasive lack of cyclical movement with standard return predictors and business cycle variables is shared among all of them.

Much of the cyclical nature gap between subjective risk premia from survey data and statis-

tical forecasts of excess returns disappears when the latter are constructed as out-of-sample rather than in-sample predictions. Thus, moving away from rational expectations models in which investors know the data-generating process and its parameters to models in which they learn about them by observing data can help reconcile the evidence from statistical forecasts and subjective excess return expectations data. Evidence from professional forecasters' subjective beliefs about GDP and inflation in [Bianchi et al. \(2022\)](#) points in a similar direction, which suggests that learning is useful for understanding the formation of macroeconomic expectations more generally, not just of return expectations.

While subjective risk premia do not vary much with standard return predictors and business cycle variables, they are not constant, though. In particular, they comove to some extent with time-varying subjective perceptions of risk, consistent with a positive risk-return tradeoff in subjective beliefs. However, the variation in subjective risk premia associated with movements in perceived risk not sufficiently aligned with asset price cycles to contribute much to an explanation of asset price fluctuations.

Therefore, to match the joint set of stylized facts of volatile asset prices, cyclical objective risk premia, and acyclical subjective risk premia, asset-pricing models need to have a time-varying beliefs wedge between subjective and objective forecasts of fundamentals, such as future dividend growth in the case of stocks or future short-term interest rates and inflation in the case of bonds. This wedge must do most of the work in generating large persistent movements in asset prices. Approaches that generate volatile asset prices instead through time-variation in risk or risk aversion—or other mechanisms that induce variation in the excess return that investors require and subjectively expect to earn—are not consistent with the evidence that subjective risk premia are largely unrelated to the state variables that capture asset price cycles.

Online Appendix

A Data Sources and Timing Assumptions

A.1 Data sources

Interest Rates: The main interest rate we use to calculate one-year excess returns is the one-year Treasury Constant Maturity rate. To extend the time series, we use annualized three-month Treasury bill yields: starting from 1934, we use *3-Month Treasury Bill: Secondary Market Rate*; before 1934, we use *Yields on Short-Term United States Securities, Three-Six Month Treasury Notes and Certificates, Three Month Treasury Bills for United States*. All data are available from FRED.

Stock Returns: For monthly stock returns, we use the value-weighted returns on the CRSP index since January 1926 from CRSP. To obtain longer-horizon returns we compound one-month returns.

Bond Returns: Monthly returns on two-, five-, seven-, and ten-year Treasury indexes come from CRSP. We only use realized returns starting from April 1951 after the Treasury-Fed Accord ended the yield control. To obtain longer-horizon returns we compound one-month returns. We subtract the one-year interest rates described in the first paragraph to obtain excess returns.

Bond Yields: Monthly zero-coupon yields come from Liu and Wu (2021) which are available starting from June 1961.¹⁴ We use these yields to construct subjective bond return expectations and the cycle factor from Cieslak and Povala (2015).

FX Rates and Interbank Interest Rates: Daily spot and forward exchange rates used to construct returns are from Datastream. The main provider on Datastream is World Markets PLC/Reuters (WMR) and we supplement data from other providers including Barclays Bank PLC (BB), Thomson/Reuters (TR), and HSBC. The mnemonics are *idisoSP* for spot rates and *idiso1Y* or *idisoYF* for 1-year forward rates.¹⁵ *id* corresponds to the data provider: *US* for WMR, *BB* for BB, *TD* for TR, and *MB* for HSBC. *iso* is the currency ISO code of each country. The spot rate series are also supplemented with Sterling-based quotes from WMR (converted to USD-based).

We obtain daily interbank interest rates and Eurocurrency deposit rates from Datastream and Global Financial Data. The providers of Eurocurrency deposit rates on Datastream include Refinitiv and Garban Information Services. Their mnemonics are *ECiso1Y* and *GSiso1Y*, respectively. The providers of interbank rates on Datastream are national sources including central banks. Interbank rates from Global Financial Data have mnemonics in the format of *IBgfd12D*. *gfd* is the ISO 3166-1 code.

Some of the series clearly contain outliers due to data errors. Following Hassan and Mano (2019), we calculate the log forward premium across data providers, exclude observations where deviations of the log interest rate differential exceed 50 bps, and splice data together. Finally, we build monthly series as the end-of-calendar-month values.

¹⁴ We thank the authors for providing the data on their website.

¹⁵ Mnemonics of spot rates from WMR do not have a clear pattern. For example, *AUSTDOS* corresponds to quotes of the Australian Dollar.

TABLE A.1
Mnemonics of Commodity Futures from Bloomberg and Datastream

This table reports the mnemonics of spot and first-, second-, and third-generic futures prices from Bloomberg. Datastream mnemonics are reported in the second row for each metal.

Commodity	Spot	First	Second	Third
Panel A: Energy				
Crude Oil		CL1 Comdty	CL2 Comdty	CL3 Comdty
Panel B: Metals				
Aluminium		LMAHDY LME Comdty LAHCASH (P)	LMAHDS03 LME Comdty LAH3MTH (P)	LMAHDS15 LME Comdty LAH15MT (P)
Copper		LMCADY LME Comdty LCPCASH (P)	LMCADS03 LME Comdty LCP3MTH (P)	LMCADS15 LME Comdty LCP15MT (P)
Gold	GOLDLNP Index GOLDBLN (P)	GC1 Comdty	GC2 Comdty	GC3 Comdty
Silver	SLVRLND Index SILVUSL (P)	SI1 Comdty	SI2 Comdty	SI3 Comdty

Commodity Prices and Open Interest: Spot rates and futures prices are obtained from Bloomberg. For metals traded on London Metal Exchange (LME), we supplement data from Datastream. Table A.1 reports the mnemonics from these databases. For commodities without reliable spot prices, we interpolate the futures curve to compute the synthetic spot prices (e.g., crude oil). For metals traded on LME, only spot prices and futures prices at three- and fifteen-month horizons are available. We interpolate the twelve-month futures prices linearly using adjacent futures as knots. The open interest data comes from *Commitments of Traders* available at the Commodity Futures Trading Commission. Open interest data before 2010 comes from [Hong and Yogo \(2012\)](#).¹⁶

A.2 Survey details and timing assumptions

For each survey, its survey month is the reported calendar month in which survey results are released. We describe in detail how surveys are conducted below:

Nagel and Xu (2022): The major surveys used are the UBS/Gallup survey, the Conference Board survey, and the Michigan Survey of Consumers. The UBS/Gallup survey typically interviews households during the first two weeks in the survey month. Questionnaires from the Conference Board survey reach households around the first of each survey month. The responses are collected before the eighteenth of the month. Interviews for the Michigan Survey of Consumers typically begin at the beginning of the survey month or the end of previous month.

Duke CFO: The CFO Survey is conducted quarterly within a two-week fielding period

¹⁶ We thank the authors for providing the data on their website.

(running from Monday of the first week through Friday of the second week). (A special case is the 2020Q1 survey, which was conducted over six weeks between February 25 and April 3.) The survey typically starts late in the middle or early in the last calendar month of each quarter and the starting date is provided. We define the survey month as the month that the starting date belongs to.

Livingston: Survey months for the Livingston survey are June and December. The questionnaires are mailed to participants in May and November right after the release of CPI (typically in the last week).

BCFF: The survey is typically released on the first day of each calendar month. The responses are collected during the last week of the month before the survey month.

Consensus Economics: For currency spot rate forecasts, the responses are recorded on the first or second Monday in each survey month. For commodity spot price forecasts, the survey responses are normally collected on the second Monday or third Monday in each survey month.

FX4casts: The survey questions are usually sent out on the last Friday of the survey month with responses collected during Friday and the following Monday and Tuesday.

This leads to the following timing assumptions: In a given survey month, we assume participants in all surveys except the FX4casts survey have access to monthly macro information with a two-month lag and price information with a one-month lag, e.g., June survey participants have information of industrial production up to April and stock prices up to May. This assumption is consistent with the Livingston Survey Documentation and the approach in Nagel and Xu (2022). We match the one-month lags of FX4casts survey to the Consensus Economics survey when constructing the currency forecasts, e.g., May survey from FX4casts to June survey from the Consensus Economics.

B Bootstrap Methods for Predictive Regressions

To correct for the potential small-sample bias in the predictive regressions, we assume the following system:

$$z_{t+1} = \alpha + \beta' \mathbf{x}_t + \eta_{t+1}, \quad (\text{B.1})$$

$$\mathbf{x}_{t+1} = \boldsymbol{\kappa} + \boldsymbol{\Phi} \mathbf{x}_t + \boldsymbol{\nu}_{t+1}, \quad (\text{B.2})$$

where \mathbf{x}_t is a $K \times 1$ vector of predictors, $\boldsymbol{\beta}$ is a $K \times 1$ vector of loadings, $\boldsymbol{\Phi}$ is a $K \times K$ coefficient matrix, and $\eta_t = \boldsymbol{\rho}' \boldsymbol{\nu}_t + \xi_t$ where ξ_t is independent from $\boldsymbol{\nu}_t$. We implement a bootstrap that involves the following steps:

1. We start with estimating a VAR(1) system for the predictors, \mathbf{x}_t . To correct for the bias in the VAR estimates, we use the approach in Amihud et al. (2009) that relies on the analytical expressions from Nicholls and Pope (1988). We denote the bias-adjusted coefficients and shocks as $\tilde{\boldsymbol{\kappa}}$, $\tilde{\boldsymbol{\Phi}}$, and $\{\tilde{\boldsymbol{\nu}}_t\}$.
2. We then estimate the predictive regression in (B.1) with OLS. We obtain coefficient estimates $\hat{\alpha}$, $\hat{\boldsymbol{\beta}}$ and residuals $\hat{\eta}_{t+1}$. We then construct pseudo samples by bootstrapping

the time-series of residual vectors $(\tilde{\boldsymbol{v}}_t, \hat{\boldsymbol{\eta}}_t)$ to preserve the cross-sectional correlations. To account for the potentially autocorrelated $\{\eta_t\}$, we use a circular block bootstrap. For the sample i , with bootstrapped residuals $(\tilde{\boldsymbol{v}}_t^i, \hat{\boldsymbol{\eta}}_t^i)$, we impose the null of no predictability by generating data as

$$z_{t+1}^{null,i} = \bar{z} + \hat{\boldsymbol{\eta}}_{t+1}^i, \quad (\text{B.3})$$

$$\boldsymbol{x}_{t+1} = \tilde{\boldsymbol{\kappa}} + \tilde{\boldsymbol{\Phi}} \boldsymbol{x}_t + \tilde{\boldsymbol{v}}_{t+1}^i. \quad (\text{B.4})$$

We then re-run the predictive regression in the sample i and record the t -statistic τ^i . The $\{\tau^i\}$ are used to obtain the small-sample p -value by comparing with the sample t -statistic $\hat{\tau}$. For the sample j , with bootstrapped residuals $(\tilde{\boldsymbol{v}}_t^j, \hat{\boldsymbol{\eta}}_t^j)$, we generate data under the alternative that $\boldsymbol{\beta} = \hat{\boldsymbol{\beta}}$ as

$$z_{t+1}^{alter,j} = \hat{\alpha} + \hat{\boldsymbol{\beta}}' \boldsymbol{x}_t + \hat{\boldsymbol{\eta}}_{t+1}^j, \quad (\text{B.5})$$

$$\boldsymbol{x}_{t+1} = \tilde{\boldsymbol{\kappa}} + \tilde{\boldsymbol{\Phi}} \boldsymbol{x}_t + \tilde{\boldsymbol{v}}_{t+1}^j. \quad (\text{B.6})$$

We re-run the predictive regression in the sample j and record the coefficients $\hat{\boldsymbol{\beta}}^j$. By comparing the average of the $\{\hat{\boldsymbol{\beta}}^j\}$ with $\hat{\boldsymbol{\beta}}$, we obtain the finite-sample bias in $\hat{\boldsymbol{\beta}}$.

C Asymptotic Inference Approach for Composite Measures of Regression Coefficients

We develop an approach to perform statistical inference on composite measures of the differences in regression coefficients between the realized excess return regressions and the survey data regressions. Looking across all J specifications of dependent variables (realized excess returns and survey expectations) and predictors (asset-class specific and business cycle variables), we can stack all observations in specification j as

$$\underbrace{\begin{pmatrix} y_{j,1} \\ \dots \\ y_{j,N_j} \end{pmatrix}}_{\boldsymbol{y}_j} = \underbrace{\begin{pmatrix} \boldsymbol{x}_{j,1} \\ \dots \\ \boldsymbol{x}_{j,N_j} \end{pmatrix}}_{\boldsymbol{X}_j} \boldsymbol{b}_j + \underbrace{\begin{pmatrix} \varepsilon_{j,1} \\ \dots \\ \varepsilon_{j,N_j} \end{pmatrix}}_{\boldsymbol{\epsilon}_j}, \quad j = 1, 2, \dots, J, \quad (\text{C.1})$$

where $\boldsymbol{x}_{j,k}$ represents k -th observation of the $1 \times K$ dimensional predictor variable vector used in specification j (with first element equal to unity).¹⁷ In regressions with realized excess returns $y_{j,k}$ is an excess return, while in regressions with survey data, $y_{j,k}$ is a subjective risk premium measured in survey data. Returns are typically from overlapping windows, but we did not write this out explicitly here. Our statistical inference procedure takes the overlap into account, though. Across different specifications j , the predictor variables can be the same, but even then the sample period may be different due to different availability

¹⁷ In our specification, $K = 2$ or 3 depending on whether past excess return is included as an additional control variable.

of excess return data or survey data in different asset classes. Measurement frequency can differ between specifications, too. We denote the corresponding calendar time of available data points in each specification as $\{T_{j,k}\}_{k=1}^{N_j}$ and measure calendar time in months. Note that

$$\hat{\mathbf{b}}_j = \mathbf{b}_j + (\mathbf{X}'_j \mathbf{X}_j)^{-1} \mathbf{X}'_j \boldsymbol{\epsilon}_j. \quad (\text{C.2})$$

Under regularity conditions, we have

$$\sqrt{N_j}(\hat{\mathbf{b}}_j - \mathbf{b}_j) \xrightarrow{p} \mathcal{N}(\mathbf{0}, \mathbf{Q}_j), \quad (\text{C.3})$$

where

$$\hat{\mathbf{Q}}_j = \left(\frac{1}{N_j} \sum_{k=1}^{N_j} \mathbf{x}'_{j,k} \mathbf{x}_{j,k} \right)^{-1} \hat{\boldsymbol{\Omega}}_j \left(\frac{1}{N_j} \sum_{k=1}^{N_j} \mathbf{x}'_{j,k} \mathbf{x}_{j,k} \right)^{-1} \quad (\text{C.4})$$

and $\hat{\boldsymbol{\Omega}}_j$ is an estimator of long-run variance of $\mathbf{x}'_{j,t} \boldsymbol{\epsilon}_t$. We may write

$$\sqrt{T}(\hat{\mathbf{b}}_j - \mathbf{b}_j) \xrightarrow{p} \mathcal{N}\left(\mathbf{0}, \frac{T}{N_j} \mathbf{Q}_j\right). \quad (\text{C.5})$$

Here T represents the maximum sample period length expressed in terms of monthly observations for any of our regressions. In our settings, N_j/T is either a constant (quarterly v.s. monthly data) or converges to 1 (missing early observations) as T grows.

For two specifications i and j , we can estimate the covariance of $\hat{\mathbf{b}}_i - \mathbf{b}_i$ and $\hat{\mathbf{b}}_j - \mathbf{b}_j$ as

$$\hat{\mathbf{V}}_{i,j} \equiv \text{cov}(\sqrt{N_i}(\hat{\mathbf{b}}_i - \mathbf{b}_i), \sqrt{N_j}(\hat{\mathbf{b}}_j - \mathbf{b}_j)) \quad (\text{C.6})$$

$$= \left(\frac{1}{N_i} \sum_{k=1}^{N_i} \mathbf{x}'_{i,k} \mathbf{x}_{i,k} \right)^{-1} \hat{\mathbf{S}}_{ij} \left(\frac{1}{N_j} \sum_{k=1}^{N_j} \mathbf{x}'_{j,k} \mathbf{x}_{j,k} \right)^{-1}, \quad (\text{C.7})$$

where $\hat{\mathbf{S}}_{ij}$ is an estimator of long-run covariance between $\mathbf{x}'_{i,k} \boldsymbol{\epsilon}_i$ and $\mathbf{x}'_{j,k} \boldsymbol{\epsilon}_j$.

We stack all \mathbf{b}_j in the $K \times J$ matrix \mathbf{B} :

$$\mathbf{B} \equiv (\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_J). \quad (\text{C.8})$$

We treat all these regressions jointly as one big system of regression equations. We can then construct an estimator of the difference between realized return-based and survey-based coefficient estimates as a linear combination of coefficients as

$$d = \mathbf{e}'_2 \mathbf{B} \mathbf{w}, \quad (\text{C.9})$$

where the $J \times 1$ weight vector $\mathbf{w} \equiv (w_1, w_2, \dots, w_J)'$ is such that the elements that multiply coefficients from the predictive regressions with excess returns as dependent variable are positive, of equal magnitude, and sum to 1 across all regressions within an asset class, while those that multiply coefficients from the survey data regressions are negative, of equal magnitude, and sum to -1 within an asset class; \mathbf{e}_2 is a $K \times 1$ vector with one as the second

element and zeros otherwise.¹⁸

Let $\hat{\mathbf{B}}$ and \hat{d} denote the estimators of \mathbf{B} and d , respectively. We have

$$(\hat{\mathbf{B}} - \mathbf{B})\mathbf{w} = \sum_{k=1}^J w_k (\mathbf{X}'_k \mathbf{X}_k)^{-1} (\mathbf{X}'_k \boldsymbol{\epsilon}_k). \quad (\text{C.10})$$

Combining (C.5) and (C.7), we have

$$\sqrt{T}(\hat{\mathbf{B}} - \mathbf{B})\mathbf{w} \xrightarrow{p} \mathcal{N}(\mathbf{0}, \mathbf{W}) \quad (\text{C.11})$$

where

$$\mathbf{W} = \sum_{k=1}^J w_k^2 \frac{T}{N_k} \mathbf{Q}_k + \sum_{i \neq j} w_i w_j \frac{T}{\sqrt{N_i N_j}} \mathbf{V}_{i,j}. \quad (\text{C.12})$$

It follows that

$$\sqrt{T}(\hat{d} - d) \xrightarrow{p} \mathcal{N}(0, \mathbf{e}'_2 \mathbf{W} \mathbf{e}_2). \quad (\text{C.13})$$

To estimate $\boldsymbol{\Omega}_j$ and $\mathbf{S}_{i,j}$, we use HAR estimators (Sun 2013) to account for autocorrelations in residuals. If the data were complete across all specifications, i.e., $\{T_{i,k}\}_{k=1}^{N_i} = \{T_{j,k}\}_{k=1}^{N_j}$, $\forall i, j$, we would have

$$\hat{\boldsymbol{\Omega}}_j = \frac{1}{N_j} \sum_{k=1}^{N_j} \sum_{s=1}^{N_j} \mathbf{x}'_{j,k} \boldsymbol{\epsilon}_{j,k} K_G \left(\frac{k}{N_j}, \frac{s}{N_j} \right) (\mathbf{x}'_{j,s} \boldsymbol{\epsilon}_{j,s})', \quad (\text{C.14})$$

$$\hat{\mathbf{S}}_{i,j} = \frac{1}{\sqrt{N_i N_j}} \sum_{k=1}^{N_j} \sum_{s=1}^{N_j} \mathbf{x}'_{i,k} \boldsymbol{\epsilon}_{i,k} K_G \left(\frac{k}{N_i}, \frac{s}{N_j} \right) (\mathbf{x}'_{j,s} \boldsymbol{\epsilon}_{j,s})', \quad (\text{C.15})$$

where $K_G(r, s) \equiv \frac{1}{B} \sum_{b=1}^B \phi_b(r) \phi_b(s)$ and the $\{\phi_k\}$ are a sequence of orthonormal basis functions. We choose the EWC estimator from Lazarus et al. (2018) and use

$$\phi_b \left(\frac{t}{T} \right) = \sqrt{2} \cos \left[\pi b \left(\frac{t - 1/2}{T} \right) \right]. \quad (\text{C.16})$$

To deal with missing observations, for each $j \in \{1, \dots, J\}$, we first project $\mathbf{x}'_{j,k} \boldsymbol{\epsilon}_{j,k}$ onto the basis functions

$$\sqrt{2} \cos \left[\pi b \left(\frac{t - 1/2}{T_{j,N_j} - T_{j,1} + 1} \right) \right], \quad b = 1, \dots, B, \quad (\text{C.17})$$

¹⁸ As a concrete example, consider the set of regressions in the equity market which uses the dividend-price ratio and industrial production growth as sole predictors. We have $J = 8$ (two predictive regressions and six survey expectations regressions) and $K = 2$. We stack the results from realized excess returns in the first two columns in \mathbf{B} and results from survey expectations regressions in the remaining columns. The weight vector in this case is a 8×1 vector:

$$\mathbf{w} = \left(\frac{1}{2}, \frac{1}{2}, -\frac{1}{6}, -\frac{1}{6}, -\frac{1}{6}, -\frac{1}{6}, -\frac{1}{6}, -\frac{1}{6} \right)'$$

Then d is the linear combination of the slope coefficients from the eight regressions.

for $t \in T_j^* \equiv \{T_{j,1}, T_{j,1}+1, \dots, T_{j,N_j}\}$. In other words, we define the time period for estimation as the span between the earliest and latest calendar dates with non-missing observations. Equation (C.14) is then modified to

$$\hat{\Omega}_j = \frac{1}{N_j} \sum_{k=1}^{N_j} \sum_{s=1}^{N_j} \mathbf{x}'_{j,k} \epsilon_{j,k} K_G \left(\frac{T_{j,k} - T_{j,1} + 1}{T_{j,N_j} - T_{j,1} + 1}, \frac{T_{j,s} - T_{j,1} + 1}{T_{j,N_j} - T_{j,1} + 1} \right) (\mathbf{x}'_{j,s} \epsilon_{j,s})'. \quad (\text{C.18})$$

This amounts to treating missing observations as non-serially correlated by setting missing residuals to zero. Datta and Du (2012) show that for the Newey-West estimator this approach has better size properties in small samples. Similarly, to estimate $\mathbf{S}_{i,j}$, we project both series onto

$$\sqrt{2} \cos \left[\pi b \left(\frac{t - 1/2}{L_{i,j}} \right) \right], \quad b = 1, \dots, B, \quad (\text{C.19})$$

for $t \in T_{i,j}^* \equiv \{\min(T_{i,1}, T_{j,1}), \min(T_{i,1}, T_{j,1})+1, \dots, \max(T_{i,N_i}, T_{j,N_j})\}$ and $L_{i,j} \equiv \max(T_{i,N_i}, T_{j,N_j}) - \min(T_{i,1}, T_{j,1}) + 1$. Equation (C.15) is then modified to

$$\hat{\mathbf{S}}_{i,j} = \frac{1}{\sqrt{N_i N_j}} \sum_{k=1}^{N_j} \sum_{s=1}^{N_j} \mathbf{x}'_{i,k} \epsilon_{i,k} K_G \left(\frac{T_{i,k} - \min(T_{i,1}, T_{j,1}) + 1}{L_{i,j}}, \frac{T_{i,s} - \min(T_{i,1}, T_{j,1}) + 1}{L_{i,j}} \right) (\mathbf{x}'_{j,s} \epsilon_{j,s})'. \quad (\text{C.20})$$

D Construction of OOS Forecasts

D.1 Constructing real-time bond excess return predictors

To construct the real-time version of the predictor as in Ludvigson and Ng (2009), we perform the following predictive regressions at time t over expanding windows:

$$\bar{R}_k^e = \gamma_0 + \gamma_1 \hat{F}_{1,k-1} + \gamma_2 \hat{F}_{1,k-1}^3 + \gamma_3 \hat{F}_{2,k-1} + \gamma_4 \hat{F}_{3,k-1} + \gamma_5 \hat{F}_{4,k-1} + \gamma_6 \hat{F}_{8,k-1} + u_k, \quad k = 2, \dots, t, \quad (\text{D.1})$$

where \bar{R}_k^e denotes the average bond excess returns and \hat{F}_j are the principal components of a broad set of macro variables.¹⁹ The predictor is then calculated as

$$LN_t = \hat{\gamma}_{0,t} + \hat{\gamma}_{1,t} \hat{F}_{1,t} + \hat{\gamma}_{2,t} \hat{F}_{1,t}^3 + \hat{\gamma}_{3,t} \hat{F}_{2,t} + \hat{\gamma}_{4,t} \hat{F}_{3,t} + \hat{\gamma}_{5,t} \hat{F}_{4,t} + \hat{\gamma}_{6,t} \hat{F}_{8,t}. \quad (\text{D.2})$$

To construct the real-time version of the predictor as in Cieslak and Povala (2015), we first perform the following regressions at time t over expanding windows:

$$y_k^n = a_n + b_n \tau_k^{CPI} + \eta_k, \quad k = 1, \dots, t, \quad (\text{D.3})$$

where y_k^n denotes the n -year nominal yield and τ_k^{CPI} denotes the trend inflation. To have a sufficiently longer time series that allows a burn-in period, here we only use bond yields with

¹⁹ Note that the estimation of \hat{F}_j still uses full-sample time series of macro variables and contains look-ahead information. However, the constructed factor no longer uses look-ahead information in bond returns.

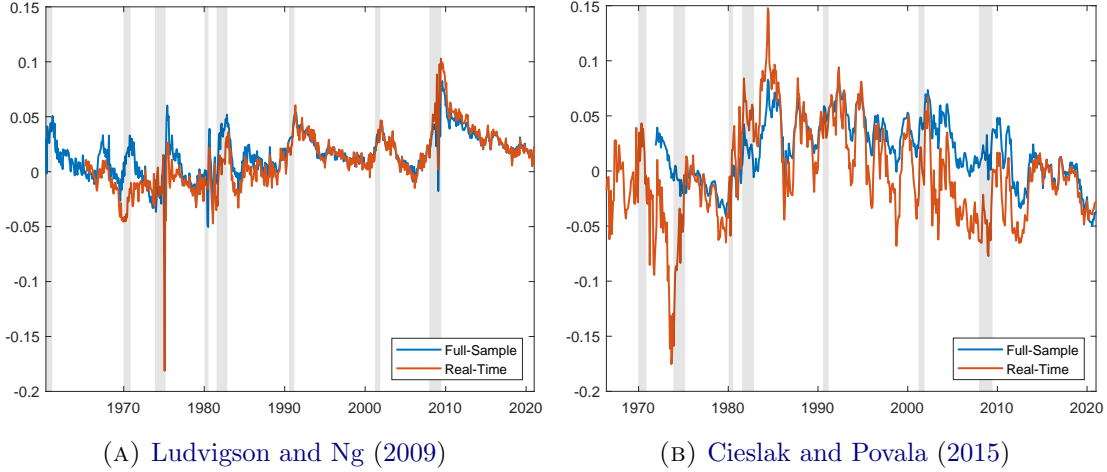


FIGURE D.1

Real-Time Bond Excess Return Predictors

The blue line in each panel plots the bond excess return predictors estimated using full-sample data. The red line in each panel plots the real-time versions of these predictors estimated over expanding windows.

maturities between one to seven years.²⁰ We then run the following predictive regressions:

$$\bar{R}_k^e = \delta_0 + \delta_1 c_{t,k-1}^1 + \delta_2 \bar{c}_{t,k-1} + \omega_k, \quad k = 2, \dots, t, \quad (\text{D.4})$$

with $c_{t,k}^n = y_k^n - \hat{a}_{n,t} + \hat{b}_{n,t} \tau_k^{CPI}$ and $\bar{c}_{t,k} = \frac{1}{6} \sum_{i=2}^7 c_{t,k}^i$. The real-time cycle factor is then calculated as

$$CYCLE_t = \hat{\delta}_{0,t} + \hat{\delta}_{1,t} c_{t,t}^1 + \hat{\delta}_{2,t} \bar{c}_{t,t}. \quad (\text{D.5})$$

We estimate the above regressions with an initial burn-in period of five years. Figure D.1 plots the time series of these two factors in comparison with their full-sample counterparts.

D.2 Individual regression coefficients

Table D.1 and Table D.2 report the detailed results of regressing OOS stock and bond excess return forecasts on asset-specific predictors and cyclical indicators. The OOS forecasts are constructed as described in Section 4.

E The Role of Predictor Persistence

In this section, we investigate whether the cyclicity wedges between objective and subjective risk premia and between objective risk premia and OOS forecasts differ depending on the persistence of the predictor variable.

²⁰ Longer-maturity yields are only available starting from August 1971.

TABLE D.1
 Regressing OOS Stock Excess Return Forecasts on Predictors

In Panels A and B, dependent variables are the quarterly OOS stock excess returns forecasts from predictive regressions over expanding windows with single predictors. OOS forecasts are shrunk toward the trailing mean excess return with optimal shrinkage estimated based on historical OOS performance in earlier periods. Forecasts in Panel A equally weight historical data in estimating predictive regressions and shrinkage, whereas forecasts in Panel B exponentially downweight past data with a quarterly discount factor of 0.982. The regressions in Panels A and B regress the OOS forecasts on the same predictor variable that was used to construct the OOS forecasts. In Panels C and D, dependent variables are combination OOS forecasts that average the forecasts (without shrinkage) obtained from different predictors. All predictors are standardized to have unit standard deviations in the full sample period. The first row in each block reports the OLS estimates multiplied by 100. EWC p -values following [Lazarus et al. \(2018\)](#) are reported in parentheses.

	Asset-Class Specific				Business-Cycle				
	CAY	D/P	EXPD	NTIS	N-IP	TERM	DEFAULT	F1	VIX ²
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Shrinkage, Equally Weighted									
Coeff	3.46	5.56	-1.72	-0.93	-0.36	1.67	-0.83	3.73	0.13
(p -value)	(0.00)	(0.00)	(0.00)	(0.21)	(0.20)	(0.00)	(0.03)	(0.00)	(0.41)
Adj. R^2	0.73	0.85	0.66	0.09	0.02	0.42	0.14	0.84	0.00
N	189	275	275	275	275	275	275	156	275
B. Shrinkage, Exponentially Weighted									
Coeff	0.75	3.70	0.16	-1.50	-0.09	0.99	-2.36	1.53	0.36
(p -value)	(0.43)	(0.01)	(0.77)	(0.43)	(0.92)	(0.17)	(0.00)	(0.21)	(0.40)
Adj. R^2	0.05	0.40	-0.00	0.04	-0.00	0.07	0.26	0.17	0.01
N	189	275	275	275	275	275	275	156	275
C. Combination Forecasts, Equally Weighted									
Coeff	0.65	1.25	-0.57	-0.65	1.08	0.58	1.47	1.15	0.42
(p -value)	(0.02)	(0.00)	(0.03)	(0.14)	(0.09)	(0.02)	(0.00)	(0.00)	(0.13)
Adj. R^2	0.11	0.30	0.06	0.06	0.08	0.09	0.23	0.34	0.06
N	275	275	275	275	275	275	275	243	275
D. Combination Forecasts, Exponentially Weighted									
Coeff	0.35	0.12	0.65	0.14	-0.43	-0.35	-0.81	0.23	0.22
(p -value)	(0.39)	(0.84)	(0.14)	(0.82)	(0.48)	(0.38)	(0.25)	(0.57)	(0.51)
Adj. R^2	0.02	-0.00	0.05	-0.00	0.00	0.02	0.04	0.01	0.01
N	275	275	275	275	275	275	275	243	275

TABLE D.2
Regressing OOS Treasury Bond Average Excess Return Forecasts on Predictors

In Panels A and B, dependent variables are the monthly OOS Treasury bond excess returns forecasts from predictive regressions over expanding windows with single predictors. OOS forecasts are shrunk toward the trailing mean excess return with optimal shrinkage estimated based on historical OOS performance in earlier periods. Forecasts in Panel A equally weight historical data in estimating predictive regressions and shrinkage, whereas forecasts in Panel B exponentially downweight past data with a monthly discount factor of 0.994. The regressions in Panels A and B regress the OOS forecasts on the same predictor variable that was used to construct the OOS forecasts. In Panels C and D, dependent variables are combination OOS forecasts that average the forecasts (without shrinkage) obtained from different predictors. All predictors are standardized to have unit standard deviations in the full sample period. The first row in each block reports the OLS estimates multiplied by 100. EWC p -values following [Lazarus et al. \(2018\)](#) are reported in parentheses.

	Asset-Class Specific		Business-Cycle				
	LN	CYCLE	N-IP	TERM	DEFAULT	F1	VIX ²
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Shrinkage, Equally Weighted							
Coeff	0.93	1.55	0.21	1.44	0.09	0.44	0.01
(p -value)	(0.00)	(0.00)	(0.04)	(0.00)	(0.14)	(0.00)	(0.77)
Adj. R^2	0.43	0.43	0.07	0.94	0.02	0.41	-0.00
N	397	393	397	397	397	397	397
B. Shrinkage, Exponentially Weighted							
Coeff	0.98	0.97	0.21	1.36	0.08	0.28	0.09
(p -value)	(0.01)	(0.03)	(0.12)	(0.00)	(0.32)	(0.13)	(0.33)
Adj. R^2	0.41	0.16	0.03	0.83	0.00	0.14	0.02
N	397	393	397	397	397	397	397
C. Combination Forecasts, Equally Weighted							
Coeff	0.54	0.09	0.80	0.55	0.67	0.39	0.15
(p -value)	(0.00)	(0.22)	(0.01)	(0.00)	(0.00)	(0.00)	(0.03)
Adj. R^2	0.45	0.02	0.27	0.63	0.31	0.23	0.12
N	397	397	397	397	397	397	397
D. Combination Forecasts, Exponentially Weighted							
Coeff	0.64	0.05	0.89	0.67	0.72	0.39	0.14
(p -value)	(0.00)	(0.59)	(0.01)	(0.00)	(0.00)	(0.03)	(0.10)
Adj. R^2	0.42	0.00	0.23	0.64	0.24	0.15	0.07
N	397	397	397	397	397	397	397

We first estimate the persistence of each predictor using OLS with an AR(1) specification. All estimates are adjusted for the finite-sample bias (Kendall 1954):

$$\hat{\rho}^{adj} = \hat{\rho} + \frac{1 + 3\hat{\rho}}{T}, \quad (\text{E.1})$$

where T is the sample size. Figure E.1 shows the estimated bias-corrected first-order autocorrelation of all the predictors in our analysis.

We then divide all predictors in each asset class, both asset-specific and business-cycle variables, into three groups based on their estimated bias-adjusted persistence: high, medium, and low. The cutoff points are the 66.7% and 33.3% percentiles, respectively. Table E.1 reports the cyclical wedges across persistence groups.

For each persistence group of predictors, we also construct a single time series of OOS combination forecasts, $\hat{\mathbb{E}}_t^C R_{t+1}^{e,j}$, where $j \in \{\text{High, Medium, Low}\}$. We then study the cyclical wedge between these OOS forecasts and in-sample forecasts in the same way as we did in Table E.1 for survey forecasts and in-sample forecasts. Table E.2 shows the results.

F Subjective Price of Risk Analysis

We run the following regressions,

$$\tilde{\mathbb{E}}_t R_{t+1}^e = \gamma_{0,i} + \gamma_{i,1} \tilde{\sigma}_t^2 + \gamma_{i,2} x_{i,t} + \gamma_{i,3} (\tilde{\sigma}_t^2 \times x_{i,t}) + \varepsilon_t, \quad (\text{F.1})$$

where $\tilde{\mathbb{E}}_t R_{t+1}^e$ denotes the time- t survey-implied excess return expectations, $\tilde{\sigma}_t^2$ is the perceived variance in the extended sample (i.e., based on fitted values), and $x_{i,t}$ denotes an asset-specific predictor or business-cycle indicator. All regressions also control for the past one-year excess returns.

If it was the case, for example, that the perceived quantity of risk was cyclical, but offset by a price of risk of the opposite cyclicity, and hence with weakened or no effect on the subjective risk premium, then we should see $\gamma_{i,3} \neq 0$.

Table F.1 shows the results. Only 3 of the 27 point estimates of $\gamma_{i,3}$ in this table are statistically significant at a 5% level. Therefore, the subjective price of risk appears to be acyclical. Hence, the observed acyclicity of the subjective risk premium must therefore be due to acyclicity in the subjectively perceived quantity of risk combined with acyclicity in the subjectively perceived quantity of risk.

G Persistence of Residuals in Subjective Risk Premia

To avoid that we are just picking up the effects of the information rigidities documented by Coibion and Gorodnichenko (2015), we look at fourth-order serial correlation ρ from the following regression at a quarterly frequency:

$$\varepsilon_t = \alpha + \rho \varepsilon_{t-4} + \eta_t, \quad (\text{G.1})$$

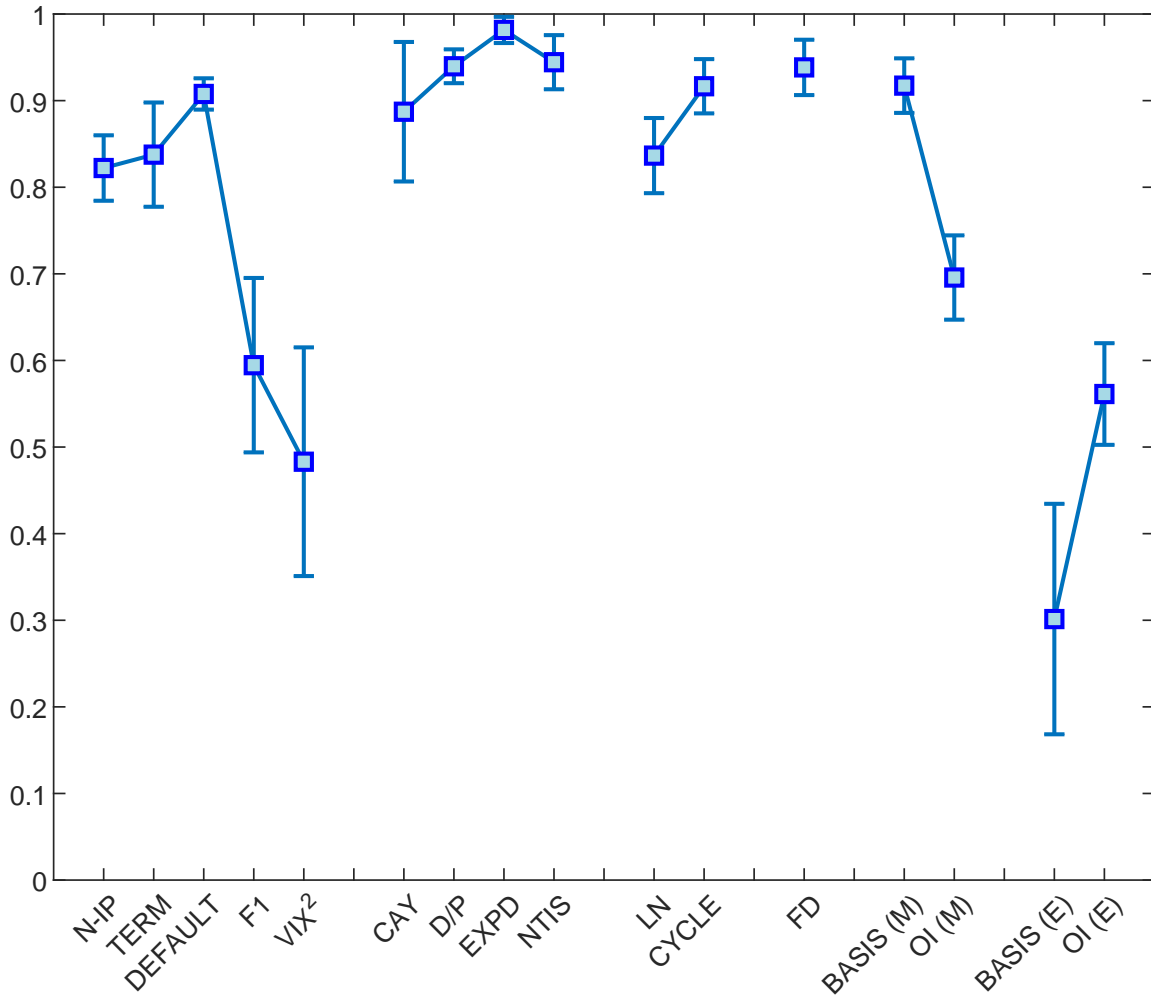


FIGURE E.1
Persistence of Predictors

Blue squares plot the estimated persistence of asset-class specific predictors and business-cycle indicators from an AR(1) specification using OLS at a quarterly frequency. All point estimates are adjusted for finite-sample bias. The vertical error bars indicate the interval of \pm two standard errors.

TABLE E.1
 Joint Statistical Significance of the Cyclicity Wedges Across Persistence Groups

This table reports the point estimates and standard errors of the following measure:

$$d = \mathbf{e}'_2 \mathbf{B} \mathbf{w},$$

where the $K \times J$ matrix \mathbf{B} horizontally concatenates the regression coefficient row vectors from J realized-return-based and survey-based regressions. The weight column vector \mathbf{w} is such that the elements that multiply coefficients from the predictive regressions with excess returns as dependent variable are positive, of equal magnitude, and sum to 1 across all regressions within an asset class, while those that multiply coefficients from the survey data regressions are negative and sum to -1 within an asset class; \mathbf{e}_2 is a vector with one as the second element and zeros otherwise to pick out the aggregated slope coefficient differences corresponding to asset-class specific predictors and business-cycle indicators. The composite measure either equally weights the four asset classes or weights them in inverse proportion to the volatility of their realized excess returns σ . “High”, “Medium”, and “Low” use predictors with high, medium, and low persistence, respectively. We multiply the point estimates d by 100. Standard errors calculated using the EWC estimator from [Lazarus et al. \(2018\)](#) are reported in parentheses (also multiplied by 100). All specifications control for past excess returns.

	Full-Sample			Survey-Sample		
	High	Medium	Low	High	Medium	Low
Stock	6.17 (1.70)	3.76 (1.40)	0.73 (1.29)	3.12 (1.36)	3.36 (1.68)	2.79 (1.66)
Treasury Bond	1.44 (0.57)	1.12 (0.48)	0.21 (0.42)	0.49 (0.59)	1.00 (0.61)	0.16 (0.40)
Foreign Exchange	5.36 (1.61)	4.58 (1.48)	1.33 (0.79)	4.52 (1.32)	4.58 (1.46)	1.56 (0.78)
Commodity						
Metals	5.37 (5.69)	5.33 (3.51)	1.51 (3.29)	19.51 (4.50)	9.29 (2.76)	4.00 (3.36)
Oil	5.02 (3.86)	4.22 (3.61)	2.54 (3.54)	3.32 (4.96)	9.27 (3.71)	3.60 (4.36)
Composite						
Equal-weighted	4.54 (1.21)	3.75 (0.84)	1.50 (0.80)	4.89 (1.03)	4.55 (0.80)	2.08 (0.91)
σ^{-1} -weighted	3.36 (0.78)	2.74 (0.58)	0.93 (0.41)	2.71 (0.65)	2.87 (0.61)	1.15 (0.37)

TABLE E.2
 Joint Statistical Significance of the Combination Forecasts' Cyclicity Wedges Across
 Persistence Groups

This table reports the point estimates and standard errors of the following measure:

$$d = \mathbf{e}_2' \mathbf{B} \mathbf{w},$$

where the $K \times J$ matrix \mathbf{B} horizontally concatenates the regression coefficient row vectors from J realized-return-based and combination-forecast-based regressions. The weight column vector \mathbf{w} is such that the elements that multiply coefficients from the predictive regressions with excess returns as dependent variable are positive, of equal magnitude, and sum to 1 across all regressions within an asset class, while those that multiply coefficients from the combination forecast regressions are negative and sum to -1 within an asset class; \mathbf{e}_2 is a vector with one as the second element and zeros otherwise to pick out the aggregated slope coefficient differences corresponding to asset-class specific predictors and business-cycle indicators. “High”, “Medium”, and “Low” use predictors with high, medium, and low persistence, respectively. We multiply the point estimates d by 100. Standard errors calculated using the EWC estimator from [Lazarus et al. \(2018\)](#) are reported in parentheses (also multiplied by 100). All specifications control for past excess returns.

	Equally-Weighted			Exponentially-Weighted		
	High	Medium	Low	High	Medium	Low
Stock	5.59 (1.69)	3.38 (1.35)	1.40 (1.19)	6.57 (1.73)	4.55 (1.37)	2.09 (1.30)
Treasury Bond	1.15 (0.51)	1.31 (0.42)	0.41 (0.42)	1.08 (0.53)	1.25 (0.43)	0.42 (0.44)

TABLE F.1
Time-varying Subjective Price of Risk

Dependent variables are the one-year-ahead excess return expectations from Nagel and Xu (2022), the CFO survey, and the Livingston survey, respectively. Column variables are described in Section 2.2. We estimate the following regression for each survey:

$$\tilde{\mathbb{E}}_t R_{t+1}^e = \gamma_{0,i} + \gamma_{i,1} \tilde{\sigma}_t^2 + \gamma_{i,2} x_{i,t} + \gamma_{i,3} (\tilde{\sigma}_t^2 \times x_{i,t}) + \varepsilon_t,$$

All predictors $x_{i,t}$ are demeaned and standardized to have unit standard deviations in the full sample period. OLS point estimates are multiplied by 100 for readability. EWC p -values following Lazarus et al. (2018) are reported in parentheses. All regressions control for the past one-year excess returns.

	Asset-Class Specific				Business-Cycle				
	CAY	D/P	EXPD	NTIS	N-IP	TERM	DEFAULT	F1	VIX ²
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Individual (NX)									
γ_1	1.31	2.44	1.99	2.66	2.26	3.34	2.56	2.44	2.27
(p -value)	(0.16)	(0.00)	(0.02)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)	(0.00)
γ_2	-0.02	0.02	0.01	-0.02	0.04	0.03	0.01	0.02	0.00
(p -value)	(0.08)	(0.20)	(0.49)	(0.12)	(0.04)	(0.01)	(0.62)	(0.02)	(0.84)
γ_3	0.82	-0.90	-0.26	0.79	-1.34	-1.43	-0.46	-0.66	-0.08
(p -value)	(0.10)	(0.09)	(0.56)	(0.13)	(0.03)	(0.01)	(0.23)	(0.00)	(0.65)
Adj. R^2	0.44	0.24	0.22	0.24	0.30	0.31	0.25	0.26	0.23
N	142	142	142	142	143	143	143	142	143
B. CFO									
γ_1	1.88	2.34	0.56	1.80	2.66	1.71	2.98	3.41	2.28
(p -value)	(0.02)	(0.01)	(0.04)	(0.23)	(0.16)	(0.20)	(0.02)	(0.04)	(0.01)
γ_2	-0.02	0.00	-0.01	0.01	0.02	0.02	0.00	0.01	0.01
(p -value)	(0.41)	(0.81)	(0.38)	(0.60)	(0.39)	(0.13)	(0.85)	(0.33)	(0.25)
γ_3	0.92	-0.34	0.15	-0.06	-0.88	-0.49	-0.36	-0.49	-0.28
(p -value)	(0.37)	(0.26)	(0.78)	(0.92)	(0.46)	(0.42)	(0.36)	(0.08)	(0.18)
Adj. R^2	0.17	0.19	0.34	0.19	0.21	0.47	0.21	0.18	0.21
N	77	77	77	77	79	79	79	77	79
C. Livingston									
γ_1	6.95	6.74	7.81	6.50	6.00	5.48	3.98	4.45	6.62
(p -value)	(0.01)	(0.03)	(0.01)	(0.15)	(0.28)	(0.11)	(0.20)	(0.24)	(0.08)
γ_2	-0.05	-0.00	0.01	0.01	0.07	-0.01	0.02	0.01	-0.02
(p -value)	(0.09)	(0.98)	(0.59)	(0.84)	(0.10)	(0.86)	(0.64)	(0.60)	(0.41)
γ_3	2.34	0.24	-1.36	-0.38	-2.12	0.74	0.49	0.34	0.58
(p -value)	(0.19)	(0.82)	(0.47)	(0.85)	(0.51)	(0.70)	(0.73)	(0.83)	(0.24)
Adj. R^2	0.30	0.24	0.25	0.24	0.36	0.25	0.28	0.31	0.25
N	138	138	138	138	139	139	139	122	139

where ε_t denote the survey expectations residual at time t . [Coibion and Gorodnichenko \(2015\)](#) find that forecasters take on average about six to seven months to fully update their forecasts, so a four-quarter lag ensures that information rigidities should not have much effect on the estimates of persistence.

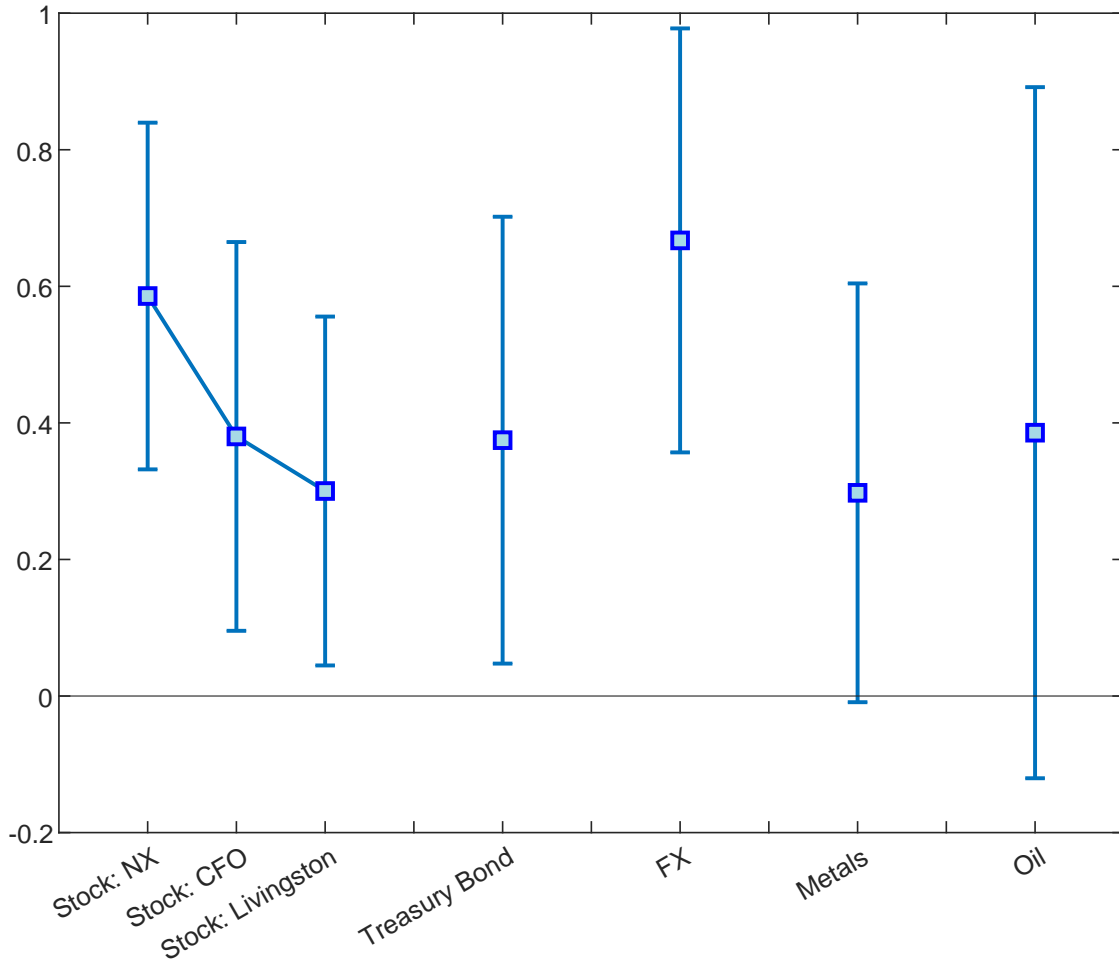


FIGURE G.1
Persistence of Subjective Risk Premium Residuals

Blue squares plot the estimated fourth-order serial correlation $\hat{\rho}$ of residuals from regressing subjective risk premia on past one-year excess returns and (for stocks) the fitted perceived variance measure. All point estimates are adjusted for finite-sample bias. The vertical error bars indicate the interval of \pm two standard errors.

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