Dynamics of Subjective Risk Premia

Stefan Nagel*
University of Chicago, NBER, CEPR, and CESifo

Zhengyang Xu†
City University of Hong Kong

August 31, 2021

PRELIMINARY AND INCOMPLETE

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 predictive regressions with realized excess returns suggest that objective risk premia vary countercyclically with business cycle variables and aggregate asset valuation measures, we find that subjective risk premia do not comove much with these variables. This lack of cyclicality of subjective risk premia is a pervasive property that holds in expectations of different groups of market participants and in different asset classes. These findings casts doubt on models that explain time-varying objective risk premia with countercyclical variation in perceived risk or risk aversion. However, we do find a link between *subjective* perceptions of risk and subjective risk premia, which points toward a positive risk-return tradeoff in subjective beliefs.

*University of Chicago, Booth School of Business, 5807 South Woodlawn Avenue, Chicago, IL 60637, e-mail: stefan.nagel@chicagobooth.edu

†City University of Hong Kong, Department of Economics and Finance, 83 Tat Chee Avenue, Kowloon, Hong Kong, e-mail: zhengyxu@cityu.edu.hk

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 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, risk premia are countercyclical, i.e., higher in recessions than in booms.

These findings sparked a large literature of rational expectations asset pricing models in which time-varying risk premia are generated via time-varying risk or time-varying risk aversion (Cochrane 2017). In these models, investors are endowed with perfect knowledge of the underlying stochastic processes and their parameters. 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 for the business cycle and asset-class specific valuation cycles: Subjective risk premia are substantially less cyclical than objec-

tive risk premia inferred from predictive regressions. This calls into question the common practice of equating time-varying in objective risk premia with time-varying risk aversion or time-varying risk. Subjectively perceived risks or risk aversion appear to be substantially less sensitive to cyclical state variables than is assumed in rational expectations 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 cyclicality 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, such as, for example, the dividend-price ratio for stock market returns, interest-rate cycles 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 yields 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 the predictable component of realized excess returns does.

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 predictive regressions using empirically realized returns.

Overall, combining the evidence from asset-specific predictors and the common cyclical predictors and all asset classes and surveys, we find that the average absolute magnitude by which a one standard deviation change in a predictor moves the subjective expected excess return is only about one quarter to one third of the average absolute magnitude by which it moves the objective expected excess return according to the predictive regression evidence using realized returns.

In some sense, this one-quarter estimate is still an overstatement of the degree of alignment of subjective and objective risk premia as the coefficients for survey expected excess returns and in predictive regressions have opposite signs in some cases. Much of the earlier literature on subjective return expectations has focused on whether the sign lines up with predictive regressions. For example, for stock market return expectations, Greenwood and Shleifer (2014) emphasize the procyclicality of individual investor return expectations. In contrast, Dahlquist and Ibert (2021) find that professional forecasters in the Livingston survey as well as asset managers issue countercyclical forecasts (see, also, Wu (2018), Wang (2021)). 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 returns in predictive regressions (and in rational expectations models built to match the predictive regression evidence).

Our findings are closely related to earlier work by Piazzesi et al. (2015) who show that subjective bond risk premia are less cyclical than predictive regression forecasts.[1] We show that this relative lack of cyclicality 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; it also holds in surveys of individual investors, CFOs, and professionals.

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. In contrast, models that produce volatile stock prices through varying expectations of fundamentals growth, e.g., via perpetual learning (Collin-Dufresne et al. (2017), Nagel and Xu (2021)) or diagnostic expectations (Bordalo et al. (2021)) with constant subjective risk premia are consistent with our evidence that subjective risk premia do not comove with cyclical indicators and excess return predictors. In a similar vein, our evidence supports 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 (2021) are not consistent with a complete lack of co-movement between state variables that predict realized excess returns and subjective risk premia. In these models, a positive correlation

[1] Other papers provide evidence that is related, but does not quite pin down the time-variation in the subjective risk premium for aggregate asset classes. Bacchetta et al. (2009) show that country-level, professional forecasters' subjective expectations errors for currency excess 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 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 is 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 co-movement of the price-dividend ratio with the subjective risk premium.

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 (2021) show, this positive relationship can be quite weak in a calibrated version of their model, which could be broadly consistent with the lack of cyclicality 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.

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, professional forecasters) we find a positive link between the level of subjective perceived stock market risk and their subjective risk premia. In other words, in terms of subjective beliefs, there is a positive risk-return tradeoff. The dynamics of perceived risks are heterogeneous between different groups of market participants, though. For example, professional investors' subjectively perceived stock market risk is more closely related to the VIX index than the risk perceived by respondents in the CFO survey. As documented recently by Lochstoer and Muir (2019), the CFO survey respondents seem to put substantially more weight on realized variance during the past year than the VIX does.

The paper is organized as follows. Section 2 introduces the data. Section 3 presents the main results on the cyclicality of subjective and objective risk premia. Section 4 looks at the subjective risk-return tradeoff. Section 5 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. 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 from the Livingston survey. The individual investor series is from Nagel and Xu (2021). It covers several surveys in the period 1972 to 1977 and has continuous quarterly coverage from 1987 onwards. 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 2000 Q3 at quarterly frequency (with gaps) and we directly use the mean respondents' expected return each period. 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 onwards, we use the ratio of twelve-month to zero-month mean level forecasts of the S&P500 stock index (or its predecessors) to measure price growth expectations. In earlier period, where the zero-month nowcast is not available, we use the annualized ratio of twelve-

month to six month forecasts. We adjust this price growth expectations with dividend yield to arrive at return expectations.[2]

For each subjective one-year expected equity 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,

$$\tilde{\mathbb{E}}_t R^e_{t+1} = \tilde{\mathbb{E}}_t R_{t+1} - R_{f,t} \tag{1}$$

For comparison, we also examine realized equity returns on the CRSP value-weighted index over the one-year forecast period that are also expressed as excess return 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. The forecasts are forecasts of 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 forecast 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

[2] We use the following decomposition:

$$\tilde{\mathbb{E}}_t R_{t+1} = \frac{\tilde{\mathbb{E}}_t P_{t+1}}{P_t} + \frac{D_t}{P_t} \tilde{\mathbb{E}}_t \left(\frac{D_{t+1}}{D_t} \right) - 1.$$

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.

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 equity market, we report the excess returns on the aggregate stock market. For Treasury bonds, we report the equal-weighted average excess returns with maturities of two, five, seven, and ten years. For foreign exchange, we report the average excess returns on the basket of developed currencies. For commodities, we report the buy-and-hold excess returns on metals and energy, respectively. Sample periods of survey expectations are reported in terms of survey time.

	Frequency	Sample Period	Mean	S.D.
A. Equity				
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	1942/04–2020/12	1.26	4.77
BCFF	Monthly	1988/01–2020/12	-0.76	1.70
C. Foreign exchange				
Realized	Monthly	1984/10–2021/06	1.78	9.76
CE	Monthly	1986/08–2021/06	0.36	3.14
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, Energy	Monthly	1984/12–2021/06	8.49	33.68
CE, Energy	Monthly	1995/08–2021/06	2.46	9.70

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

$$\tilde{\mathbb{E}}_t R^n_{t+1} \equiv \tilde{\mathbb{E}}_t \left[\frac{(1+Y^n_t)^n}{\left(1+Y^{n-1}_{t+1}\right)^{n-1}} - 1 \right] \approx \frac{(1+Y^n_t)^n}{\left(1+\tilde{\mathbb{E}}_t Y^{n-1}_{t+1}\right)^{n-1}} - 1. \tag{2}$$

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

To compare subjective risk premium with realized excess returns, we use the CRSP Treasury Index returns for maturities $n \in \{2,5,7,10\}$. As for subjective expected excess return, we form an equal-weighted aggregate 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 $\tilde{\mathbb{E}}_t S^i_{t+1}$ of the one-year ahead spot exchange rate S^i_{t+1} 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

$$\tilde{\mathbb{E}}_t R^e_{t+1} \equiv \tilde{\mathbb{E}}_t \left[\frac{F_t}{S_{t+1}} - 1 \right] \approx \frac{F^i_t}{\tilde{\mathbb{E}}_t S^i_{t+1}} - 1, \tag{3}$$

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 return on the developed market currency portfolio as an equal-weighted average of the individual currencies' $\tilde{\mathbb{E}}_t R_{t+1}^e$.

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

2.1.4 Commodity futures market

We use commodity spot price forecasts to compute 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.[3] We use the set of commodities with the longest history and highest coverage in CE: the energy sector includes Crude Oil (WTI); the metals sector includes Gold, Silver, Aluminum, and Copper. These commodites are also the major components of the S&P GSCI index. Since CE commodity forecasts are also for quarterly average, we use the same linear interpolation as before 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, with one-year futures price F_t, and holding it gets settled at maturity at $t+1$ at the spot price S_{t+1} (or the futures position exited very close to maturity at a futures price very close to the spot price):

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

[3] 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.

We obtain spot price and futures data from Datastream and Bloomberg. When spot price data is not avalialble for a commodity, we follow Koijen et al. (2018) and extrapolate spot prices from Bloomberg generic futures data. We construct two sector-level subjective risk premium series, one for metals and one for energy, by taking equal-weighted average of individual subjective expected excess returns within each sector.

We construct realized excess returns along similar lines as $R^e_{t+1} = S_{t+1}/F_t$, with equal-weighted averages within the energy and metals sectors.

2.2 Return Predictors and Cyclical Indicators

In this section we introduce the main return predictors and cyclical indicators that will be used in later 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 below 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 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 (2021), 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 the equal-weighted average bond excess returns as described in Appendix on lagged

principle components of a broad set of macro variables. We use the six-factor version of their model. The second 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 (Forthcoming) on trend inflation to obtain the short-maturity cycle and the average longer-maturity cycles. The fitted value from regressing the equal-weighted average bond excess returns on these two cycle components is then the cycle factor.

In our analysis of foreign exchange, we consider a US investor's position in a portfolio of 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 we construct the forward discount,

$$FD_t \equiv \frac{F_t}{S_t} - 1, \tag{5}$$

from one-year forward rates F_t and spot rates S_t. We then average these currency-level forward discount across all currencies in the portfolio.

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

$$Basis_t \equiv \frac{F_t}{S_t} - 1, \tag{6}$$

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 separately among all energy and metals futures, respectively. The second predictor is open interest growth following Hong and Yogo (2012). Using data from Commitments of Traders, we multiply open interests 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.[4] We then sum up dollar open interests within each sector. As a final step, we calculate percentage growth rates over one-year periods.

[4] For Aluminum, we use open interest data from London Metal Exchange instead given the limited coverage of Aluminum from Commitments of Traders.

2.2.2 Cyclical Indicators

The first cyclical 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).[5] 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 values from this regression.[6] All cyclical indicators are available at a monthly frequency. We lag N-IP and F1 by one-month to account for publication lags.

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

[6] 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.

TABLE 2
Correlations of Return Predictors and Cyclical Indicators

This table reports the unconditional correlations of return predictors and cyclical indicators. For cyclical indicators, "N-IP" is the *negative* of 12-month log change in 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); "VIX^2" is the CBOE volatility index. All indicators are countercyclical. For equity, "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 (2021); "NTIS" is the net equity expansion from Welch and Goyal (2008). For Treasury bond, "LN" is the macro factor from Ludvigson and Ng (2009); "Cycle" is the cycle factor from Cieslak and Povala (2015). For currency, "Avg. FD" is the average forward discount on the basket of developed currencies. For commodity, "Basis" is the percentage difference between futures and spot prices; "OI" is the open interest growth. "M" and "E" in the last block denote metals and energy, respectively.

	N-IP	Term	Default	F1	VIX^2	CAY	D/P	EXPD	NTIS	LN	Cycle	Avg. 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					
Avg. 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

3 Dynamics of Subjective and Objective Risk Premia

We now examine how much variation in subjective and objective expectations is associated with movements in the asset-class specific predictors and the cyclical indicators. We regress subjective expected excess returns from surveys on the predictor variables and compare the results to regressions in which realized excess returns are the dependent variable. For ease of interpretation, we standardize all predictor variables to have unit standard deviations in the full sample that we use in the predictive regressions to estimate objective risk premium dynamics. With standardized predictors we can compare amount of variation in objective and subjective risk premia by comparing the magnitudes of slope coefficients in regressions with subjective expected excess returns as dependent variable and those with realized excess returns as dependent variable. 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 realized return measurement with the one-year forecast horizon in our subjective expected return data, we use realized excess returns cumulated 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 a bootstrap approach to get coefficients adjusted for the predictive regression bias discussed in Stambaugh (1999). 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) test from Lazarus et al. (2018).

TABLE 3
Regressing Realized Equity Excess Returns on Predictors and Cyclical Indicators

Dependent variable is the one-year cumulative excess returns on the CRSP index. Column variables are described in Section 2.2. R^e_{past} denotes the past one-year excess returns. All independent variables are standardized to have unit standard deviations in the full sample period starting from December 1925. The first row in each block reports the OLS estimates multiplied by 100. The second row reports the bias-adjusted coefficients from bootstrap. The third row reports the EWC t-statistics following Lazarus et al. (2018). The fourth row reports the bootstrapped p-values. A stationary bootstrap is used with an optimal block length determined by Politis and White (2004). The full sample period is from December 1926 to December 2020.

	Standard Predictors								Cyclical Indicators									
	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	-7.30	-5.23	-5.23	1.74	1.49	4.13	4.13	3.32	3.26	4.24	3.92	1.49	1.26
{bias-adj.}	{3.24}	{3.71}	{6.01}	{5.83}	{-6.44}	{-7.22}	{-4.91}	{-4.87}	{1.54}	{1.23}	{4.41}	{4.48}	{2.81}	{2.75}	{4.58}	{4.13}	{1.77}	{1.53}
[t-stat]	[2.49]	[2.44]	[3.02]	[3.52]	[-2.82]	[-2.64]	[-1.81]	[-1.75]	[0.62]	[0.59]	[2.94]	[2.86]	[1.53]	[1.74]	[3.17]	[2.49]	[0.96]	[0.93]
(p-value)	(0.08)	(0.10)	(0.00)	(0.00)	(0.03)	(0.04)	(0.16)	(0.16)	(0.52)	(0.55)	(0.00)	(0.00)	(0.12)	(0.10)	(0.00)	(0.05)	(0.31)	(0.32)
R^e_{past}		-3.51		0.87		-3.46		-1.25		-0.67		-1.22		-0.21		-1.07		-0.96
{bias-adj.}		{-3.30}		{0.36}		{-3.49}		{-1.46}		{-1.09}		{-1.19}		{-0.29}		{-0.70}		{-1.18}
[t-stat]		[-1.90]		[0.37]		[-1.87]		[-0.61]		[-0.36]		[-0.52]		[-0.09]		[-0.45]		[-0.43]
(p-value)		(0.12)		(0.71)		(0.09)		(0.51)		(0.74)		(0.55)		(0.92)		(0.68)		(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	377	1117	1117	1129	1129	1129	1129	1129	1129	717	717	1129	1129

3.1 Stock market

To provide basis for comparison, Table 3 first reports the results of 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. One standard deviation move in the predictor variable is associated with a substantial change in objectively expected returns of 3.24 to 6.44 percentage points over a one-year forecast horizon after bias adjustment.

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 1.54 for N-IP to 4.58 for F1. However, without exception, for all predictors in both groups, the point estimates indicate a countercyclical pattern of objective risk premia: low after following booms, high following downturns in asset prices or the business cycle.

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

Table 4 shows the results of regressing subjective excess return expectations from different surveys on in-sample return predictors as well as past one-year returns. 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 is 1.12 with 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 4.41). Therefore, subjective expected excess returns of individual investors and CFOs vary much less with these standard predictor variables than objective risk premia do.

TABLE 4

Regressing Survey Equity Excess Return Expectations on Predictors and Cyclical Indicators

Dependent variable is the one-year-ahead excess return expectations from Nagel and Xu (2021), the CFO survey, and the Livingston survey, respectively. Column variables are described in Section 2.2. R^e_{past} denotes the past one-year excess returns. All predictors are standardized to have unit standard deviations in the full sample period starting from December 1925. The first row in each block reports the OLS estimates multiplied by 100. The second row reports the EWC p-values following Lazarus et al. (2018).

	Standard Predictors								Cyclical Indicators									
	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. 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^e_{past}		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^e_{past}		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^e_{past}		-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

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 DEFAULT) 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 (1.54 and 2.81, respectively), so there is not a great 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 between individuals/CFOs and professional forecasters in past returns' influence on expectations 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) with extrapolators and 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-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 variables and the lower frequencies that have been emphasized in macro-finance modeling of asset markets.

Figure 1 provides a visual summary of our results on objective and subjective risk premia

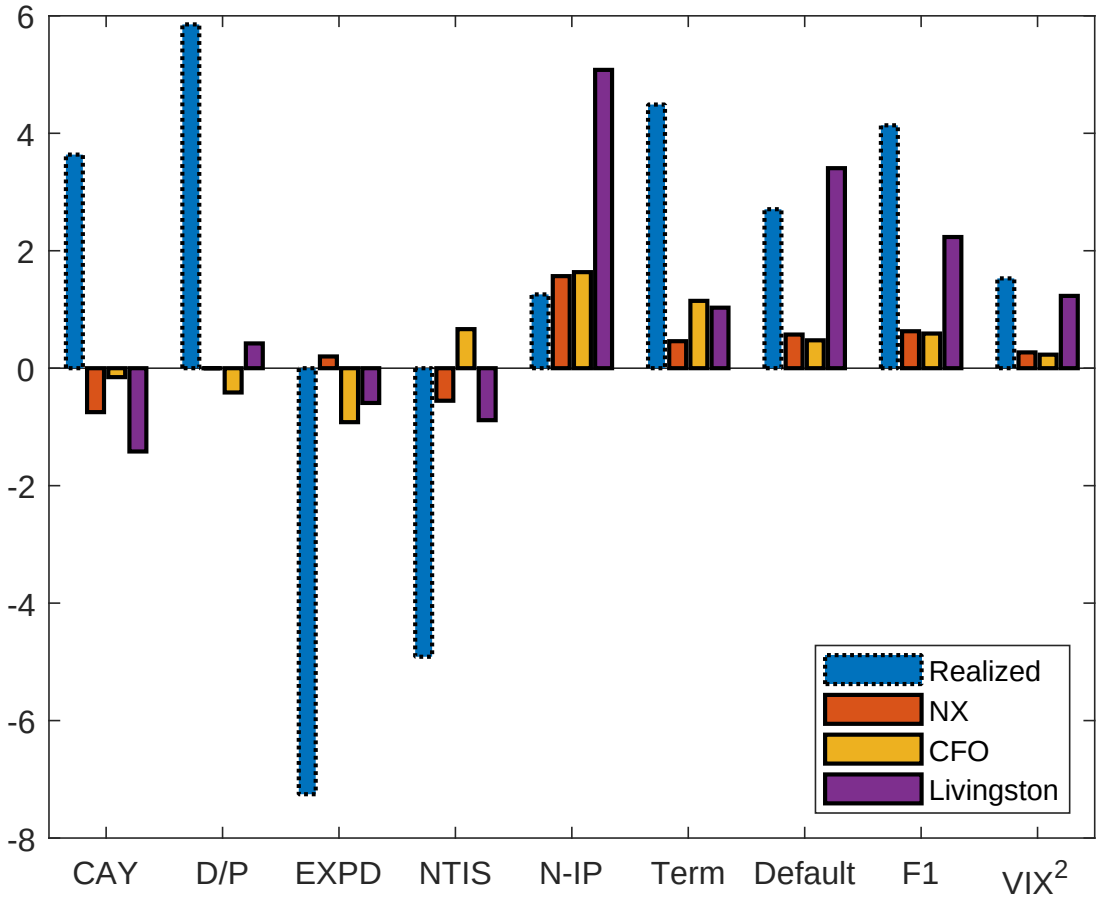


FIGURE 1
Regressing Equity Excess Returns on Predictors and Cyclical Indicators, Magnitude of Coefficients

Each bar plots the slope coefficients from regressing realized excess returns and survey excess return expectations on predictors and cyclical indicators while controlling for past one-year excess returns. The coefficients for realized excess returns are bias-adjusted using bootstrap.

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 the predictor. The blue bars show the coefficients from the realized return regressions in Table 3. The other bars show the corresponding coefficients for the same predictor with the survey expected excess returns as dependent variable as in Table 4. The figure clearly illustrates that subjective risk premia have much lower sensitivity to the 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.

In stark contrast to the results in Figure 1, in a rational expectations 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 (2021) 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 (2021) 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.

3.2 Treasury bond market

TABLE 5
Regressing Bond Excess Returns on Predictors and Cyclical Indicators

In Panel A, the 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 first row reports the OLS estimates multiplied by 100. The second row reports the bias-adjusted coefficients from bootstrap. The third row reports the EWC t-statistics following Lazarus et al. (2018). The fourth row reports the bootstrapped p-values. A stationary bootstrap is used with an optimal block length determined by Politis and White (2004). The sample period is from April 1942 to December 2020. In Panel B, the 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 first row reports the OLS estimates multiplied by 100. The second row reports the EWC p-values following Lazarus et al. (2018). The sample period is from January 1988 to December 2018. Column variables are described in Section 2.2. RX^e_{past} denotes the past one-year equal-weighted average excess returns. All independent variables are standardized to have unit standard deviations in the full sample period starting from December 1925.

	Standard Predictors				Cyclical Indicators									
	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	0.30	0.32	1.45	1.83	1.19	1.30	1.00	1.07	0.30	0.31
{bias-adj.}	{1.93}	{2.32}	{2.31}	{2.38}	{0.36}	{0.39}	{1.49}	{1.90}	{1.36}	{1.43}	{1.07}	{1.12}	{0.28}	{0.35}
[t-stat]	[4.83]	[4.61]	[3.97]	[3.94]	[0.68]	[0.61]	[2.95]	[4.10]	[1.92]	[1.60]	[1.94]	[1.63]	[1.12]	[1.16]
(p-value)	(0.00)	(0.00)	(0.02)	(0.01)	(0.57)	(0.56)	(0.00)	(0.00)	(0.07)	(0.11)	(0.04)	(0.07)	(0.23)	(0.20)
RX^e_{past}		-0.84		-0.15		-0.06		-0.81		-0.20		-0.20		-0.06
{bias-adj.}		{-0.80}		{-0.36}		{0.01}		{-0.82}		{-0.13}		{-0.09}		{0.06}
[t-stat]		[-1.22]		[-0.31]		[-0.10]		[-1.68]		[-0.29]		[-0.28]		[-0.11]
(p-value)		(0.20)		(0.78)		(0.88)		(0.11)		(0.74)		(0.77)		(0.93)
Adj. R^2	0.14	0.16	0.24	0.24	0.00	-0.00	0.09	0.11	0.02	0.02	0.03	0.03	0.00	0.00
N	717	717	578	578	945	933	945	933	945	933	717	717	945	933
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)
RX^e_{past}		-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

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 1.93 and 2.31, respectively. This means that a one standard deviation move in the predictor is associated with between 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 the CYCLE predictor variable, but at 0.83 the magnitude is still much smaller than in Panel A (2.31). Including excess returns over the past year as an additional predictor variable generally has very little effect, both in Panel A and B.

Figure 2 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 returns, shown as blue bars, and regressions with subjective expected excess returns, shown as red bars. Thus, in the Treasury bond

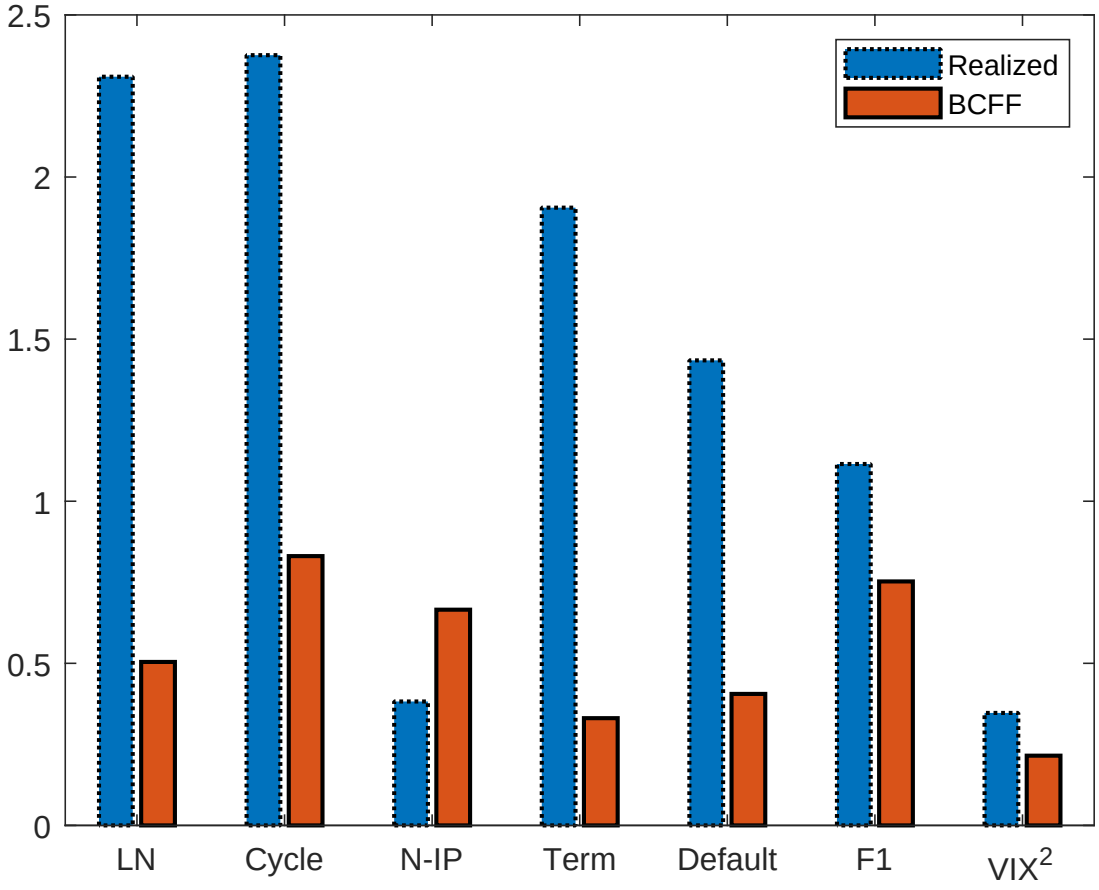


FIGURE 2
Regressing Bond Excess Returns on Predictors and Cyclical Indicators, Magnitude of Coefficients

Each bar plots the slope coefficients from regressing equally-weighted average of realized excess returns and survey excess return expectations on predictors and cyclical indicators while controlling for past one-year excess returns. The coefficients for realized excess returns are bias-adjusted using bootstrap.

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 premium on the developed 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 premium 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 3 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 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.

TABLE 6

Regressing Average FX Excess Returns on Predictors and Cyclical Indicators

In Panel A, the dependent variable is the average realized one-year excess returns on the basket of developed currencies. The first row reports the OLS estimates multiplied by 100. The second row reports the bias-adjusted coefficients from bootstrap. The third row reports the EWC t-statistics following Lazarus et al. (2018). The fourth row reports the bootstrapped p-values. A stationary bootstrap is used with an optimal block length determined by Politis and White (2004). The sample period is from October 1984 to June 2021. In Panel B, the dependent variable is the average one-year-ahead excess return expectations from CE and FX4casts. The first row reports the OLS estimates multiplied by 100. The second row reports the EWC p-values following Lazarus et al. (2018). The sample period is from August 1986 to June 2021. Column variables are described in Section 2.2. RX^e_{past} denotes the past one-year excess returns. All independent variables are standardized to have unit standard deviations in the full sample period starting from December 1925.

	Standard Predictors		Cyclical Indicators									
	Avg. 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}
[t-stat]	[2.90]	[2.47]	[2.81]	[2.36]	[1.33]	[1.20]	[2.37]	[2.65]	[2.09]	[1.79]	[2.35]	[2.15]
(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)
RX^e_{past}		-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}
[t-stat]		[-0.81]		[0.57]		[0.04]		[0.46]		[0.47]		[0.51]
(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)
RX^e_{past}		-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

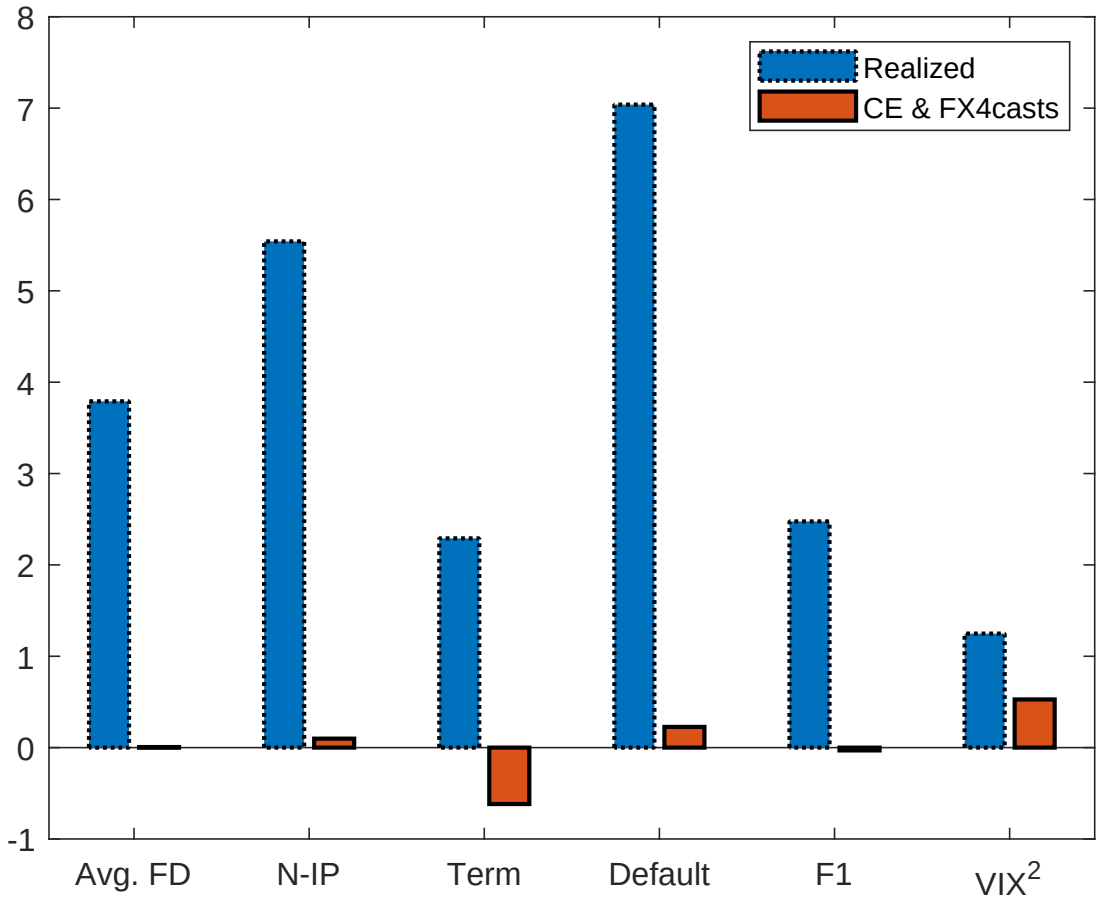


FIGURE 3
Regressing Average FX Excess Returns on Predictors and Cyclical Indicators, Magnitude of Coefficients

Each bar plots the slope coefficients from regressing average realized one-year excess returns and survey excess return expectations of developed currencies on predictors and cyclical indicators while controlling for past one-year excess returns. The coefficients for realized excess returns are bias-adjusted using bootstrap.

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 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 4 illustrates this graphically.

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.

TABLE 7

Regressing Average Metals Excess Buy-and-Hold Returns on Predictors

In Panel A, the dependent variable is the average realized one-year buy-and-hold excess returns on metals. The first row reports the OLS estimates multiplied by 100. The second row reports the bias-adjusted coefficients from bootstrap. The third row reports the EWC t-statistics following Lazarus et al. (2018). The fourth row reports the bootstrapped p-values. A stationary bootstrap is used with an optimal block length determined by Politis and White (2004). The sample period is from September 1978 to June 2021. In Panel B, the dependent variable is the average one-year-ahead buy-and-hold excess return expectations from CE. The first row reports the OLS estimates multiplied by 100. The second row reports the EWC p-values following Lazarus et al. (2018). The sample period is from August 1995 to June 2021. Column variables are described in Section 2.2. R^e_{past} denotes the average past one-year excess returns. All independent variables are standardized to have unit standard deviations in the full sample period starting from December 1925.

	Standard Predictors				Cyclical Indicators									
	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}
[t-stat]	[-1.61]	[-1.35]	[1.96]	[1.62]	[0.70]	[0.92]	[0.35]	[0.47]	[-0.54]	[-0.22]	[-0.30]	[0.06]	[1.99]	[2.55]
(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^e_{past}		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}
[t-stat]		[1.07]		[0.36]		[1.32]		[1.55]		[1.14]		[1.31]		[1.59]
(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^e_{past}		-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

3.4.2 Energy

Table 8 presents the results for energy futures excess returns. 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.

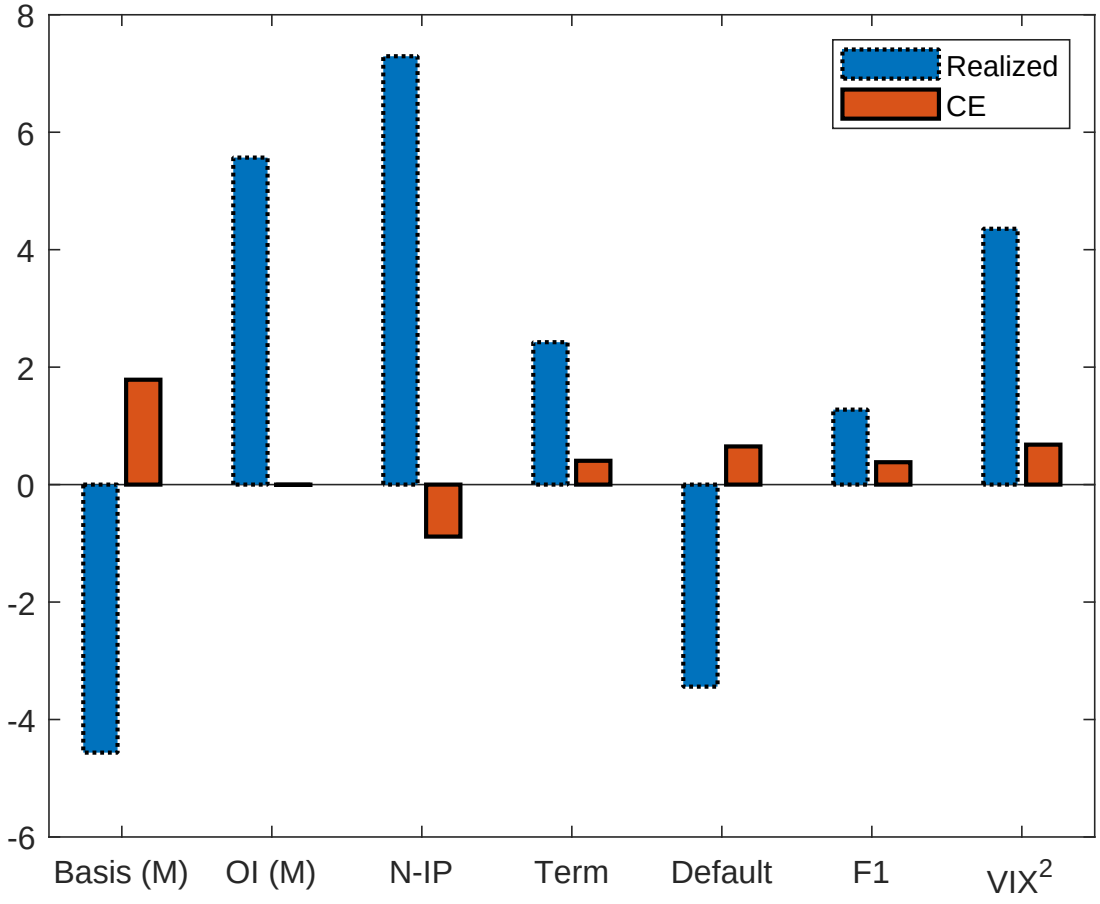


FIGURE 4
Regressing Average Metals Excess Buy-and-Hold Returns on Predictors and Cyclical Indicators, Magnitude of Coefficients

Each bar plots the slope coefficients from regressing average realized one-year buy-and-hold excess returns and survey excess return expectations of metal futures on predictors and cyclical indicators while controlling for past one-year excess returns. The coefficients for realized excess returns are bias-adjusted using bootstrap.

TABLE 8

Regressing Average Energy Excess Buy-and-Hold Returns on Predictors

In Panel A, the dependent variable is the average realized one-year buy-and-hold excess returns on energy. The first row reports the OLS estimates multiplied by 100. The second row reports the bias-adjusted coefficients from bootstrap. The third row reports the EWC t-statistics following Lazarus et al. (2018). The fourth row reports the bootstrapped p-values. A stationary bootstrap is used with an optimal block length determined by Politis and White (2004). The sample period is from December 1984 to June 2021. In Panel B, the dependent variable is the average one-year-ahead buy-and-hold excess return expectations from CE. The first row reports the OLS estimates multiplied by 100. The second row reports the EWC p-values following Lazarus et al. (2018). The sample period is from August 1995 to June 2021. Column variables are described in Section 2.2. R_{past} denotes the average past one-year buy-and-hold returns. All independent variables are standardized to have unit standard deviations in the full sample period starting from December 1925.

	Standard Predictors				Cyclical Indicators									
	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}
[t-stat]	[0.27]	[-0.12]	[0.08]	[0.74]	[1.35]	[0.83]	[-0.80]	[-0.74]	[0.42]	[0.29]	[-0.18]	[-0.63]	[1.57]	[1.38]
(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^e_{past}		-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}
[t-stat]		[-0.52]		[-0.90]		[-0.33]		[-0.62]		[-0.47]		[-0.66]		[-0.41]
(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^e_{past}		-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

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. DEFAULT in column (10) is statistically significant only when past returns are controlled for. Figure 5 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.

3.5 Some variations and summary

Figure 6 summarizes the results across all asset classes. For each survey, we first calculate the following ratio of average absolute coefficients:

$$M \equiv \frac{\sum_{k \in \mathbb{K}} |\beta_k^{Sub}|}{\sum_{k \in \mathbb{K}} |\beta_k^{Adj}|}, \tag{7}$$

where β_k^{Sub} is the slope coefficient on return predictor or cyclical indicator k from regressing survey excess return expectations, β_k^{Adj} is the bias-adjusted coefficient from regressing realized excess returns, and $\mathbb{K}$ is the group of return predictors and cyclical indicators considered. The final measure is calculated by first taking the average of M within asset classes (if there are multiple surveys) then across asset classes.[7]

To explore the robustness of our conclusions, we report results from several different specifications. First, we use coefficient point estimates obtained with (Control) our 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

[7] We treat metals and energy as in the same asset class. Treating them as separate asset classes does not quantitatively change the results.

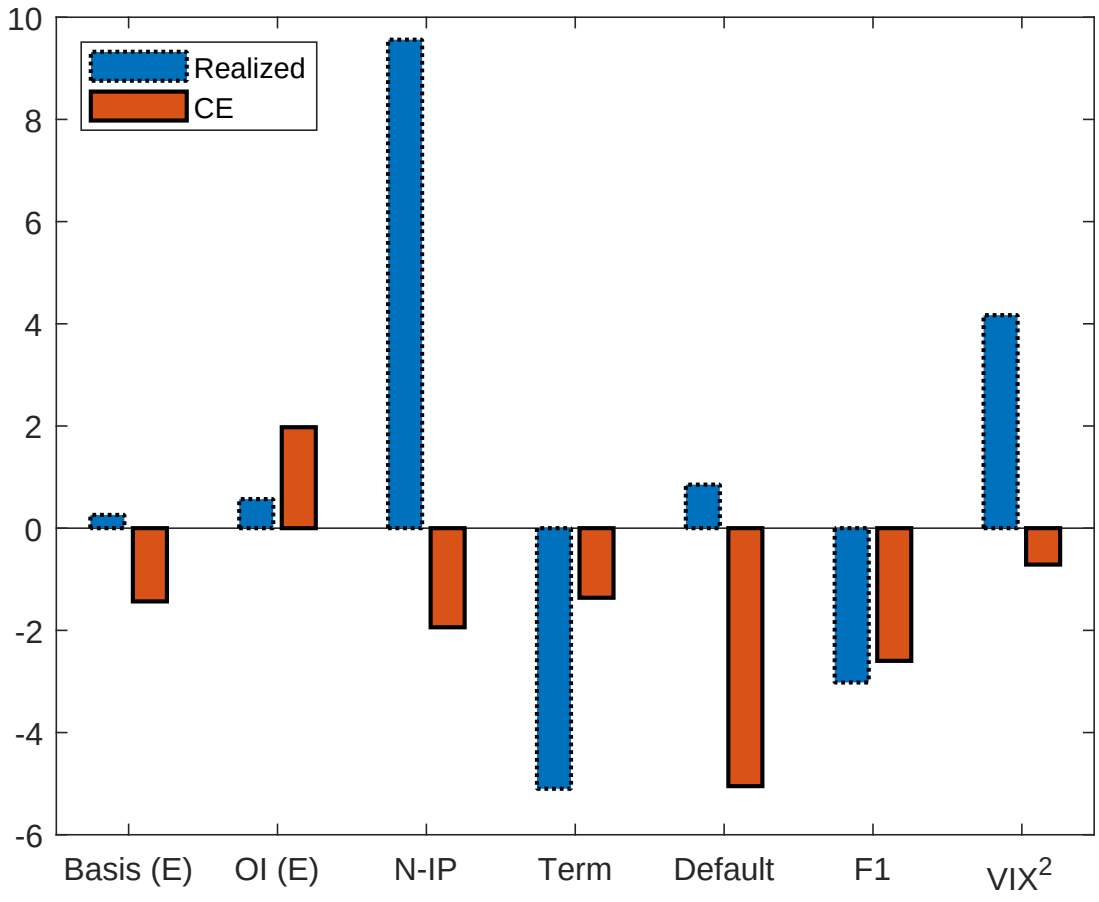


FIGURE 5
Regressing Average Energy Excess Buy-and-Hold Returns on Predictors and Cyclical Indicators, Magnitude of Coefficients

Each bar plots the slope coefficients from regressing average realized one-year buy-and-hold excess returns and survey excess return expectations of energy futures on predictors and cyclical indicators while controlling for past one-year excess returns. The coefficients for realized excess returns are bias-adjusted using bootstrap.

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 6, 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 bars on the left-hand side of the figure show the results. Based on the comparison of the first two bars with the third and fourth bar, including or not including past returns has very little effect on the ratio of absolute coefficients for objective and subjective premia. In both cases, we get a ratio of about 0.30. Using the full sample for realized returns (second and fourth bar) or a shorter sample matched to the survey data set (first and third bar) does not have much effect on the results either. The ratio stays around 0.30. Overall, there is substantially less variation of subjective risk premia with the predictor variables

One potential concern about the analysis so far could be that the set of predictors might contain some that are just 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 ratio toward one.

For this reason, the last two bars on the right-hand side focus, 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. According to rational expectations logic, these predictor variables are the prime candidates to capture the true variation in objective risk premia. As the figure shows, for these variables,

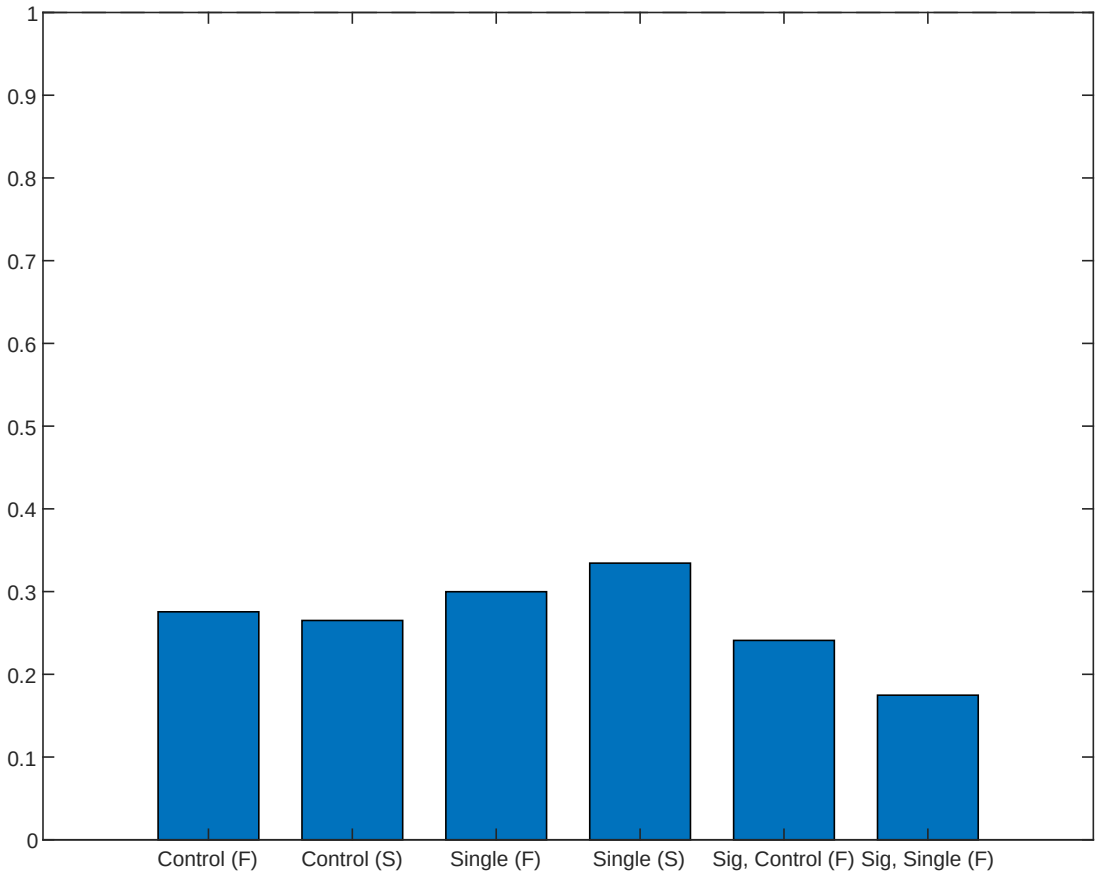


FIGURE 6
Relative Magnitude of Coefficients

In each bar, we first calculate the following ratio for each survey:

$$M \equiv \frac{\sum_{k\in\mathbb{K}} |\beta_k^{Sub}|}{\sum_{k\in\mathbb{K}} |\beta_k^{Adj}|},$$

where β_k^{Sub} is the slope coefficient on return predictor or cyclical indicator k from regressing survey excess return expectations, β_k^{Adj} is the bias-adjusted coefficient from regressing realized excess returns, and $\mathbb{K}$ is the group of return predictors and cyclical indicators considered. We then take the average of M within each asset class if there are multiple surveys and finally across asset classes. "(F)" denotes estimates using the full sample; "(S)" denotes estimates using the matched-to-survey sample; "Control" and "Single" denote estimates with and without controlling for past excess returns, respectively; "Sig" denotes measures using selected predictors whose full-sample p-values are smaller than 0.05.

the relative magnitude of the subjective expected excess return regression coefficients is even lower than 0.30. Depending on whether we include past returns in the regression or not, we obtain a ratio of slightly above or below 0.20.

In some sense, the ratio of around 0.20 is a conservative assessment of how well objective risk premia variation is matched by subjective risk premia variation because this ratio of absolute coefficients does not take into account directional mismatch between the movements of subjective and objective risk premia. As we showed earlier, for some predictors the sign of the slope coefficient is different in the realized excess return regressions and the subjective expected excess return regressions.

4 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 (2019), we construct three proxies of perceived stock market

risk. The first measure is 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 convert the range between these percentiles into an estimate of respondents' subjective variance by taking the square of the range and dividing by 2.56^2 (which would be accurate if the distribution was normal). The remaining two measures are constructed from the United States Crash Confidence Index from the International Center for Finance at Yale (Shiller (2000), Goetzmann et al. (2016)). This index has two series, one for individuals and one for institutions. They are calculated as the percent of population who attach little probability to a stock market crash in the next six months.[8] We take the negative of this index to proxy for the level of individuals' and institutions' perceived crash risk. Surveys were initially conducted at six-month intervals.[9] Starting in July 2001, the index reports a six-month moving average of monthly surveys. We match this moving average to surveys in the following months. Thus, for example, the index for November 2018 is an average of results from surveys between June 208 and November 2018, and we match this index to Livingston survey subjective return expectations in December 2018 (obtained from surveys conducted in November). For individual investor expectations, we match expectations from the first quarter of 2019 to the index moving level in December 2018.

Our interest now centers on the relationship between perceived risk and subjective excess return expectations. Figure 7 plots the subjective variance data for the CFO survey and the subjective expected excess return series. 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.

[8] The exact survey question is: "What do you think is the probability of a catastrophic stock market crash in the U. S., like that of October 28, 1929 or October 19, 1987, in the next six months, including the case that a crash occurred in the other countries and spreads to the U. S.?"

[9] The survey dates (first mailing dates) were: July 5, 1989; January 17, 1990; July 27, 1990; January 31, 1991; August 20, 1991; January 31, 1992; August 20, 1992; February 12, 1993; August 6, 1993; February 28, 1994; September 8, 1994; March 4, 1995; September 1, 1995; March 1, 1996; July 30, 1996; March 17, 1997; September 5, 1997; March 2, 1998; and September 9, 1998.

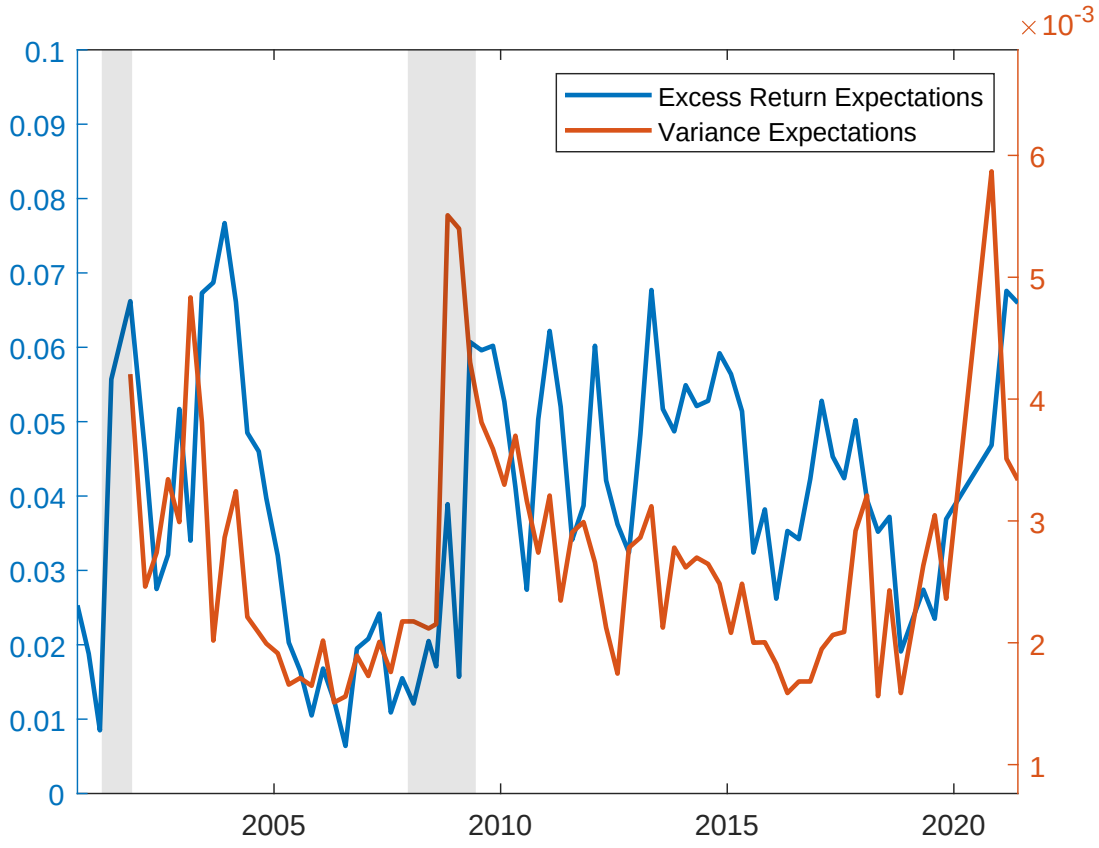


FIGURE 7
Excess Return Expectations and Variance Expectations

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 expectations of 90th and 10th percentiles of returns divided by 2.56^2, also from the CFO survey. The grey-shaded areas indicate NBER recessions.

Table 9 presents the results in regression form. In addition to the CFO survey subjective risk and expected return series, we also examine the relationship of individual investor and Livingston survey subjective risk premia to the (negative of) the individual and institutional investor crash confidence indices. To facilitate interpretation, we standardize the crash confidence series to unit standard deviations. We do not standardize the subjective variance series from the CFO survey, as the slope coefficient in a regression of subjective expected excess returns on subjective variance then has a natural economic interpretation as a relative risk aversion coefficient (in a model where the representative investor's wealth is fully invested in the stock market).

Columns (1) and (2) show that for individual investors there is a weak positive relationship between individuals' perceived risk of a stock market crash and their subjective expected excess returns. The relationship is not statistically significant, however. Controlling for past returns in column (2) raises the magnitude of the coefficient on perceived risk, but it is still statistically insignificant at conventional levels ($p = 0.11$). The coefficient of 0.60 implies that a one standard deviation rise in the perceived risk measure is associated with an increase of 0.60pp in the subjective risk premium. For comparison, this is somewhat weaker than the effect of past returns, where a one standard deviation change is associated with a change of 1.01pp in the subjective risk premium.

Columns (3) and (4) show the results for the CFO survey data. As anticipated from Figure 7, subjective variance is positively related to the subjective risk premium. The magnitudes of the slope coefficient estimates are also economically plausible as they would imply a relative risk aversion somewhere between 6 and 9. The strong link between subjective 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 variance expectations contain 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

TABLE 9
Excess Return Expectations and Variance Expectations

In Columns (1)–(6), the dependent variable is the one-year-ahead excess return expectations from surveys. "Var. Exp." is from the CFO survey and calculated as the square of interdecile range divided by 2.56^2. "Crash (Indiv.)" and "Crash (Insti.)" denote the negative of standardized Crash Confidence Index of individuals and institutions, respectively. R^e_{past} are standardized one-year excess returns that have unit standard deviations in the full sample period starting from December 1925. We report the OLS estimates and the EWC p-values following Lazarus et al. (2018) in parentheses. Estimates on Crash Indexes are multiplied by 100.

	NX		CFO		Livingston	
	(1)	(2)	(3)	(4)	(5)	(6)
Const	0.08	0.09	0.02	0.01	0.19	0.17
(p-value)	(0.00)	(0.00)	(0.06)	(0.25)	(0.03)	(0.02)
Crash (Indiv.)	0.38	0.60				
(p-value)	(0.36)	(0.11)				
Var. Exp.			6.72	8.65		
(p-value)			(0.06)	(0.04)		
Crash (Insti.)					2.53	1.76
(p-value)					(0.10)	(0.14)
R^e_{past}		1.01		0.74		-2.84
(p-value)		(0.00)		(0.02)		(0.00)
Adj. R^2	0.04	0.28	0.12	0.20	0.24	0.40
N	87	86	75	73	39	39

(2019). They find that CFO variance expectations load much more strongly on realized variance several months ago than VIX^2 does.

Columns (5) and (6) present the results for professional forecasters from the Livingston survey. The relationship between subjective risk premium and subjective risk, as measured by (the negative of) the institutional investor crash confidence index, is much stronger than for individuals. The point estimate in column (5) implies that a one standard deviation rise in perceived risk is associated with an increase in the subjective risk premium of 2.53pp. Statistically, however, the magnitude of the effect is rather uncertain, as the estimate is

only marginally significant ($p = 0.10$). To some extent, this is due to the small number of observations. The Livingston survey is available only semi-annually and hence we are left with a small number of observations in the part of the sample that overlaps with the investor crash confidence index series.

For the Livingston survey subjective expectations, the relationship with the risk perceptions captured by the institutional crash confidence index series is quantitatively quite similar to the relationship to VIX^2 Table 4. For comparison, a one standard deviation move in the VIX index is associated with a 1.65pp move in the subjective risk premium. In contrast to the CFO expectations, a component of perceived risk orthogonal to the VIX^2 seems to be less important for the professional forecasters subjective risk premia in the Livingston survey.

Overall, there is evidence for a positive risk-return tradeoff in subjective beliefs. At the same time, different groups of market participants appear to form subjective beliefs about risks in different ways. For example, using the institutional crash confidence index to explain individuals' subjective expected excess returns would result in a substantial deterioration in explanatory power. Further exploration of the formation of risk perceptions for different groups of market participants seems like a fruitful area for future research.

From the results in this section it is also clear that while subjective risk premia appear to vary with subjective risk perception, this variation on its own is too small to play a major role in generating empirically realistic asset price volatility. A one standard deviation change in subjective risk perceptions is associated with at most around 2.5pp movement in the subjective risk premium while a one standard deviation change in strong excess return predictors in the predictive regressions in Table 3 are associated with around 6-7pp in expected excess return movements. In addition, the movements in subjective risk risk perceptions are not highly correlated with movements in these return predictors.

5 Conclusion

Predictive regression evidence suggests that expected excess returns of major asset classes 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 cyclicality 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 is shared among all of them.

Subjective risk premia 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 is too small and 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 wedge between subjective and objective forecasts of fundamentals, such as, for example, 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.

Appendix

A Data Sources and Timing Assumptions

TO BE COMPLETED

B Bootstrap Methods for Predictive Regressions

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

$$z_{t+1} = \alpha + \beta' X_t + \eta_{t+1}, \tag{A.1}$$

$$X_{t+1} = \kappa + \phi X_t + \iota_{t+1}. \tag{A.2}$$

In addition, η_t and ι_t can potentially be correlated contemporaneously. We implement a bootstrap that involves the following steps:

1. We start with estimating a VAR(1) system for the predictors, 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 $\tilde{\kappa}$, $\tilde{\phi}$, and $\{\tilde{\iota}_t\}$.

2. We then estimate the predictive regression in (A.1) with OLS. We obtain coefficient estimates $\hat{\alpha}$, $\hat{\beta}$ and residuals $\hat{\eta}_{t+1}$. We then construct pseudo samples by bootstrapping the time-series of residual vectors $(\tilde{\iota}_t, \hat{\eta}_t)$ 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 $(\tilde{\iota}_t^i, \hat{\eta}_t^i)$, we impose the null of no predictability

by generating data as

$$z_{t+1}^{null,i} = \bar{z} + \hat{\eta}_{t+1}^{i}, \tag{A.3}$$

$$X_{t+1} = \tilde{\kappa} + \tilde{\phi} X_t + \tilde{\iota}_{t+1}^{i}. \tag{A.4}$$

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 the sample t-statistic $\hat{\tau}$. For the sample j, with bootstrapped residuals $(\tilde{\iota}_t^j, \hat{\eta}_t^j)$, we generate data under the alternative that $\beta = \hat{\beta}$ as

$$z_{t+1}^{alter,j} = \hat{\alpha} + \hat{\beta}' X_t + \hat{\eta}_{t+1}^{j}, \tag{A.5}$$

$$X_{t+1} = \tilde{\kappa} + \tilde{\phi} X_t + \tilde{\iota}_{t+1}^{j}. \tag{A.6}$$

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

References

Adam, Klaus, Albert Marcet, and Johannes Beutel, 2017, Stock price booms and expected capital gains, *American Economic Review* 107, 2352–2408.

Amihud, Yakov, Clifford M. Hurvich, and Yi Wang, 2009, Multiple-Predictor Regressions: Hypothesis Testing, *The Review of Financial Studies* 22, 413–434.

Bacchetta, Philippe, Elmar Mertens, and Eric Van Wincoop, 2009, Predictability in financial markets: What do survey expectations tell us?, *Journal of International Money and Finance* 28, 406–426.

Bansal, Ravi, and Amir Yaron, 2004, Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles, *The Journal of Finance* 59, 1481–1509.

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer, 2015, X-capm: An extrapolative capital asset pricing model, *Journal of Financial Economics* 115, 1–24.

Ben-David, Itzhak, John R. Graham, and Campbell R. Harvey, 2013, Managerial Miscalibration, *The Quarterly Journal of Economics* 128, 1547–1584.

Bordalo, Pedro, Nicola Gennaioli, Spencer Yongwook Kwon, and Andrei Shleifer, 2021, Diagnostic bubbles, *Journal of Financial Economics* 141, 1060–1077.

Campbell, John Y., and John H. Cochrane, 1999, By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior, *Journal of Political Economy* 107, 205–251.

Cieslak, Anna, and Pavol Povala, 2015, Expected returns in treasury bonds, *Review of Financial Studies* 28, 2859–2901.

Cochrane, John H, 2017, Macro-finance, *Review of Finance* 21, 945–985.

Collin-Dufresne, Pierre, Michael Johannes, and Lars A Lochstoer, 2017, Asset pricing when 'this time is different', *Review of Financial Studies* 30, 505–535.

Dahlquist, Magnus, and Markus Ibert, 2021, How cyclical are stock market return expectations? evidence from capital market assumptions, Technical report, Stockholm School of Economics.

De La O, Ricardo, and Sean Myers, 2021, Subjective cash flows and discount rates, *Journal of Finance* 76, 1339–1387.

Diebold, Francis X, and Canlin Li, 2006, Forecasting the term structure of government bond yields, *Journal of econometrics* 130, 337–364.

Goetzmann, William N, Dasol Kim, and Robert J Shiller, 2016, Crash beliefs from investor surveys, Technical report, National Bureau of Economic Research.

Gourinchas, Pierre-Olivier, and Aaron Tornell, 2004, Exchange rate puzzles and distorted beliefs, *Journal of International Economics* 64, 303–333.

Greenwood, Robin, and Andrei Shleifer, 2014, Expectations of returns and expected returns, *Review of Financial Studies* 27, 714–746.

Hong, Harrison, and Motohiro Yogo, 2012, What Does Futures Market Interest Tell Us about the Macroeconomy and Asset Prices?, *Journal of Financial Economics* 105, 473 – 490.

Jin, Lawrence J, and Pengfei Sui, 2021, Asset pricing with return extrapolation, *Journal of Financial Economics* forthcoming.

Kim, Don H, and Athanasios Orphanides, 2012, Term structure estimation with survey data on interest rate forecasts, *Journal of Financial and Quantitative Analysis* 47, 241–272.

Koijen, Ralph S.J., Tobias J. Moskowitz, Lasse Heje Pedersen, and Evert B. Vrugt, 2018, Carry, *Journal of Financial Economics* 127, 197 – 225.

Lazarus, Eben, Daniel J. Lewis, James H. Stock, and Mark W. Watson, 2018, HAR Inference: Recommendations for Practice, *Journal of Business & Economic Statistics* 36, 541–559.

Lettau, Martin, and Sydney Ludvigson, 2001, Consumption, Aggregate Wealth, and Expected Stock Returns, *The Journal of Finance* 56, 815–849.

Lettau, Martin, and Sydney C. Ludvigson, 2010, Chapter 11-measuring and modeling variation in the risk-return trade-off, in Yacine Ait-Sahalia, and Lars Peter Hansen, eds., *Handbook of Financial Econometrics: Tools and Techniques*, volume 1 of *Handbooks in Finance*, 617–690 (North-Holland, San Diego).

Liu, Yan, and Jing Cynthia Wu, Forthcoming, Reconstructing the Yield Curve, *Journal of Financial Economics* .

Lochstoer, Lars A, and Tyler Muir, 2019, Volatility expectations and returns, *Journal of Finance* forthcoming.

Ludvigson, Sydney C., and Serena Ng, 2009, Macro Factors in Bond Risk Premia, *The Review of Financial Studies* 22, 5027–5067.

Lustig, Hanno, Nikolai Roussanov, and Adrien Verdelhan, 2014, Countercyclical Currency Risk Premia, *Journal of Financial Economics* 111, 527–553.

Manela, Asaf, and Alan Moreira, 2017, News Implied Volatility and Disaster Concerns, *Journal of Financial Economics* 123, 137–162.

Nagel, Stefan, and Zhengyang Xu, 2021, Asset pricing with fading memory, *Review of Financial Studies* forthcoming.

Nicholls, D. F., and A. L. Pope, 1988, Bias in the Estimation of Multivariate Autoregressions, *Australian Journal of Statistics* 30A, 296–309.

Piazzesi, Monika, Juliana Salomao, and Martin Schneider, 2015, Trend and cycle in bond premia, Technical report, Stanford University.

Politis, Dimitris N., and Halbert White, 2004, Automatic Block-Length Selection for the Dependent Bootstrap, *Econometric Reviews* 23, 53–70.

Shiller, Robert J., 2000, Measuring Bubble Expectations and Investor Confidence, *Journal of Psychology and Financial Markets* 1, 49–60.

Stambaugh, Robert F., 1999, Predictive regressions, *Journal of Financial Economics* 54, 375–421.

Wang, Renxuan, 2021, Subjective return expectations, Technical report, Columbia University.

Welch, Ivo, and Amit Goyal, 2008, A Comprehensive Look at The Empirical Performance of Equity Premium Prediction, *The Review of Financial Studies* 21, 1455–1508.

Wu, Liuren, 2018, Estimating Risk-Return Relations with Analysts Price Targets, *Journal of Banking & Finance* 93, 183–197.