Time-Series and Cross-Section of Risk Premia Expectations: A Bottom-Up Approach*

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Abstract

I construct a new dataset of subjective total return expectations at the single stock level, which I then aggregate at both market and portfolio level to construct the risk premia expectations of sell-side analysts. Sell-side analysts' expectations appear to be countercyclical, contrarian and less persistent than CFOs' expectations, have strong and consistent correlations with many model-based expected risk premium measures and imply a larger discount rate channel than CFOs' and economists' forecasts. Sell-side analysts' expected market risk premia forecasts are also able to predict realised stock market risk premia. Using sell-side analysts' excess return forecasts, CAPM and Fama-French multi-factor models fit the cross-sectional dynamics of subjective expected excess returns remarkably well.

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1 Introduction

In the current asset pricing literature on beliefs there has been a shift in attention from discount rates (the central focus of rational expectations models) to cash flows as key drivers of variations in asset prices. The reason for this shift is that while subjective cash flows expectations have been shown to have a very important role in explaining asset prices in financial markets, subjective discount rates expectations have not been as promising. When proxying either cash flow expectations or return expectations, the literature has focused on survey data from different types of economic agents: when looking at cash flow expectations (of dividends or earnings), the literature has turned to sell-side analysts' forecasts; when instead looking at subjective return expectations, the literature has focused on different groups of economic agents with significant heterogeneity in the findings.[1] Within the context of one-year subjective expectations of returns, the literature has focused mostly on survey data from CFOs and economists.[2]

In this paper, by focusing on sell-side analysts' forecasts to construct both total return and dividend expectations, I provide a consistent dataset of beliefs for both discount rates and cashflows. Through a bottom-up approach, I construct a new dataset of single stock total return expectations by combining sell-side analysts' price targets and dividend per share forecasts. These expectations represent the natural counterparts to the cash flow expectations that are currently widely used in the asset pricing literature and I show that they are economically different from the expectations of CFOs. Computing total return

[1] Greenwood & Shleifer (2014) report procyclical individual investors' (e.g., CFOs) return expectations. De La O & Myers (2021) use subjective cash flow expectations provided by sell-side analysts in combination with return forecasts from the Graham-Harvey CFO survey (Ben-David et al. (2013)) and show that the discount rate channel is procyclical as well as of secondary importance with respect to the cash flow channel. Dahlquist & Ibert (2021) find that professional economists and asset managers provide countercyclical forecasts. Nagel & Xu (2022) show that subjective risk premia of different market participants are acyclical as they lack of comovement with business cycle variables and aggregate asset valuation measures.

[2] Many *sentiment* surveys of returns have been studied in the literature: the Gallup survey, the American Association of Individual Investors Investor Sentiment Survey (AA), the Investors' Intelligenece newsletter expectation (II), and the Investor Behavior Project at Yale University. The focus of this paper, however, is on surveys of *one-year return expectations*, hence the choice of the Livingston survey and the Graham-Harvey survey as benchmarks. Note, the University of Michigan Survey of U.S. consumers and the Survey of Professional Forecasters also provide data on subjective expected returns, but for a 2-3 and 10 year horizon, and hence they are not directly comparable with sell-side analysts' return forecasts which are constructed at a one-year horizon.

expectations from sell-side analysts' forecasts has the advantage of providing consistency in terms of having the same agents generating forecasts for both cash flows and discount rates. In addition, sell-side analysts' expectations - as opposed to CFOs' and economists' expectations - are available at the stock level and at the same frequency as cash flows expectations.

At the market level, I show that sell-side analysts' forecasts are countercyclical and are able to forecast realised future market risk premia - while CFOs' forecasts are not. CFOs' expected return forecasts have very low volatility - roughly, three times lower than economists' forecasts and six times lower than sell-side analysts' forecasts - and high persistency. A simple AR(1) regression on CFOs' return expectations leads to an adjusted R^2 of almost 50%: CFOs' forecasts are persistent, perhaps due to the lack of insight, and to the possible anchoring to an historical average market return. In contrast, sell-side analysts' aggregate return forecasts show less persistency, which is consistent with forecasts formed by updating beliefs as new information arrives. My results also show that analysts' expectations imply a larger discount rate channel relative to CFOs' and economists' expectations, and that they are strongly dependent on and in line with many standard model-based expected risk premium measures, such as the price-dividend ratio (P/D), the consumption wealth ratio (cay) of Lettau & Ludvigson (2001), and the variance risk premium of Bollerslev et al. (2009). Beliefs from the Livingston and IBES surveys which may capture more sophisticated investors are contrarian, whereas those from the Graham-Harvey survey are extrapolative. Therefore, my results suggest that it is important to consider heterogeneity in expectations in line with theory papers of extrapolative expectations or more generally with models of asymmetric information.[3]

In addition, in line with a model of slow moving beliefs about stock market volatility (Lochstoer & Muir (2022)), I show that sell-side analysts' market expectations are strongly positively correlated with the square of the VIX index (VIX^2). The weaker correlation of both the leads and lags VIX^2 with the sell-side analysts' expectations, relative to the

[3] See Cutler et al. (1990), De Long et al. (1990), Hong & Stein (1999), Barberis et al. (2015), Glaeser & Nathanson (2017), Barberis et al. (2018), Bordalo et al. (2019), Bastianello & Fontanier (2021), Liao et al. (2022) for models with heterogeneous and extrapolative expectations, and Barberis (2018) for a recent survey. For models with asymmetric information see among others Wang (1993).

contemporaneous one, could be linked to subjective return expectations influencing the VIX[2] - when investors have high/low risk premia expectations they trade in options, and affect the VIX index contemporaneously.

Given the quality of the stock coverage provided by sell-side analyst forecasts, I also study the cross-sectional properties of analysts' return expectations. I construct risk-factors and 25 book-to-market sorted portfolios using the standard methodologies of Fama & French (1993) and Fama & French (2015). I show that the security market line (SML) - generated by using sell-side analysts' survey data for both dependent and independent variables when estimating βs - is positively sloped and close to the theoretical SML - which is not the case when the SML is constructed using realised excess returns of both the market and the test assets. Fama & French (1993) and Fama & French (2015) find that by augmenting CAPM with additional risk factors they are able to explain the cross-section of realised average excess returns significantly better. In a similar spirit, adding the subjective expected risk factors to the subjective market risk premium expectation allows to better explain the cross-section of subjective expected excess returns.

This work is also related to the accounting and asset pricing literature focusing on price targets as a fraction of the current price. More specifically, in the time-series my work is related to Brav & Lehavy (2003), Asquith et al. (2005) and Bradshaw et al. (2013) who study the co-movement of price target revisions with stock prices, their information content and their ability to provide profitable recommendations. My work is also close to Wang (2021) who shows that aggregate stock market price return expectations of sell-side analysts are countercyclical. In the cross-section, my work is related to Dechow & You (2020) who study the cross-sectional variation in target price implied returns. It is also connected to Brav et al. (2005) and Wu (2018) who study the cross-sectional relation between subjective expected excess returns and firm attributes. Rather than firm characteristics, my work investigates the relationship between subjective expected excess returns and subjective risk factors. Jensen et al. (1972), Fama & French (2004), Baker et al. (2011) and Frazzini & Pedersen (2014) find that the empirical SML generated using realised excess returns data is at odds with the theoretical SML. I show instead that when using subjective expectations data, the SML is correctly sloped. Berk & van Binsbergen (2017) use mutual fund investors' capital allocation decisions to infer investors' discount rates and find that investors adjust for risk using betas from CAPM. There is also an extensive experimental literature showing that CAPM works well in controlled laboratory experiments (e.g., Bossaerts & Plott (2004), Bossaerts et al. (2007), Asparouhova et al. (2020)). My results show that CAPM fits the cross-sectional dynamics of subjective expected excess returns very well; furthermore, by extending the subjective market risk premium with the subjective expected returns of the other Fama-French factors, my results lead to a further improvement in explaining the subjective cross-sectional dynamics of excess returns.

This paper proceeds as follows. In Section 2 I introduce the data and the construction of the variables used for the analysis. Section 3 looks into the determinants of subjective risk premia expectations. Section 4 investigates the properties of subjective risk premia expectations from an asset pricing perspective. Section 5 provides additional results from alternative time-series and cross-sectional tests on subjective expectations, and Section 6 concludes.

2 Data and Variables Construction

2.1 Data Description

I obtain monthly data on sell-side analysts' median forecasts of dividend per share (DPS) and earnings per share (EPS) from the US Unadjusted Summary Statistics of the Thomson Reuters I/B/E/S Estimates Database (IBES going forward). This dataset covers a wide universe of US stocks starting from 6/2002 for DPS and from 3/1976 for EPS, and it provides consensus estimates of sell-side analysts' forecasts. The forecast horizons covered are quarterly (fiscal quarter Q1, Q2, Q3, and Q4), semiannual, annual (fiscal year 1, 2, 3, 4) and long-term growth (LTG).

I obtain monthly median price targets (PTG) from the IBES US Unadjusted Summary Price Targets files. This dataset covers a wide universe of US stocks only from 03/1999. All forecasts are for a twelve month horizon. Due to the availability of both DPS and PTG forecasts, the sample period of the analysis starts from 06/2002.

As already extensively argued by Bordalo et al. (2019), De La O & Myers (2021) and Bordalo et al. (2022), sell-side analysts have a strong incentive to report their expectations accurately. For example, the forecasts collected by Thomson Reuters from hundreds of brokerage and independent analysts are not anonymous but labelled by the name of the analyst or brokerage firm, which incentivizes the release of accurate forecasts. To further ease the concern about agency conflicts and potential outliers, I use median forecasts across analysts.

I collect sell-side analysts' stock recommendations from the IBES US Recommendations Summary Statistics (Consensus Recommendations) files. The dataset coverage starts in 11/1993 and it provides averages and standard deviations of analysts' recommendations calculated as integers based on a 5 standardized Thomson Reuters Recommendation scale. I then rescale the scoring system from 1 (strong buy) / 5 (strong sell) to 2 / -2 to ensure a positive (negative) score can be interpreted as positive (negative) recommendation. I use these recommendations as proxies for expectations of future stock performance.

From Compustat, I collect data on quarterly earnings (income before extraordinary items). From CRSP, I obtain daily stock prices, dividends, returns, data on the constituents of the $S\&P500$ index, cumulative share adjustment factors (CFACSHR), and cumulative price adjustment factors (CFACPR). I obtain from CRSP the one-year Treasury yield ($R_{f,t}$) which I use to construct the subjective risk premium ($\tilde{\mathbb{E}}_t \left[R^e_{t+1}\right]$) as:

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

where $\tilde{\mathbb{E}}_t \left[R_{t+1}\right]$ is the subjective one-year expected total return obtained from the surveys considered. I define the realised one-year equity premium as the 12-month excess return of the CRSP value-weighted index of the $S\&P500$ universe.[4]

The John Graham and Campbell Harvey CFO Survey (GH) is completed quarterly by 200 to 500 CFOs of major U.S. corporations representing a broad range of industries, geographic areas, and sizes. Among other things, they report their expectations of returns on the $S\&P500$ index over the next 12 months. The data is available from the third quarter of 2000

[4]The monthly risk-free rate is from Kenneth French's web site.

up to the fourth quarter of 2018.

The Livingston survey (Liv) is conducted twice a year by the Federal Reserve Bank of Philadelphia and it provides the summary one-year expectation of stock market prices of economists from industry, government, banking and academia, for the period spanning from 1952 to 2020. Similar to Nagel & Xu (2022), I adjust the median price growth expectation - defined as the ratio of the median twelve-month to the median zero-month level forecasts of the $S\&P500$ index, for this survey - with the dividend yield and sell-side analysts' dividend growth expectations to obtain total return expectations:

$$\tilde{\mathbb{E}}_{Liv,t}\left[R_{t+1}\right] = \tilde{\mathbb{E}}_{Liv,t}\left[\frac{P_{t+1}}{P_t}\right] + \frac{D_t}{P_t}\tilde{\mathbb{E}}_t\left[\frac{D_{t+1}}{D_t}\right] \tag{2}$$

Note that while Adam et al. (2017) and Nagel & Xu (2022) set $\tilde{\mathbb{E}}_t\left[\frac{D_{t+1}}{D_t}\right]$ equal to the sample average of $S\&P500$ annual dividend growth, I rely on forward expectations and use survey data from sell-side analysts to compute the expectation $\tilde{\mathbb{E}}_{IBES,t}\left[\frac{D_{t+1}}{D_t}\right]$ - so that both terms in (2) are forward looking.

I obtain CBOE data on Volatility Index from FRED, variance risk premium and forward looking expected variance risk premium data from Hao Zhou's website, and *cay* data from Amit Goyal's website.

When running regressions with subjective expectations as dependent variables, in the spirit of De La O & Myers (2021) and van Binsbergen et al. (2023), I lag independent variables to the end of the previous month relative to the consensus formation period (i.e., roughly 3 weeks before the consensus is computed each month). This ensures that the independent variables reflect the information set available at the time the forecasts are formed.[5]

[5] As reported by Wang (2021), the median (mean) analyst issues new price targets every 16 (20) days, and only 2% of these estimates are the same as the price targets issued previously - as also reported by Bouchaud et al. (2019) for earnings forecasts. Hence, given that consensus forecasts are constructed on the third Thursday of every month, by lagging the valuation ratios to the end of the previous month I am using information that the average/median analyst holds when constructing her forecasts, while at the same time ensuring that the valuation ratios are not outdated. Results obtained when using valuation ratios on the day the consensus forecasts are formed do not qualitatively change (Appendix A).

2.2 Variable Construction: One-Year Subjective Expectations

2.2.1 Fundamentals

DPS (EPS) forecasts are provided on the third week of every month for different *end* of Fiscal Years (FY) or Fiscal Quarters (QTR). This is different from PTGs which are (rolling) twelve-month horizon forecasts. Therefore, forecast revisions are not directly available for PTGs. This implies that there are twelve-month horizon forecasts at a monthly frequency for PTGs, unlike EPS/DPS forecasts, for which there are only twelve-month horizon forecasts at annual frequency. Figure 1 illustrates this point by comparing EPS forecasts and price targets to the actual EPSs and one-year ahead realised prices for Tesla. As the end of the FY approaches, the 1YR EPS forecast moves closer to the actual realised fundamental: as the year progresses, analysts acquire more information about the performance of the company and their forecasts get closer to the actual realization. In order to obtain the DPS (EPS) forecasts on a rolling window basis (just like the PTGs), I use interpolation - similar to De La O & Myers (2021) - to construct one-year forecasts.

[Figure 1 here]

I also construct the aggregate one-year $S\&P500$ dividend (earnings) growth expectations by using a methodology similar to the one described in De La O & Myers (2021). Below I describe the procedure for the aggregated dividend series, but the same methodology is applied for the aggregate earnings series. Following De La O & Myers (2021), I define the one-year subjective expected dollar dividend of the $S\&P500$ in month t as:

$$\tilde{\mathbb{E}}_t\left[Div_{t+1}\right] = \tilde{\mathbb{E}}_t\left[\sum_{i \in x_{t+1}} \frac{D_{i,t+1} S_{i,t+1}}{\widehat{Divisor}_{t+1}}\right] \tag{3}$$

where $S_{i,t}$ is the number of shares outstanding of company i at the end of the month $t-1$, $D_{i,t}$ is the ordinary dividend per share paid by company i at the end of month $t-1$, x_t is the set of companies in $S\&P500$ at the end of month $t-1$ and $\widehat{Divisor}_t$ is the approximate value of the divisor of the $S\&P500$ backed out from $\frac{\sum_{i \in x_t} P_{i,t} S_{i,t}}{S\&P500_t}$ (where $P_{i,t}$ is the price per share of company i at the end of month $t-1$ and $S\&P500_t$ is the value $S\&P500$ index at the end of month $t-1$). I approximate subjective dividend growth expectations as

$\tilde{\mathbb{E}}_t\left[\Delta d_{t+1}\right] \approx log\big(\tilde{\mathbb{E}}_t\left[Div_{t+1}\right]\big) - log\left(Div_t\right)$, I assume that analysts do not expect changes in constituents or shares outstanding to affect the price-dividend ratio of the $S\&P500$ - $\mathbb{E}^*_t\left[\sum_{x_{t+1}} \frac{D_{i,t+1}S_{i,t+1}}{\widehat{Divisor}_{t+1}}\right] = \sum_{x_t} \frac{\mathbb{E}^*_t[D_{i,t+1}]S_{i,t}}{\widehat{Divisor}_t}$ -, and I deal with the missing constituents of the $S\&P500$ by assuming $\sum_{i \in x_t} \tilde{\mathbb{E}}_t\left[D_{t+1}\right] S_{i.t} = \left(\sum_{i \in x^j_t} \tilde{\mathbb{E}}_t\left[D_{t+1}\right] S_{i.t}\right) \frac{\sum_{i\in x_t} P_{i,t}S_{i,t}}{\sum_{i\in x^j_t} P_{i,t}S_{i,t}}$, where $x^j_t \subset x_t$ is the set of companies within the $S\&P500$ universe for which expectations data is available.

2.2.2 Returns

Using the one-year consensus DPS forecasts and consensus PTGs from IBES, I construct single stock expected total returns in month t as:

$$\tilde{\mathbb{E}}_t[R_{t+1}] = \frac{PTG_{t+1} + \tilde{\mathbb{E}}_t[DPS_{t+1}]}{P_t} \tag{4}$$

where $PTG_{t+1} = \tilde{\mathbb{E}}_t[P_{t+1}]$ is the median consensus price target scaled by the cumulative price adjustment factor at the time the consensus forecasts are constructed, $\tilde{\mathbb{E}}_t[DPS_{t+1}]$ is the one-year dividend per share consensus expectations scaled by the cumulative share adjustment factor at the time the consensus forecasts are constructed, and P_t is the adjusted price at the end of month $t-1$ - similar to van Binsbergen et al. (2023) where they scale the difference between the analysts' forecast and the machine learning forecast by the closing stock price from the most recent month.[6] This is a new metric relative to the existing literature (e.g., Wu (2018)) where expected total returns are constructed using only PTGs $\left(\tilde{\mathbb{E}}_t\left[\frac{PTG_{t+1}}{P_t}\right]\right)$. I then form the aggregate $S\&P500$ one-year expected total return (IBES RET) in month t by value-weighting the individual expected total returns of the stocks belonging to the $S\&P500$ universe:

$$\tilde{\mathbb{E}}_t[R_{S\&P500,t+1}] = \frac{\sum_{i\in x^j_t} \tilde{\mathbb{E}}_t[R_{i,t+1}]ME_{i,t}}{\sum_{i\in x^j_t} ME_{i,t}} \tag{5}$$

where $ME_{i,t}$ is the market capitalization of stock i at the end of the month $t-1$.

Figure 2 illustrates the difference between the bottom-up expected return series (5) from

[6]Results obtained when returns are constructed by scaling price targets and dividend expectations by the price at the time the consensus forecasts are constructed do not qualitatively change (Appendix A).

IBES - marked in green -, the expected return series from the other surveys described in Section 2.1 - GH Survey in red and Livingston Survey in yellow - and the one-year ahead realised total returns - dashed blue.

[Figure 2 here]

2.2.3 Construction of Price-Dividend Ratio

To construct the price-dividend ratio, I first aggregate the regular dollar dividends of the $S\&P500$ constituents from CRSP on a rolling 1 year basis. This provides a time-series of dollar dividends almost perfectly replicating the dollar dividends time-series of the $S\&P500$ from Robert Shiller's website, which then I normalize by the total ME of all constituents of the $S\&P500$:[7]

$$\frac{D_t}{P_t} = \frac{\sum_{i \in x_t} D_{i,t} S_{i,t}}{\sum_{i \in x_t} ME_{i,t}} \tag{6}$$

where $D_{i,t}S_{i,t}$ is the total ordinary dollar dividend distributed by firm i in the $S\&P500$ over the last year up to time t. Through this construction the focus is on pure dividends. This approach differs from Cochrane (1991) and Cochrane (2008) where dividends paid earlier in the year are reinvested at a certain return to the end of the year, thus leading to the price-dividend ratio:

$$\frac{D_t}{P_t} = \frac{R_t}{R_{x,t}} - 1 = \frac{P_t + D_t}{P_{t-1}} \frac{P_{t-1}}{P_t} - 1 \tag{7}$$

where R_t and $R_{x,t}$ are respectively the yearly total return and price return of the index. Figure 3 shows that the measure used in this paper (dashed green line) is less mean reverting than the Cochrane's standard measure (solid blue line). Intuitively, if dividends are reinvested when prices are falling, the effect on the end-of-year dividend is negative and hence the final price-dividend ratio is higher. In contrast, when prices are increasing, and dividends are re-invested, end-of-year dividends are magnified and the final price-dividend ratio is lower. For this reason, under Cochrane's approach, the resulting price-dividend pattern is

[7]Similarly, I compute the *expected* dividend-price ratio by dividing the expected dollar dividend of the $S\&P500$ in month t - described in Section 2.2.1 - by the ME of the $S\&P500$ at the end of the month $t-1$.

more mean-reverting than following the approach used in this paper.

[Figure 3 here]

2.3 Coverage

2.3.1 CRSP/Compustat and S&P500 Universe

A potential concern when using IBES data is the amount of coverage of the IBES universe relative to the CRSP/Compustat universe and/or to the $S\&P500$ constituents. To alleviate this concern, some statistics are presented below showing that the coverage provided by IBES is of sufficient quality.

Figure 4 illustrates the quality of the coverage provided by IBES. Although the number of stocks seems to be relatively low, market capitalization coverage is substantial - on average, it is above 90% for PTGs and 85% for DPS forecasts for the period of interest - which implies that there are forecasts available for a universe of stocks which represents the majority of the CRSP/Compustat market capitalization. Figure 4 also shows that the PTG coverage is better than the DPS forecast coverage.[8]

[Figure 4 here]

When comparing the value-weighted subjective expected total return of the $S\&P500$ with the value-weighted subjective expected price return of the $S\&P500$, the difference between these two time-series is remarkably similar to the dividend-price ratio (or subjective expected dividend-price ratio) of the $S\&P500$ as illustrated in Figure 5.[9] It is reassuring that this difference is similar to the dividend price ratio of the index, considering that the value-weighted expected price return of the $S\&P500$ is the aggregate expected return of the $S\&P500$ when all DPS forecasts are assumed to be zero (IBES RETx).

[Figure 5 here]

The overall coverage of the $S\&P500$ provided by IBES is summarized in Figure 6. The coverage is above 90% for ME and number of stocks, which implies that there is a sufficient

[8] Given that expected returns require both, I set the DPS forecast to zero when they are not present in the dataset. Results do not qualitatively change if stock-month observations without dividend expectations are removed from the dataset.

[9] I explain the how I construct the price-dividend ratio in Section 3.

number of stocks to construct a proxy for the expected returns of the $S\&P500$.

[Figure 6 here]

2.3.2 Fama-French Portfolios Coverage

A standard set of test assets used in the literature for cross-sectional asset pricing tests are the Fama-French 25 portfolios double sorted by ME and book-to-market (B/M). Table 1 illustrates the time-series average quality of analysts' coverage for these portfolios. Good coverage is provided both in terms of number of stocks and ME for all portfolios (90%) except for the smallest ME quintile which has the worst coverage both in terms of stocks (60%) and ME (80%). Overall, there is enough coverage to study the subjective return properties of cross-sectional portfolios and compare the results with the properties of portfolios based on realised returns. To provide further evidence of the small impact of the lack of coverage, Figure 7 illustrates the time-series of annual returns of the standard 5 Fama-French factors when either the IBES or the full CRSP/Compustat universe is used. The difference is small, with some minor discrepancies only for the investment factor. This means that the expected excess returns of portfolios constructed by sorting stocks according to the Fama-French methodology are good approximations for the total unobservable subjective expected excess returns.

[Figure 7 and Table 1 here]

2.4 Summary Statistics of Survey Expectations

Given the stark differences in the time-series shown in Figure 2, I report in Table 2 some key summary statistics of the subjective expected return series of the $S\&P500$, and in Table 3 the correlations of survey forecasts. A few observations can be easily made. First, IBES expected returns are much higher and volatile compared to the CFOs' and the economists' expectated returns. Second, CFOs' expectations are negatively correlated with the expectations of sell-side analysts (-0.55), whereas the economists' expectations are positively correlated with sell-side analysts' expectations (0.70) - and CFOs' and economists' expectations are weakly positively correlated (0.12). The implication is that there is a lot of belief heterogeneity which I further investigate in the next Sections.

[Tables 2 and 3 here]

3 Determinants of Subjective Risk Premia

In this Section I investigate the determinants of survey excess return expectations both over time and in the cross section. Combining results from these two dimensions allows us to better understand how subjective expectations are formed.

3.1 Time-series Dimension

3.1.1 Standard Tests

To study the properties of risk premia expectations over time, in the spirit of Greenwood & Shleifer (2014) and Nagel & Xu (2022), I run regressions of the form:

$$\tilde{\mathbb{E}}_t[R^e_{t,t+12}] = \gamma_0 + \gamma_1 \ R^e_{t-12,t} + \gamma_2 \ pd_t + \epsilon_t \tag{8}$$

where $\tilde{\mathbb{E}}_t[R^e_{t,t+12}]$ is the subjective expected 12-month risk premia, and $R^e_{t-12,t}$ denotes the past 12-month return of the CRSP value-weighted index of the $S\&P500$ universe in excess of the risk-free rate, and pd_t is the log price-dividend ratio. All independent variables are standardized to have unit standard deviations in the full sample of the regressions, which allows comparisons across the slope coefficients. In a similar setting Greenwood & Shleifer (2014) reach two main conclusions. First, when recent past returns are high, individual investors expect higher returns going forward (extrapolative). Second, even after controlling for recent returns, individual investors' expectations of future returns are positively correlated with the price-dividend ratio (procyclical). On the other hand, Nagel & Xu (2022) find that the γ_2 coefficients are significantly smaller when subjective expected returns are used as dependent variables rather than realised returns. Table 4 shows that the GH survey is extrapolative in nature and acyclical (positive γ_1 and insignificant γ_2). Livingston and IBES expected risk premia instead are contrarian - negative γ_1, hence an increase (decrease) in the previous 12 months excess returns is followed by a decrease (increase) in expected risk premia - and countercyclical in nature - negative γ_2, hence they are negatively related to the price-dividend ratio, *pd*, which is consistent with the general prediction of RE models (e.g., Campbell & Cochrane (1999) and Bansal & Yaron (2004)). However, after conditioning for both lagged returns and price-dividend ratio, GH expected risk premia only depend on past excess returns (extrapolative) whereas IBES expected risk premia are only negatively related to the price-dividend ratio (countercyclical). Differently from Nagel & Xu (2022), the *pd* slope in the Livingston and IBES risk premia regressions (γ_2, -1.88 and -2.92) are similar in magnitude to the *pd* coefficients on the realised returns regressions (-4.42), whereas the GH *pd* slope coefficient is an order of magnitude smaller (0.14).[10]

[Table 4 here]

To better understand the relationship of subjective risk premia expectations with lagged returns, I run simple OLS regressions of subjective risk premia forecasts on lagged quarterly excess returns. Table 5 shows that the GH survey is extrapolative in nature - with expectations depending more on recent return realizations than on more distant ones as in Greenwood & Shleifer (2014). When the price-dividend ratio is added to the independent variables, its coefficient is not statistically significant - implying CFOs' risk premia are acyclical as discussed in Nagel & Xu (2022). The Livingston survey is instead contrarian and the *pd* coefficient is not significant after conditioning for lagged returns. Similar to the Livingston survey and in contrast to the GH survey, IBES forecasts are contrarian: when looking at past returns at quarterly frequency, the most recent return realizations have larger coefficients than more distant ones. For robustness, in Section 5.3 I show that analysts' recommendations are also contrarian. In addition, consistent with Table 4, IBES expected risk premia show a negative and significant *pd* coefficient (countercyclical).

[Table 5 here]

Taken together, this first set of results suggests that recent past returns may affect investor risk premia expectations regardless of whether the forecasters are CFOs, economists or sell-side analysts. However, while CFOs are extrapolative in nature, economists and sell-

[10] In this paper, the sample periods chosen are essentially the same across all regressions, which is not the case in Nagel & Xu (2022). Furthermore, alternative constructions of the price-dividend ratio (e.g., Cochrane (2008)'s methodology) can lead to different results.

side analysts are contrarian. In addition, after adding recent past returns, the coefficient on the *pd* is negative and significant only for IBES expected risk premia, implying that these expectations are more connected to valuation ratios than the other surveys.

A final simple way of looking at the structure of the survey risk premia expectations is to run AR regressions. Results from these regressions are reported in Table 6. When considering the AR(1) regressions without the *pd* term, all surveys display some persistence, with GH having the highest slope coefficient (0.69) and adjusted R^2 (0.45), and IBES having the smallest values (0.47 and 0.22 respectively). When looking at higher order AR regressions, it appears that the most recent lag always has the largest slope coefficient and t-statistic than later lags. Although some level of persistency could be consistent with the overlapping nature of the forecasting regressions, an excessive degree of persistency could be due to sticky expectations where forecasters are anchored to their previous observations due to lack of insight. When adding the *pd* regressor (last regression in each panel of Table 6), in the GH regression the coefficient is not significant, whereas in both the Livingston and in particular in the IBES regressions, it is negative and strongly significant, with no significant lagged effect. Again, IBES appears to be more connected to fundamentals than the Graham-Harvey survey.

[Table 6 here]

3.1.2 IBES Subjective Risk Premia and VIX^2

Given that asset pricing theories often relate risk premium to variance, I next look at the correlation of IBES with the square of the VIX index (VIX^2) - which measures the 30-day implied variance of $S\&P500$ options, and it is widely used as a measure of equity market risk. Figure 8 shows the correlation of IBES expectations with different weekly leads and lags of the VIX and VIX^2. The plots suggest that the highest correlation between the survey and the VIX/VIX^2 is the contemporaneous one (almost 80%), with the strength of the correlations falling when the VIX/VIX^2 are lagged or led.[11]

[Figure 8 here]

[11] Note that in line with the construction of the total return expectations, the time t correlation is between IBES subjective risk premia in month t, and the VIX (VIX^2) value at the end of month t-1. This ensures that the value of VIX (VIX^2) reflects the information set available at the time the forecasts are formed.

There are two implications of these results. First, the extremely high correlation between the VIX^2 and the IBES survey is in line with a model of slow moving beliefs about stock market volatility as developed by Lochstoer & Muir (2022). In their model, the subjective market risk premium can be re-written as:

$$\tilde{\mathbb{E}}_t[R^e_{t,t+1}] = A\ IV_t + B \tag{9}$$

where A and B are constants which depend on the parameter of the model, and IV_t is the implied variance at time t - which can be approximated by the VIX^2. Therefore, my empirical findings about the strong correlation between the IBES subjective beliefs and the VIX^2 are in line with models where subjective beliefs about risk play a core role in determining the asset pricing dynamics in financial markets.

The second implication of my results is related to the tent shape pattern of the correlations presented in Figure 8. The high correlation of the consensus forecast with the contemporaneous VIX^2 could imply a direction of causality in that analysts' expectations influence the VIX^2 - rather than analysts forming their expectations based on the VIX^2. When VIX/VIX^2 is added to the explanatory variables in the regressions studying the determinants of IBES risk premia expectations the adjusted R^2 significantly increase to more than 70%. However, to better understand the direction of causality between IBES and VIX^2, it would be necessary to use analyst level forecast data (rather than just consensus data). This would allow us to pin down the exact timings of the forecast releases and their impact in options markets, which could be an interesting extension for future work. In the spirit of Giglio et al. (2021), my results suggest how subjective expectations might impact portfolio decisions of sophisticated investors.

Understanding the causality link between IBES and VIX^2 would provide researchers not only with a new instrumental variable useful for empirical studies involving subjective beliefs (provided the standard exclusion restriction is satisfied), but it would also allow researchers to use the VIX (VIX^2) as a proxy of subjective expected returns of sophisticated stock market participants, and therefore to study beliefs at much higher frequencies than only monthly, quarterly or annually.

3.2 Cross-sectional Beliefs

Given the time-series properties discussed in the previous Section and the excellent cross-sectional coverage of stocks provided by IBES, the next step is to look at the cross-sectional properties of the subjective excess return expectations. A natural questions arises: are analysts' forecasts cross-sectionally consistent with standard models, like CAPM and Fama-French multi-factor models, in forming their expectations? To address this question, I run standard Fama-French time-series regressions using survey forecasts of returns rather than realised returns. Using firm fundamentals from Compustat, I sort stocks into portfolios using the standard Fama & French (1993) methodology, construct the subjective expected excess returns of the portfolios using IBES data and then run cross-sectional tests.

3.2.1 Subjective Expected Factor Returns

Figure 9 illustrates the difference between subjective expected one-year returns and future realised one-year returns of the Fama-French factors. Noticeably, subjective expected factor returns are positively correlated with future realised factor returns - with the exception of the value factor - and negatively correlated with their past realizations - with the exception of the investment factor. Overall, it would appear that subjective expected factor returns are contrarian in nature, just like the expectations of aggregate stock market returns.

[Figure 9 here]

Given that the focus here is to understand the determinants of subjective expectations, the question I am interested to answer now is whether a simple model such as CAPM is able to explain the cross-sectional variation of subjective expected excess returns. The next Section deals with this question.

3.2.2 Security Market Line under Subjective Expectations

A simple way of studying the ability of CAPM to explain the cross-sectional variation in expected asset returns, was provided by Fama & MacBeth (1973) who suggested the following two-step procedure: a set of time-series regressions followed by a cross-sectional regression. Many papers (e.g., Frazzini & Pedersen (2014)) have shown that CAPM faces many difficulties when tested with the data: in general, after running the first stage time-series regressions of the Fama-MacBeth procedure, the security market line (SML) is too flat (or even negatively sloped). This leads to the natural question of whether the cross-section of subjective expected excess returns faces the same issue.

As a benchmark, I first run simple time-series regressions of excess returns of the Fama-French 25 book-to-market sorted portfolios against the excess market return using annual data over the sample period of interest, 2002 -2020:[12]

$$R^e_{i,t} = \alpha + \beta R^e_{mkt,t} + \epsilon_t \tag{10}$$

Plotting the average excess returns of the test assets against the βs estimated from equation (10) allows us to see how well CAPM fits the data: in order to provide support to the model, the empirical SML (the line of best fit) and the theoretical SML (implied by CAPM) would at least need to be close to each other. Figure 10 shows the results from this exercise. For the sample period available, the empirical SML is *negatively* sloped which is at odds with the CAPM prediction. Therefore, this result confirms that CAPM, by itself, struggles to explain the cross-sectional dynamics of expected realised returns.

[Figure 10 here]

The next step is to check whether CAPM faces the same limitations when using subjective beliefs. To this aim, I run regressions similar to (10) but now based on subjective expected excess returns:

$$\tilde{\mathbb{E}}_t \left[R^e_{i,t+1}\right] = \tilde{\alpha} + \tilde{\beta}\tilde{\mathbb{E}}_t \left[R^e_{mkt,t+1}\right] + \tilde{\epsilon}_t \tag{11}$$

Figure 11 shows the average subjective expected excess returns against $\tilde{\beta}$s from the regression (11). Compared to Figure 10 which displays a negatively sloped SML, Figure 11 shows an empirical SML which is not only positively sloped but it is also very close to the theoretical SML. As the average adjusted R^2 from the regressions (11) is 62% - this will be discussed

[12]Subjective total returns expectations for portfolios can be constructed at a monthly frequency and generate similar qualitative results. Note, however, that after moving past the month of June, return expectations of the Fama-French portfolios computed using price targets implicitly require that the forecasters believe that the portfolio composition will not change in 12 months time.

further in Section 5.2 -, I can conclude that a substantial portion of the cross-sectional variation in subjective expected excess returns is explained by the subjective expectation of the market excess return. Hence, these findings provide support that CAPM explains well the cross-sectional variation of subjective expected stock returns.

[Figure 11 here]

4 Properties of Subjective Risk Premia

In this Section, I analyze the properties of the bottom-up $S\&P500$ one-year subjective expected total return series constructed using analysts' forecasts (IBES 1YR RET or simply IBES) and compare it to other subjective expectations of the $S\&P500$ used extensively in the literature.

4.1 Subjective Cash Flow and Discount Rate Decomposition

Following Campbell & Shiller (1988), I can write the one-year price-dividend ratio as:

$$pd_t = \kappa + \Delta d_{t+1} - r_{t+1} + \rho \; pd_{t+1} \tag{12}$$

where κ is a constant, $\rho = e^{\bar{pd}}/(1 + e^{\bar{pd}}) < 1$, and $\bar{pd}$ is the mean value of the log price-dividend ratio. Applying subjective expectations to the above equation, changes in the price-dividend ratio must be explained by changes in either one-year dividend growth subjective expectations, or one-year return subjective expectations, or subjective expectations of the future price-dividend ratio. This gives the following one-year decomposition:

$$1 = \underbrace{\frac{cov\left(\tilde{\mathbb{E}}_t[\Delta d_{t+1}], pd_t\right)}{var(pd_t)}}_{CF} + \underbrace{\frac{-cov\left(\tilde{\mathbb{E}}_t[r_{t+1}], pd_t\right)}{var(pd_t)}}_{DR} + \underbrace{\rho\frac{cov\left(\tilde{\mathbb{E}}_t[pd_{t+1}], pd_t\right)}{var(pd_t)}}_{LT} \tag{13}$$

where CF captures the influence of one-year subjective dividend growth expectations ('cash flow news'), DR captures instead the influence of one-year subjective return expectations ('discount rate news') and LT captures the long-term influence of subjective dividend growth and return expectations. These three measures can be estimated using simple OLS. In Panel A of Table 7 I extend the sample period of De La O & Myers (2021), and I compare them with the results obtained by using IBES $S\&P500$ expected returns instead of GH expectations when estimating the DR channel.[13] Two main findings should be noted. First, both the sign and magnitude of the DR channel change significantly when IBES expected returns are used instead of the GH survey: IBES implies an almost three times larger and countercyclical DR channel. Second, the magnitude of the LT channel when using IBES expectations (rather GH survey data) drops by almost 30% which implies that the impact of future subjective cash flows and discount rates is significantly lower than previously estimated.[14] It should be noted that the tests relying on IBES forecasts - rather than on CFOs' or economists' forecasts - to construct subjective expectations of *both* cash flows and total returns are more consistent, and hence probably more reliable, because the expectation data in this case is always collected from the same class of economic agents.

[Table 7 here]

4.2 Model-based vs. Survey-based Expected Risk Premia

Greenwood & Shleifer (2014) report that subjective expected returns of individual investors have inconsistent (or insignificant) correlations with model-based expected returns. In Table 8, I first confirm that CFOs' risk premia expectations have insignificant (and inconsistent) correlations with the price-dividend ratio (pd), the consumption wealth ratio (cay) and the variance risk premium (VRP). IBES beliefs are strongly correlated with all of these measures and the signs are in line with the predictions of rational expectations asset pricing models.[15]

[Table 8 here]

[13]Note that since $\tilde{\mathbb{E}}_t[pd_{t+1}] = \frac{1}{\rho}(pd_t + \tilde{\mathbb{E}}_t[r_{t+1}] - \tilde{\mathbb{E}}_t[\Delta d_{t+1}] - \kappa)$, changing the subjective return measure from GH to IBES will not only affect the DR channel, but also the LT one.

[14]Note that in Panel B of Table 7, the decomposition is obtained using semi-annual data to compare IBES and Graham-Harvey return expectations with Livingston expectations: the results show that although when using Livingston's forecasts I obtain a countercyclical discount rate channel, it is smaller and less statistically significant relative to the discount rate channel implied by IBES expectations.

[15]Table 8 also provides the correlations of the surveys with the expected variance risk premium ($\mathbb{E}[VRP]$) of Bollerslev et al. (2009) which is the theoretical measure that should predict risk premia in their model. GH and Liv are uncorrelated with it, whereas the IBES is strongly correlated.

4.3 Subjective Risk Premia Expectations and Investment Strategies

A natural follow up question is whether the predictive ability of analysts' forecasts also implies that these expectations provide a valuable information signal which can be exploited in the form of a trading strategy. I rely on the Merton (1969) portfolio allocation rule - $\alpha_t = \frac{\mathbb{E}_t[r_{t+1}]+\frac{1}{2}\sigma_r^2-r_f}{\gamma\sigma_r^2}$ - and fix the volatility (σ_r^2) to isolate the effect of expected returns in the numerator ($\mathbb{E}_t[r_{t+1}]$). I build different trading strategies which rely on different measures of $\mathbb{E}_t[r_{t+1}]$ when constructing α_t. The strategies of interest are the ones relying on the surveys (GH, Livingston and IBES) as proxies for $\mathbb{E}_t[r_{t+1}]$. As benchmarks instead, I rely on 10-year rolling-window forecasting models of excess returns based on *pd* or VRP. Figure 12 shows the performance of the different strategies when no restrictions are placed on the value and sign of the portfolio weights.[16] The strategy relying on IBES returns is very aggressive and levers its position in the stock market thus leading to a very good performance outside of the financial crisis period (the green line is steeper than the other strategies except for 2008-2009 period). As shown in Panel A of Table 9, the IBES based strategy experiences very high returns but also very high volatility. The Livingston survey also relies on leverage (although to a lesser extent) whereas the Graham-Harvey survey does not. This is consistent with CFOs' expectations of returns not being volatile and being roughly constant around 5-6%, as shown in Figure 2 and Table 2. Overall, however, all survey expectations based strategies are always long the market although to different extents. In order to appreciate the amount of leverage implied by the survey expectations, in Panel B of Table 9 I report the results on the performance of the trading strategies after implementing shorting and leverage constraints. Given the constraints, the IBES and Livingston strategies are essentially always fully invested in the stock market. However, these results should be interpreted with caution as they rely on a simple asset allocation rule and parameterization.

[Figure 12 and Table 9 here]

[16] In Panel A of Table 9, I impose a high risk-aversion parameter for this unconstrained set of strategies: this is to limit the extreme and unrealistic portfolio weights implied by the Merton (1969) portfolio allocation rule when low values of the risk-aversion parameters are used.

4.4 Predictability of Market Risk Premia

4.4.1 Standard In-Sample Market Risk Premia Predictability Tests

A critical property of subjective expected excess returns measures is whether they actually forecast future market risk premia. Here I consider the relationship between expected and realised risk premia, and I run regressions of the form:

$$R^e_{t,t+1} = \alpha + \beta X_t + \epsilon_{t+1} \tag{14}$$

where $R^e_{t,t+1}$ denotes the 12-month excess returns of the $S\&P500$, and X_t is either a survey risk premia expectation or the price-dividend ratio. If $X_t = \tilde{\mathbb{E}}_t[R^e_{t,t+1}]$ and investors have rational expectations, then the coefficients α and β in equation (14) should be equal to 0 and 1 respectively. Rational expectations should subsume all information embedded in any statistical predictor of future stock market risk premia.

Table 10 presents results from the regressions based on equation (14). This allows me to compare the forecasting power of both GH and IBES (available at quarterly frequency), and Livingston (which is only available at semi-annual frequency) against the benchmark *pd* predictive regression. The GH survey does not forecast future risk premia. In contrast, the *pd* and the other measures of expected risk premia show some degree of predictability. Livingston and IBES both have significant β at the 1% level and have adjusted R^2 (8% and 7%) which are similar in magnitude to the adjusted R^2 from the benchmark *pd* predictive regression (6%).

[Table 10 here]

Overall, both Livingston and IBES risk premia expectations display two very desirable properties: first, they have significant slope coefficients and relatively high adjusted R^2 compared to the GH survey; second, the sign of the β coefficients are correct, as higher subjective expected risk premia predict higher future risk premia.

It should be noted that the IBES and Livingston surveys are limited in their risk premia predictive ability due to their failure in forecasting the Great Financial Crisis of 2008-2009. To help gaining insight on this issue, Figure 13 illustrates the time-series of IBES risk premia forecasts in conjunction with the $S\&P500$ future realised excess returns and the VIX index. Two features are easily seen. First, as previously discussed in Section 3, the VIX index is strongly correlated with IBES expected risk premia (80%). In periods of distress, analysts' risk premia expectations increase rather than decrease. Second, the limited adjusted R^2 reported in Table 10 are due to the inability of subjective expectations to forecast the Great Financial Crisis (GFC). In the year preceding the GFC, analysts' expectations increased whereas future realised excess returns became strongly negative due to the approaching stock market crash. As the GFC is overall a tail-event/outlier, a natural question is whether controlling this event changes substantially the predictive power of subjective expectations. Table 11 answers this question and shows the results from including a dummy for the 2007-2008 period in the risk premia predictability regressions from Table 10. By comparing the rows in this table, we can see the impact of adding a dummy for the 2007-2008 period on the predictability of *pd* and my surveys. The dummy leads to a substantial increase in all of the adjusted R^2. The Graham-Harvey survey still has an insignificant slope coefficient and a low adjusted R^2 (38%) relative to the benchmark regression on *pd* (45%). The Livingston survey, on the other hand, displays a very significant slope coefficient, but also a slightly lower adjusted R^2 (41%) than the benchmark *pd* regression. IBES displays both a significant slope coefficient and a slightly higher adjusted R^2 (46%) than the other surveys or *pd*. We can therefore conclude that alternative surveys have very different forecasting powers, and that IBES has an edge on the GH survey.

[Figure 13 and Table 11 here]

4.4.2 Comparison of Survey Forecasts Performance

A natural question is to ask how different surveys compare in terms of forecasting performance and whether there is some time-variation in relative performance. To answer these questions, I rely on the unconditional test of predictive ability of Diebold & Mariano (2002) (DM test going forward) - with the small-sample correction suggested by Harvey et al. (1997) -, and the conditional test of predictive ability of Giacomini & White (2006) (GW test going forward).

Table 12 illustrates the results of the DM and GW tests when applied to IBES, GH and Liv surveys for alternative loss functions - squared errors (SE) and proportional squared errors (SPE) - and sample-periods - up-to Great Financial Crisis (GFC), post GFC, and full-sample. While SE is a standard loss function, I also consider SPE because it is robust against heteroskedasticity in the forecast errors, Taylor (2011).[17] When comparing IBES and GH, there appears to be some evidence of outperformance of the former especially in the post GFC period; in particular, this is the case when the loss function is SPE. Overall, sell-side analysts outperformed CFOs in the post GFC period. IBES seems to outperform Liv only in the post GFC period. The GW test is rejected at the 10% for both SE and SPE loss functions, whereas the DM test is rejected for the SPE loss function in the second-half and full-sample tests. Overall the evidence suggests that IBES outperforms GH, especially in the post GFC period. The comparison with Liv leads to somewhat weaker results although there is some evidence of outperformance of IBES in the post GFC period.

[Table 12 here]

5 Additional Results

5.1 Forecasting Regressions of Fundamentals

Given the results from Table 10 and Table 11, I now investigate how the forecasting power of analysts differs when looking at fundamentals rather than risk premia. To address this issue, I run regressions of future dividend (earnings) growth on the IBES expected dividend (earnings) growth. Table 13 reports the results. Analysts are better at forecasting dividends than earnings (as the former are stickier). From a simple OLS predictive regression, sell-side analysts seem to better forecast fundamentals than risk premia as the adjusted R^2s on fundamentals are substantially higher - 25%/36% in Table 13 - than the adjusted R^2 on risk premia - 8% in Table 10. However, adding an indicator function for the 2007-2008 period leads to a significant boost in the predictability of the sell-side analysts in particular for risk

[17] When splitting the sample in half (or up-to the GFC and post-GFC) for the forecast errors of GH or IBES, the Bartlett and Levene tests of homogeneity of variances reject the null with p-values smaller than 10% and 5% respectively.

premia such that the adjusted R^2s are very similar in magnitude for both fundeamentals and risk premia. Therefore, after controlling for the GFC, analysts exhibit similar forecasting ability when it comes to either fundamentals or risk premia.

[Table 13 here]

5.2 Beyond CAPM and Subjective Asset Pricing Models

Given the empirical success of the SMB and HML factors - first introduced by Fama & French (1993) - in explaining the cross-section of expected realised excess returns, one might wonder whether extending CAPM to the classic Fama-French 3-factor model allows us to better explain the cross-sectional dynamics of subjective excess returns better. Tables 14 and 16 provide the full results from the Fama-MacBeth first stage time-series regressions from Section 3.2.2. The results improve when the Fama-French 3-factor model is used rather than CAPM. Similarly, Tables 15 and 17 show the results obtained testing the Fama-French 5-factor model. These results show that, for my sample, when moving from CAPM to 3/5 Fama-French factor models, I obtain similar improvements both when using realised excess returns (αs from the first stage drop in magnitude and the average R^2 increases from 74% to 93%) and when using survey data (R^2 increases from 62% to 86%). This implies that the cross-sectional dynamics of subjective excess returns are better explained by Fama-French multi-factor models than by the simple CAPM. Therefore, although CAPM already provides a good benchmark model to explain the cross-section of subjective expectations of excess returns, a multi-factor model does a better job at capturing the full dynamics. Overall, the evidence provides implicit support that sophisticated analysts rely on some form of multi-factor model.

[Tables 14 through 17 here]

A final natural question is whether the finding above also implies that subjective factor returns price the cross-section of excess realised returns, or in other words, whether the subjective expected factor returns represent a new set of factors which can be used to price assets in financial markets. Preliminary results show that these subjective factors do not seem to explain well the realised cross-sectional variation of expected excess returns of my test assets.[18] However, future research should investigate whether these factors have some relevant explanatory power when used in conjunction with other factors.

5.3 Analysts' Recommendations: Robustness

To provide further evidence that sell-side analysts' beliefs are contrarian, I construct a sentiment metric based on analysts' stock recommendations, $SR_{i,t}$:[19]

$$SR_{i,t} \quad = \quad \mathbb{E}_t[Rec_{i,t}] \tag{15}$$

where $\mathbb{E}_t[Rec_{i,t}]$ is the consensus mean Thomson Reuters Recommendation for stock i at time t. This metric does not require a normalization by the current price and at the same time it represents a proxy of analysts' expectations of the future stock market performance. I value-weight the consensus mean stock level recommendations, $SR_{i,t}$, belonging to the S&P500 universe in a similar manner to equation (5) to construct a market level sentiment index ($SR_{m,t}$) and I run the following regression:

$$SR_{m,t} = \zeta_c + \zeta_r R^e_{t-3,t} + \zeta_{pd} pd_t + \epsilon_t \tag{16}$$

where $R^e_{t-3,t}$ is the most recent quarter excess return and pd_t is the log price-dividend ratio. Results in Table 18 show that the estimate of the coefficient ζ_r is negative and statistically significant - while the estimate for ζ_{pd} is not statistically significant -, thus providing further evidence that analysts' beliefs are contrarian in nature.

[Table 18 here]

[18] Appendix B shows the SMLs where the βs are obtained when realised excess returns of the Fama-French 25 book-to-market sorted portfolios are regressed on GH or IBES subjective excess market return expectations. The empirical SMLs are negatively sloped in both cases, and at odds with theoretical SML. Appendix C provides further evidence of why multi-factor models based on subjective expected factor returns do not explain the cross-section of realised excess-returns of the Fama-French 25 book-to-market sorted portfolios.

[19] I thank Daniel Schmidt for suggesting this extension.

6 Conclusions

When running asset pricing tests, the use of subjective expectations from different surveys can lead to stark differences in results. Given that sell-side analysts' forecasts are used to construct cash flow expectations, using sell-side analysts' - as opposed to economists' and CFOs' - total return expectations provides consistency in terms of having the same agents generating forecasts for both cash flows and discount rates. By focusing on the forecasts of sell-side analysts, through a bottom-up approach I construct the risk premia expectations of sophisticated stock market participants. I show that these expectations display multiple properties which differ substantially from those of CFOs. First, while sell-side analysts' expectations appear to be contrarian, CFOs' expectations are extrapolative: this difference highlights the importance of considering heterogeneity in expectations, both in theoretical and in empirical works. Second, IBES expectations have strong and consistent correlations with many model-based expected market risk premium measures. Third, sell-side analysts forecast risk premia better than CFOs.

When looking at the cross-sectional properties of analysts' return expectations - with subjective expectations as both dependent and independent variables - CAPM appears to perform very well as the empirical SML is correctly sloped and the adjusted R^2s are similar in magnitude to those obtained by running the same tests using realised excess returns. Adding the Fama-French factors leads to an improvement relative to CAPM in explaining the cross-sectional dynamics of subjective expected excess returns. The improvement is similar in magnitude to that obtained when switching from CAPM to Fama-French multi-factor models in a setting relying on realised excess returns for both dependent and independent variables.

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Figure 1: Tesla Forecasts. The left panel of this figure shows Tesla's earnings per share (EPS) consensus forecasts for the end of the current fiscal year (FY) - in blue - together with actual EPS which was eventually reported for the current FY - in red. The right panel shows Tesla's twelve months horizon price targets (PTG) - in blue - and realized one year ahead prices - in red. All measures are adjusted for the cumulative adjustment factors from CRSP to account for corporate events such as stock splits.

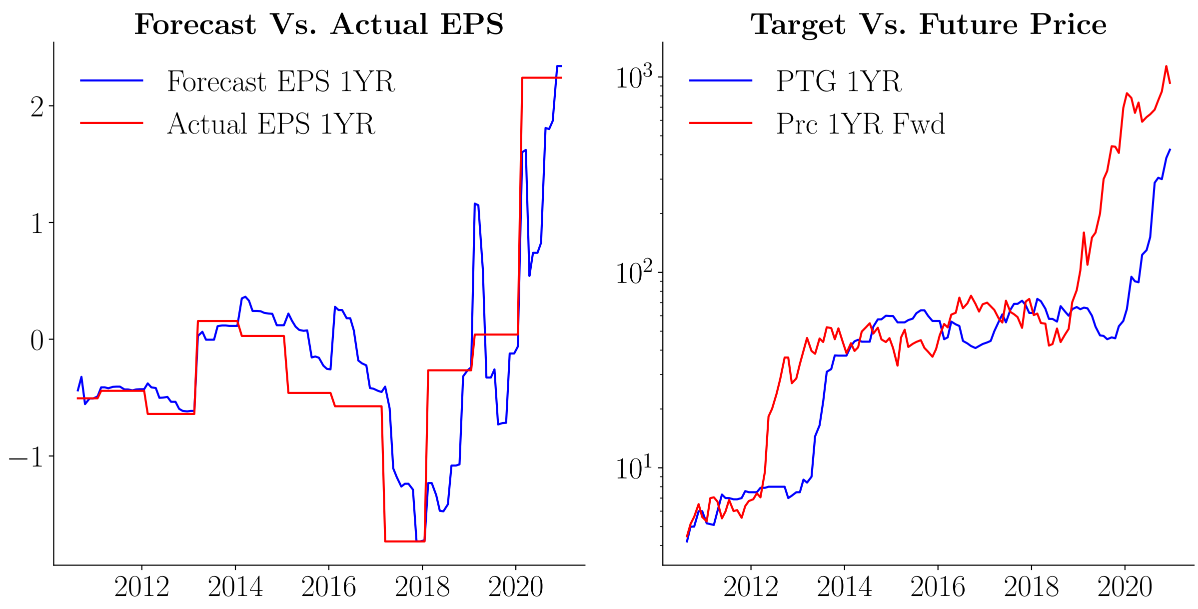


Figure 2: Time-series of $S\&P500$ Total Return Surveys Forecasts and Realization. The plot below shows: Graham-Harvey (GH, in red) one-year total return forecasts at quarterly frequency - note that the GH survey stopped reporting on a continuous basis in Q4 2018; Livingston (Liv, in yellow) one-year total return forecasts at semi-annual frequency (construction described in Section 2.1); IBES (in green) one-year total return forecasts at quarterly frequency (construction described in Section 2.2.2); finally, future one-year $S\&P500$ excess total returns are reported in dashed blue.

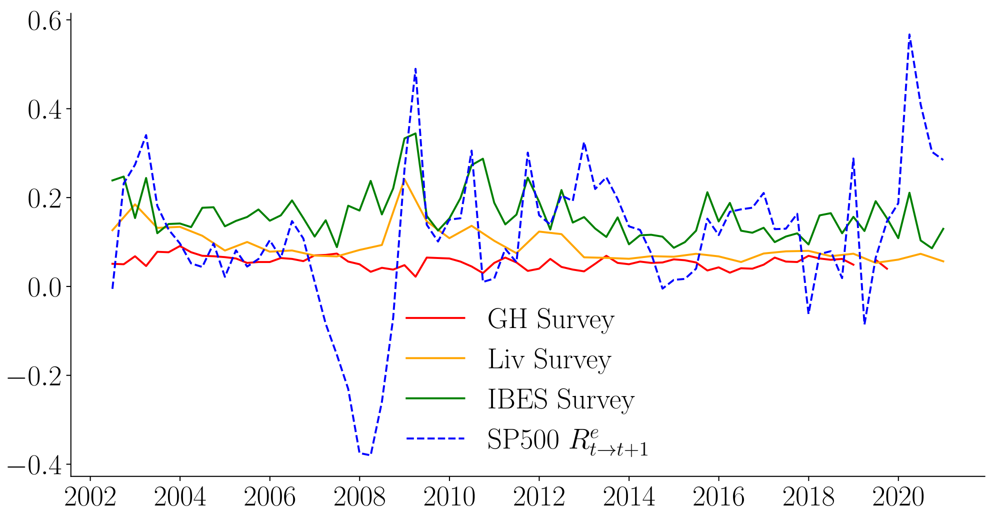


Figure 3: Comparison of alternative price-dividend ratio time-series constructions. This figure shows the log and demeaned price-dividend ratios (pd) constructed following the methodologies described in Section 2.2.3: the dashed blue line is formed by first aggregating the regular dollar dividends of the $S\&P500$ constituents from CRSP on a rolling 1 year basis and then normalizing by the total ME of all constituents of the $S\&P500$: $\frac{Div_t}{ME_t} = \frac{\sum_{i \in x_t} D_{i,t} S_{i,t}}{\sum_{i \in x_t} ME_{i,t}}$, where $\sum_{i \in x_t} D_{i,t} S_{i,t}$ is the total dollar dividend paid by all firms in the $S\&P500$ over the last year, $\sum_{i \in x_t} ME_{i,t}$ is the current sum of market capitalizations of all firms in the $S\&P500$; the solid red line is constructed using the methodology of Cochrane (1991): $\frac{D_t}{P_t} = \frac{R_t}{R_{x,t}} - 1 = \frac{P_t + D_t}{P_{t-1}} \frac{P_{t-1}}{P_t} - 1$, where R_t ($R_{x,t}$) is the $S\&P500$ one-year monthly compounded total (price) return.

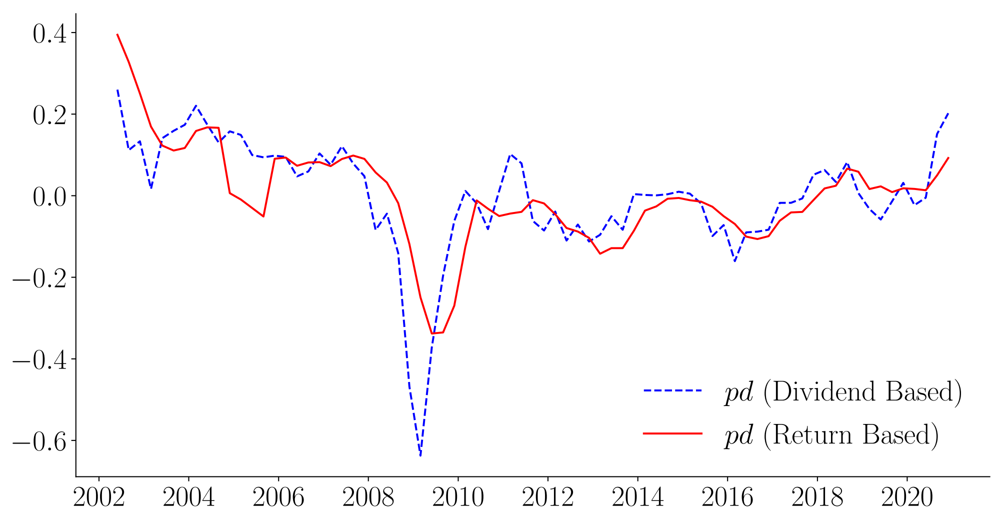
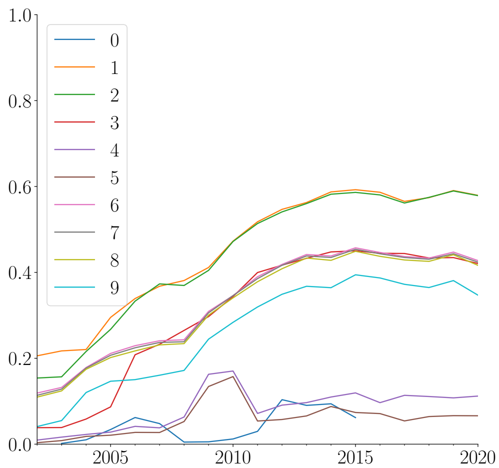
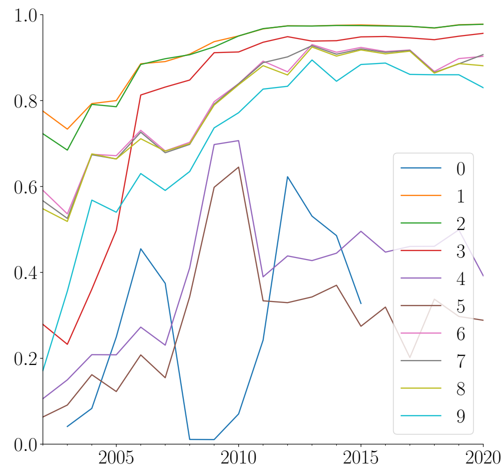


Figure 4: IBES coverage relative to CRSP-Compustat. The plots show the percentage of stocks and market capitalization (ME) coverage of IBES forecast data for different forecast horizons relative to CRSP-Compustat (CCM) data available in June of each calendar year between 2002 and 2020. Each line represents the percentage number of stocks (Panel A and C) or ME (Panel B and D) for which forecast data is available for a specific forecasting period indicator (FPI) code. Label 0 refers to LTG forecasts; Labels 1 through 5 refer to forecasts for fiscal year 1 through 5; Labels 6 through 8 refer to forecasts for fiscal quarters 1 through 4.

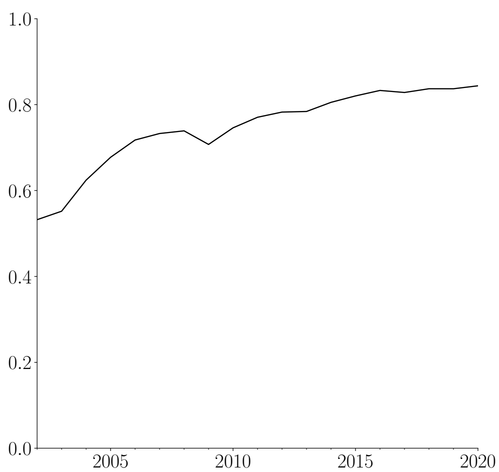
Panel A. DPS Data (% Stocks)



Panel B. DPS Data (% ME)



Panel C. PTG Data (% Stocks)



Panel D. PTG Data (% ME)

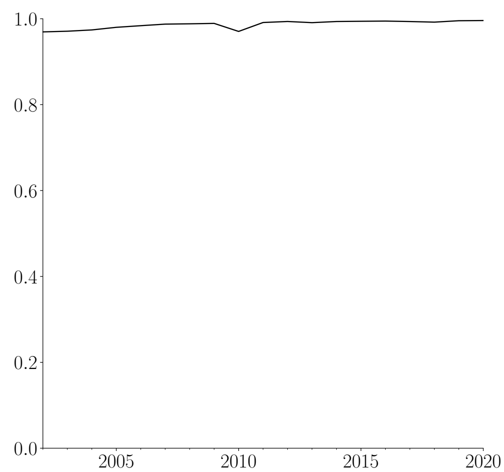


Figure 5: Difference between IBES RET and IBES RETx series. The blue line shows the difference between IBES expected total return (IBES RET) and expected price return (IBES RETx) for the $S\&P500$. The green line is the expected dividend-price ratio: $\frac{\tilde{\mathbb{E}}_t[Div_{t+1}]}{ME_t}$, where $\tilde{\mathbb{E}}_t[Div_{t+1}]$ is the one-year subjective expected dollar dividend for the $S\&P500$ and ME_t is the current total market capitalization of the $S\&P500$. The red line is the dividend-price ratio of the $S\&P500$ constructed by first aggregating the regular dollar dividends of the $S\&P500$ constituents from CRSP on a rolling 1 year basis and then normalizing by the total ME of all constituents of the $S\&P500$: $\frac{Div_t}{ME_t}$, where Div_t is the total dollar dividend paid by all firms in the $S\&P500$ over the last year.

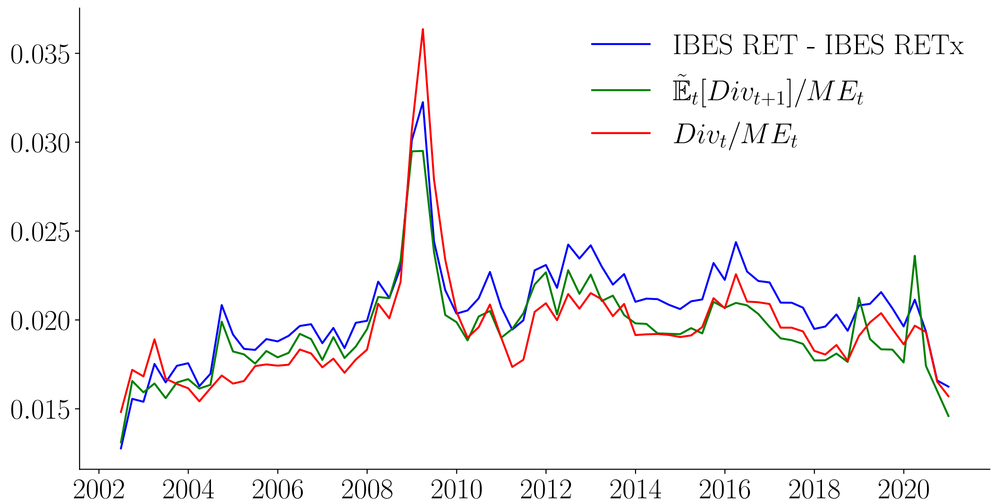


Figure 6: IBES subjective return data coverage of $S\&P500$. The blue (red) line shows the subjective expected return data coverage provided by IBES relative to the CRSP-Compustat universe as a percentage of ME (number of stocks).

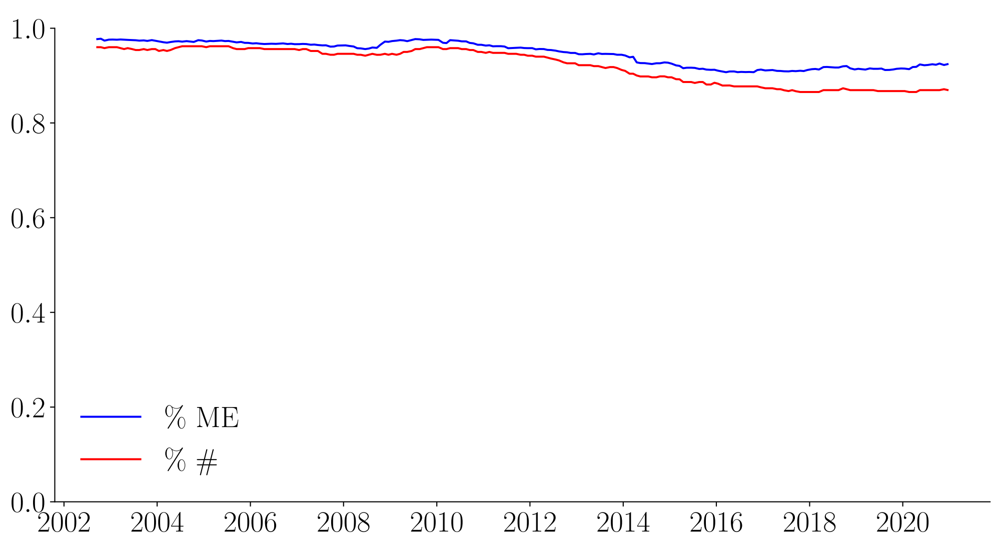


Figure 7: Comparison of realized yearly returns of Fama-French factors when constructed using the whole CRSP/Compustat universe or only the IBES universe of stocks. The blue (red) lines represent the realised one-year Fama & French (1993) factor returns when the CRSP/Compustat (IBES) universe is used.

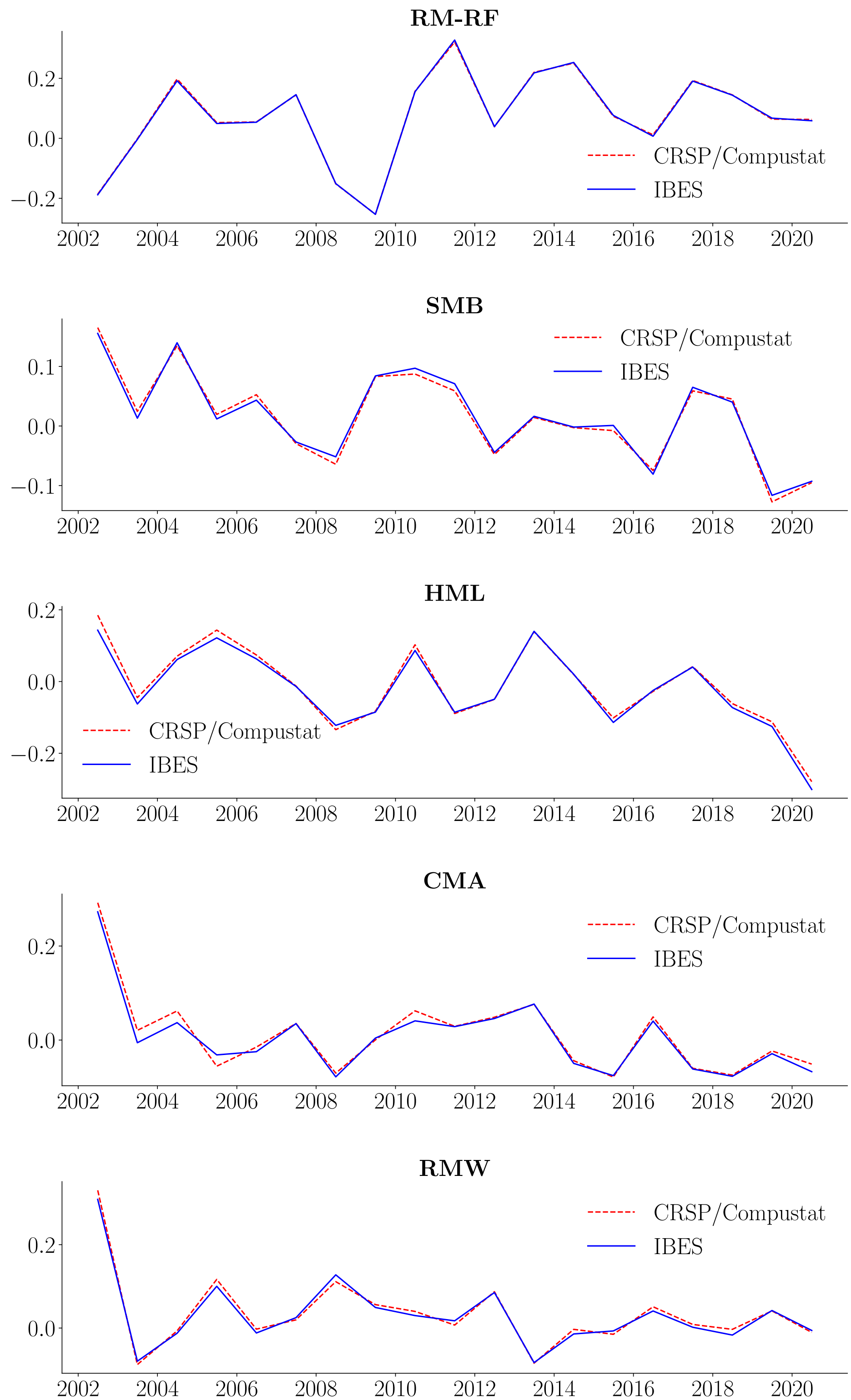


Figure 8: Correlations of IBES with VIX Panel A (B) shows the monthly correlations of IBES subjective risk premia expectations with different lags of the VIX (VIX^2) index value relative to its end of previous month value - for example, VIX_{t-4} (VIX^2_{t-4}) is the value of the VIX (VIX^2) index lagged by 4 weeks relative to the end of month value. This lead-lag structure is chosen to reflect that IBES returns are constructed by normalizing the sell-side analysts' forecasts by the end of the previous month prices. Note that all correlations have p-values smaller than 0.01%.

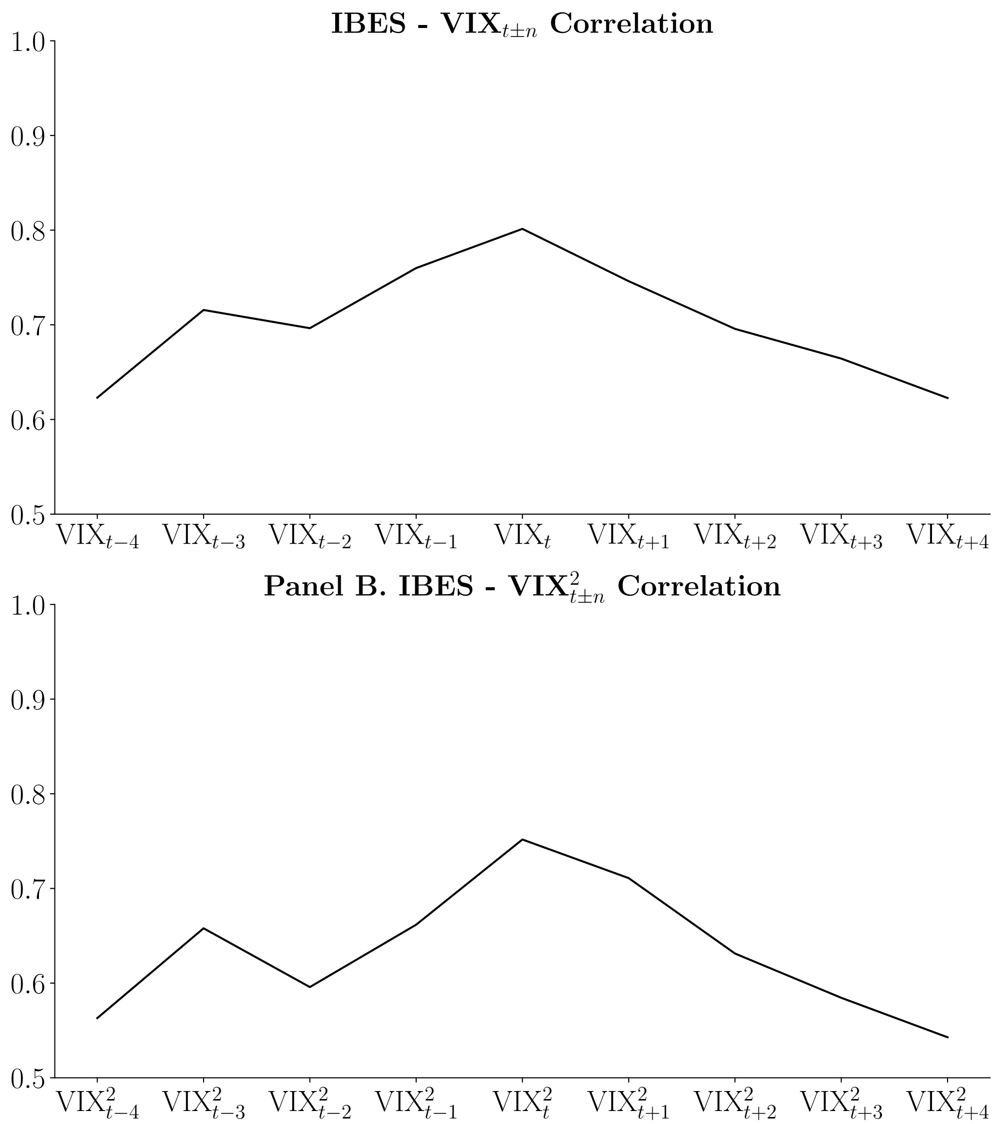


Figure 9: Realised and subjective expected returns of Fama-French (FF) factors. The plots compare the time-series evolution of the IBES subjective one-year return expectations of the FF factors (in green), their past/future realizations (blue/red), in July - after the FF portfolios have rebalanced - of every year between 2002 and 2020. Correlations between future (past) one year excess returns of the factors with their expectations for Mkt-Rf, SMB, HML, CMA and RMW: 0.03 (-0.32), 0.05 (-0.24), -0.15 (-0.56), 0.32 (0.61), 0.03 (-0.64).

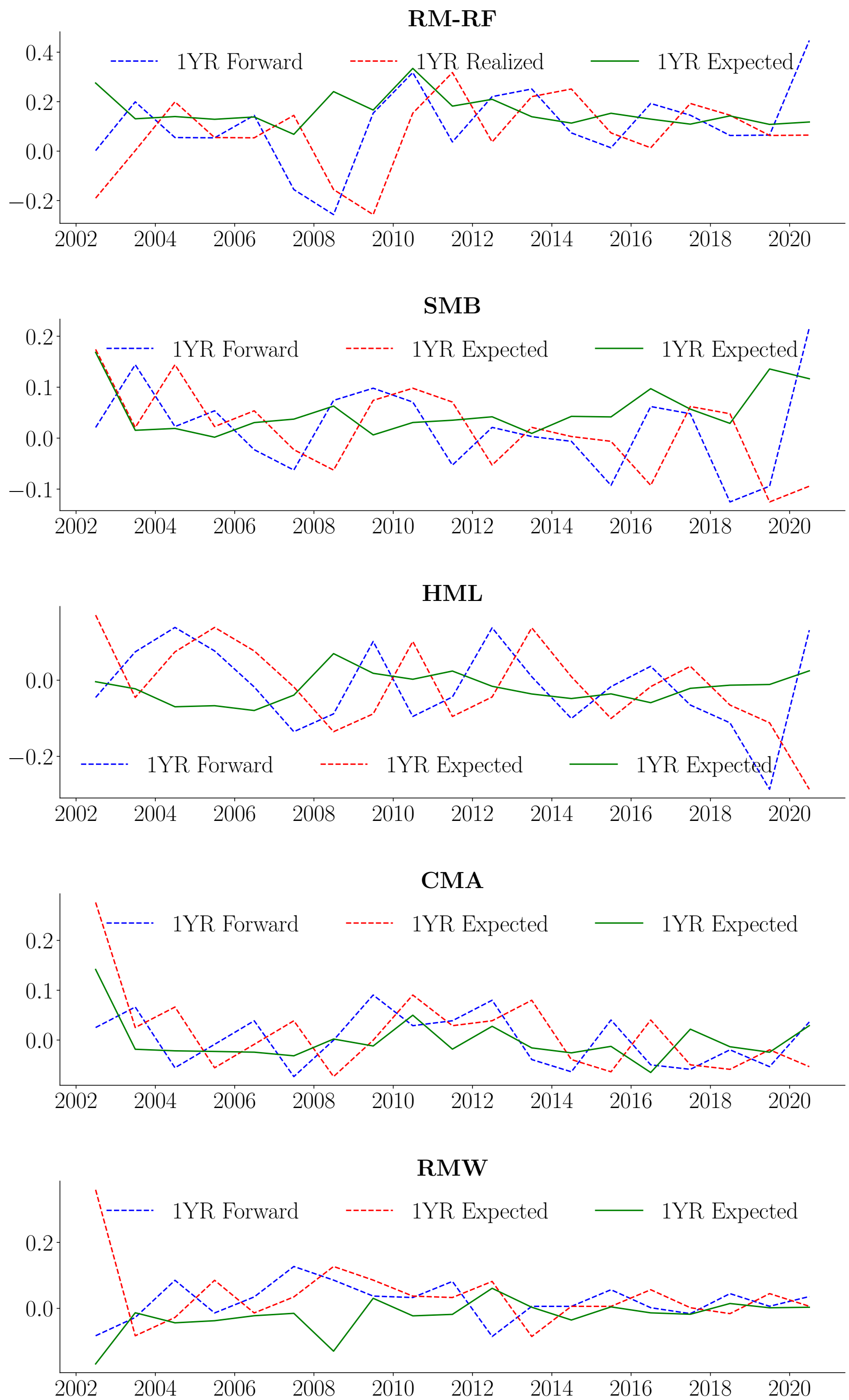


Figure 10: Security market line (SML) based on realized returns. The figure shows average one-year realised excess returns ($\mathbb{E}[R^e]$) of the Fama-French 25 (FF25) portfolios against their CAPM betas (β). βs are estimated by running time-series regressions of realised one-year excess returns of each FF25 portfolio on realised one-year market excess returns ($R^e_{i,t} = \alpha_i + \beta_i R^e_{m,t} + \epsilon_t$), in July of each year between 2002 and 2020. The green line is the empirical SML and it is the best-fit line across all the FF25 portfolios. Finally, the red line represents the theoretical SML where the slope is the sample average excess market return and the intercept is the sample average one-year Treasury yield.

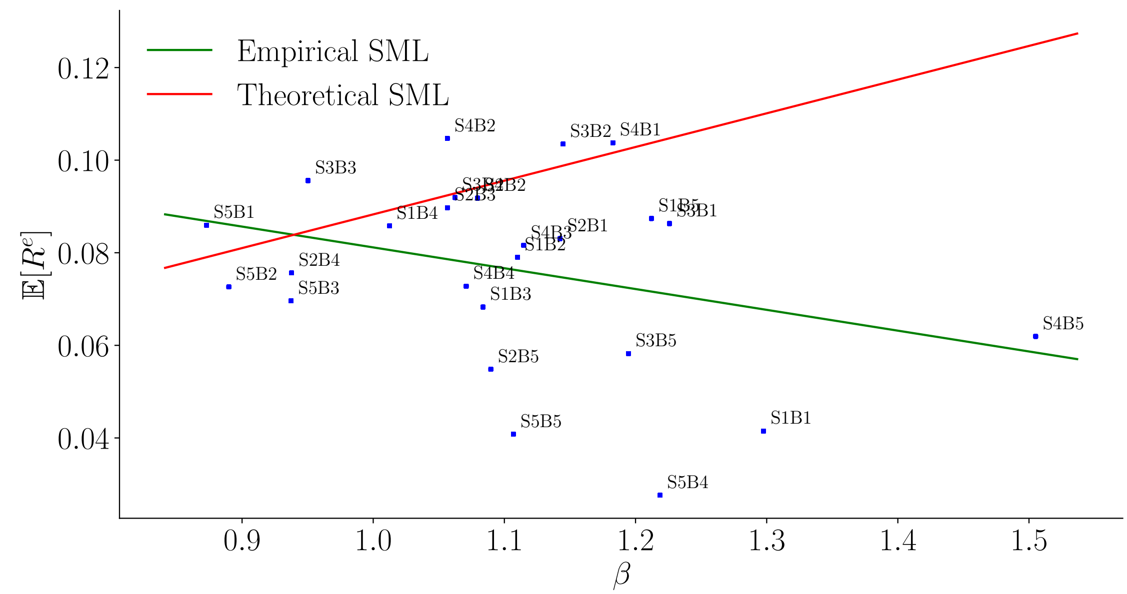


Figure 11: Security market line (SML) based on IBES subjective returns. The figure shows average one-year IBES subjective expected excess returns ($\tilde{\mathbb{E}}[R^e]$) of the Fama-French 25 (FF25) portfolios against their CAPM betas ($\tilde{\beta}$). $\tilde{\beta}$s are estimated by running time-series regressions of one-year subjective expected excess returns of each FF25 portfolio on one-year subjective market excess returns ($\tilde{\mathbb{E}}_t[R^e_{i,t+1}] = \tilde{\alpha}_i + \tilde{\beta}_i \tilde{\mathbb{E}}_t[R^e_{m,t+1}] + \tilde{\epsilon}_t$), in July of each year between 2002 and 2020. The green line is the empirical SML and it is the best-fit line across all the FF25 portfolios. Finally, the red line represents the theoretical SML where the slope is the sample average subjective expected excess market return and the intercept is the sample average one-year Treasury yield. All subjective expectations in this figure are from IBES.

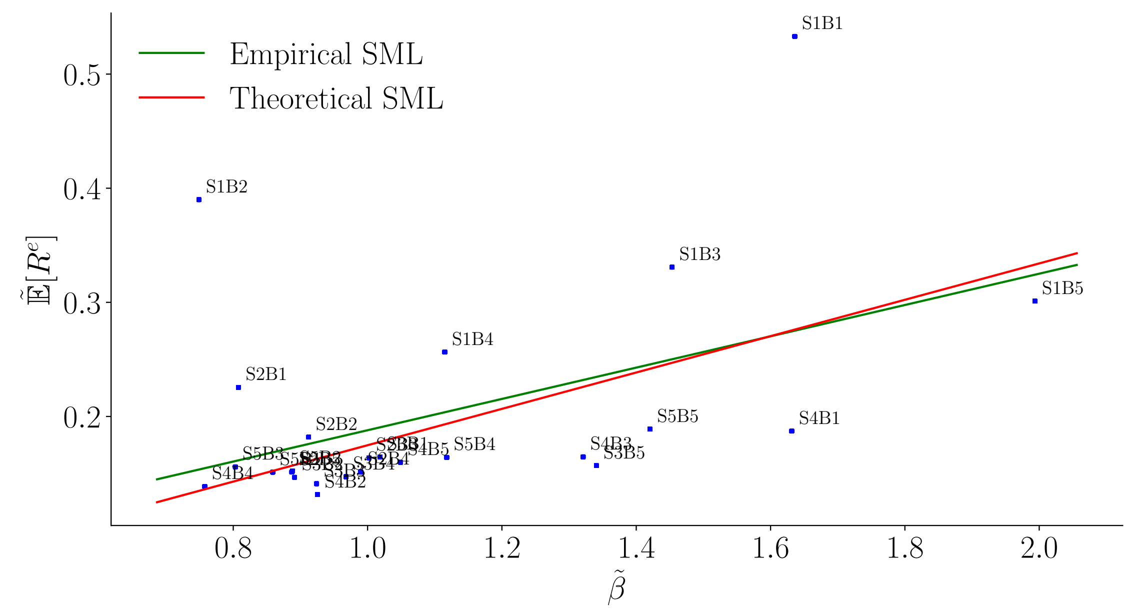


Figure 12: Forecasts and Investments. The plot compares the value over time of investing \$1 in Q2 2002 under alternative market-timing strategies (between the $S\&P500$ and a Treasury bond) based on Merton (1969) portfolio allocation rule: $\alpha_t = \frac{\mathbb{E}_t[r_{t+1}]+\frac{1}{2}\sigma_r^2 - r_f}{\gamma \sigma_r^2}$ - with σ_r set to the log-annual return volatility of the $S\&P500$ between 1926-2002 (0.72%), γ set to 10 and with only the expected return changing over time. All strategies rebalance at a semi-annual frequency and there are no borrowing or shorting constraints. In strategy GH (in red)/Liv (in yellow)/IBES (in green), the expectation term in α_t is determined by the Graham-Harvey/Livingston/IBES expectations. Mkt (in blue) is a strategy which always invests everything in the $S\&P500$ ($\alpha_t = 1$). R_f (in dashed blue) is a strategy which always invests everything in Treasury bonds ($\alpha_t = 0$). For strategy pd (VRP), I train an OLS model to predict $S\&P500$ future excess returns using the price-dividend ratio (variance risk premium) in the period between Q1 1990 - Q2 2002 (which then rolls over every rebalancing period) and use the out-of-sample forecasts of the returns as the expected returns in α_t.

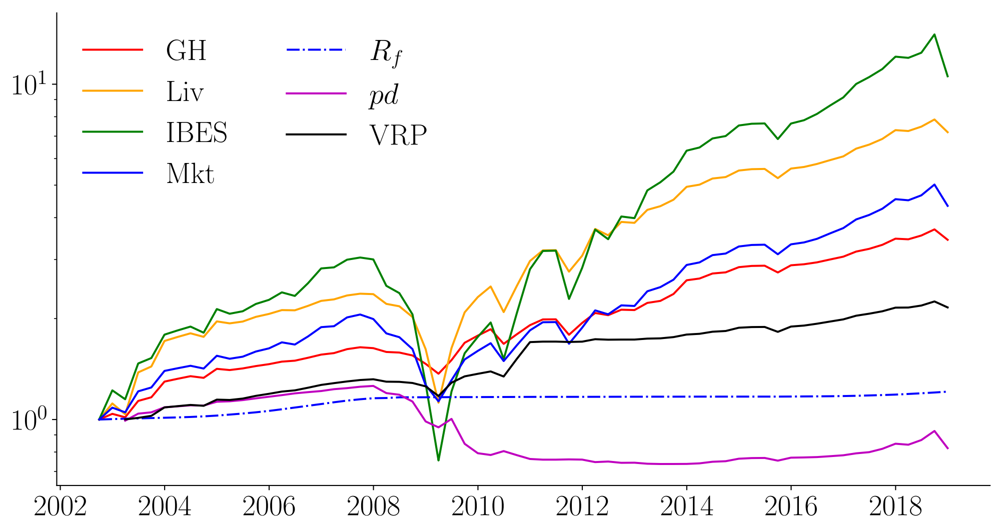


Figure 13: IBES Expected Returns, Recessions and VIX. The plot below shows: the IBES one-year total return forecasts at monthly frequency (construction described in Section 2.2.2), in green; the end of month VIX index (scaled by 100), in red; the NBER based Recession Indicators in grey shaded areas; finally, a dummy period indicating the difficulty of forecasters to predict the Great Financial Crisis is reported in the hatched yellow area. The correlations of the VIX with the IBES, the Graham-Harvey, and the Livingston surveys are: 0.81, -0.05 and 0.82.

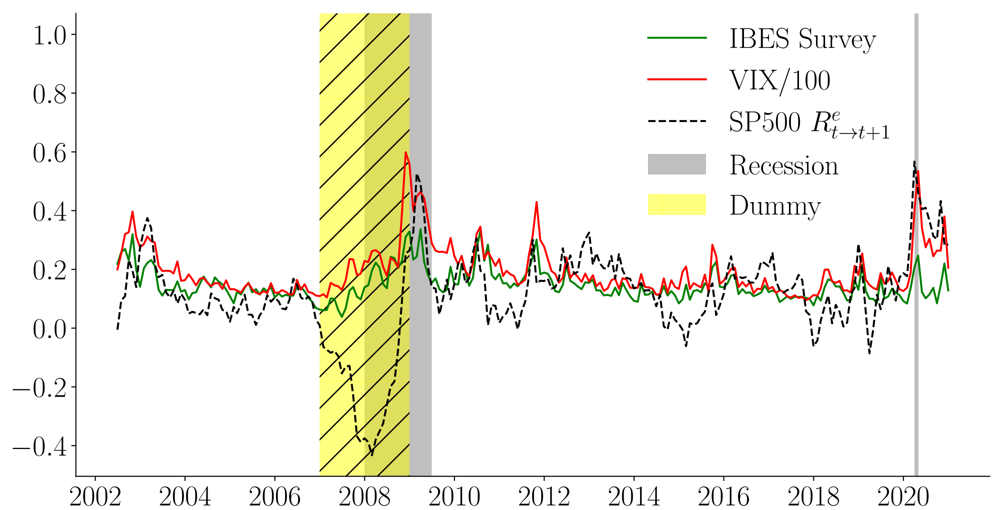


Table 1: Average Fama-French (FF) 25 portfolios coverage provided by IBES relative to CRSP-Compustat. This table shows the average coverage provided for each FF25 portfolio by IBES relative to CRSP-Compustat between 2002 and 2020. The coverage is in terms of availability of subjective expected returns at the portfolio level. Panel A provides the average coverage in terms of percentage of number of stocks, and Panel B provides the average coverage in terms of market capitalization (ME). All numbers are rounded to 1 decimal place.

Panel A

Coverage # Stocks (%)	Lo BM	BM2	BM3	BM4	Hi BM
Small	67.6	67.7	64.4	58.4	42.9
ME2	93.6	94.6	94.1	93.5	89.5
ME3	97.4	97.5	96.8	95.8	91.9
ME4	99.0	99.0	99.0	97.1	94.9
Big ME	99.9	99.8	99.3	99.7	97.7

Panel B

Coverage ME (%)	Lo BM	BM2	BM3	BM4	Hi BM
Small	82.8	83.0	80.8	77.7	69.3
ME2	94.6	95.5	94.7	93.8	90.8
ME3	97.5	97.6	97.1	95.9	91.8
ME4	99.2	99.2	99.1	97.6	94.5
Big ME	99.9	99.9	98.8	99.7	98.3

Table 2: Summary statistics of survey expectations. This table provides the average returns, the volatility and the ratio of the two for the one-year subjective total return expectations of the $S\&P500$ from the Graham-Harvey (GH) survey, the Livingston (Liv) survey and the IBES survey. The statistics for the GH survey are computed on quarterly frequency data between Q2 2002 and Q4 2018. The statistics for the Liv survey are computed on semi-annual frequency data between Q2 2002 and Q4 2020. The statistics for the IBES survey are computed on quarterly frequency data between Q2 2002 and Q4 2020.

Statistic/Survey	GH	Liv	IBES
$\mathbb{E}[R]$	5.48	9.31	16.03
$\sigma(R)$	1.32	3.90	5.40
$\mathbb{E}[R]/\sigma(R)$	4.15	2.39	2.97

Table 3: Correlations of survey expectations. This table provides the correlations for the one-year subjective total return expectations of the $S\&P500$ from the Graham-Harvey (GH) survey, the Livingston (Liv) survey and the IBES survey. The GH survey is only available up to Q4 2018 hence all correlations are based on time-series between Q2 2002 - Q4 2018. The top part of the table reports the correlation between the GH survey and IBES survey based on quarterly data. The rest of the table provides the correlation between all the surveys based on semi-annual data.

	GH	Liv	IBES
Quarterly Data			
IBES Survey	-0.55		
Semiannual Data			
GH Survey	1.00		
Liv Survey	0.12	1.00	
IBES Survey	-0.37	0.70	1.00

Table 4: Determinants of investor expectations. This table provides the time-series regression results of survey expectations of future stock market risk premia on past 12-month returns of the CRSP value-weighted index of the $S\&P500$ universe, in excess of the risk-free rate ($R^e_{t-1,t}$) and log price-dividend ratio (pd_t). The first three lines provide benchmark forecasting equity risk premia regressions. GH is the subjective one-year risk premia expectation from the Graham-Harvey survey. Liv is the subjective one-year risk premia expectation from the Livingston survey. IBES is the subjective one-year risk premia expectation from the IBES survey. Small-sample adjusted Newey-West standard errors with 4 quarter lags are shown in parentheses. *: 10% significance; **: 5% significance; ***: 1% significance. Notice that forecasting regressions with persistent regressors may yield biased coefficients in small samples (Stambaugh (1999)): adjusting for this does not change the results significantly (not showed below). In the spirit of Nagel & Xu (2022), all predictor variables are standardized to have unit variance. Slope coefficients and standard errors are multiplied by 100 - this is to allow for an easier comparison between the βs.

Regression specification: $Y_t = \gamma_0 + \gamma_1 \ R^e_{t-1,t} + \gamma_2 \ pd_t + \epsilon_t$

Y_t	γ_0	γ_1	γ_2	Adj.R^2	Sample
$R^e_{t,t+1}$	11.86***	-1.37		-0.01	Q2 2002 - Q4 2020
	(3.57)	(2.11)			
$R^e_{t,t+1}$	136.02***		-4.42***	0.06	Q2 2002 - Q4 2020
	(37.16)		(1.35)		
$R^e_{t,t+1}$	150.62**	1.08	-4.96**	0.05	Q2 2002 - Q4 2020
	(68.25)	(3.17)	(2.53)		
$\tilde{\mathbb{E}}_{GH,t}[R^e_{t,t+1}]$	3.71***	0.51**		0.09	Q2 2002 - Q4 2018
	(0.38)	(0.21)			
$\tilde{\mathbb{E}}_{GH,t}[R^e_{t,t+1}]$	0.08		0.14	-0.01	Q2 2002 - Q4 2018
	(7.33)		(0.27)		
$\tilde{\mathbb{E}}_{GH,t}[R^e_{t,t+1}]$	7.90	0.58**	-0.15	0.08	Q2 2002 - Q4 2018
	(10.34)	(0.29)	(0.38)		
$\tilde{\mathbb{E}}_{Liv,t}[R^e_{t,t+1}]$	9.08***	-2.66***		0.30	Q2 2002 - Q4 2020
	(0.98)	(0.65)			
$\tilde{\mathbb{E}}_{Liv,t}[R^e_{t,t+1}]$	60.88		-1.88	0.15	Q2 2002 - Q4 2020
	(40.4)		(1.44)		
$\tilde{\mathbb{E}}_{Liv,t}[R^e_{t,t+1}]$	36.68	-2.22**	-0.98	0.33	Q2 2002 - Q4 2020
	(31.02)	(0.92)	(1.12)		
$\tilde{\mathbb{E}}_{IBES,t}[R^e_{t,t+1}]$	15.94***	-2.78***		0.23	Q2 2002 - Q4 2020
	(0.80)	(1.00)			
$\tilde{\mathbb{E}}_{IBES,t}[R^e_{t,t+1}]$	97.03***		-2.92***	0.26	Q2 2002 - Q4 2020
	(22.31)		(0.79)		
$\tilde{\mathbb{E}}_{IBES,t}[R^e_{t,t+1}]$	73.23***	-1.76	-2.05**	0.32	Q2 2002 - Q4 2020
	(23.71)	(1.17)	(0.85)		

Table 5: Risk premia expectations and quarterly lagged returns. This table provides the time-series regression results of survey expectations of future stock market risk premia on past and lagged quarterly returns of the CRSP value-weighted index of the $S\&P500$ universe, in excess of the risk-free rate (R^e_{t-iq}) and log price-dividend ratio (pd_t). GH is the subjective one-year risk premia expectation from the Graham-Harvey survey. Liv is the subjective one-year risk premia expectation from the Livingston survey. IBES is the subjective one-year risk premia expectation from the IBES survey. R^e_{t-iq} is the i quarter lagged excess returns. Small-sample adjusted Newey-West standard errors with 4 quarter lags are shown in parentheses. *: 10% significance; **: 5% significance; ***: 1% significance. Notice that forecasting regressions with persistent regressors may yield biased coefficients in small samples (Stambaugh (1999)): adjusting for this does not change the results significantly (not showed below).

Regression specification: $\tilde{\mathbb{E}}_{Survey,t}[R^e_{t,t+1}] = \alpha + \sum_{i=1}^{T} \beta_{iq} R^e_{t-iq} + \beta_{pd}\, pd_t + \epsilon_t$

GH (2002-2018) on:	α	β_{1q}	β_{2q}	β_{3q}	β_{4q}	β_{pd}	Adj.R^2
R^e_{t-1q}	0.04***	0.09***					0.18
	(0.00)	(0.02)					
R^e_{t-1q}, R^e_{t-2q}	0.04***	0.09***	0.05**				0.21
	(0.00)	(0.03)	(0.02)				
$R^e_{t-1q}, R^e_{t-2q}, R^e_{t-3q}$	0.04***	0.09***	0.04**	0.02			0.21
	(0.00)	(0.03)	(0.02)	(0.02)			
$R^e_{t-1q}, R^e_{t-2q}, R^e_{t-3q}, R^e_{t-4q}$	0.04***	0.09***	0.04**	0.02*	-0.02		0.21
	(0.00)	(0.03)	(0.02)	(0.01)	(0.02)		
$R^e_{t-1q}, R^e_{t-2q}, R^e_{t-3q}, R^e_{t-4q}, pd_t$	0.12	0.10***	0.05*	0.03*	-0.01	-0.02	0.22
	(0.11)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	
Liv (2002-2020) on:	α	β_{1q}	β_{2q}	β_{3q}	β_{4q}	β_{pd}	Adj.R^2
R^e_{t-1q}	0.08***	-0.17					0.06
	(0.01)	(0.12)					
R^e_{t-1q}, R^e_{t-2q}	0.09***	-0.21***	-0.27***				0.26
	(0.01)	(0.08)	(0.09)				
$R^e_{t-1q}, R^e_{t-2q}, R^e_{t-3q}$	0.09***	-0.20**	-0.29***	0.04			0.24
	(0.01)	(0.10)	(0.10)	(0.11)			
$R^e_{t-1q}, R^e_{t-2q}, R^e_{t-3q}, R^e_{t-4q}$	0.09***	-0.21***	-0.25***	-0.02	-0.22***		0.35
	(0.01)	(0.07)	(0.08)	(0.09)	(0.08)		
$R^e_{t-1q}, R^e_{t-2q}, R^e_{t-3q}, R^e_{t-4q}, pd_t$	0.39	-0.17***	-0.21**	0.02	-0.21***	-0.08	0.39
	(0.24)	(0.06)	(0.10)	(0.08)	(0.08)	(0.06)	
IBES (2002-2020) on:	α	β_{1q}	β_{2q}	β_{3q}	β_{4q}	β_{pd}	Adj.R^2
R^e_{t-1q}	0.16***	-0.51***					0.48
	(0.01)	(0.05)					
R^e_{t-1q}, R^e_{t-2q}	0.16***	-0.49***	-0.16***				0.52
	(0.01)	(0.05)	(0.06)				
$R^e_{t-1q}, R^e_{t-2q}, R^e_{t-3q}$	0.16***	-0.50***	-0.14***	-0.10*			0.53
	(0.01)	(0.04)	(0.04)	(0.06)			
$R^e_{t-1q}, R^e_{t-2q}, R^e_{t-3q}, R^e_{t-4q}$	0.16***	-0.50***	-0.15***	-0.10*	-0.04		0.53
	(0.01)	(0.04)	(0.05)	(0.06)	(0.06)		
$R^e_{t-1q}, R^e_{t-2q}, R^e_{t-3q}, R^e_{t-4q}, pd_t$	0.59***	-0.44***	-0.08*	-0.05	-0.01	-0.11**	0.58
	(0.20)	(0.06)	(0.05)	(0.06)	(0.07)	(0.05)	

Table 6: Persistency of risk premia expectations. This table provides the time-series regression results of survey expectations of future stock market risk premia on past and lagged subjective risk premia expectations. GH is the subjective one-year risk premia expectation from the Graham-Harvey survey. Liv is the subjective one-year risk premia expectation from the Livingston survey. IBES is the subjective one-year risk premia expectation from the IBES survey. $\tilde{\mathbb{E}}_{Survey,t-iq}[R^e_{t-iq,t+1-1q}]$ is the i quarter lagged subjective risk premia expectation of the $S\&P500$. Small-sample adjusted Newey-West standard errors with 4 quarter lags are shown in parentheses. *: 10% significance; **: 5% significance; ***: 1% significance. Notice that forecasting regressions with persistent regressors may yield biased coefficients in small samples (Stambaugh (1999)): adjusting for this does not change the results significantly (not showed below).

Regression specification: $\tilde{\mathbb{E}}_{Survey,t}[R^e_{t,t+1}] = \alpha + \sum_{i=1}^{T} \beta_{iq}\tilde{\mathbb{E}}_{Survey,t-iq}[R^e_{t-iq,t+1-1q}] + \beta_{pd}\ pd_t + \epsilon_t$

GH (2002-2018) on:	α	β_{1q}	β_{2q}	β_{3q}	β_{4q}	β_{pd}	Adj.R^2
GH_{t-1q}	0.01**	0.69***					0.45
	(0.00)	(0.09)					
GH_{t-1q}, GH_{t-2q}	0.01**	0.59***	0.15				0.46
	(0.00)	(0.13)	(0.13)				
$GH_{t-1q}, ..., GH_{t-3q}$	0.01**	0.59***	0.18	-0.03			0.47
	(0.00)	(0.13)	(0.18)	(0.13)			
$GH_{t-1q}, ..., GH_{t-4q}$	0.01**	0.63***	0.16	-0.05	0.00		0.47
	(0.00)	(0.13)	(0.19)	(0.10)	(0.14)		
$GH_{t-1q}, ..., GH_{t-4q}, pd_t$	0.02	0.62***	0.16	-0.05	0.01	-0.00	0.46
	(0.05)	(0.13)	(0.19)	(0.11)	(0.14)	(0.01)	
Liv (2002-2020) on:	α	β_{1q}	β_{2q}	β_{3q}	β_{4q}	β_{pd}	Adj.R^2
Liv_{t-2q}	0.03**		0.57***				0.31
	(0.01)		(0.11)				
Liv_{t-2q},Liv_{t-4q}	0.03**		0.53***		0.02		0.29
	(0.01)		(0.07)		(0.09)		
$Liv_{t-2q},Liv_{t-4q},pd_t$	0.69**		0.31		0.20*	-0.17**	0.54
	(0.34)		(0.23)		(0.11)	(0.08)	
IBES (2002-2020) on:	α	β_{1q}	β_{2q}	β_{3q}	β_{4q}	β_{pd}	Adj.R^2
$IBES_{t-1q}$	0.08***	0.47***					0.22
	(0.01)	(0.10)					
$IBES_{t-1q},IBES_{t-2q}$	0.07***	0.43***	0.06				0.19
	(0.01)	(0.16)	(0.14)				
$IBES_{t-1q},...,IBES_{t-3q}$	0.07***	0.44***	0.04	0.06			0.19
	(0.02)	(0.16)	(0.16)	(0.10)			
$IBES_{t-1q},...,IBES_{t-4q}$	0.06***	0.45***	-0.00	-0.00	0.10		0.19
	(0.02)	(0.15)	(0.14)	(0.12)	(0.11)		
$IBES_{t-1q},...,IBES_{t-4q},pd_t$	0.92***	0.21	-0.06	-0.01	0.11	-0.21***	0.38
	(0.26)	(0.18)	(0.13)	(0.12)	(0.10)	(0.06)	

Table 7: Variance decomposition of price-dividend ratio. This table replicates and extends the results of De La O & Myers (2021). CF, DR and LT are defined in equation (13): CF is the slope coefficient from the regression of subjective expected log dividend growth ($\tilde{\mathbb{E}}_t[\Delta d_{t+1}]$) on the log price-dividend ratio (pd_t); DR is estimated as the slope coefficient from the regression of log subjective one-year returns on the log price-dividend ratio pd_t; finally, LT is the slope coefficient from the regression of subjective one-year log dividend-price ratio $\tilde{\mathbb{E}}_t[pd_{t+1}]$ on the log price-dividend ratio pd_t. Subscripts GH /Liv/IBES indicate that expectations from Graham-Harvey/Livingston/IBES are used to construct the DR or LT measures. CF has no subscript as the GH/Liv survey does not provide dividend forecasts and hence it is implicitly assumed that the dividends cashflows are from IBES. Note that as required by equation (13), $CF+DR_{GH}+LT_{GH} \approx 1$, $CF+DR_{IBES}+LT_{IBES} \approx 1$ and $CF + DR_{Liv} + LT_{Liv} \approx 1$. Small-sample adjusted Newey-West t-statistics with bandwith of 4 are reported. Notice that forecasting regressions with persistent regressors may yield biased coefficients in small samples (Stambaugh (1999)): adjusting for this does not change the results significantly (not showed below).

Regressions (Q2 2002 - Q4 2018)

Channel	β	$t(\beta)$	Adj.R^2(%)	$\sigma(X\beta)$(%)
CF	0.34	5.45	50.26	4.90
DR_{IBES}	0.13	2.50	16.42	1.92
DR_{GH}	-0.05	-3.05	34.30	0.74
DR_{Liv}	0.08	0.90	7.04	1.08
LT_{IBES}	0.54	6.60	63.33	7.78
LT_{GH}	0.73	11.46	80.66	10.49
LT_{Liv}	0.63	4.59	66.94	8.78

Table 8: Relationship between model-based measures of expected risk premium and survey expected risk premia. This tables displays the correlations between RE measures of expected risk premium - log price-dividend ratio (pd), consumption-wealth ratio (cay, Lettau & Ludvigson (2001)), expected variance risk premium and realised variance risk premium ($\mathbb{E}[VRP]$ and VRP, Bollerslev et al. (2009)) - and survey expected risk premia. RE measures are lagged in such a way to reflect the information available to the survey respondents at time they were taking the survey. GH is the subjective one-year risk premia expectation from the Graham-Harvey survey. Liv is the subjective one-year risk premia expectation from the Livingston survey. IBES is the subjective one-year risk premia expectation from the IBES survey. p-values are shown in brackets below the estimates.

	GH	Liv	IBES
Sample	(Q2 2002 - Q4 2018)	(Q2 2002 - Q4 2020)	(Q2 2002 - Q4 2020)
pd	0.08	-0.42***	-0.52***
	(0.50)	(0.01)	(0.00)
cay	-0.11	0.35**	0.24**
	(0.37)	(0.03)	(0.04)
$\mathbb{E}[VRP]$	-0.14	0.01	0.29**
	(0.25)	(0.93)	(0.01)
VRP	0.07	0.38**	0.28**
	(0.59)	(0.02)	(0.02)

Table 9: Forecasts and Investments. The table provides summary statistics - average returns, volatility, their ratio and certainty equivalent (assuming CRRA utility), all constructed from quarterly returns - of alternative market-timing strategies (between the $S\&P500$ and a Treasury bond) based on Merton (1969) portfolio allocation rule: $\alpha_t = \frac{\mathbb{E}_t[r_{t+1}]+\frac{1}{2}\sigma_r^2-r_f}{\gamma\sigma_r^2}$ - with σ_r set to the log-annual return volatility of the $S\&P500$ between 1926-2002 (0.72%), different values of γ are reported and with only the expected return changing over time. All strategies rebalance at a semi-annual frequency. In strategy GH /Liv /IBES, the expectation term in α_t is determined by the Graham-Harvey/Livingston/IBES survey expectations. Mkt (in blue) is a strategy which always invests everything in the $S\&P500$ ($\alpha_t = 1$). R_f (in dashed blue) is a strategy which always invests everything in Treasury bonds ($\alpha_t = 0$). For strategy *pd* (VRP), I train an OLS model to predict $S\&P500$ future excess returns using the price-dividend ratio (variance risk premium) in the period between Q1 1990 - Q4 2002 (which then rolls over every rebalancing period) and use the out-of-sample forecasts of the return as the expected return in α_t. In Panel A, there are no constraints on the strategies. In Panel B, strategies are constrained such that no shorting or leverage are allowed.

Panel A	Mkt	GH	Liv	IBES	*pd*	VRP
$\gamma = 10$						
$\mathbb{E}[R]$ (%)	2.02	1.87	3.25	4.25	-0.24	1.25
σ_R (%)	7.77	4.59	11.53	17.42	3.65	2.99
$\mathbb{E}[R]/\sigma_R$	0.26	0.41	0.28	0.24	-0.07	0.42
CEQ	0.99	1.01	0.97	0.89	0.99	1.01

Panel B	Mkt	GH	Liv	IBES	*pd*	VRP
$\gamma = 2$						
$\mathbb{E}[R]$ (%)	2.02	2.24	2.25	2.25	0.72	2.27
σ_R (%)	7.77	7.58	7.59	7.59	5.62	5.85
$\mathbb{E}[R]/\sigma_R$	0.26	0.30	0.30	0.30	0.13	0.39
CEQ	1.01	1.02	1.02	1.02	1.00	1.02
$\gamma = 5$						
$\mathbb{E}[R]$ (%)	2.02	2.42	2.22	2.25	0.50	1.84
σ_R (%)	7.77	6.84	7.55	7.59	4.33	4.93
$\mathbb{E}[R]/\sigma_R$	0.26	0.35	0.29	0.30	0.12	0.37
CEQ	1.00	1.01	1.01	1.01	1.00	1.01
$\gamma = 10$						
$\mathbb{E}[R]$ (%)	2.02	1.87	2.13	2.26	0.39	1.24
σ_R (%)	7.77	4.59	7.06	7.57	2.80	2.96
$\mathbb{E}[R]/\sigma_R$	0.26	0.41	0.30	0.30	0.14	0.42
CEQ	0.99	1.01	1.00	0.99	1.00	1.01

Table 10: Forecasting equity risk premia. The table provides the results from forecasting equity risk premia ($R^e_{t,t+1}$) regressions. $R^e_{t,t+1}$ is the 12-month return of the CRSP value-weighted index of the $S\&P500$ universe, in excess of the risk-free rate. pd is the log price-dividend ratio. GH is the subjective one-year risk premia expectation from the Graham-Harvey survey. Liv is the subjective one-year risk premia expectation from the Livingston survey. IBES is the subjective one-year risk premia expectation from the IBES survey. Small-sample adjusted Newey-West standard errors with 4 quarter lags are shown in parentheses. *: 10% significance; **: 5% significance; ***: 1% significance. Notice that forecasting regressions with persistent regressors may yield biased coefficients in small samples (Stambaugh (1999)): adjusting for this does not change the results significantly (not showed below).

Regression specifications: $R^e_{t,t+1} = \alpha + \beta X_t + \epsilon_{t+1}$

X_t	α	β	Adj.R^2	Sample
pd_t	1.36***	-0.32***	0.06	Q2 2002 - Q4 2020
	(0.37)	(0.10)		
GH_t	0.02	2.00	0.04	Q2 2002 - Q4 2018
	(0.10)	(1.88)		
Liv_t	0.02	1.13***	0.08	Q2 2002 - Q4 2020
	(0.06)	(0.41)		
IBES_t	-0.01	0.81***	0.07	Q2 2002 - Q4 2020
	(0.05)	(0.28)		

Table 11: Forecasting equity risk premia with a dummy. The table provides the results from forecasting equity risk premia ($R^e_{t,t+1}$) regressions. $R^e_{t,t+1}$ is the 12-month return of the CRSP value-weighted index of the $S\&P500$ universe, in excess of the risk-free rate. pd is the log price-dividend ratio. GH is the subjective one-year risk premia expectation from the Graham-Harvey survey. Liv is the subjective one-year risk premia expectation from the Livingston survey. IBES is the subjective one-year risk premia expectation from the IBES survey. $\mathbb{1}_{2007,2008}$ is a dummy equal to 1 during 2007-2008 and 0 otherwise. Small-sample adjusted Newey-West standard errors with 4 quarter lags are shown in parentheses. *: 10% significance; **: 5% significance; ***: 1% significance. Notice that forecasting regressions with persistent regressors may yield biased coefficients in small samples (Stambaugh (1999)): adjusting for this does not change the results significantly (not showed below). Compared to Table 10, an additional dummy for the 2007/2008 period is added.

Regression specification: $R^e_{t,t+1} = \alpha + \beta_1 X_t + \beta_2 \mathbb{1}_{2007,2008} + \epsilon_{t+1}$

X_t	α	β_1	β_2	Adj.R^2	Sample
pd_t	1.76***	-0.41***	-0.33***	0.45	Q2 2002 - Q4 2020
	(0.41)	(0.11)	(0.06)		
GH_t	0.14***	-0.13	-0.29***	0.38	Q2 2002 - Q4 2018
	(0.04)	(0.83)	(0.07)		
Liv_t	0.03	1.37***	-0.29***	0.41	Q2 2002 - Q4 2020
	(0.05)	(0.49)	(0.05)		
IBES_t	-0.00	1.01***	-0.33***	0.46	Q2 2002 - Q4 2020
	(0.06)	(0.38)	(0.06)		

Table 12: Conditional and unconditional tests of predictive ability. The table shows the values the Diebold & Mariano (2002) - with the small-sample correction suggested by Harvey et al. (1997) - and Giacomini & White (2006) tests for different loss-functions and sample periods - with the corresponding p-values in parenthesis. The null hypothesis is that the two forecast models have the same accuracy, whereas the alternative hypothesis is that they have different accuracies. F1 and F2 are the labels for the "forecasting models" being tested. GH is the subjective one-year risk premia expectation from the Graham-Harvey survey. Liv is the subjective one-year risk premia expectation from the Livingston survey. IBES is the subjective one-year risk premia expectation from the IBES survey. $\mathcal{L}$ is the loss function of choice: SE indicates a squared error loss function (i.e., the square of the difference between the excess return realization and the subjective excess return forecast), and SPE indicates a squared proportional error (i.e., the square of the difference between the excess return realization and the subjective excess return forecast scaled by subjective excess return forecast) - useful when errors are heteroskedastic, Taylor (2011). The sign of the test-statistics indicates which forecast performs better: a positive test-statistic indicates that model F1 produces larger average losses than the model F2 (F2 outperforms F1), while a negative sign indicates the opposite.

F1	F2	$\mathcal{L}$	DM Test $H_0 : \mathbb{E}[\mathcal{L}(F1) - \mathcal{L}(F2)] = 0$ $H_A : \mathbb{E}[\mathcal{L}(F1) - \mathcal{L}(F2)] \neq 0$	GW Test $H_0 : \mathbb{E}[\mathcal{L}(F1) - \mathcal{L}(F2)] = 0$ $H_A : \mathbb{E}[\mathcal{L}(F1) - \mathcal{L}(F2)] \neq 0$	Sample	Frequency
IBES	GH	SE	0.44 (0.66)	3.43 (0.18)	Q2 2002 - Q2 2009	Quarterly
		SE	-2.40** (0.02)	-4.85* (0.09)	Q3 2009 - Q4 2018	
		SE	-0.27 (0.79)	-1.01 (0.60)	Q2 2002 - Q4 2018	
		SPE	-2.28** (0.03)	-5.30* (0.07)	Q2 2002 - Q2 2009	
		SPE	-4.27*** (0.00)	-11.76*** (0.00)	Q3 2009 - Q4 2018	
		SPE	-2.21** (0.03)	-5.77* (0.06)	Q2 2002 - Q4 2018	
IBES	Liv	SE	1.54 (0.15)	2.25 (0.33)	Q2 2002 - Q2 2009	Semi-annual
		SE	-1.63 (0.12)	-5.51* (0.06)	Q3 2009 - Q4 2018	
		SE	0.49 (0.62)	0.28 (0.87)	Q2 2002 - Q4 2018	
		SPE	-1.39 (0.19)	-2.74 (0.25)	Q2 2002 - Q2 2009	
		SPE	-2.16** (0.04)	-4.87* (0.09)	Q3 2009 - Q4 2018	
		SPE	-1.77* (0.09)	-3.13 (0.21)	Q2 2002 - Q4 2018	

Table 13: Cashflow predictability regressions with IBES forecasts. Dependent variable is next year $S\&P500$ log dividend (earnings) growth; independent variables are current one-year forecasts of SP500 dividend (earnings) growths and a dummy for the 2007/2008 period, as also used in Table 11. Small-sample adjusted Newey-West standard errors with 4 quarter lags are shown in parentheses. *: 10% significance; **: 5% significance; ***: 1% significance. Notice that forecasting regressions with persistent regressors may yield biased coefficients in small samples (Stambaugh (1999)): adjusting for this does not change the results significantly (not showed below).

Regression specification: $\Delta d_{t,t+1} = \alpha + \beta_1 \tilde{\mathbb{E}}_t[\Delta d_{t,t+1}] + \beta_2 \mathbb{1}_{2007,2008} + \epsilon_{t+1}$

Dividend growth (2002 - 2020)	α	β_1	β_2	Adj.R^2
$\Delta d_{t,t+1}$ *vs* $\tilde{\mathbb{E}}_t[\Delta d_{t,t+1}]$	-0.01	0.76***		0.36
	(0.03)	(0.23)		
$\Delta d_{t,t+1}$ *vs* $\tilde{\mathbb{E}}_t[\Delta d_{t,t+1}] + \mathbb{1}_{2007,2008}$	0.01	0.76***	-0.13***	0.57
	(0.02)	(0.23)	(0.05)	

Regression specifications: $\Delta e_{t,t+1} = \alpha + \beta_1 \tilde{\mathbb{E}}_t[\Delta e_{t,t+1}] + \beta_2 \mathbb{1}_{2007,2008} + \epsilon_{t+1}$

Earnings growth (2002 - 2020)	α	β_1	β_2	Adj.R^2
$\Delta e_{t,t+1}$ *vs* $\tilde{\mathbb{E}}_t[\Delta e_{t,t+1}]$	0.02	0.93***		0.25
	(0.06)	(0.17)		
$\Delta e_{t,t+1}$ *vs* $\tilde{\mathbb{E}}_t[\Delta e_{t,t+1}] + \mathbb{1}_{2007,2008}$	0.09***	0.86***	-0.60***	0.49
	(0.03)	(0.17)	(0.16)	

Table 14: Time-series regressions of 25 Fama-French portfolios excess returns on the excess market return (CAPM) or on the Fama-French 3-factors (FF3). The regressions results reported in this table are based on annual excess returns in July of each year between 2002 and 2020. Panel A reports results from the CAPM specification: $R^e_{i,t} = \alpha + \beta_{mkt} R^e_{mkt,t} + \epsilon_t$ with average adj.R^2 of portfolios 74%. Panel B reports results from the FF3 specification: $R^e_{i,t} = \alpha + \beta_{mkt} R^e_{mkt,t} + \beta_{smb} SMB_t + \beta_{hml} HML_t + \epsilon_t$ with average adj.R^2 of portfolios 91%.

Panel A

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
α						$t(\alpha)$					
Small	-5.29	-0.18	-1.06	1.21	-0.08		-1.82	-0.10	-0.33	0.29	-0.02
ME2	-0.01	1.32	1.28	0.74	-2.45		-0.00	0.85	0.60	0.25	-0.58
ME3	-0.29	2.02	2.64	1.46	-2.87		-0.18	1.31	1.03	0.49	-0.78
ME4	1.77	2.78	0.05	-0.51	-4.76		1.54	1.74	0.02	-0.20	-1.38
Big ME	2.24	0.79	0.14	-6.10	-3.97		1.27	0.94	0.12	-2.06	-1.36
β_{mkt}						$t(\beta_{mkt})$					
Small	1.30	1.11	1.08	1.01	1.21		6.66	11.46	7.20	4.40	5.20
ME2	1.14	1.08	1.06	0.94	1.09		8.34	12.74	11.05	7.54	4.80
ME3	1.23	1.14	0.95	1.06	1.19		10.55	9.98	7.36	6.59	8.22
ME4	1.18	1.06	1.11	1.07	1.51		15.55	9.75	6.91	9.42	7.46
Big ME	0.87	0.89	0.94	1.22	1.11		11.32	19.14	11.61	7.64	4.96
Adj.R^2						$s(e)$					
Small	0.69	0.8	0.64	0.50	0.55		12.85	8.34	11.89	14.6	16.10
ME2	0.84	0.83	0.78	0.63	0.55		7.52	7.29	8.25	10.49	14.28
ME3	0.86	0.88	0.71	0.71	0.59		7.36	6.39	8.92	10.10	14.51
ME4	0.93	0.87	0.76	0.69	0.67		4.93	6.12	9.33	10.50	15.54
Big ME	0.78	0.91	0.90	0.79	0.59		6.88	4.29	4.73	9.36	13.62

Panel B

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
α						$t(\alpha)$					
Small	-9.87	-2.22	-2.82	0.42	-0.46		-4.87	-1.36	-2.66	0.37	-0.40
ME2	-2.70	-0.36	1.04	0.57	-2.02		-1.88	-0.33	0.86	0.43	-2.73
ME3	-3.40	1.46	2.93	1.70	-2.27		-2.80	1.24	1.7	1.13	-1.01
ME4	0.58	2.48	0.79	1.15	-2.42		0.57	2.08	0.43	1.05	-1.53
Big ME	0.73	2.01	0.57	-2.59	-1.31		1.22	3.00	0.48	-1.82	-0.40
β_{mkt}						$t(\beta_{mkt})$					
Small	1.37	1.12	1.06	0.95	1.14		7.23	9.66	13.25	9.92	10.99
ME2	1.19	1.08	1.02	0.89	1.01		11.54	18.51	13.93	13.92	21.52
ME3	1.28	1.13	0.91	1.01	1.12		33.71	14.01	9.49	13.80	8.67
ME4	1.21	1.04	1.06	1.00	1.39		23.98	12.50	11.54	11.06	10.48
Big ME	0.93	0.87	0.92	1.14	1.04		19.97	18.03	12.33	14.08	4.16
β_{smb}						$t(\beta_{smb})$					
Small	1.38	0.88	1.31	1.26	1.27		3.52	3.12	7.97	5.53	6.23
ME2	0.75	0.85	0.61	0.78	0.94		3.98	6.94	4.35	4.81	8.82
ME3	0.89	0.49	0.45	0.63	0.82		5.80	3.13	1.90	4.12	3.47
ME4	0.21	0.39	0.37	0.20	0.38		1.41	1.75	1.52	1.33	1.32
Big ME	0.00	-0.34	0.04	-0.67	-0.43		0.01	-2.58	0.18	-4.10	-0.85
β_{hml}						$t(\beta_{hml})$					
Small	-0.81	-0.20	0.15	0.47	0.62		-3.45	-0.97	1.47	3.82	3.88
ME2	-0.51	-0.10	0.28	0.41	0.71		-4.72	-0.97	2.63	3.92	8.96
ME3	-0.58	0.09	0.37	0.46	0.70		-5.48	0.76	2.33	3.93	6.45
ME4	-0.30	0.13	0.49	0.72	1.06		-3.65	1.10	3.15	6.72	5.21
Big ME	-0.54	0.23	0.17	0.85	0.70		-7.13	3.29	1.32	7.34	2.27
Adj.R^2						$s(e)$					
Small	0.82	0.88	0.96	0.93	0.94		9.89	6.50	4.10	5.45	5.74
ME2	0.90	0.93	0.93	0.93	0.97		5.84	4.57	4.56	4.56	3.85
ME3	0.95	0.93	0.87	0.94	0.90		4.59	4.90	6.04	4.71	7.15
ME4	0.94	0.92	0.91	0.92	0.93		4.34	4.89	5.73	5.32	6.90
Big ME	0.95	0.92	0.91	0.93	0.64		3.25	3.82	4.48	5.55	12.73

Table 15: Time-series regressions of the 25 Fama-French portfolios excess returns on the Fama-French 5-factors (FF5). The regressions results reported in this table are based on annual excess returns in July of each year between 2002 and 2020. Results are based on the FF5 specification: $R^e_{i,t} = \alpha + \beta_{mkt} R^e_{mkt,t} + \beta_{smb} SMB_t + \beta_{hml} HML_t + \beta_{cma} CMA_t + \beta_{rmw} RMW_t + \epsilon_t$ with average adj.R^2 of portfolios 93%.

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
α						$t(\alpha)$					
Small	-3.90	0.76	-1.61	-0.08	-0.28		-1.79	0.40	-1.46	-0.04	-0.13
ME2	-0.00	0.18	1.93	-0.20	-3.44		-0.00	0.12	1.18	-0.12	-2.62
ME3	-2.55	-0.17	1.42	0.82	-2.80		-1.50	-0.10	0.64	0.49	-1.05
ME4	0.71	0.50	-0.28	-0.29	-0.35		0.46	0.30	-0.13	-0.15	-0.15
Big ME	0.14	-0.02	0.14	-3.49	4.97		0.12	-0.02	0.10	-1.75	1.68
β_{mkt}						$t(\beta_{mkt})$					
Small	0.98	0.93	0.96	0.97	1.13		7.89	8.52	15.32	8.27	8.99
ME2	1.01	1.03	0.96	0.92	1.10		11.44	11.98	10.2	9.65	14.56
ME3	1.22	1.23	0.99	1.07	1.13		12.53	12.53	7.78	11.17	7.40
ME4	1.19	1.16	1.11	1.08	1.25		13.46	12.18	9.21	9.64	9.17
Big ME	0.96	1.00	0.96	1.20	0.61		14.13	16.36	11.86	10.51	3.60
β_{smb}						$t(\beta_{smb})$					
Small	1.58	0.99	1.41	1.30	1.24		6.40	4.61	11.36	5.59	4.99
ME2	0.87	0.93	0.66	0.82	0.9		5.01	5.48	3.56	4.31	6.08
ME3	0.93	0.44	0.46	0.57	0.87		4.81	2.29	1.81	3.00	2.89
ME4	0.27	0.36	0.40	0.19	0.46		1.53	1.93	1.68	0.87	1.72
Big ME	0.03	-0.40	-0.05	-0.74	-0.13		0.20	-3.33	-0.34	-3.28	-0.40
β_{hml}						$t(\beta_{hml})$					
Small	-0.49	-0.03	0.30	0.51	0.59		-2.73	-0.16	3.33	3.03	3.26
ME2	-0.32	0.02	0.35	0.44	0.65		-2.56	0.17	2.63	3.21	6.03
ME3	-0.52	0.02	0.36	0.37	0.77		-3.75	0.12	1.99	2.70	3.53
ME4	-0.22	0.07	0.52	0.69	1.20		-1.72	0.50	3.00	4.27	6.11
Big ME	-0.51	0.13	0.05	0.75	1.16		-5.27	1.53	0.41	4.59	4.77
β_{cma}						$t(\beta_{cma})$					
Small	-0.48	-0.30	-0.39	-0.20	0.13		-1.87	-1.34	-2.97	-0.82	0.52
ME2	-0.39	-0.36	-0.19	-0.21	0.07		-2.11	-2.04	-0.95	-1.07	0.43
ME3	-0.12	0.08	-0.15	0.22	-0.32		-0.61	0.39	-0.57	1.12	-1.00
ME4	-0.28	-0.02	-0.24	-0.05	-0.26		-1.51	-0.09	-0.95	-0.23	-0.90
Big ME	-0.16	0.13	0.40	0.26	-0.95		-1.16	1.02	2.37	1.09	-2.70
β_{rmw}						$t(\beta_{rmw})$					
Small	-0.86	-0.41	-0.09	0.15	-0.07		-3.45	-1.88	-0.68	0.62	-0.28
ME2	-0.34	0.02	-0.09	0.20	0.22		-1.92	0.12	-0.50	1.02	1.46
ME3	-0.11	0.25	0.30	0.08	0.19		-0.55	1.27	1.18	0.42	0.61
ME4	0.06	0.34	0.25	0.26	-0.27		0.36	1.79	1.05	1.16	-0.99
Big ME	0.15	0.3	-0.05	0.07	-0.77		1.11	2.49	-0.32	0.31	-2.27
Adj.R^2						$s(e)$					
Small	0.93	0.92	0.98	0.92	0.93		6.03	5.27	3.04	5.69	6.10
ME2	0.95	0.94	0.93	0.93	0.97		4.26	4.16	4.55	4.64	3.65
ME3	0.94	0.93	0.86	0.94	0.89		4.71	4.76	6.17	4.65	7.40
ME4	0.95	0.93	0.9	0.92	0.94		4.28	4.60	5.85	5.42	6.62
Big ME	0.95	0.96	0.93	0.93	0.85		3.27	2.95	3.94	5.54	8.20

Table 16: Time-series regressions of the 25 Fama-French portfolios subjective expected excess returns on the subjective expected excess market return (CAPM) or on the subjective expected returns of the Fama-French 3-factors (FF3). Regressions are based on annual subjective excess returns in July of each year between 2002 and 2020. Panel A reports results from the CAPM specification: $\tilde{\mathbb{E}}_t[R^e_{i,t+1}] = \tilde{\alpha} + \tilde{\beta}_{mkt}\tilde{\mathbb{E}}_t[R^e_{mkt,t+1}] + \tilde{\epsilon}_t$ with average adj.R^2 of portfolios 62%; Panel B reports results from the FF3 specification: $\tilde{\mathbb{E}}_t[R^e_{i,t+1}] = \tilde{\alpha} + \tilde{\beta}_{mkt}\tilde{\mathbb{E}}_t[R^e_{mkt,t+1}] + \tilde{\beta}_{smb}\tilde{\mathbb{E}}_t[SMB_{t+1}] + \tilde{\beta}_{hml}\tilde{\mathbb{E}}_t[HML_{t+1}] + \tilde{\epsilon}_t$ with average adj.R^2 of portfolios 82%.

Panel A

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
$\tilde{\alpha}$						$t(\tilde{\alpha})$					
Small	27.25	27.07	9.93	7.88	-1.65		1.78	2.29	1.07	1.54	-0.12
ME2	9.68	3.66	0.41	-0.62	1.00		2.39	1.33	0.23	-0.35	0.32
ME3	0.24	0.47	-0.61	-0.70	-5.66		0.10	0.44	-0.42	-0.32	-1.37
ME4	-7.28	-1.58	-4.58	1.80	-0.73		-0.90	-1.55	-1.28	0.78	-0.14
Big ME	1.44	1.08	2.79	-1.39	-3.73		1.20	1.11	1.24	-0.41	-1.05
$\tilde{\beta}_{mkt}$						$t(\tilde{\beta}_{mkt})$					
Small	1.64	0.75	1.45	1.11	1.99		1.68	1.36	2.91	4.92	1.91
ME2	0.81	0.91	1.00	0.99	0.89		3.38	7.39	13.55	11.93	6.69
ME3	1.02	0.89	0.92	0.97	1.34		5.92	14.86	15.07	10.38	5.08
ME4	1.63	0.93	1.32	0.76	1.05		2.13	15.34	4.99	7.28	2.96
Big ME	0.86	0.89	0.80	1.12	1.42		13.35	13.10	5.17	4.26	6.08
Adj.R^2						$s(e)$					
Small	0.18	0.03	0.35	0.46	0.34		20.21	16.36	12.17	7.53	17.18
ME2	0.37	0.66	0.8	0.81	0.62		6.55	4.20	3.27	3.07	4.45
ME3	0.79	0.9	0.87	0.78	0.65		3.36	1.97	2.31	3.26	6.32
ME4	0.13	0.94	0.68	0.66	0.44		22.98	1.54	5.74	3.44	7.36
Big ME	0.88	0.91	0.71	0.66	0.78		2.09	1.85	3.30	5.16	4.79

Panel B

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
$\tilde{\alpha}$						$t(\tilde{\alpha})$					
Small	16.94	24.35	9.65	11.88	-9.24		3.02	2.80	2.84	2.46	-1.21
ME2	5.76	3.4	-0.32	1.57	4.16		2.16	1.23	-0.12	0.81	1.59
ME3	-4.19	-0.57	-0.8	-0.15	-3.34		-6.70	-0.50	-0.46	-0.07	-2.00
ME4	-11.08	-1.68	1.09	2.23	0.96		-1.10	-1.45	0.52	0.92	0.50
Big ME	-1.03	1.98	6.06	6.55	0.17		-1.08	2.16	2.31	1.74	0.11
$\tilde{\beta}_{mkt}$						$t(\tilde{\beta}_{mkt})$					
Small	1.07	0.16	0.90	0.70	1.48		4.30	0.41	5.23	2.81	4.19
ME2	0.68	0.76	0.93	0.82	0.63		5.01	5.10	6.94	9.89	4.05
ME3	1.04	0.86	0.87	0.86	0.99		21.50	18.66	10.15	7.59	16.25
ME4	1.83	0.93	1.09	0.67	0.70		1.97	16.19	7.12	6.72	6.68
Big ME	0.98	0.90	0.73	0.91	1.14		18.18	15.15	4.18	4.71	11.17
$\tilde{\beta}_{smb}$						$t(\tilde{\beta}_{smb})$					
Small	3.74	2.60	2.11	0.89	3.10		12.35	4.50	11.46	2.53	5.52
ME2	1.11	0.62	0.39	0.27	0.44		7.24	3.12	2.79	2.35	2.03
ME3	0.63	0.28	0.22	0.30	0.92		12.57	4.96	2.25	2.63	7.77
ME4	-0.12	-0.02	-0.04	0.26	1.03		-0.28	-0.19	-0.23	3.69	4.69
Big ME	-0.04	-0.18	-0.23	-0.48	0.44		-0.79	-3.54	-2.07	-2.57	3.71
$\tilde{\beta}_{hml}$						$t(\tilde{\beta}_{hml})$					
Small	0.40	0.98	1.10	1.11	0.49		0.72	1.86	4.79	4.53	1.11
ME2	-0.02	0.29	0.10	0.49	0.73		-0.07	1.57	0.44	3.38	5.21
ME3	-0.35	-0.01	0.09	0.25	0.86		-4.82	-0.12	0.64	1.02	4.42
ME4	-0.66	-0.03	0.87	0.21	0.82		-1.03	-0.28	2.48	0.85	2.47
Big ME	-0.41	0.05	0.39	0.99	0.85		-5.18	0.55	1.52	3.64	4.34
Adj.R^2						$s(e)$					
Small	0.86	0.67	0.92	0.80	0.87		8.36	9.57	4.19	4.58	7.74
ME2	0.78	0.85	0.86	0.90	0.84		3.87	2.75	2.74	2.22	2.92
ME3	0.98	0.94	0.89	0.83	0.93		1.15	1.51	2.11	2.89	2.86
ME4	0.03	0.93	0.74	0.69	0.8		24.33	1.64	5.23	3.28	4.40
Big ME	0.93	0.92	0.75	0.83	0.91		1.60	1.73	3.05	3.62	3.03

Table 17: Time-series regressions of the 25 Fama-French portfolios expected excess returns on the expected returns of the Fama-French 5-factors (FF5). Regressions are based on annual subjective excess returns in July of each year between 2002 and 2020. Regression specification: $\tilde{\mathbb{E}}_t[R^e_{i,t+1}] = \tilde{\alpha} + \tilde{\beta}_{mkt}\tilde{\mathbb{E}}_t[R^e_{mkt,t+1}] + \tilde{\beta}_{smb}\tilde{\mathbb{E}}_t[SMB_{t+1}] + \tilde{\beta}_{hml}\tilde{\mathbb{E}}_t[HML_{t+1}] + \tilde{\beta}_{cma}\tilde{\mathbb{E}}_t[CMA_{t+1}] + \tilde{\beta}_{rmw}\tilde{\mathbb{E}}_t[RMW_{t+1}] + \tilde{\epsilon}_{t+1}$ with average adj.R^2 of portfolios 86%.

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
$\tilde{\alpha}$						$t(\tilde{\alpha})$					
Small	15.31	3.85	3.66	0.88	6.45		1.77	0.52	0.93	0.25	0.81
ME2	1.71	-1.31	-2.59	-0.53	-0.34		0.43	-0.50	-0.92	-0.21	-0.13
ME3	-4.77	-0.1	-3.53	-0.15	-2.61		-3.64	-0.06	-1.98	-0.06	-0.94
ME4	-11.31	-4.73	-1.49	3.38	-2.34		-0.46	-3.58	-0.24	0.95	-0.47
Big ME	-0.55	2.86	6.83	3.03	-0.93		-0.39	1.36	1.86	0.70	-0.28
$\tilde{\beta}_{mkt}$						$t(\tilde{\beta}_{mkt})$					
Small	1.10	1.13	1.17	1.21	0.72		2.60	3.13	6.04	7.06	1.85
ME2	0.84	0.97	1.03	0.92	0.86		4.30	7.50	7.40	7.41	6.77
ME3	1.05	0.83	1.01	0.88	0.93		16.34	9.64	11.46	7.48	6.81
ME4	2.04	1.09	1.21	0.63	0.83		1.70	16.73	3.96	3.56	3.39
Big ME	0.94	0.85	0.69	1.05	1.16		13.61	8.21	3.82	4.93	7.20
$\tilde{\beta}_{smb}$						$t(\tilde{\beta}_{smb})$					
Small	3.97	3.85	2.50	1.50	2.22		7.91	9.04	11.00	7.41	4.80
ME2	1.34	0.90	0.59	0.40	0.74		5.82	5.87	3.57	2.74	4.97
ME3	0.62	0.26	0.43	0.42	0.82		8.19	2.57	4.20	3.02	5.07
ME4	0.46	0.18	0.02	0.28	1.13		0.33	2.34	0.05	1.33	3.91
Big ME	-0.12	-0.23	-0.19	-0.30	0.44		-1.52	-1.88	-0.90	-1.20	2.30
$\tilde{\beta}_{hml}$						$t(\tilde{\beta}_{hml})$					
Small	-0.18	0.42	0.74	0.91	0.18		-0.32	0.91	2.98	4.11	0.36
ME2	-0.19	0.16	-0.00	0.43	0.61		-0.77	0.99	-0.02	2.66	3.74
ME3	-0.42	-0.05	0.01	0.15	0.78		-5.10	-0.46	0.11	0.98	4.40
ME4	-0.96	-0.06	0.89	0.14	0.70		-0.62	-0.71	2.27	0.61	2.21
Big ME	-0.37	0.08	0.39	1.04	0.81		-4.17	0.59	1.66	3.77	3.90
$\tilde{\beta}_{cma}$						$t(\tilde{\beta}_{cma})$					
Small	0.49	-1.30	-0.19	-0.91	1.76		0.74	-2.30	-0.62	-3.40	2.87
ME2	-0.30	-0.33	-0.03	-0.12	-0.21		-1.00	-1.62	-0.14	-0.64	-1.06
ME3	-0.08	0.08	-0.08	0.32	-0.02		-0.75	0.57	-0.60	1.72	-0.11
ME4	1.71	-0.20	-0.42	0.33	-0.40		0.91	-1.99	-0.88	1.21	-1.06
Big ME	-0.11	0.03	0.20	-0.48	-0.23		-0.97	0.16	0.70	-1.43	-0.91
$\tilde{\beta}_{rmw}$						$t(\tilde{\beta}_{rmw})$					
Small	0.13	0.93	0.26	0.26	-0.62		0.32	2.60	1.36	1.55	-1.59
ME2	-0.07	0.15	0.23	0.10	0.36		-0.39	1.15	1.65	0.81	2.83
ME3	-0.15	-0.04	0.29	0.41	-0.39		-2.40	-0.44	3.27	3.51	-2.86
ME4	2.95	0.22	-0.18	0.26	-0.30		2.47	3.36	-0.58	1.46	-1.23
Big ME	-0.24	-0.09	0.19	-0.08	-0.28		-3.46	-0.89	1.04	-0.38	-1.75
Adj.R^2						$s(e)$					
Small	0.89	0.85	0.95	0.91	0.89		7.55	6.41	3.43	3.05	6.95
ME2	0.82	0.90	0.88	0.90	0.90		3.46	2.30	2.48	2.21	2.24
ME3	0.98	0.94	0.94	0.91	0.95		1.15	1.53	1.56	2.08	2.42
ME4	0.25	0.97	0.72	0.72	0.81		21.37	1.15	5.41	3.12	4.34
Big ME	0.96	0.91	0.73	0.81	0.92		1.23	1.84	3.20	3.80	2.87

Table 18: Sell-side Analysts' Recommendations. This table provides the results of the time series regressions of aggregate sell-side analysts' recommendations on the most recent quarter excess return of the S&P500 ($R^e_{t-3,t}$) and the log-price dividend ratio (pd_t). $SR_{m,t}$ is the S&P500 value-weighted average of IBES consensus mean sell-side analysts' stock level recommendations. Small-sample adjusted Newey-West standard errors with 4 quarter lags are shown in parentheses. *: 10% significance; **: 5% significance; ***: 1% significance. Notice that forecasting regressions with persistent regressors may yield biased coefficients in small samples (Stambaugh (1999)): adjusting for this does not change the results significantly (not showed below).

Regression specification: $Y_t = \xi_c + \xi_r \ R^e_{t-3,t} + \xi_{pd} \ pd_t + \epsilon_t$

Y_t	ξ_c	ξ_r	ξ_{pd}	Adj.R^2	Sample
$SR_{m,t}$	0.49	-0.16**	0.07	0.02	Q2 2002- Q4 2020
	(0.25)	(0.07)	(0.07)		

A Appendix: Alternative IBES Expected Return Construction

In this Section, the main time-series and cross-sectional tests are repeated for IBES total return expectations constructed by normalising price targets and one-year dividend expectations by the price at the time the IBES consensus forecasts are formed. Expected returns at the single stock level are aggregated at the $S\&P500$ level by weighting the forecasts by the market capitalizations at the time the consensus is formed. Valuation ratios and metrics at the time the consensus forecasts are created (or the closest date before that date) are used in the tests. Table A1 illustrates the results, which are similar to those presented in Tables 4, 7, 8, 10 and 11.

[Table A1 here]

Tables A2 and A3 show the results when repeating the first-stage Fama-MacBeth procedure described in Sections 3.2.2 and 5.2 under the alternative subjective expected returns construction. Similarly to previous results, CAPM/FF3/FF5 models fit the cross-section of subjective returns expectations well.

[Tables A2 and A3 here]

B Appendix: Additional SML Plots

Figures B1 and B2 show the SML when realised excess returns are regressed on CFOs and sell-side analysts' risk premia expectations. The subjective expectations are not able to explain the cross-sectional variation of Fama-French 25 book-to-market sorted portfolios.

[Figures B1 and B2 here]

C Appendix: New Factors?

Given the results from Section 3.2.2, one might wonder whether the expected factor returns constructed using IBES surveys are also able to explain realised excess returns and thus represent a new set of 'factors'. I therefore run simple time-series predictive regressions with realised excess returns of the 25 Fama-French book-to-market sorted portfolios as dependent variables and expected factor returns as independent variables:

$$R^e_{i,t+1} = \alpha + \beta \tilde{\mathbb{E}}_t \left[R_{Factors,t+1}\right] + \epsilon_{t+1} \tag{17}$$

where β is a vector of slope coefficients for each expected return factors, and $\tilde{\mathbb{E}}_t \left[R_{Factors,t+1}\right]$ is a matrix with all the time-series of expected return factors. Tables C1 and C2 show the results: the subjective expected market excess return has no explanatory power (average adjusted R^2 is negative); adding subjective expected size and value risk factors leads to a small increase in pricing ability (average adjusted R^2 increases to 19%). Finally, the subjective investment and profitability factors display an increase in pricing ability (average adjusted R^2 increases to 31%). The takeaway is that some of these subjective expected risk factors may have some pricing ability, and they could still turn out to be useful when used in conjunction with other factors. To check whether these expected return factors have additional information, I run spanning regressions in the spirit of Barillas & Shanken (2017) and Barillas & Shanken (2018). Table C3 shows the result of spanning regressions of subjective expected factor returns on the realised or the remaining subjective expected factor returns. The results are mixed as the standard Fama-French 5 factor model do not seem to span the subjective expected factor returns counterparts: all αs are statistically significant at the 10% level with the exception of the expected RMW factor which however has a low adjusted R^2. When running spanning tests amongst subjective expected factors, they all display insignificant intercept with the exception of the subjective expected HML factor which, however, has a very low R^2. The evidence seems to suggest that the subjective Fama-French factors are not spanned by the combinations of the other subjective factors or by the combinations of the realised versions of the Fama-French factors.

[Tables C1 through C3 here]

Figure B1: Security market line (SML) and CFO expectations. The figure shows average one-year realised excess returns ($\mathbb{E}[R^e]$) of the Fama-French 25 (FF25) portfolios against their CFO expectation based CAPM beta (β_{CFO}). β_{CFO}s are estimated by running time-series regressions of realised one-year excess returns of each FF25 portfolio on one-year subjective market excess returns - from the GH survey - ($R^e_{i,t+1} = \alpha_i + \beta_{CFO,i}\tilde{\mathbb{E}}_{GH,t}[R^e_{m,t+1}] + \epsilon_{t+1}$), in July of each year between 2002 and 2020. The green line is the empirical SML and it is the best-fit line across all the FF25 portfolios. Finally, the red line represents the theoretical SML where the slope is the sample average subjective GH expected excess market return and the intercept is the sample average one-year Treasury yield.

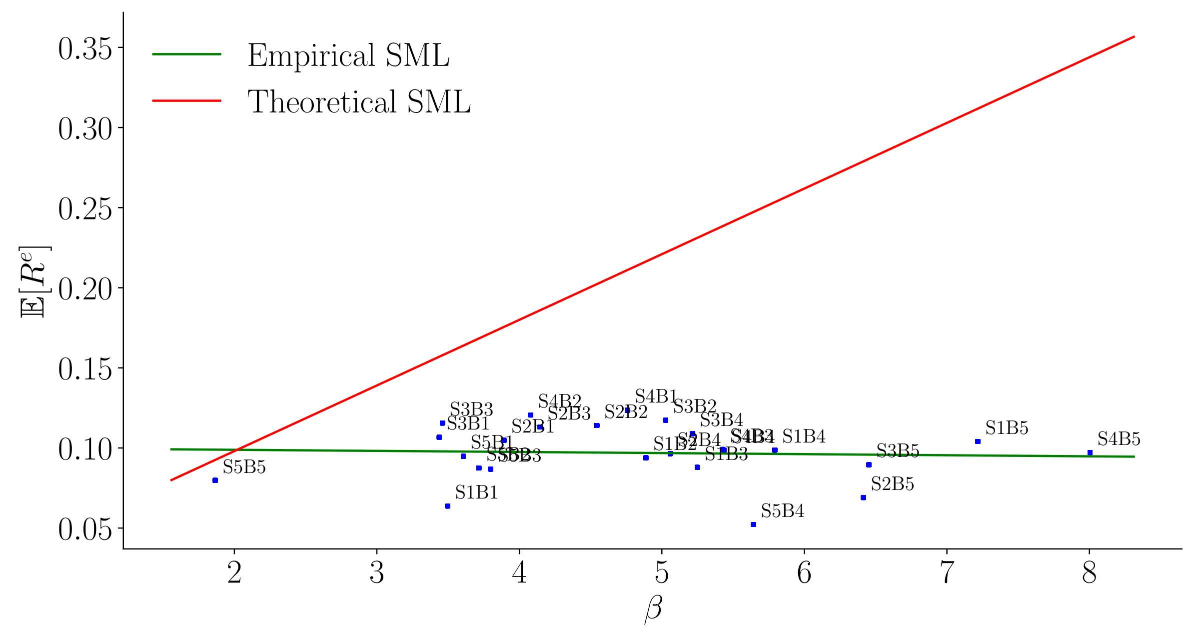


Figure B2: Security market line (SML) and IBES expectations. The figure shows average one-year realised excess returns ($\mathbb{E}[R^e]$) of the Fama-French 25 (FF25) portfolios against their IBES expectation based CAPM beta (β_{IBES}). β_{IBES}s are estimated by running time-series regressions of realised one-year excess returns of each FF25 portfolio on one-year subjective market excess returns - from the IBES - ($R^e_{i,t+1} = \alpha_i + \beta_{IBES,i}\tilde{\mathbb{E}}_{IBES,t}[R^e_{m,t+1}] + \epsilon_{t+1}$), in July of each year between 2002 and 2020. The green line is the empirical SML and it is the best-fit line across all the FF25 portfolios. Finally, the red line represents the theoretical SML where the slope is the sample average subjective IBES expected excess market return and the intercept is the sample average one-year Treasury yield.

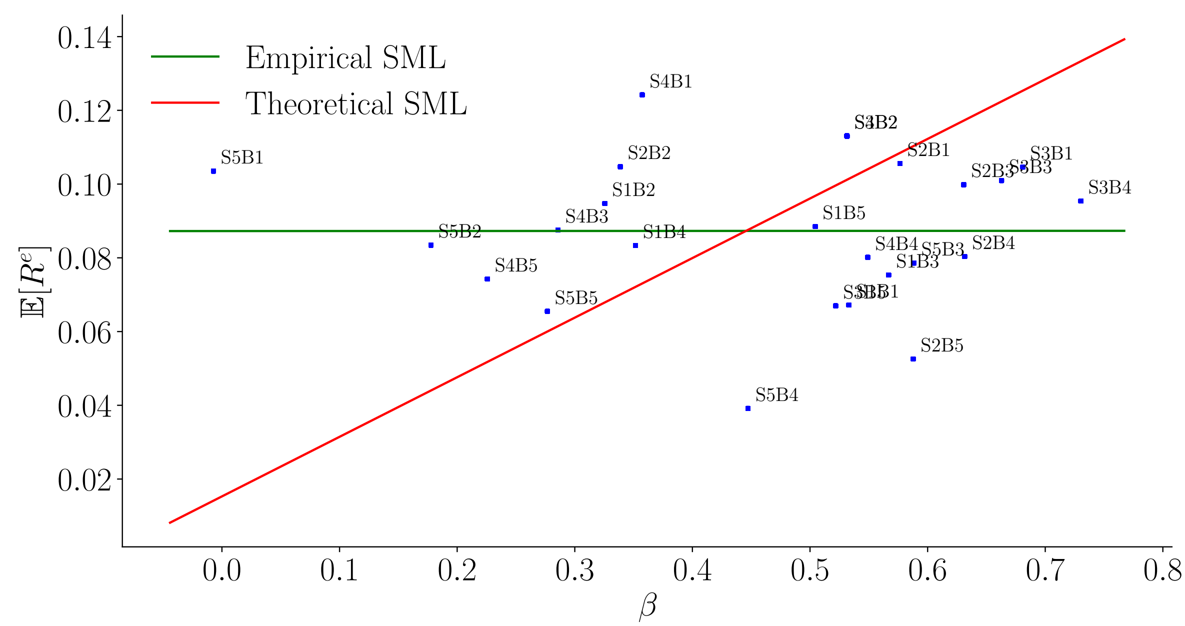


Table A1: Main time-series results for alternative IBES subjective return construction. The tables below report the results of the main tests when IBES total return expectations are constructed by normalising price targets and one-year dividend expectations by the price at the time the consensus forecasts are calculated by IBES (this is denoted by IBES* below). The aggregation at the $S\&P500$ level is achieved by using market capitalizations at the time the consensus is formed. Valuation ratios/measures are also taken at the time the consensus is created or at the closest time possible before that date. Panel A shows the time-series regression results of IBES* subjective risk premia on past 12-month returns of the CRSP value-weighted index of the $S\&P500$ universe, in excess of the risk-free rate ($R^e_{t-1,t}$) and log price-dividend ratio (pd_t) - in the spirit of Nagel & Xu (2022), all predictor variables are standardized to have unit variance and slope coefficients are multiplied by 100 (this is to allow comparison between the β). Panel B shows equity risk premia predictability regressions based on IBES* subjective risk premia. Panel C shows the correlation of IBES* subjective risk premia with model-based measures of expected risk premium. Panel D shows the variance decomposition of the price-dividend ratio. CF, DR and LT are defined in equation (13): the methodology is identical to the one described in Table 7. Small-sample adjusted Newey-West standard errors with 4 quarter lags are shown in parentheses for Panels A and B. Panel C displays p-values in the parentheses. *: 10% significance; **: 5% significance; ***: 1% significance.

Panel A *Regression specification*: $Y_t = \gamma_0 + \gamma_1\ R^e_{t-1,t} + \gamma_2\ pd_t + \epsilon_t$

Y_t	Intercept	$R^e_{t-12,t}$	pd_t	Adj.R^2	Sample
$\tilde{\mathbb{E}}_{IBES^*,t}[R^e_{t,t+12}]$	15.82***	-3.08***		0.16	Q2 2002 - Q4 2020
	(1.04)	(1.09)			
$\tilde{\mathbb{E}}_{IBES^*,t}[R^e_{t,t+12}]$	117.20***		-3.56***	0.21	Q2 2002 - Q4 2020
	(30.15)		(1.05)		
$\tilde{\mathbb{E}}_{IBES^*,t}[R^e_{t,t+12}]$	92.90**	-1.72	-2.69*	0.24	Q2 2002 - Q4 2020
	(43.94)	(1.72)	(1.54)		

Panel B *Regression specification*: $R^e_{t,t+1} = \alpha + \beta_1 X_t + \beta_2 \mathbb{1}_{2007,2008} + \epsilon_{t+1}$

X_t	α	β_1	β_2	Adj.R^2	Sample
$\tilde{\mathbb{E}}_{IBES^*,t}[R^e_{t,t+12}]$	0.02	0.63**		0.07	Q2 2002 - Q4 2020
	(0.02)	(0.25)			
$\tilde{\mathbb{E}}_{IBES^*,t}[R^e_{t,t+12}]$	0.02	0.87***	-0.34***	0.49	Q2 2002 - Q4 2020
	(0.04)	(0.25)	(0.06)		

Panel C *Correlation Results*

Correlation	pd	cay	VRP	VIX^2	Sample
IBES*	-0.47***	0.30***	0.37***	0.85***	Q2 2002 - Q4 2020
	(0.00)	(0.01)	(0.00)	(0.00)	

Panel D *Variance decomposition of pd*

Channel	β	$t(\beta)$	Adj.R^2(%)	$\sigma(X\beta)$(%)	Sample
CF	0.36	5.78	52.32	4.99	Q2 2002 - Q4 2018
DR_{IBES^*}	0.14	2.31	10.80	1.91	Q2 2002 - Q4 2018
LT_{IBES^*}	0.51	6.30	50.67	6.99	Q2 2002 - Q4 2018

Table A2: Time series regressions of the 25 Fama-French portfolios subjective expected excess returns on the subjective expected excess market return (CAPM) or on the subjective expected returns of the Fama-French 3-factors (FF3) based on alternative IBES subjective return construction. The tables below rely on IBES total return expectations constructed by normalising price targets and one-year dividend expectations by the price at the time the consensus forecasts are calculated by IBES. Regressions are based on annual subjective excess returns in July of each year between 2002 and 2020. Panel A reports results from the CAPM specification: $\tilde{\mathbb{E}}_t[R^e_{i,t+1}] = \tilde{\alpha} + \tilde{\beta}_{mkt}\tilde{\mathbb{E}}_t[R^e_{mkt,t+1}] + \tilde{\epsilon}_t$ with average adj.R^2 of portfolios 73%; Panel B reports results from the FF3 specification: $\tilde{\mathbb{E}}_t[R^e_{i,t+1}] = \tilde{\alpha} + \tilde{\beta}_{mkt}\tilde{\mathbb{E}}_t[R^e_{mkt,t+1}] + \tilde{\beta}_{smb}\tilde{\mathbb{E}}_t[SMB_{t+1}] + \tilde{\beta}_{hml}\tilde{\mathbb{E}}_t[HML_{t+1}] + \tilde{\epsilon}_t$ with average adj.R^2 of portfolios 87%.

Panel A

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
$\tilde{\alpha}$						$t(\tilde{\alpha})$					
Small	20.24	24.3	7.53	9.87	-5.39		1.50	2.35	0.91	2.10	-0.52
ME2	4.86	1.96	0.64	0.11	-0.74		1.05	0.88	0.36	0.05	-0.20
ME3	-0.71	-1.84	0.25	0.12	-6.73		-0.51	-1.48	0.20	0.06	-1.93
ME4	-2.07	-0.65	-1.00	-0.94	-30.71		-0.64	-0.85	-0.34	-0.44	-2.12
Big ME	0.39	-0.08	3.68	3.13	-2.10		0.43	-0.13	3.76	1.41	-1.27
$\tilde{\beta}_{mkt}$						$t(\tilde{\beta}_{mkt})$					
Small	2.40	1.06	1.76	1.07	2.41		2.90	2.38	4.22	6.43	3.43
ME2	1.26	1.10	1.02	0.97	1.14		4.59	11.91	14.73	13.57	5.89
ME3	1.12	1.08	0.89	0.97	1.53		14.00	15.54	17.84	14.43	7.97
ME4	1.34	0.89	1.12	0.99	3.49		3.82	19.05	4.69	7.44	3.14
Big ME	0.88	0.91	0.74	0.86	1.34		23.75	25.92	15.42	4.73	17.81
Adj.R^2						$s(e)$					
Small	0.50	0.19	0.58	0.54	0.65		22.54	18.63	14.06	9.25	16.64
ME2	0.64	0.8	0.84	0.83	0.70		8.92	5.22	4.28	4.16	7.05
ME3	0.87	0.92	0.9	0.85	0.81		4.15	2.99	2.91	3.91	7.01
ME4	0.21	0.97	0.68	0.82	0.67		22.75	1.61	7.24	4.38	22.93
Big ME	0.92	0.96	0.85	0.67	0.90		2.47	1.88	2.90	5.68	4.26

Panel B

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
$\tilde{\alpha}$						$t(\tilde{\alpha})$					
Small	15.36	22.46	9.40	10.39	-1.43		3.31	4.71	4.09	3.96	-0.43
ME2	0.07	-1.62	-1.70	0.51	-0.20		0.05	-1.46	-1.18	0.41	-0.15
ME3	-5.11	-4.17	-0.62	-0.21	-3.64		-8.11	-6.74	-0.4	-0.14	-2.96
ME4	-2.97	-1.37	1.21	-1.06	-23.51		-0.90	-1.53	0.49	-0.61	-2.73
Big ME	-1.50	0.01	5.73	6.94	1.46		-2.21	0.01	5.13	3.24	1.27
$\tilde{\beta}_{mkt}$						$t(\tilde{\beta}_{mkt})$					
Small	1.33	0.10	0.89	0.57	1.39		4.84	0.35	7.50	2.81	6.48
ME2	0.96	0.95	0.91	0.75	0.73		8.60	13.28	11.53	10.90	9.45
ME3	1.11	1.02	0.81	0.8	1.09		25.16	28.34	9.96	9.84	14.21
ME4	1.43	0.91	1.11	0.81	2.39		4.13	18.20	5.10	9.75	3.83
Big ME	1.00	0.96	0.69	0.77	1.12		23.34	24.60	9.31	4.32	24.36
$\tilde{\beta}_{smb}$						$t(\tilde{\beta}_{smb})$					
Small	3.41	2.73	2.02	1.22	2.12		7.38	11.82	15.69	5.64	8.45
ME2	1.42	0.86	0.61	0.52	0.99		6.92	8.10	5.88	7.59	7.06
ME3	0.62	0.47	0.34	0.48	0.72		10.16	8.67	5.55	5.07	5.08
ME4	-0.10	0.04	-0.28	0.50	1.89		-0.31	0.94	-0.97	4.59	2.41
Big ME	-0.06	-0.13	-0.16	-0.28	0.07		-1.44	-2.19	-1.88	-1.46	0.81
$\tilde{\beta}_{hml}$						$t(\tilde{\beta}_{hml})$					
Small	0.76	0.95	1.22	0.64	1.60		1.76	3.68	6.97	4.02	8.49
ME2	-0.13	-0.19	-0.10	0.30	0.54		-1.07	-2.33	-0.99	3.64	5.09
ME3	-0.43	-0.16	0.01	0.17	0.83		-9.50	-3.88	0.09	1.29	6.83
ME4	-0.19	-0.10	0.23	0.21	2.02		-0.79	-1.43	1.54	1.22	4.33
Big ME	-0.33	-0.05	0.26	0.49	0.61		-7.20	-1.07	3.03	3.06	7.55
Adj.R^2						$s(e)$					
Small	0.87	0.81	0.96	0.86	0.93		11.26	9.16	4.22	5.18	7.35
ME2	0.91	0.97	0.93	0.94	0.94		4.39	2.15	2.75	2.47	3.07
ME3	0.98	0.98	0.93	0.92	0.95		1.47	1.42	2.36	2.77	3.51
ME4	0.11	0.97	0.66	0.90	0.80		24.19	1.62	7.45	3.28	17.89
Big ME	0.96	0.96	0.88	0.72	0.95		1.81	1.82	2.63	5.24	2.96

Table A3: Time-series regressions of the 25 Fama-French portfolios expected excess returns on the expected returns of the Fama-French 5-factors (FF5) based on alternative IBES subjective return construction. The table below relies on IBES total return expectations constructed by normalising price targets and one-year dividend expectations by the price at the time the consensus forecasts are calculated by IBES. Regressions are based on annual subjective excess returns in July of each year between 2002 and 2020. Regression specification: $\tilde{\mathbb{E}}_t[R^e_{i,t+1}] = \tilde{\alpha} + \tilde{\beta}_{mkt}\tilde{\mathbb{E}}_t[R^e_{mkt,t+1}] + \tilde{\beta}_{smb}\tilde{\mathbb{E}}_t[SMB_{t+1}] + \tilde{\beta}_{hml}\tilde{\mathbb{E}}_t[HML_{t+1}] + \tilde{\beta}_{cma}\tilde{\mathbb{E}}_t[CMA_{t+1}] + \tilde{\beta}_{rmw}\tilde{\mathbb{E}}_t[RMW_{t+1}] + \tilde{\epsilon}_{t+1}$ with average adj.R^2 of portfolios 89%.

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
$\tilde{\alpha}$						$t(\tilde{\alpha})$					
Small	22.55	16.35	9.39	3.96	5.69		2.78	2.21	2.91	1.10	1.07
ME2	2.54	-3.38	-3.62	-2.19	-2.97		0.82	-2.06	-1.72	-1.24	-1.22
ME3	-4.44	-3.22	-3.64	-1.58	-2.10		-4.58	-2.94	-2.61	-0.76	-0.75
ME4	-18.67	-3.74	-3.95	-1.68	-1.27		-1.10	-3.81	-0.69	-0.63	-0.11
Big ME	-0.23	0.46	6.14	4.65	0.97		-0.18	0.30	2.78	1.11	0.40
$\tilde{\beta}_{mkt}$						$t(\tilde{\beta}_{mkt})$					
Small	0.81	0.49	0.89	0.98	0.91		1.63	1.08	4.51	4.48	2.80
ME2	0.76	1.06	1.04	0.93	0.93		4.06	10.55	8.09	8.67	6.25
ME3	1.05	0.95	1.02	0.91	0.97		17.78	14.32	12.0	7.21	5.71
ME4	2.68	1.08	1.44	0.85	0.85		2.59	17.97	4.12	5.20	1.18
Big ME	0.90	0.93	0.66	0.90	1.14		11.14	9.81	4.9	3.52	7.77
$\tilde{\beta}_{smb}$						$t(\tilde{\beta}_{smb})$					
Small	3.15	2.90	2.00	1.43	1.82		6.40	6.45	10.21	6.55	5.66
ME2	1.33	0.91	0.68	0.62	1.06		7.09	9.09	5.32	5.77	7.19
ME3	0.58	0.43	0.45	0.53	0.65		9.81	6.43	5.34	4.21	3.82
ME4	0.44	0.13	-0.11	0.53	1.06		0.43	2.15	-0.31	3.27	1.47
Big ME	-0.11	-0.14	-0.15	-0.19	0.09		-1.33	-1.45	-1.09	-0.75	0.61
$\tilde{\beta}_{hml}$						$t(\tilde{\beta}_{hml})$					
Small	0.35	0.81	0.93	0.62	1.31		0.61	1.54	4.08	2.46	3.51
ME2	-0.24	-0.22	-0.21	0.21	0.37		-1.12	-1.86	-1.43	1.72	2.15
ME3	-0.42	-0.22	-0.10	-0.00	0.83		-6.11	-2.8	-1.07	-0.01	4.24
ME4	-1.26	-0.11	0.49	0.10	1.93		-1.05	-1.65	1.22	0.54	2.32
Big ME	-0.26	-0.04	0.21	0.68	0.69		-2.79	-0.36	1.38	2.32	4.04
$\tilde{\beta}_{cma}$						$t(\tilde{\beta}_{cma})$					
Small	0.74	-0.82	0.25	-0.79	0.77		0.77	-0.94	0.66	-1.86	1.23
ME2	0.12	-0.29	-0.01	-0.11	-0.03		0.32	-1.49	-0.05	-0.53	-0.09
ME3	-0.15	0.09	-0.01	0.22	-0.09		-1.32	0.68	-0.06	0.91	-0.27
ME4	1.71	-0.15	-1.02	0.10	1.45		0.85	-1.27	-1.52	0.33	1.04
Big ME	-0.08	0.05	0.19	-0.63	-0.26		-0.51	0.27	0.73	-1.28	-0.92
$\tilde{\beta}_{rmw}$						$t(\tilde{\beta}_{rmw})$					
Small	-0.77	0.32	0.04	0.43	-0.66		-1.24	0.56	0.15	1.57	-1.63
ME2	-0.34	0.06	0.22	0.28	0.32		-1.44	0.51	1.38	2.11	1.74
ME3	-0.18	-0.10	0.38	0.27	-0.27		-2.48	-1.24	3.57	1.71	-1.28
ME4	2.94	0.24	0.22	0.11	-2.34		2.27	3.26	0.5	0.52	-2.59
Big ME	-0.2	-0.04	0.03	0.01	-0.06		-2.01	-0.31	0.18	0.03	-0.34
Adj.R^2						$s(e)$					
Small	0.89	0.79	0.96	0.89	0.94		10.31	9.41	4.10	4.58	6.75
ME2	0.93	0.97	0.94	0.95	0.94		3.93	2.09	2.68	2.24	3.10
ME3	0.99	0.98	0.96	0.93	0.95		1.23	1.39	1.77	2.63	3.55
ME4	0.29	0.98	0.68	0.89	0.86		21.57	1.25	7.28	3.39	15.05
Big ME	0.96	0.95	0.86	0.71	0.95		1.69	1.97	2.81	5.32	3.06

Table C1: Time series regressions 25FF portfolios excess returns on the IBES subjective expected excess market return (CAPM) or on the subjective expected FF 3-factors (FF3). Regressions are based on annual excess returns in July of each year between 2002 and 2020. Panel A reports results from the CAPM specification: $R^e_{i,t+1} = \alpha + \beta_{mkt}\tilde{\mathbb{E}}_t[R_{mkt-rf,t+1}] + \epsilon_{t+1}$ with average adj.R^2 of portfolios -3%. Panel B reports results from the FF3 specification: $R^e_{i,t+1} = \alpha + \beta_{mkt}\tilde{\mathbb{E}}_t[R_{mkt-rf,t+1}] + \beta_{smb}\tilde{\mathbb{E}}_t[SMB_{t+1}] + \beta_{hml}\tilde{\mathbb{E}}_t[HML_{t+1}] + \epsilon_{t+1}$ with average adj.R^2 of portfolios 19%.

Panel A

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
α						$t(\alpha)$					
Small	-1.89	4.21	-1.62	2.65	0.70		-0.16	0.41	-0.13	0.21	0.05
ME2	1.24	5.00	-0.21	-2.17	-4.24		0.13	0.42	-0.02	-0.19	-0.31
ME3	-0.54	2.72	-0.62	-2.26	-1.74		-0.05	0.22	-0.06	-0.22	-0.12
ME4	6.64	2.71	4.14	-0.86	3.78		0.60	0.24	0.35	-0.07	0.25
Big ME	10.47	5.47	-1.65	-3.31	2.08		1.11	0.65	-0.19	-0.30	0.25
β_{mkt}						$t(\beta_{mkt})$					
Small	0.53	0.33	0.57	0.35	0.50		0.86	0.57	0.84	0.55	0.68
ME2	0.58	0.34	0.63	0.63	0.59		0.91	0.46	0.92	0.95	0.77
ME3	0.68	0.53	0.66	0.73	0.52		0.84	0.61	1.01	1.08	0.65
ME4	0.36	0.53	0.29	0.55	0.23		0.46	0.69	0.39	0.72	0.29
Big ME	-0.01	0.18	0.59	0.45	0.28		-0.01	0.29	0.98	0.60	0.62
Adj.R^2						$s(e)$					
Small	-0.03	-0.05	-0.03	-0.05	-0.04		21.04	18.02	20.46	21.82	25.13
ME2	-0.00	-0.04	-0.00	-0.00	-0.03		16.23	17.53	17.66	17.72	22.30
ME3	0.00	-0.02	0.01	0.00	-0.04		18.47	18.41	16.86	19.08	23.50
ME4	-0.04	-0.02	-0.05	-0.02	-0.06		16.76	17.08	19.81	19.47	28.09
Big ME	-0.06	-0.05	0.01	-0.04	-0.05		13.23	13.84	14.52	20.68	19.25

Panel B

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
α						$t(\alpha)$					
Small	-15.85	-7.62	-13.04	-11.92	-11.46		-0.98	-0.59	-0.97	-0.92	-0.65
ME2	-11.44	-6.90	-15.33	-15.48	-17.46		-1.03	-0.58	-1.63	-1.80	-1.29
ME3	-17.22	-10.20	-18.58	-14.95	-13.74		-1.28	-0.90	-2.92	-1.65	-1.13
ME4	-4.58	-11.91	-18.07	-12.66	-12.76		-0.38	-1.16	-1.59	-1.43	-0.63
Big ME	3.93	-6.68	-14.81	-24.95	-20.52		0.32	-0.77	-1.61	-1.96	-2.20
β_{mkt}						$t(\beta_{mkt})$					
Small	1.03	0.98	1.4	1.32	1.52		1.32	1.73	2.55	2.5	2.29
ME2	1.18	1.17	1.66	1.60	1.67		1.98	2.07	4.14	4.75	3.07
ME3	1.52	1.47	1.77	1.70	1.69		2.01	2.44	6.56	4.69	4.00
ME4	1.05	1.52	1.57	1.68	1.52		1.57	2.92	3.55	5.07	1.79
Big ME	0.28	0.98	1.45	1.78	1.43		0.39	2.49	3.56	3.86	2.63
β_{smb}						$t(\beta_{smb})$					
Small	0.34	-0.59	-1.32	-1.31	-1.89		0.43	-0.88	-1.98	-1.90	-2.67
ME2	-0.24	-1.25	-1.46	-1.53	-1.98		-0.35	-2.37	-3.30	-3.01	-3.34
ME3	-0.51	-1.49	-1.31	-1.63	-2.50		-0.75	-2.14	-2.82	-3.17	-3.98
ME4	-0.81	-1.38	-1.28	-2.37	-2.25		-1.24	-2.46	-2.64	-5.57	-2.93
Big ME	-0.03	-1.10	-1.14	-1.57	-0.74		-0.05	-2.40	-3.11	-4.31	-1.39
β_{hml}						$t(\beta_{hml})$					
Small	-1.80	-1.86	-2.07	-2.51	-2.38		-1.59	-2.02	-2.38	-2.28	-1.77
ME2	-1.84	-2.11	-2.64	-2.41	-2.56		-1.69	-1.96	-2.67	-2.69	-2.33
ME3	-2.50	-2.34	-2.97	-2.36	-2.59		-1.96	-1.88	-3.35	-2.11	-2.38
ME4	-1.85	-2.54	-3.55	-2.51	-3.12		-1.34	-2.37	-3.03	-2.53	-1.98
Big ME	-0.92	-2.09	-2.25	-3.58	-3.40		-0.75	-1.97	-2.08	-2.32	-4.84
Adj.R^2						$s(e)$					
Small	-0.08	-0.03	0.08	0.08	0.09		21.55	17.88	19.42	20.46	23.49
ME2	0.02	0.14	0.32	0.29	0.22		16.07	15.90	14.52	14.90	19.43
ME3	0.10	0.22	0.41	0.25	0.30		17.52	16.04	12.97	16.53	19.30
ME4	0.04	0.30	0.33	0.46	0.14		16.14	14.18	15.78	14.08	25.30
Big ME	-0.15	0.28	0.33	0.36	0.24		13.78	11.46	11.92	16.19	16.37

Table C2: Time series regressions 25FF portfolios excess returns on the IBES subjective expected Fama-French 5-factors (FF5). Regression are based on annual excess returns in July of each year between 2002 and 2020. Regression specification: $R^e_{i,t+1} = \alpha + \beta_{mkt}\tilde{\mathbb{E}}_t[R_{mkt-rf,t+1}] + \beta_{smb}\tilde{\mathbb{E}}_t[SMB_{t+1}] + \beta_{hml}\tilde{\mathbb{E}}_t[HML_{t+1}] + \beta_{cma}\tilde{\mathbb{E}}_t[CMA_{t+1}] + \beta_{rmw}\tilde{\mathbb{E}}_t[RMW_{t+1}] + \epsilon_{t+1}$ with average adj.R^2 of portfolios 31%.

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
α						$t(\alpha)$					
Small	-19.22	-10.83	-17.75	-15.50	-8.84		-0.72	-0.50	-0.72	-0.60	-0.31
ME2	-20.95	-3.73	-10.59	-16.20	-15.99		-1.12	-0.20	-0.65	-0.89	-0.69
ME3	-18.22	-13.23	-19.11	-13.16	-13.11		-0.89	-0.84	-1.27	-0.73	-0.56
ME4	-5.20	-10.78	-12.70	-9.09	-11.05		-0.33	-0.74	-0.72	-0.61	-0.37
Big ME	-2.38	-13.23	-12.05	-22.19	-25.82		-0.17	-1.34	-1.07	-1.39	-1.31
β_{mkt}						$t(\beta_{mkt})$					
Small	1.25	1.21	1.69	1.57	1.51		0.95	1.13	1.38	1.23	1.07
ME2	1.69	1.10	1.52	1.71	1.71		1.83	1.19	1.89	1.89	1.50
ME3	1.64	1.73	1.87	1.72	1.77		1.62	2.22	2.51	1.94	1.52
ME4	1.17	1.55	1.40	1.62	1.59		1.50	2.16	1.61	2.20	1.09
Big ME	0.64	1.38	1.41	1.77	1.76		0.94	2.81	2.53	2.24	1.80
β_{smb}						$t(\beta_{smb})$					
Small	1.20	0.13	-0.73	-0.74	-1.34		0.81	0.11	-0.53	-0.51	-0.84
ME2	0.78	-0.79	-1.07	-1.11	-1.41		0.75	-0.76	-1.18	-1.09	-1.10
ME3	0.27	-0.49	-0.81	-0.99	-2.05		0.24	-0.56	-0.97	-0.99	-1.57
ME4	0.16	-0.68	-0.83	-1.94	-1.47		0.18	-0.84	-0.85	-2.35	-0.89
Big ME	1.04	-0.14	-0.58	-0.86	-0.02		1.35	-0.25	-0.93	-0.97	-0.02
β_{hml}						$t(\beta_{hml})$					
Small	-1.80	-1.77	-1.96	-2.38	-2.12		-1.07	-1.29	-1.25	-1.45	-1.16
ME2	-1.86	-1.91	-2.40	-2.24	-2.31		-1.57	-1.61	-2.33	-1.93	-1.58
ME3	-2.40	-2.16	-2.81	-2.12	-2.31		-1.85	-2.16	-2.95	-1.86	-1.54
ME4	-1.70	-2.33	-3.31	-2.20	-2.81		-1.69	-2.53	-2.96	-2.33	-1.50
Big ME	-0.91	-1.99	-2.05	-3.33	-3.33		-1.03	-3.17	-2.88	-3.28	-2.66
β_{cma}						$t(\beta_{cma})$					
Small	0.43	0.33	-0.02	0.14	1.01		0.22	0.21	-0.01	0.07	0.47
ME2	-0.27	0.96	1.12	0.37	0.86		-0.19	0.68	0.93	0.27	0.50
ME3	0.69	0.65	0.48	0.97	0.62		0.45	0.56	0.43	0.73	0.35
ME4	0.95	0.92	1.27	1.01	1.15		0.80	0.84	0.96	0.90	0.52
Big ME	0.22	0.10	1.01	1.20	0.04		0.22	0.13	1.21	1.01	0.03
β_{rmw}						$t(\beta_{rmw})$					
Small	1.70	1.62	1.27	1.41	2.03		1.35	1.58	1.09	1.15	1.50
ME2	1.64	1.63	1.70	1.28	1.95		1.85	1.84	2.21	1.47	1.79
ME3	1.85	2.43	1.43	2.09	1.71		1.91	3.27	2.00	2.45	1.53
ME4	2.41	2.03	1.84	1.87	2.64		3.20	2.95	2.21	2.65	1.88
Big ME	1.95	1.93	1.85	2.37	1.49		2.98	4.11	3.48	3.13	1.59
Adj.R^2						$s(e)$					
Small	-0.09	0.00	0.02	0.03	0.10		21.66	17.58	20.04	20.98	23.28
ME2	0.12	0.21	0.44	0.29	0.27		15.17	15.21	13.20	14.86	18.72
ME3	0.19	0.51	0.48	0.42	0.31		16.63	12.76	12.22	14.61	19.13
ME4	0.38	0.51	0.45	0.60	0.23		12.90	11.79	14.32	12.10	24.00
Big ME	0.23	0.64	0.61	0.59	0.27		11.24	8.05	9.12	12.99	16.03

Table C3: Spanning regressions of IBES subjective expected return factors. This table provides the results of time-series spanning regressions of subjective expected factor one-year returns in July of each year between 2002 and 2020. The first and second columns in both Panel A and Panel B represent the dependent variable and intercept value of each spanning regression. The remaining columns are the independent variables of the regressions: in Panel A, only one-year realised Fama-French factor returns are used to span the subjective expected factor returns; in Panel B, only subjective expected Fama-French factor returns are used. *: 10% significance; **: 5% significance; ***: 1% significance.

Panel A

	α	Mkt-Rf	SMB	HML	CMA	RMW	Adj.R^2
$\tilde{\mathbb{E}}[Mkt-Rf]$	18.90***		-0.46	0.47	0.95***	-0.22	0.46
	(2.00)		(0.29)	(0.32)	(0.33)	(0.26)	
$\tilde{\mathbb{E}}[SMB]$	10.39***	-0.33		0.24	0.62**	-0.26	0.23
	(3.67)	(0.21)		(0.29)	(0.31)	(0.21)	
$\tilde{\mathbb{E}}[HML]$	-7.37**	0.28	0.20		-0.01	0.07	0.05
	(3.72)	(0.19)	(0.24)		(0.32)	(0.20)	
$\tilde{\mathbb{E}}[CMA]$	-8.38***	0.39***	0.35**	-0.01		-0.09	0.51
	(2.66)	(0.14)	(0.18)	(0.22)		(0.17)	
$\tilde{\mathbb{E}}[RMW]$	3.50	-0.23	-0.37	0.12	-0.21		0.14
	(5.39)	(0.26)	(0.30)	(0.35)	(0.42)		

Panel B

	α	$\tilde{\mathbb{E}}[Mkt-Rf]$	$\tilde{\mathbb{E}}[SMB]$	$\tilde{\mathbb{E}}[HML]$	$\tilde{\mathbb{E}}[CMA]$	$\tilde{\mathbb{E}}[RMW]$	Adj.R^2
$\tilde{\mathbb{E}}[Mkt-Rf]$	-12.34	1.29**	0.14	-1.89**	0.44	1.99***	0.49
	(12.25)	(0.61)	(0.68)	(0.78)	(0.92)	(0.58)	
$\tilde{\mathbb{E}}[SMB]$	-2.62	0.34	-0.57	0.09	-0.19	-0.4	-0.10
	(8.84)	(0.44)	(0.49)	(0.56)	(0.66)	(0.42)	
$\tilde{\mathbb{E}}[HML]$	-6.92	0.50	-1.34*		-1.06	0.30	0.03
	(12.39)	(0.61)	(0.69)	(0.79)	(0.93)	(0.59)	
$\tilde{\mathbb{E}}[CMA]$	-6.81	0.50*	-0.31	0.10	0.06	0.30	0.30
	(5.25)	(0.26)	(0.29)	(0.33)	(0.39)	(0.25)	
$\tilde{\mathbb{E}}[RMW]$	4.01	-0.06	-0.41	0.33	-0.73	-0.43	0.19
	(6.01)	(0.30)	(0.33)	(0.38)	(0.45)	(0.28)	