Time-Series and Cross-Section of Risk Premia Expectations: Evidence from Financial Analysts *

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Abstract

I study the impact of sell-side analysts' total return expectations on financial decision-making and their properties. My findings reveal that analysts' subjective risk premia are positively correlated with institutional mutual fund flows and drive adjustments in mutual fund stock allocations. Furthermore, unlike the beliefs of CFOs, economists, and asset managers, I find that analysts' subjective risk premia predict future realized excess returns at both aggregate and individual stock levels. In out-of-sample tests, analysts' beliefs outperform other surveys. Finally, the introduction of the new expected dividend component in analysts' total return expectations leads to stronger countercyclical dynamics.

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Beliefs are central to understanding asset prices, and understanding the properties of stated beliefs and their relevance in financial markets remains a first-order question.[1] Established literature on retail investors' beliefs has shown that return expectations significantly deviate from rational benchmarks, appearing extrapolative, pro-cyclical, and not very informative of future outcomes (e.g., Greenwood & Shleifer (2014)). Conversely, the growing literature on heterogeneous beliefs in asset pricing models (e.g., Bhamra & Uppal (2014); Barberis et al. (2015); Martin & Papadimitriou (2022)) has spurred investigations into the return expectations of other market participants. These participants' beliefs could align more closely with those of rational agents who trade against the more irrational agents in the economy. For example, recent studies have examined the return expectations of economists (De La O & Myers (2021), Nagel & Xu (2023)), sell-side analysts (Jensen (2022)), and large asset managers (Dahlquist & Ibert (2024); Couts et al. (2024)), yielding mixed results. In this paper, in the spirit of Greenwood & Shleifer (2014), I provide novel evidence of the significance of sell-side analysts' beliefs in shaping investor decisions by examining the relationship between these beliefs and equity mutual fund flows and holdings. Furthermore, I show that these beliefs provide valuable insights into future outcomes at both the aggregate and individual stock levels. This is evidenced by their predictive power in both in-sample and out-of-sample tests. Finally, I show that sell-side analysts' forecasts are closer to those predicted by rational expectations models than those of retail investors.

When proxying for either cash flow expectations or return expectations, the literature has often relied on survey data from various types of economic agents. When studying cash flow expectations (such as dividends or earnings), the literature has often relied on sell-side analysts' forecasts (e.g., De La O & Myers (2021), Bordalo et al. (2024)). In contrast, when examining one-year subjective expectations of returns, the literature has predominantly focused on survey data from CFOs, economists, and, more recently, large asset managers (e.g., Greenwood & Shleifer (2014), De La O & Myers (2021), Dahlquist & Ibert (2024)).[2] In

[1]Recent reviews and outlooks on the literature of subjective beliefs are provided by Brunnermeier et al. (2021) and Adam & Nagel (2023).

[2]Many sentiment surveys of returns have been studied in the literature, such as the Gallup survey, the American Association of Individual Investors Investor Sentiment Survey (AAII), the Investors' Intelligence newsletter expectation (II), and the Investor Behavior Project at Yale University. However, this paper focuses specifically on surveys of one-year return expectations, hence the choice of the Livingston survey and

this paper, I develop a dataset of consistent beliefs regarding both cash flows and discount rates by focusing on sell-side analysts' forecasts from the Thomson Reuters Institutional Brokers Estimate System (I/B/E/S) to construct both dividend and total return expectations. Through a bottom-up approach, I assemble a dataset of single stock total return expectations by combining sell-side analysts' price targets with dividend per share forecasts. These expectations serve as natural counterparts to the cash flow projections commonly used in asset pricing literature. I show that these expectations differ significantly from those of CFOs and large asset managers. Although they align more closely with the beliefs of economists, significant differences exist in their relationship with fund flows and predictive ability. Finally, sell-side analysts' expectations - unlike those of CFOs, economists, and asset managers - are available at the stock level and at the same frequency as cash flow expectations. This allows for a more granular analysis compared to other survey data.

In the spirit of Greenwood & Shleifer (2014), I start my empirical analysis by showing that sell-side analysts' expectations play a potentially important role in driving asset allocation decisions of both mutual fund investors and mutual fund managers. I achieve this by studying the relationship between sell-side analysts' total return expectations at both mutual fund aggregate flows and mutual fund stock level holdings.

When looking at flows, I find that sell-side analysts' equity risk premium is strongly correlated with US equity institutional mutual fund flows, but negatively correlated with US equity retail mutual fund flows. Additionally, consistent with Greenwood & Shleifer (2014), I find that CFOs' consensus equity premium expectation, serving as a proxy for retail beliefs, is positively correlated with US equity retail mutual fund flows. Furthermore, sell-side analysts' subjective equity premium predicts US equity institutional mutual fund flows, while CFOs' subjective equity premium predicts US equity retail mutual fund flows. These results are robust after controlling for past returns and valuation ratios, which mutual

the Graham-Harvey CFOs survey as benchmarks. The University of Michigan Survey of U.S. Consumers and the Survey of Professional Forecasters also provide data on subjective expected returns, but these are for 2-3 year and 10-year horizons, respectively. This makes them not directly comparable with sell-side analysts' return forecasts, which are constructed for a one-year horizon. Similarly, the long-term Capital Market Assumptions (CMAs) of major asset managers typically provide annualized return expectations over a long horizon, usually spanning 7 to 10 years. Given the recent interest in these expectations for short term predictions, I also include them in my analysis for comparison purposes.

fund investors might use in their investment processes. One potential interpretation is that sophisticated investors predominantly invest in institutional mutual funds, while less sophisticated investors primarily invest in retail mutual funds.[3] These results relate my work to the extensive literature examining the relationship between mutual fund flows, stock price movements, rational markets, and sentiment (e.g., Berk & Green (2004), Lou (2012), Guercio & Reuter (2014), Peng & Wang (2023), Kaniel et al. (2023)). I conclude this analysis by showing that innovations in sell-side analysts' return expectations for a stock are significant positive determinants of innovations in allocations to the same stock. This finding remains robust even after controlling for innovations in various valuation ratios, past returns, and previous changes in allocations. It underscores the significant relationship between mutual fund managers' investment decisions and sell-side analysts' return expectations.

Examining the informativeness of sell-side analysts' beliefs reveals that their subjective equity premia can predict future market and single-stock excess returns. In-sample univariate predictive regression results indicate that the slope coefficients are statistically significant at both the aggregate and single-stock levels. Conversely, the subjective equity premium estimates from CFOs, economists, and asset managers are not statistically significant.[4] Consensus sell-side analysts' beliefs show a positive out-of-sample R^2, thereby confirming their predictive ability out-of-sample. Additionally, they exhibit superior forecasting ability compared to alternatives. Taken together these results highlight the informational content of these forecasts, especially when compared to other survey results.

I also examine the properties of sell-side analysts' expectations and show that their equity premium forecasts display very high volatility - approximately 20% higher than those of economists, over three times larger than CFOs' forecasts, and five times larger than asset managers' market equity premium. In this paper, I introduce a novel expected dividend component to sell-side analysts' return expectations. Both the expected price component and the expected dividend component show a positive correlation with many standard model-

[3]When studying differences in investment flow patterns between retail and institutional funds, Salganik-Shoshan (2016) finds that clients of institutional mutual funds use more sophisticated selection criteria than clients of retail mutual funds.

[4]Couts et al. (2024) present similar findings when examining the predictive analysis at the equities asset-class level, specifically focusing on the beliefs held by large asset managers.

based expected equity risk premium measures such as the dividend-price ratio (D/P), the cyclically-adjusted price-earnings ratio ($CAPE$) yield, the consumption wealth ratio (cay) from Lettau & Ludvigson (2001), the variance risk premium from Bollerslev et al. (2009), and the square of the CBOE Volatility Index (VIX^2). The expected dividend component, in particular, is strongly counter-cyclical, adding a new dimension of countercyclicality to the total return expectations of sell-side analysts. While beliefs from the IBES surveys, which may capture more sophisticated investors, are countercyclical and contrarian, those from the Graham-Harvey CFOs survey are extrapolative. Therefore, my results also suggest that it is important to consider heterogeneity in expectations, in line with theoretical papers that incorporate both extrapolative and contrarian expectations, such as the X-CAPM model of Barberis et al. (2015) or alternatively with models of asymmetric information.[5]

Given the quality of the stock coverage provided by sell-side analysts' 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, 2015). I show that the empirical security market line (SML), derived from sell-side analysts' survey data for both dependent and independent variables when estimating βs, is positively sloped and closely aligns with the theoretical SML. This is not the case when the SML is constructed using realised excess returns of both the market and the test assets. Fama & French (1993, 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. Similarly, 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 that focuses 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 comovement of price target revisions with stock prices, their information content, and their ability to provide profitable recommendations. I contribute to the literature by

[5] See also Cutler et al. (1990), De Long et al. (1990), Hong & Stein (1999), Glaeser & Nathanson (2017), Barberis et al. (2018), Bordalo et al. (2019), Liao et al. (2022), Bastianello & Fontanier (2023) for models with heterogeneous and extrapolative expectations, and Barberis (2018) for a recent survey. For models with asymmetric information see among others Wang (1993).

showing that sell-side analysts' subjective risk premia predict future excess returns at both the market and single stock level. My work is also close to Wang (2021), who shows that the aggregate stock market price return expectations of sell-side analysts are contrarian. Conversely, by relying on dividend expectation forecasts, I augment the price return forecasts to total return forecasts. Recently, Dahlquist & Ibert (2024) and Couts et al. (2024) gather data on long-term capital market assumptions (CMAs) published by major asset managers. Specifically, Dahlquist & Ibert (2024) show that return expectations from the CMAs are countercyclical. My results show that analysts' subjective market and stock level excess returns expectations are not only contrarian, but also countercylical. 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 investigate the cross-sectional relationship between subjective expected excess returns and firm attributes. Rather than focusing on firm characteristics, I examine the relationship between subjective expected excess returns and subjective risk factors. It should be noted that when constructing total return expectations I rely on forward-looking dividend expectations rather than the historical dividends used in previous literature.

Previous studies such as Jensen et al. (1972), Fama & French (2004), Baker et al. (2011), and Frazzini & Pedersen (2014) have found that the empirical SML generated using realized excess returns data deviates from the theoretical SML. However, I show that when using subjective expectations data, the SML is correctly sloped. Additionally, 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)). More recently, Jensen (2022) shows that traditional asset pricing models explain subjective risk compensation well. My results show that CAPM and Fama-French multi factors models fit the cross-sectional dynamics of subjective expected excess returns very well.

This paper proceeds as follows. In Section 1, I introduce the data and the construction of the variables used for the analysis. Section 2 examines the relationship between subjective equity risk premia measures and mutual fund flows and holdings. Section 3 investigates the predictive power and forecasting performance of subjective equity risk premia expectations. Section 4 explores the determinants of subjective equity risk premia expectations, and Section 5 concludes the paper.

1 Data and Variables Construction

In this section, I outline the survey data and the method used to construct subjective return expectations. I also detail the return predictors and business cycle variables. Appendix A.1 provides detailed information on the timing assumptions used to align data on returns, predictor variables, and survey data.

1.1 Data Description

In this work, I utilize various data sources. Section 1.1.1 details the different surveys considered in this work, while Section 1.1.2 outlines the non-survey data used.

1.1.1 Survey Data

I obtain monthly data on sell-side analysts' median forecasts of dividend per share (DPS) from the US Unadjusted Summary Statistics of the Thomson Reuters I/B/E/S Estimates Database (hereafter referred to as IBES). This dataset encompasses a broad range of US stocks starting from May 2002 for DPS and provides consensus estimates of sell-side analysts' forecasts. The forecast horizons included are quarterly (fiscal quarters Q1, Q2, Q3, and Q4), semi-annual, annual (fiscal years 1, 2, 3, and 4), and long-term growth (LTG).

Additionally, I obtain monthly median price targets (PTG) from the IBES US Unadjusted Summary Price Targets files. This dataset covers a wide array of US stocks from March 1999. The vast majority of price target forecasts are for a twelve-month horizon. Given the availability of both DPS and PTG forecasts, the sample period begins in May 2002. For the time-series tests, I concentrate on the S&P 500 universe of stocks, as these stocks generally receive more comprehensive analyst coverage.

As extensively argued by Bordalo et al. (2019), De La O & Myers (2021) and Bordalo et al. (2024), 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 are labeled with the name of the analyst or brokerage firm. This labeling incentivizes analysts to release accurate forecasts. To further mitigate concerns about agency conflicts and potential outliers, I use median forecasts across analysts.

The John Graham and Campbell Harvey CFO Survey (GH) is conducted quarterly and completed by 200 to 500 CFOs of major U.S. corporations, representing a broad range of industries, geographic areas, and company sizes. Among other topics, they report their expectations of returns on the S&P 500 index over the next 12 months. The data is available from the third quarter of 2000 to the fourth quarter of 2020, though there are some gaps in the dataset.

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. I follow Nagel & Xu (2023) and obtain the total return expectations by starting from the ratio of the twelve-month to zero-month mean level forecasts of the $S\&P500$ index to measure price growth expectations ($\widetilde{\mathbb{E}}_t[P_{t+1}]/P_t$) and adjust them with the dividend yield (D_t/P_t):

$$\widetilde{\mathbb{E}}_t[R_{t+1}] = \frac{\widetilde{\mathbb{E}}_t[P_{t+1}]}{P_t} + \frac{D_t}{P_t}\widetilde{\mathbb{E}}_t\left[\frac{D_{t+1}}{D_t}\right] - 1 \tag{1}$$

where $\widetilde{\mathbb{E}}_t\left[\frac{D_{t+1}}{D_t}\right]$ is the subjective growth rate in annual dividends. Following Nagel & Xu (2023) and Adam et al. (2017), I set the $\widetilde{\mathbb{E}}_t\left[\frac{D_{t+1}}{D_t}\right]$ as the sample average of the S&P annual dividend growth over the post-WWII sample period 1946-2020 (equal to 1.064).

Finally, I also use the long-term annualized US equity premium expectations from the Capital Market Assumptions of large institutional asset managers, as made available by Dahlquist & Ibert (2024). The CMA data is inconsistent in its reporting frequency and the return expectations have heterogeneous horizons (usually 7 to 10 years). Nonetheless, I construct a consensus forecast across the CMAs by averaging the annualized US equity premium reported in the last quarter of each year. This methodology allows for the construction of consensus beliefs across a reasonable number of asset managers within a narrow time frame, facilitating comparison across surveys and the study of the determinants of consensus expectations. Couts et al. (2024) propose an alternative construction for the consensus belief, which accounts for time variation in the composition of asset managers in the sample. However, this methodology has the drawback of being forward-looking, as the consensus belief is constructed from the time fixed effects of a full sample regression. Regardless, in Appendix A.2, I repeat the analysis following the methodology of Couts et al. (2024) using data from Dahlquist & Ibert (2024) and show that the main results remain unchanged.

1.1.2 Other Data

From WRDS, I obtain monthly time series of financial ratios per company, namely the price-to-earnings ratio before extraordinary items (PE), price-to-book ratio (PB), price-to-sales ratio (PS), and enterprise value multiple (EVM). From CRSP, I obtain daily stock prices, dividends, returns, data on the constituents of the S&P 500 index, cumulative share adjustment factors (CFACSHR), and cumulative price adjustment factors (CFACPR). I also use repurchase-adjusted dividend-price ratio of the CRSP value-weighted index from Nagel & Xu (2023).

I obtain the one-year Treasury Constant Maturity rate from the FRED database at the Federal Reserve Bank of St. Louis. I construct the subjective equity premium ($\tilde{\mathbb{E}}_t\left[R^e_{t+1}\right]$) as:

$$\tilde{\mathbb{E}}_t\left[R^e_{t,t+12}\right] = \tilde{\mathbb{E}}_t\left[R_{t,t+12}\right] - R_{f,t} \tag{2}$$

where $\tilde{\mathbb{E}}_t\left[R_{t+1}\right]$ is the subjective one-year expected total return obtained from the surveys considered and $R_{f,t}$ is the one-year Treasury Constant Maturity rate available in the information set at the start of the surveys. Similarly, I define the realized one-year equity premium as the 12-month return of the CRSP value-weighted index of the S&P 500 universe in excess of the one-year Treasury Constant Maturity rate.

From Robert Shiller's website, I collect data on the cyclically adjusted price-earnings

(CAPE) ratio. I obtain CBOE data on the forward-looking expected variance risk premium ($\mathbb{E}[VRP]$) of Bollerslev et al. (2009) from Hao Zhou's website, and the log consumption-wealth ratio (cay) of Lettau & Ludvigson (2001) from Amit Goyal's website.

From the CRSP Survivor-Bias-Free US Mutual Funds data, I obtain information on mutual funds' total net assets (TNAs), net monthly returns, asset allocations, and other characteristics such as fund fees and institutional/retail fund indicators. As my empirical analysis focuses on US equities, I only include domestic US equity mutual funds, excluding those specializing in bonds and international equities. Following Lou (2012), I construct monthly fund returns as net returns plus 1/12 of annual fees and expenses.

1.2 Variable Construction: IBES Subjective Expectations

In this section, I describe the data collection, construction, and coverage of the IBES total return expectations.

1.2.1 Fundamentals

Dividend per share (DPS) forecasts are provided in the third week of every month for different fiscal years (FY) or fiscal quarters (QTR). This differs from PTGs, which are rolling twelve-month horizon forecasts. Consequently, forecast revisions are not directly available for PTGs. While PTGs have twelve-month horizon forecasts available monthly, DPS forecasts have twelve-month horizon forecasts only on an annual basis. Similar to De La O & Myers (2021), I use interpolation to obtain one-year DPS forecasts on a rolling window basis, aligning them with the PTGs.

1.2.2 Returns

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

$$\tilde{\mathbb{E}}_t[R_{t,t+12}] = \frac{PTG_{t,t+12} + \tilde{\mathbb{E}}_t[DPS_{t,t+12}]}{P_{t-1}} \tag{3}$$

where $PTG_{t,t+12} = \tilde{\mathbb{E}}_t[P_{t,t+12}]$ is the median consensus price target scaled by the cumulative price adjustment factor at the time the consensus forecasts are constructed; $\tilde{\mathbb{E}}_t[DPS_{t,t+12}]$ 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-1} is the adjusted price at the end of month $t-1$.[6] This is a new metric relative to the existing literature (e.g., Wu (2018)) where expected total returns are constructed using only PTGs $\left(\frac{PTG_{t,t+12}}{P_{t-1}}\right)$. 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:

$$\tilde{\mathbb{E}}_t[R_{S\&P500,t,t+12}] = \frac{\sum_{i \in x_t^j} \tilde{\mathbb{E}}_t[R_{i,t,t+12}] ME_{i,t-1}}{\sum_{i \in x_t^j} ME_{i,t-1}} \tag{4}$$

where $ME_{i,t-1}$ is the market capitalization of stock i at the end of the month $t-1$ and $x_t^j \subset x_t$ is the set of companies within the $S\&P500$ universe for which expectations data is available.

Figure 1 illustrates the difference between the bottom-up subjective US equity risk premia series (4) from IBES (marked in green), the GH Survey (red), the Livingston Survey (yellow), the consensus CMA survey (black), and the one-year ahead realised total returns (blue).

[Figure 1 here]

1.2.3 Coverage

A potential concern when using IBES data is the extent of coverage of the IBES universe relative to the CRSP/Compustat universe and/or the S&P 500 constituents. To address this concern, Appendix A.3 presents descriptive statistics showing that the coverage provided by IBES is of good quality.

[6]Similarly, van Binsbergen et al. (2023) scale the difference between the analysts' forecast and the machine learning forecast by the closing stock price from the most recent month.

1.3 Summary Statistics of Survey Expectations

Given the stark differences in the time-series shown in Figure 1, I report key summary statistics of the consensus subjective equity risk premia series of the $S\&P500$ in Panel A of Table 1, and the correlations of survey forecasts in Panel B of Table 1. Several key observations emerge. First, IBES risk premia are much higher and more volatile compared to the excess return expectations of CFOs, asset managers, and economists. Second, CFOs' expectations are negatively correlated with those of sell-side analysts (-0.03) and CMAs' beliefs (-0.27), whereas economists' expectations are positively correlated with sell-side analysts' expectations (0.74) and CMAs' beliefs (0.33). Finally, CFOs' and economists' expectations are positively correlated (0.35), and CMA consensus beliefs are positively correlated with sell-side analysts' expectations (0.34). These findings indicate significant belief heterogeneity, which I further investigate in the following sections.

[Table 1 here]

2 Expectations, Mutual Fund Flows, and Holdings

In the spirit of Greenwood & Shleifer (2014), I underscore the importance of IBES subjective risk premia by examining their relationship with investor behavior through mutual fund flows. At a more micro level, I show how innovations in total return expectations are related to innovations in stock holdings.

2.1 Expectations and Fund Flows

By relying on the CRSP Survivor-Bias-Free US Mutual Funds data, I construct monthly aggregate US equity mutual fund flows between time $t-1$ and t as:

$$Flow_{CRSP,t} = \frac{\sum_j (TNA_{j,t} - (1 + R_{j,t})TNA_{j,t-1})}{\sum_j TNA_{j,t-1}} \tag{5}$$

where $R_{j,t}$ represents the net fund returns of mutual fund j. This construction is similar to the standard approach taken in the literature (e.g., Chen et al. (2008), Coval & Stafford (2007), Chen et al. (2010), Lou (2012)) although I aggregate flows across US equity retail mutual funds, US equity institutional mutual funds, and all US equity mutual funds. Table 2 shows the contemporaneous correlations between mutual fund flows and the following measures: the Graham-Harvey CFO one-year subjective equity premium (GH), the consensus Livingston one-year subjective equity premium (Liv), the consensus CMA annualised long-term US equity premium (CMA), and the IBES one-year subjective equity premium (IBES).

[Table 2 here]

When comparing correlations between GH beliefs and US mutual fund flows, I find a positive and statistically significant correlation (0.23), consistent with the results in Greenwood & Shleifer (2014). Conversely, IBES beliefs appear uncorrelated with aggregate US equity mutual fund flows (-0.11), potentially questioning the connection between IBES expectations and investor behavior. However, examining fund flows at a more granular level (retail vs. institutional funds) reveals significant changes. GH expectations are positively correlated with retail mutual fund inflows (0.23) but uncorrelated with institutional mutual fund inflows (-0.05). In contrast, IBES expectations are strongly positively correlated with institutional mutual fund inflows (0.28) and negatively correlated with retail mutual fund inflows (-0.34).

The key takeaway is that examining only aggregate mutual fund inflows can obscure the relevance of IBES risk premia expectations due to the 'contrarian' relationship between retail mutual fund flows and IBES risk premia. While GH and IBES expectations show interesting dynamics with mutual fund flows, both Liv and CMA beliefs are uncorrelated with contemporaneous mutual fund flows.

When considered in isolation, the pairwise correlations between retail flows and GH expectations, as well as institutional flows and IBES expectations, may appear intuitive. Flows reflect the asset allocation decisions of investors based on their beliefs, with retail flows reflecting the beliefs of extrapolative agents and institutional flows reflecting the beliefs of more sophisticated agents.

2.2 Expectations and Future Flows

Subjective risk premia also appear to predict future investment decisions. Figure 2 displays the slope coefficients and adjusted R^2 from the regressions of the form:

$$Flow_{t,t+h} = \alpha + \beta \tilde{\mathbb{E}}_t[R^e_{t,t+12}] + \epsilon_{t,t+h} \tag{6}$$

where $Flow_{t,t+h} = \sum_{j=1}^{h}(1 + Flow_{t+j-1.t+j})$ is the monthly compounded inflow rate between t and $t+h$ for either all mutual funds (All MF), or retail mutual funds (Retail MF), or institutional mutual funds (Institutional MF), and $\tilde{\mathbb{E}}_t[R^e_{t,t+12}]$ is the subjective equity premium constructed from survey data. Panels A to C show that the GH subjective equity premium positively predicts flows at 1, 2, and 3-month horizons for all US equity mutual funds and at a 1-month horizon for US equity retail mutual funds. However, it does not predict US equity institutional mutual fund flows. Conversely, Panels D to F show that the IBES subjective equity premium predicts flows at a 12-month horizon for all US equity mutual funds and at 1, 2, 3, 6, and 12-month horizons for US equity institutional mutual funds. It negatively predicts US equity retail mutual fund flows at 1 and 2-month horizons. The predictive ability of GH expectations at the retail mutual fund level and IBES expectations at the institutional mutual fund level seems to drive their predictive ability at the aggregate mutual fund industry level.

A natural concern is whether the predictability of fund flows might be influenced by proxies of risk premia expectations (e.g., lower price-dividend ratios) or past excess returns in the stock market, as mutual fund investors may be influenced by past equity performance. This concern is addressed in Appendix A.4, where Figure A3 repeats the flow predictability analysis after adding additional controls to (6). The results for the coefficient estimates on the IBES subjective equity premium remain robust both qualitatively and quantitatively after controlling for past excess stock market returns and the log price-dividend ratio.

These results suggest that the relevance and importance of IBES expectations is uncovered when looking at institutional mutual fund flows. As a final observation from comparing Panel A and Panel D, while CFOs' expectations predict all US equity mutual fund flows at short horizons, IBES expectations predict inflows at longer horizons. Understanding how and why heterogeneous beliefs have a differential impact on aggregate market dynamics seems a natural extension for future research.

[Figure 2 here]

2.3 Expectations and Holdings

The evidence in the previous sections suggests that IBES total return expectations influence the flows - and thus the demand - of mutual fund investors. Next, I examine whether IBES beliefs are related to the investment decisions of equity mutual fund managers. To do this, I use the mutual fund asset allocation data for equity mutual funds from CRSP. I consider all US equity mutual funds with holdings in stocks belonging to the S&P500 index and construct averages of the monthly changes in percentage TNA in each stock across all funds. I focus on S&P500 stocks because analysts provide better coverage for these stocks, and they are widely held by mutual funds. In Table 3, I estimate a panel regression of the average monthly change in percentage TNA in stock i ($\Delta\bar{h}_{i,t}$) on the lagged monthly change in consensus IBES expected total return on stock i ($\Delta\widetilde{\mathbb{E}}_{t-1}^{IBES}[R_{i,t-1,t+11}]$) and various lagged controls ($X_{i,t-1}$), such as changes in price-to-fundamental ratios (e.g., price-earnings ratio), past returns, and the lagged average monthly change in percentage TNA in stock i. The regression specification is:

$$\Delta\bar{h}_{i,t} = \alpha_{t-1} + \beta\Delta\widetilde{\mathbb{E}}_{IBES,t-1}[R_{i,t-1,t+11}] + \gamma X_{i,t-1} + \epsilon_{i,t} \tag{7}$$

Column (1) in Table 3 presents the results from the univariate estimate. The coefficient estimate is positive and statistically significant at the 5% level, suggesting that innovations in IBES expected total returns in a stock positively impact innovations in the average change in percentage TNA across mutual funds in the same stock. The magnitude of the estimate is small (0.010%), which aligns with the recent literature on inelastic demand curves (e.g., Gabaix & Koijen (2021), Van der Beck (2022), Gabaix & Koijen (2024)). Column (2) in Table 3 augments the regression specification by controlling for various innovations in fundamental-to-price ratios widely used by financial practitioners, as well as past stock returns and past innovations in the average change in percentage TNA across mutual funds in the stock. The coefficient estimate on the innovations in IBES expected total returns remains strongly statistically significant, although somewhat larger in magnitude (0.016%). The main takeaway is that innovations in sell-side analysts' total return expectations significantly influence the innovations in the asset allocation decisions of mutual fund managers across different stocks, even after controlling for innovations in classic valuation ratios and past returns. A cautious interpretation of my finding is that it indicates correlation rather than a clearly established causal effect. This finding further underscores the importance of these beliefs in the decision-making processes of fund managers.

[Table 3 here]

3 Predictability of Subjective Risk Premia

In this section, I study the predictive ability of sell-side analysts' subjective risk premia. In regressions where the dependent variable comprises overlapping excess returns, I follow Nagel & Xu (2023) and employ a stationary block bootstrap method to address the autocorrelations in residuals caused by the overlapping return windows in the dependent variable. The bootstrap approach allows me to obtain Stambaugh (1999) bias-adjusted coefficients. Appendix A.5 provides a brief summary of the Nagel & Xu (2023) bootstrap approach and an extension I rely on in the following sections.

3.1 In-Sample Predictability Tests

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

$$R^e_{t,t+12} = \alpha + \beta \widetilde{\mathbb{E}}_{i,t}[R^e_{t,t+12}] + \epsilon_{t+12} \tag{8}$$

where $R^e_{t,t+12}$ denotes the 12-month excess returns of the $S\&P500$, and $\widetilde{\mathbb{E}}_{i,t}[R^e_{t,t+12}]$ is the subjective one-year equity premium from survey i. If investors have rational expectations, then the coefficients α and β in equation (8) 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 4 presents results from estimating the regressions based on equation (8) at the consensus level. Among all surveys considered, only the IBES consensus subjective equity premium has a positive and statistically significant coefficient, with a bias-adjusted coefficient of 0.82 and bootstrapped p-value under the null of no predictability of 2%. Furthermore, when looking at the bootstrapped p-values under the null of 'rational forecasts' - i.e., no intercept and slope coefficient of 1 - I cannot reject the null as the p-values for both the intercept and slope coefficients are larger than 30%. Taken together, the in-sample analysis suggests that only IBES has predictive power across the surveys and although the coefficient estimate is smaller than 1, I cannot reject the null of 'rational forecasts'.

[Table 4 here]

A natural question is whether the predictive ability of IBES can be subsumed by some classic predictors. Table 5 extends the analysis based on (8) to:

$$R^e_{t,t+12} = \alpha + \beta \widetilde{\mathbb{E}}_{i,t}[R^e_{t,t+12}] + \gamma X_t + \epsilon_{t+12} \tag{9}$$

where X_t is a model-based predictor such as the log price-dividend ratio (pd), the log CAPE ratio ($cape$), the aggregate log consumption-wealth ratio (cay), or the expected variance risk premium ($\mathbb{E}[VRP]$). The results show that after controlling for pd, cay or $\mathbb{E}[VRP]$, the coefficient estimate on IBES subjective equity premium remains significant at 5% level. When controlling for $cape$, neither predictor is statistically significant. Overall, the evidence suggests that the predictive ability of the IBES subjective equity premium is not subsumed by classic predictors in the literature.

[Table 5 here]

As a robustness test, I study the predictive ability of analysts' single stock risk premia expectations within the context of S&P500 stocks. Table 6 shows the panel regression results for the specification:

$$R^e_{i,t,+12} = \alpha_i + \alpha_t + \beta\widetilde{\mathbb{E}}^{IBES}_t[R^e_{i,t,t+12}] + \gamma X_{i,t} + \epsilon_{i,t+12} \tag{10}$$

where α_i are stock fixed effects, α_t are year-month fixed effects, $\widetilde{\mathbb{E}}^{IBES}_t[R^e_{i,t,t+12}]$ is the IBES subjective one-year equity premium, and $X_{i,t}$ includes various controls such as past yearly stock excess returns and price-to-fundamental ratios (e.g., price-earnings ratio, price-to-book ratio, and enterprise value multiple). All specifications in Table 6 show that the coefficient estimates on IBES subjective equity premium are positive and statistically significant at the 1% level. The coefficient estimates are notably smaller than 1 in magnitude (they range between 0.189 and 0.426 across specifications), thereby providing suggestive evidence of under-reaction in single stock subjective risk premia. Overall, the analysis reveals that analysts' forecasts are informative for predicting future risk premia and approach the rational benchmark more closely than previous findings on retail investors' beliefs, which have been shown to negatively predict future returns (e.g., Greenwood & Shleifer (2014)).

[Table 6 here]

3.2 Out-of-Sample Predictability Test

In this section I study the out-of-sample (OOS) predictive ability of the subjective equity risk premia across different surveys.

3.2.1 Out-of-Sample R^2

Starting from the baseline regression specification:

$$R^e_{t,t+12} = \alpha + \beta\widetilde{\mathbb{E}}_{i,t}[R^e_{t,t+12}] + \epsilon_{t+12} \tag{11}$$

I compare the out-of-sample performance of survey subjective equity risk premia from different surveys i in the spirit of Campbell & Thompson (2008) and Welch & Goyal (2008). I evaluate the out-of-sample performance by constructing the out-of-sample R^2_{OOS} statistic:

$$R^2_{OOS} = 1 - \left[\sum_{t=0}^{T}\left(R^e_{t,t+12} - \widetilde{\mathbb{E}}_t[R^e_{t,t+12}]\right)^2\right] / \left[\sum_{t=0}^{T}\left(R^e_{t,t+12} - \overline{R^e}_{t,t+12}\right)^2\right] \tag{12}$$

where $t = 0$ is the start of my sample (05/2002) and $\overline{R^e}_{t,t+12}$ is the historical arithmetic average yearly excess market return estimated from 30 years of data with an expanding window - note that the results are not sensitive to the look-back period. A positive value for R^2_{OOS} implies that the historical average return has a higher average mean squared error than the predictive regression. Table 4 shows the R^2_{OOS} results from the analysis. The main finding is that while GH and CMA display a negative OOS R^2 (-2.40% and -11.02% respectively), Livingston and IBES display a positive OOS R^2 (16.55% and 6.92% respectively). This result provides further evidence that the IBES subjective equity premium is informative in predicting future realised excess returns, while there is lack of evidence for GH and CMA. In the next section I directly compare the forecasting performance of the different surveys and show that IBES dominates the rest.

3.2.2 Comparison of Survey Forecasts Performance

After evaluating the out-of-sample performance against an historical benchmark, the next natural question is whether IBES subjective beliefs have better forecasting ability than consensus expectations from other surveys. To answer this question, I rely on the conditional and unconditional tests of predictive ability proposed by Giacomini & White (2006), with the unconditional test being similar to the Diebold & Mariano (2002) test of unconditional forecasting performance. Moving forward, I will refer to these tests as 'GW-U' and 'GW-C'.

Table 7 illustrates the results of the GW-U and GW-C tests when comparing the forecasting performance of IBES return expectations with those from other surveys.[7] I consider two alternative loss functions - squared errors (SE) and proportional squared errors (SPE) - and three sample periods - up to and including the Great Financial Crisis (GFC), post-GFC, and the full sample. While SE is a standard loss function, I also consider SPE because it is

[7] To avoid the timing of the risk-free rate impacting the comparison in predictive ability, I compare the return expectations across surveys rather than subjective risk premia.

robust against heteroskedasticity in forecast errors (Taylor (2011)), a prominent feature in the data.

When comparing IBES and GH, there is strong evidence that IBES outperforms GH in the post-GFC sample, with p-values smaller than 5% for both conditional and unconditional tests. Additionally, the SPE loss function indicates strong outperformance by IBES in the full sample, driven by its performance in the second half of the sample. This result is expected, as Figure 1 shows that analysts did not foresee the GFC, leading to abnormally high forecast errors. In contrast, the GH survey's low volatility meant its forecast errors were not significantly larger than usual.

When comparing IBES to Livingston, the evidence is similar: IBES significantly outperforms in the post-GFC sample (p-values smaller than 5%) for both loss functions and shows outperformance in the full sample for the SPE loss function.

Comparing CMA with IBES, there is again strong evidence of IBES outperformance (p-values smaller than 5%). For the GW-U test with SE loss functions, IBES shows outperformance at the 5% level in the second half of the sample. The SPE loss function also indicates IBES outperformance for both the post-GFC and full samples (at the 5% and 1% levels, respectively). For the GW-C test with SPE loss functions, there is evidence of IBES outperformance in both the post-GFC and full samples (p-values smaller than 10% and 5%, respectively).

Overall, these results suggest that the IBES beliefs outperform other survey counterparts in predicting future returns, particularly in the latter part of the sample due to the analysts' inability to predict the GFC.

[Table 7 here]

4 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 for a better understanding of how subjective expectations are formed. As in Nagel & Xu

(2023), I adjust p-values for heteroskedasticity and autocorrelation in regression residuals using the equal-weighted cosine (EWC) test from Lazarus et al. (2018) in regressions with survey measures as dependent variables.

4.1 Time-series Dimension

In this section, I examine the determinants of subjective equity risk premia from different surveys in the time-series dimension.

4.1.1 Standard Tests

To study the properties of risk premia expectations over time, in the spirit of Greenwood & Shleifer (2014), Nagel & Xu (2023) and Dahlquist & Ibert (2024), I run regressions of the form:

$$\tilde{\mathbb{E}}_t[R^e_{t,t+12}] = \alpha + \beta \ R^e_{t-13,t-1} + \gamma \ cape_{t-1} + \epsilon_t \tag{13}$$

where $\tilde{\mathbb{E}}_t[R^e_{t,t+12}]$ is the subjective expected one-year equity risk premium constructed in month t, and $R^e_{t-13,t-1}$ denotes the past 12-month return of the CRSP value-weighted index of the S&P 500 universe in excess of the one-year Treasury Constant Maturity rate, measured at the end of the month before the start of the survey. Additionally, $cape_{t-1}$ is the log cyclically adjusted price-earnings ratio at the end of the month before the start of the survey.

In a similar setting, Greenwood & Shleifer (2014) conclude that when recent past returns are high, retail investors expect higher return expectations going forward, showing an extrapolative behavior. I confirm this finding, as the coefficient estimate on past excess returns is positive and significant at the 5% level. However, when examining the Livingston and IBES surveys, the coefficient estimates on past excess returns are negative and statistically significant at the 1% level, with an adjusted R^2 of roughly 27%. This suggests that, unlike CFOs, sell-side analysts and economists tend to be contrarian.

Furthermore, looking at the relationship with the CAPE ratio, both surveys are highly countercyclical, evidenced by the negative coefficient estimate (around -0.18) on $cape_{t-1}$, significant at the 1% level. In contrast, the consensus CMA is acyclical and not correlated with past returns.[8]

[Table 8 here]

As a robustness, I confirm the countercylicality of sell-side analysts stock level subjective risk premia in Table 9. I run panel level regressions of analysts' subjective stock risk premia on past yearly stock excess returns and valuation ratios:

$$\widetilde{\mathbb{E}}_{IBES,t}[R^e_{i,t,t+12}] = \alpha_i + \alpha_t + \beta R^e_{i,t-13,t-1} + \gamma X_{i,t-1} + \epsilon_{i,t} \tag{14}$$

where $R^e_{i,t-13,t-1}$ represents past yearly excess returns for stock i, α_i and α_t denote stock and year-month fixed effects respectively, and $X_{i,t-1}$ includes a variety of commonly used valuation ratios: price-earnings ratio ($PE_{i,t-1}$), enterprise value multiple ($EVM_{i,t-1}$), price-to-sales ratio ($PS_{i,t-1}$), and price-to-book ratio ($PB_{i,t-1}$). The results across all specifications confirm that analysts' stock-level subjective risk premia are contrarian: the coefficient estimates on past excess returns are negative and statistically significant at the 1% level. Analysts' expectations are also countercyclical: the coefficient on the price-to-book (P/B) valuation ratio is negative and statistically significant at least at the 5% level across specifications. When fundamentals (book value) are high relative to market prices, analysts expect higher subjective risk premia on the stock.

[Table 9 here]

4.1.2 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 10, I confirm that CFOs' risk premia expectations also show insignificant or inconsistent correlations with the dividend-price ratio (dp), the consumption wealth ratio (cay), the CAPE yield ratio, and the expected variance risk premium ($\mathbb{E}[VRP]$).[9] In contrast, IBES beliefs

[8]This CMA data analysis uses a methodology different from both Dahlquist & Ibert (2024) and Couts et al. (2024) to ensure consistency across all surveys in terms of timing, thereby facilitating a more straightforward comparison, as discussed in Section 1.1.1. Notably, if we adopt the aggregation approach from Couts et al. (2024), the consensus CMA is contemporaneously countercyclical, as detailed in Appendix A.2.

[9]The expected variance risk premium ($\mathbb{E}[VRP]$) of Bollerslev et al. (2009) is the theoretical measure that

are strongly correlated with all of these measures (except the *cay* ratio), with correlation signs aligning with predictions from rational expectations asset pricing models. Although the consensus from the Livingston survey shows positive and significant correlations at the 1% level with *cay*, $\mathbb{E}[VRP]$, and VIX^2, it is uncorrelated with the dividend-price ratio, while IBES consensus shows a positive and statistically significant correlation estimate at the 1% level. This highlights that there are some important differences between IBES and Livingston as already shown by the results both in Section 2 and Section 3.

Additionally, I decompose the IBES subjective equity premium into its components: the risk premium implied from the price return expectation - IBES (Prc) - and the expected dividend price ratio - IBES (DP). I then compute the correlations between these components and the model-based expected risk premium. The IBES (Prc) component is countercyclical, showing positive correlations with all model-based expected returns. The IBES (DP) component is strongly positively correlated with the log dividend-price ratio (0.84) and the CAPE yield (0.53), but uncorrelated with $\mathbb{E}[VRP]$. This suggests that the overall strong positive correlation between the IBES subjective equity premium and *dp* or *cape* is driven by both the price and expected dividend components. Interestingly, the IBES (DP) component is uncorrelated with the *cay* ratio while IBES(Prc) is only weakly positively correlated, explaining the weak positive correlation with the overall IBES market subjective equity premium. Finally, all survey expectations, except GH, are strongly positively correlated with the VIX^2 – indicating that higher variance (risk) in financial markets corresponds to higher subjective equity risk premia in these consensus surveys.

Overall, these results confirm that the subjective equity premium of sell-side analysts is countercyclical, driven by both expected price and expected dividend components. The inclusion of the expected dividend component is a novel contribution relative to the past literature on price targets.

[Table 10 here]

should predict risk premia in their model.

4.2 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 classic Fama & French (1993, 2015) methodology, construct the subjective expected excess returns of the portfolios using IBES data, and then conduct cross-sectional tests.

4.2.1 Subjective Expected Factor Returns

Given that the focus here is to understand the determinants of subjective expectations, the question I am now interested in answering is whether a simple model such as CAPM can explain the cross-sectional variation of subjective expected excess returns. The next section addresses this question.

4.2.2 Security Market Line under Subjective Expectations

A straightforward method to study the ability of CAPM to explain the cross-sectional variation in expected asset returns was provided by Fama & MacBeth (1973), who suggested a two-step procedure involving a set of time-series regressions followed by a cross-sectional regression. Many studies (e.g., Frazzini & Pedersen (2014)) have shown that CAPM faces significant challenges when tested with empirical data: typically, 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 raises the question of whether the cross-section of subjective expected excess returns encounters 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:[10]

$$R_{i,t}^{e} = \alpha + \beta R_{mkt,t}^{e} + \epsilon_t \tag{15}$$

Plotting the average excess returns of the test assets against the βs estimated from the regression (15) allows us to see how well CAPM fits the data. To support the model, the empirical SML (the line of best fit) and the theoretical SML (implied by CAPM) would need to be at least close to each other. Figure 3 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 realized excess returns.

[Figure 3 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 (15) but now based on subjective expected excess returns:

$$\tilde{\mathbb{E}}_t \left[R_{i,t+12}^{e}\right] = \tilde{\alpha} + \tilde{\beta}\tilde{\mathbb{E}}_t \left[R_{mkt,t+12}^{e}\right] + \tilde{\epsilon}_t \tag{16}$$

Figure 4 shows the average subjective expected excess returns against $\tilde{\beta}$s from the regression (16). In contrast to Figure 3 which displays a negatively sloped SML, Figure 4 shows an empirical SML that is not only positively sloped but also very close to the theoretical SML. With an average adjusted R^2 of 60% from the regressions (16) - discussed further in Section 4.2.3 - I 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. These findings support the conclusion that CAPM explains the cross-sectional variation of subjective expected stock excess returns well. In other words, these results indicate that beliefs across portfolios are broadly consistent with CAPM.

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

[Figure 4 here]

4.2.3 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, it is natural to consider whether extending CAPM to the classic Fama-French 3-factor model allows us to better explain the cross-sectional dynamics of subjective expected excess returns. Tables A3 and A5 in Appendix A.6 present the full results from the Fama-MacBeth first stage time-series regressions from Section 4.2.2. The results show improvement when the Fama-French 3-factor model is used instead of CAPM. Similarly, Tables A4 and A6 display the results obtained when testing the Fama-French 5-factor model. For my sample, moving from CAPM to 3/5 Fama-French factor models lead to significant improvements. When using realised excess returns, the average α from the first stage decreases in magnitude and the average R^2 increases from 74% to 93%. When using survey data, the average R^2 increases from 60% to 85%. This indicates that the cross-sectional dynamics of subjective expected excess returns are better explained by Fama-French multi-factor models than by the simple CAPM. Therefore, although CAPM provides a good benchmark model for explaining the cross-section of subjective expectations of excess returns, multi-factor models offer a more comprehensive understanding of the dynamics involved.

5 Conclusions

This study sheds light on the pivotal role of sell-side analysts' total return expectations in financial decision-making and their inherent properties. By examining the subjective risk premia provided by sell-side analysts, this research uncovers several key insights that distinguish these analysts from other market participants such as CFOs, economists, and asset managers.

Firstly, the positive correlation between sell-side analysts' subjective risk premia and institutional mutual fund inflows underscores the critical link between analysts' expectations and institutional investor behavior. This connection is further reinforced by the observation that changes in these risk premia lead to adjustments in mutual fund stock allocations, highlighting the practical impact of analysts' beliefs on investment strategies.

Furthermore, sell-side analysts' return forecasts provide valuable insights into future outcomes. Analysts' subjective risk premia predict future realized excess returns at both aggregate and individual stock levels, showing greater predictive abilities compared to surveys from CFOs, economists, and asset managers. Out-of-sample tests reveal that analysts' beliefs offer superior forecasts for future realized returns, underscoring their value in financial forecasting.

Finally, I examine belief dynamics in both time-series and cross-sectional perspectives. In the time-series analysis, I emphasize the contrarian and countercyclical nature of sell-side analysts' subjective risk premia. These characteristics, influenced both by expected price and expected dividend components, align with various predictors of the equity risk premium observed in rational expectations models. Additionally, the inclusion of the new expected dividend component in analysts' total return expectations enhances the countercyclical dynamics. In the cross-sectional analysis, when examining the properties of analysts' excess return expectations, using subjective expectations as both dependent and independent variables, the CAPM performs well, as evidenced by the correctly sloped empirical Security Market Line (SML). Overall, analysts' return expectations are more informative and closer to rational benchmarks than retail investors' beliefs.

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Figure 1: Time-series of equity premium survey forecasts and realization. The plot below shows the time series of four different consensus subjective equity premium expectations ($\widetilde{\mathbb{E}}_t[R^e_{t,t+h}]$): 'GH' represents the consensus one-year subjective equity premium from the Graham-Harvey survey at quarterly frequency; 'Liv' represents the consensus one-year subjective equity premium from the Livingston survey at semi-annual frequency; 'CMA' represents the consensus long-term annualized US equity premium from the Capital Markets Assumptions surveys at annual frequency; 'IBES' represents the consensus one-year subjective equity premium from the I/B/E/S at monthly frequency. Additionally, future one-year $S\&P500$ excess total returns ($R^e_{t,t+12}$) are represented by the dotted blue line.

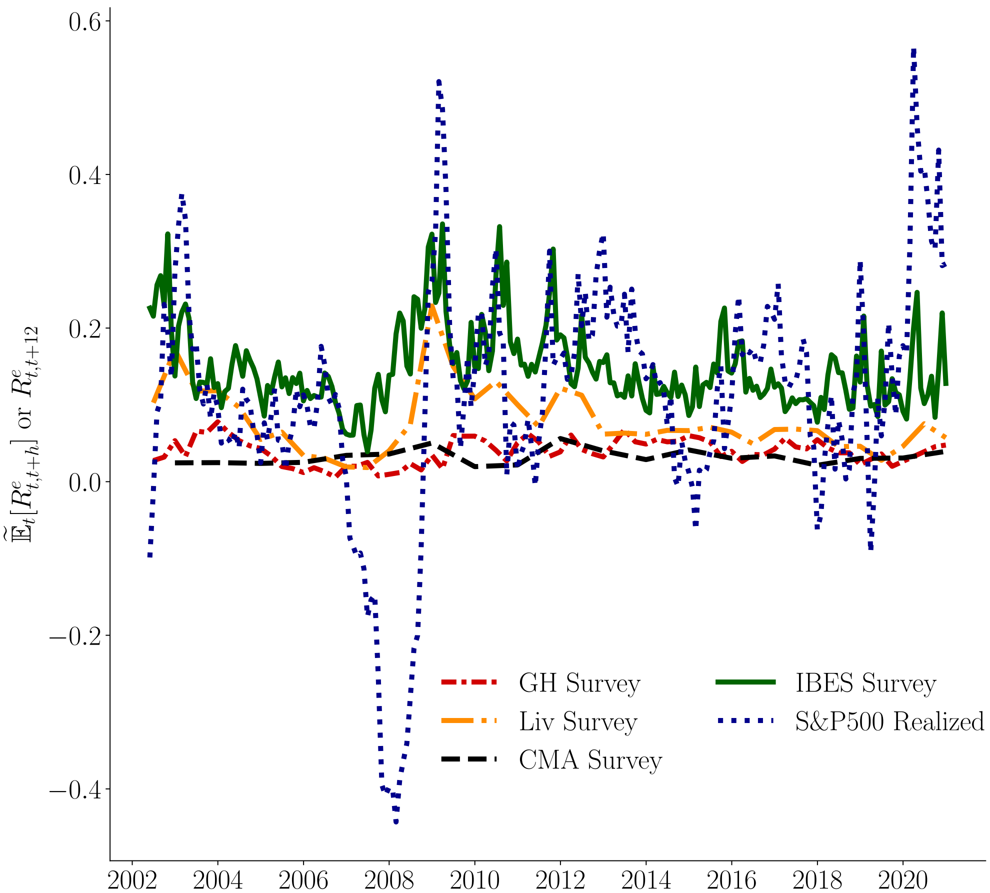

Figure 2: Equity mutual fund flow predictability. Panel A to Panel F display the slope coefficients estimates (β) - with 95% confidence intervals - in black (left y-axis), and the adjusted R^2 in red (right y-axis) from the regression: $Flow_{t,t+h} = \alpha + \beta\tilde{\mathbb{E}}_t[R^e_{t,t+12}] + \epsilon_{t,t+h}$, where h is the horizon in months, $Flow_{t,t+h}$ is the monthly compounded flow rate between t and $t+h$ into either all mutual fund (ALL MF), or retail mutual fund (Retail MF), or institutional mutual fund (Institutional MF). $\tilde{\mathbb{E}}_t[R^e_{t,t+12}]$ is the one-year subjective equity premium from either GH or IBES. Newey-West standard errors with one year bandwith are used to construct the confidence intervals.

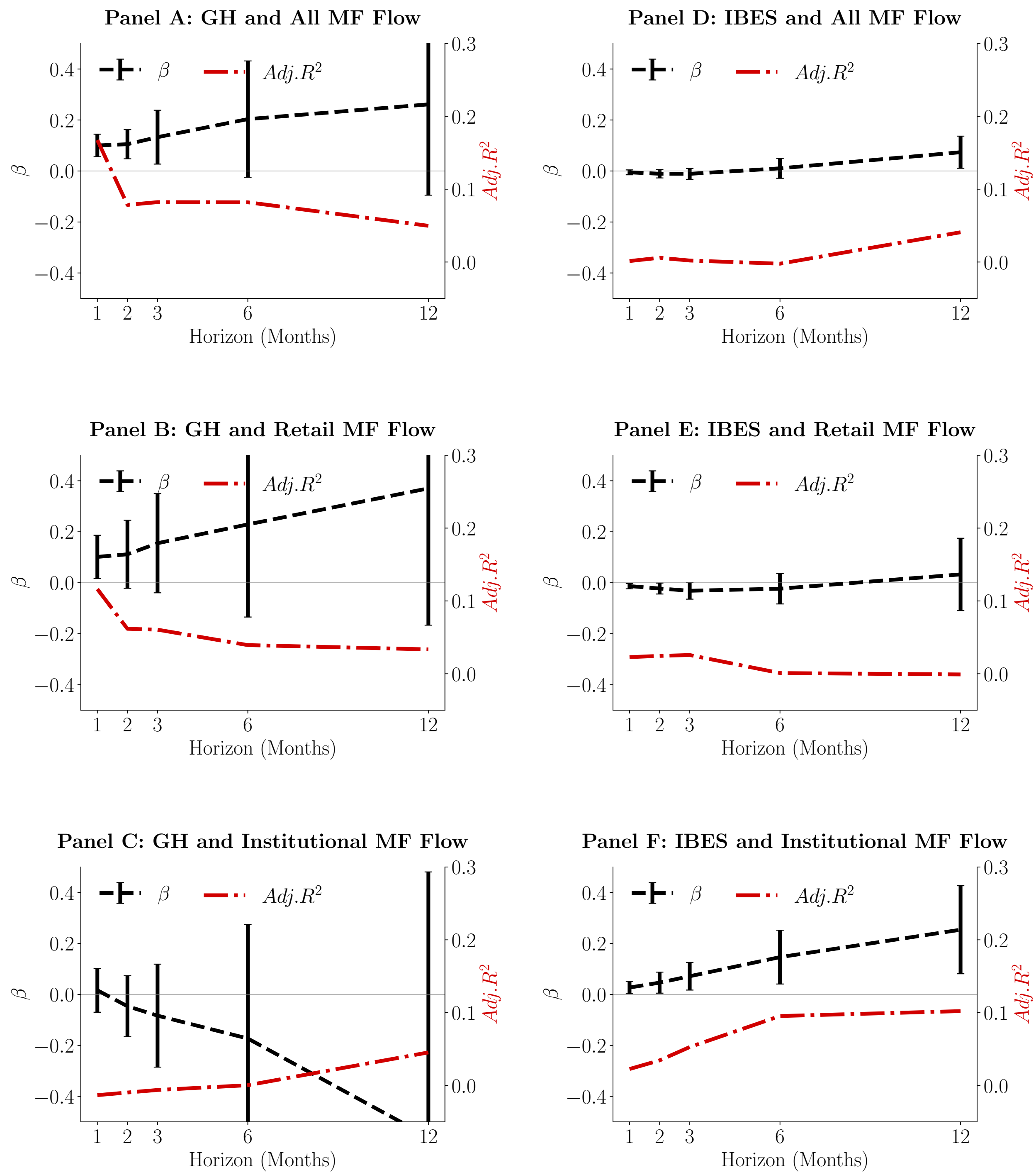

Figure 3: Security market line (SML) based on realized returns. The figure shows in blue solid squares the average one-year realized excess returns ($\mathbb{E}[R^e]$) of the Fama-French 25 (FF25) portfolios against their CAPM betas (β) based on the IBES universe of stocks. The FF25 portfolios are sorted by market capitalization (M) and book-to-market (B), labeled as S$\#_1$B$\#_2$, where S1/S5 indicates small/large market cap and B1/B5 indicates small/large book-to-market. The βs are estimated by running time-series regressions of realized one-year excess returns of each FF25 portfolio on realized 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 Security Market Line (SML), representing the best-fit line across all FF25 portfolios. The red line denotes the theoretical SML, where the slope is the sample average excess market return, and the intercept is the sample average one-year Treasury yield.

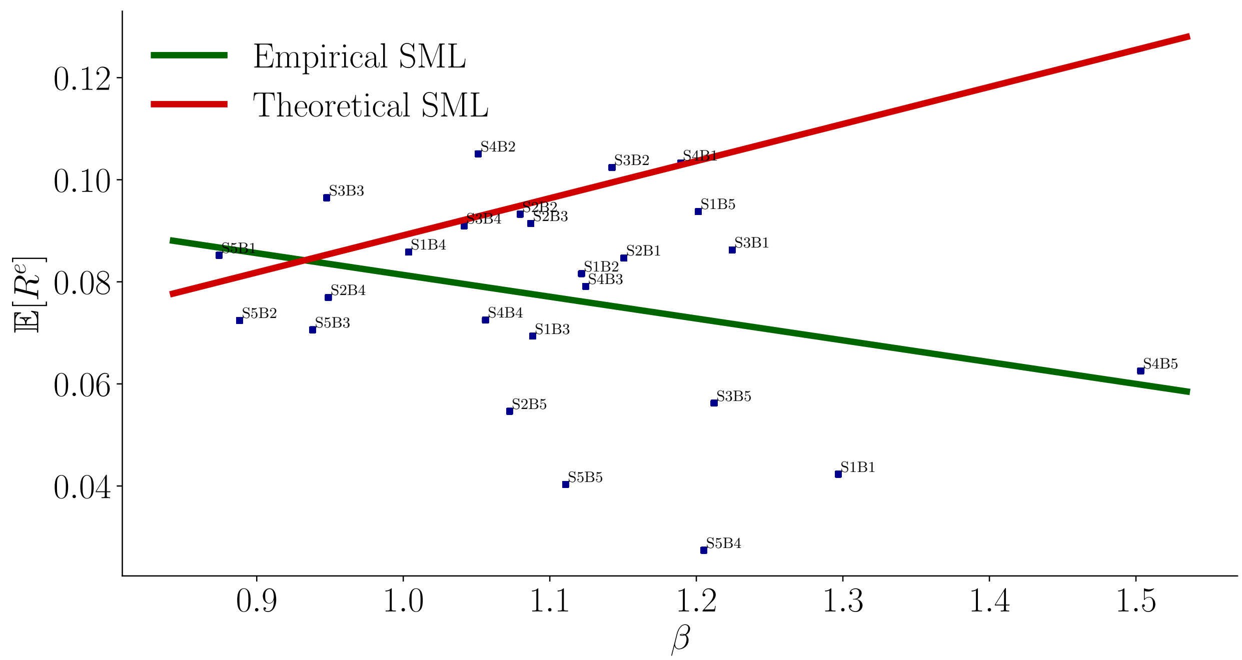

Figure 4: Security market line (SML) based on IBES subjective returns. The figure shows in blue solid squares the average IBES subjective expected one-year excess returns ($\tilde{\mathbb{E}}[R^e]$) of the Fama-French 25 (FF25) portfolios against their CAPM subjective betas ($\tilde{\beta}$) based on the IBES universe of stocks. The FF25 portfolios are sorted by market capitalization (M) and book-to-market (B), labeled as S$\#_1$B$\#_2$, where S1/S5 indicates small/large market cap and B1/B5 indicates small/large book-to-market. The $\tilde{\beta}$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 Security Market Line (SML), representing the best-fit line across all FF25 portfolios. The red line denotes 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.

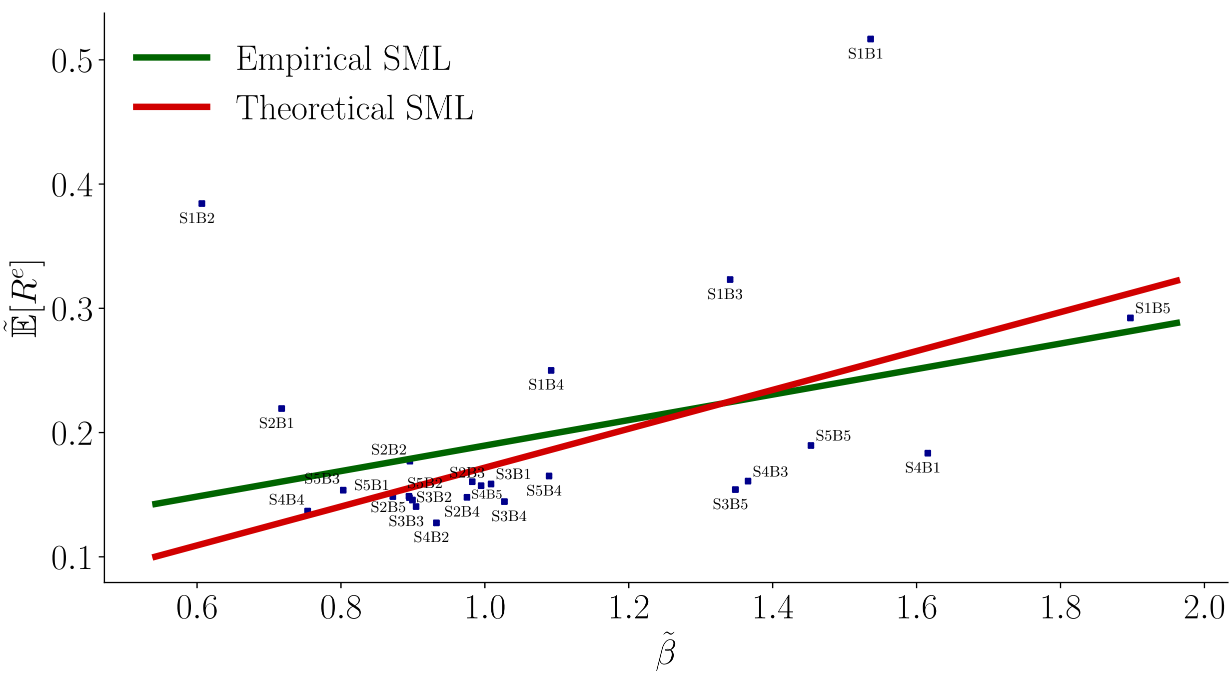

Table 1: Summary statistics of equity risk premium expectations. Panel A presents the mean, volatility, and their ratio for the subjective equity premium across different surveys. Panel B displays the correlations between these surveys. 'GH' represents the consensus one-year subjective equity premium from the Graham-Harvey survey at quarterly frequency. 'Liv' represents the consensus one-year subjective equity premium from the Livingston survey at semi-annual frequency. 'CMA' represents the consensus long-term annualized US equity premium from the Capital Markets Assumptions surveys at annual frequency. 'IBES' represents the consensus one-year subjective equity premium from the I/B/E/S at monthly frequency. N represents the number of observations available in the overlapping sample period.

Panel A: Averages and Volatilities

Survey	GH	Liv	CMA	IBES
Mean (%)	3.97	9.91	3.22	14.73
Std.Dev. (%)	1.70	4.38	0.99	5.31
Mean/Std.Dev.	2.34	2.26	3.26	2.77
N	71	38	19	224
Date	Q2/2002-Q4/2020	Q2/2002-Q4/2020	Q4/2002-Q4/2020	05/2002-12/2020

Panel B: Correlations

Survey	GH	Liv	CMA	IBES
GH	1.00			
Liv	0.35	1.00		
CMA	-0.27	0.33	1.00	
IBES	-0.03	0.74	0.34	1.00

Table 2: CRSP mutual fund flows and subjective equity risk premium expectations. This table provides the contemporaneous pair-wise correlations between the subjective equity risk premia from alternative surveys ($\tilde{\mathbb{E}}_{i,t}[R^e_{t,t+h}]$) and the monthly flows of US Equity Mutual funds - MF CRSP (All) -, the monthly flows of institutional US Equity Mutual funds - MF CRSP (Inst) - and the monthly flows of retail US Equity Mutual Funds - MF CRSP (Retail). 'GH' represents the consensus one-year subjective equity premium from the Graham-Harvey survey at quarterly frequency. 'Liv' represents the consensus one-year subjective equity premium from the Livingston survey at semi-annual frequency. 'CMA' represents the consensus long-term annualized US equity premium from the Capital Markets Assumptions surveys at annual frequency. 'IBES' represents the consensus one-year subjective equity premium from the I/B/E/S at monthly frequency. Flows are defined as: $Flow_{CRSP,t} = \frac{\sum_i (TNA_{i,t} - (1+R_{i.t})TNA_{i,t-1})}{\sum_i TNA_{i,t-1}}$, where $TNA_{i,t}$ and $R_{i,t}$ are respectively the total net asset values and the net fund returns of mutual fund i in the mutual fund universe under consideration. p-values are shown in brackets below the estimates. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero correlation coefficient. N is the number of observations in the sample period. $Flow_{CRSP,t} = \frac{\sum_i (TNA_{i,t} - (1+R_{i.t})TNA_{i,t-1})}{\sum_i TNA_{i,t-1}}$, where $TNA_{i,t}$ and $R_{i,t}$ are respectively the total net asset values and the net fund returns of mutual fund i in the mutual fund universe under consideration. p-values are shown in brackets below the estimates. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero correlation coefficient. N is the number of observations in the sample period.

Flows	GH	Liv	CMA	IBES
MF CRSP (All)	0.23**	0.11	-0.19	-0.11
	(0.05)	(0.53)	(0.45)	(0.12)
MF CRSP (Inst)	-0.05	0.25	-0.03	0.28***
	(0.67)	(0.13)	(0.89)	(0.00)
MF CRSP (Retail)	0.23*	0.04	-0.37	-0.34***
	(0.06)	(0.83)	(0.12)	(0.00)
N	71	38	19	224
Date	Q2/2002-Q4/2020	Q2/2002-Q4/2020	Q4/2002-Q4/2020	05/2002-12/2020

Table 3: Mutual fund holdings and sell-side analysts' stock expected returns. The table provides the coefficient estimates of the panel regression of the average innovations in percentage TNA in stock i across all mutual funds in CRSP ($\Delta\bar{h}_{i,t} = \bar{h}_{i,t} - \bar{h}_{i,t-1}$) on lagged consensus innovation in IBES one-year total return expectations of stock i ($\Delta\widetilde{\mathbb{E}}_{IBES,t-1}[R_{i,t-1,t+11}] = \widetilde{\mathbb{E}}_{IBES,t-1}[R_{i,t-1,t+11}] - \widetilde{\mathbb{E}}_{IBES,t-2}[R_{i,t-2,t+10}]$) and various lagged controls ($X_{i,t-1}$). The controls include: lagged innovations in price-earnings ratio ($\Delta PE_{i,t-1} = PE_{i,t-1} - PE_{i,t-2}$), lagged innovations in entreprise value multiple ($\Delta EVM_{i,t-1} = EVM_{i,t-1} - EVM_{i,t-2}$), lagged innovations in price-to-sales ratio ($\Delta PS_{i,t-1} = PS_{i,t-1} - PS_{i,t-2}$), lagged innovations in price-to-book ratio ($\Delta PB_{i,t-1} = PB_{i,t-1} - PB_{i,t-2}$), past monthly stock excess returns ($R_{i,t-2,t-1}$), and lagged average innovations in percentage TNA in stock i across all mutual funds in CRSP ($\Delta\bar{h}_{i,t-1} = \bar{h}_{i,t-1} - \bar{h}_{i,t-2}$). All specifications include year-month fixed effects. The sample includes all S&P500 stocks held by mutual funds as recorded on CRSP. Standard errors (in parentheses) are clustered by year-month and stock. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero coefficient. N refers to the total number of observations.

$$\Delta\bar{h}_{i,t} = \alpha_{t-1} + \beta\Delta\widetilde{\mathbb{E}}_{IBES,t-1}[R_{i,t-1,t+11}] + \gamma X_{i,t-1} + \epsilon_{i,t}$$

	$\Delta\bar{h}_{i,t}$ (%)	
	(1)	(2)
$\Delta\widetilde{\mathbb{E}}_{IBES,t-1}[R^e_{i,t-1,t+11}]$	0.010**	0.016***
	(0.005)	(0.005)
$\Delta PE_{i,t-1}$ x 10^{-5}		-0.438
		(0.565)
$\Delta EVM_{i,t-1}$ x 10^{-5}		-0.364
		(0.281)
$\Delta PS_{i,t-1}$		-0.001
		(0.002)
$\Delta PB_{i,t-1}$ x 10^{-3}		0.172
		(0.108)
$\Delta\bar{h}_{i,t-1}$ (%)		-0.026
		(0.021)
$R^e_{i,t-2,t-1}$		-0.054***
		(0.013)
N	76794	75636
Adjusted R^2	0.176	0.181
Year-Month FE	Yes	Yes
Date	05/2002-12/2020	

Table 4: Forecasting equity risk premium. The table provides the results from forecasting equity risk premia regressions. $R^e_{t,t+12}$ is the 12-month return of the CRSP value-weighted index of the $S\&P500$ universe, in excess of the risk-free rate. $\widetilde{\mathbb{E}}_{i,t}[R^e_{t,t+h}]$ is the consensus subjective equity premium from survey i. 'GH' represents the consensus one-year subjective equity premium from the Graham-Harvey survey at quarterly frequency. 'Liv' represents the consensus one-year subjective equity premium from the Livingston survey at semi-annual frequency. 'CMA' represents the consensus long-term annualized US equity premium from the Capital Markets Assumptions surveys at annual frequency. 'IBES' represents the consensus one-year subjective equity premium from the I/B/E/S at monthly frequency. As in Nagel & Xu (2023), a stationary boostrap is used with an optimal block length determined by Politis & White (2004). In each block: 'OLS coeff' reports the OLS estimates, {bias-adj.} reports the bias-adjusted coefficients from bootstrap; [t-stat] reports the EWC t-statistic (without bias adjustment) following Lazarus et al. (2018); (p-value$_{\{\beta=0\}}$) reports the bootstrapped p-values under the null of no predictability; (p-value$_{\{\alpha=0,\beta=1\}}$) reports the bootstrapped p-values under the null of 'rational forecasts'. Appendix A.5 provides further details on the bootstrap procedure. Out-of-sample R^2 are constructed as: $R^2_{OOS} = 1 - \left[\sum_{t=0}^{T}\left(R^e_{t,t+12} - \widetilde{\mathbb{E}}_t[R^e_{t,t+12}]\right)^2\right] / \left[\sum_{t=0}^{T}\left(R^e_{t,t+12} - \overline{R^e}_{t,t+12}\right)^2\right]$, where $R^e_{t,t+12}$ is the realized future one-year market excess return, $\widetilde{\mathbb{E}}_t[R^e_{t,t+12}]$ is the one-year subjective equity premium from a survey, and $\overline{R^e}_{t,t+12}$ is the historical average one-year market excess return obtained from an expanding 30 years window.

$$R^e_{t,t+12} = \alpha + \beta\widetilde{\mathbb{E}}_{i,t}[R^e_{t,t+h}] + \epsilon_{t+12}$$

i		GH	Liv	CMA	IBES
Intercept	OLS coeff	0.00	0.01	0.02	0.01
	{bias-adj.}	{-0.02}	{-0.00}	{-0.00}	{-0.01}
	[t-stat]	[0.04]	[0.11]	[0.36]	[0.10]
	(p-value$_{\{\beta=0\}}$)	(0.97)	(0.92)	(0.65)	(0.94)
	(p-value$_{\{\alpha=0,\beta=1\}}$)	(0.97)	(0.94)	(0.65)	(0.93)
$\widetilde{\mathbb{E}}_{i,t}[R^e_{t,t+12}]$	OLS coeff	2.42	0.93	3.07	0.69
	{bias-adj.}	{3.04}	{1.07}	{3.60}	{0.82}
	[t-stat]	[1.06]	[2.23]	[1.54]	[2.56]
	(p-value$_{\{\beta=0\}}$)	(0.45)	(0.10)	(0.15)	(0.02)
	(p-value$_{\{\alpha=0,\beta=1\}}$)	(0.64)	(0.87)	(0.27)	(0.29)
	$Adj.R^2$	0.05	0.04	-0.02	0.05
	R^2_{OOS}	-2.40%	16.55%	-11.02%	6.92%
	N	71	38	19	224
	Date	Q2/02-Q4/20	Q2/02-Q4/20	Q4/02-Q4/20	05/02-12/20

Table 5: Forecasting equity risk premium with controls. The table provides the results from forecasting equity risk premia regressions with additional controls with respect to Table 4. $R^e_{t,t+1}$ is the 12-month return of the CRSP value-weighted index of the $S\&P500$ universe, in excess of the risk-free rate. $\widetilde{\mathbb{E}}_{i,t}[R^e_{t,t+12}]$ is the subjective equity premium from survey i. The controls considered are the log price-dividend ratio (pd), the log of the cyclically adjusted price-earnings ratio ($cape$, Campbell & Shiller (1988)), the consumption-wealth ratio (cay, Lettau & Ludvigson (2001)), and the expected variance risk premium ($\mathbb{E}[VRP]$, Bollerslev et al. (2009)). As in Nagel & Xu (2023), a stationary boostrap is used with an optimal block length determined by Politis & White (2004). In each block: 'OLS coeff' reports the OLS estimates, {bias-adj.} reports the bias-adjusted coefficients from bootstrap; [t-stat] reports the EWC t-statistic (without bias adjustment) following Lazarus et al. (2018); (p-value$_{\{\beta=0\}}$) reports the bootstrapped p-values under the null of no predictability. Appendix A.5 provides further details on the bootstrap procedure.

$$R^e_{t,t+12} = \alpha + \beta\widetilde{\mathbb{E}}_{IBES,t}[R^e_{t,t+12}] + \gamma X_t + \epsilon_{t+12}$$

X		pd	$cape$	cay	$\mathbb{E}[VRP]$
$\widetilde{\mathbb{E}}_{IBES,t}[R^e_{t,t+12}]$	OLS coeff	0.75	0.45	1.06	0.70
	{bias-adj.}	{0.77}	{0.60}	{1.13}	{0.82}
	[t-stat]	[2.60]	[1.02]	[8.16]	[2.65]
	(p-value$_{\{\beta=0\}}$)	(0.03)	(0.37)	(0.00)	(0.02)
X	OLS coeff	0.09	-0.12	-1.54	-0.00
	{bias-adj.}	{0.11}	{0.04}	{-1.94}	{-0.00}
	[t-stat]	[0.56]	[-0.65]	[-4.83]	[-0.54]
	(p-value$_{\{\beta=0\}}$)	(0.65)	(0.69)	(0.00)	(0.58)
	$Adj.R^2$	0.06	0.03	0.18	0.05
	N	224	224	75	224
	Date	05/2002-12/2020	05/2002-12/2020	06/2002-12/2020	05/2002-12/2020

Table 6: Forecasting single stock equity risk premia. The table provides the results from the panel level regression of realized stock excess returns on subjective stock excess return expectations. $R^e_{i,t,t+12}$ is the realized twelve month excess return of stock i, $\widetilde{\mathbb{E}}_{IBES,t}[R^e_{i,t,t+12}]$ is the IBES sell-side analyst consensus one-year excess return expectation on stock i, and $X_{i,t}$ represent stock level controls. The controls include: price-earnings ratio ($PE_{i,t}$), entreprise value multiple ($EVM_{i,t}$), price-to-sales ratio ($PS_{i,t}$), price-to-book ratio ($PB_{i,t}$), and past yearly stock excess returns ($R^e_{i,t-12,t}$). All specifications include year-month and stock fixed effects. The sample includes all S&P500 stocks covered by IBES sell-side analysts. Standard errors (in parentheses) are clustered by year-month and stock. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero coefficient. N refers to the total number of observations.

$$R^e_{i,t,t+12} = \alpha_i + \alpha_t + \beta\widetilde{\mathbb{E}}_{IBES,t}[R^e_{i,t,t+12}] + \gamma X_{i,t} + \epsilon_{i,t+12}$$

	$R^e_{i,t+12}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\widetilde{\mathbb{E}}_{IBES,t}[R_{i,t,t+12}]$	0.351***	0.218***	0.426***	0.270***	0.216***	0.189***
	(0.080)	(0.060)	(0.084)	(0.061)	(0.060)	(0.049)
$R^e_{i,t-12,t}$					-0.113***	-0.085***
					(0.021)	(0.020)
$PE_{i,t}$ x 10^{-4}						0.015
						(0.208)
$EVM_{i,t}$ x 10^{-4}						-0.283
						(0.163)
$PS_{i,t}$						-0.026***
						(0.004)
$PB_{i,t}$						0.001
						(0.001)
N	99253	99253	99252	99252	98823	97281
Adjusted R^2	0.026	0.306	0.099	0.369	0.376	0.386
Year-month FE	No	Yes	No	Yes	Yes	Yes
Stock FE	No	No	Yes	Yes	Yes	Yes
Date	05/2002-12/2020					

Table 7: Conditional and unconditional tests of predictive ability of equity return expectations. The table shows the values of the conditional and unconditional tests of predictive ability of Giacomini & White (2006) 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' represents the consensus one-year subjective equity premium from the Graham-Harvey survey at quarterly frequency. 'Liv' represents the consensus one-year subjective equity premium from the Livingston survey at semi-annual frequency. 'CMA' represents the consensus long-term annualized US equity premium from the Capital Markets Assumptions surveys at annual frequency. 'IBES' represents the consensus one-year subjective equity premium from the I/B/E/S at monthly frequency. $\mathcal{L}$ is the loss function of choice: SE indicates a squared error loss function (i.e., the square of the difference between the return realization and the subjective return forecast), and SPE indicates a squared proportional error (i.e., the square of the difference between the return realization and the subjective return forecast scaled by subjective return forecast) - useful when errors are heteroskedastic, Taylor (2011). The sign of the test-statistics indicates which forecast model 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. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero test-statistic. SPE indicates a squared proportional error (i.e., the square of the difference between the return realization and the subjective return forecast scaled by subjective return forecast) - useful when errors are heteroskedastic, Taylor (2011). The sign of the test-statistics indicates which forecast model 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. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero test-statistic.

F1	F2	$\mathcal{L}$	Unconditional PA Test (GW-U) $H_0: \mathbb{E}[\mathcal{L}(F1) - \mathcal{L}(F2)] = 0$ $H_A: \mathbb{E}[\mathcal{L}(F1) - \mathcal{L}(F2)] \neq 0$	Conditional PA Test (GW-C) $H_0: \mathbb{E}[\mathcal{L}(F1) - \mathcal{L}(F2)] = 0$ $H_A: \mathbb{E}[\mathcal{L}(F1) - \mathcal{L}(F2)] \neq 0$	N	Sample	Frequency
GH	IBES	SE	-0.26 (0.61)	-3.36 (0.19)	37	Q2/2002 - Q2/2011	Quarterly
		SE	+10.78*** (0.00)	+8.64** (0.01)	34	Q3/2011 - Q4/2020	
		SE	+0.09 (0.77)	+0.87 (0.65)	71	Q2/2002 - Q4/2020	
		SPE	+3.53* (0.06)	+3.87 (0.14)	37	Q2/2002 - Q2/2011	
		SPE	+12.37*** (0.00)	+10.15*** (0.01)	34	Q3/2011 - Q4/2020	
		SPE	+6.35** (0.01)	+9.93*** (0.01)	71	Q2/2002 - Q4/2020	
Liv	IBES	SE	-3.02* (0.08)	-1.73 (0.42)	19	Q2/2002 - Q2/2011	Semi-annual
		SE	+4.87** (0.03)	+8.15** (0.02)	19	Q4/2011 - Q4/2020	
		SE	-0.39 (0.53)	-0.82 (0.66)	38	Q2/2002 - Q4/2020	
		SPE	+1.53 (0.22)	+3.83 (0.15)	19	Q2/2002 - Q2/2011	
		SPE	+6.49** (0.01)	+6.37** (0.04)	19	Q4/2011 - Q4/2020	
		SPE	+6.71*** (0.01)	+7.38** (0.02)	38	Q2/2002 - Q4/2020	
CMA	IBES	SE	-0.31 (0.58)	-2.29 (0.32)	9	Q4/2002 - Q4/2010	Annual
		SE	+4.09** (0.04)	+3.89 (0.14)	10	Q4/2011 - Q4/2020	
		SE	+0.53 (0.47)	+0.57 (0.75)	19	Q4/2002 - Q4/2020	
		SPE	+2.42 (0.12)	+2.50 (0.29)	9	Q4/2002 - Q4/2010	
		SPE	+4.71** (0.03)	+4.93* (0.08)	10	Q4/2011 - Q4/2020	
		SPE	+7.07*** (0.01)	+7.12** (0.03)	19	Q4/2002 - Q4/2020	

Table 8: Determinants of market level investor expectations. This table provides the time-series regression results of consensus subjective equity risk premia on past yearly excess returns of the CRSP value-weighted index of the $S\&P500$ universe ($R^e_{t-13,t-1}$) and log CAPE ratio ($cape_{t-1}$). 'GH' represents the consensus one-year subjective equity premium from the Graham-Harvey survey at quarterly frequency. 'Liv' represents the consensus one-year subjective equity premium from the Livingston survey at semi-annual frequency. 'CMA' represents the consensus long-term annualized US equity premium from the Capital Markets Assumptions surveys at annual frequency. 'IBES' represents the consensus one-year subjective equity premium from the I/B/E/S at monthly frequency. EWC p-values constructed following Lazarus et al. (2018) are reported in parentheses. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero coefficient.

$$\widetilde{\mathbb{E}}_{i,t}[R^e_{t,t+12}] = \alpha + \beta R^e_{t-13,t-1} + \gamma\ cape_{t-1} + \epsilon_t$$

$\widetilde{\mathbb{E}}_{i,t}[R^e_{t,t+12}]$	Intercept	$R^e_{t-13,t-1}$	$cape_{t-1}$	$Adj.R^2$	N	Sample
$\tilde{\mathbb{E}}_{GH,t}[R^e_{t,t+1}]$	0.04***	0.03**		0.05	71	Q2/2002-Q4/2020
	(0.00)	(0.04)				
$\tilde{\mathbb{E}}_{GH,t}[R^e_{t,t+1}]$	0.08***		-0.01	0.00	71	Q2/2002-Q4/2020
	(0.01)		(0.11)			
$\tilde{\mathbb{E}}_{GH,t}[R^e_{t,t+1}]$	0.15***	0.05**	-0.04**	0.13	71	Q2/2002-Q4/2020
	(0.01)	(0.02)	(0.03)			
$\tilde{\mathbb{E}}_{Liv,t}[R^e_{t,t+1}]$	0.09***	-0.15***		0.27	38	Q2/2002-Q4/2020
	(0.00)	(0.01)				
$\tilde{\mathbb{E}}_{Liv,t}[R^e_{t,t+1}]$	0.68***		-0.19***	0.50	38	Q2/2002-Q4/2020
	(0.00)		(0.01)			
$\tilde{\mathbb{E}}_{Liv,t}[R^e_{t,t+1}]$	0.59***	-0.07	-0.16***	0.54	38	Q2/2002-Q4/2020
	(0.00)	(0.12)	(0.01)			
$\tilde{\mathbb{E}}_{CMA,t}[R^e_{t,t+n}]$	0.03***	-0.01		-0.04	19	Q4/2002-Q4/2020
	(0.01)	(0.32)				
$\tilde{\mathbb{E}}_{CMA,t}[R^e_{t,t+n}]$	0.07		-0.01	-0.03	19	Q4/2002-Q4/2020
	(0.12)		(0.30)			
$\tilde{\mathbb{E}}_{CMA,t}[R^e_{t,t+n}]$	0.06	-0.00	-0.01	-0.09	19	Q4/2002-Q4/2020
	(0.11)	(0.47)	(0.29)			
$\tilde{\mathbb{E}}_{IBES,t}[R^e_{t,t+1}]$	0.16***	-0.17***		0.27	224	05/2002-12/2020
	(0.00)	(0.00)				
$\tilde{\mathbb{E}}_{IBES,t}[R^e_{t,t+1}]$	0.74***		-0.18***	0.33	224	05/2002-12/2020
	(0.00)		(0.00)			
$\tilde{\mathbb{E}}_{IBES,t}[R^e_{t,t+1}]$	0.59***	-0.10	-0.14**	0.41	224	05/2002-12/2020
	(0.00)	(0.10)	(0.01)			

Table 9: Determinants of stock level investor expectations. This table provides the panel level time-series regression results of survey expectations of stock equity risk premia ($\widetilde{\mathbb{E}}_{IBES,t}[R^e_{i,t,t+12}]$) on past yearly excess stock returns ($R^e_{t-13,t-1}$), and various common valuation ratios $X_{i,t-1}$: price-earnings ratio ($PE_{i,t-1}$), entreprise value multiple ($EVM_{i,t-1}$), price-to-sales ratio ($PS_{i,t-1}$), and price-to-book ratio ($PB_{i,t-1}$). Standard erros (in parantheses) are clustered by year-month and stock. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero coefficient.

$$\widetilde{\mathbb{E}}_{IBES,t}[R^e_{i,t,t+12}] = \alpha_i + \alpha_t + \beta R^e_{i,t-13,t-1} + \gamma X_{i,t-1} + \epsilon_{i,t}$$

	$\widetilde{\mathbb{E}}_{IBES,t}[R_{i,t,t+12}]$			
	(1)	(2)	(3)	(4)
$R^e_{i,t-13,t-1}$	-0.136***	-0.120***	-0.135***	-0.124***
	(0.018)	(0.014)	(0.016)	(0.012)
$PE_{i,t-1}$ x 10^{-4}	0.0715	0.0783	0.438	0.460
	(0.172)	(0.134)	(0.442)	(0.401)
$EVM_{i,t-1}$ x 10^{-4}	-0.014	-0.013	0.060	0.052
	(0.174)	(0.147)	(0.163)	(0.124)
$PS_{i,t-1}$ x 10^{-4}	-2.869	10.13	-50.98***	-0.204
	(10.020)	(8.838)	(18.200)	(12.840)
$PB_{i,t-1}$ x 10^{-4}	-13.520***	-11.240***	-11.570***	-6.178**
	(3.553)	(3.403)	(3.242)	(2.592)
N	99924	99924	99924	99924
Adjusted R^2	0.088	0.204	0.254	0.368
Year-month FE	No	Yes	No	Yes
Stock FE	No	No	Yes	Yes
Date	05/2002-12/2020			

Table 10: Relationship between model-based and survey-based equity risk premium. This tables displays the correlations between RE measures of expected equity risk premium - log dividend-price ratio (*pd*), log of the inverse of the Cyclically Adjusted Price Earnings ratio (*cape yield*, Campbell & Shiller (1988)) consumption-wealth ratio (*cay*, Lettau & Ludvigson (2001)), expected variance risk premium ($\mathbb{E}[VRP]$, Bollerslev et al. (2009)), the square of CBOE Volatility Index (VIX^2) - and survey expected equity risk premia. 'GH' represents the consensus one-year subjective equity premium from the Graham-Harvey survey, 'Liv' represents the consensus one-year subjective equity premium from the Livingston survey, 'CMA' represents the consensus long-term annualized US equity premium from the Capital Markets Assumptions surveys, 'IBES (Ret)' represents the consensus one-year subjective equity premium from the I/B/E/S. 'IBES (Prc)' indicates the subjective one-year price return expectations from the I/B/E/S. 'IBES (DP)' indicates the difference between 'IBES (Tot)' and 'IBES (Prc)', which captures the expected forward looking dividend price ratio. p-values are shown in brackets below the estimates. All correlations are computed to ensure that model-based measures are always available at the time the surveys are conducted. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero coefficient. Sample period: 05/2002 - 12/2020.

Correlations	GH	Liv	CMA	IBES (Ret)	IBES (Prc)	IBES (DP)
dp	-0.34***	0.18	0.68***	0.18***	0.13*	0.84***
	(0.00)	(0.28)	(0.00)	(0.01)	(0.06)	(0.00)
cape yield	0.13	0.75***	0.17	0.58***	0.48***	0.53***
	(0.30)	(0.00)	(0.49)	(0.00)	(0.00)	(0.00)
cay	-0.11	0.32*	-0.13	0.14	0.23*	-0.01
	(0.35)	(0.05)	(0.59)	(0.24)	(0.05)	(0.96)
$\mathbb{E}[VRP]$	-0.10	0.60***	0.36	0.41***	0.42***	0.18***
	(0.39)	(0.00)	(0.12)	(0.00)	(0.00)	(0.01)
VIX^2	-0.03	0.77***	0.50**	0.74***	0.70***	0.39***
	(0.78)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)

A Internet Appendix: Additional Details and Results

A.1 Timing of Surveys

The Graham-Harvey CFO survey is conducted quarterly and is typically reported in the last month of each quarter. The survey usually begins in the penultimate month of the quarter and concludes at the beginning of the final month. When analyzing the determinants of the survey, I consider information sets available at the end of the first month of the quarter to avoid look-ahead bias. For examining the predictive ability of the survey, I analyze returns from the end of the last month of the quarter onward.

The Livingston survey questionnaires are mailed in May and November each year, following the monthly release of the Consumer Price Index (CPI) by the government. Respondents are requested to return the questionnaires before the next CPI release in the subsequent month (June and December, respectively). To study the determinants, I rely on information sets available in the month before the questionnaire's release, ensuring that the survey participants' information is not forward-looking. Given the unknown final date of the survey, I analyze the predictive ability by examining returns from the end of June and December onward to avoid look-ahead bias.

The CMAs do not follow a fixed schedule. For my analysis, I aggregate data at the end of the last quarter of each calendar year and consider the information set available at the end of the third quarter to avoid look-ahead bias. When evaluating predictive ability, I analyze returns in the following calendar year.

The IBES consensus forecasts are constructed on the third Thursday of every month. When examining determinants, I consider the information set available at the end of the preceding month, similar to the methodology of De La O & Myers (2021) and van Binsbergen et al. (2023).[11]

[11] 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 similarly reported by Bouchaud et al. (2019) for earnings forecasts. Therefore, 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 their forecasts, while at the same time ensuring that the valuation ratios are not outdated.

A.2 Results following Couts et al. (2024)

In this section, I replicate all the main analyses for the consensus CMA expectations constructed as suggested in Couts et al. (2024).

A.2.1 Construction

In order to address the sparsity and heterogeneity of the CMA data, Couts et al. (2024) suggest constructing consensus beliefs across CMAs through a two-step procedure. This method, while inherently forward-looking, accounts for the varying composition of asset managers in the sample over time. The procedure consists in first estimating the following panel regression:

$$\mu_{j,e,t} = \bar{\mu}_{e,j} + \bar{\mu}_{e,t} + \eta_{j,e,t} \tag{17}$$

where $\mu_{j,e,t}$ is the annualized long-term equity risk premium of firm j at time t, $\bar{\mu}_{e,j}$ is the institution fixed effect, and $\bar{\mu}_{e,t}$ is the year fixed effect. It should be noted that the specification has no intercept. The second step involves modifying the average of the time series of $\mu_{e,t}$ through:

$$\mu_{e,t} = \left[\frac{1}{T}\sum_{t=1}^{T}\left(\frac{1}{J_t}\sum_{j=1}^{J_t}\mu_{j,e,t}\right)\right] + \left(\bar{\mu}_{e,t} - \frac{1}{T}\sum_{t=1}^{T}\bar{\mu}_{e,t}\right) \tag{18}$$

Finally, Couts et al. (2024) use $\mu_{e,t}$ as their consensus CMA belief. By using the CMA data made available by Dahlquist & Ibert (2024), I follow the two-step procedure and create a consensus CMA equity premium, which I label as 'CMA (Alt)'.[12,13]

[12] The consensus CMA return expectation is obtained by following the same procedure and replacing $\mu_{j,e,t}$ with $\mu_{j,t}$, which is the CMA US equity return expectation of firm j at time t.

[13] Between 1997 and 2004, and 2006 to 2007, there is only one asset manager in the sample. This implies that (17) will not be able to differentiate between time and firm fixed effects in those years. Similarly to Couts et al. (2024), who only have one manager in the early part of their sample, I set $\bar{\mu}_{e,t}$ equal to the subjective beliefs of the only asset manager available in those early years.

A.2.2 Results

Table A1 replicates all the tests in Sections 2, 3, and 4 using the consensus equity premium of the CMAs following the methodology of Couts et al. (2024), CMA (Alt).

Panel A reports summary statistics and correlations with subjective risk premia from other surveys. Compared to the CMA consensus belief I used in Sections 2, 3, and 4, the CMA (Alt) has a lower mean (2.54 relative to 3.22 before) and higher volatility (1.49 relative to 0.99 before). Furthermore, CMA (Alt) is only weakly positively correlated (0.19) with the previous consensus CMA belief.

Panel B presents the results from the standard predictability analysis, indicating that CMA (Alt) has no predictive power, with the slope coefficient showing a p-value of 0.18. Moreover, CMA (Alt) has a large and negative out-of-sample R^2.

Panel C compares the forecasting performance of IBES return expectations with CMA (Alt), showing that IBES outperforms, particularly in the unconditional predictive ability test of Giacomini & White (2006). Panel D illustrates that the consensus CMA (Alt) is uncorrelated with lagged yearly excess returns and the log CAPE ratio.

Panel E displays the correlations between CMA (Alt) and the one-year lagged model-based measures of equity risk premium, indicating that CMA (Alt) is strongly positively correlated only with the consumption-wealth ratio. Importantly, CMA (Alt) has a positive correlation (0.28) with the CAPE yield. This correlation is weaker than that found in Couts et al. (2024) (0.60). The reason for this is two-fold. First, Couts et al. (2024) rely on an extended dataset which is not available at the time of writing. Second, Couts et al. (2024) compute the correlation of their consensus belief with the log CAPE yield at the end of the same calendar year, while I use the log CAPE yield at the end of the previous calendar year to better reflect the information set available at the time the forecasts were formed. The correlation between CMA (Alt) and the log CAPE yield at the end of the same calendar year is, in fact, 0.45, which aligns more closely with the finding of Couts et al. (2024).

[Table A1 here]

A.3 Sell-Side Analysts' Coverage

The overall coverage of the $S\&P500$ provided by IBES is summarized in Figure A1. The coverage exceeds 90% for both market capitalization and the number of stocks, indicating that there is a comprehensive universe of stocks available to construct a reliable proxy for the expected returns of the $S\&P500$.

[Figure A1 here]

A.3.1 Fama-French Portfolios Coverage

A standard set of test assets used in the literature for cross-sectional asset pricing tests is the Fama-French 25 portfolios, which are double sorted by market capitalization (ME) and book-to-market (B/M). Table A2 illustrates the time-series average quality of analysts' coverage for these portfolios. Good coverage is provided in terms of both the number of stocks and ME for all portfolios (above 90%) except for the smallest ME quintile, which has the worst coverage both in terms of stocks (60%) and ME (80%). Overall, there is sufficient coverage to study the subjective return properties of cross-sectional portfolios and compare the results with the properties of portfolios based on realized returns.

To provide further evidence of the minimal impact of coverage gaps, Figure A2 illustrates the time series of annual returns of the standard five Fama-French factors when using either the IBES or the full CRSP/Compustat universe. The difference is small, with minor discrepancies only for the investment factor. This indicates 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 A2 and Table A2 here]

A.4 Fund Flows and Return Expectations

I further explore the countercyclicality results in Section 2.2 by running regressions at the asset-manager level:

$$Flow_{t,t+h} = \alpha + \beta \tilde{\mathbb{E}}_t[R^e_{t,t+12}] + \gamma X_t + \epsilon_{t,t+h} \tag{19}$$

where X_t includes both past h-period stock market excess returns ($R^e_{t-h,h}$) and the repurchase-adjusted log dividend price ratio of the CRSP value-weighted index (pd_t). The results are qualitatively and quantitatively consistent (at the 10% significance level) with the findings presented in Figure 2.

[Figure A3 here]

A.5 Bootstrap Procedure - Nagel & Xu (2023)

In my analysis, I rely on the bootstrap method for predictive regressions proposed by Nagel & Xu (2023). Below, I provide a brief summary of the procedure and outline my extension to test for 'rational forecasts'.

To address potential small-sample bias in predictive regressions, the authors begin with the following system:

$$z_{t+1} = \alpha + \beta' X_t + \eta_{t+1} \tag{20}$$

$$X_{t+1} = \kappa + \phi X_t + \iota_{t+1} \tag{21}$$

where η_t and ι_{t+1} may be contemporaneously correlated. The benchmark procedure consists of the following steps:

1. Estimate the bias-adjusted coefficients ($\widetilde{\kappa}$, $\widetilde{\phi}$, and $\{\widetilde{\iota}_t\}$) of a VAR(1) system for the predictors using the approach of Amihud et al. (2008), which relies on the analytical expressions from Nicholls & Pope (1988).

2. Estimate the predictive regression (20) with OLS and obtain the estimates for $\widetilde{\alpha}$, $\widetilde{\beta}$, and $\widetilde{\eta}_{t+1}$.

3. Construct pseudo-samples by bootstrapping the time series of $(\widetilde{\iota}_t, \hat{\eta}_t)$ and use a circular block bootstrap to account for potentially autocorrelated $\{\eta_t\}$.

4. For each sample i, Nagel & Xu (2023) impose the null hypothesis of no predictability by generating data as:

$$
\begin{aligned}
z_{t+1}^{null,i} &= \bar{z} + \hat{\eta}_{t+1}^{i} &(22)\\
X_{t+1} &= \widetilde{\kappa} + \widetilde{\phi} X_t + \widetilde{\iota}_{t+1}^{i} &(23)
\end{aligned}
$$

   After running the predictive regression in sample i, they record the t-statistic τ^i. The collection of $\{\tau^i\}$ is used to obtain the small-sample p-value by comparing it to the sample t-statistic $\hat{\tau}$. In Table 4, this p-value is labelled as as (p-value$_{\{\beta=1\}}$).

5. The final step involves generating data under the alternative hypothesis $\beta = \widehat{\beta}$ as:

$$
\begin{aligned}
z_{t+1}^{null,i} &= \widehat{\beta}' X_t + \hat{\eta}_{t+1}^{i} &(24)\\
X_{t+1} &= \widetilde{\kappa} + \widetilde{\phi} X_t + \widetilde{\iota}_{t+1}^{i} &(25)
\end{aligned}
$$

   After running the predictive regressions for the bootstrapped sample, they obtain the finite-sample bias-adjusted $\hat{\beta}$ by comparing the average of $\{\hat{\beta}^j\}$ with the original estimate of $\hat{\beta}$.

I extend this procedure to test for 'rational forecasts' (i.e., $\alpha = 0$ and $\beta = 1$). To do so, I impose the null hypothesis of rational forecasts by generating data as:

$$
\begin{aligned}
z_{t+1}^{null,i} &= X_t + \hat{\eta}_{t+1}^{i} &(26)\\
X_{t+1} &= \widetilde{\kappa} + \widetilde{\phi} X_t + \widetilde{\iota}_{t+1}^{i} &(27)
\end{aligned}
$$

I re-ran the predictive regressions and recorded the t-statistics $\tau^{*,i}$ (for no intercept and a slope coefficient of 1). The collection of $\{\tau^{*,i}\}$ is used to obtain small-sample p-values by comparing them to the sample t-statistics $\hat{\tau}^*$ (for no intercept and a slope coefficient of 1). In Table 4, these p-values are labeled as (p-value$_{\alpha=0,\beta=1}$).

A.6 First Stage Fama-MacBeth Results

In this section I provide additional results on the Fama-MacBeth first stage results. Tables A3 and A5 provide the full results from the Fama-MacBeth first stage time-series regressions from Section 4.2.2. The results improve when the Fama-French 3-factor model is used rather than CAPM. Similarly, Tables A4 and A6 show the results obtained testing the Fama-French 5-factor model.

[Tables A3 through A6 here]

Figure A1: IBES subjective return data coverage of $S\&P500$. The blue line shows the subjective expected return data coverage provided by IBES relative to the CRSP-Compustat S&P500 universe as a percentage of market capitalization, ME. The red line shows the coverage of IBES relative to the CRSP-Compustat S&P500 universe as a percentage of number of stocks, #.

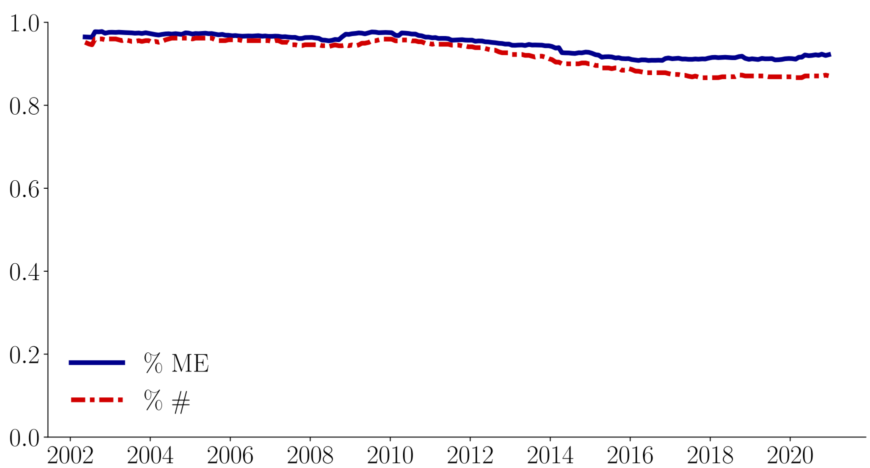

Figure A2: Fama-French 5 factors based on CRSP/Compustat vs. IBES universe. The plots shows the comparison of realized yearly returns of the 5 Fama-French factors when constructed using the whole CRSP/Compustat universe or only the IBES universe of stocks. 'RM-RF' is the excess market return; 'SMB' is the size factor; 'HML' is the value factor; 'CMA' is the investment factor; 'RMW' is the profitability factor. The red (blue) lines represent the realised one-year Fama-French factor returns when the CRSP/Compustat (IBES) universe is used.

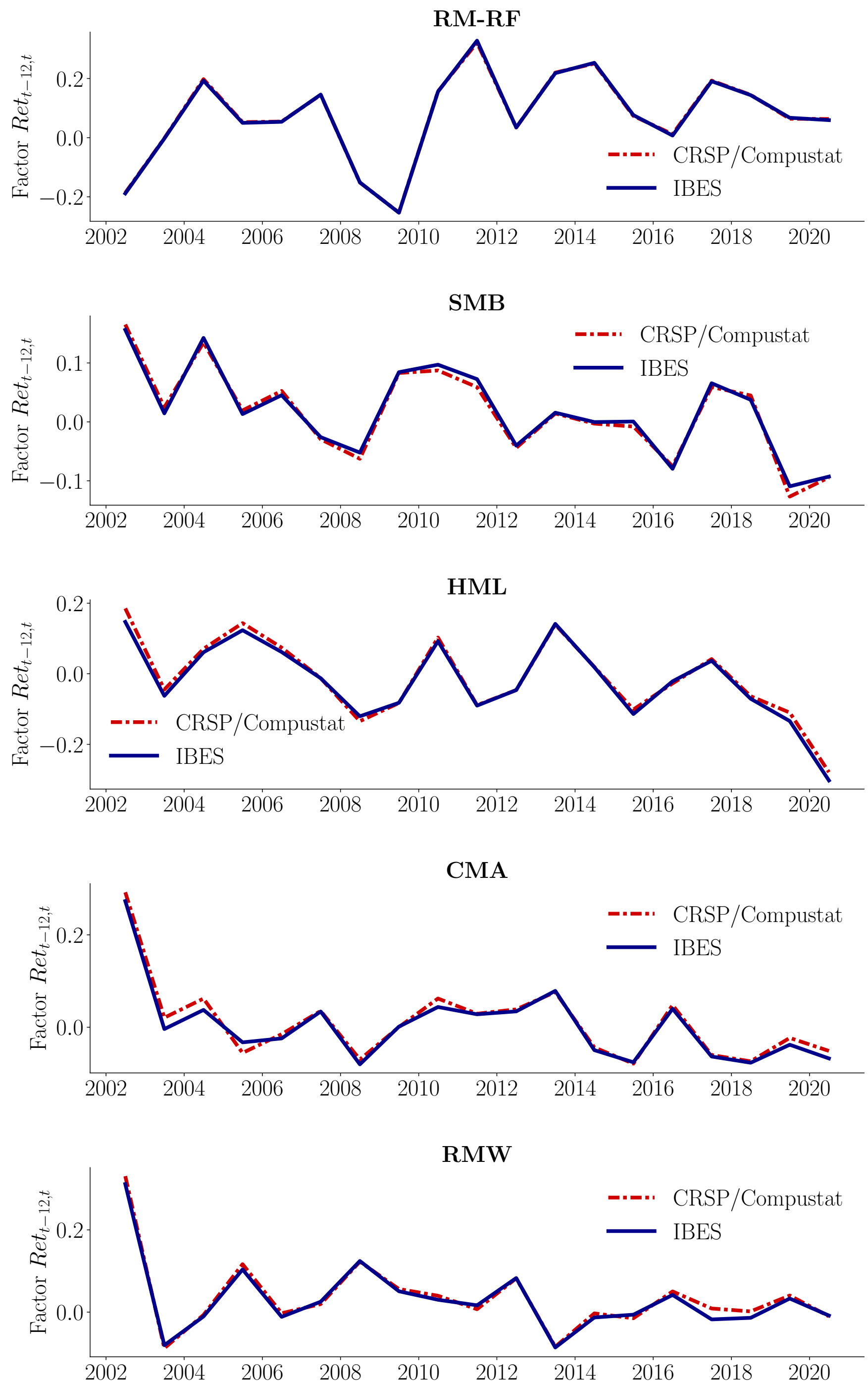

Figure A3: Equity mutual fund flow predictability. Panel A to Panel F display the slope coefficients (β) - with 90% confidence intervals - in black (left y-axis) and the adjusted R^2 in red (right y-axis), from the regression: $Flow_{t,t+h} = \alpha + \beta\tilde{\mathbb{E}}_t[R^e_{t,t+12}] + \gamma X_t + \epsilon_{t,t+h}$, where h is the horizon in months, $Flow_{t,t+h}$ is the monthly compounded flow rate between t and $t+h$ into either all mutual fund (All MF), or retail mutual fund (Retail MF), or institutional mutual fund (Institutional MF). $\tilde{\mathbb{E}}_t[R^e_{t,t+12}]$ is the subjective one-year equity premium from either GH or IBES and X_t are controls including past h-period stock market excess returns ($R^e_{t-h,t}$) and the log price-dividend ratio of the CRSP value-weighted index (pd_t). Newey-West standard errors with twelve months bandwith are used to construct the confidence intervals.

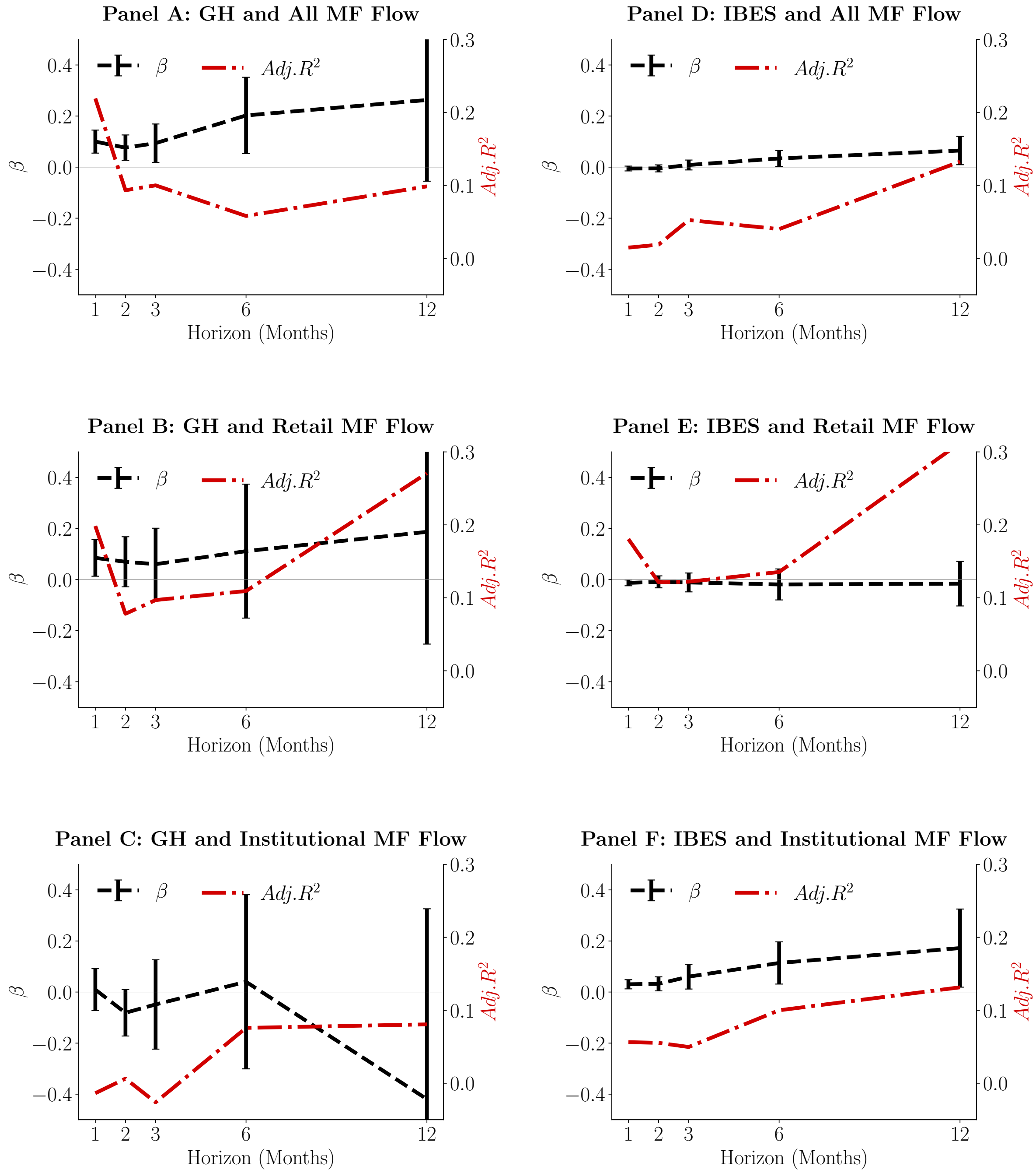

Table A1: Analyses Based on CMA Consensus Beliefs According to Couts et al. (2024). This table replicates all main tests using CMA consensus forecasts of Couts et al. (2024). 'GH' represents the consensus one-year subjective equity premium from the Graham-Harvey survey. 'Liv' represents the consensus one-year subjective equity premium from the Livingston survey. 'CMA' represents the consensus long-term annualized US equity premium from the Capital Markets Assumptions surveys constructed as an average across managers' beliefs in the last calendar quarter of each year. 'IBES' represents the consensus one-year subjective equity premium from the I/B/E/S. 'CMA (Alt)' represents the consensus CMA following Couts et al. (2024). MF CRSP (All) is the annual inflow into all CRSP equity mutual funds. MF CRSP (Inst) is the annual inflow into institutional CRSP equity mutual funds. MF CRSP (Retail) is the annual inflow into retail CRSP equity mutual funds. GW-U and GW-C are the unconditional and conditional tests of predictability ability of Giacomini & White (2006), with p-values in parentheses. SE and SPE indicate the use of squared errors and squared proportional errors loss functions, respectively, in the GW-U and GW-C tests. *dp* is the log dividend-price ratio. *cape* is the log CAPE ratio. *cay* is the consumption-wealth ratio. $\widetilde{\mathbb{E}}[VRP]$ is the expected variance risk premium. VIX^2 is the square of the CBOE Volatility Index. Panel A provides summary statistics; Panel B provides the results from the predictability regression of future excess returns on subjective risk premia based on a bootstrap procedure - Table 5 and Appendix A.5 provide further details on the bootstrap and out-of-sample R^2 (R^2_{OOS}); Panel C compares the forecasting performance of IBES and CMA (Alt) consensus return expectations; Panel D shows the relationship between CMA (Alt) consensus subjective risk premium and one-year lagged past yearly returns and log CAPE ratio; Panel E shows the correlations between CMA (Alt) and one-year lagged model-based measures of equity risk premium. The sample period is from Q4 2002 to Q4 2020, with an annual frequency and 19 observations.

Panel A: Statistics

Summary Stat.	Mean (%)	Std.Dev. (%)	Mean/Std.Dev.	
CMA (Alt)	2.54	1.49	1.70	
December Correlation	GH	Liv	CMA	IBES
CMA (Alt)	0.07	0.30	0.19	0.30

Panel B: Predictability Regression, $R^e_{t,t+1} = \alpha + \beta\widetilde{\mathbb{E}}_{CMA\ (Alt),t}[R^e_{t,t+1}] + \epsilon_{t+1}$

	Intercept	$\widetilde{\mathbb{E}}_{CMA\ (Alt),t}[R^e_{t,t+1}]$	Adj.R^2	R^2_{OOS}
OLS	0.21	-3.78	0.05	-0.19
{bias-adj.}	{0.20}	{-4.05}		
[t-stat]	[6.51]	[-2.67]		
(p-value$_{\{\beta=0\}}$)	(0.02)	(0.18)		
(p-value$_{\{\alpha=0,\beta=1\}}$)	(0.03)	(0.14)		

Panel C: Comparing Forecasting Ability

CMA (Alt) vs. IBES	GW-U	GW-C	N	Date
SE	-0.10 (0.75)	-1.96 (0.38)	9	Q4/2002 - Q4/2010
SE	+4.56** (0.03)	+4.31 (0.12)	10	Q4/2011 - Q4/2020
SE	+2.11 (0.15)	+1.79 (0.41)	19	Q4/2002 - Q4/2020
SPE	+3.76* (0.05)	+3.22 (0.20)	9	Q4/2002 - Q4/2010
SPE	+4.64** (0.03)	+4.59 (0.10)	10	Q4/2011 - Q4/2020
SPE	+5.18** (0.02)	+5.13* (0.08)	19	Q4/2002 - Q4/2020

Panel D: Determinants, $\widetilde{\mathbb{E}}_{i,t}[R^e_{t,t+1}] = \alpha + \beta R^e_{t-1} + \gamma\ cape_{t-1} + \epsilon_t$

$\widetilde{\mathbb{E}}_{i,t}[R^e_{t,t+12}]$	Intercept	R^e_{t-1}	$cape_{t-1}$	$Adj.R^2$
$\tilde{\mathbb{E}}_{CMA,t}[R^e_{t,t+n}]$	0.03*	-0.01		-0.02
	(0.06)	(0.28)		
$\tilde{\mathbb{E}}_{CMA,t}[R^e_{t,t+n}]$	0.11		-0.02	0.03
	(0.28)		(0.42)	
$\tilde{\mathbb{E}}_{CMA,t}[R^e_{t,t+n}]$	0.10	-0.01	-0.02	-0.02
	(0.36)	(0.73)	(0.51)	

Panel E: Correlations of CMA (Alt) with Expected Equity Premium Measures

dp	*cape yield*	*cay*	$\widetilde{\mathbb{E}}[VRP]$	VIX^2
-0.21	0.29	0.78***	-0.11	0.37
(0.38)	(0.22)	(0.00)	(0.66)	(0.12)

Table A2: Comparing IBES vs. CRSP-Compustat coverage. This table shows the average coverage provided for each of the Fama-French 25 (FF25) portfolios by IBES relative to CRSP-Compustat between 2002 and 2020. The FF25 portfolios are double sorted by market capitalization (ME) and book-to-market (BM). 'Lo BM' and 'Hi BM' refer to the lowest and highest book-to-market quintiles, respectively, while 'Small ME' and 'Big ME' refer to the smallest and largest market capitalization quintiles, respectively. The coverage is presented in terms of the availability of subjective expected returns at the portfolio level. Panel A provides the average coverage as a percentage of the number of stocks, and Panel B provides the average coverage as a percentage of market capitalization (ME). All values are rounded to one decimal place.

Panel A

Coverage # Stocks (%)	Lo BM	BM2	BM3	BM4	Hi BM
Small ME	67.7	67.6	64.5	58.5	43.0
ME2	93.6	94.7	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 ME	82.8	82.9	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 A3: Testing CAPM and Fama-French 3-factor models with realized returns. The table presents the results from the time-series regressions of 25 Fama-French (FF25) portfolios excess returns on the excess market return (CAPM) or on the Fama-French 3-factors (FF3). The FF25 portfolios are double sorted by market capitalization (ME) and book-to-market (BM). 'Lo BM' and 'Hi BM' refer to the lowest and highest book-to-market quintiles, respectively, while 'Small ME' and 'Big ME' refer to the smallest and largest market capitalization quintiles, respectively. Results are based on annual excess returns in July of each year between 2002 and 2020. CAPM regression specifciation (Panel A): $R^e_{i,t} = \alpha + \beta_{mkt} R^e_{mkt,t} + \epsilon_t$, with average adj.$R^2$ of portfolios 74%. FF3 regression specification (Panel B): $R^e_{i,t} = \alpha + \beta_{mkt} R^e_{mkt,t} + \beta_{smb} SMB_t + \beta_{hml} HML_t + \epsilon_t$, with average adjusted R^2 across portfolios of 91%.

Panel A

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
α						$t(\alpha)$					
Small	-5.2	0.0	-0.98	1.29	0.64		-1.81	0.00	-0.31	0.30	0.14
ME2	0.10	1.47	1.24	0.79	-2.33		0.05	0.96	0.58	0.27	-0.56
ME3	-0.28	1.93	2.76	1.52	-3.19		-0.18	1.29	1.08	0.51	-0.87
ME4	1.68	2.87	-0.26	-0.43	-4.68		1.45	1.72	-0.09	-0.17	-1.34
Big ME	2.16	0.78	0.24	-6.02	-4.05		1.23	0.94	0.20	-2.04	-1.40
β_{mkt}						$t(\beta_{mkt})$					
Small	1.30	1.12	1.09	1.00	1.20		6.81	11.58	7.19	4.25	5.05
ME2	1.15	1.08	1.09	0.95	1.07		8.21	12.46	11.09	7.53	4.84
ME3	1.22	1.14	0.95	1.04	1.21		10.61	10.4	7.35	6.25	8.12
ME4	1.19	1.05	1.12	1.06	1.50		15.56	9.10	7.16	9.63	7.35
Big ME	0.87	0.89	0.94	1.21	1.11		11.41	19.39	11.95	7.65	4.98
Adj.R^2						$s(e)$					
Small	0.69	0.79	0.64	0.49	0.53		12.86	8.51	11.9	14.89	16.35
ME2	0.83	0.83	0.79	0.63	0.56		7.82	7.30	8.41	10.59	13.93
ME3	0.86	0.88	0.72	0.69	0.59		7.34	6.25	8.79	10.26	14.68
ME4	0.93	0.86	0.77	0.70	0.67		5.02	6.21	9.17	10.28	15.68
Big ME	0.78	0.91	0.9	0.79	0.59		6.85	4.24	4.70	9.34	13.48

Panel B

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
α						$t(\alpha)$					
Small	-9.63	-2.28	-2.80	0.30	-0.02		-4.64	-1.47	-2.60	0.26	-0.02
ME2	-2.75	-0.30	0.78	0.48	-1.96		-1.97	-0.27	0.61	0.36	-2.81
ME3	-3.33	1.38	2.99	1.70	-2.82		-2.85	1.21	1.71	1.09	-1.24
ME4	0.53	2.57	0.36	1.20	-2.53		0.52	2.15	0.20	1.19	-1.58
Big ME	0.76	1.97	0.71	-2.69	-1.51		1.33	3.02	0.64	-1.86	-0.47
β_{mkt}						$t(\beta_{mkt})$					
Small	1.36	1.14	1.06	0.95	1.13		7.07	9.66	12.38	10.08	10.43
ME2	1.19	1.08	1.06	0.90	1.00		11.79	17.50	13.13	13.08	21.62
ME3	1.27	1.13	0.91	0.99	1.14		35.43	14.69	9.49	12.70	8.51
ME4	1.22	1.03	1.08	0.99	1.40		24.08	11.76	12.14	11.39	10.79
Big ME	0.92	0.87	0.92	1.13	1.05		20.18	18.50	12.61	14.19	4.24
β_{smb}						$t(\beta_{smb})$					
Small	1.35	0.92	1.29	1.29	1.31		3.31	3.21	7.77	5.97	5.67
ME2	0.81	0.85	0.65	0.79	0.88		4.46	6.84	4.41	4.44	9.61
ME3	0.87	0.46	0.42	0.61	0.84		6.03	3.09	1.77	3.71	3.37
ME4	0.20	0.38	0.37	0.16	0.39		1.38	1.65	1.61	1.03	1.34
Big ME	-0.00	-0.34	0.01	-0.65	-0.43		-0.04	-2.60	0.04	-4.01	-0.86
β_{hml}						$t(\beta_{hml})$					
Small	-0.78	-0.26	0.16	0.48	0.61		-3.15	-1.21	1.60	3.93	3.61
ME2	-0.54	-0.11	0.25	0.40	0.72		-5.29	-1.19	2.32	3.41	9.39
ME3	-0.58	0.10	0.36	0.47	0.69		-5.21	0.87	2.28	3.90	6.19
ME4	-0.30	0.14	0.47	0.72	1.06		-3.68	1.17	3.18	6.42	5.16
Big ME	-0.53	0.23	0.18	0.83	0.67		-7.00	3.27	1.41	6.82	2.17
Adj.R^2						$s(e)$					
Small	0.81	0.87	0.95	0.93	0.94		10.09	6.65	4.36	5.37	5.78
ME2	0.90	0.93	0.93	0.93	0.97		5.89	4.68	4.79	4.71	3.58
ME3	0.94	0.93	0.86	0.93	0.9		4.61	4.77	6.14	5.05	7.36
ME4	0.94	0.91	0.91	0.93	0.94		4.43	4.95	5.56	5.09	6.80
Big ME	0.95	0.93	0.91	0.92	0.64		3.23	3.80	4.45	5.71	12.68

Table A4: Testing Fama-French 5-factor model with realized returns. The table presents the results from the time-series regressions of the 25 Fama-French (FF25) portfolios- excess returns on the Fama-French 5-factors (FF5). The FF25 portfolios are double sorted by market capitalization (ME) and book-to-market (BM). 'Lo BM' and 'Hi BM' refer to the lowest and highest book-to-market quintiles, respectively, while 'Small ME' and 'Big ME' refer to the smallest and largest market capitalization quintiles, respectively. Results are based on annual excess returns in July of each year between 2002 and 2020. FF5 regression 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 adjusted R^2 across portfolios of 93%.

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
α						$t(\alpha)$					
Small	-3.57	0.56	-1.71	0.06	0.29		-1.67	0.28	-1.46	0.03	0.13
ME2	-0.14	0.21	1.54	-0.39	-3.39		-0.09	0.14	0.89	-0.23	-2.88
ME3	-2.39	-0.18	1.42	0.81	-3.40		-1.42	-0.11	0.64	0.46	-1.25
ME4	0.53	0.33	-0.75	-0.49	-0.48		0.33	0.21	-0.37	-0.28	-0.21
Big ME	0.23	-0.00	0.18	-3.64	4.68		0.20	-0.00	0.13	-1.75	1.59
β_{mkt}						$t(\beta_{mkt})$					
Small	0.96	0.95	0.97	0.95	1.12		7.73	8.12	14.28	8.11	8.78
ME2	1.01	1.03	1.00	0.94	1.09		11.34	11.76	9.96	9.72	16.01
ME3	1.20	1.23	1.00	1.06	1.16		12.41	12.93	7.73	10.45	7.35
ME4	1.20	1.17	1.13	1.09	1.26		13.14	12.81	9.64	10.51	9.45
Big ME	0.95	1.00	0.97	1.20	0.62		14.06	16.50	12.03	10.01	3.66
β_{smb}						$t(\beta_{smb})$					
Small	1.56	1.03	1.40	1.32	1.29		6.39	4.46	10.47	5.72	5.13
ME2	0.94	0.94	0.70	0.83	0.84		5.33	5.45	3.54	4.35	6.27
ME3	0.92	0.42	0.42	0.54	0.90		4.79	2.22	1.63	2.68	2.90
ME4	0.26	0.34	0.39	0.15	0.48		1.45	1.89	1.70	0.75	1.84
Big ME	0.02	-0.4	-0.09	-0.71	-0.13		0.17	-3.31	-0.55	-2.99	-0.39
β_{hml}						$t(\beta_{hml})$					
Small	-0.46	-0.09	0.31	0.51	0.58		-2.61	-0.56	3.26	3.09	3.23
ME2	-0.35	0.01	0.33	0.45	0.65		-2.77	0.09	2.30	3.26	6.76
ME3	-0.51	0.02	0.35	0.36	0.76		-3.71	0.17	1.90	2.53	3.41
ME4	-0.22	0.06	0.50	0.69	1.20		-1.73	0.50	3.00	4.73	6.36
Big ME	-0.50	0.13	0.06	0.74	1.12		-5.21	1.50	0.49	4.34	4.66
β_{cma}						$t(\beta_{cma})$					
Small	-0.48	-0.27	-0.42	-0.16	0.13		-1.86	-1.11	-2.99	-0.64	0.48
ME2	-0.39	-0.38	-0.19	-0.26	0.07		-2.10	-2.09	-0.91	-1.31	0.50
ME3	-0.12	0.09	-0.13	0.27	-0.32		-0.61	0.47	-0.47	1.29	-0.99
ME4	-0.27	0.01	-0.22	-0.10	-0.26		-1.41	0.08	-0.88	-0.47	-0.95
Big ME	-0.17	0.12	0.39	0.20	-0.91		-1.18	0.98	2.29	0.81	-2.57
β_{rmw}						$t(\beta_{rmw})$					
Small	-0.91	-0.41	-0.07	0.08	-0.09		-3.69	-1.78	-0.50	0.36	-0.35
ME2	-0.34	0.02	-0.08	0.22	0.22		-1.91	0.11	-0.39	1.16	1.67
ME3	-0.13	0.24	0.30	0.08	0.19		-0.66	1.29	1.19	0.38	0.61
ME4	0.08	0.38	0.25	0.32	-0.28		0.41	2.08	1.07	1.56	-1.05
Big ME	0.14	0.30	-0.02	0.11	-0.81		1.04	2.52	-0.10	0.44	-2.40
Adj.R^2						$s(e)$					
Small	0.93	0.91	0.97	0.93	0.93		5.97	5.63	3.28	5.67	6.15
ME2	0.95	0.94	0.93	0.93	0.98		4.31	4.23	4.85	4.69	3.29
ME3	0.94	0.94	0.86	0.93	0.89		4.69	4.60	6.26	4.91	7.62
ME4	0.94	0.93	0.91	0.93	0.94		4.42	4.43	5.68	5.00	6.44
Big ME	0.95	0.96	0.93	0.92	0.85		3.26	2.93	3.91	5.81	8.19

Table A5: Testing CAPM and Fama-French 3-factor models with subjective expected returns. The table presents the results from the time-series regressions of the 25 Fama-French (FF25) portfolios subjective expected one-year excess returns on the subjective expected one-year excess market return (CAPM) or on the subjective expected one-year returns of the Fama-French 3-factors (FF3). The FF25 portfolios are double sorted by market capitalization (ME) and book-to-market (BM). 'Lo BM' and 'Hi BM' refer to the lowest and highest book-to-market quintiles, respectively, while 'Small ME' and 'Big ME' refer to the smallest and largest market capitalization quintiles, respectively. Results are based on annual subjective excess returns in July of each year between 2002 and 2020. CAPM regression specification (Panel A): $\tilde{\mathbb{E}}_t[R^e_{i,t+1}] = \tilde{\alpha} + \tilde{\beta}_{mkt}\tilde{\mathbb{E}}_t[R^e_{mkt,t+1}] + \tilde{\epsilon}_t$, with average adj.$R^2$ of portfolios 60%; FF3 regression specification (Panel B): $\tilde{\mathbb{E}}_t[R^e_{i,t+1}] = \tilde{\alpha} + \tilde{\beta}_{mkt}\tilde{\mathbb{E}}_t[R^e_{mkt,t+1}] + \tilde{\beta}_{smb}\tilde{\mathbb{E}}_t[SMB_{t+1}] + \tilde{\beta}_{hml}\tilde{\mathbb{E}}_t[HML_{t+1}] + \tilde{\epsilon}_t$, with average adjusted R^2 across portfolios of 82%.

Panel A

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
$\tilde{\alpha}$						$t(\tilde{\alpha})$					
Small	27.64	28.94	11.34	7.92	-0.46		1.74	2.4	1.26	1.60	-0.03
ME2	10.71	3.68	0.68	-0.47	0.77		2.44	1.34	0.35	-0.25	0.25
ME3	0.08	0.50	-0.11	-1.62	-5.68		0.03	0.43	-0.07	-0.82	-1.27
ME4	-6.94	-1.86	-5.27	1.89	0.16		-0.90	-1.74	-1.40	0.84	0.03
Big ME	1.2	0.88	2.80	-0.54	-3.78		1.03	0.96	1.16	-0.14	-1.06
$\tilde{\beta}_{mkt}$						$t(\tilde{\beta}_{mkt})$					
Small	1.54	0.61	1.34	1.09	1.90		1.44	1.02	2.68	4.81	1.93
ME2	0.72	0.90	0.98	0.98	0.89		2.61	6.70	12.24	11.03	6.86
ME3	1.01	0.90	0.90	1.03	1.35		5.16	14.00	13.96	12.31	4.45
ME4	1.62	0.93	1.37	0.75	0.99		2.17	12.42	4.79	7.47	2.70
Big ME	0.87	0.89	0.8	1.09	1.45		13.68	15.01	4.67	3.52	6.17
Adj.R^2						$s(e)$					
Small	0.15	-0.00	0.31	0.47	0.34		20.53	16.8	11.91	7.2	15.88
ME2	0.27	0.65	0.77	0.78	0.63		6.97	4.12	3.37	3.23	4.25
ME3	0.76	0.88	0.86	0.83	0.63		3.59	2.06	2.27	2.90	6.50
ME4	0.14	0.93	0.68	0.67	0.41		21.94	1.63	5.84	3.34	7.29
Big ME	0.88	0.91	0.68	0.57	0.78		2.01	1.81	3.44	5.87	4.84

Panel B

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
$\tilde{\alpha}$						$t(\tilde{\alpha})$					
Small	14.31	23.33	9.90	11.61	-8.18		2.58	2.80	2.77	2.58	-1.17
ME2	5.81	3.15	0.27	1.62	4.56		2.31	1.24	0.09	0.68	2.20
ME3	-4.78	-0.54	-0.20	-0.63	-3.58		-7.83	-0.43	-0.12	-0.36	-2.46
ME4	-10.4	-1.66	0.11	2.74	1.55		-1.08	-1.34	0.05	1.13	0.73
Big ME	-1.08	1.70	6.32	8.61	0.07		-1.13	1.89	2.31	2.08	0.05
$\tilde{\beta}_{mkt}$						$t(\tilde{\beta}_{mkt})$					
Small	1.19	0.16	0.88	0.70	1.53		4.61	0.40	4.91	2.90	4.55
ME2	0.64	0.76	0.90	0.80	0.62		5.16	5.57	6.17	6.84	4.91
ME3	1.06	0.87	0.85	0.91	1.01		22.27	16.4	9.80	9.61	14.12
ME4	1.83	0.94	1.11	0.66	0.67		2.00	13.57	6.71	5.98	5.54
Big ME	0.99	0.90	0.70	0.79	1.15		17.26	17.67	3.76	3.94	11.52
$\tilde{\beta}_{smb}$						$t(\tilde{\beta}_{smb})$					
Small	3.82	2.80	2.11	0.91	2.88		11.20	5.45	11.38	3.05	6.09
ME2	1.19	0.64	0.40	0.30	0.41		7.31	3.75	2.83	2.28	2.47
ME3	0.68	0.29	0.23	0.27	0.97		19.98	4.56	2.68	3.03	6.72
ME4	-0.24	-0.06	0.04	0.23	1.06		-0.52	-0.62	0.18	3.55	4.96
Big ME	-0.06	-0.18	-0.22	-0.46	0.49		-1.19	-3.29	-1.91	-2.06	4.19
$\tilde{\beta}_{hml}$						$t(\tilde{\beta}_{hml})$					
Small	0.29	0.83	1.04	1.10	0.57		0.53	1.41	4.27	4.73	1.42
ME2	-0.02	0.30	0.18	0.49	0.81		-0.09	1.75	0.82	3.05	6.12
ME3	-0.32	0.02	0.12	0.31	0.89		-4.14	0.18	0.88	1.67	4.30
ME4	-0.66	-0.01	0.83	0.26	0.84		-0.99	-0.05	2.11	1.12	2.70
Big ME	-0.38	0.02	0.40	1.10	0.87		-5.11	0.22	1.54	3.13	5.12
Adj.R^2						$s(e)$					
Small	0.85	0.68	0.91	0.82	0.87		8.47	9.44	4.27	4.14	6.99
ME2	0.76	0.87	0.84	0.88	0.87		3.99	2.48	2.78	2.37	2.49
ME3	0.98	0.93	0.89	0.88	0.92		1.09	1.56	2.04	2.45	3.06
ME4	0.04	0.92	0.73	0.70	0.81		23.19	1.71	5.43	3.18	4.19
Big ME	0.93	0.92	0.73	0.77	0.92		1.6 0	1.69	3.20	4.33	2.92

Table A6: Testing Fama-French 5-factor model with subjective expected returns. The table presents the results from the time-series regressions of the 25 Fama-French (FF25) portfolios subjective expected one-year excess returns on the subjective expected one-year returns of the Fama-French 5-factors (FF5). The FF25 portfolios are double sorted by market capitalization (ME) and book-to-market (BM). 'Lo BM' and 'Hi BM' refer to the lowest and highest book-to-market quintiles, respectively, while 'Small ME' and 'Big ME' refer to the smallest and largest market capitalization quintiles, respectively. Results are based on annual subjective excess returns in July of each year between 2002 and 2020. FF5 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 adjusted R^2 across portfolios of 85%.

	Lo BM	BM2	BM3	BM4	Hi BM		Lo BM	BM2	BM3	BM4	Hi BM
$\tilde{\alpha}$						$t(\tilde{\alpha})$					
Small	13.54	2.44	2.82	2.70	4.16		1.51	0.32	0.69	0.74	0.55
ME2	0.90	-1.13	-2.35	-1.21	0.98		0.22	-0.48	-0.81	-0.46	0.42
ME3	-5.21	-0.02	-2.6	-1.12	-2.93		-4.30	-0.01	-1.47	-0.52	-0.92
ME4	-15.7	-4.86	-2.96	3.68	-1.83		-0.67	-4.02	-0.46	1.03	-0.37
Big ME	-0.27	2.53	7.17	4.09	-0.93		-0.19	1.24	1.83	0.84	-0.28
$\tilde{\beta}_{mkt}$						$t(\tilde{\beta}_{mkt})$					
Small	1.20	1.25	1.24	1.15	0.87		2.57	3.18	5.77	6.03	2.20
ME2	0.86	0.98	1.04	0.95	0.82		4.08	7.87	6.89	6.96	6.79
ME3	1.07	0.84	0.99	0.96	0.94		16.91	8.76	10.75	8.54	5.66
ME4	2.35	1.12	1.25	0.62	0.82		1.93	17.75	3.77	3.33	3.20
Big ME	0.93	0.85	0.65	0.99	1.18		12.71	7.97	3.21	3.89	6.90
$\tilde{\beta}_{smb}$						$t(\tilde{\beta}_{smb})$					
Small	4.01	3.94	2.51	1.37	2.25		8.00	9.35	10.92	6.69	5.30
ME2	1.43	0.88	0.6	0.47	0.64		6.29	6.61	3.74	3.22	4.97
ME3	0.66	0.27	0.41	0.39	0.86		9.71	2.66	4.16	3.27	4.78
ME4	0.59	0.14	0.10	0.26	1.17		0.46	2.13	0.28	1.28	4.26
Big ME	-0.15	-0.23	-0.18	-0.29	0.49		-1.96	-1.97	-0.84	-1.05	2.68
$\tilde{\beta}_{hml}$						$t(\tilde{\beta}_{hml})$					
Small	-0.33	0.30	0.69	0.93	0.21		-0.59	0.62	2.69	4.04	0.44
ME2	-0.19	0.18	0.08	0.43	0.71		-0.74	1.23	0.43	2.59	4.85
ME3	-0.40	-0.02	0.04	0.21	0.81		-5.18	-0.18	0.37	1.57	4.03
ME4	-1.05	-0.04	0.86	0.19	0.72		-0.72	-0.49	2.15	0.85	2.32
Big ME	-0.33	0.05	0.39	1.19	0.83		-3.71	0.42	1.60	3.86	4.04
$\tilde{\beta}_{cma}$						$t(\tilde{\beta}_{cma})$					
Small	0.65	-1.28	-0.30	-0.67	1.38		0.98	-2.30	-0.98	-2.50	2.47
ME2	-0.41	-0.26	-0.04	-0.17	-0.12		-1.35	-1.48	-0.21	-0.86	-0.68
ME3	-0.07	0.07	-0.02	0.23	-0.07		-0.82	0.54	-0.16	1.47	-0.31
ME4	1.36	-0.16	-0.49	0.30	-0.35		0.79	-1.84	-1.04	1.12	-0.98
Big ME	-0.09	0.01	0.2	-0.66	-0.2		-0.88	0.08	0.68	-1.84	-0.82
$\tilde{\beta}_{rmw}$						$t(\tilde{\beta}_{rmw})$					
Small	0.25	0.99	0.30	0.29	-0.55		0.52	2.49	1.37	1.48	-1.37
ME2	-0.07	0.18	0.26	0.15	0.34		-0.32	1.45	1.70	1.09	2.79
ME3	-0.17	-0.05	0.31	0.36	-0.42		-2.66	-0.5	3.36	3.15	-2.47
ME4	3.11	0.30	-0.21	0.22	-0.18		2.53	4.69	-0.61	1.18	-0.69
Big ME	-0.26	-0.10	0.15	-0.18	-0.24		-3.46	-0.91	0.73	-0.71	-1.38
Adj.R^2						$s(e)$					
Small	0.88	0.85	0.94	0.90	0.89		7.81	6.56	3.57	3.18	6.60
ME2	0.81	0.91	0.87	0.89	0.92		3.53	2.07	2.51	2.27	2.01
ME3	0.98	0.93	0.94	0.93	0.93		1.05	1.60	1.53	1.87	2.78
ME4	0.27	0.97	0.71	0.71	0.80		20.22	1.05	5.55	3.11	4.26
Big ME	0.96	0.91	0.69	0.78	0.92		1.23	1.78	3.40	4.24	2.85