Doing well to doing good? Shifts in ESG Investing*

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Abstract

This study investigates the potential shifts in ESG performance over time, examining whether ESG cycles exist. We employ a Markov Regime-Switching model with time-varying transition probabilities to analyze the performance of ESG built on MSCI USA Index constituents. Our methodology incorporates the Composite Leading Indicator (CLI) and the Media Climate Change Concerns (MCCC) index as exogenous variables to explain regime transitions. The analysis identifies two distinct regimes, with the MCCC index significantly outperforming business cycle indicators in filtering regime shifts. Climate sentiment-based regime identification proves effective for sectors with high exposure to climate risks. Finally, the decomposed analysis reveals that the MCCC index shows superior performance in identifying Environmental regimes compared to Social and Governance components, confirming that climate sentiment indicators exhibit stronger explanatory power for environmental factors.

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1 Introduction

The Global Sustainable Investment Alliance (GSIA) estimates that sustainable investment accounted for USD 35.3 trillion in assets under management (AUM) in 2020, representing more than one-third of global assets managed by professional managers (GSIA, 2021). Societal changes, natural disasters, regulatory developments, and cultural factors primarily drive this trend (Becker et al., 2022; Riedl and Smeets, 2017; He et al., 2022). This increasing broad interest attracts all types of investors (Starks, 2023). Positive shifts in investor ESG preferences drive the positive performance of ESG assets (Pedersen et al., 2021; Pástor et al., 2021), and flows induced by the ESG preferences predominantly explain the notable performance of sustainable investing over the last decade (Van der Beck, 2021). However, these shifts in ESG preferences are not only positive. The recent ESG backlash, particularly evident in the US (Zhang, 2024), suggests that markets are entering a new regime. This reversal in preferences signals a pivot in capital flows into ESG funds. More broadly, we may ask if the current downturn is not the last episode of a recurring cyclical pattern rather than an isolated market event.

To answer this question, this paper investigates the potential shifts in ESG performance over time. We identify distinct regimes at both global and sectoral levels over the period from January 2013 to December 2022. This regime identification provides crucial insights for understanding ESG performance dynamics. These insights benefit investors who integrate ESG criteria into their investment processes. They also provide better understanding of how ESG preferences evolve over time.

In theory, ESG assets have lower expected returns in equilibrium as investors derive non-pecuniary utility from holding them, leading to negative ESG risk premium (Pedersen et al., 2021; Pástor et al., 2021). However, higher ESG stocks would also generate higher returns if ESG preferences or climate concerns unexpectedly strengthen (Pástor et al., 2022). Van der Beck (2021) shows that investors are rewarded instead of penalized for investing in ESG assets, as the outperformance of high-ESG stocks relative to low ESG-stocks coincides with the rise in institutional investor's demand for sustainability. This debate naturally raises the question of the existence of ESG cycles. We examine whether these cycles primarily relate to ESG sentiment concerns from investors or stem from business cycle information. We address these questions through an empirical analysis. Our analysis focuses on the United

States market using the MSCI USA Index and its components, spanning January 2013 to December 2022. We assume that ESG returns are time-varying. Using an ESG risk-adjusted returns approach, we analyze ESG cycles using a Markov Regime-Switching (MRS) model with time-varying transition probabilities (TVTP) on the global US market and its sectors. We allow the transition probabilities to vary with the Composite Leading Indicator (CLI) and the Media Climate Change Concerns (MCCC) index as exogenous variables. Variation in climate-related investor sentiment explains a significant portion of observed green asset outperformance, as shown through media content analysis and legislative communication studies (Ardia et al., 2023; Santi, 2023; DeMiguel et al., 2025). Integrating such sentiment variables into switching regime models would help identify ESG regimes by incorporating these variables directly within the analytical framework.

Our analysis identifies two distinct regimes in the US ESG market. The MCCC index performs as a superior exogenous variable compared to the CLI in identifying these regimes. This finding indicates that shifts in ESG performance regimes result primarily from changes in investor ESG preferences related to climate concern sentiment. We conduct a sectoral analysis selecting the most sensitive climate risk sectors. Using the MCCC index as exogenous variable, we identify distinct regimes for these sectors, confirming the power of climate sentiment indicator in filtering regime shifts. When comparing the three ESG pillars, the MCCC index manifests superior performance in identifying regimes for environmental metrics compared to social and governance components. This finding reinforces the connection between climate sentiment and environmental performance within the broader ESG framework.

This paper contributes to the sustainability field by providing empirical evidence of ESG performance dynamics through regime identification methodology. Although the analysis of ESG performance behavior has been examined with regime-switching models in other studies (Ardia et al., 2023; Santi, 2023; DeMiguel et al., 2025), our approach brings a more comprehensive analysis. First, we create ESG portfolios rather than using existing ESG indices. Second, we incorporate a climate sentiment indicator in the model to better filter different regimes. Third, we provide a detailed sector analysis. These methodological innovations allow for a deeper understanding of ESG performance dynamics across different market conditions and sectors.

For institutional investors, our analysis provides a framework for integrating climate sentiment indicators into investment decision-making processes. This enables better understanding of ESG performance cycles while supporting informed allocation strategies that account for regime-dependent dynamics.

The remainder of this paper is organized as follows. Section 2 introduces the literature review. Section 3 describes the data used in this paper. Section 4 describes the methodology proposed. Section 5 presents our empirical results. Section 6 concludes our research paper.

2 Related Literature

Pástor et al. (2021) proposes an equilibrium model that accounts for sustainability characteristics and generates two distinct theoretical results. First, green assets have lower expected returns because investors derive non-pecuniary utility from holding these assets and because these assets serve as hedges against climate risks. This finding aligns with Pedersen et al. (2021), who argue that the ESG risk premium is negative. Second, positive shifts in investor ESG preferences drive the outperformance of green assets over time.

The theory assumes that investors expect a reward for their exposure to carbon emissions risk (Bolton and Kacperczyk, 2021; Eskildsen et al., 2024) and more broadly to ESG externalities risks (Pedersen et al., 2021). Pástor et al. (2021) establishes that shifts in demand create a divergence between ESG expected returns and realized returns. Empirical evidence confirms that green stocks outperformed brown stocks between 2012 and 2020 (Pástor et al., 2022). This outperformance stems from the rising prominence of environmental concerns among investors, indicating that shifts in investor preferences, rather than changes in fundamentals, drive the return differentials.

Shifts in investor preferences may be explained by exogenous shocks. Variation in climate-related investor sentiment explains a significant portion of the observed green asset outperformance (Ardia et al., 2023; Santi, 2023). Ardia et al. (2023) constructs an index using content from mainstream media. Regressing stock returns on this sentiment indicates that green stocks outperform brown stocks when media expresses concerns about climate change. Moreover, DeMiguel et al. (2025) documents that green stocks outperform brown stocks following tweets promoting environmental transition regulation from members of the

US Congress.

Shifts in ESG investor preferences (Starks, 2023) lead to substantial capital flows to ESG assets (Becker et al., 2022; Ceccarelli et al., 2024; Hartzmark and Sussman, 2019). This reallocation of capital has price pressure on ESG stocks. ESG-related capital flows have a direct impact on asset prices (Cheema-Fox et al., 2019; Bennani et al., 2018). Van der Beck (2021) shows that high-ESG stocks outperformed during periods of rising institutional demand. This indicates the role of characteristic-based demand in shaping realized returns in ESG markets. Traditional asset pricing models typically assume homogeneous investor preferences and rely primarily on portfolio-level return data. In a seminal paper, Koijen and Yogo (2019) proposes the introduction of characteristics-based demand to account for investor heterogeneity. This system provides a more flexible framework for asset pricing by allowing demand to vary across assets and investors. However, the empirical implementation of such models remains constrained by the limited availability of granular holdings data. Koijen and Yogo (2019) relies on 13F institutional holdings but fails to capture a large segment of the market. Handziuk (2024) proposes a data augmentation approach that improves the estimation of institutional demand. Darolles et al. (2023) uses a causal mediation framework to account for the demand heterogeneity impact in ESG asset pricing. Recent contributions shift toward models that treat returns as endogenous outcomes of investor heterogeneity. These advances highlight the necessity to account for demand-based, endogenous factors in ESG markets.

Literature increasingly recognizes that ESG performance impacts shift across time periods. Macro-financial conditions, including climate awareness intensity, regulatory shifts, and economic uncertainty, directly influence ESG strategy effectiveness. Capital markets exhibit well-established regime-dependent dynamics (Hamilton, 1989; Guidolin and Timmermann, 2007). Markov Regime-Switching (MRS) models capture shifts in asset return behavior over time (Hamilton and Susmel, 1994; Filardo, 1994; Gray, 1996). Filardo (1994) extends the model by incorporating time-varying transition probabilities, enhancing its ability to detect structural shifts. Darolles et al. (2019) applies the MRS model to assess size risk premia dynamics. Additionally, Ouchen (2022), Bhattacharjee and De (2022), and Kossentini et al. (2024) employ regime-switching techniques to evaluate the time-varying behavior of ESG risk and performance, primarily using sustainable indices as their foundation.

The widespread adoption of ESG integration in investment processes leads investors to assess the ESG contribution at the performance level. In his survey, Coqueret (2022) highlights that the inconclusive results on ESG performance contribution stem from heterogeneous ESG impacts. Differences across ESG pillars and regional contexts contribute to this ambiguity (Ziegler et al., 2008; Bennani et al., 2018; Starks, 2023; Van Duuren et al., 2016), yet sectoral dynamics and temporal variation emerge as the primary heterogeneity drivers. These factors influence both portfolio construction and performance attribution (Bruno et al., 2022; Loew et al., 2024). Several studies highlight that sectors such as energy, utilities, and financials exhibit differing sensitivities to ESG factors, both in terms of return contribution and risk mitigation (Makridou et al., 2024; Imperiale et al., 2023; Buallay, 2019). Additionally, ESG contribution is time-varying. Bennani et al. (2018) report a structural break in ESG performance around 2014, with positive excess returns emerging more clearly thereafter. Moreover, Drei et al. (2019) show that the performance of ESG factors declined in subsequent years, potentially due to shifts in policy direction. Both sector-specific characteristics and the evolving nature of sustainable investing over time are crucial to understanding the ESG-related performance.

3 Data

This paper decomposes and characterizes ESG returns over time. The dataset comprises firms from the MSCI USA Index spanning January 2013 to December 2022. Data are sourced from Refinitiv. This section outlines the dataset construction methodology. Section 3.1 details ESG ratings. Section 3.2 describes additional variables. Section 3.3 discusses the dataset's summary statistics.

3.1 ESG score

We collect US firms' ESG ratings at month-end from January 2013 to December 2022. Firm-level ESG ratings data come from Refinitiv ESG (formerly Thomson Reuters ASSET4 ESG) database. Sustainability research widely uses Refinitiv as a data provider (Berg et al., 2022; Demers et al., 2021). Refinitiv ESG ratings are considered as the most reliable exogenous methodology measures (Berg et al., 2022). Additionally, Refinitiv exhibits fewer incentives to issue higher ESG scores for firms with better stock return performance, given its low index licensing incentives (Agrawal et al., 2023).

The Refinitiv ESG database covers over 15,500 public and private companies globally, with historical data dating back to 2002. Firms' annual reports, websites, CSR reports, and NGO reports serve as primary sources from which analysts collect ESG raw data. The scoring process compiles over 630 company-level ESG metrics. Analysts select 186 metrics as most comparable and material per industry, categorizing them into ten groups. These groups form the three pillars: Environmental (E), Social (S), and Governance (G). Refinitiv calculates ESG scores using these pillars, applying industry-specific weights for environmental and social categories while maintaining consistent governance weights across industries. The database normalizes scores on a scale of 0 to 100, also presenting them as letter grades from D- to A+. Refinitiv regularly updates its ESG database, with the most recent five years of data subject to potential revision. Berg et al. (2021) reveals that Refinitiv ESG continuously rewrites historical ratings, constituting an ongoing practice rather than an isolated incident. A methodological critique from Dobrick et al. (2023) exposes a systematic size bias within the rating framework, as ESG scores correlate positively with firm size, causing large-capitalization companies to receive disproportionately favorable ESG assessments. Moreover, Chen (2023) discovers that numerous raw variables remain inactive in Refinitiv's database, never influencing final ESG calculations. Their analysis also identifies companies whose evaluation methodology has stagnated since 2002, despite significant shifts in global economic landscapes and sustainability standards. Comparative analysis by Muck and Schmidl (2024) confirms that Refinitiv's sector-specific weighting creates significant sectoral disparities in mean scores, while alternative equal-weighting methods yield more consistent cross-industry assessments.

3.2 Others variables

We collect monthly stock price return data for constituents of the of the MSCI USA Index from Refinitiv, spanning January 2013 to December 2022. This universe offers a broader constituent coverage relative to S&P500. Industry classifications are derived from MSCI Sector Names utilizing the Global Industry Classification Standard (GICS®). For sector-level analysis, we employ the eleven MSCI sector indices[1]that collectively represent the US equity market. These sector indices, also based on GICS, allow us to investigate ESG returns behavior among sectors. They may exhibit varying sensitivity to economic conditions, climate sentiments and endogenous ESG cycles.

The GICS classification system, developed jointly by MSCI and S&P Dow Jones, differs significantly from concurrent systems such as Standardized Industry Classification (SIC) or North American Industry Classification System (NAICS). While SIC and NAICS maintain high correspondence, GICS classifications display more disagreement with others (Bhojraj et al., 2003). Despite these differences, GICS excels at identifying industrial peers and its evolving methodology aligns with market demand, making it particularly viable for sector classification (Moats, 2019). Additionally, we extract common risk factors from Kenneth French's website.

We collect US CLI data from the OECD spanning January 2013 to December 2022[2]. The CLI is an index designed to provide early signals of turning points in business cycles. It is constructed from multiple series including producer price changes, hours worked, and profitability changes, among other economic indicators. These series capture the leading movements of the coincident index (Boehm and Summers, 1999).

This indicator shows fluctuations in economic activity around its long-term potential level. Long et al. (2022) argues that it has robust influence over financial markets. Changes in CLI predict the cross-section of aggregate returns, while its predictive power cannot be explained by established risk factors. The selection of the CLI as our conditioning variable reflects establish practice within the regime-switching literature (Filardo, 1994; Perez-Quiros and Timmermann, 2001; Darolles et al., 2019).

We also collect Media Climate Change Concerns (MCCC) data from January 2013 to December 2022[3]. Based on studies arguing that mass media powerfully increases public awareness about environmental issues, Ardia et al. (2023) constructs this index to capture shifts in climate change concerns. The index is constructed from major US newspapers and newswires. The methodology accounts for concerns based on the percentage of risk words in the text. It also accounts for the degree of negativity to differentiate between positive and

[1]The sector indices comprise: MSCI USA Energy Index, MSCI USA Materials Index, MSCI USA Industrials Index, MSCI USA Consumer Discretionary Index, MSCI USA Consumer Staples Index, MSCI USA Health Care Index, MSCI USA Financials Index, MSCI USA Information Technology Index, MSCI USA Communication Services Index, MSCI USA Utilities Index, and MSCI USA Real Estate Index.

[2]The OECD provides the CLI data on their website: https://www.oecd.org/en/data/indicators/composite-leading-indicator-cli.html

negative articles. For more information about the methodology, please refer to Ardia et al. (2023).

The authors refer to UMC indicator, which represent the shock component of the MCCC index, in their paper. They use these indicators to identify the impact on green and brown asset prices following concern shocks. The UMC constitutes the unexpected component of the MCCC index. It represents the prediction error of an autoregressive model with exogenous variables (ARX). This study assumes that the MCCC index follows a random walk process characterized by an intercept $\alpha = 0$ and a slope $\beta = 1$. Subsequently, we use the ΔMCCC_t as the measure of change in climate concerns sentiment. We note, as precisely stated by the authors, that risk of endogeneity may exist. This endogeneity may arise due to a potential feedback loop. An exogenous shock leads to increased climate concerns and affects prices of concerned stocks. This amplifies investor concerns about climate change impact and strengthens the market impact.

3.3 Summary Statistics

Table 1 presents the cross-sectional summary statistics of our dataset. Our sample encompasses stocks in the MSCI USA Index (Global) and the eleven MSCI Index sectors from January 2013 to December 2022.

Stock constituents of the MSCI USA Index exhibit an average ESG score of 56.48. The high standard deviation of 18.36 indicates significant heterogeneity within this universe. The lower decile displays scores below 30.96, while the upper decile exceeds 79.15. The distribution exhibits left-skewed characteristics. Sectoral analysis reveals that Consumer Staples (66.10), Materials (64.09), and Utilities (59.96) sectors have the highest average ESG scores. These results appear surprising given the emissions profile of Materials and Utilities sectors. Both sectors emit large quantities of greenhouse gases. Such emissions should negatively impact the Environmental (E) pillar of ESG scores. One possible explanation stems from methodological differences in ESG scoring systems. Ehlers et al. (2024) explains that these sectors achieve higher Emission scores specifically because firms within them report their emission policies. Companies receive compensatory scoring benefits for policy measures they implement. In contrast, sectors with low carbon intensity, such as Healthcare and Finan-

[3]The MCCC index is available on : https://sentometrics-research.com

cials, exhibit lower emission scores. Companies in these sectors frequently omit reporting on these topics, considering them immaterial to their operations. Consequently, these sectors display lower environmental scores despite generating minimal carbon emissions. Among sectors with poor ESG performance, Communication Services (49.64), Energy (50.54), and Consumer Discretionary (52.20) rank lowest.

Table 1: **Summary statistics at Global and Sector level.** This table presents firm-level cross-sectional summary statistics of ESG ratings and stock returns (month-to-date), expressed as percentages, of the constituents of the MSCI USA Index (Global) and eleven MSCI sector indices over the period from January 2013 to December 2022.

	Observation	Mean	St.Dev	10%	25%	50%	75%	90%
Global								
ESG Rating	72432	56.48	18.36	30.96	43.58	58.55	70.79	79.15
Return (%)	74273	0.90	8.85	-8.92	-3.74	1.00	5.57	10.43
Health Care								
ESG Rating	8145	58.13	18.48	32.05	43.89	60.76	73.21	80.77
Return (%)	8590	1.16	8.92	-8.67	-3.53	1.08	5.95	10.79
Financials								
ESG Rating	11355	54.44	16.92	33.02	42.17	53.03	67.50	76.34
Return (%)	11576	0.92	7.49	-7.74	-3.12	1.26	5.23	9.09
Cons Discr								
ESG Rating	10531	52.20	19.42	23.83	38.38	54.06	67.15	77.42
Return (%)	10733	0.83	9.69	-9.70	-4.30	0.83	5.95	11.34
Cons Staples								
ESG Rating	4637	66.10	15.68	43.08	58.55	69.25	76.84	83.81
Return (%)	4707	0.86	7.16	-7.03	-3.60	0.80	4.69	8.58
Energy								
ESG Rating	4402	50.54	21.12	21.31	34.47	51.23	68.75	77.26
Return (%)	4557	0.21	12.26	-13.07	-5.97	0.23	6.05	12.84
Industrials								
ESG Rating	9434	57.34	17.54	31.91	44.60	60.495	70.24	77.43
Return (%)	9498	1.01	8.04	-8.48	-3.35	1.21	5.61	10.23
Com Svcs								
ESG Rating	2308	49.64	19.24	21.68	34.76	51.02	66.76	73.12
Return (%)	2474	0.40	10.90	-11.34	-5.57	0.29	6.37	12.34
Real Estate								
ESG Rating	4395	59.82	18.60	35.39	45.825	63.87	74.4	81.47
Return (%)	4372	0.38	7.13	-7.69	-3.67	0.60	4.61	8.50
Technology								
ESG Rating	11292	54.92	18.29	29.93	42.45	55.55	69.70	78.71
Return (%)	11709	1.29	9.61	-9.80	-3.94	1.34	6.49	11.97
Materials								
ESG Rating	3770	64.09	15.67	42.44	53.86	67.57	75.83	81.79
Return (%)	3822	0.98	8.68	-9.32	-3.67	1.06	5.54	10.81
Utilities								
ESG Rating	3816	59.96	15.58	36.61	48.26	62.95	70.86	77.66
Return (%)	3844	0.66	5.97	-6.60	-2.90	1.52	4.31	7.45

4 Methodology

This section outlines the methodology for computing risk-adjusted ESG returns and presents the endogenous regime-switching model.

4.1 ESG Returns

We construct the ESG returns following the methodology established by Pedersen et al. (2021). We categorize constituents in the MSCI USA Index into portfolios based on the quintile of their ESG scores on a monthly basis from January 2013 to December 2022. We subsequently compute the return for the following month as the spread returns between high ESG stocks and low ESG stocks. Portfolios are constructed equally-weighted and are rebalanced on the final day of each calendar month.

Pedersen et al. (2021) constructs the ESG portfolio based on the raw stocks returns. However, multiple risk factors influence raw stock performance (Fama and French, 1993, 2012, 2015; Carhart, 1997). Fama and French (1993) documents that large-cap portfolios are characterized by weak market beta and low exposure to HML and SMB factors, while small-cap portfolios display opposite characteristics. We assume these risk factors affect extreme quintile ESG raw returns differently. Controlling for these risks becomes essential for accurate analysis. Several additional considerations support this approach. Dobrick et al. (2023) establishes that ESG scores correlate positively with firm size. Muck and Schmidl (2024) argues that sector-specific weighting in ESG scoring methodology creates substantial sectoral disparities in mean scores. Furthermore, asymmetric behavior exists between ESG assets and non-ESG assets (Darolles and Faverjon, 2025; Coadou and Darolles, 2025). Bennani et al. (2018) shows that performance contribution from long-short portfolio strategies based on individual ESG criteria does not originate uniformly from both portfolio legs. These arguments suggest that calculating ESG returns from raw returns is inappropriate. ESG quintiles exhibit asymmetric exposures to common risk factors.

To isolate the ESG effect while controlling for common risk factors' impact on portfolio returns, we employ risk-adjusted returns directly in our analysis. We follow the methodology used by Darolles et al. (2019) for analyzing the size effect.

Our approach involves regressing the performance returns of high and low ESG portfolios separately against established common risk factors documented in academic literature. This methodology, enables us to extract the pure ESG contribution by removing the influence of systematic risk factors that could otherwise distort our assessment of ESG performance attribution. We thus perform the following regression for each portfolio p, with $p = (HighESG, LowESG)$ and $t = (1, ..., T)$:

$$R_{p,t} = \alpha_p + \beta_{p,1}(R_{m,t} - R_{f,t}) + \beta_{p,2}SMB_t + \beta_{p,3}HML_t + \beta_{p,4}RMW_t + \beta_{p,5}CMA_t + \beta_{p,6}MoM_t + \epsilon_{p,t} \quad (1)$$

where $R_{p,t}$ denotes the return of portfolio p at time t; $R_{m,t} - R_{f,t}$ is the excess return of the market over the risk-free rate; SMB_t captures the size effect, defined as the return spread between small and large firms; HML_t captures the value effect, defined as the return spread between high book-to-market (cheap) and low book-to-market (expensive) stocks; RMW_t reflects the profitability effect, measuring the return spread between firms with robust and weak profitability; CMA_t represents the investment effect, defined as the return spread between firms that invest conservatively and those that invest aggressively; and MoM_t captures the momentum effect, measured as the return spread between recent winner and loser stocks.

We can then compute the risk-adjusted ESG spread, where $\hat{\alpha}_i$ is the OLS estimated alpha from Equation 1 for the extreme ESG quintile portfolios: $i = (HighESG, LowESG)$

$$RA\ Spread_{(ESG)} = \hat{\alpha}_{(HighESG)} - \hat{\alpha}_{(LowESG)} \quad (2)$$

The resulting ESG spread can be considered as the the risk adjusted returns versions of the ESG spread returns methodology proposed by Pedersen et al. (2021). This method allows us to isolate the pure ESG contribution after controlling for the asymmetric influence that common risk factors exert on the raw returns of extreme ESG quintiles. The methodology establishes an ESG-adjusted return time series used in the regime-switching model described in the next section.

4.2 Time-Varying ESG return

Shifts in ESG investor preferences create distinct subperiods during which ESG performance exhibit specific behavioral patterns. Detecting these ESG cycles through exogenous methods presents significant analytical challenges for two primary reasons.

The first challenge involves accurately identifying the timing boundaries of subperiods. Establishing precise beginning and end dates proves difficult. Dungey et al. (2015) illustrates this issue by examining twenty-two studies on the 2007-2011 financial crisis. These studies reached consensus on the crisis start date but disagreed on its end date. The second challenge concerns quantifying characteristics-based demand, which influences ESG assets returns. This demand component proves difficult to measure precisely, yet drives performance variations across different market regimes. These measurement limitations require alternative analytical approaches to identify and analyze ESG cycles effectively.

Our analytical framework examines ESG regime dynamics through a two-step methodology. We begin by implementing an univariate Markov Regime-Switching model with time-varying transition probabilities, which enables us to estimate the transition probabilities that characterize each ESG regime. This approach provides a robust statistical foundation for identifying periods when ESG performance exhibits distinct behavioral patterns. Following the regime identification, we calculate regime-dependent risk-adjusted ESG performance and systematically analyze their statistical properties across both global and sectoral dimensions. This second phase allows us to understand how ESG effects vary not only over time but also across different industry segments, providing granular insights into the heterogeneous nature of sustainable investment performance.

4.2.1 Markov Regime-Switching (MRS)

Our methodological approach begins with implementing a univariate Markov Regime-Switching model incorporating time-varying transition probabilities (TVTP) to identify endogenous ESG cycles and calculate state-dependent ESG risk premia. This framework assumes two distinct regimes, s_t, that can randomly take two possible values : $s_t = 1, s_t = 2$. The transition probabilities and statistical characteristics of ESG performance during each regime are endogenously determined through the data analysis process. We enhance the traditional approach (Hamilton, 1989) by incorporating dynamic transition probabilities rather than static ones. Following the methodology established by Filardo (1994), we allow these probabilities to fluctuate based on two-month lagged logarithmic changes of the x_t. We estimate separate models where x_t represents the CLI in one specification and the MCCC index in another. The transition probabilities are assumed to follow a first order Markov chain:

$$p_t = P_r(s_t = 1|s_{t-1} = 1, \Delta x_{t-2}) \tag{3}$$

$$1 - p_t = P_r(s_t = 2|s_{t-1} = 1, \Delta x_{t-2}) \tag{4}$$

$$q_t = P_r(s_t = 2|s_{t-1} = 2, \Delta x_{t-2}) \tag{5}$$

$$1 - q_t = P_r(s_t = 1|s_{t-1} = 2, \Delta x_{t-2}) \tag{6}$$

We allow transition probabilities to vary depending distinctly on the two month lagged changes Δx_{t-2}. This specification follows Darolles et al. (2019). We employ two-month lagged CLI changes in the regime switching model and apply identical lag structure to the MCCC index to maintain analytical consistency.

$$p_t = \Phi(d_1 \Delta x_{t-2}), \tag{7}$$

$$q_t = \Phi(d_2 \Delta x_{t-2}), \tag{8}$$

where Φ represents the cumulative density function of a standard normal variable, with d_1 and d_2 correspond to the transition probabilities loadings on the lagged changes in the respective respective index. We use a maximum likelihood (ML) method to estimate parameter vectors for each model specification.

4.2.2 The ESG returns: Time-varying

Our methodology concludes by computing the time-varying ESG spread using the parameters derived from the univariate MRS model. We employ a decision criterion that identifies regime occurrence at time t when the corresponding conditional filtered probability exceeds the 0.5 threshold. This classification process enables us to decompose the complete time series into two distinct state-dependent subsequences. The first subsequence captures the risk-adjusted ESG spread values observed exclusively during months classified as regime 1.

The second subsequence contains observations from regime 2 periods. This decomposition enables us to calculate the average risk-adjusted return for each regime-specific ESG spread.

$$RA\ Spread_{(ESG,s_t)} = \widehat{\alpha}_{(HighESG,s_t)} - \widehat{\alpha}_{(LowESG,s_t)}, \quad \forall s_t \in (1,2) \tag{9}$$

$\hat{\alpha}_{(i,s_t)}$ are the ML estimators of the mean risk-adjusted returns in each regime for the extreme quintile portfolios. We conduct global and sectoral analyses from January 2013 to December 2022 to assess our MRS model's consistency across different markets. Our analysis operates at two levels. We initially examine the aggregate US equity market using the MSCI USA Index, subsequently extending our analysis to the eleven constituent sectors through sector-specific MSCI indices.

5 Empirical results

This section presents the empirical results of our regime-switching analysis. Section 5.1 presents findings for the global US market using CLI and MCCC index as exogenous variables in our models. Section 5.2 presents results at the sectoral level applying the same methodology using exclusively the MCCC index. Finally, Section 5.3 presents disaggregated results for individual ESG pillars.

5.1 Do ESG regime cycles exist?

Figure 1 illustrates the cumulative returns of the ESG-adjusted returns, rebased to 100, spanning February 2013 to December 2022, under two different model specifications. Panel A presents filtered probabilities using the Composite Leading Indicator (CLI) as the exogenous factor. Panel B displays outcomes using the MCCC index. Both panels contrast the cumulative ESG-adjusted returns with their respective filtered probabilities of bull regimes generated by the MRS model and the recession periods designated by the NBER. The filtered probabilities represent the likelihood of operating within a bullish ESG regime at time *t*, conditional on information available at time *t-1*.

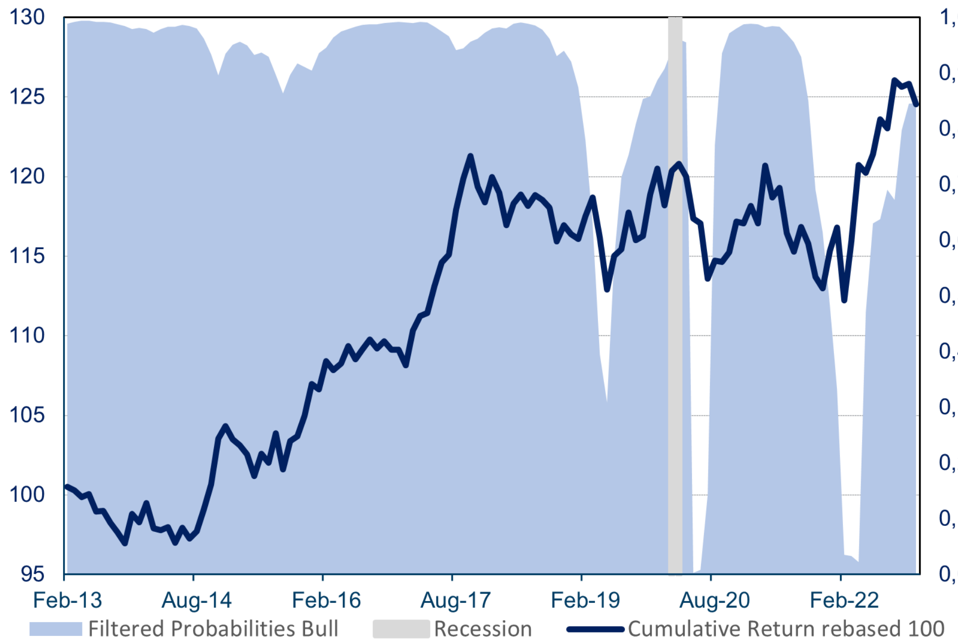
Figure 1 shows that both approaches enable clear identification of bullish and bearish periods through their respective cumulative return patterns. Panel A reveals that the CLI-based model captures distinct regime transitions that generally align with established ESG market phases. Panel B proves that the MCCC-based specification delivers superior regime identification with enhanced precision in timing and intensity of transitions.

Comparative examination reveals that the MCCC-based model significantly outperforms the CLI approach in identifying ESG contraction regimes. This superior performance proves particularly evident during February 2021 to April 2022, where the climate sentiment index show enhanced precision in detecting regime shifts. Notably, the climate sentiment index provides superior detection capabilities during market stress periods, especially pronounced during post-pandemic recovery conditions. Traditional macroeconomic indicators fail to capture the nuanced investor sentiment shifts that drive ESG asset performance, while the MCCC index successfully identifies these critical market transitions. These results highlight the distinct informational advantages of climate-related sentiment measures over traditional macroeconomic indicators for capturing ESG market dynamics.

Table 2 presents summary statistics for monthly ESG-adjusted returns of the US stock market, comparing unconditional statistics with regime-switching results using two different exogenous variables in the transition probabilities: the CLI and the MCCC index. The Static column reports summary statistics for risk-adjusted returns from our methodological framework described in Section 4.1. These statistics are computed over the entire sample period without regime identification, providing a baseline for evaluating the regime-switching models. Panel A displays results using the Composite Leading Indicator (CLI) as the exogenous variable driving transition probabilities, while Panel B presents equivalent results using the MCCC index as the exogenous variable. The results derive from the MRS model outlined in Section 4.2.

The static ESG average returns generate 0.19% with a volatility of 1.39%. Results obtained using CLI as the exogenous variable show distinct performance patterns across market regimes. During bullish periods, the average monthly risk-adjusted ESG returns generate 0.25%, above the unconditional average returns. Conversely, bearish periods deliver negative returns of -0.35%. The median equals 0.21% during bullish regimes and -0.42% during bearish periods, highlighting the pronounced asymmetry between market states. The volatility of 2.59% in bearish periods indicates higher distribution heterogeneity compared to bullish periods (1.19%) and exceed static figures. The return distributions exhibit right-skewed patterns across both regimes. Skewness measures indicate more pronounced positive

Panel A



Panel B

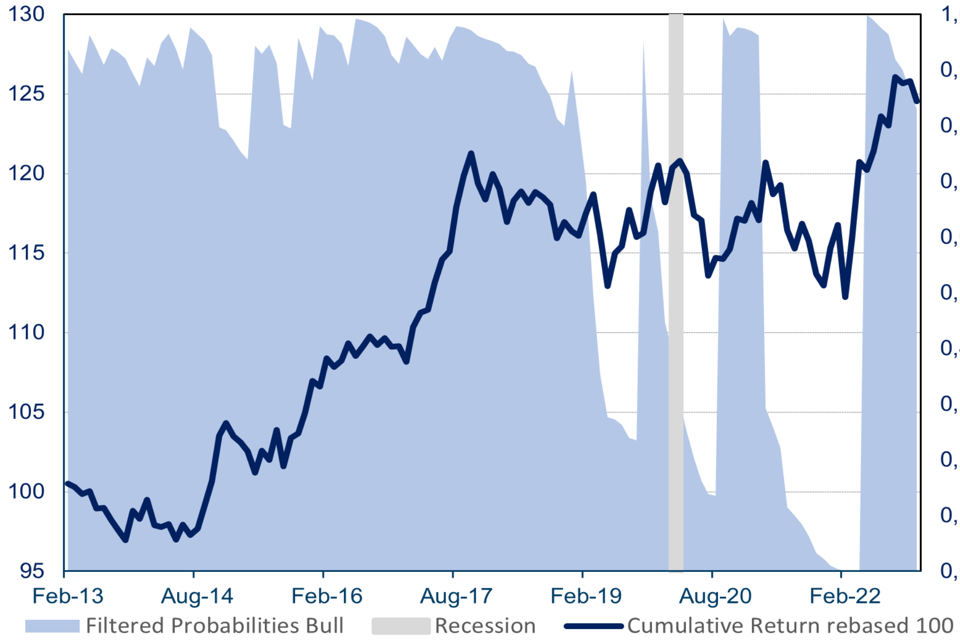


Figure 1: **Filtered Probabilities and Cumulative Returns over Time** This figure presents cumulative ESG-adjusted returns rebased to 100 over the period February 2013 to December 2022 under two model specifications. Panel A displays results using the Composite Leading Indicator (CLI) as the exogenous factor, while Panel B shows outcomes using the MCCC index. Both panels contrast cumulative ESG returns with filtered probabilities of bullish regimes derived from MRS models and official recession periods designated by the National Bureau of Economic Research (NBER). The filtered probabilities represent the conditional likelihood of operating within a bullish ESG regime at time t, given information available at time $t-1$.

values during bullish regimes compared to bearish regimes. Additionally, the results reveal flatter distributions characterized by negative kurtosis and limited tail characteristics across both market states.

Results obtained using the MCCC index exhibit similar patterns, although the bearish regime presents different characteristics. Mean returns during bearish periods are -0.09%. These returns significantly exceed corresponding values under the CLI specification. Volatility during this regime is 1.42%, which is lower than the CLI specification. This indicates that climate-related sentiment captures less severe but potentially more persistent market downturns. During the bullish regime, the MCCC-based model delivers higher returns on average than both, the static and CLI-based regime-switching model. This result suggests superior timing capabilities for ESG investment market during favorable conditions.

These results corroborate with Figure 1. Panel A identifies shorter periods concentrated around acute market stress events. This approach produces more pronounced negative returns and volatility during brief bearish phases. Panel B captures longer periods of market underperformance. The MCCC-based model extends beyond immediate stress events, identifying sustained periods of weaker ESG performance.

Table 2: **Summary Statistics for US Market by Regime** This table presents summary statistics for monthly ESG-adjusted returns of the US stock market from February 2013 to December 2022. The static column reports summary statistics of the static ESG-adjusted returns resulting from Equation 9. Panel A presents regime-switching results calculated using the Composite Leading Indicator (CLI), while Panel B shows results using the MCCC index, where transition probabilities vary based on these respective indicators. Results are presented for bull market conditions (Regime 1) and bear market conditions (Regime 2) under each indicator specification. All returns are expressed in percentage terms.

		Panel A: CLI Regime-Switching		**Panel B: MCCC Regime-Switching**	
	Static	Regime 1 (Bull)	Regime 2 (Bear)	Regime 1 (Bull)	Regime 2 (Bear)
Mean	0.19	0.25	-0.35	0.29	-0.09
Median	0.18	0.21	-0.42	0.19	-0.28
Min	-3.89	-2.39	-3.89	-2.21	-3.89
Max	4.12	3.09	4.12	2.85	4.12
Volatility	1.39	1.19	2.59	1.05	1.42
Skewness	-0.05	0.07	0.42	0.15	0.17
Kurtosis	0.13	-0.64	-1.20	-0.65	-0.80

Figure 2 presents the relationship between the two exogenous variables and filtered regime probabilities, spanning January 2013 to December 2022. Panel A displays the two-month lagged CLI changes alongside the respective filtered probabilities of bullish regimes generated by the MRS model and recession periods designated by the NBER. Panel B presents the two-month lagged MCCC index changes with corresponding filtered probabilities and recession indicators.

The correlation coefficient between the filtered probability associated with an bullish ESG regime and the two-month lagged CLI changes reaches 36.22%. This coefficient is statistically significant at the 1% confidence level. This indicates that endogenous ESG regimes correlate significantly with the business cycle in the US market. However, the moderate magnitude of this correlation coefficient suggests that economic regime shifts do not entirely explain the filtered probability dynamics. The correlation using the two-month lagged climate sentiment index changes equals 0.09%. This coefficient lacks statistical significance. This suggest that climate sentiment indicators provide limited direct explanatory power for ESG regime transitions when compared to traditional macroeconomic indicators.

The predictive capacity of the CLI deteriorated during the COVID-19 crisis, prompting re-analysis for the pre-pandemic period. The correlation coefficient improves substantially during the pre-pandemic period, reaching 56.20%. However, the correlation with the MCCC index remains low at 0.08% during the pre-pandemic period.

While we would expect greater correlation, the highly volatile nature of the MCCC index may cause these results in this analysis. Indeed, CLI changes exhibit relatively smooth patterns over time, while MCCC changes display highly dynamic and volatile movements. This volatility difference may affect results, especially for regime identification.

Our findings clearly identify two distinct regimes in which ESG performance varies between bullish and bearish market conditions. Notably, our results indicate that ESG cycles are more clearly identified using a climate sentiment indicator in the model rather than a business cycle indicator. This corroborates the importance of ESG investor preferences in driving the ESG market dynamics. Therefore, we retain solely the MCCC index and encourage us to seek alternatives to CLI using more dynamic indicators. Candidates that may be considered include the Aruoba-Diebold-Scotti index, the Consumer Confidence index, or the Economic Policy Uncertainty index.

Panel A

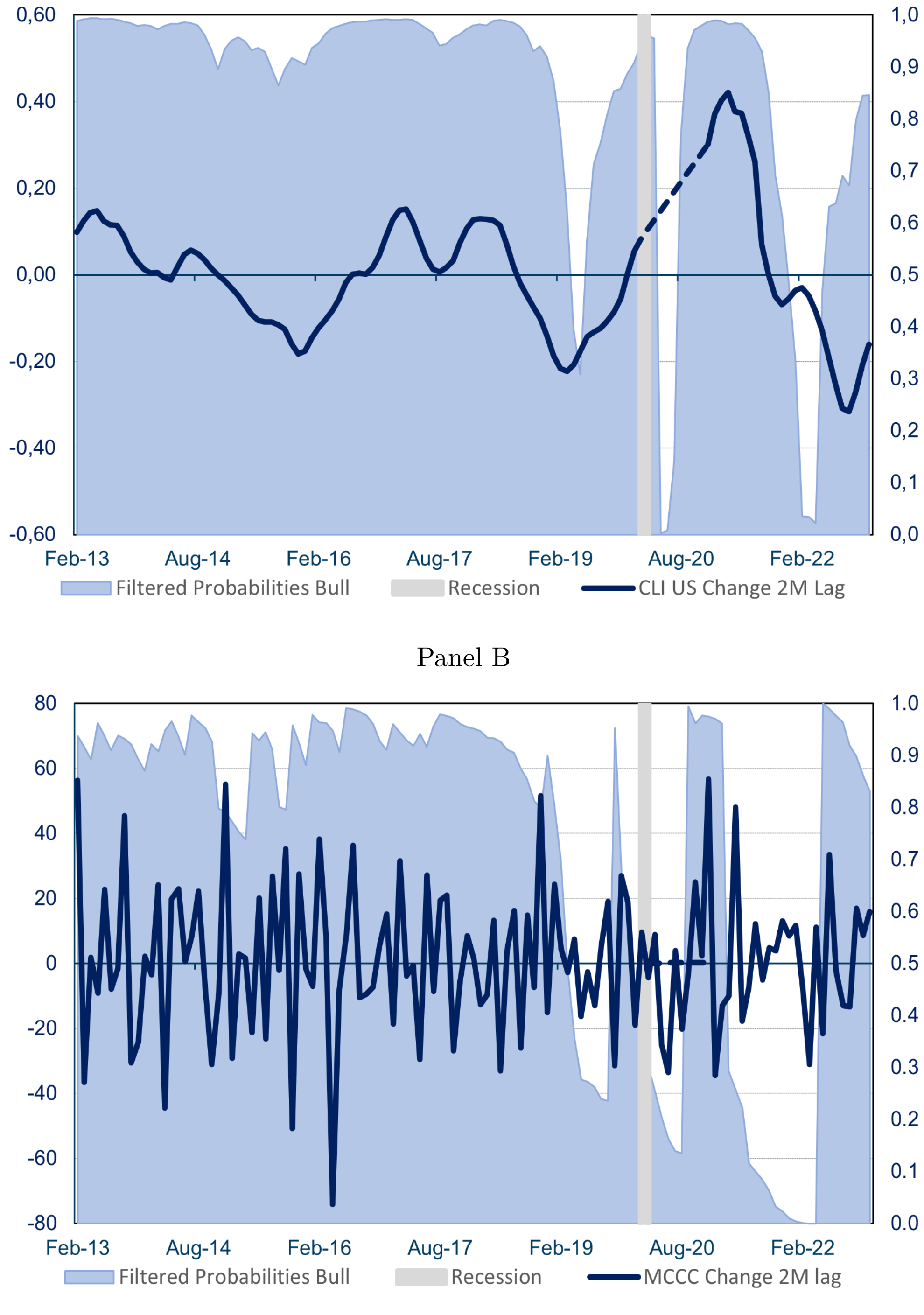


Figure 2: **Filtered Probabilities and Changes in CLI and MCCC over Time** This figure illustrates the relationship between distinct exogenous variables and filtered bullish regime probabilities derived from MRS models over the period February 2013 to December 2022. Panel A displays two-month lagged changes in the CLI[4] alongside filtered probabilities of bull regimes and recession periods designated by the National Bureau of Economic Research (NBER). Panel B presents two-month lagged changes in the MCCC index with corresponding filtered probabilities and recession indicators.

5.2 Is Climate investors react at the sector level?

Since the MCCC index measures climate concerns, we expect some sectors to exhibit greater sensitivity to climate sentiment due to their environmental externalities and regulatory risks. This sectoral analysis addresses this heterogeneity. In this section, we present our results at the sector level. Specifically, we analyze key sectors considered highly exposed to climate risks. MSCI (2023) asserts that Energy, Utilities, and Materials represent the sectors with the highest climate risk exposure. Sautner et al. (2023) notes that Industrials also face high exposure to such risks. We also analyze the Communication Services and the Real Estate sectors[5].

Figure 3 presents cumulative ESG-adjusted returns, rebased to 100, from February 2013 to December 2022 for selected sectors. This analysis uses the MCCC index as the exogenous variable in MRS models. Each subfigure incorporates filtered probabilities of bullish ESG regimes, along with official recession periods as defined by the NBER.

We observe that the model identifies clear regime patterns for most climate-sensitive sectors. However, the model shows less distinct regime transitions for the Energy sector.

Table 3 displays statistical outcomes for the eleven sectors in the US during two different regimes identified through the Markov Regime-Switching model using the MCCC index as the exogenous variable. Our analysis focuses exclusively on climate-sensitive sectors.

During bullish periods, Communication Services (7.02%) delivers the highest average ESG returns among climate-sensitive sectors. Real Estate (4.30%) and Industrials (2.75%) follow with strong positive performance. Materials (2.08%) shows solid returns, while Utilities (0.77%) and Energy (0.17%) exhibit modest positive performance. Interestingly, we find that the core climate sensitive sectors — Energy, Utilities and Materials — deliver lower returns than their peers.

Conversely, in bearish regimes, experience more severe contractions. Energy (-1.17%), Materials (-1.50%) and Utilities (-2.83%) experience the most severe contractions among climate-sensitive sectors. Real Estate (-0.54%) shows moderate negative performance. Industrials (-0.39%) and Communication Services (-0.28%) present relative resilience during bearish conditions. This evidence indicates that these sectors experience asymmetric re-

[4]Graphically, we replace data points in the CLI time series during the COVID-19 crisis to smooth exacerbated fluctuations.

[5]Figure A.2 in the Appendix presents regime identification results for the eleven US sectors.

sponses depending on changes in climate concerns. The asymmetric response highlights the downside risk associated with these sectors.

Volatility patterns across climate-sensitive sectors reveal significant heterogeneity during different market regimes. Communication Services exhibits the highest volatility at 7.48% during bullish periods, followed by Energy at 5.15%. Materials (3.65%) and Real Estate (3.67%) maintain moderate volatility levels, while Utilities (1.81%) and Industrials (1.56%) manifest relatively lower volatility. During bear market conditions, sector volatilities display considerable variation. Communication Services (4.31%) and Utilities (3.18%) exhibit elevated volatility levels, indicating pronounced sector-specific sensitivity to bearish market conditions. Materials (3.21%) and Real Estate (2.37%) show moderate volatility increases. Industrials (2.02%) and Energy (1.54%) emerge as the most resilient climate-sensitive sectors with relatively contained volatility during contractions.

Figure 4 presents the relationship between filtered probabilities of upward ESG states, NBER recession dates, and two-month lagged monthly changes in the MCCC across climate-sensitive sectors.

We analyze correlation coefficients between filtered probabilities of upward ESG states and two-month lagged MCCC changes. The climate sentiment index produces different correlation patterns across climate-sensitive sectors. Energy, Utilities, and Materials sectors present varying degrees of sensitivity to climate sentiment measures. Energy exhibits a negative correlation (-26%) with climate sentiment measures, while Materials exhibits positive correlation (+15%). Communication Services and Utilities both show statistically insignificant correlations with climate sentiment indicators, indicating limited direct influence of environmental sentiment on ESG performance in these sectors. Industrials exhibits the strongest positive correlation (49%) among climate-sensitive sectors, indicating substantial sensitivity to climate sentiment changes. This pronounced response likely captures the sector's significant exposure to both climate-related operational risks and transition-related investment opportunities. Real Estate exhibits a negative relationship (-12%).

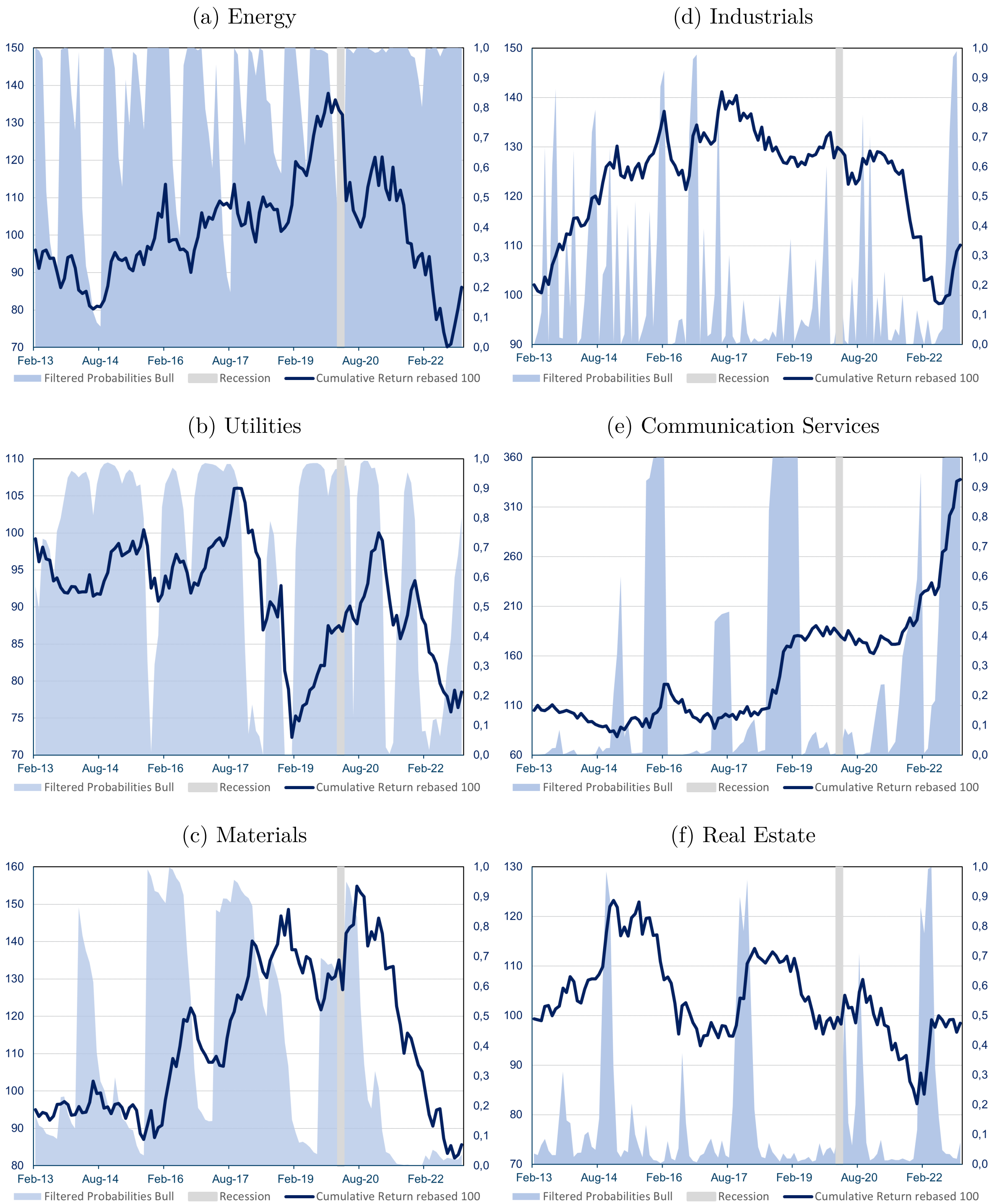
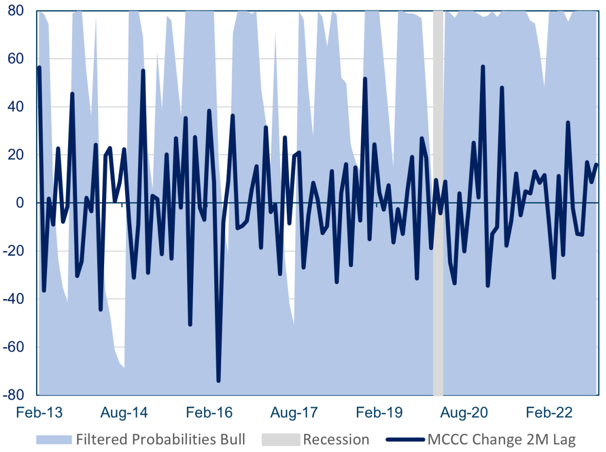
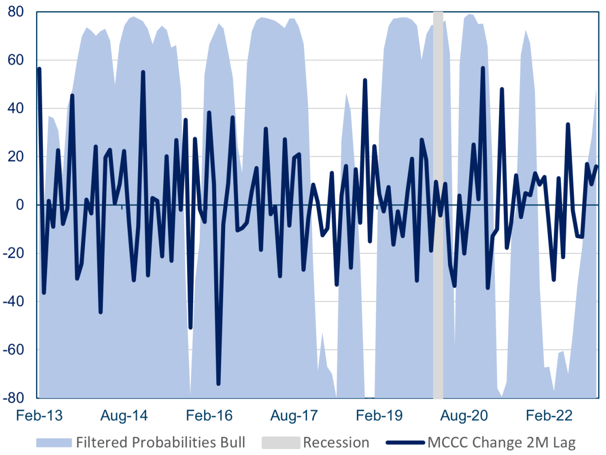


Figure 3: **Filtered Probabilities and Cumulative ESG Returns across Climate-Sensitive Sectors** This figure presents cumulative ESG-adjusted returns, rebased to 100, from February 2013 to December 2022 for selected climate-sensitive sectors using the MCCC index as the exogenous variable in the MRS model. Each panel corresponds to a specific sector or the global series, with Panel A showing Energy, Panel B Utilities, Panel C Materials, Panel D Industrials, Panel E Communication Services, and Panel F Real Estate. Each subfigure includes filtered probabilities of bullish ESG regimes derived from the MCCC index-based MRS model, along with official recession periods as defined by the NBER.

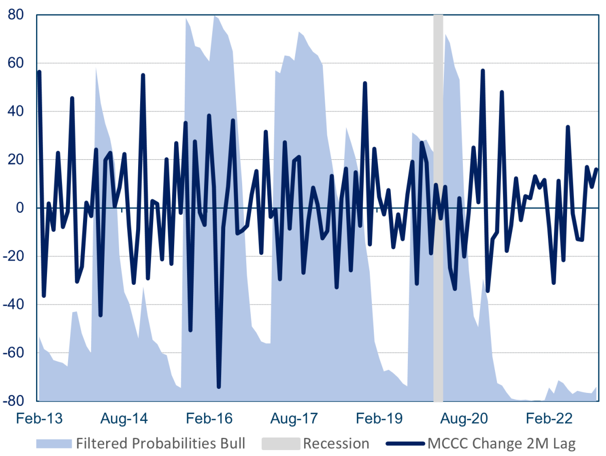
(a) Energy



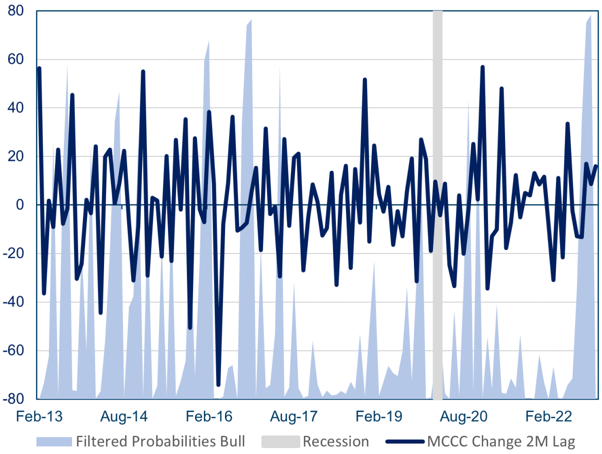
(b) Utilities



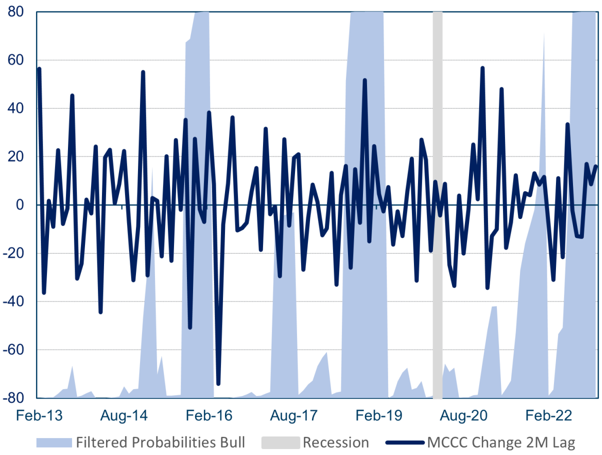
(c) Materials



(d) Industrials



(e) Communication Services



(f) Real Estate

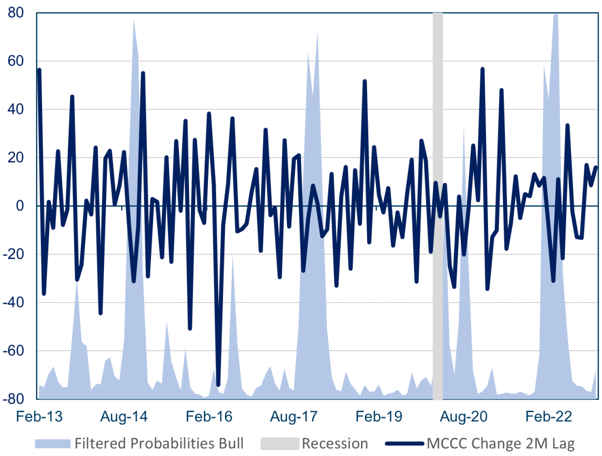


Figure 4: **Filtered Probabilities and Changes in MCCC Index across Climate-Sensitive Sectors** This figure presents two-month lagged changes in the MCCC index alongside filtered bullish regime probabilities from February 2013 to December 2022 for selected climate-sensitive sectors. Each panel corresponds to a specific climate-sensitive sector, with Panel A showing Energy, Panel B Utilities, Panel C Materials, Panel D Industrials, Panel E Communication Services, and Panel F Real Estate. Each subfigure includes filtered probabilities of bullish ESG regimes derived from the MCCC index-based MRS model, along with official recession periods as defined by the NBER.

Table 3: **Summary Statistics by Sector - MCCC index-Based Markov-Switching Model** This table presents summary statistics of monthly ESG-adjusted returns across the eleven MSCI USA sector indices, separated by market regimes identified through the Markov-switching model using the MCCC index as the exogenous variable. The table distinguishes between bullish (Reg.1) and bearish (Reg.2) periods for each sector.

	Cons Staples		*Discr*		*Materials*		*Financials*		*IT*		*Utilities*	
	Reg.1 (Bull)	Reg.2 (Bear)	Reg.1 (Bull)	Reg.2 (Bear)	Reg.1 (Bull)	Reg.2 (Bear)	Reg.1 (Bull)	Reg.2 (Bear)	Reg.1 (Bull)	Reg.2 (Bear)	Reg.1 (Bull)	Reg.2 (Bear)
Mean	-0.14	-0.06	2.17	0.11	2.08	-1.50	0.36	0.35	0.17	0.05	0.77	-2.83
Median	-0.20	-0.32	3.70	0.04	2.31	-1.55	0.03	0.31	0.00	0.28	0.64	-2.85
Min	-7.25	-6.82	-6.37	-5.78	-7.61	-8.70	-5.84	-1.19	-6.77	-7.92	-3.06	-12.34
Max	7.95	6.92	9.53	6.10	11.87	4.87	5.48	2.19	10.75	7.33	6.57	4.75
Variance	2.85	3.10	5.15	2.43	3.65	3.21	2.27	0.93	3.11	4.92	1.81	3.18
Skewness	0.08	0.04	-0.37	-0.03	-0.10	-0.10	-0.15	0.07	0.26	-0.11	0.23	-0.77
Kurtosis	0.60	-0.44	-1.11	-0.28	0.51	-0.30	0.15	-1.06	0.66	-1.24	0.28	2.52

	Industrials		*Real Estate*		*Energy*		*Health Care*		*Com Svcs*	
	Reg.1 (Bull)	Reg.2 (Bear)	Reg.1 (Bull)	Reg.2 (Bear)	Reg.1 (Bull)	Reg.2 (Bear)	Reg.1 (Bull)	Reg.2 (Bear)	Reg.1 (Bull)	Reg.2 (Bear)
Mean	2.75	-0.39	4.30	-0.54	0.17	-1.17	0.30	0.34	7.02	-0.28
Median	2.71	-0.12	5.76	-0.38	0.56	-0.96	0.42	0.54	5.67	-0.68
Min	0.32	-7.92	-4.81	-6.01	-17.37	-4.60	-4.79	-10.26	-9.10	-11.33
Max	6.54	3.62	8.72	5.89	10.68	0.86	5.26	9.09	21.39	11.92
Variance	1.56	2.02	3.67	2.37	5.15	1.54	2.15	4.75	7.48	4.31
Skewness	0.52	-0.74	-1.09	-0.10	-0.57	-0.79	-0.07	-0.13	0.02	0.01
Kurtosis	0.39	1.04	0.98	-0.43	0.34	0.03	-0.16	-0.83	-0.68	-0.06

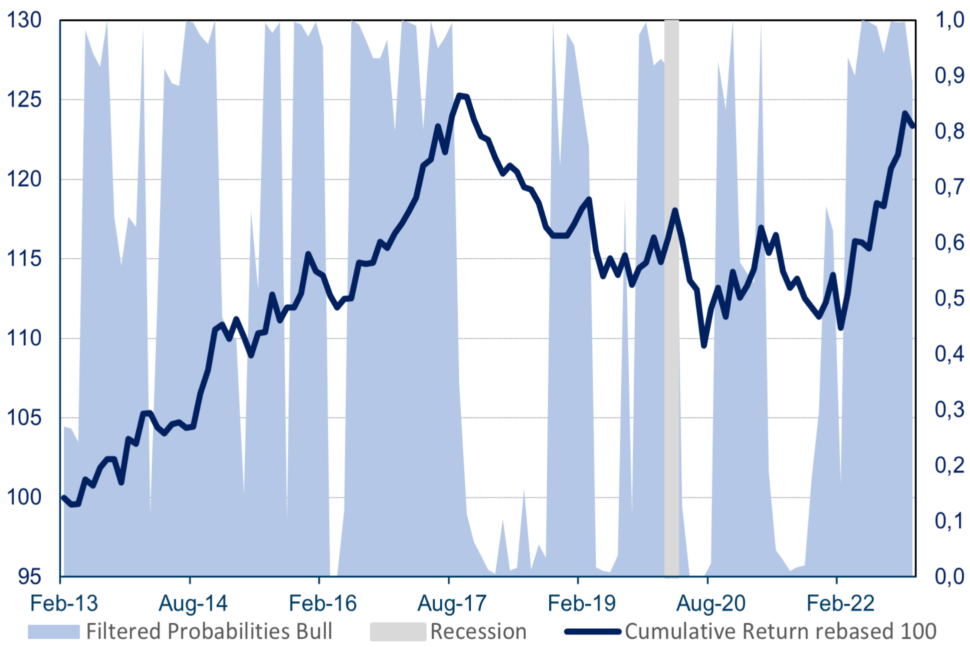
5.3 ESG Pillar-Specific Analysis

Given that the MCCC index specifically measures climate concerns, this indicator may not represent the optimal factor variable for switching regime models applied to composite ESG scores. ESG scores encompass environmental, social, and governance dimensions that extend beyond climate-related factors alone. To address this limitation, this section examines the analysis of the ESG US market through a decomposed approach. We examine each of the three ESG pillars separately: Environmental, Social, and Governance performance. This methodology allows us to assess whether the MCCC index establishes differential explanatory power across the distinct components of ESG measurement. We follow the methodology developed in Section 4, applying it separately to Environmental, Social, and Governance scores.

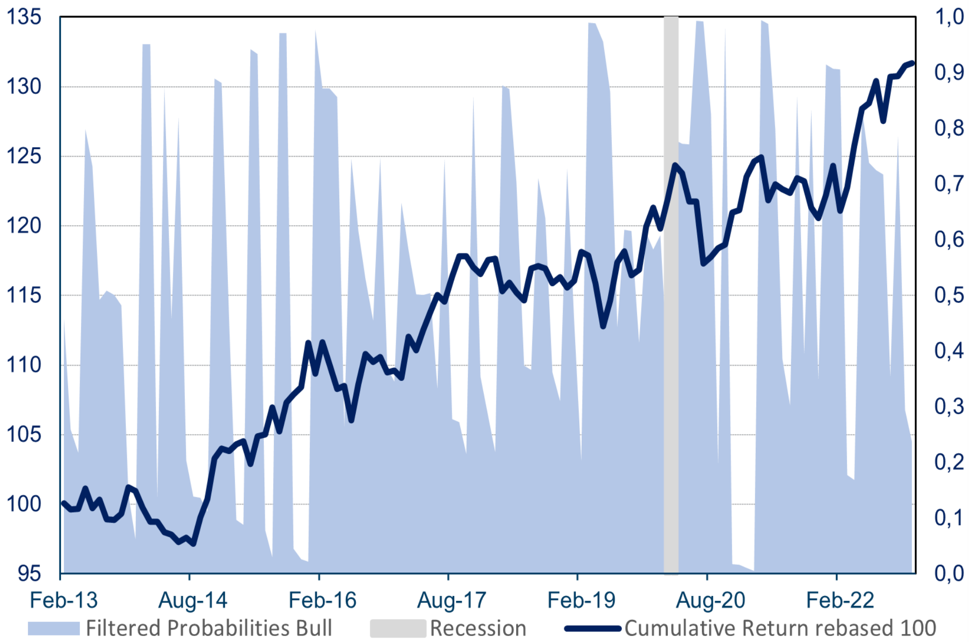
Figure 5 illustrates the cumulative returns of the ESG-adjusted spread, rebased to 100, spanning February 2013 to December 2022, decomposed across the three ESG components using the MCCC index as the exogenous factor. Panel A displays outcomes for Environmental performance, Panel B shows results for Social performance, and Panel C presents results for Governance performance. All panels contrast the cumulative ESG returns with their respective filtered probabilities of bullish regimes generated by the MRS model.

The results corroborate our expectations. The MCCC index shows superior performance in filtering Environmental regimes compared to Social and Governance components. This finding confirms that climate sentiment indicators exhibit stronger explanatory power for environmental factors than for other ESG dimensions. Future research could extend this analysis using Social and Governance sentiment indicators. Such indicators would determine whether preference shifts in these dimensions drive respective performance cycles.

Panel A



Panel B



Panel C

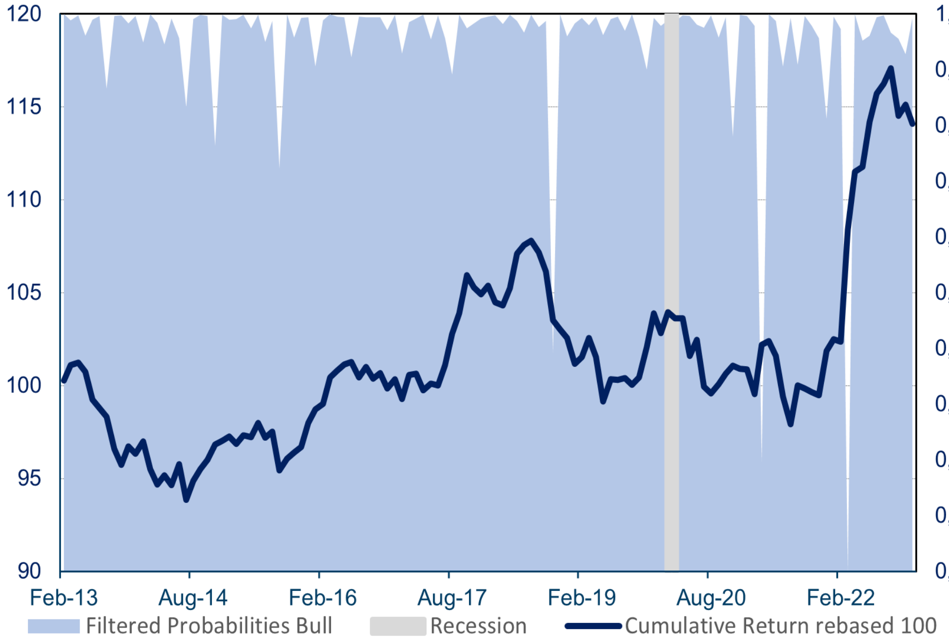


Figure 5: **Filtered Probabilities and Cumulative Returns across ESG Pillars** This figure presents cumulative spread returns rebased to 100 from February 2013 to December 2022 for each ESG pillar analyzed separately using the MCCC index as the exogenous variable in the MRS model. Panel A displays results for Environmental pillar, Panel B shows outcomes for Social pillar, and Panel C presents results for Governance pillar. Each subfigure includes filtered probabilities of bullish regimes derived from the MCCC index-based MRS model, along with official recession periods designated by the National Bureau of Economic Research (NBER).

6 Conclusion

This paper examines the time-varying nature of ESG performance and identifies distinct regimes characterizing ESG market dynamics. Through empirical analysis of the United States market using the MSCI USA Index and its components from January 2013 to December 2022, we employ a Markov Regime-Switching (MRS) model with time-varying transition probabilities to examine ESG cycle patterns. Our methodology incorporates the Composite Leading Indicator (CLI) and the Media Climate Change Concerns (MCCC) index as exogenous variables to determine whether ESG regime shifts stem from business cycle information or investor sentiment related to climate concerns.

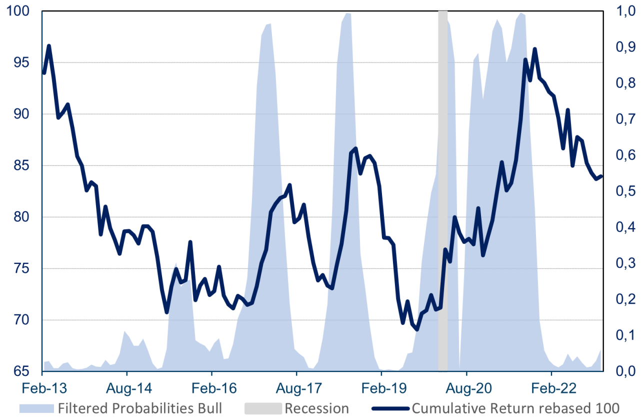
Our analysis yields three principal findings. First, ESG performance exhibits distinct regime patterns predominantly driven by climate sentiment rather than traditional business cycle indicators. The MCCC index outperforms the CLI in identifying ESG regimes. This indicates that performance shifts result primarily from changes in climate-related investor preferences. Climate sentiment proves effective for regime identification across climate-sensitive sectors. However, Energy deviates from this pattern. Third, when decomposing ESG performance across its three pillars, the MCCC index shows superior explanatory power for environmental metrics compared to social and governance components, confirming the alignment between climate sentiment and environmental performance.

These findings contribute to the sustainability field by providing empirical evidence of ESG performance dynamics through regime identification methodology. Our study addresses demand-based asset pricing challenges by incorporating climate sentiment variables through time-series analysis of returns within switching regime frameworks. This study documents how investor sentiment can be integrated into analytical frameworks for understanding ESG market behavior.

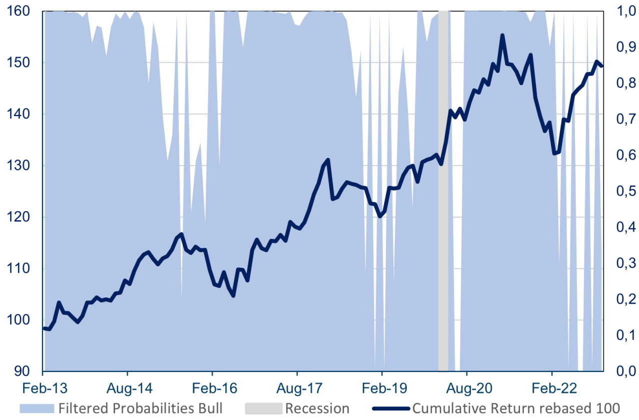
For institutional investors, our analysis provides a framework for integrating climate sentiment indicators into investment decision-making processes. This enables better understanding of ESG performance cycles while supporting informed allocation strategies that account for regime-dependent dynamics.

Appendices

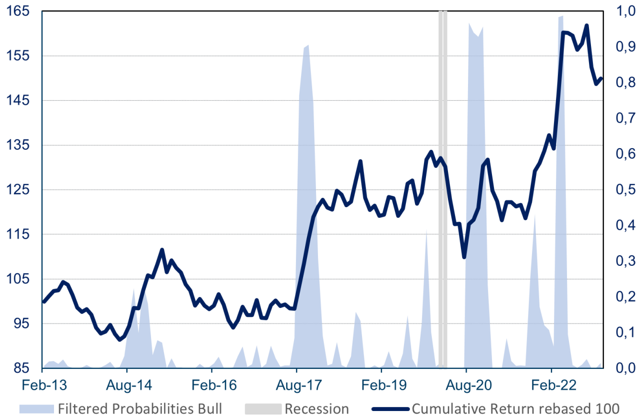
(a) Cons Staples



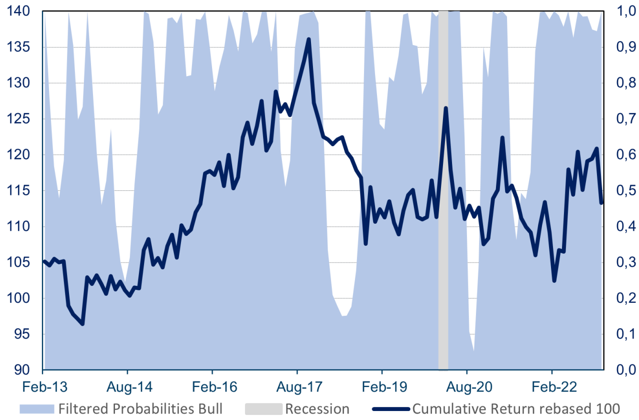
(d) Financial



(b) Cons Disc



(e) Technology



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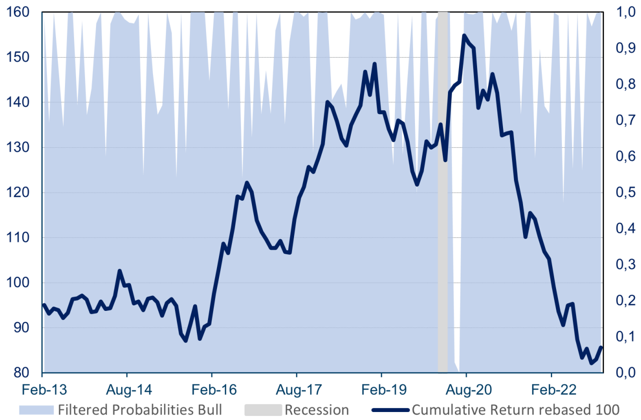
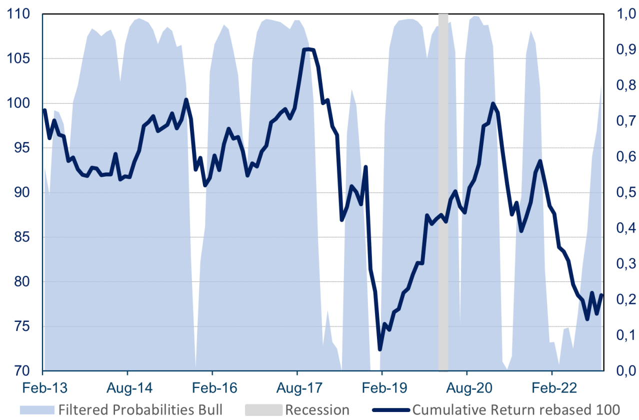
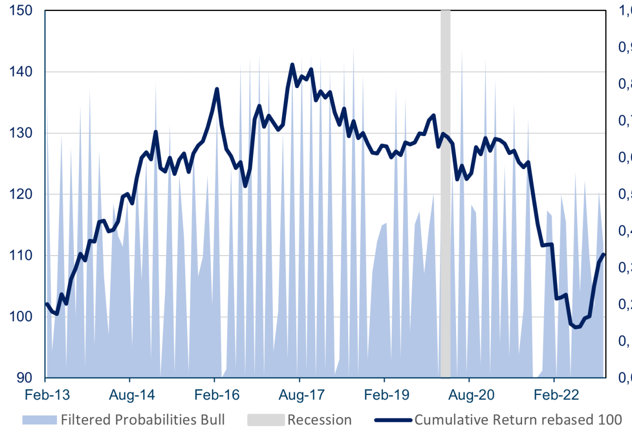


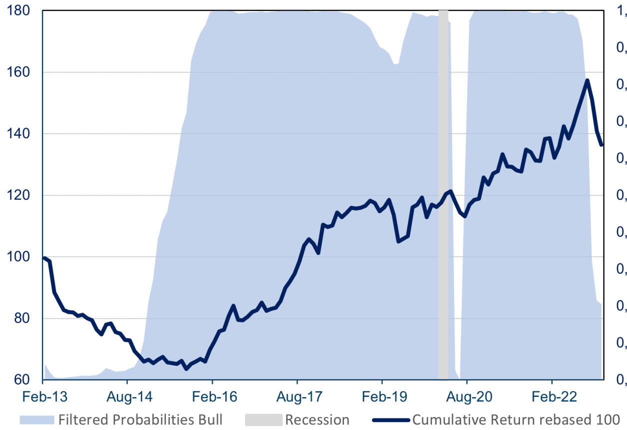
(f) Utilities



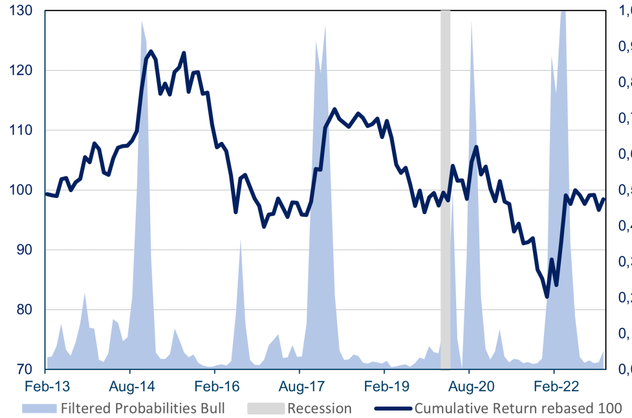
(a) Industrials



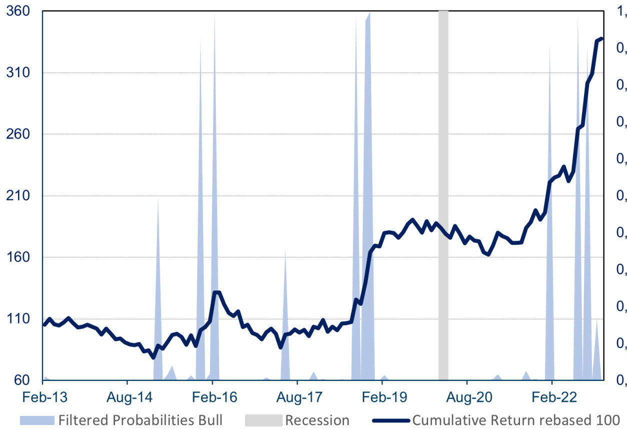
(d) Health Care



(b) Real Estate



(e) Com Svcs



(c) Energy

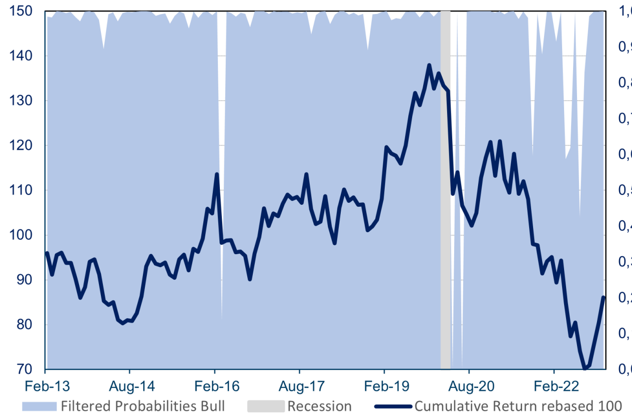
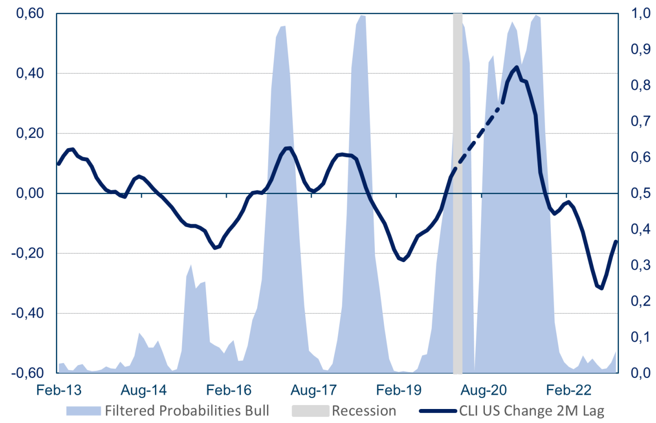


Figure A.2: **Filtered Probabilities and Cumulative ESG Returns across All Sectors - CLI-Based** TThis figure presents cumulative ESG-adjusted returns, rebased to 100, from February 2013 to December 2022 for the eleven MSCI USA sector indices using the Composite Leading Indicator (CLI) as the exogenous variable in the MRS model. Each panel corresponds to a specific sector, with panels showing Consumer Staples, Consumer Discretionary, Materials, Financials, Technology, Utilities, Industrials, Real Estate, Energy, Health Care, and Communication Services. Each subfigure includes filtered probabilities of bullish ESG regimes derived from the CLI-based MRS model, along with official recession periods as defined by the NBER.

(a) Cons Staples



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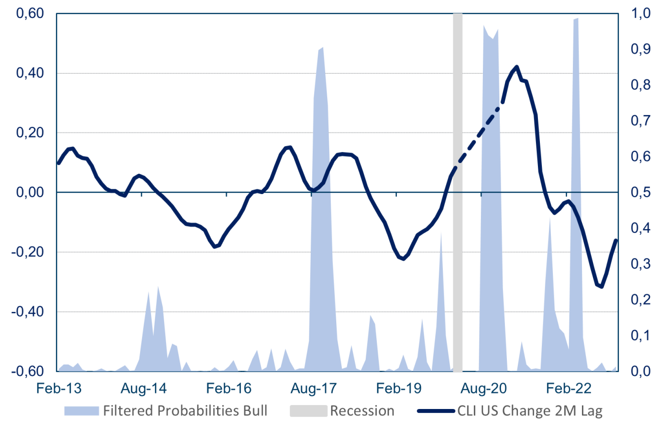
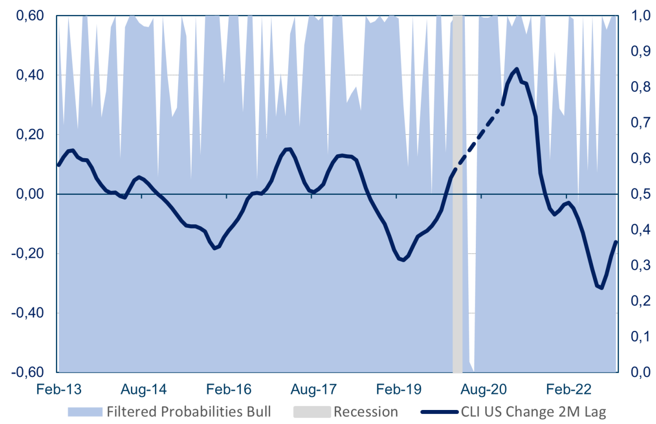
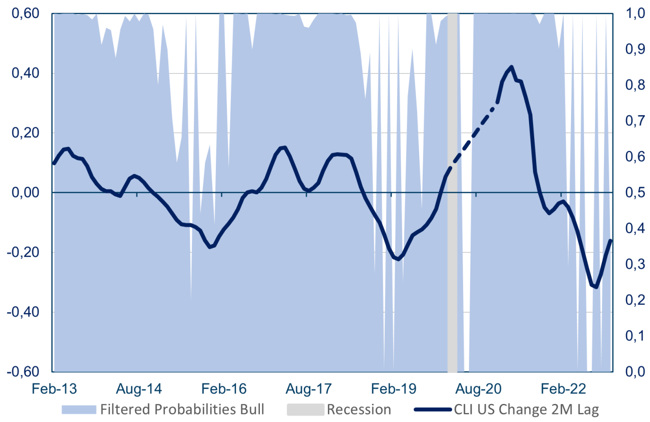


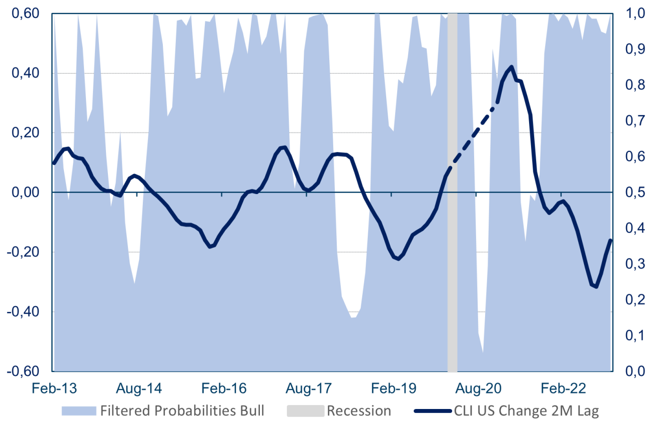
(c) Materials



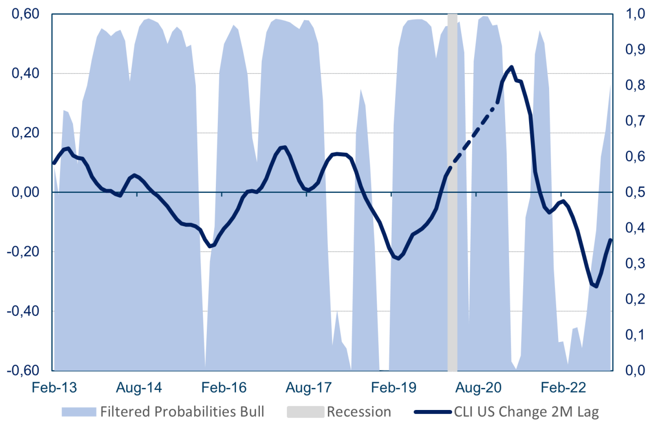
(d) Financial



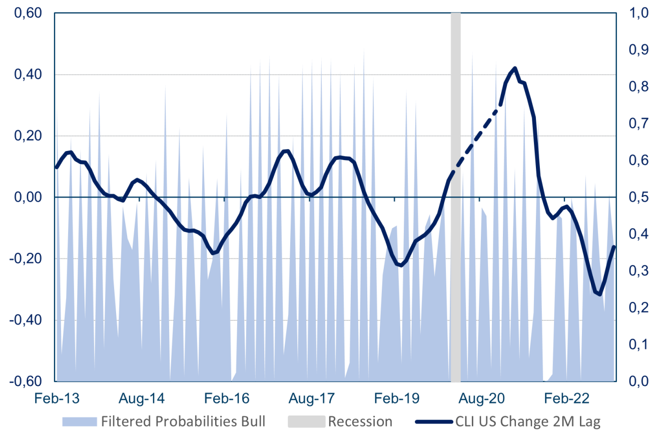
(e) Technology



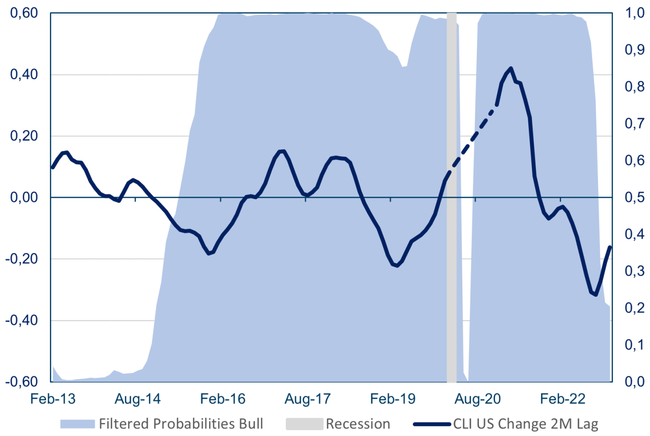
(f) Utilities



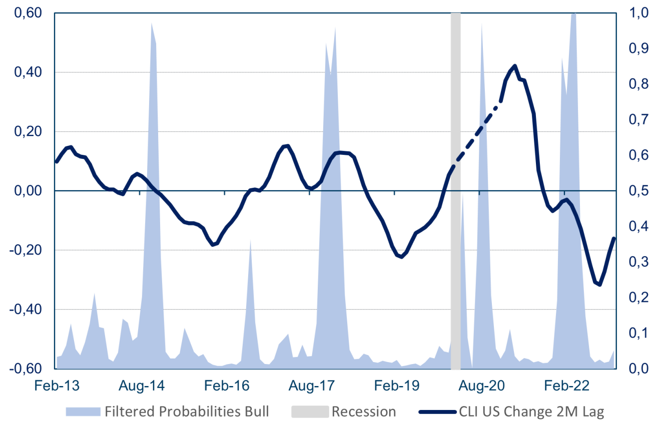
(a) Industrials



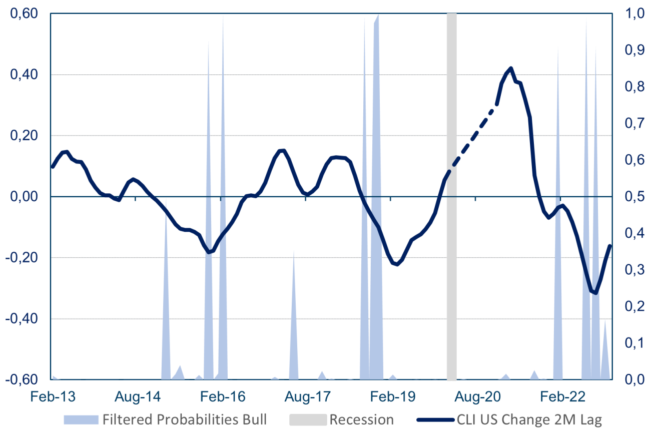
(d) Health Care



(b) Real Estate



(e) Com Svcs



(c) Energy

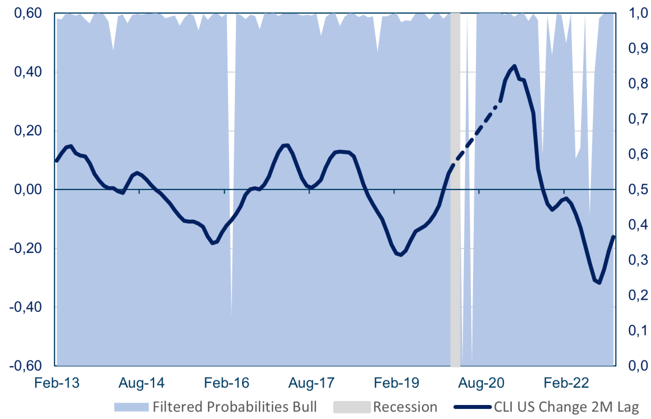
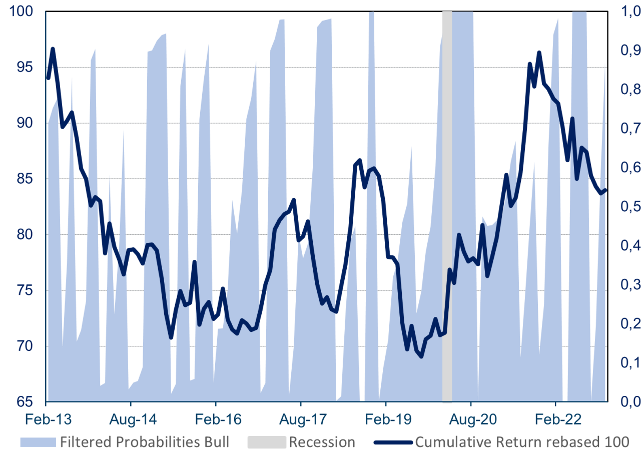
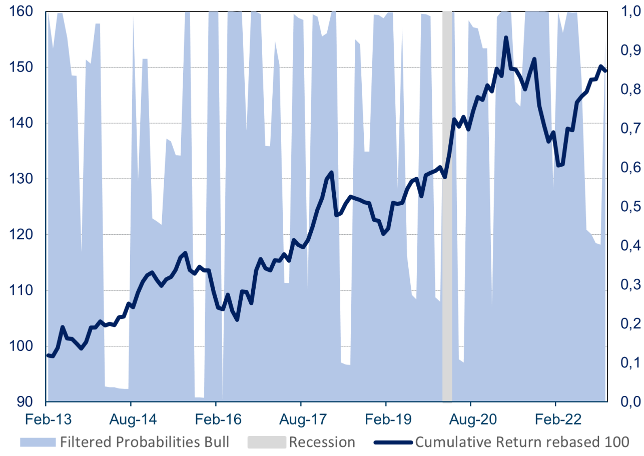


Figure A.4: **Filtered Probabilities and Changes in CLI across All Sectors** This figure presents two-month lagged changes in the Composite Leading Indicator (CLI) and filtered bullish regime probabilities from February 2013 to December 2022 for the eleven MSCI USA sector indices. Each panel corresponds to a specific sector, with panels showing Consumer Staples, Consumer Discretionary, Materials, Financials, Technology, Utilities, Industrials, Real Estate, Energy, Health Care, and Communication Services. Each subfigure includes filtered probabilities of bullish ESG regimes derived from the CLI-based MRS model, along with official recession periods as defined by the NBER.

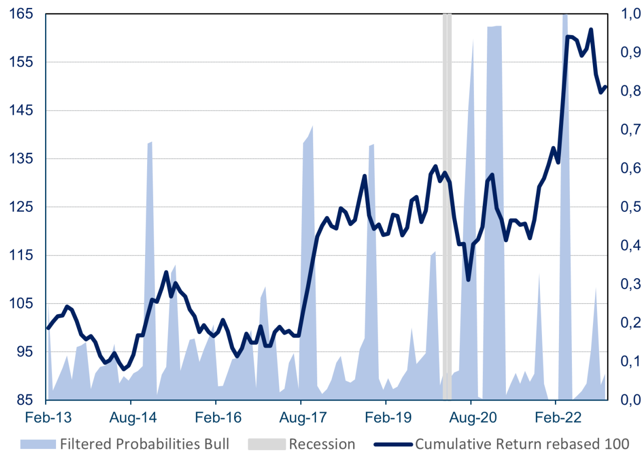
(a) Cons Staples



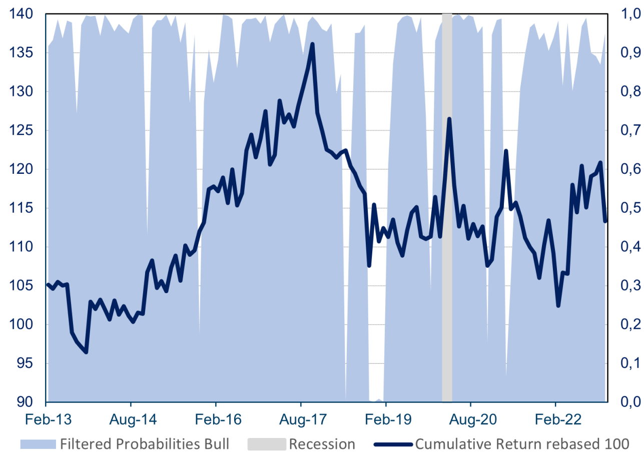
(d) Financial



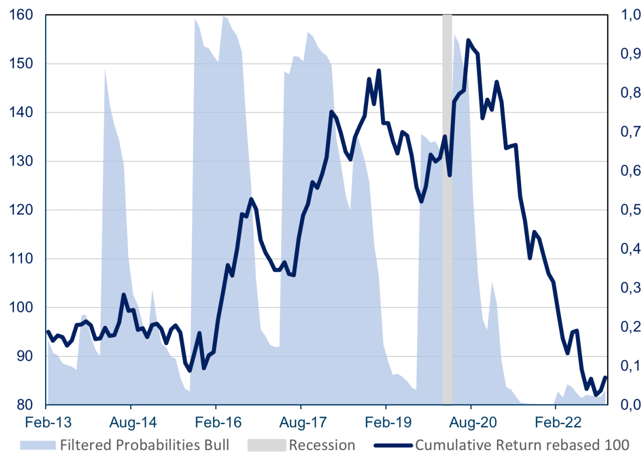
(b) Cons Disc



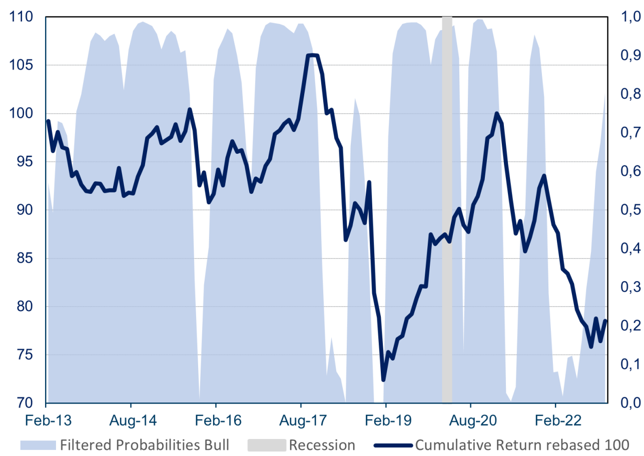
(e) Technology



(c) Materials



(f) Utilities



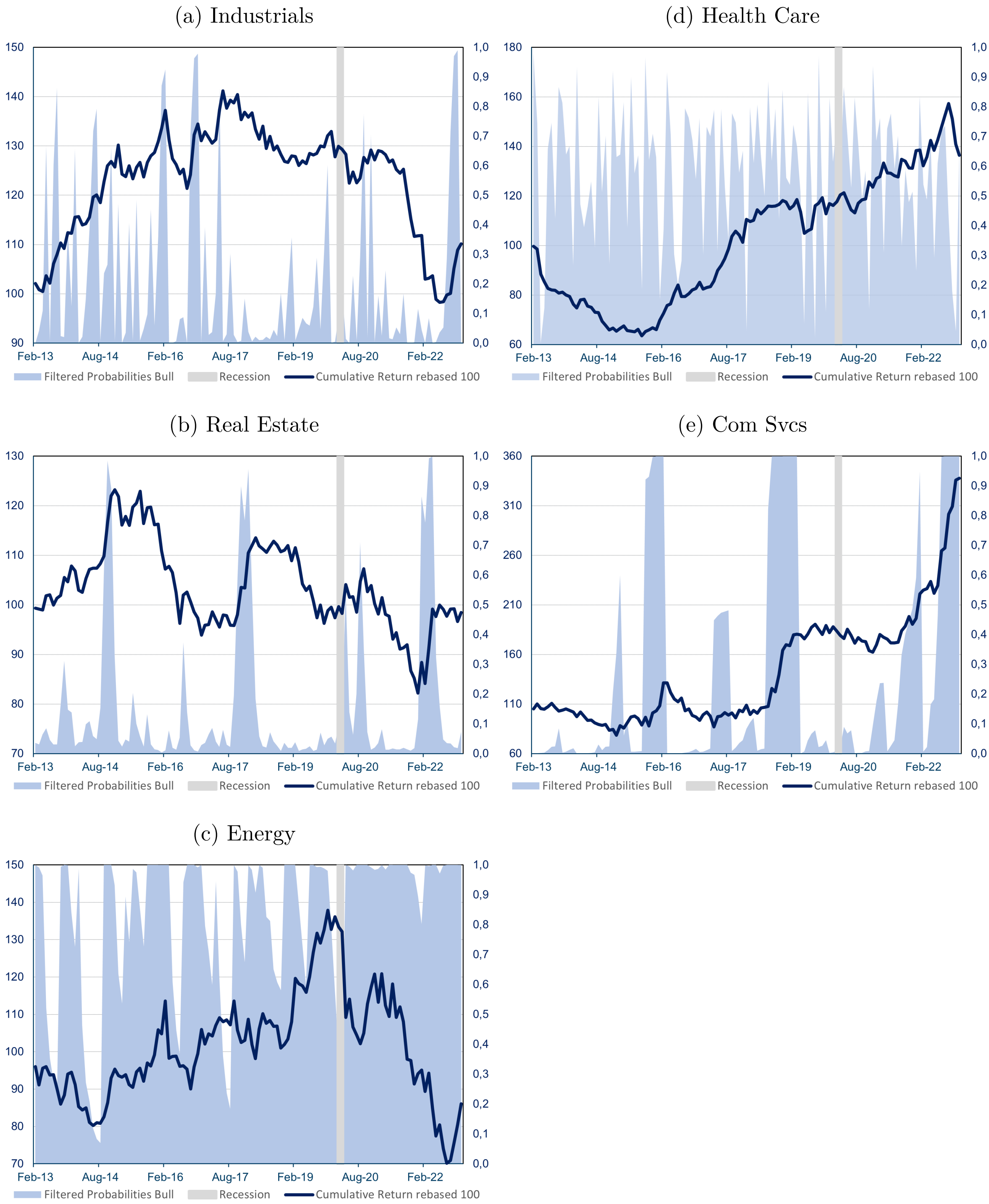
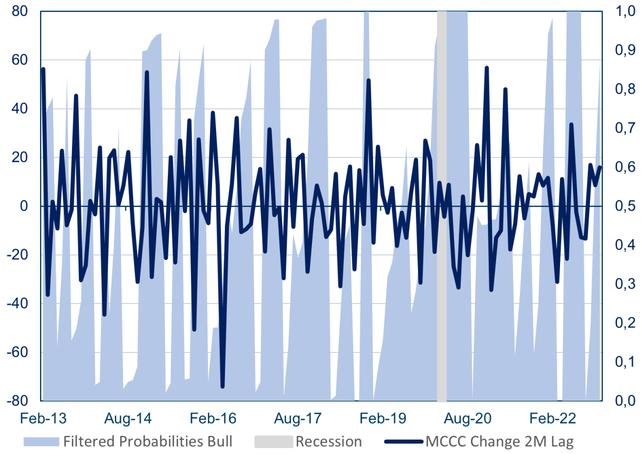
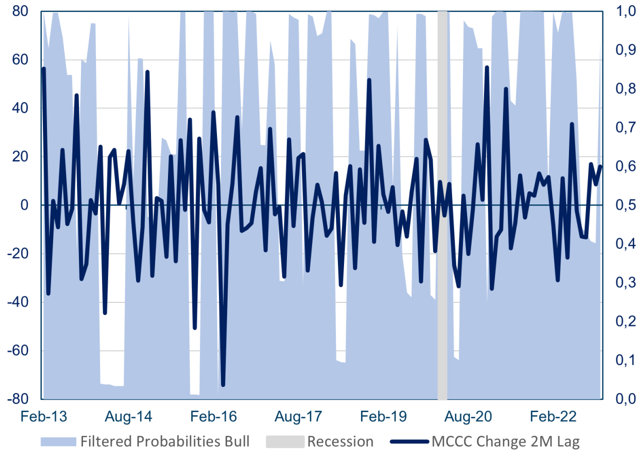


Figure A.6: **Filtered Probabilities and Cumulative ESG Returns across All Sectors - MCCC-Based** This figure presents cumulative ESG-adjusted returns, rebased to 100, from February 2013 to December 2022 for the eleven MSCI USA sector indices using the MCCC index as the exogenous variable in the MRS model. Each panel corresponds to a specific sector, with panels showing Consumer Staples, Consumer Discretionary, Materials, Financials, Technology, Utilities, Industrials, Real Estate, Energy, Health Care, and Communication Services. Each subfigure includes filtered probabilities of bullish ESG regimes derived from the MCCC index-based MRS model, along with official recession periods as defined by the NBER.

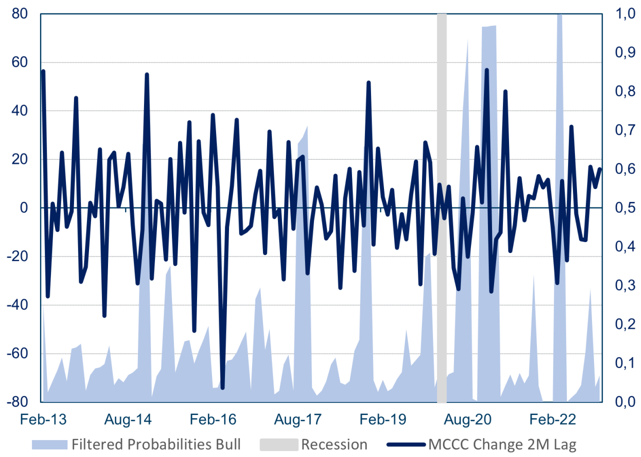
(a) Cons Staples



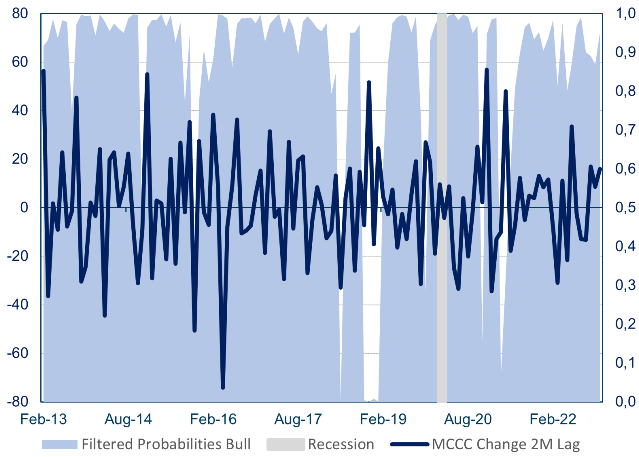
(d) Financial



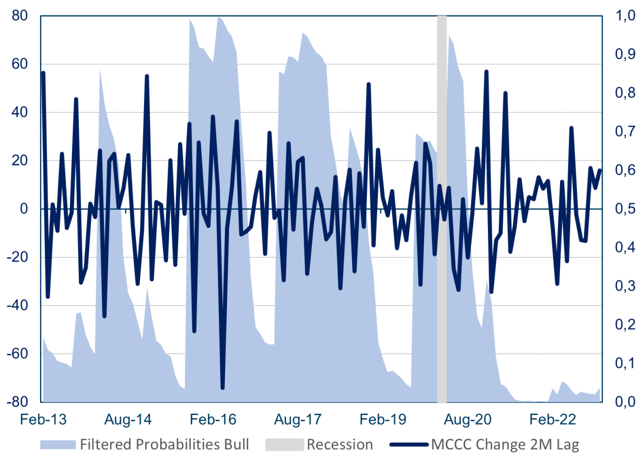
(b) Cons Disc



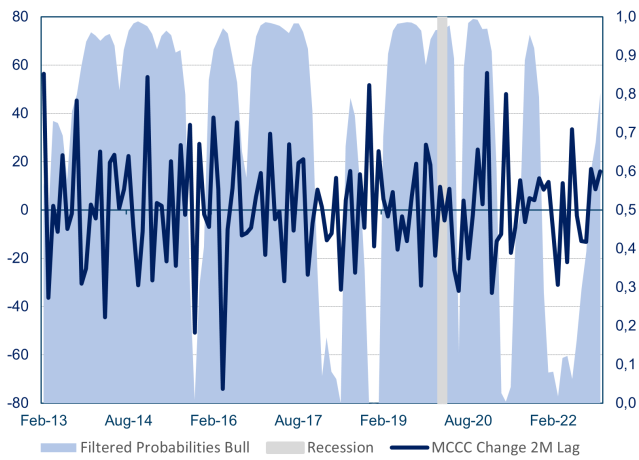
(e) Technology



(c) Materials



(f) Utilities



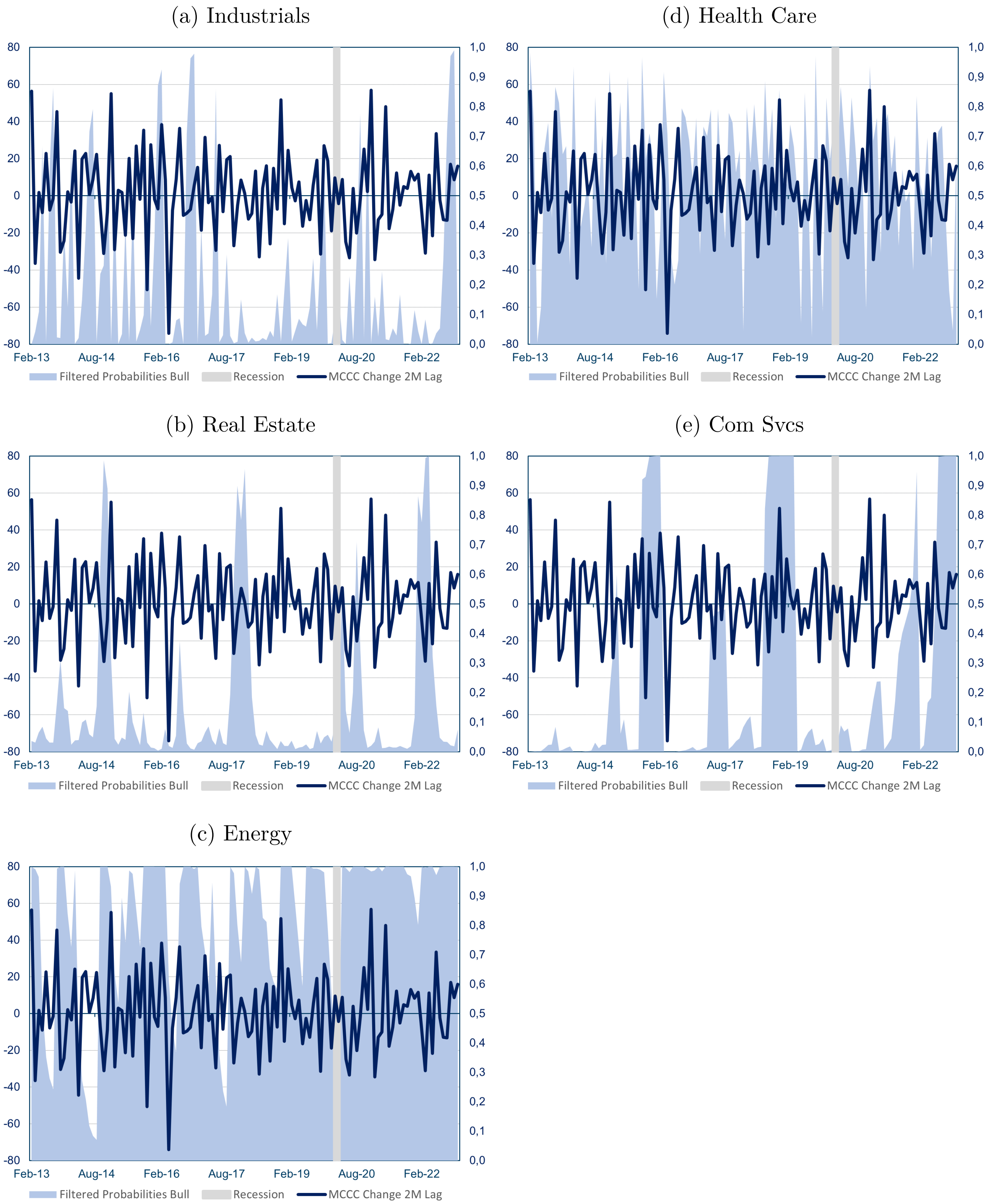


Figure A.8: **Filtered Probabilities and Changes in MCCC Index across All Sectors** This figure presents two-month lagged changes in the MCCC index and filtered bullish regime probabilities from February 2013 to December 2022 for the eleven MSCI USA sector indices. Each panel corresponds to a specific sector, with panels showing Consumer Staples, Consumer Discretionary, Materials, Financials, Technology, Utilities, Industrials, Real Estate, Energy, Health Care, and Communication Services. Each subfigure includes filtered probabilities of bullish ESG regimes derived from the MCCC index-based MRS model, along with official recession periods as defined by the NBER.

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