

Survey Expectations and Stock Price Theories*

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Abstract

Motivated by the observation that survey expectations are inconsistent with the notion that stock investors hold rational return expectations, we investigate whether alternative expectations hypotheses entertained in the asset pricing literature are consistent with the survey evidence. We empirically test (1) the notion that survey forecasts constitute rational but risk-neutral forecasts of future returns, and (2) the notion that survey forecasts are ambiguity averse/robust forecasts of future returns. We find that these alternative hypotheses are also strongly rejected by the data, albeit for different reasons. Hypothesis (1) is rejected because survey return forecasts are not in line with risk-free interest rates and because survey excess returns are predictable. Hypothesis (2) is rejected because agents are not always pessimistic about future returns, instead often display overly optimistic return expectations. We speculate as to what kind of expectations theories might be consistent with the available survey evidence.

*The views expressed in this paper do not necessarily represent those of the Bank of Canada.

1 Introduction

Expectations play an important role in macroeconomics and asset pricing. The predominant approach in these fields is to impose the assumption of rational expectations, which equates the subjective probability distribution perceived by the agents within the model with the objective probability distribution perceived by an outside observer equipped with a large sample of data generated by the economy. The rational expectations approach is elegant, internally consistent, and it eliminates the need to empirically study the formation of subjective expectations—but the assumption about expectations underlying it could be false. Recognizing this, Manski (2004) calls on researchers to collect survey data on expectations. Measurement of expectations allows researchers to consider alternatives to the rational expectations assumption in an empirically disciplined way.

A growing body of research in asset pricing follows this approach by examining survey data on investor stock market return expectations. This literature finds that the time-series dynamics of investor return expectations in surveys are in conflict with the predictions of influential rational expectations asset-pricing theories. Models like Campbell and Cochrane (1999) generate volatile asset prices and predictable returns by making risk premia counter-cyclical. By virtue of the rational expectations assumption, the subjective beliefs of investors in these models agree with the objective distribution, and hence these theories predict that the representative investor perceives counter-cyclical expected returns. In contrast, the survey evidence in Vissing-Jorgensen (2003), Bacchetta et al. (2009), Adam, Marcet and Beutel (2017) and Greenwood and Shleifer (2014) suggests that investor return expectations are pro-cyclical: Subjective expected returns are higher following high realized stock market returns and in times of high price-dividend ratios.

In these studies of return expectations, and more generally in much of the literature using survey measures of expectations, researchers interpret the elicited expectations as a representation of subjective beliefs that are distinct from respondents' preferences. More specifically, the typical interpretation assumes that people do not confound the probability of a state of the world with the desirability of this state when they answer survey questions about subjective beliefs. Recently, Cochrane (2011) suggested that a particular form of confounding of beliefs and preferences could reconcile rational expectations models with the survey evidence (see also Cochrane (2017)). Cochrane asserts that

"If people report the risk-neutral expectation, then many surveys make sense [sic]." (p. 1068)

Under risk-neutral expectations, outcomes are weighted by their probabilities multi-

plied with the marginal utility associated with the respective outcome (and rescaled so that the weights sum to one). In other words, risk-neutral expectations give more weight than the actual (physical) expectation to outcomes in high marginal utility states.

While the traditional interpretation of non-confounding of beliefs and preferences may be plausible—after all, without evidence to the contrary, it seems natural start with the assumption that people report what they are asked to report—its validity is ultimately an empirical question. In this paper we therefore examine the empirical validity of Cochrane’s assertion. Return expectations are an excellent setting for studying this issue because asset pricing theory provides a sharp prediction: risk-neutral expectations of returns on traded assets should equal the risk-free rate. For instance, if a survey respondent is asked to state the expected rate of return on a diversified portfolio of stocks over the next 12 months, Cochrane’s risk-neutral expectations hypothesis predicts that the respondent should respond with the 12-month risk free rate as their expected rate of return.

We use several different surveys of individual investors, professional investors, and Chief Financial Officers (CFO) covering various sample periods from the 1980s until recently. The implication of the risk-neutral expectations hypothesis that expected returns equal the risk-free rate is strongly rejected. Unconditionally, survey expectations of stock market returns exceed the risk-free rate by 1 to 5 percentage points depending on the survey and sample period and the difference is highly statistically significant. Conditionally, the risk-neutral expectations hypothesis predicts that deviations of survey expected returns from the risk-free rate should be random measurement errors that is unrelated to cyclical variables. However, we find that for almost all surveys and forecast horizons, the stock market’s price-dividend (P/D) ratio predicts the direction of the deviation. Specifically, for individual investors and CFOs, the deviation is pro-cyclical: expected stock returns exceed the risk-free rate when the P/D ratio is high.

Overall, the empirical evidence strongly rejects the hypothesis that survey respondents report a risk-neutral expectation. As we show, this is a rejection in a very general sense. We can allow for differences in opinion, heterogeneous preferences, and biased subjective beliefs and we still obtain that risk-neutral expected returns equal the risk-free rate. In the absence of trading frictions, heterogeneous individuals should adjust the risk-profile of their portfolio and their borrowing and lending such that their future time-discounted expected marginal utilities align with the current risk-free rate. As a consequence, their risk-neutral expected rates of return are all equal to the risk-free rate. The rejection in our tests thus implies that there exists no internally consistent probability measure that can reconcile the observed survey

data with the risk-neutral expectations hypothesis in a frictionless setting.

These results also hold up if we replace Treasury yields with variable mortgage rates as alternative risk-free rate proxy. To the extent that there is a friction-induced wedge between borrowing and lending rates, a collateralized borrowing rate may be a better proxy for the risk-neutral expected return than a Treasury rate. However, using this alternative risk-free rate proxy does not materially change the results.

While the data clearly reject the risk-neutral expectations hypothesis for survey expected returns, this still leaves open the possibility that preferences and beliefs are confounded in other ways. For example, Manski (2017) reviews several examples from the literature in which individuals appear to overestimate the probability of extremely bad outcomes such as death or being a crime victim. In asset pricing, a distorted probability measure that overweights bad outcomes can be used to represent ambiguity aversion or concerns about model misspecification (Hansen and Sargent (2001) (2001)). Bhandari, Borovička, and Ho (2016) use survey expectations of macroeconomic variables to estimate such distorted probabilities. However, the fact that decision-making of ambiguity averse or robustness-seeking individuals can be modeled using a distorted probability measure does not imply that survey responses would necessarily reflect such distorted probabilities. For this reason, we investigate this issue empirically.

If ambiguity aversion or robustness-seeking is reflected in the beliefs elicited in surveys, we should find that survey expected returns should be pessimistically biased relative to rational expectations of returns. To test this prediction, we compare survey expected returns to realized rates of return. Unconditionally, we find that the expected stock market returns reported in surveys are approximately unbiased as forecasts of realized returns. Conditionally, taking into account predictable variation in the wedge between survey expected returns and realized returns, we find that investors are roughly as many times optimistic as they are pessimistic. These findings are inconsistent with the idea that survey expectations have a pessimistic bias due to ambiguity aversion or robustness concerns.

In summary, our findings show that the expected returns elicited in surveys are not risk-neutral expectations. More generally, we do not find evidence of marginal utility weighting or a distortion towards overweighting of bad outcomes in survey expectations. The fact that the (pro-cyclical) empirical time-series dynamics of expected returns reported in surveys differ starkly from the (counter-cyclical) predictions of leading rational expectations models therefore cannot be explained away by positing that individuals report risk-neutral expectations. It does not appear possible to simultaneously match asset price dynamics and the survey evidence without entertaining some departure from rational expectations, such as extrapolative expect-

tations (Barberis et al. (2015)), learning about underlying trends in price growth (Adam et al. (2016, 2017)), or learning from life-time experience (Collin-Dufresne, Johannes, and Lochstoer (2016), building on Malmendier and Nagel (2011) (2015)).

The remainder of the paper is structured as follows. In Section 2, we derive testable implications of the risk-neutral expectations and pessimistic expectations hypotheses. After describing the data sources in section 3, we present the empirical results in 4. Section 5 concludes.

2 Hypotheses about Survey Expectations

Let R_{t+1} denote a one-period return on a stock market index realized over the period t to $t + 1$ and let R_t^f denote the one-period return offered by a risk-free asset over the same periods. As a benchmark, we consider an investor i who can freely trade in both instruments. The effects of trading constraints will be discussed below. The investor's first order conditions imply that the returns must satisfy

$$1 = E_t^{\mathcal{P}^i} [M_{t+1}^i R_{t+1}] \quad (1)$$

$$1 = E_t^{\mathcal{P}^i} [M_{t+1}^i] R_t^f, \quad (2)$$

where M_{t+1}^i is the agents' one-period stochastic discount factor (SDF) from t to $t + 1$ and $E_t^{\mathcal{P}^i}$ is an expectations operator that is based on some (potentially subjective) probability measure \mathcal{P}^i . Specific asset pricing theories give rise to specific forms of the SDF^i or make specific assumptions about \mathcal{P}^i , but we shall not be concerned with this here: the testable implications derived below will rely exclusively on equations (1) and (2) being satisfied for some M^i and some probability measure \mathcal{P}^i . In fact, we can even allow M^i and \mathcal{P}^i to differ across investors.

Equations (1) and (2) assume that agents can (at the margin) freely trade in the stock and in the bond market. This is in line with the assumptions made in a wide range of representative agent asset pricing models, e.g., the ones in the tradition of Campbell and Cochrane (1999) or Bansal and Yaron (2004). Limited participation models, e.g., the one considered by Guvenen (2009), postulate that some agents only trade in the bond market but have no access to the stock market, while others have access to both markets. For agents without access to the stock market, equation (1) will not necessarily be satisfied. For agents with access to both markets, equations (1) and (2) both hold. To avoid that our empirical results are tainted by limited stock market access, we shall consider below mainly survey sources for which we know that survey respondents do have stock market access.

2.1 Risk-Neutral Expectations

Let $\mathcal{E}_t^i[\cdot]$ denote the expectations of i measured in a survey.

The hypothesis put forward by Cochrane (2011, 2017) is that survey returns are expectations of risk-neutral stock returns, i.e.,

$$\mathcal{E}_t^i[R_{t+1}] = E_t^{\mathcal{P}^i} \left[\frac{M_{t+1}^i}{E_t^{\mathcal{P}^i} [M_{t+1}^i]} R_{t+1} \right] + \varepsilon_t^i, \quad (3)$$

where the term pre-multiplying $R_{t,t+1}$ inside the expectations operator is a Radon-Nikodym term, which transforms the ‘physical’ probability of future states, which enter the computation of the expectation $E_t^{\mathcal{P}^i}[\cdot]$, into a ‘risk-neutral’ or ‘marginal-utility weighted’ probability.¹ The measurement error ε_t^i captures the fact that we measure the true expectations only with noise.

Note that Cochrane’s (2011, 2017) hypothesis is stronger than what is stated in equation (3): it additionally postulates that \mathcal{P}^i is a ‘rational’ or ‘objective’ probability measure. This additional constraint, however, turns out not to be relevant for the arguments that follow, prompting us to proceed with the more general case in which agents are allowed to have objective or subjective beliefs.

Equation (3) implies that future returns that materialize in states in which marginal utility and thus the SDF is high (low) are treated by agents as if they are more (less) likely than under the objective measure and thus lead to an upward (downward) ‘distortion’ of the expected returns relative to plain return expectations. Under the risk-neutral return hypothesis, survey expectations can thus look ‘distorted’, when wrongly interpreting them as plain return expectations. The risk-neutral return expectations thus gives a chance to bring rational expectations asset pricing theories in line with the survey evidence.

¹Let s_t denote the state in t and $p^i(s_{t+1}|s_t)$ the physical probability (implied by \mathcal{P}^i) of reaching state s_{t+1} in $t+1$, given that we are in state s_t . The risk neutral probability $n^i(s_{t+1}|s_t)$ of reaching state s_{t+1} given state s_t is then

$$n^i(s_{t+1}|s_t) \equiv p^i(s_{t+1}|s_t) \frac{M^i(s_{t+1}|s_t)}{E_t^{\mathcal{P}^i} [M^i(s_{t+1}|s_t)]},$$

so that under the considered hypothesis, we get

$$\mathcal{E}_t^i[R_{t+1}] = E_t^{n^i} [R_{t+1}] + \varepsilon_t,$$

where $E_t^{n^i}[\cdot]$ is the expectations operator that integrates over states using the probabilities $n^i(s_{t+1}|s_t)$.

Equation (3) together with equations (1) and (2) implies

$$\mathcal{E}_t^i[R_{t+1}] = R_t^f + \varepsilon_t^i, \quad (4)$$

which shows that under the risk-neutral return hypothesis survey expectations of future stock returns must equal - up to a measurement error - the risk-free interest rate. This is intuitive, as under the risk-neutral measure all expected returns are identical and thus equal to the risk-free interest rate. This implication of the risk-neutral return hypothesis can be tested empirically. Specifically, since it is possible to interpret returns as nominal returns and the stochastic discount factor as a nominal discount factor, one can test equation (4) directly using the nominal return expectations from the survey sources and the nominal risk-free interest rates. A failure of equation (4) to hold will thereby imply that there exist no (objective or subjective) probability measure \mathcal{P}^i that is consistent with the risk-neutral return hypothesis.

Let $\mathcal{E}_t[R_{t+1}]$ denote the mean (or median) of a cross section of survey return forecasts $\{\mathcal{E}_t^i[R_{t+1}]\}$. Since equation (4) holds for every investor, it also holds for the mean (median) of these survey return expectations, i.e.,

$$\mathcal{E}_t[R_{t+1}] - R_t^f = \varepsilon_t, \quad (5)$$

where ε_t is the cross-sectional mean (median) of the individual measurement errors ε_t^i . We assume $E[\varepsilon_t] = 0$, but we allow ε_t to be autocorrelated over time.

Unconditional test. We can then examine the risk-neutral expectations hypothesis by estimating a in

$$\mathcal{E}_t[R_{t+1}] - R_t^f = a + \varepsilon_t. \quad (\text{RN-U}) \quad (6)$$

and testing of $H_0 : a = 0$.

Conditional test. In addition to this prediction about unconditional means, the risk-neutral expectations hypothesis also implies a strong prediction about the time-series dynamics: Since the wedge $\mathcal{E}_t[R_{t+1}] - R_t^f$ should be zero except for measurement error, it should not be correlated with any covariates that are uncorrelated with the measurement error. For example, macroeconomic variables or standard market return predictors in asset pricing should not be correlated with the wedge. On the other hand, this wedge would be strongly correlated with such variables under interesting alternative hypotheses. For example, if respondents report rational expectations without risk-adjustment, the wedge in reported expectations should be equal to the conditional market risk premium (absent measurement error). Any covariates x_t that are correlated with wedge $\mathcal{E}_t[R_{t+1}] - R_t^f$ should predict $R_{t+1} - R_t^f$ with the same sign. We therefore consider the specification

$$\mathcal{E}_t[R_{t+1}] - R_t^f = a_0 + a_1'x_t + \varepsilon_t. \quad (\text{RN-C}) \quad (7)$$

where the vector x_t includes predictor variables that could, for example, capture variation in $E_t[R_{t+1}] - R_t^f$. The risk-neutral expectations hypothesis implies $H_0 : a_0 = 0 \wedge a_1 = 0$.

2.2 Pessimistic Expectations

A less extreme hypothesis than the risk-neutral expectations hypothesis is one where investor expectations are pessimistically biased, but not all the way down to the risk-free rate. For example, under the robust or ambiguity averse expectations hypothesis, stock market investors make decisions *as if* they hold pessimistically biased expectations about asset returns compared with rational expectations. The SDF in these models can be represented as $M_{t+1}^i = A_{t+1}^i Q_{t+1}^i$, where A_{t+1}^i is a conventional marginal utility-based SDF and Q_{t+1}^i , with $E_t[Q_{t+1}^i] = 1$, can be viewed as a belief distortion that overweights bad states of the world.

Whether expectations reported in surveys reflect these belief distortions is an open question. Bhandari, Borovička, and Ho (2016)), for example, assume so. However, this need not be the case. Even if investor choices and asset prices can be accurately characterized by viewing Q_{t+1}^i as a belief distortion, this does not imply that when investors are asked to state their expectations in a survey, they report the expectations distorted by Q_{t+1}^i . Whether they do so is an empirical question that we investigate here. Resolving this issue is important for interpretation of survey measures of expectations and also for the empirical measurement of ambiguity aversion.

The hypothesis that the belief distortion affects survey expectations implies

$$\mathcal{E}_t^i[R_{t+1}] = E_t[Q_{t+1}^i R_{t+1}] + \varepsilon_t^i \quad (8)$$

Since R is the return on a risky asset that pays off systematically more in good states, its payoff is negatively correlated with Q . Therefore,

$$\mathcal{E}_t^i[R_{t+1}] = E_t[R_{t+1}] + cov(Q_{t+1}^i, R_{t+1}) + \varepsilon_t^i < E_t[R_{t+1}] + \varepsilon_t^i \quad (9)$$

i.e., the belief distortion leads to a pessimistic bias in expectations.²

Since (9) holds for every individual, it also holds for the mean (or median)

$$\mathcal{E}_t[R_{t+1}] < E_t[R_{t+1}] + \varepsilon_t \quad (10)$$

²To the extent that ambiguity aversion is responsible for much of the equity premium, then $M_{t+1}^i \approx \frac{1}{R_{F,t}} Q_{t+1}^i$. If so, we are back to the risk-neutral expectations hypothesis, where $\mathcal{E}_t^i[R_{t+1}] \approx R_t^f$.

where ε_t is the cross-sectional mean (median) of the individual measurement errors ε_t^i .

Unconditional test. Based on (10) we can then examine the pessimistic expectations hypothesis by estimating the average pessimism bias $b \equiv E[\mathcal{E}_t(R_{t+1}) - E_t(R_{t+1})]$ in

$$\mathcal{E}_t[R_{t+1}] - E_t[R_{t+1}] = b + e_t \quad (11)$$

where $e_t = \mathcal{E}_t(R_{t+1}) - E_t(R_{t+1}) - b$ is a composite residual with $E[e_t] = 0$ that contains ε_t as well as the time-varying part of the beliefs wedge that is not due to ε_t . The inequality (10) implies $H_0 : b < 0$.

However, $E_t[R_{t+1}]$ is unobservable. One approach is to substitute in $R_{t+1} = E_t[R_{t+1}] + \eta_{t+1}$, which yields

$$\mathcal{E}_t[R_{t+1}] - R_{t+1} = b + e_t - \eta_{t+1} \quad (\text{PE-U1}) \quad (12)$$

A potential problem with this approach is that average realized returns can be substantially different from rational conditional expected returns over extended periods of time. Since some of our survey series are quite short, this could be a serious problem. For example, the 1990s were a period in which return predictions from forecasting regressions based on the dividend yield (which indicated low expected returns) differed substantially from (high) average realized returns during this period. If survey expectations are on average below average realized returns during this period, this may not be an indication of pessimistic beliefs but sampling error. Put differently, since even somewhat precise estimation of expected returns requires very long sample periods, just replacing $E_t[R_{t+1}]$ with realized returns could be very inefficient.

An alternative and likely more efficient approach is to substitute the fitted value, $\hat{E}_t[R_{t+1}]$, from a predictive regression

$$R_{t+1} = k_0 + k_1' z_t + u_t. \quad (13)$$

where z_t could include commonly used return predictors like, e.g., the dividend yield. The fitted value is also a noisy estimate of the conditional expected returns, but it should be substantially more precise than the average realized return over a relatively short time period. In particular, to yield more precise estimates, the first stage regression to generate $\hat{E}_t[R_{t+1}]$ could be run on a sample that is much longer than the survey expectations time series. A longer time series would also help to reduce small-sample biases.

For this approach to be valid in this unconditional test in terms of consistency, z_t does not necessarily have to be in the information set of survey respondents since

this would not bias the estimate of the unconditional mean wedge b . But if it's not, statistical power is lost, as any deviation of $\hat{E}_t[R_{t+1}]$ from $E_t[R_{t+1}]$ adds noise. Using this approach, we then estimate

$$\mathcal{E}_t[R_{t+1}] - \hat{E}_t[R_{t+1}] = b + e_t + \omega_t \quad (\text{PE-U2}) \quad (14)$$

where $\omega_t \equiv E_t[R_{t+1}] - \hat{E}_t[R_{t+1}]$. Since $\hat{E}_t[R_{t+1}]$ is a generated variable, we need to adjust the standard errors accordingly. Appendix A provides the asymptotic distribution.

Conditional test. Pessimism due to ambiguity aversion would not only imply pessimism relative to rational expectations on average, but also conditionally, period by period. As already indicated in (11), the expectations wedge may be time-varying. Since the inequality (10) holds in every state, it also holds if we condition on a vector of covariates x_t , with $E[\varepsilon_t|x_t] = 0$, so that

$$E\{\mathcal{E}_t[R_{t+1}] - E_t[R_{t+1}]|x_t\} < 0 \quad (15)$$

Assuming that this conditional expectation is approximately linear in x_t , we have

$$\mathcal{E}_t[R_{t+1}] - E_t[R_{t+1}] = b_0 + b_1'x_t + e_t, \quad (16)$$

where $e_t = \varepsilon_t + \mathcal{E}_t[R_{t+1}] - E_t[R_{t+1}] - E\{\mathcal{E}_t[R_{t+1}] - E_t[R_{t+1}]|x_t\}$ and so $E[e_t|x_t] = 0$.³ The pessimism hypothesis implies that $b_0 + b_1'x_t < 0$. For this linear model to be consistent with this inequality, x_t needs to be suitably bounded. The rational expectations alternative implies $b_0 = 0 \wedge b_1 = 0$.

We can again follow two approaches to deal with the unobservability of $E_t[R_{t+1}]$ in (16). The first approach is to substitute in $R_{t+1} = E_t[R_{t+1}] + \eta_{t+1}$, which yields

$$\mathcal{E}_t[R_{t+1}] - R_{t+1} = b_0 + b_1'x_t + e_t - \eta_{t+1} \quad (\text{PE-C1}) \quad (17)$$

For $E[\eta_{t+1}|x_t] = 0$ to hold, we require that x_t is in the information set of survey respondents. As before, this approach suffers from the fact that R_{t+1} is an extremely noisy proxy for $E_t[R_{t+1}]$.

The second approach substitutes the fitted value, $\hat{E}_t[R_{t+1}]$, from the predictive regression (13), which yields

$$\mathcal{E}_t[R_{t+1}] - \hat{E}_t[R_{t+1}] = b_0 + b_1'x_t + e_t + \omega_t \quad (\text{PE-C2}) \quad (18)$$

³At this point, we do not need to assume that x_t is in the time- t information set of survey respondents. If it's not, all it means is that we cannot replace $E\{E_t[R_{t+1}]|x_t\}$ by $E_t[R_{t+1}|x_t]$. However, for implementation of the estimation in terms of observables below, we will need the assumption that x_t is in the survey respondents information set.

where $\omega_t = E_t[R_{t+1}] - \hat{E}_t[R_{t+1}]$, as before in the unconditional case above. To have $E[\omega_t|x_t] = 0$, we need that x_t is in the information set of survey respondents and is included in z_t . We show in Appendix A how to obtain the asymptotic distribution of the estimator in this case.

3 Data

We use data on stock market return expectations from several different data sets, which, to the best of our knowledge, cover all available quantitative data on U.S. stock market return expectations of individuals who are not professional forecasters. Table 1 provides summary statistics for the different survey data sets.

3.1 Survey data sources

The first data set is the Duke CFO Global Business Outlook, a quarterly survey conducted by Duke University’s Fuqua School of Business and CFO magazine. As Table 1 shows, the sample contains about 400 observations per quarter. Respondents in the survey provide the rate of return they expect on the S&P500 index over the next year. We obtain the median and mean responses from this survey.

The second data set is the UBS/Gallup survey.⁴ The survey is based on a nationally representative sample. But to participate in the survey, respondents need to hold stocks, bonds, or mutual funds of a combined value of at least \$10,000. We use data from February 1999 onwards when the survey was conducted on a regular monthly basis until 2007 with about 700 observations per month. We also observe whether the respondent household holds more than \$100,000 in stocks, bonds or mutual funds. As Table 1 shows, this subsample of wealthy households accounts for somewhat less than half of the sample. We use data from two survey questions about expected returns. The first question asks about the return that the respondent expects from an investment in the stock market during the next twelve months. This question is available until April 2003. The second expectations question asks for the return that the respondents expect on their own portfolio. This question was in the survey until October 2007.

The third data set is a series constructed by Nagel and Xu (2018) that uses additional surveys to extend the UBS/Gallup survey forward and backward in time. We use the data from 1987m6 onwards when observations are available monthly without

⁴The archive is available at <http://ropercenter.cornell.edu/ubs-index-investor-optimism/>

Table 1: Summary Statistics of Survey Data

The table shows summary statistics for the survey data sets we use in this study. We aggregate the individual survey responses in terms of means or medians within monthly or quarterly time periods as shown in the second column. The last two columns show the time series mean and standard deviation of the aggregated mean or median percentage expected return series.

Survey source	Aggreg.	Periods	Forecast Horizon	Sample	Avg. # obs. per period	Aggreg.	$\mathcal{E}[R]$ Mean	$\mathcal{E}[R]$ S.D.
CFO	quarter	2000q3 - 2016q1	1yr		390	mean	5.72	1.56
						median	5.14	1.25
UBS own	month	1999m2 - 2007m10	1yr	all	702	mean	10.31	2.68
				median	8.28	2.31		
			1yr	>100k	310	mean	10.16	2.71
				median	8.55	2.29		
UBS market	month	1999m2 - 2003m4	1yr	all	706	mean	10.76	3.16
				median	8.73	2.76		
			1yr	>100k	311	mean	10.47	3.27
				median	8.85	2.69		
UBS extended	month	1972m8 - 2016m2 (w/ gaps)	1yr		n/a	mean	9.46	2.23
Shiller individual	quarter	1999m1 - 2015m8	3m		75	mean	0.89	1.30
						median	1.34	1.23
			6m		77	mean	2.13	1.60
						median	2.70	1.28
			1yr		81	mean	5.09	2.98
						median	5.67	1.97
10yr		76	mean	37.05	24.19			
median	22.55	27.07						
Shiller professional	quarter	1999m1 - 2015m8	3m		60	mean	0.57	1.41
						median	1.37	1.25
			6m		63	mean	2.00	1.92
						median	3.71	1.34
			1yr		69	mean	5.12	3.08
						median	7.36	2.87
10yr		65	mean	70.74	25.84			
median	56.85	20.18						

gaps. In this series, the missing market return expectation in the UBS/Gallup survey from 2003 to 2007 is imputed from the own portfolio return expectation as the fitted value from a regression of expected market returns on own portfolio expectations in the part of the sample where both are available. This series further includes mean one-year return expectations from Ameriks et al. (2016) (one survey in 2014). The series is then extended using data from surveys that do not have percentage return expectations, but coarser measures of investor beliefs. This is done by regressing the available return expectations on the average reported probability of a rise in the stock market in the Michigan Survey of Consumers (available from 2002 to 2016) and the fitted value is used to extend the percentage expectations series. This extended series is then regressed on a measure of the proportion of respondents expecting a rise in the stock market in surveys conducted by the Conference Board (1987-2016, monthly) and the fitted value used to extend the expected return series.

The final two data sets are surveys are from Robert Shiller and the Investor Behavior Project at Yale University.⁵ The surveys are based on two samples: wealthy individual investors and institutional investors. Each individual response includes the day on which the survey was completed. The data set starts in January 1999 and we use data until August 2015. The average number of responses per quarter is 75 (60) for the individual (institutional) investor data set. Survey respondents are asked to forecast the percentage change in the Dow Jones Industrial Index over various horizons (3 months, 6 months, 1 year and 10 years).

3.2 Matching with returns data

In the tests of the risk-neutral expectations hypothesis, we compare survey expectations to risk-free rates over a matched maturity. For maturities from 3 to 6 months, our baseline tests use daily U.S. Treasury Bill yields, obtained from the FRED database at the Federal Reserve Bank of St. Louis. For maturities from one to ten years, we use daily zero-coupon yields from (Grkaynak, Sack, and Wright 2007).⁶ We also explore alternative specifications in which we use the 1-year adjustable mortgage rate from the FRED database as a proxy for individuals' collateralized borrowing rates. Since this series has been discontinued at the end of 2015, the empirical results using mortgage interest rate have 2015 as their sample end. We convert all yields into effective yields over the the relevant maturity.

⁵The surveys are available at <http://som.yale.edu/faculty-research/our-centers/international-center-finance/data>

⁶The periodically updated data is available at <http://www.federalreserve.gov/pubs/feds/2006>

For each survey source and survey forecast horizon we use the risk-free interest of a corresponding maturity prevailing at the reported survey date. For the CFO survey, we know a reference date, which is a day very close to when the survey was sent (by fax). The survey administrators request a response within a few days from this reference date. We match the survey responses with the risk-free rate on the reference date. For the UBS/Gallup survey, we know the 2-3 week period in which the survey took place and we use the average daily yield during this period. The extended UBS/Gallup series is monthly and we match survey expectations with the yield at the end of the month preceding the survey month. For the Shiller data sets, for which we observe the response date of each individual survey response, we match each survey response with the interest rate prevailing on the day of the survey. Since the Shiller surveys ask about price growth on the DJIA, but the test of the risk-neutral expectations hypothesis requires a total return, we adjust the price growth series by adding the DJIA dividend yield at the end of the month preceding the survey date, adjusted for the relevant forecasting horizon assuming the dividend yield stays constant.

In tests of the pessimism hypothesis, we compare survey expectations with returns or price growth of stock market indices. In case of the CFO survey, we match the survey expectations with the total return on the S&P500 index over the one-year period starting from the reference date. For the UBS/Gallup survey, we use the return of the same series over the one-year period starting from first day of interview period. For the monthly extended UBS/Gallup series, we use a one-year total return on the S&P500 index from the end of the month prior to the survey month. For the Shiller surveys, we use price growth on the DJIA realized over the relevant horizon starting from the date of individual response.

Having computed the wedges between survey expectations and returns, we then aggregate the data to time series by computing means or medians within months or quarters as shown in the second column of Table 1.

3.3 Matching with conditioning variables

In several tests, we use the price-dividend (P/D) ratio as a conditioning variable (RN-C, PE-C1, PE-C2). We use the S&P500 P/D ratio for the CFO and UBS surveys, the CRSP value-weighted index P/D ratio for the UBS extended series and the PE-C2 test with the Shiller survey, and the DJIA P/D ratio for the PE-C1 test with the Shiller surveys. In terms of timing, we use the P/D ratio measured at the end of the last month preceding survey reference date for the CFO survey, at the end of the last month preceding first day of interview period for the UBS survey, and

at the end of the last month preceding the date of the individual response for the Shiller surveys.

Furthermore, some tests use an estimate of objective conditional expected returns $\hat{E}_t[R_{t+1}]$ that we construct from a predictive regression with the price dividend ratio (PE-U2, PE-C2). We use monthly returns or price growth and the S&P500 P/D ratio for the CFO survey and the CRSP value-weighted index P/D ratio for all the other tests. When we construct the fitted value $\hat{E}_t[R_{t+1}]$, we do so using a P/D ratio that is timed relative to the survey date in the same way as explained above, with the exception of the Shiller survey where we use the P/D ratio at the end of the quarter preceding the interview quarter. To construct multi-period forecasts, we iterate on the monthly forecasts based on the assumption that the P/D ratio follows an AR(1) process.

4 Empirical Results

4.1 Risk-neutral expectations hypothesis

Table 2 reports results for the RN-U test based on equation (6) using Treasury rates as risk-free rates. This test looks at the most basic implication of the risk-neutral expectations hypothesis: Are subjective expected returns on average equal to the risk-free rate over the forecast horizon? As the table shows, the answer is a clear no. For surveys from all sources and horizons except the Shiller individual investor survey using medians over a 10-year horizon, the subjective expected returns elicited in the surveys exceed risk-free rates by several percentage points. As the t -statistics and p -values show, we can reject the risk-neutral expectations hypothesis at extremely high levels of significance. There is also a remarkable degree of consistency across different types of survey respondents. Subjective expected returns exceed risk-free rates, contradicting the risk-neutral expectations hypothesis, for business practitioners (CFOs), professional investors, wealthy individuals, and individual investors.

The risk-neutral expectations hypothesis not only implies that the unconditional average subjective expected excess return is equal to the risk free rate, but also that this equality holds conditionally, state by state. The RN-C tests based on (7) reported in Table 3 shed light on this conditional version of the risk-neutral expectations hypothesis. We use Treasury rates as risk-free rates and the P/D ratio as the regressor x_t that could drive time-variation in subjective expected excess returns under the alternative hypothesis. We obtain bias-adjusted coefficient estimates and simulate F -statistics under the risk-neutral expectations null hypothesis as described in Appendix B.

Table 2: Unconditional Test of the Risk-Neutral Expectations Hypothesis

This table presents tests of the RN-U hypothesis. The column labeled a reports the mean of the subjective expected return (in terms of percent) in excess of the risk-free rate (based on Treasury securities) over the relevant horizon. The t -statistics and p -values are based on a Newey-West estimator with 4 lags for quarterly data and 12 lags for monthly data.

Survey Source			a	t -statistic	p -value for $H_0 : a = 0$	
CFO		mean	3.89	9.47	0.0000	
		median	3.55	8.43	0.0000	
UBS own	all	mean	6.55	12.53	0.0000	
		median	4.52	9.99	0.0000	
	>100k	mean	6.40	12.36	0.0000	
		median	4.79	10.82	0.0000	
UBS market	all	mean	6.64	13.31	0.0000	
		median	4.61	14.13	0.0000	
	>100k	mean	6.36	12.29	0.0000	
		median	4.74	15.80	0.0000	
UBS extended		5.80	20.10	0.0000		
Shiller individual	3m	mean	1.00	4.71	0.0000	
		median	1.45	6.73	0.0000	
	6m	mean	2.29	7.98	0.0000	
		median	2.86	11.22	0.0000	
	1yr	mean	5.02	9.26	0.0000	
		median	5.81	13.14	0.0000	
	10yr	mean	8.90	2.34	0.0194	
		median	-5.33	-1.19	0.2341	
	Shiller professional	3m	mean	0.68	2.28	0.0223
			median	1.48	5.19	0.0000
6m		mean	2.16	3.82	0.0001	
		median	3.86	8.94	0.0000	
1yr		mean	5.24	5.23	0.0000	
		median	7.43	8.41	0.0000	
10yr		mean	42.47	10.79	0.0000	
		median	28.88	7.88	0.0000	

The main test of the risk-neutral expectations hypothesis is the test of the joint hypothesis $a_0 = 0$ and $a_1 = 0$. As the results in Table 3 show, this hypothesis is rejected at 5% level for all but 4 of the 27 survey series. Like the unconditional tests in Table 2 the conditional tests here indicate that there is a substantial wedge between the subjective expectations of returns and risk-free rates.

To what extent does this wedge vary with the P/D ratio? The bias-adjusted point estimates of a_1 point to an interesting difference between individual and professional investors. For almost all survey series with individual investor respondents and CFOs, the estimates of a_1 either indicate a statistically significant positive relationship of subjective expected excess returns to the P/D ratio or the estimates are not significantly different from zero. In contrast, the subjective expected excess returns of professional investors in the Shiller survey are, with one exception (mean series at 10-year horizon), negatively related to the P/D ratio at the 5% significance level. For both individuals, CFOs, and professionals, however, the joint hypothesis of $a_0 = 0$ and $a_1 = 0$ is overwhelmingly rejected.

The statistically weak relationship between subjective expectations and the P/D ratio in Table 3 contrasts with the much stronger relationship documented in Greenwood and Shleifer (2014). The key difference is that here we examine subjective expected *excess* returns while Greenwood and Shleifer use expectations of total returns as dependent variable. During our sample period, the P/D ratio and Treasury rates are positively correlated and hence subtracting the risk-free rate from the subjective expected return weakens the positive relationship with the P/D ratio.

However, for the UBS extended series, where we have the longest time series, and hence more statistical power than for the shorter series, we can still reject the hypothesis $a_1 = 0$ with a high level of statistical confidence. Figure 1 shows the fitted values of subjective expected returns in excess of Treasury rates based on the bias-adjusted point estimates of a_0 and a_1 along with two-standard-error bands from the RN-C test regression (7) for the UBS extended sample. The figure shows that the estimated subjective conditional expected excess return is, in conflict with the predictions of the risk-neutral expectations hypothesis, far above zero throughout the whole sample. The lower boundary of the two-standard-error bands never include zero anywhere. Since the survey expectations in a given period likely contain substantial measurement error, the projection in Figure 1 might provide a better description of the time-series dynamics of the true subjective expectations than the raw measures of subjective expected excess returns. But even the raw series of $\mathcal{E}_t[R_{t+1}] - R_t^f$ never dips below zero.

The results we have presented so far could potentially be rationalized under the risk-neutral return hypothesis if individuals are borrowing constrained and face very

Table 3: Conditional Test of the Risk-Neutral Expectations Hypothesis

This table presents tests of the RN-C hypothesis where we regress subjective expected returns in excess of Treasury rates on the lagged price-dividend ratio. The columns labeled a_0 and a_1 report the intercept and slope coefficients, respectively, from these regressions. We report the a_1 estimates multiplied by a factor of 1000. They are bias-adjusted as described in Appendix B. The last two columns report Monte Carlo p -values obtained by simulating F -statistics under the null hypothesis as described in Appendix B.

Survey Source			a_0	a_1 $\cdot 10^3$	p -value for $H_0 : a_0 = a_1 = 0$	p -value for $H_0 : a_1 = 0$
CFO		mean	-1.39	8.66	0.0044	0.2307
		median	0.08	5.48	0.3937	0.2628
UBS own	all	mean	1.09	6.57	0.0000	0.0589
		median	-2.65	8.92	0.1860	0.0057
	>100k	mean	0.02	7.86	0.0000	0.0302
		median	-2.03	8.48	0.0106	0.0160
UBS market	all	mean	-0.52	7.96	0.0000	0.0059
		median	-0.91	6.17	0.0000	0.0221
	>100k	mean	-1.72	9.00	0.0000	0.0148
		median	-0.36	5.66	0.0000	0.2243
UBS extended		2.24	5.79	0.0000	0.0002	
Shiller individual	3m	mean	0.03	1.95	0.0029	0.4759
		median	0.04	2.66	0.0000	0.0852
	6m	mean	2.61	-0.47	0.0000	0.8115
		median	3.66	-1.43	0.0000	0.5086
	1yr	mean	10.46	-9.77	0.0000	0.0141
		median	9.18	-6.02	0.0001	0.5184
	10yr	mean	34.51	-50.86	0.9759	0.4601
		median	-1.58	-11.40	0.8236	0.8359
Shiller professional	3-months	mean	4.26	-6.45	0.0005	0.0068
		median	4.99	-6.34	0.0000	0.0015
	6m	mean	9.48	-13.20	0.0000	0.0001
		median	9.58	-10.19	0.0000	0.0005
	1yr	mean	19.51	-25.89	0.0000	0.0052
		median	20.39	-23.54	0.0000	0.0016
	10yr	mean	83.88	-76.17	0.0000	0.0844
		median	76.47	-87.97	0.0000	0.0200

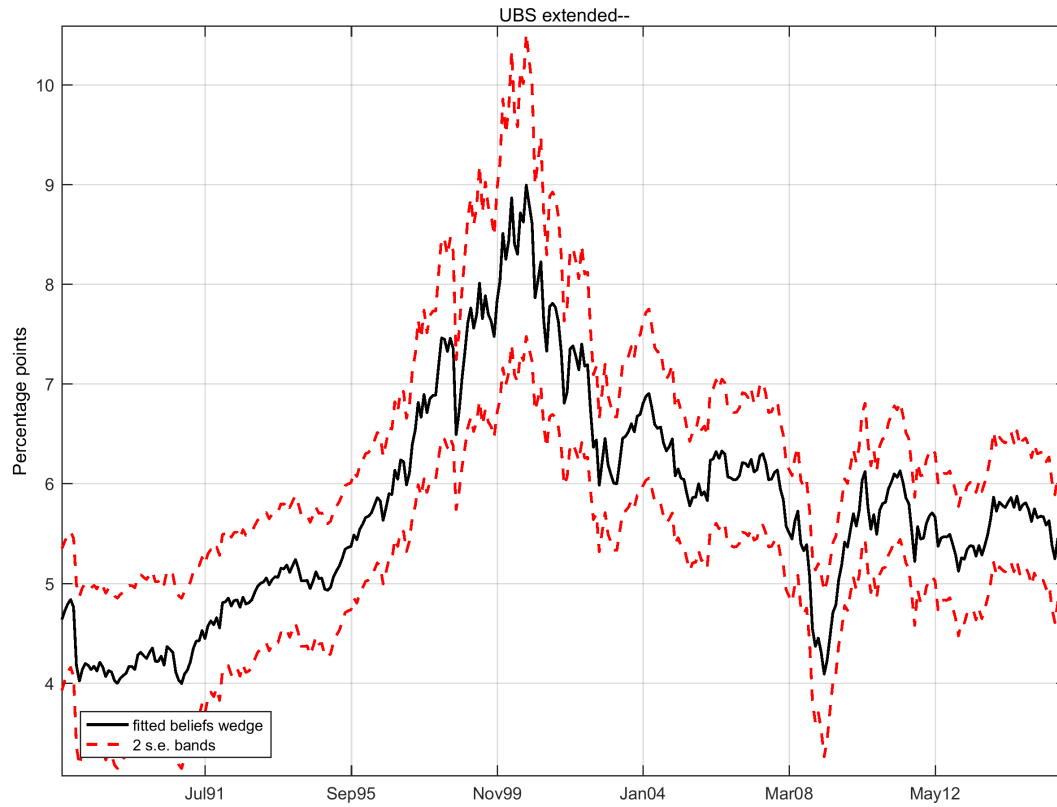


Figure 1: Fitted values from regression (7) of subjective expected returns in excess of Treasury rates on the P/D ratio in the UBS extended sample

high shadow interest rates, with the consequence that their risk-neutral expectations of stock returns could be substantially higher than Treasury rates. However, the fact that the RN-U and RN-C tests reject the risk-neutral expectations hypothesis for the subsample of wealthy investors in the UBS survey, the Shiller individual investor survey (which is also based on a sample of wealthy individuals), CFOs, and professional investors in the Shiller survey cast doubt on this alternative explanation. First, for these samples of wealthy investors and professionals, the borrowing constraints story does not appear plausible—especially if it requires shadow rates that are four or more percentage points above Treasury rates. Second, the point estimates of a for the CFO, UBS wealthy, and Shiller individual survey at the 1-year horizon in Table 2 are very similar to the a estimated from the full UBS sample, which suggests that the on average less wealthy individuals in the full UBS sample are not systematically different from wealthy investors and professionals in terms of their subjective expected return.

A more subtle friction-based explanation could be that there is a wedge between borrowing and lending rates. If the borrowing margin is relevant for many households, the Treasury rates that we have used so far may not be the relevant interest rates in households' Euler equation (2). Instead, borrowing rates may be more relevant. For this reason, we re-run the RN-U and RN-C tests with subjective expected excess returns calculated relative to one-year adjustable mortgage rates. We use a collateralized borrowing rate rather than an unsecured borrowing rate to avoid contamination by a substantial credit spread.

Table 4 presents the results. The basic message from this table is that there isn't much difference to the earlier tests with excess returns relative to Treasury rates. For example, in the unconditional test, we still reject the risk-neutral expectations hypothesis for all (one-year horizon) series, just as we did in Table 2. The point estimates for a are slightly smaller, but all of them are still substantially greater than zero by about one to five percentage points. Similarly, for the conditional test of the hypothesis $a_0 = a_1 = 0$, we reject the null at a 5% level for all but one of the survey expectations series. Overall, taking into account the potential effects of differences in borrowing and lending rates doesn't help much to rescue the risk-neutral expectations hypothesis.

4.2 Pessimism hypothesis

The results so far suggest that subjective expectations of returns exceed risk free rates by substantial amounts, which is inconsistent with the risk-neutral expectations hypothesis. However, this still leaves the possibility that their expectations are pes-

Table 4: Unconditional and Conditional Tests of the Risk-Neutral Expectations Hypothesis: Adjustable Mortgage Rates as Risk-free Rate

This table presents tests of the RNU-U and RN-C hypotheses using one-year adjustable mortgage rates as risk-free rate to compute excess returns. We use only survey series where the forecasting horizon is one year. For the unconditional test RN-U, the column labeled a reports the mean of the subjective expected excess return. The corresponding p -values are based on a Newey-West estimator with 4 lags for quarterly data and 12 lags for monthly data. For the conditional test RN-C, the columns labeled a_0 and a_1 report the intercept and slope coefficients, respectively, from regressions of subjective expected excess returns on the lagged price-dividend ratio. We report the a_1 estimates multiplied by a factor of 1000. They are bias-adjusted as described in Appendix B. The last two columns report Monte Carlo p -values obtained by simulating F -statistics under the null hypothesis as described in Appendix B.

Survey Source			Unconditional		Conditional			
			a	p -val. $H_0 : a = 0$	a_0	a_1 $\cdot 10^3$	p -val. $H_0 : a_0 = a_1 = 0$	p -val. $H_0 : a_1 = 0$
CFO	mean	1.65	0.0000	-4.63	9.87	0.0086	0.0220	
	median	1.24	0.0008	-4.05	8.37	0.0087	0.0287	
UBS own	all	mean	5.13	0.0000	-0.98	7.29	0.0012	0.0747
		median	3.10	0.0000	-4.92	9.95	0.0394	0.0049
	>100k	mean	4.98	0.0000	-2.18	8.76	0.0001	0.1043
		median	3.37	0.0000	-4.29	9.52	0.0557	0.0033
UBS market	all	mean	5.03	0.0000	-4.19	10.00	0.0002	0.0045
		median	3.00	0.0001	-7.20	11.35	0.0019	0.1163
	>100k	mean	4.74	0.0000	-6.82	12.77	0.0000	0.0007
		median	3.13	0.0000	-7.13	11.39	0.0010	0.0313
UBS extended		4.28	0.0000	0.68	5.67	0.0000	0.0133	
Shiller individual	1yr	mean	3.09	0.0000	1.79	2.50	0.0000	0.6854
		median	3.66	0.0000	3.28	0.79	0.0000	0.7146
Shiller professional	1yr	mean	3.11	0.0001	14.02	-19.76	0.0028	0.0693
		median	5.33	0.0000	14.79	-17.19	0.0000	0.0256

Table 5: Unconditional Tests of the Pessimism Hypothesis

This table presents unconditional tests of the pessimism (PE-U) hypothesis. The columns labeled with PE-U1 report the mean of the subjective expected return in excess of the realized return over the forecast horizon along with the associated t -statistic and p -value based on a Newey-West estimator with 4 lags for quarterly data and 12 lags for monthly data. The columns labeled with PE-U2 report the mean of the subjective expected return in excess of the fitted value from a regression of the relevant return or price growth for each survey on the lagged P/D ratio, with regression parameters estimated with data from 1926-2017. The t -statistics and p -values in this case are computed based on the asymptotic approximation outlined in Appendix A, including a Newey-West estimator of the covariance matrix using 4 lags for quarterly data and 12 lags for monthly data.

Survey Source			PE-U1			PE-U2			
			b	t -stat.	p -val. $H_0 : b \leq 0$	b	t -stat.	p -val. $H_0 : b \leq 0$	
CFO		mean	-1.61	-0.43	0.6663	-0.60	-0.44	0.6714	
		median	-3.69	-1.05	0.8526	-1.70	-1.49	0.9320	
UBS own	all	mean	7.59	1.62	0.0526	7.09	3.18	0.0007	
		median	5.56	1.21	0.1141	5.06	2.37	0.0088	
	>100k	mean	13.69	2.01	0.0222	6.94	3.12	0.0009	
		median	12.07	1.81	0.0351	5.33	2.51	0.0060	
UBS market	all	mean	13.97	2.07	0.0193	9.84	3.23	0.0006	
		median	11.94	1.79	0.0366	7.81	2.70	0.0035	
	>100k	mean	13.69	2.01	0.0222	9.55	3.11	0.0009	
		median	12.07	1.81	0.0351	7.94	2.76	0.0028	
UBS extended			-1.86	-0.72	0.7636	2.10	1.82	0.0348	
Shiller individual	3-months	mean	-0.55	-0.68	0.7513	-0.51	-1.10	0.8645	
		median	-0.31	-0.38	0.6497	-0.07	-0.15	0.5611	
	6m	mean	-0.01	-0.01	0.5030	-0.61	-0.91	0.8179	
		median	0.41	0.25	0.4030	-0.04	-0.06	0.5255	
	1yr	mean	0.52	0.17	0.4323	0.28	0.23	0.4104	
		median	1.11	0.36	0.3578	0.87	0.75	0.2256	
	10yr	mean	11.53	0.50	0.3088	8.26	0.50	0.3096	
		median	-2.01	-0.08	0.5326	-6.73	-0.37	0.6425	
	Shiller professional	3-months	mean	-0.59	-0.62	0.7334	-0.83	-1.84	0.9673
			median	0.05	0.05	0.4794	-0.04	-0.08	0.5333
6m		mean	-0.08	-0.05	0.5181	-0.74	-1.12	0.8683	
		median	1.12	0.65	0.2587	0.96	1.60	0.0553	
1yr		mean	0.58	0.20	0.4218	0.31	0.31	0.3777	
		median	2.60	0.89	0.1864	2.56	2.66	0.0039	
10yr		mean	43.18	2.27	0.0115	40.35	2.94	0.0016	
		median	25.81	1.43	0.0761	25.61	2.08	0.0186	

simistically biased relative to objective expectations of returns under the real-world probability measure. The alternative is that survey respondents simply do what the survey asks them to do: provide the expected return under their perceived real-world probability measure. In this section, we report results from tests of this pessimistic expectations hypothesis.

Table 5 reports the results from unconditional tests. In the the left block of columns, we compare the subjective expectations of returns to the returns that were realized subsequently over the forecast horizon (PE-U1 tests). The estimates of the coefficient b show by how much the subjective expectation on average exceeds the realized return. We also report p -values for a one-sided test of the weak pessimism hypothesis $b \leq 0$. In the right block of columns in Table 5, we compare the subjective expectations with fitted values from a regression of realized returns on the lagged dividend yield estimated over the 1926-2017 period (PE-U2 tests).

Both types of tests deliver fairly similar results. Focusing first on the p -values of the PE-U1 test, we cannot reject the weak pessimism hypothesis for more than two thirds of the subjective expectations series. However, the weak pessimism hypothesis includes $b = 0$ and only one third of the t -statistics associated with the b estimates are negative. Moreover, none of the t -statistics (the smallest being -1.05) would allow to reject the null of unconditional optimism. If anything, it looks like there may be a tendency towards optimism rather than pessimism. But overall, there is little evidence of deviations from unbiasedness. In particular, the mean is also insignificantly different from zero for the UBS extended series for which we have the longest time series and (among the 1-year horizon series) the smallest standard error and highest statistical power. Thus, subjective expected returns appear to be, on average, close to unbiased, which is inconsistent with a substantial pessimism bias.

One concern with the PE-U1 tests could be that realized returns are just too noisy to provide much statistical power when we compare subjective expected returns with realized returns, especially given the relatively short sample for which survey expectations are available. For this reason, the PE-U2 tests replace the realized return with the fitted value from a predictive regression, with the standard errors adjusted for the estimation uncertainty in the predictive regression parameters. As the estimates in Table 5 show, the resulting point estimates of b are almost all closer to zero. Even so, the absolute value of the t -statistics are often bigger than in the PE-U1 column because the standard errors are much smaller, consistent with an increase in statistical power. But in terms of direction, the picture is mixed. Some estimates of b are greater than zero, while some are smaller. We can reject the weak pessimism hypothesis at the 5% level for 12 of the 27 series. Thus, this test, too, suggests that subjective expectations are not far from being unbiased.

Table 6: Conditional Tests of the Pessimism Hypothesis

This table presents tests of the PE-C hypothesis where we regress on the lagged P/D ratio the subjective expected returns in excess of realized returns (PE-C1) or the subjective expected return in excess of the fitted value from a regression of realized returns on the lagged P/D ratio (PE-C2) estimated over the 1926-2017 time period. Based on these regression estimates, we determine, at every point in time, whether we can reject the pessimism hypothesis (weakly negative predicted subjective excess return) or the optimism hypothesis (weakly positive predicted subjective excess return) at a 5% level. In the PE-C1 case, the regressions are bias-adjusted as described in Appendix B. In the PE-C2 case, the t -statistics for this test are computed based on the asymptotic approximation outlined in Appendix A, including a Newey-West estimator of the covariance matrix using 4 lags for quarterly data and 12 lags for monthly data.

			PE-C1			PE-C2			
			Share reject pess.	Share no reject	Share reject. opt.	Share reject pess.	Share no reject	Share reject. opt.	
CFO		mean	0.1212	0.7121	0.1667	0.1774	0.2903	0.5323	
		median	0.0645	0.7581	0.1774	0.0690	0.3276	0.6034	
UBS own	all	mean	0.3504	0.6239	0.0256	0.9429	0.0571	0.0000	
		median	0.3419	0.6325	0.0256	0.7333	0.2571	0.0095	
	>100k	mean	0.3504	0.6239	0.0256	0.9333	0.0667	0.0000	
		median	0.3504	0.6239	0.0256	0.7810	0.2190	0.0000	
UBS market	all	mean	0.8889	0.1111	0.0000	0.8627	0.1373	0.0000	
		median	0.5714	0.4286	0.0000	0.8235	0.0980	0.0784	
	>100k	mean	0.4444	0.5556	0.0000	0.8235	0.1569	0.0196	
		median	0.4762	0.4921	0.031	0.8235	0.1176	0.0588	
UBS extended			0.1563	0.5313	0.3125	0.5455	0.2415	0.2131	
Shiller indiv.	3-months	mean	0.1692	0.2769	0.5538	0.0000	0.5077	0.4923	
		median	0.1846	0.4000	0.4154	0.0769	0.6923	0.2308	
	6m	mean	0.2154	0.5692	0.2154	0.0615	0.4154	0.5231	
		median	0.2308	0.6000	0.1692	0.1692	0.5385	0.2923	
	1yr	mean	0.1846	0.6000	0.2154	0.2308	0.4769	0.2923	
		median	0.0154	0.2154	0.7692	0.3077	0.4462	0.2462	
	10yr	mean	0.1077	0.7846	0.1077	0.3714	0.1429	0.4857	
		median	0.7077	0.2923	0.0000	0.3143	0.0857	0.6000	
	Shiller prof.	3-months	mean	0.1231	0.4769	0.4000	0.0000	0.2615	0.7385
			median	0.1538	0.8462	0.0000	0.0000	1.0000	0.0000
6m		mean	0.1846	0.5846	0.2308	0.0000	1.0000	0.0000	
		median	0.1385	0.7692	0.0923	0.0000	1.0000	0.0000	
1yr		mean	0.1846	0.7846	0.0308	0.0000	1.0000	0.0000	
		median	0.1846	0.7538	0.0615	0.9538	0.0462	0.0000	
10yr		mean	0.2615	0.4308	0.3077	0.8000	0.2000	0.0000	
		median	0.1846	0.1538	0.6615	0.5714	0.3143	0.1143	

Table 6 presents two versions conditional tests of the pessimism hypothesis. It reports the share of observed price-dividend and expectations pairs, for which one can reject conditional pessimism (thus implying optimistic expectations), reject conditional optimism (thus implying conditional pessimism), or can reject neither of the two hypotheses (referred to as undecidable expectations, labeled in the table as no reject). The tests use a significance level of 5%. In the PE-C1 version of the test (left block of columns), we look at the predicted wedge between subjective expected returns with subsequently realized returns, in the PE-C2 version of the test (right block of columns), the wedge is calculated as the difference between the subjective expected return and the fitted value from a predictive regression of realized returns on the lagged price-dividend ratio estimated over a long time period 1926-2017.

The first notable result from Table 6 is that many observations cannot be classified as either optimistic or pessimistic: the average number of undecidable observations is often above 50%. Thus, subjective expected excess returns are a substantial fraction of the time in the vicinity, statistically speaking, of objective expected returns. Nevertheless, for a substantial number of observations we can reject pessimism. However, in which direction the test tends to reject more often depends on the survey. Figure 2, which shows the fitted values of subjective expected returns in excess of the estimated objective expected returns on the P/D ratio along with two-standard-error bands from the PE-C2 test regression (18) for the UBS extended sample, helps understand the sample dependence. The deviations of subjective expected returns from estimated objective expected returns is pro-cyclical. In boom times, like the 1990s, investors are too optimistic. Following crashes, like in early 2009, investors are too pessimistic. The UBS/Gallup survey includes observations from the late 90s, but no observations from the financial crisis and its aftermath. In contrast, the other survey include observations from the financial crisis and subsequent years. This partly explains why these other surveys on average have fewer optimistic observations than the UBS/Gallup sample.

Thus, even though subjective expectations are unconditionally close to unbiased, there is a substantial time-varying conditional bias. This conditional bias flips sign and is often an optimism bias, inconsistent with the pessimistic expectations hypothesis.

5 Conclusion

Our empirical findings show that subjective stock return expectations from a number of different surveys are not consistent with the idea that survey respondents report expectations under a risk-neutral probability measure. We show that both

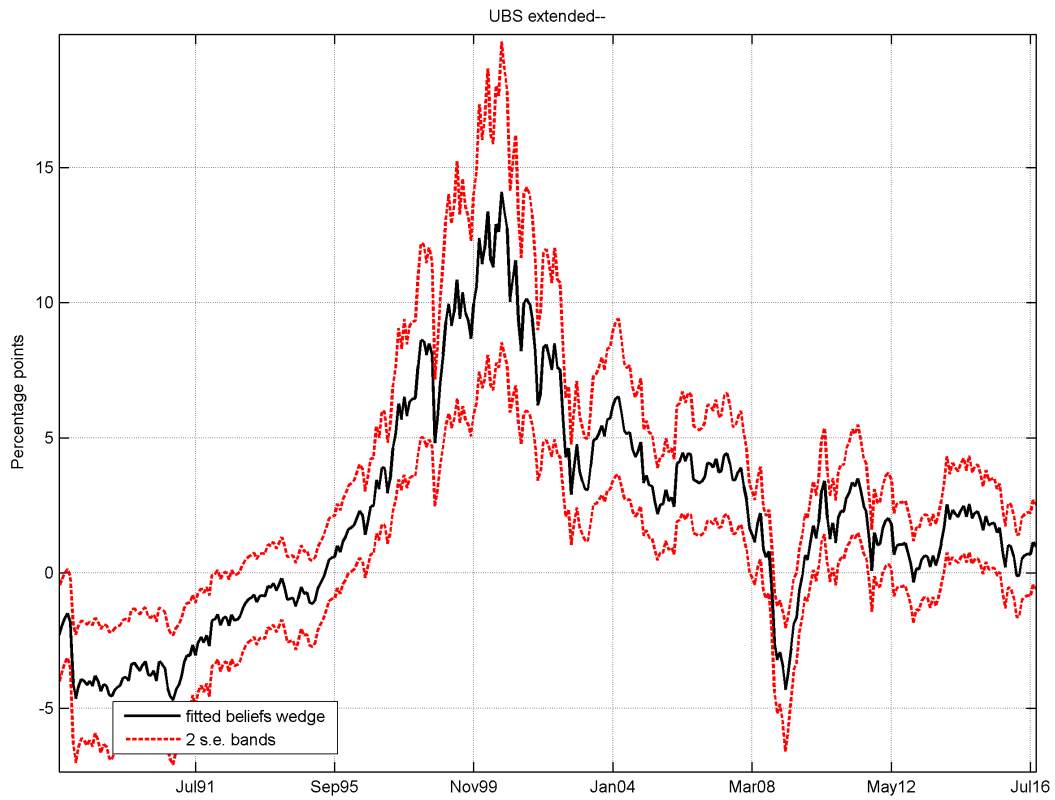


Figure 2: Fitted values from regression (18) of subjective expected returns in excess of the estimated objective expected returns on the P/D ratio in the UBS extended sample. The objective expected returns are estimated from regression (13) of realized returns on P/D ratio over a longer sample 1926-2017.

the unconditional and conditional properties of subjective return expectations deviate substantially from the prediction of the risk-neutral expectations hypothesis that subjective expected return should be equal to a maturity-matched risk-free rate. Allowing for differences in borrowing and lending rates or restricting the sample to individuals who are unlikely to be borrowing-constrained does not change this basic conclusion.

More generally, we don't find evidence that individuals report "risk-adjusted" expectations that are pessimistically distorted relative to the empirical distribution of stock returns. Unconditionally, average subjective expected returns are close to average realized returns without a significant bias. Conditionally, there are substantial deviations of subjective expected returns from the objective expected returns generated by empirical predictability regressions, but these deviations are optimistic in some periods and pessimistic in others, and they cancel out on average.

Our results therefore suggest that the predictable time-variation in the subjective expectations error around this unconditional mean of approximately zero is the most interesting property of these aggregated return expectations series that research should further investigate. For example, learning from experience (Malmendier and Nagel (2011), (2015)), return extrapolation (Barberis et al. (2015)), or learning from price growth (Adam et al. (2016, 2017)) could contribute to these time-varying subjective expectations errors.

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Appendix

A Asymptotic distribution of test statistics

A.1 PE-U2

Using \hat{E}_t as short form for $\hat{E}_t[R_{t+1}]$ and \mathcal{E}_t for $\mathcal{E}_t[R_{t+1}]$, we can rewrite (14) as

$$\mathcal{E}_t = b + \hat{E}_t + e_t - (\hat{E}_t - E_t) \quad (\text{A.1})$$

and we can treat this as a generated regressors problem with the coefficient on \hat{E}_t known and equal to one.

With the first stage regression written as

$$R_{t+1} = Z_t'k + u_{t+1} \quad (\text{A.2})$$

where $Z_t \equiv (1, z_t)'$, $k = (k_0, k_1)'$ and $\hat{E}_t = Z_t'\hat{k}$.

The derivation follows Wooldridge (2001), Appendix 6A.

Let T_1 be the sample size of the survey data and T_2 the size of the sample used to estimate $\hat{E}_t[R_{t+1}]$, with $T_2 > T_1$. When we take limits, $T_1 \rightarrow \infty$, we keep $\phi = T_1/T_2$ fixed, so that $T_2 \rightarrow \infty$ at the same rate.

Usual OLS calculations yield

$$\sqrt{T_1}(\hat{b} - b) = T_1^{-1/2} \sum_{t=T_2-T_1+1}^{T_2} \left[e_t - (\hat{E}_t - E_t) \right] \quad (\text{A.3})$$

where

$$T_1^{-1/2} \sum_{t=T_2-T_1+1}^{T_2} (\hat{E}_t - E_t) = \frac{1}{T_1} \frac{\sqrt{T_1}}{\sqrt{T_2}} \left(\sum_{t=T_2-T_1+1}^{T_2} Z_t' \right) \sqrt{T_2}(\hat{k} - k) \quad (\text{A.4})$$

$$= \sqrt{\phi}G\sqrt{T_2}(\hat{k} - k) + o_p(1) \quad (\text{A.5})$$

and where $G = E[Z']$ is the probability limit of $T_1^{-1} \sum_{t=T_2-T_1+1}^{T_2} Z_t'$.

We have

$$\sqrt{T_2}(\hat{k} - k) = \hat{C}^{-1}T_2^{-1/2} \sum_{t=1}^{T_2} Z_t u_{t+1} \quad (\text{A.6})$$

$$= \hat{C}^{-1}T_2^{-1/2} \left(\sum_{t=T_2-T_1+1}^{T_2} Z_t u_{t+1} + \sum_{t=1}^{T_2-T_1} Z_t u_{t+1} \right) \quad (\text{A.7})$$

with

$$\hat{C} = \frac{1}{T_2} \sum_{t=1}^{T_2} Z_t Z_t', \quad \text{where} \quad \hat{C} \xrightarrow{p} E[Z_t Z_t'] \quad (\text{A.8})$$

Substituting back into (A.3) and denoting $C \equiv E[Z_t Z_t']$, we get

$$\begin{aligned} \sqrt{T_1}(\hat{b} - b) &= T_1^{-1/2} \left\{ \sum_{t=T_2-T_1+1}^{T_1} [e_t - \phi G C^{-1} Z_t u_{t+1}] \right\} \\ &\quad - (T_2 - T_1)^{-1/2} \sqrt{\phi(1-\phi)} G C^{-1} \left(\sum_{t=T_2-T_1+1}^{T_2} Z_t u_{t+1} \right) + o_p(1) \quad (\text{A.9}) \end{aligned}$$

By the central limit theorem, as $T_1 \rightarrow \infty$, with ϕ fixed, $\sqrt{T_1}(\hat{b} - b)$ is asymptotically normal.

Simple (but unrealistic) case: With $Z_t u_{t+1}$ and e_t uncorrelated at all leads and lags, and with e_t serially uncorrelated, we get an asymptotic variance of $\sqrt{T_1}(\hat{b} - b)$ of

$$\text{Var}[e_t] + \phi G C^{-1} E[Z_t Z_t' u_{t+1}^2] C^{-1} G'. \quad (\text{A.10})$$

We can estimate the first term as

$$\frac{1}{T_1} \sum_{t=T_2-T_1+1}^{T_2} \hat{e}_t^2 \quad (\text{A.11})$$

and the expectation in the second term as

$$\frac{1}{T_2} \sum_{t=1}^{T_2} Z_t Z_t' \hat{u}_{t+1}^2 \quad (\text{A.12})$$

with

$$\hat{e}_t = \mathcal{E}_t - \hat{E}_t - \hat{b}, \quad \hat{u}_{t+1} = R_{t+1} - R_t^f - Z_t' \hat{k}, \quad (\text{A.13})$$

and $\phi = T_1/T_2$.

With serially correlated $\{e_t\}$, the first term in (A.10) should be replaced by a HAC-estimator (e.g., Newey-West). When there is additionally also correlation between e_t and nearby lags of $Z_t u_{t+1}$, we need to add to (A.10) a third term that captures the covariances of e_t and nearby lags $Z_t u_{t+1}$.

A.2 PE-C2

The derivation follows the same lines as above in the PE-U2 case. Bring $E_t[R_{t+1}]$ to the RHS of (16) and treat like a generated regressor with coefficient constrained to one. The only difference to earlier derivation to the PE-U2 case is that here we estimate slopes as well as a constant.

B Bias adjustment

Consider the system

$$\mathcal{E}_t[R_{t+1}] - R_t^f = a_0 + a_1 x_t + u_t \quad (\text{A.14})$$

$$x_t = \rho_0 + \rho_1 x_{t-1} + \xi_t \quad (\text{A.15})$$

$$u_t = \chi u_{t-1} + \eta_t + \lambda \xi_t, \quad (\text{A.16})$$

where η_t and ξ_t are independent i.i.d. normal random disturbances. Equation (A.14) is the regression equation (13) from the main text, but here for a scalar regressor x_t which is the P/D ratio in our empirical implementation. Equation (A.15) captures the fact that x_t is persistent. Equation (A.16) allows for non-zero covariance in the residuals of equations (A.14) and (A.15) and for persistence in the residuals of equation (A.14). In the special case without persistence ($\chi = 0$), equation system (A.14)-(A.16) reduces to one similar as that considered in Section 2 in Stambaugh (1999), although there with realized returns as dependent variable. Since the empirical evidence suggests that $\chi > 0$, we consider the more general case.

For the empirically plausible case with $\chi \neq 0$, the regressor x_t and the residual u_t in equation (A.14) depend both on lagged values of ξ_t , whenever $\lambda \neq 0$. OLS estimates of the coefficients (a_0, a_1) in equation (A.14) are then asymptotically biased. Furthermore, even if $\chi = 0$, OLS estimates suffer from a small-sample bias for $\lambda \neq 0$ (Stambaugh (1999)). To address both issues, we proceed as follows:

1. We estimate equation (A.15) using OLS and perform Monte-Carlo simulations to correct for the small-sample bias of the OLS estimates of ρ_0 and ρ_1 .
2. We lag equation (A.14) by one period, multiply by χ , and subtract the result from equation (A.14). This delivers

$$\begin{aligned} \mathcal{E}_t[R_{t+1}] - R_t^f &= a_0(1 - \chi) + \chi(\mathcal{E}_{t-1}[R_t] - R_{t-1}^f) \\ &+ a_1 x_t - \chi a_1 x_{t-1} + \lambda \xi_t + \eta_t, \end{aligned} \quad (\text{A.17})$$

which can be estimated using non-linear least squares (NLLS), given the observed explanatory variables and the estimates of ξ from step 1. This delivers consistent estimates for $\chi, \lambda, \sigma_\eta^2, a_0$ and a_1 . We then compute the value of the F -statistic from our hypothesis tests $H_0 : a = b = 0$ and $H_0 : b = 0$.

3. We then derive the small sample distribution of the F -statistic. This is done by simulating (A.14)-(A.16), using our parameter estimates (with some of the parameters changed to the value they assume under the considered null). We estimate (A.17) on the simulated data and compute the F -statistic for the simulated data.
4. To compute the small-sample bias corrected estimates of a_0 and a_1 , we use the NLLS estimates from step 3 to perform a bias correction of the NLLS estimates from step 2. We report these bias corrected OLS estimates of a_0 and a_1 in the tables of the main text.