Tactical Asset Allocations of Large Asset Managers

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Abstract

Collecting market outlooks of asset managers, I study short-term expectations that summarize the relative risk and return attractiveness across asset classes. These tactical asset allocation views are reflected in positioning data from a survey of fund managers, in the time-series asset allocations of mutual funds, and in futures positioning. Allocation mutual funds' equity portfolio weights are two to three percentage points lower when managers' are "underweight" rather than "overweight" equities relative to their strategic asset allocations. Prompting a large-language model to infer expectations about macroeconomic fundamentals from the text-based outlooks, such a repositioning happens whenever the perceived growth outlook deteriorates.

Keywords: Beliefs, expectations formation, institutional investors.
JEL codes: G11, G12, H23.

1 Introduction

Understanding asset management firms' asset allocations is central to understanding asset prices. The world portfolio of all investable assets is estimated to be around USD 250 trillion, 50% of which are held by such asset managers.[1] Institutional investors' asset allocation decisions typically comprise a strategic asset allocation (SAA) component, which reflects long-term investment objectives and risk tolerance, and a tactical asset allocation (TAA) component, which reflects shorter-term adjustments intended to exploit perceived market opportunities.

Recent research has studied the long-term (e.g., ten-year) subjective risk and return expectations that guide the SAAs of institutional investors.[2] However, there is little evidence of the short-term (e.g., one-year) expectations that guide their TAAs. Understanding the expectations embedded in TAAs is important as they may help explain short-term asset price movements.

This paper models institutional portfolio weights for asset class k as the sum of a strategic and a tactical component:

$$w^k = w^{\text{SAA},k} + w^{\text{TAA},k} = w^{\text{SAA},k} + \underbrace{\overbrace{\theta^k}^{\text{sensitivity}} \times \overbrace{\nu^k}^{\text{view}}}_{\text{tactical (active) tilt}}, \tag{1}$$

where ν is a forward-looking "view" on asset class k that summarizes its relative attractiveness vis-à-vis other asset classes in terms of both risk and return. The sensitivity θ may summarize risk aversion or, more practically, tracking error constraints relative to the SAA.

The paper hand collects data on large asset managers' tactical views across asset classes from asset managers' market outlook publications. Views are typically expressed on a dis-

[1] See Mueller-Glissmann, Ferrario, Giglio, and Oppenheimer (2025) and Thinking Ahead Institute (2024b). I use "asset managers" for traditional, long-only asset managers. Hedge funds are also asset managers, but their assets under management are relatively small (see Barth, Joenväärä, Kauppila, and Wermers, 2023).

[2] See, e.g., Andonov and Rauh (2022), Dahlquist and Ibert (2024a), Dahlquist and Ibert (2024b), Couts, Gonçalves, and Loudis (2024b), Couts, Gonçalves, Liu, and Loudis (2024a), Böni, Brüggemann, and Kroencke (2025), and Begenau, Liang, and Siriwardane (2025). For a textbook treatment of SAA, see Campbell and Viceira (2002).

crete scale from very underweight (−2), underweight (−1), neutral (0), overweight (+1), to very overweight (+2), all relative to the SAA.

I first show that the hand-collected views align with positioning data from a survey of global fund managers. I then relate asset managers' views on equities and fixed income to expectations about macroeconomic fundamentals, which I obtain from the text-based market outlooks using a large-language model (LLM). The key determinant of asset managers' TAA views across broad asset classes is the perceived economic growth outlook: when the perceived growth outlook deteriorates and the perceived chance of a recession rises, asset managers' views' on equities decrease and views on fixed income increase.

I then match the views to asset managers' allocation mutual funds—funds that invest in both equities and bonds—and futures positioning data from the Commodity Futures Trading Commission (CFTC). At the heart of this paper is to estimate whether and how the forward-looking views translate into portfolio demand, i.e., to estimate the sensitivities θ in Equation (1). This is important as, after all, subjective expectations only matter to the extent that they affect actual choices.

I estimate sensitivities of 0.9 to 1.6 for equities and bonds. That is, when asset managers turn from overweight equities (+1 view) to underweight (−1 view), their allocation funds on average have 1.8 to 3.2 percentage points lower equity (higher bond) portfolio weights. That said, while statistically significant, the estimated sensitivities are arguably economically small. In turn, the large equity price changes typically associated with a turning economic outlook despite relatively little turnover from asset managers are broadly consistent with the inelastic markets hypothesis (see, e.g., Gabaix and Koijen, 2021).

Asset managers' expectations versus BofA fund manager survey. I hand-collect data from 25 large asset managers' monthly and quarterly publications that describe their short-term market outlooks. The outlook documents are different from the documents that contain the Capital Market Assumptions (CMAs) that are studied in, e.g., Dahlquist and Ibert (2024a) or Couts et al. (2024b). The former are published on a higher frequency (e.g., monthly) and describe short-term expectations, whereas the latter are published on a lower

frequency (e.g., annually) and describe long-term expectations. The first outlook document I collect is from 2014 and the last is from 2025.

The first results in the paper relate the hand-collected expectations to aggregate survey responses about current asset allocations from the Bank of America (BofA) Global Fund Manager Survey. The monthly BofA fund manager survey is well-known among practitioners and frequently discussed in the financial media.[3] Unfortunately, the BofA fund manager survey is well guarded. If researchers want to use the BofA survey at all, they have to infer the average responses from graphs in .pdf documents (see, e.g., Bastianello and Peng, 2024; Gonçalves, Melone, and Ricciardi, 2025), scatters of which sometimes can be found online.

I compare the forward-looking tactical views with the net % of respondents that are currently overweight a given asset class from the BofA fund manager survey. I find that the time-series correlations between average tactical views and BofA survey responses are statistically positive for six out of eight asset classes. That is, on average BofA survey respondents do as asset managers say. For instance, when the asset managers in my sample express a positive view on equities, the respondents of the BofA survey indicate that they are currently overweight equities.

The tactical outlook documents are text based. I prompt an LLM to infer an asset manager's expectation about the following variables: the probability of a recession, the global growth outlook, the global inflation outlook, short-term and long-term interest rates, volatility in financial markets, and equity valuations. The "LLM-survey" responses based on the outlook documents also correlate positively with corresponding responses from the BofA survey.

A large literature in asset pricing tries to understand the macroeconomic drivers of asset prices (see, e.g., Cochrane, 2017, for a survey), so I relate asset managers' expectations about macroeconomic fundamentals to their tactical views. I find that expectations about the

[3]See, e.g., https://www.ft.com/content/d43b2929-74b4-4121-9c58-1eba5be321bc. Anecdotally, BofA wants to charge researchers several hundreds of thousands USD for access to the monthly .pdf documents containing the aggregate responses as access to the survey entails becoming a BofA client. The results in this paper show that, going forward, researchers can create their own "survey" from documents that are publicly available.

growth outlook and the perceived chance of a recession are the primary drivers of managers' tactical views about equities and bonds, both in the time series and in the cross section of managers. When the perceived growth outlook deteriorates and the perceived chance of a recession rises, managers swiftly shift from equities to bonds and vice versa.

Tactical views and allocation funds' portfolio weights. I then match managers' tactical views to the allocation mutual funds they manage, manager by manager. Data on allocation funds and their portfolio weights in equities, bonds, and other asset classes comes from Morningstar.

I regress funds' equity and bond portfolio weights on their corresponding tactical views, including fund fixed effects and thereby identifying the coefficient estimates using time-series variation. Assuming that SAA weights are constant over time but may vary across funds, the slope coefficient estimates in these regressions identify the sensitivities in Equation (1). The slope coefficient estimates range from 0.8 to 1.6 for equities and bonds. This means that asset allocation funds' have 1.8 to 3.2 percentage points lower equity (higher bond) portfolio weights when they turn from overweight equities to underweight equities. I find similar results when I control for measures that may drive SAAs over time, in particular measures of the long-term equity premium.

Dahlquist and Ibert (2024a) find that the long-term equity return expectations of large asset managers are countercyclical in the time series (high when equity valuations are low and vice versa). Further, they find that asset managers' long-term equity return expectations are heterogeneous in the cross section of managers and reflected in the asset allocation funds they manage: managers with larger US equity premium expectations invest significantly more in US equities than managers with lower US equity premium expectations.

Long-term risk and return expectations matter for SAAs, which in turn can help explain cross-sectional variation in asset allocation funds' portfolio weights. For instance, an asset manager that is strategically bearish on US equities may launch and offer funds with low target allocations to US equities. The focus of this paper is on the time-series relation between portfolio weights and TAA views. In the time series, SAA and TAA interact and

both may contribute to variation in portfolio weights. This paper shows that asset managers' tactical views are reflected in their time-series portfolio demand, even when controlling for measures that may drive SAAs over time.

Tactical views and futures positioning. Anecdotal evidence suggests that TAA views are implemented via derivatives, in particular futures, for trading in futures minimizes transaction costs (see, e.g., Dahlquist and Harvey, 2001). Since 2011, the Traders in Financial Futures (TFF) report from the CFTC separates futures positioning data into four groups of traders: asset managers, dealers, leveraged funds (i.e., hedge funds), and others.

Consistent with the anecdotal evidence, I find that asset managers' tactical views correlate positively with respective futures positioning in the S&P 500, US ten-year Treasury notes, and commodity futures. For instance, when asset managers shift from being overweight equities to a neutral equity position, asset managers' S&P 500 net futures positions scaled by open interest decrease by three percentage points. I find similar results when I run time-series regressions futures positions on the aggregate BofA survey responses that are available since 2004.

The BofA survey not only surveys asset managers and the CFTC not only groups asset managers in the "asset manager" category. Both datasets also contain "asset owners" (e.g., pension funds, insurance companies, and sovereign wealth funds).[4] Still, the expectations in this paper—solely from asset managers—align with the BofA survey and the CFTC futures positioning data. This points to a high degree of consistency across institutional investors' short-term expectations and positioning. Specifically, the results are consistent across four different datasets: hand-collected data, the BofA fund manager survey, data on asset managers' allocation funds from Morningstar, and CFTC futures positioning data.

[4]Pension funds own around USD 50 trillion, insurance companies around USD 35 trillion, and sovereign wealth funds around USD 12 trillion (Thinking Ahead Institute, 2024a). Parts of these assets are managed internally and parts are outsourced to asset managers, see Goyal and Wahal (2008).

Related literature. First, the paper contributes a large literature on the subjective risk and return expectations of market participants.[5] Several papers study institutional investors (see the references in footnote one), but most of these papers focus on the properties of long-term (e.g., ten-year) risk and return expectations. Instead, I study short-term expectations (see also Gandhi, Gormsen, and Lazarus, 2023; Bastianello and Peng, 2025). Different from much of the literature, the short-term forward-looking views that I study are not actually return expectations. Instead, they balance risk and return and are expressed relative to the SAA.[6]

Bastianello and Peng (2024) also use data from the BofA survey. However, they focus on a question in the BofA survey that asks whether respondents perceive equities to be overvalued, from which they back out and study subjective equity return expectations using an AR(1) assumption. Instead, I focus on questions from the BofA survey that indicate whether respondents are currently "overweight" in a given asset class. I show that the responses from these questions correlate with asset managers' forward-looking TAA views, which are at the center stage of the outlook documents that asset managers publish.

Second, the paper contributes to an important literature that estimates the sensitivities of portfolio choices to subjective expectations (see, e.g., Kézdi and Willis, 2011; Amromin and Sharpe, 2014; Ameriks, Kézdi, Lee, and Shapiro, 2020; Giglio, Maggiori, Stroebel, and Utkus, 2021; Laudenbach, Weber, Weber, and Wohlfart, 2024; Beutel and Weber, 2022; Andries, Bianchi, Huynh, and Pouget, 2025). A common theme from this literature is that these sensitivites are economically small, and my paper is no different. However, most of these papers focus on households and retail investors.

Third, the paper contributes to a literature on demand-system asset pricing as it provides a microfoundation for asset managers' demand across asset classes (see, e.g., Koijen and

[5] See, e.g., Vissing-Jorgensen (2003); Bacchetta, Mertens, and van Wincoop (2009); Amromin and Sharpe (2014); Greenwood and Shleifer (2014); Nagel and Xu (2023); Gormsen and Huber (2025).

[6] There are also several papers that study the expectations of Chinese fund managers, as Chinese regulation asks managers to provide market outlooks (see, e.g., Ammer, John and Rogers, John and Wang, Gang and Yu, Yang, 2022, 2025; Long, Yao, and Zaremba, 2025; D'Acunto, Liu, Ma, and Wu, 2025). Conceptually, these outlooks are similar to the outlooks that I study, but the outlooks of Chinese managers do not include a forward-looking tactical view variable, which is the main variable in my analysis.

Yogo, 2019; Gabaix and Koijen, 2021). Conceptually similar approaches of microfounding asset demand exist for households (see, e.g., Gabaix, Koijen, Mainardi, Oh, and Yogo, 2025), public pension funds (see, e.g., Andonov, Jansen, and Rauh, 2025), and target-date funds (see, e.g., Parker, Schoar, and Sun, 2023).

Fourth, as asset managers implement their TAA views at least partly via futures, the paper also contributes to a literature on the derivative usage of mutual funds (see, e.g., Koski and Pontiff, 1999; Choi, Kim, and Randall, 2024; Barth, Kahn, Monin, and Sokolinskiy, 2024). That asset managers use futures to implement their TAA views is consistent with Kaniel and Wang (2025), who show that mutual funds use derivatives to amplify, not hedge, equity returns. Further, as asset managers tend to be long futures and futures are in zero net supply, TAA views can also help explain time variation in short futures positions of dealers and hedge funds. This is relevant to understanding cash-futures basis trades (see, e.g., Barth and Kahn, 2025).

2 Data

2.1 Asset managers' tactical views

I hand-collect monthly and quarterly market outlook documents from 25 large asset managers.[7] Many of these documents are collected using the Wayback Machine, which stores historical webpages. The documents summarize past market movements, discuss the investment outlook, and often provide a table that summarizes the manager's tactical forward-looking views across asset classes. Figures A1, A2, and A3 in the Appendix provide examples of three such tables and the forward-looking expectations contained in them.

The tactical views are typically expressed on a scale from very underweight, underweight, neutral, overweight, to very overweight, which I map to a scale from -2 to $+2$ with 0

[7]These are: Allianz Global Investors, Amundi, Bank of America / Merril Lynch, Barclays, Blackrock, BNP Paribas, BNY Mellon, Citi, Columbia Threadneedle, DWS, Fidelity, Franklin Templeton, Invesco, Investec, JP Morgan, Morgan Stanley, NEI, Neuberger Berman, Nuveen, Santander, Schroders, T. Rowe Price, UBS, Wisdom Tree, and Wilmington Trust.

indicating neutrality. For a few managers, the scale ranges from -1 to $+1$ or from -3 to $+3$. The views are expressed relative to the long-term SAA. Figure A4 in the Appendix illustrates a model portfolio that highlights the difference between SAA and TAA with actual portfolio weights.

Forecast horizons differs slightly across managers, but the views generally express a forecast over a 3-18 month period. For instance, Fidelity in Figure A2 writes that "these views are informed by a subjective assessment of the relative attractiveness of asset classes and subclasses over a 6- to 18-month horizon." Importantly, as is evident from the figure, the views do not only reflect expected returns, but also risk considerations.

The asset classes that managers consider are not exactly standardized and not all asset managers provide views for the same asset classes. However, all asset managers provide forecasts for a set of "'broad" asset classes, which are primarily equities and fixed income (bonds). Some managers also treat cash, credit, or commodities as broad asset classes. Most managers also forecast a set of "narrower" asset classes that are nested within the broad asset classes (e.g., regional equity forecasts). As the views are expressed relative to the SAA, they are negatively correlated across broad asset classes. For instance, if an asset manager considers equities and fixed income as broad asset classes, they have to be underweight fixed income when they are overweight equities, and vice versa. I study views for equities, fixed income (bonds), cash, commodities, credit, and regional equity forecasts.

The earliest report I collect is from 2014 and the latest from 2025. There is a reasonable cross-section of seven managers as of 2018. Thus, the plots that show cross-sectional averages in this paper start in 2018. The panel regressions include all available data since 2014. Many managers publish monthly documents, but some only quarterly. Moreover, sometimes there are gaps in the data for a given asset manager. To obtain a more balanced panel and in order to be able to take meaningful cross-sectional averages at a given point in time, I forward fill managers' tactical views by up to 13 weeks.

2.2 BofA fund manager survey

The BofA fund manager survey is a monthly sentiment and positioning survey conducted by BofA. Each month, the survey gathers responses from roughly 150–250 institutional fund managers across the world, collectively overseeing hundreds of billions of dollars in assets under management. Respondents include traditional asset managers such as managers of mutual funds, but also asset owners such as pension funds or sovereign wealth funds. BofA compiles a summary document that shows aggregate responses for a variety of questions covering economic expectations and asset allocations. The summary document is reserved for BofA clients, but sometimes the document—or snippets thereof—can be found online.

As in Bastianello and Peng (2024), I infer aggregate responses to specific questions from plots in these documents using the WebPlotDigitizer tool. I then construct a time series of weekly data and interpolate between missing values. Even though I can only noisily infer aggregate responses from the plots without having access to the underlying data, the survey is a useful complement to the hand-collected data, as it provides a time series of more than 20 years (most of the BofA variables that I infer start in 2004).

2.3 Large-language model survey

The market outlook documents that I collect are text-based and, thus, I can create my own "survey" of asset managers by prompting a LLM. I ask ChatGPT-4o-mini to infer an asset manager's expectations about whether a global recession is likely or not, whether global equities are overvalued, whether financial market volatility is expected to increase, whether the global growth outlook is expected to improve, whether global inflation is expected to rise, whether short-term interest rates are expected to rise, and whether long-term interest rates are expected to rise.

For comparison purposes, the questions are framed similar to the ones in the BofA survey, and I collect answers on a discrete scale from -1, 0, to $+1$, with -1 indicating a fall/deterioration and $+1$ indicating a rise/improvement (for the directional questions). Similarly, BofA typically plots the net % of respondents that agree with a particular statement, a variable

that ranges from −100% to +100%. The complete prompt is in Appendix B. Similar to the hand-collected data on tactical views, I forward fill the responses from the LLM survey by up to 13 weeks.

2.4 Asset allocation funds

I match the tactical views of each manager with the funds that the manager manages using Morningstar's *BrandingName* variable, manager by manager. The sample is all alloctions funds globally (identified using Morningstar's *GlobalBroadCategoryGroup* variable), US domiciled and non-US domiciled. From Morningstar, I obtain data on asset allocation funds' portfolio weights across a variety of asset classes. I winsorize these portfolio weights at the 1st and 99th percentiles. Note that a given asset manager typically manages multiple funds. I drop target-date and exchanged-traded funds.

The final sample includes 2206 funds. These funds manage around USD 1.1 trillion in assets as of 2025. All allocation funds in Morningstar manage around USD 8.3 trillion. These are conservative estimates as Huang, Lu, Song, and Xiang (2025) show that funds in standard mutual fund databases have institutional twins, which the numbers in this paragraph do not account for.

I obtain portfolio weights for the following asset classes (variable names from Morningstar are in parentheses): equity (*AssetAllocEquityNet*), bonds (*AssetAllocBondNet*), cash (*AssetAllocCashNet*, credit (*FixedIncPrimarySectorCorporateBondNet*), emerging markets equities (*EquityRegionEmergingNet*), European equities (*EquityRegionEurozoneNet*), Japanese equities (*EquityRegionJapanNet*), and UK equities (*EquityRegionUKNet*).

2.5 Futures positioning data

The TFF report is a weekly breakdown, published by the CFTC, of the open interest in financial futures contracts such as interest rate futures, currencies, and equity indices. The TFF report classifies large trader positions into four categories: dealers / intermediaries, asset managers / institutional, leveraged funds, and other reportables. For the asset man-

ager category, the CFTC writes: "These are institutional investors, including pension funds, endowments, insurance companies, mutual funds and those portfolio/investment managers whose clients are predominantly institutional." Thus, similar to the BofA survey, the data not only include traditional asset managers, but also asset owners. Each weekly release shows how much open interest (i.e. the total number of contracts outstanding) is held long, short, and in spreading (i.e., both long and short) positions by each of those trader categories. The TFF is available since 2011.

Similar to Moskowitz, Ooi, and Pedersen (2012), I construct asset managers' (AM) net positions in a given futures contract as

$$\text{AM net positions} = \frac{\text{AM long positions} - \text{AM short positions}}{\text{Open interest}}. \tag{2}$$

This signed measure shows whether asset managers are net long or short in aggregate, and scales their net positions by the open interest. I collect futures positioning data for S&P 500 futures, Nikkei 225 stock index futures (i.e., Japanese equities), MSCI Emerging Markets Index futures (i.e., emerging markets equities), ten-year US Treasury notes futures, 3-month SOFR futures (i.e., cash), and Bloomberg Commodity Index futures.

Asset managers' S&P 500 net futures positions were worth around USD 260 billion as of 05/20/2025, and their ten-year US Treasury note futures positions were worth around USD 230 billion.[8] Barth et al. (2024) report that asset managers were exposed to 58% of USD 2.04 trillion in open interest as of January 2024 across all Treasury futures contracts (not just the ten-year futures contract).

Table 1 shows summary statistics for selected variables.

[8] As of 05/20/2025 asset managers held 1,126,011 long and 250,324 short positions in (consolidated) S&P 500 futures. The contract size is USD 50 times the S&P 500 index level. Technically, there are e-mini S&P 500 futures with a notional of USD 50 per contract, micro e-mini S&P 500 futures with a notional of USD 5, and there used to be S&P 500 futures with a notional of USD 250 per contract. I use the consolidated S&P 500 futures series, which consolidates all these economically equivalent contracts and which is scaled to a USD 50 notional. The S&P 500 index closed at 5,940.46 on 05/20/2025, so asset managers' net futures positions were worth around USD 260 billion.

3 Asset managers' expectations versus BofA survey

3.1 Tactical views versus BofA survey positioning

I start by comparing the hand-collected data on asset managers' forward-looking tactical views to survey responses from the BofA fund manager survey. In particular, the BofA survey asks respondents whether they are currently "overweight" equities and, similarly, whether they are "overweight" bonds.

Panel (a) of Figure 1 shows the net % of respondents in the BofA that are overweight equities (orange line and right y-axis) together with the average tactical view from the hand-collected data (blue line and left y-axis). The two lines correlate positively with each other. Interestingly, repositioning from overweight to underweight equities can happen rather swiftly (e.g., at the beginning of 2022). Panel (b) shows a similar plot for the average fixed income view and the net % of respondents in the BofA survey that are overweight bonds. As mentioned before, views for equities and bonds are negatively correlated, as managers have to be underweight one broad asset class when they are overweight another.

The time series is limited, but additional evidence comes from the cross section of asset classes. Figure 2 shows plots of the average tactical view for a given narrower asset class together with the net % of respondents in the BofA survey that are overweight that asset class. The BofA survey that I have access to considers cash, commodities, Japanese equities, European equities, UK equities, and emerging markets equities. In general, the average tactical views are positively correlated with positioning from the BofA survey.

Table 3 shows the corelation coefficients between the BofA survey net % overweight variable and the average tactical view for a given asset class. The table also shows p-values for the null hypothesis of a zero correlation. All correlations are positive and statistically different from zero, except for Japanese and emerging markets equities.[9]

[9]For the time series regressions and correlations in this paper, I compute the p-values using a stationary block bootstrap with an expected block length of one year, which accounts for serial correlation in the errors. As is standard practice, I impose the null hypothesis.

3.2 LLM survey versus BofA survey responses

Next, I compare the average survey response from the LLM survey of the text-based outlook documents to corresponding responses from the BofA survey. Recall that I prompt the LLM to infer a manager's expectations on a scale from -1, 0, and $+1$, and that, similarly, BofA plots the net % of respondents that agree with a particular statement. I then average managers' expectations from the LLM survey at a given point in time for a given question and plot them together with the BofA survey response.

Figure 3 shows these plots. The expectations from the LLM survey are highly correlated with the BofA survey responses. For instance, Panel (a) shows that the LLM infers that managers perceive a recession to be likely whenever BofA survey respondents perceive a recession to be likely. Similarly, Panel (b) shows that the LLM infers that managers expect the global growth outlook to improve whenever BofA survey respondents expect the growth outlook to improve. Panel (f) shows whether asset managers perceive equities to be overvalued. Consistent with historically high equity valuations over my sample period, the LLM score for whether equities are overvalued is on average positive.

It is worth emphasizing that the correlations between the LLM survey and the BofA survey seem unlikely to be mechanical. The prompt explicitly asks the LLM to only consider an attached .pdf document, without any reference to the BofA survey. I then average these responses at a given point in time across managers, and these averages correlate with the BofA survey responses. I also ask the LLM to provide a one-to-two sentence justification from the queried .pdf document, and these justifications seem reasonable. Finally, look-ahead bias in the responses also seems unlikely: the LLM infers a high likelihood of a recession in 2022 and 2025, but no recession has materialized subsequently.

4 Determinants of tactical views

This section studies the determinants of asset managers' tactical views. The LLM-survey answers from the previous section are endogenous and correlated with each other, which

makes them harder to interpret in a multivariate regression. For instance, the expected direction of short-term interest rates may be a function of expected inflation and growth (e.g., through a Taylor rule). The literature sometimes distinguishes between economic growth and inflation shocks as primitive macroeconomic shocks (see, e.g., Beber, Brandt, and Luisi, 2015; Dahlquist and Hasseltoft, 2020). Thus, I start by relating asset managers' tactical views to their perceived growth and inflation outlooks.

Specification (1) and (2) of Panel A in Table 3 show the results of time-series and cross-sectional regressions of asset managers' tactical equity views on their perceived directions of economic growth and their perceived directions of inflation, which I obtain from the LLM survey. Specifications that include manager fixed effects identify the coefficients using time-series variation, whereas specifications that include time fixed effects identify the coefficients using cross-sectional variation. Specifications (1) and (2) of Panel B repeat these specifications, but the dependent variable is the tactical fixed income view.

The p-values for the null hypothesis of a zero coefficient are in parentheses. In the panel regressions regression errors are likely correlated within managers, as expectations tend to be persistent. As in Dahlquist and Ibert (2024b), I obtain the p-values for tests of zero coefficients using a wild cluster bootstrap with the null hypothesis imposed (see Roodman, Nielsen, MacKinnon, and Webb, 2019). I resample the residuals at the manager level, which accounts for the within-manager correlation in the errors, and I compute the variance-covariance matrix to compute the t-statistic for each simulation run using double clustered standard errors by manager and time.[10]

Specifications (1) and (2) show that an increase in the expected growth outlook is associated with larger tactical views for equities and lower tactical views for fixed income, both in the time series and the cross section. For instance, in specification (1) of Panel A, a one-unit

[10] Alternatively, one could instead rely entirely on asymptotic cluster-robust standard errors clustered by manager (and by time), but the number of clusters (managers) is arguably too small for the asymptotic theory underlying clustered inference to be reliable. Moreover, the panel data are unbalanced. The wild cluster bootstrap is recommended in such cases, as conventional cluster-robust tests tend to be oversized when the number of clusters is small and the panel is unbalanced (see, e.g., MacKinnon, Nielsen, and Webb, 2023). Consistent with this, in my results the p-values from clustered standard errors are typically smaller than those from the wild cluster bootstrap.

increase in the expected growth outlook is associated with a 0.416 larger tactical view on equities. While the coefficient estimates for the perceived direction of inflation are in general negative, the coefficient estimates are not statistically different from zero.

That an increase in perceived growth is associated with a higher equity view is not obvious. It means that tactical equity views are procyclical in the time series, i.e., high when expected growth is high and low when expected growth is low. The views trade off risk against return, and conventional wisdom suggests that equity Sharpe ratios—a typical measure of risk versus return—are countercyclical over the business cycle (see, e.g., Campbell and Cochrane, 1999; Lustig and Verdelhan, 2012). For instance, in Campbell and Cochrane (1999) the representative agent expects higher Sharpe ratios when expected growth is low (i.e., in a recession). Related, Giglio et al. (2021) highlight that in rare-disaster models the representative agent expects higher equity returns when they expect a higher chance of a disaster, but they find that Vanguard investors expect the opposite.[11]

Whether procyclical tactical views are rational or not remains an open question. The results in Gómez-Cram (2022) suggest that there is some merit to procyclical views in recessions (see also Moench and Stein, 2021). Further, Jensen and Lazarus (2025) argue that expected return to variance ratios, in contrast to Sharpe ratios, are actually procyclical. What can be said, in combination with the sections that follow, is that asset managers are not increasing their equity portfolio weights when the growth outlook deteriorates (i.e., they are not buyers of equity).

Specifications (3) and (4) in each panel of Table 3 add further variables from the LLM survey. First, the perceived growth outlook remains robustly associated with the tactical views. Second, taking the partial-equilibrium logic from above as given, the coefficient estimates on the remaining variables have the expected signs, though statistical significance is sometimes mixed. The perceived chance of a recession is associated with a lower equity view and a larger fixed income view. A perceived rise in long-term interest rates is associated

[11] That an increase in perceived growth is associated with lower fixed income views is likely related to the fact that bonds have hedged equity risks over the last two decades and that recessions have been deflationary (see, e.g., Campbell, Sunderam, and Viceira, 2009; Campbell, Pflueger, and Viceira, 2020).

with a lower fixed income view. Higher perceived equity valuations are associated with lower equity views and larger fixed income views. Equity valuations can be converted to expected equity returns under an AR(1) assumption (see, e.g., Bastianello and Peng, 2024).

The first four specifications in each panel use expectations from the LLM survey that are available since 2014. The previous section shows that the forward-looking tactical views correlate positively with the current positioning data from the BofA survey. Moreover, the LLM survey responses correlate positively with the corresponding responses from the BofA survey. The BofA data are available since 2004, so it seems to natural to use the BofA data to extend the time series. Thus, specification (5) in each panel runs a time-series regression using the aggregated responses from the BofA survey. In general, specification (5) in each panel confirms the previous results: an increase in the perceived growth outlook and a decrease in the perceived chance of a recession are associated with larger equity views, whereas the opposite is true for fixed income views.

5 Tactical views and allocation funds' portfolio weights

5.1 Broad asset classes

This section estimates the sensitivities of allocation mutual funds' portfolio weights to asset managers' tactical asset allocation views.

Equation (1) implies a regression. From Equation (1), I want to control for a fund's strategic asset allocation to identify θ, which is the sensitivity to tactical asset allocation views. Although strategic and tactical asset allocations may be correlated and sometimes difficult to distinguish (e.g., SAAs are based on valuations, see Dahlquist and Ibert, 2024b, and TAAs can be, too, as the examples in the appendix show), controlling for a fund's SAA ensures that managers' actually act on their tactical views and not just their strategic ones.

Specification (1) in Panel A of Table 4 shows a regression of the equity portfolio weight on the tactical equity view. The p-values for the null hypothesis of a zero coefficient from a wild cluster bootstrap are once again in parentheses. The specification includes fund fixed

effects. If SAAs are constant over time, they are absorbed by the fund fixed effects.

It does not seem unreasonable to assume that SAAs are constant over time for the allocation mutual funds that I study. Presumbaly, long-term strategic expectations determine the investment mandate of a fund and mandates are constant over time. For instance, a manager who is strategically bearish on equities may launch funds with low target equity allocations (e.g., 20-80 as opposed to 60-40 funds). The coefficient estimate on the tactical equity view is 0.873, meaning that a one-unit increase in the tactical view is associated with a 0.873-percentage-point larger allocation to equities. Recall that the tactical view variable typically ranges from -2 to $+2$.

That said, strategic asset allocations may vary over time. In a standard portfolio choice model with one risky asset, the strategic asset allocation to the risky asset is $w = 1/\gamma(\mu - r_f)/\sigma^2$, where μ is the long-term expected return on the risky asset. So, if strategic asset allocations vary over time, one of their key drivers is the long-term equity premium $\mu - r_f$. Thus, specification (2) in Panel A of Table 4 controls for a measure of the "objective" long-term equity premium that is constructed as the inverse of the US cyclically-adjusted price-to-earnings ratio (CAPE) less a long-term real interest rate (as in Dahlquist and Ibert, 2024b). The coefficient estimate on the tactical view is 0.800 and similar to above, whereas the coefficient estimate on the long-term equity premium is not statistically different from zero.

For twelve managers in the sample, I have data on their actual subjective long-term (US) equity premium expectations based on Capital Market Assumptions (the data come from Dahlquist and Ibert, 2024b). Specification (3) controls for these subjective equity premia. While the sample size is reduced, the results are similar to the one in specification (2). This is expected as Dahlquist and Ibert (2024a,b) show that time-series variation in long-term subjective equity premia is well described by the long-term objective equity premium above.

Specification (4) in Panel A of Table 4 includes time fixed effects as opposed to fund fixed effects and thereby identifies the coefficient estimate on the tactical view using cross-sectional variation. The coefficient estimate on the tactical view is not statistically different from zero. Moreover, the adjusted R^2 is significantly lower compared to the specifications

with fund fixed effects. As one could expect, the cross-sectional variation in asset allocation funds' equity portfolio weights is mostly driven by preset target (strategic) asset allocations (e.g., whether a fund has a 20% target equity allocation or an 80% one) as opposed to short-term tactical views.

Panel B of Table 4 repeats the analysis of Panel A with the bond portfolio weight as the dependent variable and the fixed income tactical view as the independent variable. The results are generally similar compared to Panel A, but the coefficient estimates on the tactical views are slightly larger, ranging from 1.472–1.607. Moreover the coefficient estimate on the objective equity premium is statistically different from zero in specification (2), with the expected sign.

Economically, the coefficient estimates are arguably small. The tactical view variables range from -2 to $+2$. Hence, with the most extreme change of views, the tactical view variable changes by four units. This implies a $4 \times 1.607 = 6.43$ percentage point change in fixed income weights, using the largest sensitivity estimate. More realistically, the tactical view variable varies from -1 tom $+1$ (see Figure 1). The small economic magnitudes imply that investment mandates are rather tight. That is, fund managers stay close to their benchmark weights, even when they perceive a short-term active opportunity.

Table 4 shows specifications with portfolio weights as the dependent variable, not accounting for mechanical weight changes due to realized returns. Said differently, the table shows that, in the end, asset managers have one to two percentage points lower weights on equities when they are underweight rather than overweight equities, but not how much of that underweight position is due to potentially low realized returns on equities. Unfortunately, I do not have data on the returns earned on the equity and bond parts of asset managers' allocation funds to back out active trades (i.e., changes in quantities). That said, the next section studies quantities (futures positions) and provides evidence that allocation funds actively change their exposures to different asset classes over time.[12]

[12]The futures analysis scales asset manager net long positions by open interest, which can move even if asset managers do not change their net long positions. However, the results in the next section seem to be driven by changes in asset manager net long positions rather than changes in open interest.

Figure 4 summarizes some results from this subsection. The figure plots the average allocations to equities and bonds for the asset managers in the sample together with their average equity and fixed income tactical views.[13]

5.2 Narrow asset classes

Additional evidence once again comes from the cross section of asset classes. Table 5 shows regression of portfolio weights in narrow asset classes across equities and fixed income on their respective tactical views. For instance, specification (1) shows a regression of asset allocation funds' portfolio weights in emerging markets equities on the respective asset managers' tactical views on emerging markets equities. All regressions control for the respective broad asset class view (equity or fixed income). The reason is that, for instance, emerging markets equities portfolio weights might be higher just because the broad stance on equities is "overweight."

The table shows results that are broadly consistent with the ones from the previous subsection. That is, narrow asset class views are positively related to their portfolio weights in asset managers' allocation funds. For instance, specification (1) in Table 5 shows that a one-unit increase in the tactical view on emerging markets equities is associated with a 0.23-percentage-point larger portfolio weight on emerging markets equities (the average weight on emerging market equities is 6.58%, see Table 1). In general, all coefficient estimates are positive, and four out of six are statistically different from zero.

6 Tactical views and futures positioning

Futures are highly liquid and only require margin, not full cash outlay. Thus, it is natural to hypothesize that asset managers "overlay" (on top of their SAA) short-term TAA views via futures. The asset allocation weights from Section 5 in principle include futures positions, as Morningstar adjusts the weights for derivative exposures. However, the previous analysis

[13] As some funds have a quarterly reporting period for holdings and some have a monthly one, the data underlying the figure interpolates between missing holdings to eliminate such seasonalities.

does not tell whether asset managers buy spot or via derivatives. A direct test for whether asset managers use futures to implement their TAA views is to regress the futures positioning data from the CFTC on asset managers' TAA views.

Panel A of Table 6 shows regressions of net futures positions scaled by open interest by asset class on the corresponding tactical view variable.[14] As before, whenever the dependent variable corresponds to a narrow asset class, I include the broad asset class view as a control variable.

Panel A shows results that are largely consistent with the results from the previous subsections, particularly for the broad asset classes of equities, bonds, and commodities. For instance, specification (1) shows that a one-unit increase in the tactical view on equities is associated with a three-percentage-point larger asset manager net position in S&P 500 futures. Specification (4) shows that a one-unit increase in the tactical view on fixed income is associated with a six-percentage-point increase in US ten-year treasury note futures positions. The results for the narrow asset classes are mixed and in general not statistically different from zero.

The results for S&P 500 futures are broadly consistent with Kaniel and Wang (2025) who show that—contrary to prior research—mutual funds use derivatives to amplify, not hedge, equity returns. Kaniel and Wang (2025) use fund-by-fund data on derivatives usage from regulatory N-PORT filings, which are available since 2019. Indeed, specification (1) in Panel A of Table 6 suggests that asset managers use equity futures to express their TAA views.

Economically, the coefficient estimates are not directly comparable to the ones from the previous subsection, as the dependent variable is not a portfolio weight. However, the coefficient estimates are in the same ballpark as before once the dependent variable is standardized. For instance, from Table 4, a one-unit increase in the tactical view on equities was associated with a 0.872-percentage-point larger equity share. The time-series standard

[14] Panel A shows panel regressions. As the dependent variable is constant for a given cross section, the panel regressions are akin to a time-series regression of futures positions on the cross-sectional averages of the tactical views. In the panel regression, as the dependent variable is constant for a given cross section, the errors are correlated for a given cross section. The wild cluster bootstrap allows the errors to be correlated for a given cross section (as well as for a given manager).

deviation of allocation funds' equity shares is around 6%, so this represents a move of about 1/6 of a standard deviation. The standard deviation of asset managers' net futures positions is around 10%. Thus, a three-percentage-point move represents a little less than 1/3 of a standard deviation. I compute the time-series standard deviation as the cross-sectional average of the time-series standard deviations of portfolio weights for each fund.

Panel B of Table 6 repeats the specifications shown in Panel A but again using only variables from the BofA survey that are available for a longer time series. In general, Panel B confirms the results of Panel A. For instance, specification (1) in Panel B shows that when the respondents in the BofA survey turn from 0% overweight to 100% overweight equities, S&P 500 net futures positions scaled by open interest increase by around ten percentage points.

Figure 5 plots asset managers' S&P 500 and US ten-year note futures positions over time together with the cross-sectional average of the corresponding tactical views at each point in time. The plots also include the aggregate BofA survey responses that are available for a longer time series. The figure confirms the regression results from Table 6 and shows a high time-series correlation between all three series. For completeness Figure 6 provides similar plots for the narrower asset classes.

Futures are in zero net supply, but asset manager demand for futures still transmits to spot markets through hedging of dealers and hedge funds. Figure 5 shows that asset managers are net long futures. For S&P 500 futures, the TFF data show that dealers tend to take the short positions. For ten-year US treasury note futures, leveraged funds (a.k.a. hedge funds) tend to take the short positions. The leveraged funds' short positions in Treasury futures are part of a well-known basis trade (see, e.g., Barth and Kahn, 2025), in which leveraged funds sell Treasury futures and buy spot.

7 Conclusion

There is no role for understanding asset demand in representative agent asset pricing models—prices adjust such that the representative agent is content to hold the supply of

assets. However, understanding asset demand of different market participants is central to the demand-system models that have recently been developed in the asset pricing literature (see, e.g., Gabaix and Koijen, 2021). Offering support for such models, practitioners are frequently concerned with flows and "positioning" across asset classes, as is evident from the BofA fund manager survey.

Understanding what shapes the asset demand of asset managers is particularly important. The world portfolio of all investable assets is estimated to be around USD 250 trillion, 50% of which are held by asset managers. This paper hand-collects and analyzes the TAA views of large asset managers. I show that the perceived economic growth outlook and the perceived chance of a recession are the key determinants of TAA views across asset classes. TAA views are reflected in the time-series allocations of allocation funds and are likely implemented via futures. I estimate that asset managers have 1.8 to 3.2 percentage points lower equity portfolio weights when they turn from overweight equities to underweight equities. That said, while statistically significant, the estimated sensitivities are arguably economically small. In turn, the large equity price changes typically associated with a turning economic outlook are broadly consistent with the inelastic markets hypothesis.

It is also worth emphasizing that asset managers' short-term expectations and asset allocations are remarkably consistent across four different datasets: the hand-collected data on TAA views, the BofA fund manager survey, the asset allocation fund data from Morningstar, and the CFTC futures positioning data. Finally, the results also illustrate how LLMs can be used to extract expectations from unstructured text, allowing researchers to build datasets of institutional expectations that were previously inaccessible.

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Table 1: Summary statistics

	Mean	SD	p5	p25	p50	p75	p95	N
Panel A: Tactical asset allocation views								
Equities	0.16	0.89	−1.00	−1.00	0.00	1.00	1.00	4052
Bonds	−0.25	0.92	−2.00	−1.00	0.00	1.00	1.00	3885
Cash	0.23	0.93	−1.00	−1.00	0.00	1.00	1.00	2328
Commodities	0.16	0.69	−1.00	0.00	0.00	1.00	1.00	1775
Credit	0.45	0.74	−1.00	0.00	0.00	1.00	2.00	1004
EM equities	0.39	0.84	−1.00	0.00	0.00	1.00	2.00	3079
EU equities	−0.15	0.87	−2.00	−1.00	0.00	0.50	1.00	2126
UK equities	−0.12	0.82	−2.00	0.00	0.00	0.00	1.00	1261
Japan equities	0.24	0.74	−1.00	0.00	0.00	1.00	1.00	2153
Panel B: BofA fund manager survey net % overweight								
Equities	25.95	27.60	−31.07	8.19	34.87	47.71	57.90	1020
Bonds	−45.40	21.06	−69.53	−60.55	−50.80	−35.26	5.10	1020
Cash	23.88	13.74	1.96	13.52	23.07	34.71	45.96	1020
Commodities	0.73	14.70	−26.02	−7.97	1.80	10.51	23.90	906
EM equities	17.64	19.98	−17.13	2.47	21.02	33.29	44.62	1019
EU equities	13.80	24.13	−28.69	−3.76	15.99	34.19	47.96	1016
UK equities	−17.55	10.93	−36.30	−25.30	−17.11	−10.35	−0.18	1018
Japan equities	6.09	21.33	−26.75	−9.89	3.77	22.59	42.05	1019
Panel C: Large-language model survey								
Growth (g)	0.12	0.90	−1.00	−1.00	0.00	1.00	1.00	4052
Recession prob.	0.07	0.67	−1.00	0.00	0.00	1.00	1.00	4052
Inflation (π)	0.18	0.73	−1.00	0.00	0.00	1.00	1.00	4052
Panel D: Asset allocation funds portfolio weights (in %)								
Equities	43.43	25.54	0.00	23.90	43.09	62.10	87.54	56319
Bonds	39.62	24.26	0.00	21.00	38.51	57.41	81.67	52115
Cash	7.17	11.29	−2.42	2.03	4.93	9.72	24.84	18121
Credit	17.97	14.56	0.00	5.85	15.78	28.47	42.76	27490
EM equities	6.58	14.15	0.00	0.80	2.56	5.38	30.60	37281
EU equities	8.22	11.95	0.00	2.00	4.88	8.76	30.74	43705
UK equities	4.21	6.54	0.00	0.59	1.90	4.08	20.04	30241
Japan equities	1.93	2.16	0.00	0.03	1.32	3.05	6.10	42515
Panel E: Net futures positions scaled by open interest (in %)								
S&P 500	24.98	9.62	9.27	18.26	25.31	30.42	43.74	748
UST 10-year	10.29	14.81	−16.18	0.77	8.32	23.88	31.93	748
SOFR 3-month	−0.46	4.91	−8.30	−3.43	−0.44	2.11	8.64	358
BBG Comm.	32.36	24.39	0.04	12.64	28.67	51.83	73.15	747

The table shows summary statistics for tactical asset allocation views (Panel A), the respondents in the BofA survey that are net & overweight in a given asset class (Panel B), the large-language model survey using the text-based market outlooks (Panel C), the portfolio weights of allocation funds in a given asset class (Panel D), and asset managers' net futures positions scaled by open interest (Panel E). The data dimensions are manager-week in Panel A, week in Panel B, manager-week in Panel C, fund-month in Panel D, and week in Panel E. The shown summary statistics are means, standard deviations (SD), and percentiles (p).

Table 2: Correlations between tactical views and net % overweight from BofA survey

Asset class	N	ρ	p-value (H_0: $\rho = 0$)
Equities	285	0.797	0.000
Fixed income	284	0.827	0.000
Cash	286	0.581	0.010
Commodities	282	0.660	0.000
Japanese equities	285	0.247	0.260
European equities	278	0.545	0.009
UK equities	267	0.472	0.042
Emerging markets equities	285	0.251	0.270

The table shows time-series correlations between average (across managers) tactical asset allocation views and the net % of BofA survey respondents that are overweight in the corresponding asset class. The data frequency is weekly. The table also shows p-values for the null hypothesis of a zero correlation. The p-values are obtained using a stationary block bootstrap with an expected block length of 52 weeks, with the null hypothesis imposed.

Table 3: Tactical views versus expectations about macroeconomic fundamentals

	Panel A: Equities					*Panel B: Fixed income*				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Growth	0.416	0.310	0.239	0.163	0.325	−0.342	−0.299	−0.199	−0.227	−0.061
	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)	(0.000)	(0.014)	(0.010)	(0.008)	(0.155)
Inflation	−0.036	−0.041	−0.065	−0.008	−0.146	−0.124	−0.097	−0.076	−0.085	0.137
	(0.333)	(0.370)	(0.031)	(0.854)	(0.098)	(0.136)	(0.141)	(0.245)	(0.094)	(0.036)
Recession prob.			−0.274	−0.143	−0.392			0.199	0.026	0.290
			(0.003)	(0.114)	(0.000)			(0.023)	(0.543)	(0.000)
Short-term rates			−0.082	−0.041	0.144			−0.048	0.039	−0.088
			(0.168)	(0.500)	(0.070)			(0.510)	(0.527)	(0.090)
Long-term rates			0.086	−0.013	−0.139			−0.195	−0.127	−0.249
			(0.100)	(0.779)	(0.360)			(0.020)	(0.094)	(0.038)
Volatility			−0.141	−0.174				−0.008	−0.017	
			(0.094)	(0.061)				(0.934)	(0.902)	
Equity valuations			−0.199	−0.389	−0.021			0.160	0.252	−0.232
			(0.002)	(0.001)	(0.792)			(0.020)	(0.012)	(0.014)
N	4052	3913	4039	3900	881	3886	3748	3873	3735	880
Time FE	N	Y	N	Y		N	Y	N	Y	
Manager FE	Y	N	Y	N		Y	N	Y	N	
Adj. R^2	0.364	0.268	0.427	0.362	0.718	0.378	0.309	0.428	0.337	0.705

The table shows regressions of tactical asset allocation views for equities (Panel A) and fixed income (Panel B) on perceived macroeconomic fundamentals. Specifications (1)–(4) of each panel use panel data on asset managers' tactical asset allocation views and their perceptions, which are obtained using a large-language model survey. Specification (5) in each panel uses weekly time-series data on the net % of respondents from the BofA survey that are overweight equities (Panel A) or bonds (Panel B), together with perceptions from the BofA survey. p-values for the null hypotheses of zero coefficients are in parentheses. The p-values in specifications (1)–(4) are from a wild-cluster bootstrap with the null hypothesis imposed, bootstrapping by manager and double clustering the variance-covariance matrix by week and manager in each simulation run. The p-values in both specifications (5) are from a stationary block bootstrap with an expected block length of 52 weeks, with the null hypothesis imposed.

Table 4: Allocation funds' portfolio weights versus tactical views

Panel A: Equities

	(1)	(2)	(3)	(4)
Tactical view equities	0.872	0.798	1.143	1.999
	(0.000)	(0.005)	(0.016)	(0.274)
Obj. equity premium		−0.480		
		(0.229)		
Subj. equity premium			−0.733	
			(0.133)	
N	56319	56319	20305	56446
Time FE	N	N	N	Y
Fund FE	Y	Y	Y	N
Adj. R^2	0.871	0.872	0.872	0.015

Panel B: Fixed income

	(1)	(2)	(3)	(4)
Tactical view fixed income	1.612	1.477	1.522	0.517
	(0.000)	(0.000)	(0.001)	(0.273)
Obj. equity premium		−0.936		
		(0.000)		
Subj. equity premium			−0.448	
			(0.072)	
N	52115	52115	20306	52208
Time FE	N	N	N	Y
Fund FE	Y	Y	Y	N
Adj. R^2	0.857	0.858	0.857	0.009

The table shows regressions of asset allocation funds' portfolio weights in equities (Panel A) and bonds (Panel B) on the equity and fixed income tactical asset allocation views of the corresponding asset manager. The data dimension is fund-month. Obj. equity premium refers to $\ln(1+1/\text{CAPE})-r_f$, where CAPE is Shiller's cyclically-adjusted price-to-earnings ratio and r_f is the ten-year real US Treasury yield. Subj. equity premium refers to the corresponding asset managers' long-term US subjective equity premium from Dahlquist and Ibert (2024b). p-values for the null hypotheses of zero coefficients are in parentheses. The p-values are from a wild-cluster bootstrap with the null hypothesis imposed, bootstrapping by manager and double clustering the variance-covariance matrix by month and manager in each simulation run.

Table 5: Allocation funds' portfolio weights versus narrow tactical views

Panel A: Equities

	(1) EM	(2) EU	(3) UK	(4) Japan
Narrow asset class view	0.227	0.240	0.050	0.075
	(0.043)	(0.019)	(0.440)	(0.006)
Tactical view equities	−0.113	0.002	−0.105	0.036
	(0.208)	(0.097)	(0.098)	(0.378)
N	37281	43705	30241	42515
Time FE	N	N	N	N
Fund FE	Y	Y	Y	Y
Adj. R^2	0.963	0.935	0.940	0.817

Panel B: Fixed income

	(1) Cash	(2) Credit
Narrow asset class view	0.290	1.393
	(0.295)	(0.000)
Tactical view fixed income	0.054	−0.010
	(0.859)	(0.971)
N	18121	27490
Time FE	N	N
Fund FE	Y	Y
Adj. R^2	0.552	0.824

The table shows regressions of asset allocation funds' portfolio weights in emerging markets (EM) equities, European equities (EU), United Kingdom equities (UK), and Japanese equities (all in Panel A) as well as in cash and credit (in Panel B) on the corresponding asset class views of the corresponding asset manager. I refer to all these asset classes as "narrow" asset classes. Credit refers to corporate bonds. All specifications also include the managers' tactical asset allocation views on equities and fixed income ("broad" asset classes), respectively. The data dimension is fund-month. p-values for the null hypotheses of zero coefficients are in parentheses. The p-values are from a wild-cluster bootstrap with the null hypothesis imposed, bootstrapping by manager and double clustering the variance-covariance matrix by month and manager in each simulation run.

Table 6: Futures positions versus tactical views and BofA survey positioning

Panel A: Futures positions on tactical views

	Equities			Fixed income		Commodities
	(1) US	(2) EM	(3) Japan	(4) Bonds	(5) Cash	(6) Commodities
Asset class view	3.122	−0.431	2.776	5.768	0.418	11.516
	(0.002)	(0.750)	(0.128)	(0.016)	(0.230)	(0.002)
Broad asset class view		1.054	3.272		0.130	
		(0.338)	(0.076)		(0.615)	
N	4471	3448	2299	4294	2175	2031
Manager FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.171	0.098	0.194	0.289	0.032	0.172

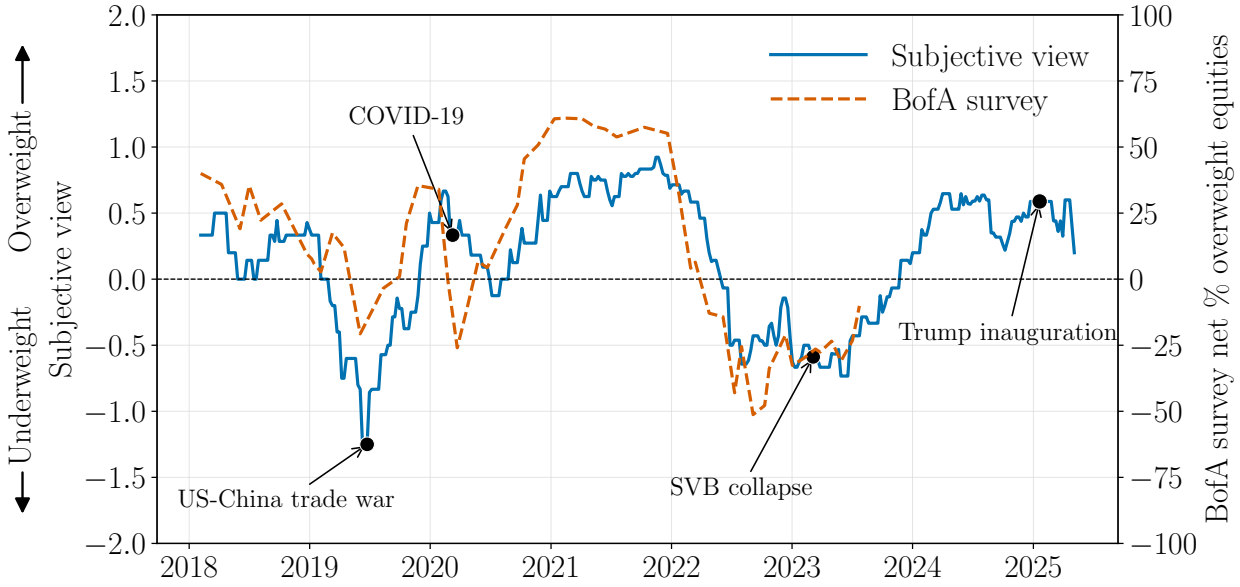
Panel B: Futures positions on BofA survey net % overweight

	Equities			Fixed income		Commodities
	(1) US	(2) EM	(3) Japan	(4) Bonds	(5) Cash	(6) Commodities
Net % OW	0.106	0.338	0.269	0.332	−0.039	0.548
	(0.034)	(0.002)	(0.104)	(0.016)	(0.494)	(0.068)
Net % OW (broad)		0.114	−0.013		0.038	
		(0.422)	(0.892)		(0.374)	
N	654	631	654	653	262	650
Adj. R^2	0.137	0.276	0.137	0.219	0.050	0.119

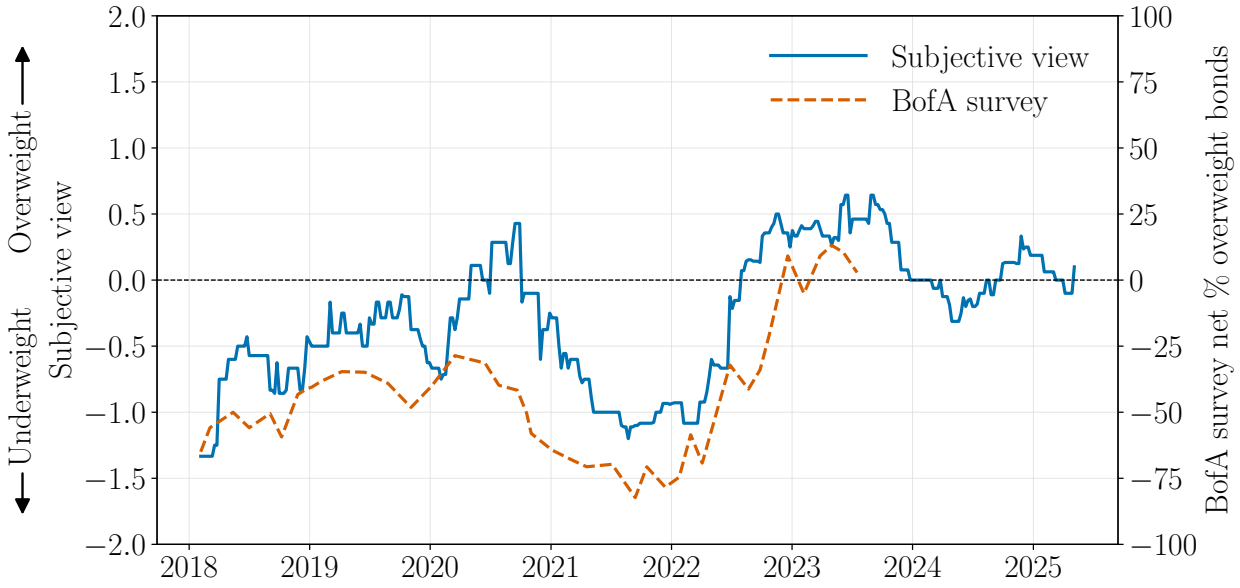
Panel A of the table shows regressions of net futures positions scaled by open interest in a given asset class (e.g., S&P 500 futures) on corresponding tactical asset allocation views (e.q., equities). Panel B shows regressions of net futures positions scaled by open interest on the net % of respondents in the BofA survey that are overweight in the corresponding asset class. Specifications (2) and (3) in Panel A also include the asset managers' tactical view on the broad asset class of equities, and specification (5) includes the broad tactical view on fixed income. Similarly, specifications (2), (3), and (5) in Panel B include the net % of respondents in the BofA survey that are overweight broad equities and bonds, respectively. Specifications (1) in both panels consider S&P 500 futures, (2) MSCI Emerging Markets Index futures, (3) Nikkei 225 futures, (4) ten-year US Treasury note futures, (5) three-month SOFR futures), and (6) Bloomberg Commodity Index futures. The data dimensions are manager-week in Panel A and week in Panel B. p-values for the null hypotheses of zero coefficients are in parentheses. The p-values in Panel A are from a wild-cluster bootstrap with the null hypothesis imposed, bootstrapping by manager and double clustering the variance-covariance matrix by week and manager in each simulation run. The p-values in Panel B are from a (residual) stationary block bootstrap with an expected block length of 52 weeks, with the null hypothesis imposed.

Figure 1: Subjective broad asset class views and BofA survey positioning

(a) Equity view and BofA survey net % overweight equities

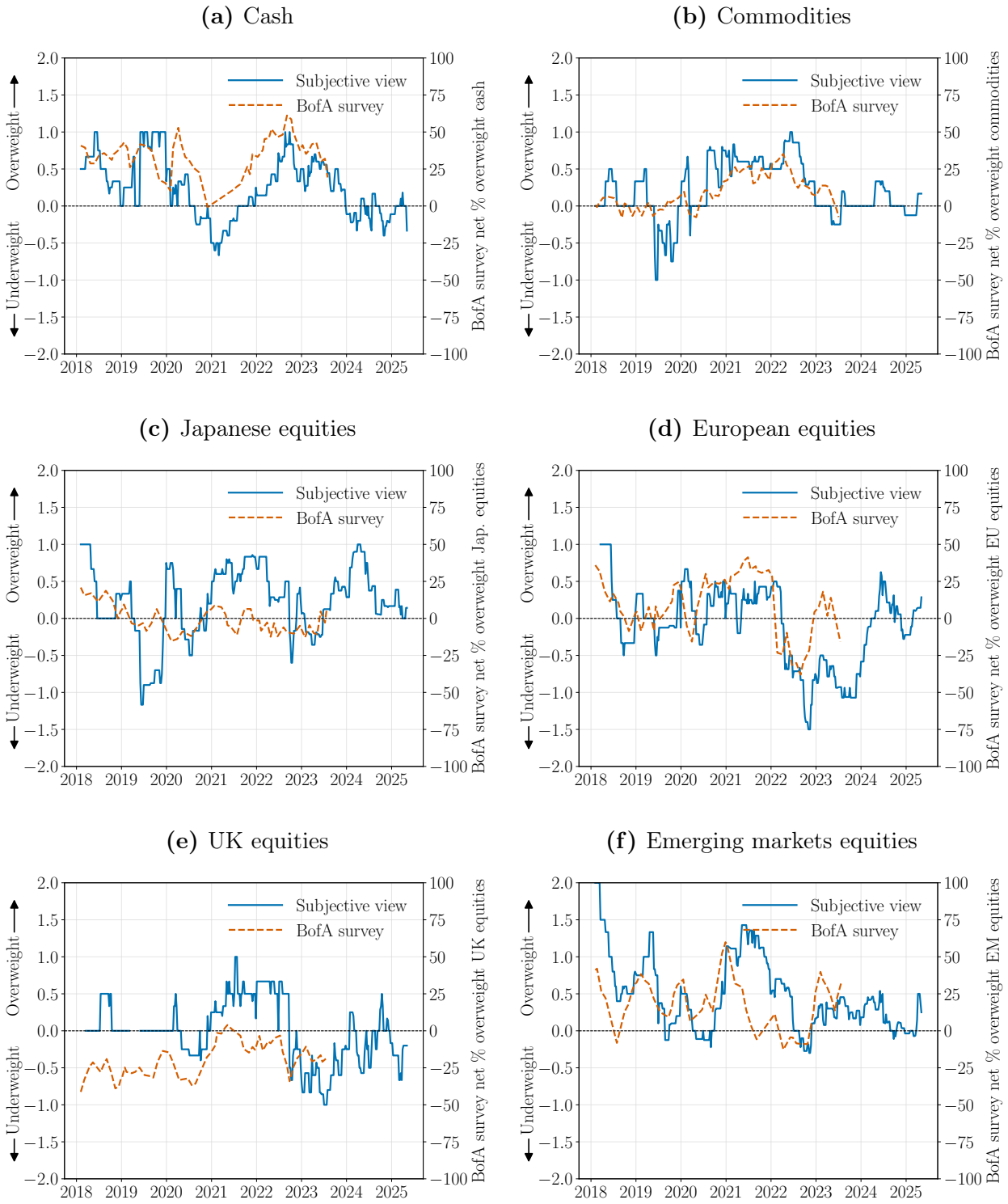


(b) Fixed income view and BofA survey net % overweight bonds



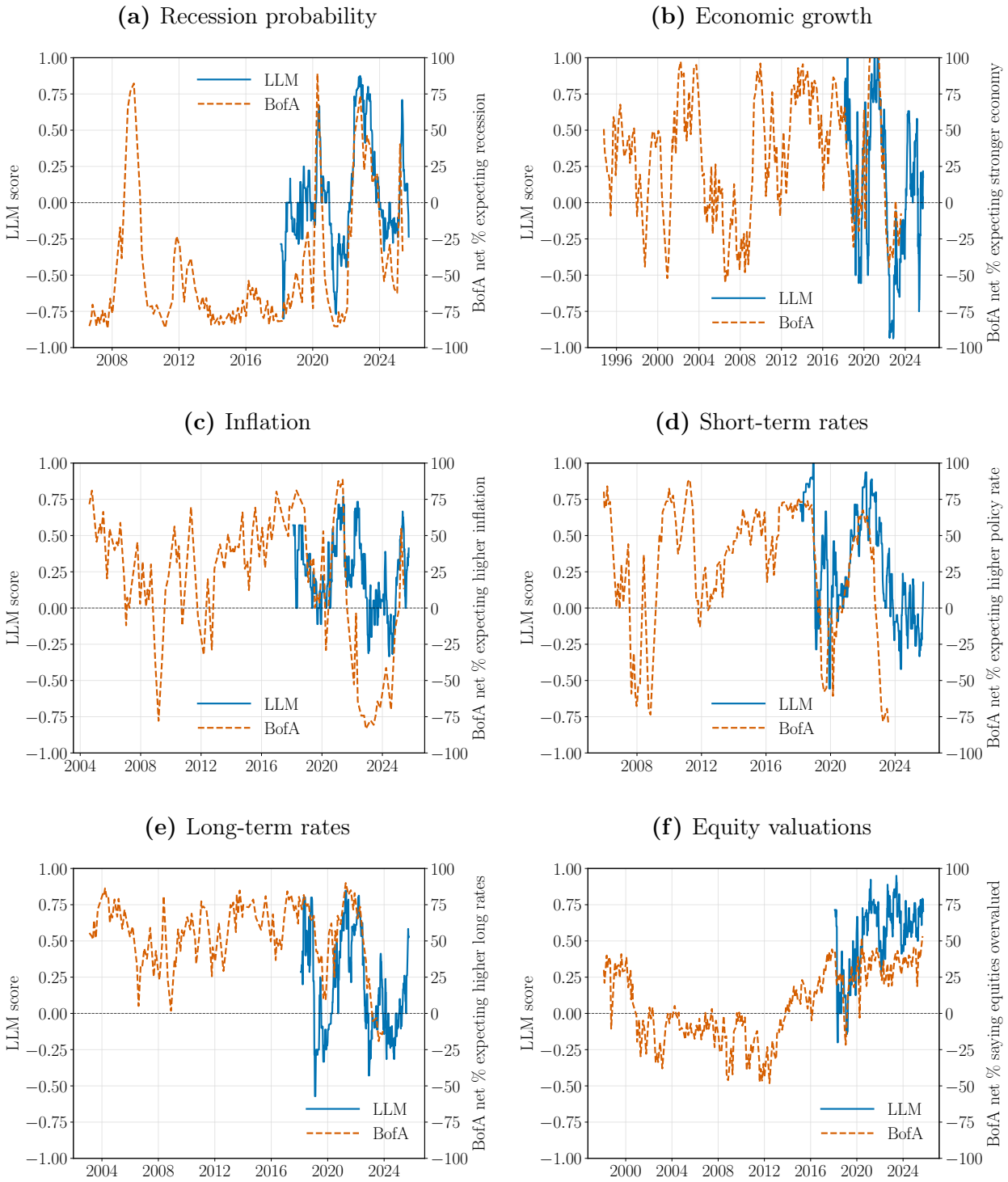
The figure plots asset managers' average tactical views for equities and fixed income together with the net % of respondents in the Bank of America Global Fund Manager Survey that are overweight equities and bonds, respectively. Views are typically expressed on a scale from −2 to +2, with 0 indicating "neutral."

Figure 2: Subjective narrow asset class views and BofA survey positioning



The figure plots asset managers' average tactical views across narrow asset classes together with the net % of respondents in the Bank of America Global Fund Manager Survey that are overweight a particular asset class. Views are typically expressed on a scale from −2 to +2, with 0 indicating "neutral."

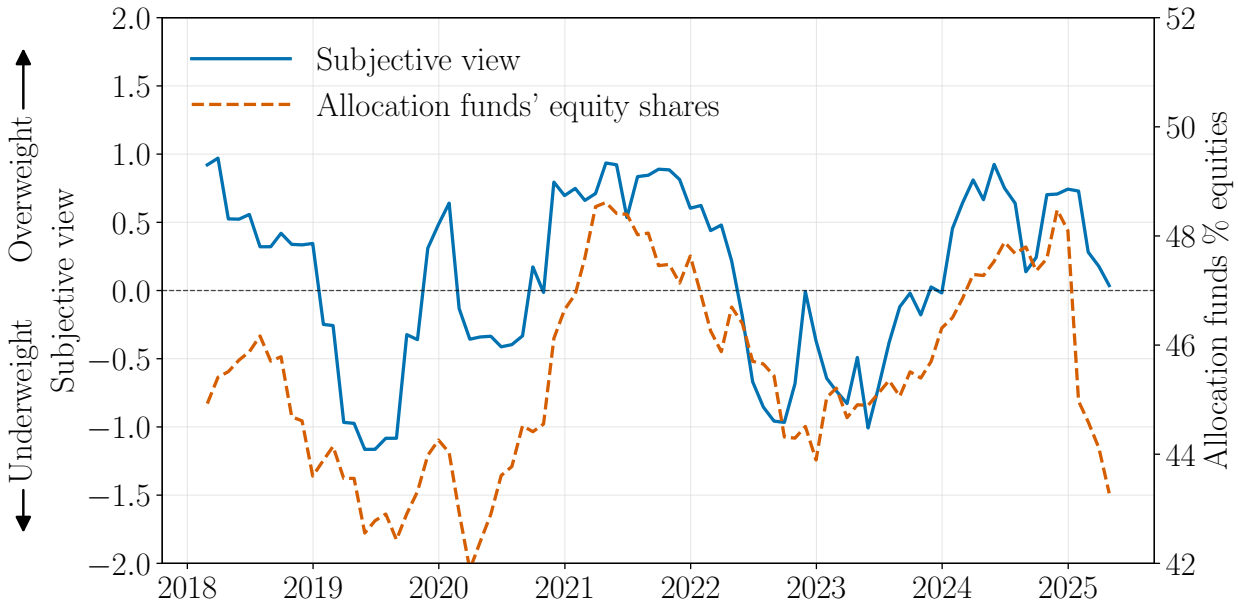
Figure 3: LLM survey of macro variables versus BofA survey



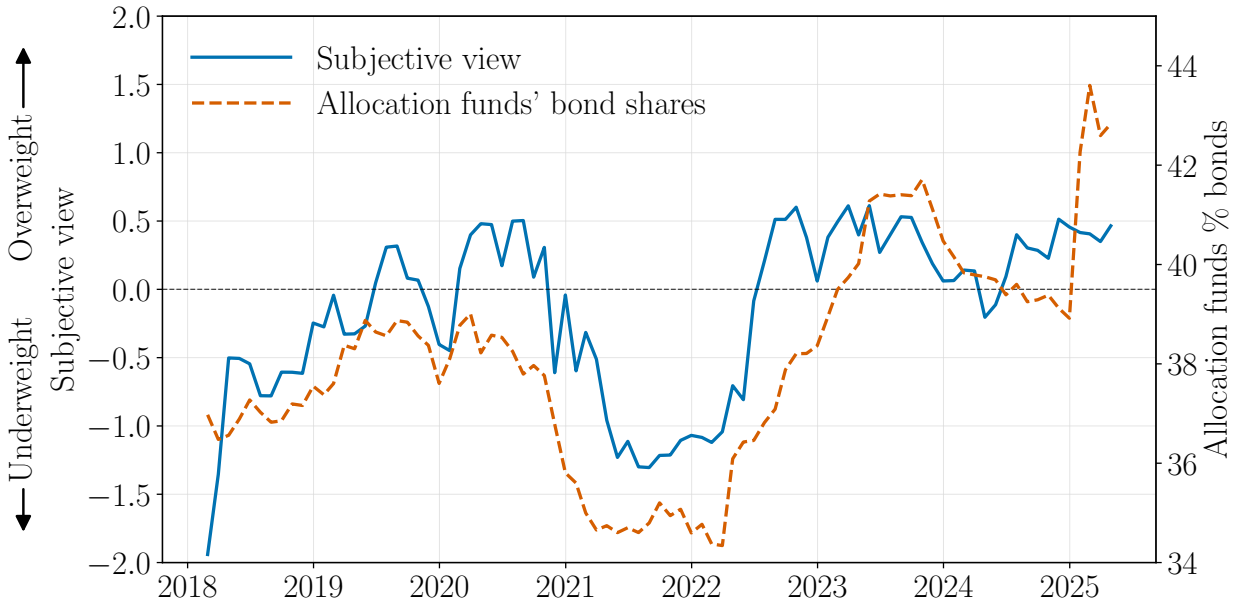
The figure plots asset managers' subjective expectations inferred using a large-language model (LLM) together with the net % of respondents in the Bank of America Global Fund Manager Survey who believe a recession is likely (panel (a)), that believe growth, inflation, short-term rates, and long-term rates are increasing (panels (b)–(e)), and who believe equities are overvalued (panel (f)).

Figure 4: Subjective broad asset class views and allocation funds

(a) Equity view and asset allocation funds' equity shares



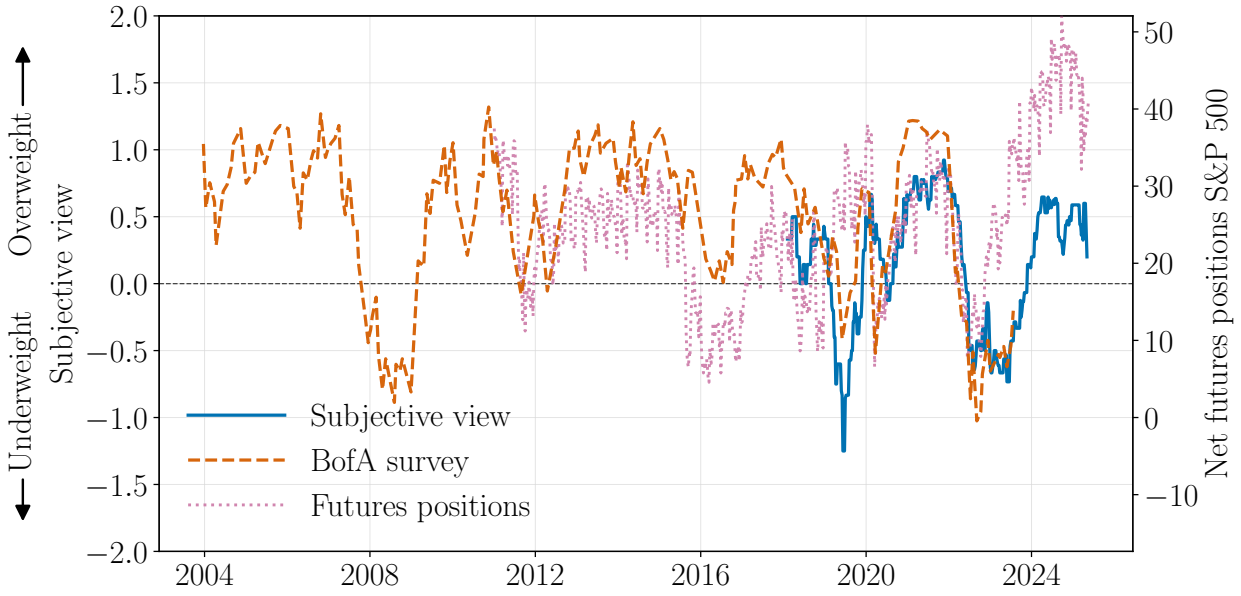
(b) Fixed income view and asset allocation funds' bond shares



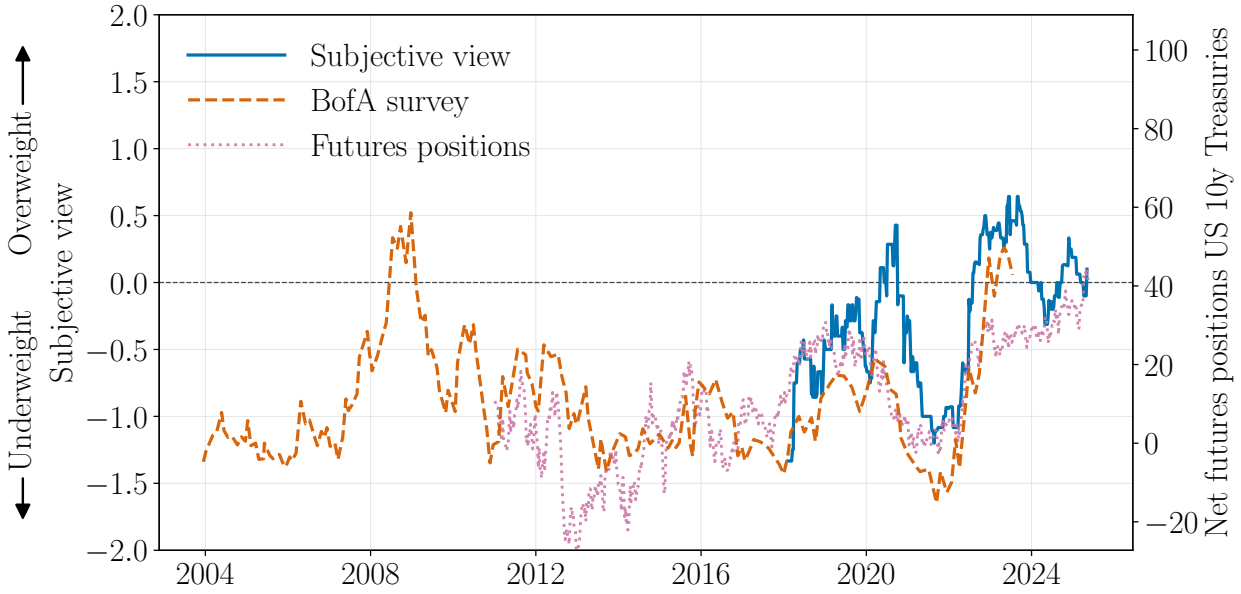
The figure plots asset managers' average (across managers) tactical views for equities and fixed income together with the average portfolio weights in equities and bonds of the allocation funds they are managing. Views are typically expressed on a scale from −2 to +2, with 0 indicating "neutral."

Figure 5: Broad asset class views, BofA survey, and CFTC futures positioning

(a) Equity view and S&P 500 futures positioning

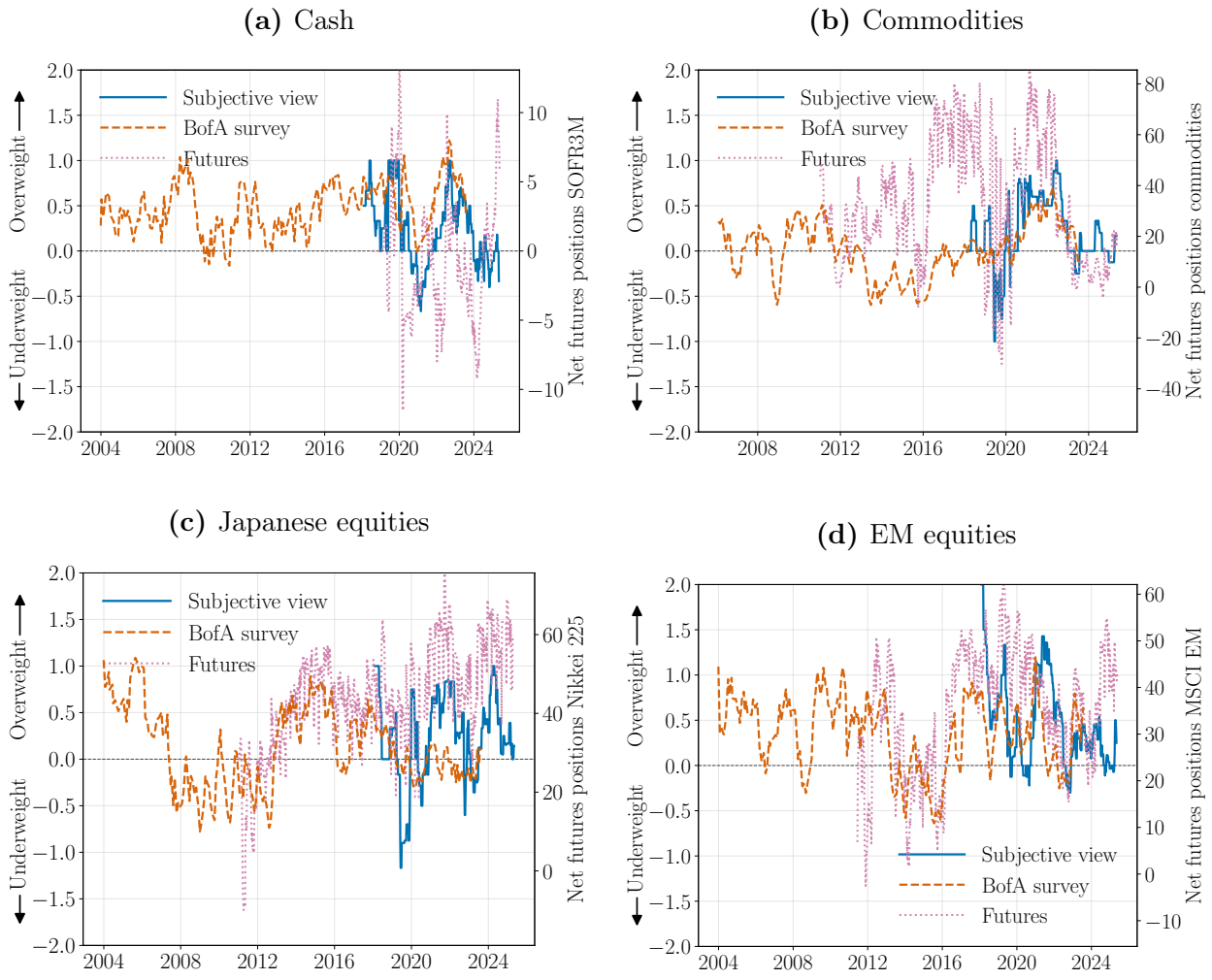


(b) Fixed income view and US 10-year Treasury futures positioning



The figure plots asset managers' average (across managers) tactical views for equities and fixed income together with the net % of respondents in the Bank of America Global Fund Manager Survey that are overweight equities and bonds, respectively, as well as the net futures positions scaled by open interest of asset managers in the S&P 500 index and ten-year US Treasury notes using data from the CFTC.

Figure 6: Narrow asset class views, BofA survey, and CFTC futures positioning



The figure plots asset managers' average (across managers) tactical views for narrow asset classes together with the net % of respondents in the Bank of America Global Fund Manager Survey that are overweight a particular asset class as well as the net futures positions scaled by open interest of asset managers using data from the CFTC.

A Appendix

Figure A1: Tactical asset allocation table of T. Rowe Price

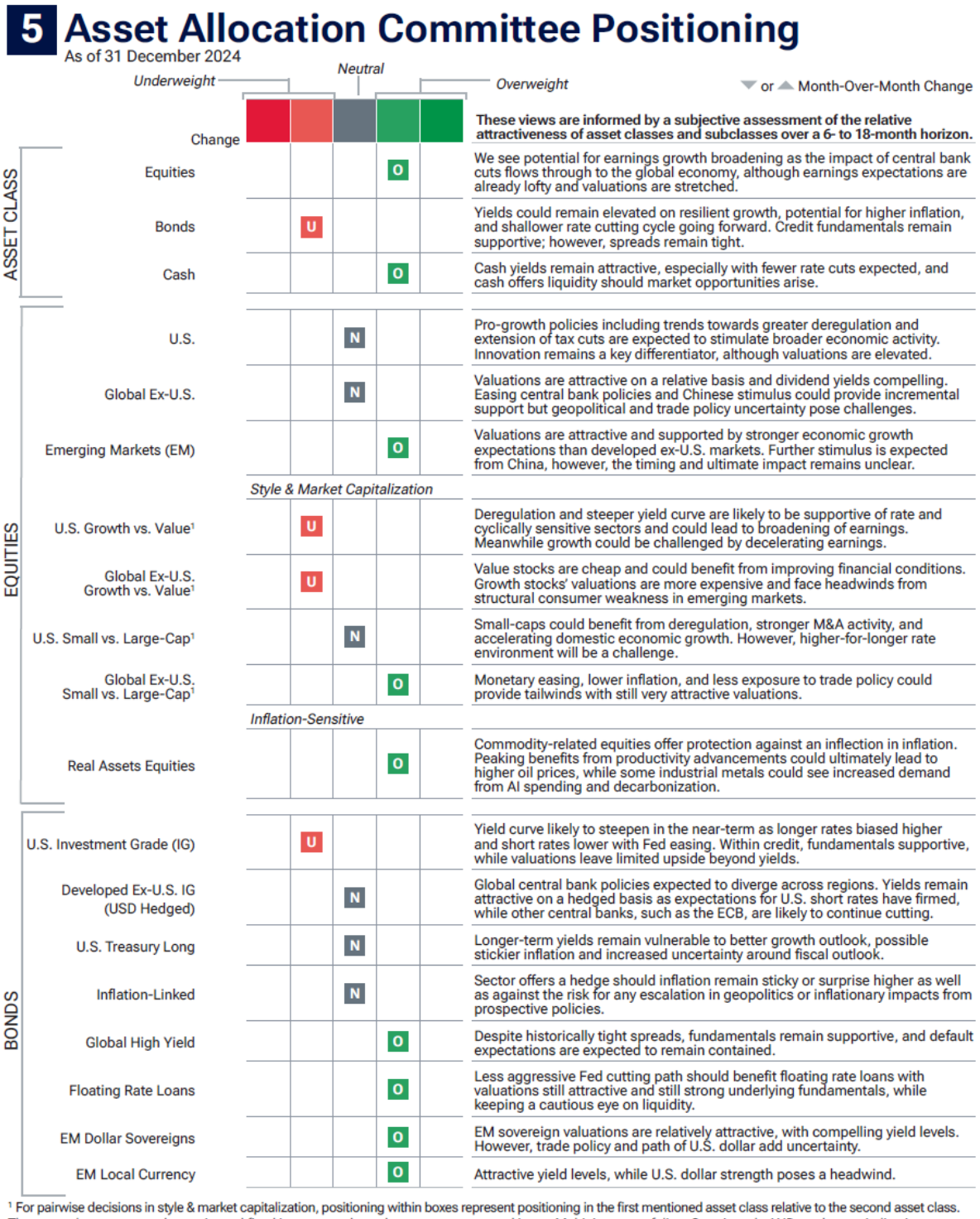


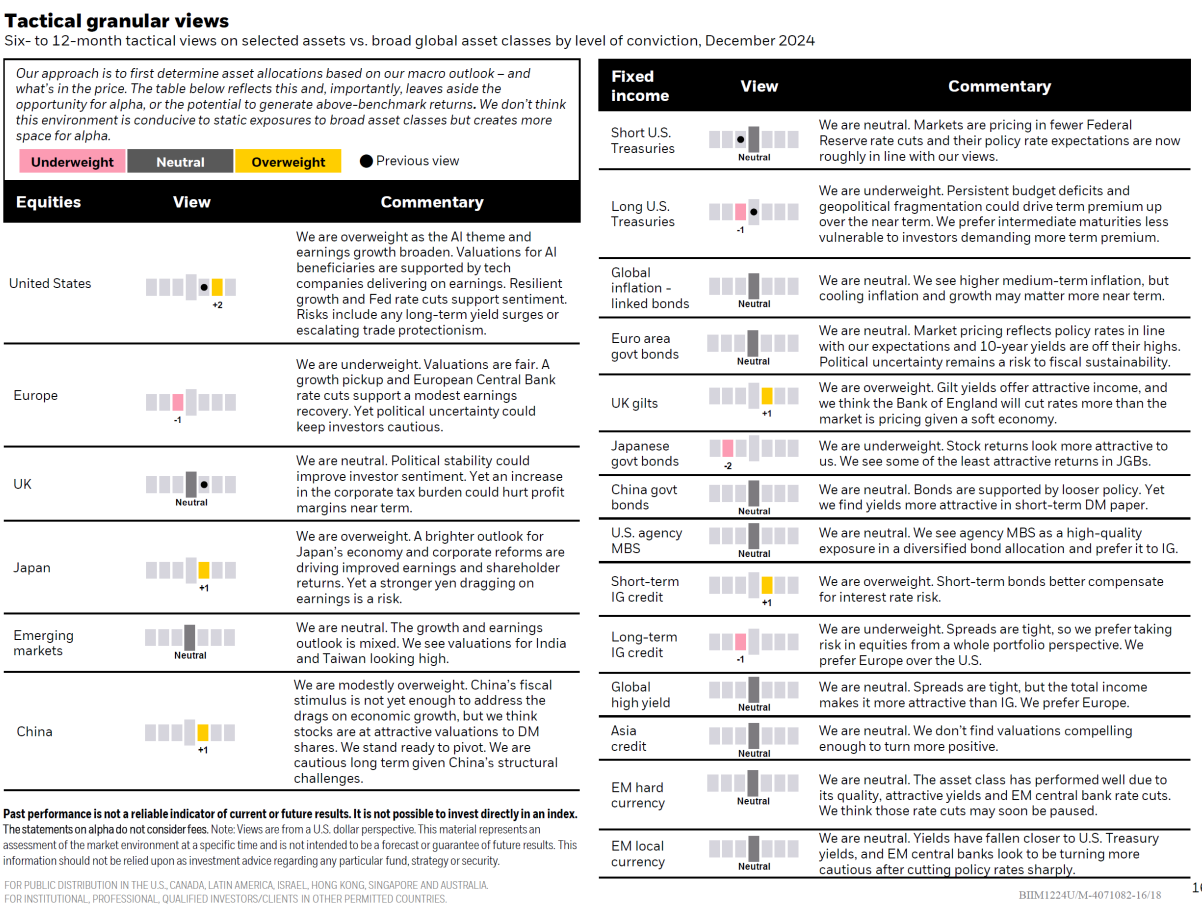
Figure A2: Tactical asset allocation table of Fidelity

TAA views summary

		−−	−	=	+	++	Snapshot of views
Equities	**Equities**			●			Maintaining neutral equities amid high uncertainty. Prefer to stay nimble as both downside and upside risks remain.
	US			●	←		Reducing US to neutral on the back of policy uncertainty, which has resulted in growth and earnings downgrades and has called US exceptionalism into question.
	Europe			→	●		Cheap valuations and a reversal of US exceptionalism, combined with the developments on the German fiscal front – which have the potential to help address the region's structural headwinds and in turn unlock the very high saving rate – means we are turning more constructive on Europe.
	UK			●			Earnings revisions remain uninspiring, however sterling weakness will support multinational large caps.
	Japan			●			Positive earnings momentum balances out trade policy uncertainty and the possibility of a hawkish BOJ surprise.
	Emerging markets				●		We are constructive on the back of firmer conviction in China. We believe the rally this time to be better supported by fundamentals, especially in the tech sector post AI developments. India, which is the second largest component of the region, should also perform well.
	Asia Pacific ex. Japan		●				Australia's weak outlook keeps us cautious. This is our preferred funding source.
Credit	**Credit**			●			Strong fundamentals balance out tight valuations. We prefer to earn carry.
	Investment grade		●				Spreads in IG remain very tight and we prefer the risk-reward of other areas of credit.
	High yield			●			Fundamentals remain robust and all-in-yields still look attractive, especially as rates are coming down. We prefer short-dated HY.
	Emerging market debt			●			Hard currency EMD is beginning to look more attractive but we're waiting for more US policy clarity.
Government bonds	**Government bonds**				●		Slowing growth and attractive valuations mean we tilt towards government bonds.
	US Treasuries			●			The Fed is less inclined to cut given tariff-driven inflation concerns. However, USTs remain a good hedge for downside growth surprises and should benefit from rate cuts over the medium term.
	Euro core (Bund)			→	●		We continue to prefer bunds as European inflation moderation continues.
	UK Gilts				●		Gilts offer decent value without US-style, self-induced price risks from tariffs. Inflation remains a concern, but we expect it to moderate.
	Japanese gov. bonds		●				The BOJ is on a different cycle to Europe and the US and could hike more than the market has priced in – this is our preferred funding source.
	Inflation linked bonds (US TIPS)			→	●		Inflation looks more fairly priced. Linkers are still a decent hedge against a stagflation scenario.
Cash / currencies	**Cash**		●				Underweight cash to fund our overweight government bonds position.
	US dollar		●	←			USD is expensive and US exceptionalism is fading. Erratic policymaking is sparking de-dollarisation.
	Euro				●		Overweight Euro on account of the big fiscal shift in Europe, especially Germany.
	Japanese yen				●		The BOJ remains on a policy normalisation path and the yen is attractively valued.
	Sterling		●				There is no obvious catalyst in sight for Sterling support given the poor fundamentals.
	Emerging markets FX			●			Dispersion has increased and trade policy uncertainty makes this a good time to neutralise.

Source: Fidelity International, 1 May 2025. Views reflect a typical time horizon of 12–18 months and provide a broad starting point for asset allocation decisions. However, they do not reflect current positions for investment strategies, which will be implemented according to specific objectives and parameters.

Figure A3: Tactical asset allocation table of BlackRock



Tactical granular views

Six- to 12-month tactical views on selected assets vs. broad global asset classes by level of conviction, December 2024

Our approach is to first determine asset allocations based on our macro outlook – and what's in the price. The table below reflects this and, importantly, leaves aside the opportunity for alpha, or the potential to generate above-benchmark returns. We don't think this environment is conducive to static exposures to broad asset classes but creates more space for alpha.

Underweight | Neutral | Overweight | ● Previous view

Equities	View	Commentary
United States	+2	We are overweight as the AI theme and earnings growth broaden. Valuations for AI beneficiaries are supported by tech companies delivering on earnings. Resilient growth and Fed rate cuts support sentiment. Risks include any long-term yield surges or escalating trade protectionism.
Europe	-1	We are underweight. Valuations are fair. A growth pickup and European Central Bank rate cuts support a modest earnings recovery. Yet political uncertainty could keep investors cautious.
UK	Neutral	We are neutral. Political stability could improve investor sentiment. Yet an increase in the corporate tax burden could hurt profit margins near term.
Japan	+1	We are overweight. A brighter outlook for Japan's economy and corporate reforms are driving improved earnings and shareholder returns. Yet a stronger yen dragging on earnings is a risk.
Emerging markets	Neutral	We are neutral. The growth and earnings outlook is mixed. We see valuations for India and Taiwan looking high.
China	+1	We are modestly overweight. China's fiscal stimulus is not yet enough to address the drags on economic growth, but we think stocks are at attractive valuations to DM shares. We stand ready to pivot. We are cautious long term given China's structural challenges.

Fixed income	View	Commentary
Short U.S. Treasuries	Neutral	We are neutral. Markets are pricing in fewer Federal Reserve rate cuts and their policy rate expectations are now roughly in line with our views.
Long U.S. Treasuries	-1	We are underweight. Persistent budget deficits and geopolitical fragmentation could drive term premium up over the near term. We prefer intermediate maturities less vulnerable to investors demanding more term premium.
Global inflation - linked bonds	Neutral	We are neutral. We see higher medium-term inflation, but cooling inflation and growth may matter more near term.
Euro area govt bonds	Neutral	We are neutral. Market pricing reflects policy rates in line with our expectations and 10-year yields are off their highs. Political uncertainty remains a risk to fiscal sustainability.
UK gilts	+1	We are overweight. Gilt yields offer attractive income, and we think the Bank of England will cut rates more than the market is pricing given a soft economy.
Japanese govt bonds	-2	We are underweight. Stock returns look more attractive to us. We see some of the least attractive returns in JGBs.
China govt bonds	Neutral	We are neutral. Bonds are supported by looser policy. Yet we find yields more attractive in short-term DM paper.
U.S. agency MBS	Neutral	We are neutral. We see agency MBS as a high-quality exposure in a diversified bond allocation and prefer it to IG.
Short-term IG credit	+1	We are overweight. Short-term bonds better compensate for interest rate risk.
Long-term IG credit	-1	We are underweight. Spreads are tight, so we prefer taking risk in equities from a whole portfolio perspective. We prefer Europe over the U.S.
Global high yield	Neutral	We are neutral. Spreads are tight, but the total income makes it more attractive than IG. We prefer Europe.
Asia credit	Neutral	We are neutral. We don't find valuations compelling enough to turn more positive.
EM hard currency	Neutral	We are neutral. The asset class has performed well due to its quality, attractive yields and EM central bank rate cuts. We think those rate cuts may soon be paused.
EM local currency	Neutral	We are neutral. Yields have fallen closer to U.S. Treasury yields, and EM central banks look to be turning more cautious after cutting policy rates sharply.

Past performance is not a reliable indicator of current or future results. It is not possible to invest directly in an index. The statements on alpha do not consider fees. Note: Views are from a U.S. dollar perspective. This material represents an assessment of the market environment at a specific time and is not intended to be a forecast or guarantee of future results. This information should not be relied upon as investment advice regarding any particular fund, strategy or security.

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Figure A4: Model portfolio Citi

Global USD with Hedge Funds and 15% Illiquids (PE & RE): Risk Level 3

Risk Level 3 is designed for investors with a blended objective who require a mix of assets and seek a balance between investments that offer income and those positioned for a potentially higher return on investment. Risk Level 3 may be appropriate for investors willing to subject their portfolio to additional risk for potential growth in addition to a level of income reflective of his/her stated risk tolerance

Classification	Strategic (%)	Tactical* (%)	Active (%)
Cash	2.0	1.0	-1.0
Fixed Income	39.0	40.0	1.0
Developed Investment Grade	32.4	31.7	-0.7
US	20.1	30.0	9.9
Government	9.0	14.6	5.6
Inflation-Linked	1.2	2.3	1.0
Short	2.6	3.6	1.0
Intermediate	3.7	5.8	2.0
Long	1.4	2.9	1.5
Securitized	6.4	6.1	-0.3
Credit	4.7	9.3	4.6
Short	0.8	1.8	1.0
Intermediate	2.6	6.2	3.6
Long	1.3	1.3	0.0
Europe	9.4	1.5	-7.9
Government	7.3	0.4	-6.9
Credit	2.1	1.1	-1.0
Australia	0.2	0.2	0.0
Government	0.2	0.2	0.0
Japan	2.7	0.0	-2.7
Government	2.7	0.0	-2.7
Developed High Yield	3.3	1.8	-1.5
US	2.5	1.5	-1.0
Europe	0.8	0.3	-0.5
Emerging Market Debt	3.3	4.5	1.2
Asia	0.6	0.8	0.3
Local currency	0.3	0.0	-0.3
Foreign currency	0.3	0.8	0.5
EMEA	1.7	1.8	0.1
Local currency	0.8	0.1	-0.8
Foreign currency	0.8	1.8	0.9
LatAm	1.1	1.9	0.8
Local currency	0.5	0.5	0.0
Foreign currency	0.5	1.4	0.8
Thematic Fixed Income	0.0	2.0	2.0
US Bank Loans	0.0	0.0	0.0
Preferreds	0.0	2.0	2.0
Thematic 3	0.0	0.0	0.0
Thematic 4	0.0	0.0	0.0
Thematic 5	0.0	0.0	0.0

Classification	Strategic (%)	Tactical* (%)	Active (%)
Equities	32.0	32.0	0.0
Developed Equities	27.4	24.1	-3.3
Developed Large Cap Equities	23.9	22.0	-1.9
US	16.8	15.1	-1.7
Canada	0.9	0.9	-0.0
UK	1.0	1.0	-0.1
Switzerland	0.7	0.6	-0.0
Europe ex UK ex Switzerland	2.1	2.2	0.1
Asia ex Japan	0.8	0.8	-0.0
Japan	1.5	1.4	-0.1
Developed Small/ Mid Cap Equities	3.5	2.1	-1.5
US	2.1	2.0	-0.1
Non-US	1.5	0.1	-1.3
Emerging All Cap Equities	4.6	4.4	-0.2
Asia	3.8	3.8	0.0
China	1.3	1.2	-0.1
Asia (ex China)	2.5	2.6	0.1
EMEA	0.3	0.1	-0.2
LatAm	0.5	0.5	-0.0
Brazil	0.3	0.3	-0.0
LatAm ex Brazil	0.2	0.2	-0.0
Thematic Equities	0.0	3.5	3.5
Global Equity REITs	0.0	0.0	0.0
US Mortgage REITs	0.0	0.0	0.0
Global Healthcare	0.0	0.0	0.0
Global Pharma	0.0	0.0	0.0
Cyber Security	0.0	1.0	1.0
Fintech	0.0	0.0	0.0
Natural Resources	0.0	0.0	0.0
Oil Services	0.0	0.0	0.0
Equal-Weighted S&P 500	0.0	2.5	2.5
Commodities	0.0	0.0	0.0
Composite Commodities	0.0	0.0	0.0
Thematic Commodities	0.0	0.0	0.0
Gold	0.0	0.0	0.0
Thematic 2	0.0	0.0	0.0
Thematic 3	0.0	0.0	0.0
Thematic 4	0.0	0.0	0.0
Thematic 5	0.0	0.0	0.0
Hedge Funds	12.0	12.0	0.0
Private Equity	10.0	10.0	0.0
Real Estate	5.0	5.0	0.0
Total	100.0	100.0	0.0

Active = the difference between tactical and strategic allocations. Minor differences may result due to rounding.

B Large-language model prompt

```
You are a strict extractor. Here is a PDF from an asset manager. Read ONLY the attached PDF via file_search and answer per the requested JSON schema.

Unless otherwise stated, consider forward-looking expectations over the next ~3-18 months. Solely based on the attached PDF, do you think that the asset manager
    1) believes that a global recession is likely, has a neutral stance, or that a recession is unlikely?
    2) believes that global equities are currently overvalued/overpriced/elevated/overstretched/overbought, fairly valued, or undervalued/underpriced/low/understretched/oversold?
    3) expects the global growth outlook (e.g., GDP growth) to improve, remain the same, or deteriorate?
    4) expects global inflation (e.g., year-over-year CPI indexes) to rise, remain the same, or fall?
    5) expects short-term interest rates (e.g., the Fed policy rate) to rise, remain the same, or fall?
    6) expects long-term interest rates (e.g., the 10-year US Treasury yield) to rise, remain the same, or fall?
    7) expects volatility in financial markets (e.g., the VIX) to rise, remain the same/persist, or fall?

OUTPUT CONTRACT
- For ALL metrics (1-7), return:
  - direction: -1, 0, or 1
    - recession_probability: 1 = recession likely; 0 = neutral/uncertain; -1 = recession unlikely.
    - valuation_view_equities: 1 = overvalued; 0 = fairly valued/unclear; -1 = undervalued.
    - growth_outlook, inflation_outlook, policy_rate_outlook, ust10y_outlook, volatility_outlook: -1 = fall/decrease/deterioration, 0 = neutral/uncertain, 1 = rise/increase/improvement.
  - magnitude: number in [0, 1]; set to 0 when direction=0.
  - confidence: number in [0, 1].
  - quote: 1-2 full sentences that support the assessment; include page if available.
  - page: page number or null if not available.
IF the PDF is unclear/mixed or provides no forward view, use direction=0 and magnitude=0 for the relevant metric(s), and use a low confidence (<=0.3). ALWAYS use a low confidence (<=0.3) if you cannot reliably answer the question. Cite the most relevant uncertainty statement in the quote.

MAGNITUDE CUE GUIDE (applies to all metrics)
```

```
25  - Purpose: magnitude captures the size/intensity of the expected change on a 0-1
    scale. Direction carries the sign (-1, 0, 1). Choose magnitude based on wording
    strength; stronger language => higher magnitude. If direction=0, set magnitude=0.
26  - Strong increase/decrease (magnitude ~0.8-1.0): ‘‘sharp’’, ‘‘surge’’, ‘‘plunge’’, ‘‘major’’,
     ‘‘significant’’, ‘‘considerable’’, ‘‘substantial’’, ‘‘strong acceleration/deceleration’’, ‘‘
    boom’’, ‘‘base case recession’’, ‘‘material deterioration/improvement’’.
27  - Moderate increase/decrease (magnitude ~0.5-0.7): ‘‘moderate’’, ‘‘meaningful’’, ‘‘
    noticeable’’, ‘‘firm’’, ‘‘pick-up/slowdown’’, ‘‘some acceleration/contraction’’, ‘‘we expect
    X to increase/decrease’’.
28  - Mild/slight (magnitude ~0.2-0.4): ‘‘somewhat’’, ‘‘slight’’, ‘‘modest’’, ‘‘a bit’’, ‘‘
    softening/tightening’’, ‘‘edge higher/lower’’, ‘‘drift’’.
29  - Unchanged/neutral/uncertain (direction=0 => magnitude=0): ‘‘broadly unchanged’’, ‘‘
    remain near current’’, ‘‘stable’’, ‘‘mixed/unclear/no strong bias’’.
30
31  """
```

Listing 1: Extraction prompt and output contract

Note that the large-language model prompt also asks about the "magnitudes" of the views. I do not use the results of these prompts for the main results in the paper, but the results are similar when I do use them. I drop all responses with a low confidence, i.e., confidence lower than 0.3.