From Climate to Economy: Understanding Climate Risks in the U.S. Market

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Abstract

To what extent do asset markets effectively price climate risk focusing on the responsiveness of U.S. firms to climate change? How does the implementation of climate policies across diverse U.S. states influence national-level transition risks, and are these risks adequately factored into market valuations of U.S. firms?

The primary aim of our research is to delve into the extent to which asset markets accurately price climate risk, with a particular focus on climate transition and physical risk. Specifically, our aim is to investigate whether U.S. firms' proactive responses to climate-related challenges are adequately reflected in market valuations. A crucial aspect of our research contribution lies in the integration of a climate change indicator at the state level into our model. It is imperative to acknowledge that not all U.S. states are equally equipped to respond to the policy void created by federal inaction in the U.S. This necessitates a nuanced approach to risk measurement. The challenge lies not in disentangling state risk from nationwide risk, but rather in recognising the significance of state-level information. By incorporating state-level risks into our analysis, we aim to highlight their importance in optimising portfolios. Neglecting state-level risks renders portfolios suboptimal, as it represents a critical risk factor that cannot be overlooked. Our results show that U.S. climate policy uncertainty and economic conditions significantly explain portfolio returns. State-level factors such as temperature anomalies, economic policy uncertainty, and economic conditions offer deeper insights into risk and performance, with temperature anomalies notably affecting returns. These findings emphasize the importance of integrating state-level climate risks into portfolio strategies for better risk management.

- **Keywords:** Climate transition risk · Climate physical risk · Market valuation · U.S. firms · Climate policy · U.S. State-level policies · Asset pricing · Climate change adaptation · Environmental regulation · Sustainability disclosure

1 Introduction

The Earth's changing climate poses significant challenges globally and for the U.S., particularly due to the uncertainties around its economic impacts. Financial regulators have recognized climate change as a key source of corporate risk, emphasizing the need to address the spillover effects of climate-related risks. Understanding the relationship between climate-induced transition risks and U.S. market dynamics is essential for effective economic strategies.

Our primary objective is to investigate whether asset markets appropriately price climate risk, particularly climate transition and physical risk, and, notably, whether U.S. energy sector, manufacturing, and transportation proactive responses to it are factored into these market valuations. Additionally, we aim to understand how different states in the U.S. implement climate change policies and measure climate-specific transition risks at the state level. To address these crucial inquiries, we pose a pivotal research question: "To what extent do asset markets effectively price climate risk, particularly transition risk, focusing on the responsiveness of U.S. firms to climate challenges? Furthermore, how does the implementation of climate policies across diverse U.S. states influence national-level transition risks, and are these risks adequately factored into market valuations of U.S. firms?". More specifically, we seek to understand how firms in different U.S. states are affected by climate risks and uncertainties.

Our research methodology is underpinned by a core principle of invariance, crucial for addressing the challenge of omitted variables in asset pricing. By accounting for arbitrarily rotated factors that comprehensively cover the factor space, we ensure a consistent estimation of risk premia, even in scenarios where underlying risk exposures remain unidentified. Inspired by the work of Giglio and Xiu [2021] we advocate the application of Principal Component Analysis (PCA) to reconstruct the factor space. Subsequently, we employ Principal Components (PCs) as controls in cross-sectional regressions alongside observable factors. Our approach is designed to accommodate the inherent differences in data frequencies. Often, factors of interest, such as climate risk indicators, are available only at lower frequencies compared to returns, which are typically accessible at higher frequencies. Recognizing this challenge, we emphasize the importance of adopting the mixed-frequency adaptation of the methodology proposed by Giglio and Xiu [2021]. This adaptation is crucial to effectively capture and analyze the dynamics of climate risk factors across different temporal scales.

Given the complexity of climate risk, it is challenging to capture a company's exposure across all dimensions with a single measure. This study focuses on two key aspects: climate transition risk and physical risk. To enhance the analysis, we integrate a state-level climate change indicator, examining how U.S. firms respond to climate challenges amidst the varied capacities of states to address gaps in federal policy.

Our findings demonstrate that market valuations adequately reflect these responses, evidenced by statistically significant coefficients and risk premia across various models. The use of varying principal components enhanced the model fit and refined risk premia estimates, underscoring the robustness and applicability of our results. Key factors such as climate policy uncertainty (CPU_{US}), economic policy uncertainty (EPU_{US}), and economic conditions ($ECON_{US}$) were found to have diverse impacts on portfolio performance, confirming their importance in financial model-

ing and empirical finance. This analysis not only aligns with established financial principles but also offers crucial insights into the pricing of state-level risk factors, such as temperature anomalies ($Tanomalies$), highlighting the significant implications of climate-sensitive sectors and underscoring the necessity for investors to integrate comprehensive risk assessments in their investment strategies.

Not all U.S. states are equally equipped to address the policy void left by federal inaction on climate change. Research highlights that partisanship (Bromley-Trujillo et al., 2016; Egan and Mullin, 2017; Benegal and Scruggs, 2018), economic considerations (Huang et al., 2007; Chandler, 2009; Matisoff and Edwards, 2014), exposure to climate impacts, and issue salience (Bromley-Trujillo and Poe, 2018; Bromley-Trujillo, Holman, and Sandoval, 2019) significantly influence a state's willingness to enact climate policies. However, partisan divides and the lobbying power of fossil fuel and utility sectors often impede progress, leaving many states hesitant to implement robust climate measures. Despite these challenges, sub-national initiatives, such as state-level greenhouse gas reduction targets and participation in programs like the Regional Greenhouse Gas Initiative (RGGI), demonstrate states' potential to substantially contribute to national and global climate goals (Lutsey and Sperling, 2008; Fosten and Nandi [2023]).

This research shifts the focus from national policies to a more nuanced analysis of regional climate risk, emphasizing the importance of state-level dynamics. Sub-national actions are increasingly recognized as critical to achieving emissions reductions, as reflected in the growing prominence of local initiatives on global platforms. For instance, the "Cities, Regions, and Built Environment" day at COP26[1] highlighted the role of cities and regions in combating climate change. Approximately half of U.S. states have established emissions targets, with over ten actively participating in initiatives like the RGGI, a market-based program aimed at emissions reduction (Fosten and Nandi [2023]). This divergence between federal and state policies, particularly along partisan lines, underscores the need for research that captures the localized nature of climate risks.

A central objective of this study is to assess state-level climate risk, with a specific focus on climate transition risk. Given the impracticality of capturing daily or weekly fluctuations in climate news and policy changes, we adopt a monthly data approach. This methodology, supported by a mixed-frequency adaptation of Giglio and Xiu [2021], enables a comprehensive analysis of climate risk factors at both national and state levels, providing critical insights into the interplay between sub-national initiatives and broader market dynamics.

Monthly data has proven critical for capturing the multifaceted dimensions of physical and transition climate risks in recent research. For instance, Sheng et al. [2022] analyzed the impact of temperature growth and volatility on climate risk across 50 U.S. states using data from 1984 to 2019. Similarly, Yang et al. [2022] examined climate transition risk spillovers in six major financial markets, utilizing month-end CO2 emissions as a proxy due to data limitations. Furthermore, Campos-Martins and Hendry [2023] investigated the global effects of climate change news on financial markets, integrating daily and monthly climate indices provided by Ardia et al. [2023] and Engle et al. [2020] to offer a comprehensive view. The challenges of timely environmental data availability are well-

[1]The UN Climate Change Conference of the Parties (COP26) at the Scottish Event Campus (SEC) in Glasgow on 31 October – 13 November 2021, brought parties together to accelerate action towards the goals of the Paris Agreement and the UN Framework Convention on Climate Change.

documented. For example, Fosten and Nandi [2023] highlighted the lack of up-to-date information on regional CO2 emissions and energy consumption in U.S. states, constrained by annual data publication schedules and significant lags. This underscores the difficulty of real-time monitoring, a critical consideration for climate risk analysis.

In light of these constraints, our research adopts a mixed-frequency approach based on the framework of Giglio and Xiu [2021]. Key climate indicators such as CO2 emissions, temperature anomalies, and indices like Climate Policy Uncertainty (CPU) and Economic Policy Uncertainty (EPU) are only available monthly, while firm-level daily returns are accessible at higher frequencies. To reconcile these differences, we utilize a three-pass estimation method to estimate risk premia for observable factors while addressing omitted or unobservable factors. This approach is particularly suited for climate risk research, given the scarcity of accurate, high-frequency climate-related data at the state level. By adapting this methodology, we ensure robust analysis of the interplay between climate risk factors and financial market responses, contributing to a deeper understanding of how climate risks are priced at both the national and state levels.

Conventional estimators of risk premia in linear asset pricing models may be biased when certain factors are omitted, as highlighted by Giglio and Xiu [2021]. To address this issue, they propose a three-pass method to estimate the risk premium of an observable factor, even when not all factors are specified or observed. This methodology aligns with our research objectives, where we encounter a mix of observed and unobserved risk factors, particularly climate transition risk at both the state and national levels. According to Giglio and Xiu [2021], the risk premium of an observable factor can be accurately identified as long as the combined set of observed and unobserved factors spans the true factor space.

Investors are increasingly concerned with nontradable risks, such as climate-related factors, which are not readily captured by traditional portfolios Giglio et al. [2021]. Estimating the risk premium of these nontradable factors requires constructing a tradable portfolio that isolates these risks while holding other factors constant. However, conventional risk premium estimators, like the Fama-MacBeth (1973) approach, are vulnerable to omitted variable bias when models fail to account for all priced sources of risk. Our research, like Giglio and Xiu [2021], seeks to address this limitation by applying their novel three-pass methodology, which leverages the high dimensionality of available assets and the concept of rotation invariance to recover the risk premium of observable factors, even when not all true risk factors are included in the model. We contrast the results from this methodology with those obtained from the traditional Fama-MacBeth (1973) model.

The three-pass methodology by Giglio and Xiu [2021] is grounded in the principles of rotation invariance, applicable to risk premia within linear factor models. They consider a model with p factors and aim to estimate the risk premium associated with one factor (g_t). The key insight is that the risk premium of g_t remains unaffected by rotating the $p-1$ control factors. This implies that linear combinations of the original factors can serve as controls, as long as the rotated model captures the same underlying risk. Giglio and Xiu [2021] show that knowing the identities of all true factors is not necessary for estimating the risk premium of a specific factor. Their approach combines principal component analysis (PCA) with two-pass cross-sectional regressions to provide consistent estimates of the risk premium for any observed factor. This methodology is well-suited

for our research, where unobserved climate-related factors and their associated risk premiums are central to understanding market dynamics.

Drawing on insights from Campos-Martins and Hendry [2023], future research on geoclimatic volatility could incorporate individual or country-level climate news, as variations in climate exposures may result from factors like policy stringency, activism, geological events, and carbon emissions. Our research aims to fill a gap in the literature by being the first to analyze both climate transition and physical risks across U.S. energy and energy-dependent firms, considering the diverse climate policies at state and federal levels and how these differences shape the climate risk profiles of firms.

Measuring firm-level climate risk exposure presents several challenges. Despite growing regulatory pressure and investor demand for transparency, firms remain reluctant to disclose their climate risk exposure. This is particularly evident in the limited availability of carbon emissions data, often restricted to traditional sectors like manufacturing and utilities, and the omission of indirect carbon costs embedded in supply chains (Shapiro, 2021). Moreover, the evolving nature of climate change creates uncertainty about its long-term effects on firms, complicating both government and corporate decision-making (Barnett et al. [2020]). Additionally, while historical emissions data is useful for assessing past practices, forward-looking perspectives are increasingly vital for understanding a firm's climate exposure and its adaptability in the transition to sustainability—key to advancing climate finance research (Giglio et al. [2021]).

To address these challenges, our research aims to bridge the gap in climate risk literature by enhancing the measurement of transition risk, often referred to as "carbon risk," within the U.S. market. We focus on understanding the intersection of climate risk, political uncertainty, and economic factors, analyzing a comprehensive dataset of U.S. energy firms and firms highly dependent on energy. By addressing these complexities, we seek to contribute valuable insights into firm-level climate risk exposure, helping improve risk management strategies and support informed decision-making in the transition to a sustainable economy.

Investors and financial regulators are increasingly recognizing the risks associated with climate change, sparking a growing body of research on the complex relationship between climate transition risks and physical climate risks. While this area of study remains less developed compared to more traditional finance topics, there is a noticeable shift toward understanding how climate-related events impact various markets and sectors. Climate risks are generally categorized into two primary types: (1) physical risks, which refer to the direct impacts of climate events, both acute (e.g., droughts, floods, wildfires) or chronic (e.g., rising temperatures, loss of biodiversity), and (2) transition risks, which arise from inadequate responses to climate change and the need for businesses to adapt to sustainable practices, such as low-carbon manufacturing. These distinctions are explored in the work of scholars like Giglio et al. [2021], FSB [2022], Stroebel and Wurgler [2021], and Baudino and Svoronos [2021]. As financial markets face the growing pressures of climate change, understanding these distinct risk categories is crucial for investors and regulators alike. As Giglio et al. [2021] points out, recognizing and differentiating between these risk types is essential, as they often do not materialize simultaneously and can have varying impacts on asset valuations.

In this research, we focus primarily on transition risk, while also incorporating selected metrics of physical risk, which has traditionally been the focus of much existing literature. According to

Campos-Martins and Hendry [2023], news of specific natural disasters is unlikely to significantly impact global financial markets unless such events become more frequent. As a result, investors often discount physical risks due to their long-term nature, whereas transition risks tend to manifest in the short term. Despite the close relationship between physical and transition risks, literature suggests that physical risks are more localized and predictive, and their long-term effects may be overlooked by investors. However, we include physical risks in our analysis by using the temperature anomalies indicator for each U.S. state and the climate policy uncertainty (CPU) index developed by Gavriilidis [2021]. The CPU index, derived from news coverage in eight major U.S. newspapers, serves as a proxy for both transition and physical risks at the national level.

Building on the work of Sheng et al. [2022], who examined the impact of climate risks — specifically temperature growth and volatility — on economic activity across 50 U.S. states from 1984 to 2019, we further integrate temperature anomalies ($Tanomalies$) as a physical risk indicator at the state level. Their study found a consistent negative impact of climate risks on economic activity, contingent on state-level economic and policy-related uncertainties. We compute $Tanomalies$ using temperature data from the National Oceanic and Atmospheric Administration (NOAA), enhancing our ability to examine the relationship between climate dynamics and economic activity at both the state and national levels. This approach allows us to explore both physical and economic risks in greater detail, offering a comprehensive view of climate-related challenges.

Hartlieb and Eierle [2024] examined whether auditors consider climate change-related risks when determining audit pricing. They found that clients with higher exposure to climate risks, as indicated by country-level proxies like natural disasters and societal awareness, incur higher audit fees. This supports our research aim of linking climate risk to firm financial performance. Specifically, by using physical climate risk measures at the county level, including the number of natural disasters and local climate change awareness, they found a positive correlation between audit fees and climate-related risks in the clients' headquarters counties.

To strengthen our analysis, we incorporate physical climate risk measures at the state level, using data from the Federal Emergency Management Agency (FEMA) on the number of natural disasters. This measure captures the impact of extreme weather events, which can significantly affect firm performance, as evidenced by previous studies (e.g., Chava, 2014; Huang et al., 2018). Given that climate change is increasing the frequency of various events, such as hurricanes, storms, and freezing temperatures, this approach provides a comprehensive view of the risks businesses face across U.S. states. Our use of state-level data also eliminates potential biases related to legal differences across countries, ensuring that our findings are more applicable to the U.S. context.

This measure improves upon prior research by including a wider range of natural disasters, such as heatwaves, droughts, floods, and severe cold, which are all exacerbated by climate change (e.g., Banholzer et al., 2014). By accounting for a broader spectrum of events, our approach offers a more holistic understanding of the physical climate risks that businesses encounter, enhancing the robustness of our analysis.

The findings of Campos-Martins and Hendry [2023] suggest that while acute physical climate risks may not trigger global shocks, chronic risks have no significant direct impact. Transition risks, however, are intricately linked to policies, regulations, technological advancements, and evolving

climate patterns, highlighting the need to account for both physical and transition climate risks in our analysis. As Yang et al. [2022] points out, transition risk differs fundamentally from physical risk, and investors' expectations regarding climate policies, technological advancements, and physical risk collectively influence firms' exposure to transition risks, often leading to a reassessment of asset values.

The interconnection between physical and transition risks is apparent, as even regions not directly impacted by physical risks can face indirect consequences due to international relations with more vulnerable areas. Despite this overlap, the primary systemic risks to financial markets are anticipated to stem from exposure to transition risks, particularly in the case of a disorderly transition (Campos-Martins and Hendry [2023]). Recent literature has expanded to include various interconnected risks, such as regulatory and policy risks, technological shifts affecting sustainable energy competitiveness (Chenet et al. [2015], Gonzalez-Salazar et al. [2018]), and changes in social norms and legal frameworks. However, there is a significant gap in research, particularly in the energy market, which is highly influenced by government policies and subject to political and economic fluctuations. Our study aims to address this gap.

While several studies have examined the impact of climate change on real estate assets using physical climate risk factors (e.g., sea-level rise, flooding, and hurricanes), equity asset analysis lacks a comprehensive set of risk measures. Existing proxies, such as ESG ratings and CO2 emissions, are often criticized for their coverage and reliability (Stanny [2018]). As noted by Giglio et al. [2021], there is significant room for improvement in climate risk exposure measures, particularly for equity assets. Moreover, measuring transition risk is challenging due to its unobservable nature, with researchers typically relying on proxies that capture only certain aspects of transition risk. This lack of precision in defining and measuring transition risk, as highlighted by Meinerding et al. [2023], poses a significant hurdle in understanding its full impact on firms and financial markets.

Recent studies, such as Giglio et al. [2021], predict significant shifts in the pricing of climate risks over time, with investor focus on these risks emerging more recently. Global events, like the 2009 UN Climate Change Conference and the SEC's climate change disclosure guidance in 2010, have been key in shaping societal views on climate change (Engle et al. [2020]). Our research spans from March 1, 2000, to March 1, 2023, to capture these evolving dynamics in the pricing of climate risks.

This study contributes to the expanding field of climate finance in several ways. First, we build on research examining the impact of localized climate events on asset prices, such as Bressan et al. [2023] and Pástor et al. [2022], who explore how climate events influence asset cash flows, discount rates, and the return premiums between green and non-green assets. While empirical evidence on carbon risk premiums is mixed, our research extends these studies by considering both transition and physical climate risks at national and state levels in the U.S., offering a more comprehensive analysis of climate risks and their implications for asset pricing.

We also align with recent works focused on hedging climate risk. For instance, Engle et al. [2020] constructs a hedging portfolio using a climate news index, and Alekseev et al. [2022] introduces a method to hedge climate risk using extreme heat events and shareholder disclosures. Our study adopts a similar mimicking portfolio approach to construct a climate change portfolio, running preliminary analyses to identify trends and projecting climate news innovations onto ESG-

sorted portfolios. This approach enhances the robustness of our findings by capturing the complex relationships between unobserved climate factors and state-level influences.

This paper explores the dynamics of climate risk, focusing on both national and state-level factors. The key challenge is not differentiating between state and nationwide risks, but rather recognizing the critical role of state-specific risks. Without considering state-level information, we overlook significant sources of risk. Our focus on local climate transition and physical risks is essential, as these risks can manifest both nationally and within individual states. Building on insights from Fosten and Nandi [2023], who highlight the autonomy of U.S. states in climate policy and emissions targets, we emphasize that state-level transition risks are a crucial factor in portfolio optimization. Neglecting these risks leads to suboptimal portfolios, aligning with the approach of Engle et al. [2020] in their climate risk hedging work.

The structure of the paper is as follows: Section 2 reviews the relevant literature, Section 3 details the methodology, Section 4 presents the key variables, data sources, and descriptive statistics, Section 5 discusses the empirical results, Section 6 provides robustness checks, and Section 7 concludes the study.

2 Literature Background:

In recent years, investor concerns regarding the spillover effects of climate change have grown significantly, as it affects asset returns through two primary channels: physical risk and transition risk (Clapp et al. [2017]). Physical risk encompasses financial losses or increased costs due to acute or chronic climate events, such as hurricanes, wildfires, and floods. Transition risk, often referred to as "carbon risk," arises from the economic adjustments necessary for transitioning to a low-carbon economy, driven by changes in policies, technological advancements, and shifting public preferences. This risk is especially tied to uncertainties around the pace and timing of the transition, which can lead to abrupt changes in asset prices, particularly in response to sudden policy shifts or carbon pricing legislation (Carney [2015]).

Expanding on this, Bolton and Kacperczyk [2023] introduced the concept of "carbon-transition risk," which encompasses a wide range of shocks, including shifts in climate policies, reputational impacts, market preferences, and technological innovations. While much of the literature focuses on how transition risk directly impacts the economy, less attention has been given to how these risks propagate across sectors and regions. Understanding the transmission of climate transition risk, particularly through intersectoral or interstate linkages, is crucial for grasping the interconnectedness of economic systems and the potential spillover effects across the broader economy.

Industries reliant on fossil fuels and energy-intensive operations are particularly vulnerable to transition risks. The pace of decarbonization plays a key role in determining long-term impacts, including asset fluctuations and the risk of "stranded" assets, as highlighted by the European Central Bank (ECB, 2019) and the Network for Greening the Financial System (NGFS, 2020). Additionally, legal risks associated with non-compliance with climate-related regulations and inadequate climate impact disclosures further amplify these challenges, underscoring the urgency for a comprehensive approach to managing climate-related financial risks.

Recognizing the critical role of U.S. state-level climate policies, Bergquist and Warshaw [2023b] emphasized the need for a comprehensive measure of state-level climate policy. They developed an aggregate index spanning 2000-2020, based on 25 individual policies, revealing significant variations in state policies. Interestingly, their findings suggest that more stringent state climate policies do not harm state economies, highlighting the proactive role U.S. states play in mitigating climate change. This underscores the importance of understanding state-specific climate risks, a key focus of our research.

[Figure 1 around here]

Figure 1 illustrates the varying commitment to clean energy transitions across U.S. states, highlighting proactive states like New York, California, and Massachusetts, which align with liberal policy stances, and states like Texas and Ohio, which showed early leadership but later retrenched. Additionally, states such as Colorado, Minnesota, and Washington have adopted significant climate policies despite not being traditionally recognized for their liberal stances, emphasizing that climate policy commitments are distinct from broader policy liberalism and warrant independent measurement.

A pivotal shift in U.S. climate policy occurred during Donald Trump's administration, which ac-

tively rolled back regulations aimed at reducing carbon emissions. This regulatory rollback starkly contrasted with growing concerns about environmental degradation and mounting pressure from investors for companies to integrate climate risks into their strategies. By 2015, environmental concerns influenced $2.15 trillion worth of institutional investor assets, reflecting a 17% increase from the previous year. During Trump's tenure, the U.S. withdrew from the Paris Climate Agreement, dismantled the Clean Power Plan, and eased regulations on fuel economy and energy-efficient appliances. His appointments of climate skeptics, staff reductions at the EPA, and curbs on state-level initiatives underscored his administration's stance on environmental governance. Anticipating these developments, Rabe (2011) predicted a surge in state-level climate policy activity following 2016, a trend we explore further in this research.

Some states have been slower to enact climate policies due to factors such as political resistance, economic dependencies on fossil fuels, and varying levels of public support. States with economies heavily reliant on fossil fuels may resist stringent climate regulations due to potential economic disruptions. Additionally, political landscapes and lobbying by interest groups can significantly influence climate policy adoption. This variability across states is crucial for our research as it impacts the assessment of climate risks and the effectiveness of mitigation strategies, providing a comprehensive understanding of the broader implications for national climate goals and economic resilience.

Our research aligns with recent studies exploring firm-level measures of climate risk. For instance, Sautner et al. [2023] and Li et al. [2020] use textual analysis of earnings call transcripts to quantify corporate climate risk, with a focus on the share of discussions related to climate topics. Sautner et al. [2023] introduce the Climate Change Exposure measure, finding that companies in countries with stronger climate regulations exhibit higher exposure. Unlike traditional carbon risk measures, much of the variation in climate exposure occurs at the firm level. Similarly, Kölbel et al. [2020] examine climate risk disclosures in annual reports and find that transition risks significantly impact CDS market spreads, while physical risks do not. Additionally, Huynh and Xia [2023] investigate the relationship between corporate bond returns and the Climate Change News Index, showing that bonds with high climate news betas are more expensive, potentially serving as hedges against climate risks. Kruttli et al. [2021] empirically examine firm-level uncertainty arising from extreme weather events, particularly hurricanes, within a theoretical framework that distinguishes between "incidence uncertainty" (the likelihood of a firm being affected) and "impact uncertainty" (the severity of consequences if affected). Their findings indicate that stock options of firms located in hurricane landfall regions experience significant increases in implied volatility both before and after impact, suggesting that investors initially underestimate uncertainty. However, this underreaction diminishes following Hurricane Sandy, indicating a learning effect. Despite hurricanes being idiosyncratic shocks, the study demonstrates that they influence firms' expected returns through both cash flow and discount rate channels. Additionally, the persistence of hurricane-related discussions in earnings calls long after landfall highlights the prolonged nature of uncertainty. These findings align with the argument in this research that firms remain insufficiently adapted to extreme weather risks and that markets struggle to efficiently price novel climatic risks, underscoring inefficiencies in how extreme weather-related uncertainty is incorporated into asset prices especially at

U.S. state level.

Our research aligns with studies exploring the impact of climate-related risks on portfolio performance. For example, Alekseev et al. [2022] examine climate hedging portfolios constructed by mutual fund managers after local extreme heat events. Van der Ploeg and Rezai [2020] focus on the vulnerability of fossil fuel assets to market devaluation, highlighting the role of transition risk driven by renewable technology advancements and evolving climate policies such as the Paris Agreement. They suggest that assets in these industries face heightened exposure to market uncertainties, with the return on a stranded asset portfolio serving as a proxy for market expectations regarding the transition to a low-carbon economy. This proxy reflects investor sentiment on the risks associated with sustainability shifts in global markets.

Additionally, Fang et al. [2023] investigate the existence of a "pollution premium" in U.S. stock returns, focusing on mandatory toxic emissions disclosures rather than greenhouse gases. Their study reveals a 5.52% annual return spread on a long-short portfolio based on toxic emissions, attributing this "pollution premium" to the higher regulatory risks faced by polluting firms. This further emphasizes the broader impact of climate-related risks on financial market dynamics.

Our research builds on recent studies examining the stock return implications of corporate carbon emissions, with significant contributions from Bolton and Kacperczyk [2021], who explore U.S. and global equity markets. They find that higher emissions are associated with elevated returns, with indirect emissions showing explanatory power beyond industry effects. Their work also uses levels and percentage changes in emissions as proxies for long-term and short-term transition risks, identifying a transition risk premium primarily in North American, European, and Asian stocks.

Our study extends the emerging literature on transition risk, which, while still in its early stages, is rapidly expanding. Bolton and Kacperczyk [2023] observed that companies with higher carbon emissions often experience heightened stock returns across various sectors and regions, including Asia, Europe, and North America. This aligns with the theoretical predictions of Pástor et al. [2022], who suggested lower expected returns for green assets, and with empirical evidence from Giglio et al. [2021], which shows retail investors anticipating negative returns on ESG investments.

Additionally, we build on the work of Engle et al. [2020] and Alekseev et al. [2022], who found that stocks with lower climate risk exposure tend to outperform during periods of negative climate-related news. This nuanced view highlights the dynamic relationship between climate risk exposure and stock performance, offering valuable insights into how market sentiment and climate-related news interact. Our research further contributes by examining spillover risks and liquidity dynamics, enhancing the understanding of these complex financial market relationships.

In a parallel vein, Faccini et al. [2023] made a noteworthy contribution by constructing news-based risk factors intricately linked to both physical and transition risks. Their findings shed light on the fact that climate policy risks, notably, are now embedded in U.S. stocks, particularly gaining prominence after 2012. Adding depth to our comprehension, Choi et al. [2020] documented the underperformance of carbon-intensive firms relative to those with lower carbon emissions during periods of unusually high local temperatures. This underscores the heightened sensitivity of investors to climate risks under specific environmental conditions.

Turning our attention to climate physical risks, Acharya et al. [2022] revealed a compelling as-

sociation between higher heat stress exposure among S&P500 corporations and a 45 basis points higher (un-levered) expected return per annum. This trend has been consistently observed since 2013. Additionally, Cuculiza et al. [2021] emphasised that sell-side equity analysts actively incorporate climate news into their earnings forecasts, illuminating the market's sensitivity to climate change events as reflected in analysts' forecast revisions.

The current research on measuring systemic climate risk primarily relies on static, retrospective approaches, often using deterministic transition scenarios. This contrasts with more advanced studies on the systemic risk of financial institutions, particularly during financial crises, with key contributions from Engle [2004], Allen et al. (2012), Adrian and Brunner-Meier (2016), and Acharya and Thakor [2016]. Similarly, Bua et al. [2022] examine physical and transition climate risk premia in euro area equity markets, developing novel indicators based on text analysis to assess climate risk premiums.

Li et al. [2020] contribute to firm-level climate risk measurement by analyzing earnings call transcripts, distinguishing between physical and transition risks. Their study finds that firms exposed to high transition risk, particularly those that do not proactively address it, have been undervalued, reflecting growing investor concern over climate issues. They also highlight that proactive responses, such as reducing carbon intensity, are linked to more effective efforts to mitigate climate risks.

Building on these approaches, our research combines measures of both physical and transition climate risks to address a critical gap in climate finance literature: the pricing of climate risk in capital markets. By incorporating both risk dimensions, we offer a more comprehensive perspective on how climate risks influence asset valuations, contributing to the ongoing development of this field.

In the realm of assessing climate risk, various methodologies have been employed to measure the global financial landscape and its inherent vulnerabilities. For instance, studies such as that by Engle [2004] adopt an approach focused on common volatility shocks, capturing contemporaneous movements that simultaneously impact all financial markets. Alternatively, other measures leverage innovative techniques like text mining, as exemplified by Ardia et al. [2023], who construct a daily Media Climate Change Concerns index using news articles from major U.S. newspapers and newswires. In alignment with these approaches, we incorporate a similar climate risk factor based on U.S. newspaper coverage proposed by Gavriilidis [2021], allowing for analysis across a broader time span. This risk factor facilitates a comprehensive examination of climate-related concerns and their potential implications for financial markets.

According to Rebonato et al. [2023], asset prices often exhibit limited responsiveness to climate-related news, presenting a challenge in aligning market reactions with the anticipated economic effects of climate policies. While climate risk introduces additional volatility to asset prices, Rebonato et al. [2023] argues that market prices often underestimate or overlook the impact of both transitional and physical climate risks on companies' cash flows. Unlike more observable factors such as unemployment or inflation, climate risk lacks a clear, tangible proxy, making its integration into market valuations more complex. This muted price sensitivity to climate news creates a puzzle, as it contradicts the expected economic outcomes of climate policies. Our research seeks to address this gap by improving the measurement of climate risk, focusing on both physical and transitional risks, and thereby enhancing our understanding of their effects on asset pricing.

Macroeconomic models, such as integrated assessment models (e.g., Nordhaus [2018] and Golosov et al. [2014]), often use carbon pricing to internalize climate externalities and explore the social cost of carbon in equilibrium. While these models offer valuable insights, practical applications like those by the Network for Greening the Financial System (NGFS) turn to scenario analysis to navigate transition risks. However, historical evidence shows that the implementation of climate policies is complex, influenced by factors like policy timing, suboptimal policy mixes, uncertainty, international coordination, technology advancements, and shifting consumer preferences.

The existing literature on systemic climate risk predominantly relies on static, retrospective measures linked to deterministic transition scenarios. This contrasts with the more dynamic approaches used in assessing systemic risk within financial institutions, particularly during financial crises, as seen in the works of Engle et al. [2020], Adrian and Brunner-Meier (2016), and Acharya and Thakor [2016]. For instance, Engle [2004] examines common volatility shocks that affect all financial markets simultaneously, while Ardia et al. [2023] employs text mining techniques to track climate change concerns in U.S. media, using a daily Media Climate Change Concerns index.

Additionally, Campos-Martins and Hendry [2023] propose a novel approach for assessing common movements in the Oil and Gas industry, leveraging a global volatility framework. Meanwhile, Son et al. [2023] uses vector autoregressive models (VAR) to analyze liquidity spillovers between ETFs and their underlying portfolios, offering another methodological perspective for studying systemic climate risks. Our research contributes to this evolving landscape by exploring new methods to measure and understand climate transition risk.

These diverse methodologies have significantly advanced our understanding of climate risks within the financial sector, employing dynamic frameworks and forward-looking approaches. Acknowledging this progress, our methodology seeks to bridge a current gap in the literature by introducing a more dynamic and forward-looking approach to assessing climate risk.

Overall, this comprehensive body of research serves as a robust foundation for our own inquiry, spotlighting the intricate ways in which climate risks are interwoven with U.S. market. It underscores the multi-dimensional relationship between climate-related factors and stock prices. As we navigate the literature gap concerning climate transition risk effects on the energy and highly depended energy markets, it is crucial to acknowledge the dynamic interplay between these risks and the ever-evolving market landscape.

2.1 Mimicking Portfolio Techniques:

Climate risk, the potential negative impact of climate change on future cash flows, is becoming an increasingly critical concern for investors. While the market has begun to price this risk, assets with higher climate exposure are often undervalued relative to their intrinsic riskless value. As a result, investors expect higher returns to compensate for holding assets vulnerable to climate risk.

A practical way to address this is through the formulation of a climate risk factor, which represents a weighted average of financial assets based on their climate exposure. Investors indifferent to climate risk may hold this portfolio for its higher expected return, while those seeking to hedge against climate risk would short the portfolio, anticipating a negative risk premium and reduced

returns in exchange for reduced risk.

To empirically assess climate risk, measures of climate-related news—such as text-based analysis of media coverage or physical indicators like temperature extremes—are essential. If climate risks exceed market expectations, the climate hedge factor should appreciate, with alpha generated when the factor is missing. Over time, as the market adjusts to new scientific insights, pricing should better reflect the scientific consensus. In this context, holding a climate hedge portfolio will typically yield negative returns in the absence of climate risk news but positive returns when such news arises.

Climate change analysis highlights the importance of two distinct factors, physical risk and transition risk, as key elements in understanding climate-related financial risks. Physical risk refers to the hazards associated with rising temperatures, extreme weather events, and other climate-related phenomena, while transition risk arises from the economic adjustments necessary to shift to a low-carbon economy, often driven by policy changes. Although both factors typically carry positive risk premiums, they are often negatively correlated. For example, stringent regulations might increase transition risk but reduce physical risk by mitigating future climate impacts. Conversely, a severe hurricane season could elevate both risks, while advancements in carbon sequestration technology might lower them.

To construct factor-mimicking portfolios for non-investable factors like climate news, two primary methods are used. The first is the maximum correlation portfolio, as introduced by Huberman and Kandel (1987) and Lamont (2001), which regresses the news series on asset returns to identify a portfolio with maximum correlation to the news. The second approach involves a two-step process: first, determining each asset's sensitivity to the news series, then combining this information through a cross-sectional regression (such as Fama and MacBeth (1973) or Lehmann and Modest (1988)) to create the portfolio. These methods estimate risk premiums by averaging excess returns of the corresponding hedge portfolios, with Jurczenko and Teiletche (2019, 2022) demonstrating that these approaches are special cases within a broader asset pricing framework aimed at creating minimum-variance portfolios with specific correlations to news series. However, their model assumes that the assets span the factor space.

Prominent papers in this area include those by Fama and MacBeth (1973), Chen, Roll, and Ross (1986), Huberman, Kandel, and Stambaugh (1987), Breeden, Gibbons, and Litzenberger (1989), Lamont (2001), Balduzzi and Robotti (2008), Lönn and Schotman (2017), and Roll and Srivastava (2018). Giglio and Xiu [2021] explore the asymptotic properties of different estimators in large cross-sections and investigate their robustness to model specification errors. In this paper, akin to Engle et al. [2020], we apply the mimicking portfolio approach as advocated by Lamont (2001) as additional exercise.

A newer, promising approach by Alekseev et al. [2022] improves hedging performance by using data on how mutual fund managers trade in response to idiosyncratic changes in their climate risk beliefs. This quantity-based approach predicts capital reallocation around such belief shocks, which can move equilibrium prices. Alekseev et al. [2022] demonstrate that a portfolio long on stocks that investors buy following negative climate belief shocks and short on stocks they sell appreciates in value during periods of negative aggregate climate news shocks. This method benefits from rich cross-sectional trading responses rather than relying solely on time-series price information.

In this research, as additional exercise, we adopt an econometric approach to forming hedge portfolios, following standard methods in the asset pricing literature similar to those used by Engle et al. [2020]. If climate risk is indeed a significant factor influencing asset markets (i.e., a factor driving the comovement of various assets), it is possible to construct a well-diversified portfolio whose returns isolate exposure to that risk factor. This enables investors to hedge their climate risk exposure by trading this portfolio, without altering their exposures to other risk factors.

The new mimicking portfolio approach is more efficient than traditional sorting or maximum correlation approaches, utilizing advanced methodologies for estimating large-dimensional covariance matrices in short samples (De Nard et al. [2022]).

We encountered similar challenges as Engle et al. [2020]) in implementing this mimicking portfolio approach. One significant challenge is the limited number of months with observed climate news realizations, juxtaposed with a large set of assets available for forming hedge portfolios. This raises concerns about data mining, potentially leading to hedge portfolios that perform well in-sample but lack stability out-of-sample. To mitigate this, we use characteristics that proxy for a firm's exposure to climate risk to parameterize the weights of the hedge portfolios parsimoniously. For instance, one such characteristic could be firm ESG combined score.

Ultimately, our goal is to construct a hedge portfolio for climate change shocks (CC_t). This portfolio should have unit exposure (β) to climate risk shocks (CC_t) but no exposure to any other risk factors (v_t). This ensures that investors can adjust their exposure to climate risk by trading in this portfolio without modifying their exposure to other risk factors. The asset pricing literature has traditionally followed two main approaches to construct hedge portfolios: the Fama-MacBeth cross-sectional regression approach and the mimicking portfolio approach. Our research builds on the theoretical insights provided by Giglio and Xiu [2021] regarding the properties of these estimators in large-dimensional settings.

3 Methodology:

Aligned with the framework proposed by Giglio and Xiu [2021], our methodology unfolds in three distinct phases. Initially, we employ Principal Component Analysis (PCA) to extract factors and their loadings from a comprehensive panel of test asset returns, thereby reconstructing the factor space, which represents an unknown rotation of the p factors. Subsequently, we conduct a cross-sectional regression solely utilizing the Principal Components (PCs), excluding the factor of interest, g_t, to ascertain their respective risk premia. In the third step, we proceed to estimate a time series regression of g_t onto the PCs, illuminating the relationship between g_t and the latent factors while mitigating potential measurement errors associated with g_t. The risk premium of g_t is subsequently derived as the product of its loadings on the PCs (computed in the third step) and their respective risk premia (computed in the second step). According to the authors, the invariance principle elucidated above ensures the robust identification of the risk premium associated with g_t, irrespective of the rotation of true factors occurring during the extraction of PCs.

In this section, we introduce the three-pass risk premia estimator devised by Giglio and Xiu [2021], which effectively addresses both omitted variable and measurement error biases encountered in the estimation of risk premia within linear factor models. Let us consider a general linear factor model comprising p factors:

$$r_t = \beta\gamma + \beta v_t + u_t, \quad \text{where} \quad E(v_t) = E(u_t) = 0, \quad \text{and} \quad \text{Cov}(u_t, v_t) = 0 \tag{1}$$

The authors Giglio and Xiu [2021] define v_t as the innovations of the p factors, this means the zero factors, r_t represents the excess returns on each n portfolios of assets, u_t represents the idiosyncratic error terms, β are factor loadings, and γ represents the vector of risk premia for the p factors.

Thus, this methodology empowers us to analyse the factor loadings of the risk premia associated with climate-related risk factors (g_t), even in the absence of complete observation of all true factors (v_t).

Let g_t be a set of d observable factors whose risk premia we will estimate. The term g_t is related to the unobservable factors v_t as follows:

$$g_t = \delta + \eta v_t + z_t, \quad \text{where} \quad E(z_t) = 0, \quad \text{and} \quad \text{Cov}(z_t, v_t) = 0 \quad (2) \tag{2}$$

Where η represents the relation between g_t and the unobservable factors v_t, and z_t is a measurement error in g_t. The risk premium of g_t is defined as the expected excess return of a portfolio with a beta equal to 1 with respect to g_t and a beta equal to 0 with respect to all other factors[2] (including the unobservable variables), and this corresponds to: $\gamma_g = \eta\gamma$.

From the preceding equations (1) and (2), it becomes evident that neither η (the loading of g_t on the unobservable factors) can be identified if the factors v_t remain unobserved. Addressing this challenge, as outlined by Giglio and Xiu [2021], hinges on a potent property inherent to risk premia in linear factor models, termed rotation invariance. This property states that the product $\eta\gamma$ can be

[2]According with Giglio and Xiu [2021] this specification nests the case where g_t is the first factor by choosing η to be the vector (1, 0, 0, 0, ..., 0) and setting δ and z_t to zero.

identified even if one observes only an arbitrary full-rank rotation of the factors. This means, if one just observes $\hat{v}_t = Hv_t$, where H is a full-rank $p \times p$ matrix but observes neither v_t nor H. Having that in consideration, we can rewrite the model as following:

$$r_t = \beta H^{-1} H\gamma + \beta H^{-1} H v_t + u_t, \tag{3}$$

$$g_t = \delta + \eta H^{-1} H v_t + z_t. \tag{4}$$

Assuming that $\hat{\eta} = \eta H^{-1}$, $\hat{\gamma} = H\gamma$, and $\hat{\beta} = \beta H^{-1}$, we can rewrite the model in terms of the rotated factors $\widehat{v}_t$:

$$r_t = \hat{\beta}\hat{\gamma} + \hat{\beta}\widehat{v}_t + u_t, \tag{5}$$

$$g_t = \delta + \hat{\eta}\widehat{v}_t + z_t. \tag{6}$$

Assuming that $\widehat{v}_t$ needs to be observed in order to identify $\hat{\eta} = \eta H^{-1}$ (represents the vector of regression coefficients of g_t on $\widehat{v}_t$) as well as $\hat{\gamma} = H\gamma$ (represents the risk premia of $\widehat{v}_t$, which can be obtained via standard cross-sectional regressions). According to Giglio and Xiu [2021], we cannot recover η or γ separately because we do not know H, we can still identify the risk premium of g_t due to: $\hat{\eta}\hat{\gamma} = \eta H^{-1} H\gamma = \eta\gamma = \gamma_g$.

It is important to note that this invariance property is just a specific property to γ_g and it does not hold for other quantities in the model, such as η, γ, or β.

Following these steps, the Giglio and Xiu [2021] three-pass procedure first estimates the rotated factors $\widehat{v}_t$ via PCA. Second, it estimates, via a two-pass cross-sectional regression, $\hat{\gamma} = H\gamma$, meaning it estimates the risk premia of $\widehat{v}_t$. Third, it estimates $\hat{\eta} = \eta H^{-1}$ by using a time series regression of g_t onto the estimated $\widehat{v}_t$. Additionally, the risk premia of g_t, $\eta\gamma$, can be ultimately estimated by taking the product of the estimates of $\hat{\eta}$ and $\hat{\gamma}$ from the previous steps.

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Having presented a broader idea surrounding the Giglio and Xiu [2021] methodology, the next subsection delves deeper into the three-pass estimator. This subsection discusses in detail the role of each step. After that, subsection 2 discusses the methodology's application to mixed-frequency data.

3.1 The Three-Pass Estimator

First, the model assumes constant risk premia and loadings. According with Giglio and Xiu [2021] is recommended to use in this methodology a characteristic-sorted portfolios instead of individual stocks. According with the main asset pricing literature, one of the main advantages of using portfolios is that their risk exposure is more stable over time.

Second, the model assumes weak assumptions on the structure of the errors, and this model holds in presence of nonstationary process with heteroskedasticity and dependence in both the time series and the cross-sectional dimensions.

Third, the model imposes that the zero-beta rate is equal to the observed treasury bill rate.

In this model, we denote, similar to Giglio and Xiu [2021], R as the $n \times T$ matrix of excess returns, V the $p \times T$ matrix of factors, G the $d \times T$ matrix of observable factors, U the $n \times T$ matrix of idiosyncratic errors, and lastly, Z the $d \times T$ matrix of measurement error. According to Giglio and Xiu [2021], the model can be written as the following:

$$R = \beta\gamma l_T^\top + \beta V + U. \tag{7}$$

Writing $(\bar{R}, \bar{V}, \bar{G}, \bar{U}, \bar{Z})$ as the respective matrices of the demeaned variables, the previous equation can be written as the following:

$$\bar{R} = \beta\bar{V} + \bar{U}. \tag{8}$$

We need only the demeaned version of equation (2), given that for nontradable factors, the mean of g_t, δ, does not have a meaningful relevance or interpretation. We can write in matrix notation g_t as the following:

$$\bar{G} = \eta\bar{V} + \bar{Z}. \tag{9}$$

This methodology does not require the true factors V to be known or observed; it only makes use of the excess returns R and the factors of interest G.

According to Giglio and Xiu [2021], this model guarantees that by applying PCA to the panel of observed return innovations $\bar{R}$, we can recover both β and $\bar{V}$ up to some invertible matrix H as long as $n, T \to \infty$.

According to the three-pass estimator, and given observable returns R and the factors of interest G, the three-pass steps of the estimator for $\gamma_g = \eta\gamma$ can be written as follows:

PCA step: According to this step, we should extract the principal components (PCs) of returns by conducting the PCA of the matrix $\frac{1}{nT}\bar{R}^T\bar{R}$. Define the estimator for the respective factors and their loadings as:

$$\hat{V} = T^{\frac{1}{2}}\left(\xi_1 : \xi_2 : \ldots : \xi_{\hat{p}}\right)^T \quad \text{and} \quad \hat{\beta} = T^{-1}\bar{R}\hat{V}^T, \tag{10}$$

where $\xi_1, \xi_2, \ldots, \xi_{\hat{p}}$ represents the normalized eigenvalues (of length 1) corresponding to the largest $\hat{p}$ eigenvalues of the matrix $\frac{1}{nT}\bar{R}^T\bar{R}$ and $\hat{p}$ is some consistent estimator of the number of factors that follows specific assumptions (Giglio and Xiu [2021]). Thus, this step recovers the factors v (by rotating $H\bar{V}$ for some unobserved invertible matrix H) by extracting the PCs of returns and selecting the first $\hat{p}$ of them. Giglio and Xiu [2021] propose to extract the PCs from the $T \times T$ matrix,

$\frac{1}{nT}\bar{R}^T\bar{R}$, and normalize the estimated factors such that $\hat{V}\hat{V}^T = I_p$. Once the PCs are extracted in this stage, the second stage estimates their risk premia.

Cross-sectional regression step: In this step, we run a cross-sectional ordinary least squares (OLS) regression of average returns ($\bar{R}$) onto the estimated factor loadings ($\hat{B}$), with the objective of obtaining the risk premia of the estimated latent factors:

$$\hat{\gamma} = \left(\hat{\beta}^T\hat{\beta}\right)^{-1}\hat{\beta}^T\bar{r}. \tag{11}$$

The estimation of the risk premia in this step can be done in several ways. Similar to Giglio and Xiu [2021], we decided to estimate using an OLS regression for simplicity[3].

Time series regression step: The last step is characterized by running a time series regression of g_t onto the extracted factors from the first step and then obtaining the estimator $\hat{\eta}$, and the fitted value of the observable factor, $\hat{G}$, as follows:

$$\hat{\eta} = \hat{G}\hat{V}^T\left(\hat{V}\hat{V}^T\right)^{-1}, \tag{12}$$

$$\hat{G} = \hat{\eta}\hat{V}. \tag{13}$$

As stated before, the estimator of the risk premium for the observable factor g_t is obtained by combining the estimate results from step 2 and step 3:

$$\hat{\gamma}_g = \hat{G}\hat{V}^T\left(\hat{V}\hat{V}^T\right)^{-1}\left(\hat{\beta}^T\hat{\beta}\right)^{-1}\hat{\beta}^T\bar{r}. \tag{14}$$

The three-pass estimator can be written as:

$$\hat{\gamma}_g = \hat{G}\hat{V}^T\left(\hat{V}\hat{V}^T\right)^{-1}\left(\hat{\beta}^T\hat{\beta}\right)^{-1}\hat{\beta}^T\bar{r}. \tag{15}$$

In sum, this final step stands as a notable contribution of Giglio and Xiu [2021] to the literature, augmenting the standard two-pass procedure with a critical third step. As highlighted by Giglio and Xiu [2021], this step holds particular significance as it bridges the gap between the opaque risk premia associated with latent factors and those predicted by economic theory. This aspect is crucial for addressing our research question, as it allows for the consideration of latent factors as climate risk variables, encompassing both climate transition and physical risk at both the U.S. nationwide and state level.

[3]According with Giglio and Xiu [2021] it is possible to estimate the risk premia using either generalized least squares (GLS) regression or weighted least squares (WLS) regression, but either of the two estimations will require estimating a larger number of parameters. Thus, these estimators will not improve the asymptotic efficiency of the OLS to the first order.

3.2 The Three-Pass Estimator for Mixed-frequency

Given the limited availability of high-frequency climate risk factors and economic policy indicators at both U.S. wide and state level, with accurate information only accessible at a monthly frequency, we have chosen to employ the three-pass estimation methodology for mixed frequencies outlined by Giglio and Xiu [2021]. This approach is particularly suited for scenarios where g_t, representing factors such as macroeconomic and climate data, is available solely at a lower frequency (e.g., monthly), while returns of test assets are accessible at a higher frequency (e.g., daily).

Let us assume that $\Delta = \frac{1}{m}$ be the sampling frequency of high-frequency returns. Let $a^h_{t+k\Delta}$ denote the high-frequency return from $t + (k-1)\Delta$ to $t + k\Delta$ for $a = r$, u, and v. By recycling the old notation a_t and using it as the low-frequency cumulative return for $t-1$ to t, that is, $a_t := \sum_{k=1}^{m-1} a^h_{t+k\Delta}$. According to Giglio et al. (2021), we should assume that the high-frequency test asset returns follow a linear factor model as the following:

$$r^h_{t+k\Delta} = \beta\gamma\Delta + \beta v^h_{t+k\Delta} + u^h_{t+k\Delta}, \tag{16}$$

for $1 \leq k \leq m$ and $1 \leq t \leq T$. Then we revise the procedure to make use of high-frequency returns.

Precisely, in the first two steps of the three-pass procedure, we conduct a PCA and cross-section regression as highlighted previously, however, now using $r^h_{t+k\Delta}$ in order to obtain $\hat{V}^h$, $\hat{\beta}^h$, and $\hat{\gamma}^h$, respectively, where the subscript h emphasizes the use of high-frequency data and the subscript l represents the use of low-frequency data. Note that in this case $\hat{V}^h$ is a $d \times (mT)$ matrix of the estimated high-frequency factors. Additionally, for the third step, we instead regress g_t onto the low-frequency cumulative returns of the high-frequency factors:

$$\hat{\eta}^\iota = \bar{G}\left(\hat{V}^\iota\right)^T \left(\hat{V}^\iota\left(\hat{V}^\iota\right)^T\right)^{-1}, \tag{17}$$

Where $\hat{V}^\iota = \hat{V}^h(\iota_m I_T)$. Consequently, the new risk premia estimator is given by:

$$\hat{\gamma}^m_g = m \times \hat{\eta}^\iota \hat{\gamma}^h. \tag{18}$$

Where the multiplier m ensures that the risk premia estimates are in the same unit as those based on low-frequency data (e.g., monthly frequency). According to Giglio and Xiu [2021], this estimator is asymptotically equivalent to the benchmark estimator in the previous session ($\hat{\gamma}_g$). Note that in this case the sample size is replaced by mT and the variance Σ^v is replaced by $\Sigma^v\Delta$. Supposing that all the assumptions highlighted by Giglio and Xiu [2021] hold for the lower frequency cumulative returns, v_t and u_t. Additionally, suppose that $\hat{p} \xrightarrow{p} p$; then as $n, T \to \infty$, with probability approaching 1, there exist some invertible matrix (H^h), such that:

$$\hat{\gamma}^h - H^h\gamma\Delta = m^{-1}H^h\bar{v} + O_P(n^{-1} + T^{-1}), \tag{19}$$

$$\hat{\eta}^\iota - \eta\left(H^h\right)^{-1} = \bar{Z}\bar{V}^T\left(\bar{V}\bar{V}^T\right)^{-1}\left(H^h\right)^{-1} + O_P(n^{-1} + T^{-1}). \tag{20}$$

Moreover, as a final result[4], we obtain the following estimator:

$$\hat{\gamma}_g^m = \hat{\gamma}_g + O_P(n^{-1} + T^{-1}). \tag{21}$$

[4]Recall that the sample average return, $\bar{v}^h = \frac{1}{mT}\sum_{t=1}^{T}\sum_{k=1}^{m} v_{t-1+k}^h$, represents the leading term of $\hat{\gamma}^h - H^h\gamma\Delta$. Additionally, the sample average remains exactly the same regardless of the sampling frequency of the observed returns ($\bar{v}^h = m^{-1}\bar{v}$).

4 Data

We conducted our empirical analysis on a dataset comprising 20 portfolios, collectively representing 1287 U.S. firms[5] across 38 different U.S. states[6]. Having a large cross-section and an extended time series of test assets is essential for ensuring the consistency and desirable asymptotic properties of the three-pass estimator. Additionally, a substantial number of test assets is recommended by Lewellen et al. (2010), who express skepticism regarding asset pricing tests based on a limited cross-section of assets with potentially strong low-dimensional factor structures. A robust dataset helps mitigate concerns about model misspecification and enhances the reliability of our empirical findings.

In this research, similar to Engle et al. [2020], we accumulate the monthly asset returns of firms into portfolios based on firm characteristics. Specifically, we use the ESG combined scores of firms to model their risk exposures. We implement this characteristics-based approach by utilizing firm-level environmental performance scores constructed by the ESG data provider Thomson Reuters [7]. These scores are employed as characteristics to sort individual stocks and form portfolios.

The risk exposures of individual assets depend directly on these characteristics, so sorting the assets by characteristics ensures that the resultant portfolios have constant risk exposures. In the context of our analysis, firms are ranked from 1 to N (where N is the total number of firms, in this case, 1287) based on their ESG scores. Rank 1 is assigned to the firm with the highest ESG combined score, while rank N is assigned to the firm with the lowest ESG score. To facilitate a more nuanced analysis, the rankings are standardized to a range between -0.5 and +0.5 (standardized rank $= (rank - 0.5)/N$). This standardization allows for a consistent comparison across firms. Consequently, portfolio 1 includes firms with the lowest ESG scores according to the Eikon Database, whereas portfolio 20 comprises firms with the highest ESG scores. Each portfolio thus reflects a spectrum of ESG performance based on standardized rankings. This portfolio-based approach offers a more granular understanding of regional climate risks and facilitates the analysis of how these risks impact asset pricing and portfolio performance. This approach offers several advantages. Firstly, it allows for the creation of a robust and extensive panel of test assets, facilitating the estimation of principal components [8] in the initial step without additional assumptions. Moreover, portfolios

[5]This research includes data on both energy sectors and firms that are highly dependent on energy, such as those in manufacturing, utilities, and transportation, thereby encompassing information on both energy providers and users.

[6]In this research, the scope of analysis was confined to 38 U.S. states, a limitation dictated by the availability of data relevant to our study. The dataset includes only those states where the firms under investigation are located, thus defining the geographical boundaries of our analysis. The states represented in this research include: Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, Florida, Georgia, Illinois, Indiana, Kansas, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, and Wisconsin.

[7]The ESG Combined Score is an overall firm score, between 0 to 100, based on the reported information in the environmental, social and governance pillars (ESG score) with an ESG controversies overlay. It provides an overall assessment of a company's performance in these areas, indicating its commitment to sustainability, responsible business practises, and ethical conduct. The higher the score the better is the firm performance. Note that ESG combined scores (annual) are not available for every time period between 2000 and 2023. To address this data gap, we use forward fill and/or backward fill methods, applying the most recent available ESG score for each firm in instances where the score is missing for a particular year. Additionally, the same corresponding ESG combined score is attributed to all months within the same year.

[8]Our research utilizes the approach established by Giglio and Xiu [2021] to estimate the dimension of the factor space, denoted as $\hat{p}$, which indicates the number of latent factors. This approach considers both the number of latent factors and a maximum allowable factor count ($p_{\max}$). Instead of relying solely on information criteria, their method

provide test assets with more stable exposures (i.e., betas) to risk factors, as portfolio weights reflect time-varying risk exposures captured by firm characteristics.

Our approach in this paper builds on measures of firms' environmental exposures produced by third-party ESG data providers. There has been a growing interest in ESG investing among investors, who are increasingly demanding assets that fulfill certain environmental (E), social (S), and governance (G) criteria. Given this trend, measuring the ESG characteristics of firms has become an important task for investors. Firm-level ESG scores are available from numerous providers that collect raw data from sources such as firms' disclosures, SEC filings, and reports by governments or NGOs. These raw data are then translated into numerical ESG scores using proprietary algorithms.

Our approach aligns with the methodology outlined by Giglio and Xiu [2021], which emphasizes the analysis of portfolio returns in relation to various factors. In our analysis, we incorporated both state-specific and nationwide climate risk factors. Notably, the methodology proposed by Giglio and Xiu [2021] is well-suited for large datasets, allowing for the inclusion of multiple test portfolios without significant computational costs. This framework provided a robust foundation for our research, enabling us to comprehensively evaluate climate risk disparities among U.S. states and their implications for asset pricing.

Moreover, our dataset covers a substantial period from March 1, 2000, to March 1, 2023, encompassing a total of $T = 277$ months, with an average of approximately 21.74 trading days per month. Daily adjusted close prices were sourced from the Eikon database for all included firms, enabling us to compute accumulated returns. Since we apply a mixed-frequency methodology following Giglio and Xiu [2021], we accumulated the excess returns to align firm information with a monthly frequency. This adjustment allows us to harmonize high-frequency data with monthly risk factors, ensuring consistency in our analysis. We then aggregated this data into distinct portfolios based on the firms' specific ESG characteristics.

The inclusion of a large cross-section of potentially diverse test assets, as in our study, adheres to recommendations by Lewellen et al. (2010). They caution against asset pricing tests relying on small cross-sections with a strong, low-dimensional factor structure. By contrast, our approach leverages a broad range of portfolios, enhancing the robustness and generalizability of our findings across different market conditions and risk environments. By combining firm-level excess returns with state-specific risk factors, we aim to uncover the nuanced effects of climate transition and physical risks across different U.S. states. This methodology allows us to bridge the gap between high-frequency financial data and lower-frequency risk indicators, providing a robust framework for our empirical analysis. This approach not only enhances the precision of our findings but also underscores the importance of incorporating regional environmental factors into financial modeling and decision-making.

[Table 1 around here]

Table 1 presents summary statistics for the monthly returns of the 20 portfolios. Mean monthly

is supported by the empirical behavior of eigenvalues, ensuring analytical consistency. Applying this approach, we observed a significant drop in eigenvalues beyond the 10th principal component of the covariance matrix of returns. Thus, we set $p_{\max}$ to 10, as the first ten components capture most of the significant variance in the dataset, reflecting the underlying factor structure suggested by the data. This parameter setting enhances our factor model, aligning with established empirical finance practices and better representing the complexities of financial returns data.

returns range from -0.00551 (portfolio 4) to 0.00624 (portfolio 20), indicating variability in portfolio performance, with some portfolios showing positive returns while others underperformed. Median returns corroborate these findings, showing consistent performance trends across the period. Portfolios with lower mean returns, such as Portfolio 1, 2, and 4, suggest higher exposure to negative risk factors, whereas Portfolios 19 and 20 exhibit higher returns, potentially due to superior ESG practices or favorable market conditions. Standard deviation ranges from 0.00149 (portfolio 20) to 0.00914 (portfolio 1), reflecting varying levels of return volatility. Higher standard deviations in portfolios 1 and 3 indicate greater risk and volatility, while lower values in Portfolios 16 and 20 suggest more stable performance. Skewness values range from -3.00706 (Portfolio 1) to 1.63249 (portfolio 13), with negative skewness prevalent across most portfolios, indicating a tendency for returns to be lower than the mean, with potential for extreme negative returns. kurtosis values range from 1.88071 (portfolio 15) to 12.16327 (portfolio 7), indicating distributions with heavier tails than a normal distribution. Portfolios 1, 6, and 7 exhibit high kurtosis, suggesting a higher likelihood of extreme returns. These findings underscore significant risk exposure across portfolios and highlight the importance of understanding the risk-return trade-off in ESG-oriented investments.

Overall, the variation in mean returns across portfolios emphasizes that firms with higher ESG scores may offer distinct risk and return profiles, reinforcing the need for thorough due diligence when integrating ESG factors into investment strategies.

While the asset pricing literature has proposed an extremely large number of factors (Harvey et al. (2016), McLean and Pontiff [2016]), in this research we focus on a few representative ones that we consider important for our main research objective. Additionally, following Giglio and Xiu [2021] the risk premia estimate[9] for any factors using the three-pass methodology do not depend on whether other factors are included in g_t.

The factors under consideration encompass both tradable and nontradable categories. Tradable factors include market returns (in excess of the risk-free rate), size (SMB), and value (HML) provided by Fama-French three factor models[10] (Wharton Research Data Services [2024]). Additionally, we incorporate the Fama-French five equity factors -market (MKT), size (SMB), value (HML), operating profitability (RMW), and investment (CMA) - as defined by Fama and French (2015). These factors are obtained at a monthly frequency providing a comprehensive set of variables to analyze asset returns and their sensitivities to various market dynamics. Nontradable factors comprise indicators of economic activity at both national and state levels, as well as climate risk metrics encompassing both transitional and physical risks.

To gauge economic activity, we utilize economic indexes at both the state ($ECON_{States}$) and national levels ($ECON_{US}$), sourced from Baumeister et al. [2021]. This data allows us to capture the economic development of each state and its broader impact on portfolio performance. The economic condition indicators enable us to study the responses of individual states to a range of macroeconomic

[9]Recall that the observable factors g_t in the three-pass methodology proposed by Giglio and Xiu [2021] can be either an individual factor or groups of factors. In our research g_t represents a group of factors.

[10]The Fama-French portfolios are constructed from the intersections of two portfolios based on size, measured by market equity (ME), and three portfolios based on the ratio of book equity to market equity (BE/ME), which serves as a proxy for value. The returns from these portfolios are used to construct the Fama-French factors. Eugene Fama and Kenneth French demonstrated that these factors capture a statistically significant portion of the variation in stock returns.

shocks, natural disasters like droughts, hurricanes, and wildfires, and federal economic policies. These policies include fiscal, monetary, trade, and industrial measures, as well as state-specific fiscal measures, environmental regulations, transportation policies, infrastructure programs, energy market (de)regulation, property tax reforms, and land-use rules.

As additional measures of policy uncertainty, we incorporate economic policy uncertainty indicators at both the state (EPU_{States}) and U.S. - wide levels (EPU_{US}), obtained from PolicyUncertainty.com [n.d.], with data available on a monthly basis. As per the methodology provided by the authors, a higher index value indicates heightened levels of uncertainty. The construction of the EPU index entails an exhaustive process, involving the analysis of daily and weekly newspapers from Washington DC and each state across the United States, including national papers like the NY Times or Wall Street Journal. EPU_{States} is tailored to assess uncertainty stemming from state and local policy matters. Each state-specific policy term set encompasses descriptors for executive positions, legislative bodies, policy initiatives subject to citizen votes, and regulatory bodies overseeing diverse sectors such as environment, labor, transportation, banking, energy, utilities, and financial services. This tailored approach ensures that the set of terms is unique to each state, reflecting the distinct titles, officials, regulatory bodies, and departmental structures across states. By leveraging the EPU_{States} indicator, our research offers a nuanced analysis of how state-level policies and regional economic dynamics influence climate change risk across states, while also assessing whether these policies are reflected in firm returns. This granular perspective enhances our understanding of the unique challenges and opportunities associated with climate change adaptation and mitigation efforts at the U.S. state level.

The increasing polarization in American politics over recent decades has led to significant government dysfunction, prompting the need to consider its economic implications. To capture this, we incorporated a novel high-frequency indicator of partisan conflict (PCI_{US}) in the U.S., developed by Azzimonti [2018], as an additional risk factor in our analysis. According to Azzimonti [2018] and existing economic theories, heightened economic policy uncertainty or greater volatility in fiscal shocks tends to suppress economic activity. The partisan conflict index is a high-frequency measure constructed using a search-based methodology. It quantifies the frequency of newspaper articles that report disagreements among lawmakers about policy, both within and between national political parties, normalized by the total number of articles published within a given period. This approach provides a comprehensive indicator of partisan conflict over an extended timeframe. Philadelphia (2018) demonstrates that the long-term trend of this index mirrors patterns in political polarization and income inequality, underscoring its relevance to economic analysis. Philadelphia's findings suggest a strong correlation between economic policy uncertainty (EPU) and partisan conflict, both measures often moving in tandem. For example, legislative deadlines, such as those for fiscal policies, force policymakers to make critical decisions by specific dates, thereby amplifying uncertainty about future economic policy. However, it is important to note that EPU can also arise from factors unrelated to partisan conflict, such as uncertainty over monetary policy or policy decisions by foreign governments. By incorporating the partisan conflict index as a risk factor, we aim to better understand its role in driving economic uncertainty and its broader impact on U.S. firms.

Prior studies have employed various methods to measure climate risks, including country-level

climate risk indices, the occurrence of specific extreme weather events in particular regions (Dessaint and Matray [2017]), corporate climate-related disclosures, and firm-level carbon emissions. In this research we incorporated the Climate Policy Uncertainty Index for the U.S. (CPU_{US}), developed by Gavriilidis [2021]. This index serves as a proxy for the national-level climate risk index[11]. Gavriilidis [2021] establishes the link between the CPU index and CO2 emissions. By analysing the scaled frequency of articles across eight major U.S. newspapers, the CPU index captures significant events pertaining to climate policy. Gavriilidis [2021] find a robust and negative relationship between climate policy uncertainty, as measured by the CPU index, and CO2 emissions, both at the aggregate and sectoral levels. This suggests that higher levels of uncertainty regarding climate policy tend to discourage energy consumption and non-essential transportation while incentivizing renewable energy adoption and climate-friendly innovations, ultimately leading to reduced CO2 emissions. Consequently, we view the CPU index as a critical climate risk indicator for our analysis, providing valuable insights into the dynamics between climate policy uncertainty and emissions outcomes, not only measuring climate physical risk but as well climate transition risk.

[Figure 2 around here]

In figure 2, we conducted a comparative analysis by normalizing both the Climate Policy Uncertainty (CPU_{US}) index and the U.S. economic index indicator from 2000 to 2023. Notably, the figure reveals numerous spikes throughout the sample period, coinciding with significant events related to climate policy. For instance, spikes occur in June 2001 following President Bush's statement rejecting the Kyoto Protocol, December 2007 with the EPA's enactment of new energy legislation pertaining to vehicle greenhouse gas emissions, and January 2017 when Volkswagen pleaded guilty in the emissions scandal. Other notable spikes coincide with key events such as President Trump's announcement of the U.S. withdrawal from the Paris Accord in June 2017, global strikes preceding the UN Climate Action Summit in September 2019, and the EPA's introduction of new greenhouse gas emission standards for aircraft in December 2020. These events underscore the dynamic nature of climate policy and its profound impact on market sentiment and asset pricing. Moreover, studying these fluctuations at the state level provides valuable insights into how regional differences in climate policy implementation and response strategies contribute to overall market dynamics, thereby enhancing our understanding of climate risk and its implications for portfolio management.

Figure 2 allowed us to observe the temporal dynamics and potential correlations between these two indicators. Our analysis revealed notable similarities, particularly evident during specific periods

[11] Gavriilidis [2021] employs a comprehensive search strategy to identify relevant articles in eight prominent U.S. newspapers. These articles contain specific terms related to climate policy and uncertainty, as well as keywords associated with environmental regulations and legislation. The selected terms include variations such as "uncertainty" or "uncertain" and "carbon dioxide" or "climate" or "climate risk" or "greenhouse gas emissions" or "greenhouse" or "CO2" or "emissions" or "global warming" or "climate change" or "green energy" or "renewable energy" or "environmental" and ("regulation" or "legislation" or "White House" or "Congress" or "EPA" or "law" or "policy" (including variants such as "uncertainties", "regulatory", "policies", etc). Gavriilidis' search covers the period from April 1987 onwards. The eight newspapers included in the study are the Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today, and the Wall Street Journal. For each newspaper, the number of relevant articles per month is scaled relative to the total number of articles during the same month. Subsequently, these scaled series are standardized to have a unit standard deviation and then averaged across newspapers on a monthly basis. Finally, the averaged series are normalized to ensure a mean value of 100 for the period spanning from April 1987 to August 2022. This rigorous methodology allows for a comprehensive analysis of climate policy uncertainty trends across major U.S. newspapers over the specified timeframe.

such as between 2009 and 2010, and more recently during the first half of 2020. These observed spikes coincide with pivotal events in both climate policy and economic activity, highlighting the interconnectedness between climate change impacts and U.S. economic dynamics.

Moreover, examining the relationship between the CPU index and the U.S. economic index indicator provides valuable insights into how climate policy uncertainty influences economic conditions. For instance, periods of heightened uncertainty surrounding climate policy decisions may contribute to fluctuations in economic activity, impacting investment decisions, consumer behavior, and overall market sentiment. Conversely, efforts to mitigate climate change through policy interventions may also stimulate economic growth through investments in renewable energy, infrastructure, and technological innovation. Understanding the interplay between climate policy uncertainty and economic indicators is essential for policymakers, investors, and other stakeholders seeking to navigate the complex interactions between climate change and economic resilience.

To assess climate physical risk measures, we incorporate temperature anomalies ($Tanomalies$) at the state level. In their study, Sheng et al. [2022] examine the impact of climate risk, specifically temperature growth and its volatility, on the coincident indicator of the 50 U.S. states using a panel data setup spanning from 1984 to 2019. Their findings reveal that climate risks exert a negative influence on economic activity, irrespective of variations in temperature growth or its volatility. Importantly, they highlight that the detrimental effects of climate risks depend on the economic and policy-related uncertainty regime within states. Following a similar analytical approach, we include temperature anomalies ($Tanomalies$) as an additional indicator of climate physical risk at each U.S. state level, collected on a monthly basis. We utilize average temperature data (in degrees Fahrenheit) for each state sourced from the National Centers for Environmental Information (NOAA/NCEI) [n.d.].

Sheng et al. [2022] provide robust evidence supporting the hypothesis that higher levels of economic and policy-related uncertainty exacerbate the adverse effects of climate risk on economic activity. They suggest that elevated uncertainty amplifies the supply and demand-side transmission channels through which temperature growth and temperature anomalies and its volatility affect the real economy. Consequently, we consider temperature anomalies as a vital climate physical risk measure at the U.S. state level, essential for our comprehensive analysis.

Finally, as an additional measure of climate physical risk at the U.S. state level, we utilize the number of natural disasters declared by the Federal Emergency Management Agency (FEMA [12]) in each county.

Following Hartlieb and Eierle [2024], we source data on declared natural disasters from the FEMA database to develop a regional climate risk index for clients' physical climate risks. The FEMA dataset encompasses relatively large disasters that have had a significant impact on local economies. It includes information on the incident type (e.g., flood, storm, fire, hurricane, snow, tornado, earthquake), event start and end dates, affected areas (state and county), and types of assistance

[12]FEMA dataset, known as Disaster Declarations Summaries, provides a summarized account of all federally declared disasters, beginning with the first disaster declaration in 1953. It includes all three types of disaster declarations: major disasters, emergencies, and fire management assistance. The dataset features declared recovery programs and geographic areas, with county-level data available from 1964 onwards (Fire Management records are considered partial due to the historical nature of the dataset).

programs declared. Similar, we computed a monthly physical risk measure ($Natural_{Risk}$) as the total number of declared natural disasters in a state where any given firm has been headquartered in the previous five years. However, it is important to note that major firms may have plants located far from their headquarters, meaning that local natural disasters in the headquarter county do not necessarily pose significant risks such as production or supply chain disruptions.

As an additional measure of climate transition risk factors at the state level, we incorporated the climate policy index developed by Bergquist and Warshaw [2023b]. This index, constructed using data from 25 individual policies, provides a comprehensive measure of state-level climate policies over the period 2000–2020. By capturing variations across states that are often overlooked in single-policy analyses, the climate policy index enables a more nuanced understanding of regional climate policy dynamics. Including this indicator in our analysis underscores the significance of state-level risk factors and their role in shaping the broader landscape of climate transition risks.

Finally, table 2 provides details on the data code and scope utilized in this research.

[Table 2 around here]

5 Empirical Analysis

In this section, we present our main empirical findings. We extract the set of latent factors from the panel of asset returns and relate them to a large set of tradable and non-tradable observable and unobserved factors. The traditional equity factors, such as the Fama-French factors, show different sensitivities to risk premia. While unbserved factors such as climate policy uncertainty in the U.S. (CPU_{US}) and the U.S. economic conditions indicator ($ECON_{US}$) exhibit significant explanatory power on portfolio returns. These findings elucidate how both observed and unobserved factors influence the performance of energy firms with specific ESG characteristics. Moreover, incorporating state-level risk factors, such as temperature anomalies ($Tanomalies$), economic policy uncertainty (EPU_{State}), and economic conditions ($ECON_{State}$), provides deeper insights into portfolio performance and risk. Our results indicate that these state-level factors are statistically significant and should be carefully integrated into portfolio management strategies for more robust risk assessment and mitigation. Specifically, certain state-level factors, such as temperature anomalies ($Tanomalies$), appear to be priced over the cross-section of returns and have substantial implications for portfolio performance. While the impact of economic policy uncertainty and economic conditions is relevant, it may not be as pronounced or consistent. Investors should therefore consider these state-level factors in their portfolio strategies, with particular emphasis on climate-related risks.

5.1 Latent Factor Structure of the Large Panel of Assets

We begin by analyzing the latent factor structure of U.S. firms' returns, drawing on the methodology introduced by Giglio and Xiu [2021] to estimate the dimension of the factor space, denoted as $\hat{p}$. This dimension represents the number of latent factors identified in the data, with a maximum allowable factor count ($p_{\max}$) determined based on the empirical behavior of eigenvalues. Instead of relying solely on information criteria, their approach emphasizes analytical consistency by examining the structure and robustness of eigenvalues.

Table 3 presents the risk premia associated with U.S.-wide latent factors, measured as the ratio of each factor's eigenvalue to the sum of all eigenvalues of the sample covariance matrix of our 20 test portfolios. These estimates provide a comprehensive view of the factor-driven variation in returns. The first column corresponds to the intercept, representing the zero-beta rate, while subsequent columns detail the risk premia for each factor. Instead of reporting standard errors, Table 3 provides variance estimates for the risk premia, offering a robust measure of uncertainty. Each row corresponds to a different estimate derived using $\hat{p}$, ranging from 1 to $p_{\max}$.

Our analysis identified a notable decline in the eigenvalues of the covariance matrix beyond the 10th principal component, suggesting that the first ten components adequately capture the significant variance within the dataset. Consequently, we set $p_{\max} = 10$, aligning our analysis with the underlying factor structure implied by the data dynamics. This parameterization refines our factor model, ensuring it effectively represents the complexities

[Table 3 around here]

In Table 3, the intercept values, representing the estimated risk-free rate (zero-beta rate), are

consistently estimated at 0.0045 across all factors, indicating a stable and positive baseline return. This stability underscores robustness in the zero-beta rate estimates, serving as a reliable benchmark for expected returns in the absence of factor exposures.

The risk premia for both observed and latent factors exhibit significant variation, highlighting the distinct pricing dynamics associated with each factor. The climate policy uncertainty (CPU_{US}) factor shows a positive risk premium of 0.1063, indicating that climate-related risks are modestly priced into returns. Specifically, an increase in the climate policy uncertainty index in the U.S. prompts investors to demand higher returns as compensation for bearing these risks. This underscores the notion that portfolios with greater exposure to climate policy uncertainty require a higher premium, reflecting the market's recognition of climate-related risks. These findings reinforce the critical importance of integrating both transitional and physical climate risk factors into financial decision-making, as emphasized by Giglio et al. [2021], FSB [2022], Stroebel and Wurgler [2021], and Baudino and Svoronos [2021].

Among the Fama-French three-factor model (FF3), the size premium (SMB) and value premium (HML) display significant positive risk premia of 0.1761 and 0.2774, respectively, indicating their continued relevance in asset pricing. In contrast, the market factor (MKT) shows a near-zero premium of -0.0099, highlighting its limited explanatory power in this context. Similarly, the Fama-French five-factor model (FF5) demonstrates robust pricing effects, with premiums for HML (0.2774) and CMA (0.3254) remaining significant, while the profitability factor (RMW) presents a notable negative premium of -0.1612, suggesting nuanced interactions with returns.

State-level temperature anomalies ($Tanomalies$) exhibit a positive risk premium of 0.1422, underscoring the growing importance of climate physical risks in asset pricing. This finding indicates that investors demand higher returns as compensation for exposure to state-level temperature anomalies, reflecting the market's acknowledgment of the economic and financial impacts of climate variability. The positive premium suggests that temperature anomalies, as a proxy for climate-related disruptions, are increasingly relevant in shaping investment strategies. This highlights the critical need to integrate climate physical risks into portfolio construction and risk management frameworks, particularly as these factors gain prominence in influencing asset returns at localized levels.

Furthermore, both state-level economic policy uncertainty (EPU_{States}) and economic conditions ($ECON_{States}$) exhibit substantial positive premiums of 0.2241 and 0.1700, respectively, underscoring their significant influence on returns. These findings are supported by Hassan et al. [2017], according with the authors political risks appears to play out at firm level.

A comparison of the economic policy uncertainty at the national level (EPU_{US}) and state level (EPU_{States}) reveals distinct pricing dynamics. Both factors exhibit positive risk premia, indicating that they are priced into returns, but their magnitudes suggest differing levels of influence. Specifically, EPU_{States} has a higher risk premium (0.2241) compared to EPU_{US} (0.0723), emphasizing that uncertainty at the state level has a more pronounced impact on asset returns. This disparity may stem from the localized nature of state-level economic conditions, which can directly affect firm performance and regional economic stability. In contrast, national-level economic policy uncertainty, while still relevant, appears to have a relatively smaller influence in the context of these

results. Additionally, the variance of the risk premia for EPU_{US} (0.4404) is significantly larger than that for EPU_{States} (0.1065), suggesting greater uncertainty and variability in how national policy uncertainty is priced compared to its state-level counterpart.

These findings underline the importance of considering state-level economic factors in portfolio construction and risk management. The stronger and more stable pricing of EPU_{States} highlights its critical role in shaping investment strategies, particularly for portfolios with significant exposure to region-specific risks. This insight aligns with the broader observation that localized factors often have a more direct and immediate impact on asset pricing than aggregated national measures.

Additionally, the analysis of the Partisan Conflicts Index (PCI_{US}) provides a novel perspective on how political polarization and policymaking dysfunction influence asset pricing, complementing the earlier findings on economic policy uncertainty at both the national (EPU_{US}) and state levels (EPU_{States}). All three risk factors capture dimensions of political and economic uncertainty, yet they differ in scope and magnitude, revealing nuanced impacts on portfolio returns.

The PCI_{US} index, with an estimated negative risk premia of -0.3114 and a variance of 0.3664, highlights the adverse impact of heightened political polarization on returns. This contrasts with the positive risk premia observed for both EPU_{US} (0.0723) and EPU_{States} (0.2241). The discrepancy suggests that while general economic policy uncertainty may contribute to higher required returns, investors demand more returns in order to bear those risks, the partisan nature of conflicts introduces additional risks that investors discount more negatively. This aligns with the notion that extreme polarization and legislative gridlock can hinder effective policymaking, thereby dampening economic activity and reducing market confidence.

When comparing the variability of the risk premia, PCI_{US} (variance = 0.3664) exhibits a level of uncertainty more akin to EPU_{US} (variance = 0.4404) than to EPU_{States} (variance = 0.1065). This similarity underscores the shared characteristic of being national-level risk factors, where macroeconomic volatility and policy unpredictability are more pronounced. Conversely, EPU_{States} with its smaller variance and higher risk premium, suggests that localized uncertainty factors are not only more stable but also more directly influential in pricing regional firm-level risks, answering or main research question that, in fact, we should consider state-level risk factors. These findings resonate with the work of Hassan et al. [2017], which emphasizes that political risks often manifest at the firm level and may differ significantly based on geographic and policy contexts.

The interplay between these factors also suggests that while EPU_{States} captures localized economic uncertainty, PCI_{US} reflects a broader systemic risk resulting from political polarization. The negative risk premia associated with PCI_{US} may indicate that markets anticipate prolonged inefficiencies and economic challenges arising from partisan conflicts, further amplifying risks during periods of heightened polarization. This aligns with the broader observation that political risks at the national level can have cascading effects, influencing both market sentiment and firm performance across regions.

Together, these results highlight the importance of incorporating both political and economic uncertainty measures, at multiple levels, into asset pricing models. The contrasting dynamics between PCI_{US}, EPU_{US} and EPU_{States} underscore the need to account for both localized and systemic risks when evaluating portfolios. By integrating these insights into our discussion, we can strengthen the

argument that PCI and EPU capture complementary but distinct dimensions of uncertainty, and their differential pricing dynamics reflect varying investor perceptions of risk under different political and economic conditions. Furthermore, the negative pricing of PCI_{US} suggests that political polarization introduces distinct challenges that can exacerbate the pricing of other risk factors, such as economic policy uncertainty. Future research could explore how interactions between these factors affect different sectors or firms with varying geographic exposures.

The comparison between the economic conditions at the national level ($ECON_{US}$) and the state level ($ECON_{States}$) reveals differing impacts on return portfolios. While both factors are priced into returns, their effects vary significantly in magnitude and direction.

At the national level, $ECON_{US}$ exhibits a negative risk premium of -0.0574, indicating that unfavourable economic conditions at the national scale are associated with lower returns. In contrast, $ECON_{States}$ shows a positive risk premium of 0.1700, suggesting that state-level economic conditions contribute positively to returns. This divergence underscores the nuanced role that localized economic dynamics play in asset pricing. The variance of the risk premia for $ECON_{US}$ (0.3185) is higher than that for $ECON_{States}$ (0.1140), indicating greater uncertainty in the pricing of national economic conditions compared to state-level conditions. This variability may reflect the broader and more heterogeneous influences captured by national economic measures, which aggregate diverse regional trends.

These findings suggest that state-level economic conditions, while often overlooked, play a vital role in shaping portfolio performance. The positive and more stable pricing of $ECON_{States}$ highlights its significance for investors, particularly those seeking exposure to region-specific growth opportunities. Conversely, the negative pricing of $ECON_{US}$ signals that macroeconomic downturns at the national level are detrimental to portfolio returns, aligning with the broader literature emphasizing the adverse effects of aggregate economic shocks on financial markets.

The variance analysis reveals key insights into model stability and factor pricing uncertainty. The variance of zero-beta rate estimates remains negligible across all factors, reinforcing the reliability of baseline return estimates. Conversely, the variance of risk premia estimates ranges from 0.1065 (EPU_{States}) to 0.4404 (EPU_{US}), reflecting the increased uncertainty associated with national-level policy risks relative to state-level factors. Notably, the variance for $Tanomalies$ (0.1188) and $ECON_{States}$ (0.1140) is relatively low, suggesting stable pricing for these factors despite their unique implications for returns.

These findings underscore the complex interplay of risk premia across national and state-level factors, highlighting their collective influence on asset pricing dynamics. The integration of climate risks, economic policy uncertainty, and established Fama-French factors offers a robust and multifaceted framework for understanding how various risks are reflected in returns. The observed stability of the zero-beta rate, alongside the intricate pricing of both observed and latent factors, underscores the importance of diversifying risk sources in portfolio construction and investment strategies. Notably, state-level factors, particularly temperature anomalies, play a pivotal role in pricing returns, emphasizing the critical need to account for localized climate and economic risks. These results affirm that state-level risk factors are meaningfully priced in the cross-section of returns, reinforcing their significance in shaping investment decisions and risk management approaches.

[Figure 4 to Figure 10 around here]

Additionally, figure 4 displays the trends in the cumulative sum of the original and cleaned[13] climate policy uncertainty (CPU_{US}) factors in the U.S., with the cleaned data revealing a more pronounced decrease and subsequent increase, suggesting it captures specific elements of uncertainty more effectively. This refined measure of the CPU_{US} index is essential for analysing its direct impact on portfolio performance, particularly as portfolios exposed to higher climate policy uncertainty demonstrate higher expected returns. This positive risk premium, supported by robust regression analysis, underscores the importance of incorporating climate policy uncertainty in asset pricing models, especially for portfolios heavily invested in sectors vulnerable to climate policy shifts.

Figure 5 focuses on the economic policy uncertainty (EPU_{US}) indicator, showing a general increase in policy uncertainty from 2013 to 2023, with the cleaned factor offering a smoother depiction of these trends. Figure 6 illustrates the trends in the original and cleaned economic conditions ($ECON_{US}$) indicators, with both versions reflecting the significant economic events and cycles affecting the U.S. economy. The cleaned factor, while smoother, aligns closely with the original, highlighting key economic downturns and recoveries with less noise, providing a clearer view of economic influences on portfolio returns. Both factors illustrate the significant rise in uncertainty during key periods such as the 2008 financial crisis and the COVID-19 pandemic, emphasizing the need for dynamic portfolio management in response to policy shifts.

Figure 7 presents the original and cleaned temperature anomalies ($Tanomalies$) factors at the state level, indicating a general increase in temperature anomalies until 2011, followed by a reduction. The cleaned factor provides a more consistent representation of this trend, suggesting that portfolios need to consider state level environmental factors in risk assessments due to their significant impact on performance, especially in climate-sensitive sectors.

Figures 8 and 9 examine the cumulative sums of the original and cleaned economic policy uncertainty (EPU_{States}) and economic conditions ($ECON_{States}$) indicators at the state level. Both show that economic policy uncertainty initially increased until around 2014 before decreasing, while economic conditions generally improved until the 2008 crisis and then gradually recovered. The cleaned factors for both indicators offer a clearer and less volatile view of these trends, reinforcing the importance of considering state-level economic dynamics in investment strategies.

Finally, figure 10 illustrates the cumulative sum of the Partisan Conflict Index (PCI_{US}) factor for the U.S. between 2000 and 2023. Both the original and cleaned factors demonstrate a significant decline during the 2008–2009 global financial crisis, reaching their lowest cumulative point. This reflects the amplified impact of partisan conflict on portfolio performance during periods of severe economic uncertainty. Following the crisis, both series recover steadily, with the cleaned factor capturing a smoother and more gradual upward trend. The cleaned factor (thick line) provides a clearer view of the long-term, cumulative impact of partisan conflict, offering a less volatile representation of the trend over time. This highlights persistent effects of partisan conflict on portfolio returns,

[13]The "cleaned" factor refers to a filtered or smoothed representation of the original Climate Policy Uncertainty (CPU) risk factor, reducing short-term fluctuations or noise. Giglio and Xiu [2021] methodology applies this cleaning process, typically using techniques like rolling windows or cumulative transformations to emphasize long-term trends in the data. This cleaned factor line is thus intended to highlight the persistent effects of CPU on returns, offering a clearer view of cumulative impact while reducing short-term volatility.

rather than transient spikes or drops. The cleaned factor provides a more reliable representation of the cumulative impact of partisan conflict on portfolio returns, particularly useful for long-term investment strategies. The differences between the two lines also demonstrate the variability inherent in the raw PCI data, which could obscure meaningful trends without such methodological adjustments.

Overall, these figures highlight the dynamic and impactful nature of economic and climate-related factors on portfolio performance. The analysis confirms that refined, cleaned indicators, a smoothed representation of the original risk factor, can provide more accurate insights into how various economic and policy-related uncertainties influence market dynamics, offering valuable information for investors aiming to optimize risk-adjusted returns in an environment shaped by both economic and environmental changes.

5.2 Risk Premia of U.S. Wide Factors

This subsection analyzes a comprehensive set of tradable and non-tradable factors specific to the U.S. economy, including the climate policy uncertainty index (CPU_{US}), which serves as a proxy for both climate transition and physical risks. Additionally, we consider key macroeconomic factors such as the economic policy uncertainty index (EPU_{US}) and the economic conditions indicator ($ECON_{US}$), which captures the impact of climate risk shocks on the U.S. economy. We compare the risk premia associated with these U.S.-wide factors using both the Fama-MacBeth two-pass regression model and the methodology outlined by Giglio and Xiu [2021]. Our analysis focuses on estimating the market price of risk (λ) for each factor. The dataset spans 277 months and includes 20 test portfolios, with a target factor for each model, assuming a maximum of $p_{\max} = 10$ principal components for the Giglio and Xiu (2021) methodology.

[Table 4 around here]

5.2.1 Climate Policy Uncertainty Index

In Table 4, the standard Fama-MacBeth (FM) estimates reveal an intercept of 0.0037, which is highly significant with a p-value less than 0.001, alongside a significant risk premium of 0.9555 ($p < 0.01$). This suggests a strong positive exposure to the CPU_{US} factor, indicating that climate policy uncertainty is priced into portfolio returns, reflecting its substantial role in the risk premium associated with the underlying portfolios.

In contrast, when applying the three-pass methodology (Table 4) with 10 principal components (PCs), the intercept increases slightly to 0.0045, accompanied by a standard error of 0.0006. The estimated risk premium adjusts to 0.1063 with a standard error of 0.2000. The positive risk premium suggests that climate policy uncertainty is correlated with higher portfolio returns for U.S. firms with strong ESG characteristics. This indicates that investors demand a premium to bear the risk associated with climate policy uncertainty, signalling the growing importance of ESG factors in risk-return assessments.

The goodness-of-fit measure R_g^2 further supports these findings, showing that a significant portion of the variation in portfolio returns can be attributed to climate policy uncertainty. Specifically,

for the CPU_{US} factor, the R_g^2 value of 0.5941 indicates that climate policy uncertainty plays a critical role in explaining the cross-sectional variation in returns, particularly for ESG-oriented portfolios. Overall, both models—standard Fama-MacBeth and Giglio and Xiu (2021) — suggest that the CPU_{US} factor is indeed priced into U.S. portfolio returns, with the three-pass methodology providing a more nuanced adjustment in risk premia. The results highlight the critical importance of integrating climate-related factors, such as climate policy uncertainty, into investment strategies, given their substantial impact on asset returns, particularly for firms with high ESG scores. These findings align with prior research emphasizing the significant influence of climate policy uncertainty on economic and financial conditions [Giglio et al., 2021, FSB, 2022, Stroebel and Wurgler, 2021, Baudino and Svoronos, 2021]. In addition, this study contributes to the growing literature on the intricate relationship between equity prices and climate change dynamics, which often presents contrasting findings.

For instance, Bolton and Kacperczyk [2021] and Bolton and Kacperczyk [2023] demonstrate that climate change is priced into financial markets, revealing that higher CO_2 - emitting firms tend to generate higher returns, while Bansal et al. [2021] show that low-frequency global temperature variations negatively affect global stock markets. Complementing these findings, Gong et al. [2023] report that increases in climate change risk tend to increase stock returns for fossil fuel companies in global markets. Additionally, Yang et al. [2022] highlight that rising temperatures at the location of listed firms cause significant negative shocks to stock prices, with smaller and high book-to-market value firms being more adversely affected. Together, these findings underscore the multifaceted and region-specific nature of climate risk pricing in financial markets, reinforcing the need for a nuanced understanding of how climate policy uncertainty and broader climate dynamics shape equity returns. This study not only broadens the scope of existing literature but also emphasizes the importance of further exploring the interaction between climate-related risks and firm characteristics to develop more effective and sustainable investment strategies.

5.2.2 Macroeconomic Factors

In the standard Fama-MacBeth (FM) estimation, the intercept for EPU_{US} is estimated at 0.0035, with a standard error of 0.0001, indicating a highly significant baseline return across all portfolios ($p < 0.001$). The FM risk premia estimate of 1.6015, accompanied by a standard error of 0.1395, signifies a strong positive relationship with economic policy uncertainty ($p < 0.01$). This suggests that firms react significantly to changes in regulatory or policy environments related to economic policy uncertainty, highlighting the impact of macroeconomic factors on portfolio returns.

When utilizing the three-pass methodology with 10 principal components (PCs), we observe consistent results in the analysis of EPU_{US}. The intercept remains stable at 0.0045, demonstrating robustness across different model specifications. However, the risk premia associated with EPU_{US} is lower at 0.0723, with a relatively high standard error of 0.2917. This suggests some variability in the influence of economic policy uncertainty, indicating that the market's response to this factor may fluctuate depending on other conditions. These findings emphasize the need for more comprehensive factor models to capture the complex and sometimes uncertain effects of policy-related risks on

financial markets.

Following the methodology outlined by Giglio and Xiu [2021], the inclusion of the Partisan Conflict (PCI_{US}) index as a risk factor in analysing U.S. firms' portfolio returns sheds light on the impact of political polarization on asset pricing. Using a three-pass regression framework with 10 principal components (PCs), the intercept of the model is estimated at 0.0045, with a standard error of 0.0004, indicating the model provides a reliable baseline for explaining portfolio returns. The estimated risk premia associated with the PC factor is -0.3114, with a variance of 0.3664, reflecting substantial variability in how partisan conflict impacts portfolio returns. Notably, while the risk premia is negative, the R_g^2 value for the PC factor is 0.5283, indicating that approximately 52.8% of the variation in portfolio returns is explained by this factor. This high explanatory power highlights the relevance of partisan conflict as a systematic risk factor in understanding return patterns, particularly in an environment of increasing political polarization.

Furthermore, the results from the Standard Fama-MacBeth (FM) methodology complement these findings, reinforcing the importance of the PCI_{US} as a priced risk factor. Under the FM approach, the intercept is estimated at 0.0032 with a standard error of 0.0001, providing a similarly reliable baseline. The risk premia for PCI_{US} is estimated at 1.8075, with a standard error of 0.1659, suggesting a significant and positive relationship between partisan conflict and portfolio returns under this methodology. These results contrast with the negative risk premia obtained using the Giglio and Xiu [2021] approach, underscoring the sensitivity of pricing estimates to the methodology employed. These findings strongly support the existing literature by providing a conceptual framework that differentiates between the Partisan Conflicts Index (PCI) and the Economic Policy Uncertainty Index (EPU).

Azzimonti [2018] highlights that while PCI and EPU share similar computational methodologies, they measure different dimensions of political and economic risks. Our results reflect this distinction, as the negative risk premium associated with PCI_{US} suggests that heightened partisan conflict erodes investor confidence and dampens returns.

In contrast, the positive risk premia for EPU_{US} and EPU_{States} indicate that economic policy uncertainty, though disruptive, can create opportunities that are priced into returns. The literature demonstrates that PCI and EPU can diverge under specific conditions, such as wars or national security threats. For example, during the 9/11 attacks or World War I, EPU increased sharply due to uncertainty about government policy, while PCI remained low because of bipartisan unity. This observation aligns with our finding that PCI_{US}'s negative risk premium reflects systemic inefficiencies and heightened risks during periods of political polarization, which are distinct from the broader economic uncertainty captured by EPU.

Furthermore, the literature underscores how extreme partisan conflict (high PCI) can lead to government gridlock or shutdowns, reducing the effectiveness of policies and amplifying economic risks. Our results support this notion, as the negative pricing of PCI_{US} highlights the detrimental impact of such conflicts on investor sentiment and market stability. Azzimonti [2018] also suggests that moderate levels of PCI may align with heightened EPU as investors grapple with policy uncertainty. For instance, during debates over the debt ceiling, Obamacare, and the tax expirations of 2012, disagreements between parties led to elevated uncertainty about economic policies. Our

results align with this interpretation, as both EPU_{US} and EPU_{States} exhibit positive risk premia, indicating that these uncertainties are priced into returns when partisan conflict is moderate.

An important distinction noted in the literature is that PCI is unaffected by monetary policy, whereas EPU may respond to changes such as Federal Reserve actions. This reinforces our findings, where PCI represents a unique dimension of risk that investors price separately from the broader economic uncertainty captured by EPU.

Moreover, our analysis highlights the higher risk premium for EPU_{States} compared to EPU_{US}, suggesting a more pronounced impact of localized economic uncertainty on asset pricing. The literature supports this by emphasizing that PCI_{US} captures broader systemic risks tied to political polarization, which can amplify the pricing of localized uncertainties, as reflected in EPU_{States}. The distinctions outlined in the literature provide a theoretical foundation for interpreting the interplay between PCI and EPU. Specifically, they justify the observed differences in risk premia and variances in our results, as well as the broader narrative that political and economic uncertainties impact asset pricing in unique and sometimes divergent ways. This reinforces the importance of analyzing these factors together, as their combined effects offer a more comprehensive view of the risks faced by investors. By integrating these insights into our discussion, we strengthen the argument that PCI and EPU capture complementary but distinct dimensions of uncertainty. Their differential pricing dynamics reflect varying investor perceptions of risk under different political and economic conditions.

Next, we examine the updated results for the Economic Conditions Indicator ($ECON_{US}$) in the U.S. In the standard FM estimation, $ECON_{US}$ shows a highly significant positive intercept of 0.0040 ($p < 0.001$), indicating a baseline positive return that is consistent with the other models. The FM risk premia estimate of 2.6936 (with a standard error of 0.2288) suggests a strong relationship with economic conditions ($p < 0.01$). This result underscores the sensitivity of portfolios to changes in economic indicators such as economic growth, inflation, and monetary policy, confirming the importance of economic conditions in influencing asset pricing.

Additionally, using the three-pass methodology with 10 PCs, the intercept remains stable at 0.0045 (with a standard error of 0.0006), while the risk premia estimate decreases slightly to -0.0574, with a standard error of 0.3477. This decrease suggests that the impact of economic conditions on portfolio returns is less pronounced when accounting for the higher-dimensional variation captured by the principal components. However, the variation in the risk premia highlights the complexity of modelling economic conditions and their effects on investment returns.

These findings underscore the significant impact of both economic policy uncertainty (EPU_{US}) and economic conditions ($ECON_{US}$) in the U.S. on portfolio returns, particularly for firms with strong ESG characteristic. Moreover, the results resonate with the methodology proposed by Giglio et al. [2021], which emphasizes the importance of incorporating climate-related risks and policy uncertainty into asset pricing models. This approach is further supported by Sheng et al. [2022], who demonstrate that increased uncertainty exacerbates the adverse effects of climate risks on economic activity and investment returns.

In summary, both EPU_{US} and $ECON_{US}$ significantly affect portfolio returns, underscoring the importance of macroeconomic indicators in portfolio management decisions. These findings

provide valuable insights for investors seeking to navigate economic uncertainties and capitalize on opportunities, particularly in the energy sector and with regard to ESG considerations.

5.3 Fama-French Factors

Table 5 presents the estimated risk premia associated with the Fama-French factors, obtained through the Fama-MacBeth two-pass regression model and the three-pass estimation method proposed by Giglio and Xiu [2021]. The analysis centers on two prominent models: the Fama-French Three-Factor Model (FF3), which includes the Market (MKT), Size (SMB), and Value (HML) factors, and the Fama-French Five-Factor Model (FF5), which adds Profitability (RMW) and Investment (CMA) to the original three factors. The dataset spans a period of 277 months and is based on 20 test portfolios, specifically designed to capture the characteristics of U.S. energy firms, including those with high energy dependence and varying levels of ESG performance.

[Table 5 around here]

In the Fama-MacBeth two-pass regression model estimates for the Fama-French risk factors (Table 5), the intercept remains consistently positive, approximately 0.0040 for the Fama-French Three-Factor Model (FF3) and 0.0042 for the Five-Factor Model (FF5). This suggests a stable baseline return across all portfolios, which could reflect a general market equilibrium not entirely captured by the included factors. The risk premia estimates for the individual factors reveal considerable variability, emphasizing their distinct contributions to portfolio returns.

Specifically, the market factor (MKT) exhibits a robust positive risk premium of 5.0783, with a standard error of 0.3428, underscoring the substantial compensation investors demand for bearing systematic market risk. The size factor (SMB) shows a modest positive risk premium of 0.3206, suggesting a mild preference for smaller firms, which aligns with the historical tendency of small-cap stocks to outperform their larger counterparts during certain market conditions. In contrast, the value factor (HML) demonstrates a significantly positive risk premium of 9.9083, reinforcing the consistent outperformance of value stocks relative to growth stocks, a phenomenon often attributed to the market's undervaluation of financially stable, lower-growth firms.

The empirical results derived from the Three-Pass Regression methodology applied to the Fama-French Five-Factor Model (FF5) provide further granularity (Table 5). The intercept remains stable at approximately 0.0045, consistent with the findings from the FF3 model and reaffirming the presence of an unexplained positive baseline return. Interestingly, the market factor (MKT) presents a negative risk premium of -0.0099, accompanied by a reduced standard error of 0.1426. This divergence suggests that the 3PRF methodology, which leverages principal components to account for latent systematic factors, captures different dynamics in market risk compared to traditional FM estimation.

The size factor (SMB) and value factor (HML) display more moderate risk premia under the 3PRF method, with estimates of 0.1761 and 0.2774, respectively, alongside reduced standard errors, indicating improved precision in their estimation. The additional factors introduced in the FF5 model—profitability (RMW) and investment (CMA)—exhibit significant variability. For instance, RMW shows a negative risk premium of -2.9438 in the FM model, which moderates substantially

to -0.1612 under the three-pass methodology, suggesting that profitability may not be a consistent driver of returns in this sector. Meanwhile, CMA demonstrates a notable positive risk premium of 8.4491 in the FM model, which decreases to 0.3254 under the three-pass methodology, reflecting the sensitivity of investment-related returns to model specifications.

These findings indicate that while the Fama-French factors capture critical dimensions of risk relevant to broader markets, their explanatory power for U.S. energy firms with strong ESG characteristics is somewhat limited. The consistently positive intercepts across both models suggest that significant aspects of returns remain unexplained, pointing to the need for additional factors that account for sector-specific risks, such as regulatory changes, technological innovation, or environmental policies.

The strong positive risk premium for HML aligns with the historical outperformance of value stocks, emphasizing their role as a critical driver of returns. In contrast, the variability in MKT and SMB estimates highlights their sensitivity to methodological changes and prevailing market conditions, necessitating cautious interpretation in practical applications. These findings underscore the importance of considering both traditional equity factors and unique sectoral attributes when analyzing portfolios in the energy sector.

Moreover, the three-pass estimation method proposed by Giglio and Xiu [2021] refines risk premium estimates by incorporating a richer structure of principal components, effectively capturing latent systematic risks that might otherwise be overlooked. This nuanced approach is particularly beneficial for specialized portfolios, as it provides deeper insights into risk premia dynamics. The methodology's ability to adjust for latent factors suggests its potential for broader applications in asset pricing models, especially in environments characterized by high complexity or sector-specific nuances.

Overall, the application of the Fama-French frameworks to U.S. energy firms with strong ESG characteristics highlights the necessity of integrating both traditional equity factors and sector-specific considerations into asset pricing models. These findings offer valuable insights for investors and portfolio managers aiming to optimize risk-adjusted returns in energy-focused investment strategies, while also addressing the unique challenges and opportunities posed by ESG considerations and the evolving energy landscape.

5.4 U.S. State Level Factors

A significant contribution of our research lies in the integration of a climate change indicator at the state level into our asset pricing model. This addition reflects the heterogeneity in states' abilities to address the policy void created by federal inaction on climate change. While some U.S. states have implemented proactive climate policies and regulatory measures, others remain less equipped to manage the associated risks. This variability necessitates a more granular approach to risk measurement, one that goes beyond a uniform nationwide perspective and accounts for the nuanced impact of state-level factors on investment dynamics. The challenge is not solely in isolating state-specific risks from broader national trends but in recognizing and quantifying the unique insights state-level information provides. By incorporating state-level transition risk into our analysis, we underscore

its critical role in optimizing portfolio returns and enhancing the understanding of how localized climate policies and economic conditions influence financial markets. This approach highlights the increasing relevance of geographically disaggregated data in investment decision-making and risk management, particularly in the context of climate-related financial risks. The primary findings derived from state-level factors are presented in Table 6. These results are obtained using the Fama-MacBeth two-pass regression model and the three-pass regression methodology introduced by Giglio and Xiu [2021]. Together, these methods allow for a comprehensive examination of how state-level transition risks interact with broader market forces to shape portfolio outcomes.

[Table 6 around here]

5.4.1 Temperature Anomalies

Based on the results presented in Table 6, the integration of temperature anomalies ($Tanomalies$) at the U.S. state level into the asset pricing model provides valuable insights, addressing a key research question. The findings indicate that temperature anomalies constitute a significant risk factor that U.S. firms and investors should incorporate into their risk assessments and portfolio management strategies. Specifically, higher average temperature anomalies in degrees Fahrenheit are associated with increased investor demand for higher portfolio returns, reflecting the compensation required for bearing the associated climate risk.

The results show that the intercept remains positive and statistically significant across all models, including both the Standard Fama-MacBeth (FM) model and the Giglio and Xiu [2021] three-pass regression methodology. This indicates a consistent baseline return across portfolios, irrespective of model specifications. Notably, the risk premium for $Tanomalies$ differs substantially between the two methods. In the Standard FM model, the risk premium is estimated at 4.2121, whereas the Giglio and Xiu methodology (using 10 principal components) produces a more refined estimate of 0.1422 with significantly reduced standard errors. These differences suggest that the more sophisticated three-pass regression methodology captures nuanced dynamics of climate risk with greater precision.

Temperature anomalies are identified as a critical source of climate-related risk, particularly for the energy sector. Extreme temperatures can disrupt energy production, distribution, and demand, thereby impacting the operational performance and costs of U.S. firms. Investors demand higher premiums to compensate for these risks, particularly in portfolios with lower ESG rankings (e.g., portfolio 1). Conversely, portfolios with higher ESG rankings (e.g., portfolio 20) tend to exhibit lower sensitivity to $Tanomalies$, likely due to better risk management practices and proactive measures to mitigate climate-related risks.

These results underscore the utility of integrating state-level climate risk factors into financial models. The detailed outputs from regression analyses provide a nuanced understanding of how such factors influence portfolio returns and asset pricing. The findings demonstrate that temperature anomalies as a state-level risk factor significantly affect the portfolio performance of energy and energy-dependent firms, highlighting the importance of localized climate data in assessing financial risks.

These findings have several implications. For risk management, energy firms and investors may

need to consider temperature anomalies as a significant risk factor when managing portfolios. For investment strategy, incorporating climate-related risk factors, such as temperature anomalies, could enhance portfolio performance. Furthermore, insights from this analysis could inform policy decisions related to climate resilience and energy and highly dependent energy sector planning.

Overall, the positive and significant risk premia estimates for $Tanomalies$ underscore their substantial impact on the portfolio performance of U.S. firms. The findings emphasize the importance of integrating climate-related risk factors into investment strategies and risk management practices. Additionally, the observed relationship between ESG performance and the influence of temperature anomalies on portfolio returns reinforces the value of incorporating ESG considerations into investment analysis. Portfolios with higher ESG scores demonstrate greater resilience to climate-related risks, as evidenced by their reduced sensitivity to $Tanomalies$. These results highlight the necessity for investors to account for both ESG performance and climate risks in assessing the risk-return profiles of their investments, especially in sectors vulnerable to climate change

5.4.2 Macroeconomic State Level Factors

Our analysis of economic policy uncertainty at the state level (EPU_{States}) reveals significant insights into its impact on portfolio performance. Table 6 shows that the intercept remains consistently positive and statistically significant across models, ranging from 0.0032 in the Standard Fama-MacBeth (FM) model to 0.0045 in the Giglio and Xiu [2021] methodology. This result reflects a stable baseline level of portfolio performance that is unaffected by the modelled factors, underscoring the robustness of the underlying return structure.

The risk premia for EPU_{States} exhibit positive values across both methodologies, with 1.5217 in the Standard FM model and a more modest 0.2241 using the three-pass methodology. This positive risk premium implies that heightened economic policy uncertainty at the state level leads to increased compensation demands from investors. These findings align with Baker et al. (2016), who highlighted the adverse effects of elevated policy uncertainty on investment and stock returns. At the state level, economic policy uncertainty captures local economic conditions and regulatory landscapes, which vary across regions and can significantly impact regional investments.

Changes in EPU_{States} often signal shifts in investor sentiment and market expectations, influencing portfolio allocation decisions. Understanding the timing and implications of these changes can provide investors with strategic advantages, enabling them to manage associated risks more effectively and optimize returns.

Similarly, our analysis of state-level economic conditions ($ECON_{States}$) provides comprehensive insights into their influence on portfolio performance. As shown in Table 6 the intercept remains consistently positive, fluctuating slightly from 0.0041 (Standard FM model) to 0.0045 (Giglio and Xiu methodology). These results indicate a stable underlying return level, reinforcing the reliability of the model.

The risk premia for $ECON_{States}$ range from 2.8582 in the Standard FM model to 0.1700 in the Giglio and Xiu methodology. These estimates suggest that stronger economic conditions at the state level positively impact portfolio returns, likely driven by improved corporate earnings,

heightened investor confidence, and favourable regional dynamics. Conversely, adverse economic shocks, including climate-related shocks, are associated with higher risk premiums, consistent with theoretical expectations (Chen, Roll, and Ross, 1986). This underscores the critical role of state-level economic health in shaping investment opportunities and portfolio performance.

State-level economic conditions ($ECON_{States}$) reflect regional economic fundamentals, influencing local market dynamics and investment prospects. Investors are likely to favour regions with stronger economic performance, anticipating higher returns from such areas. For instance, robust economic growth in specific states can benefit industries such as real estate, retail, and services, prompting shifts in portfolio sector allocations. Conversely, economic downturns or shocks increase risk premiums, reflecting heightened uncertainty and potential losses.

The variability in risk premia estimates, suggests that the impact of economic conditions indicator at the state level on portfolio performance is complex and multifaceted. We cab state that $ECON_{States}$ reflect the economic health across states, influencing local market dynamics and investment opportunities. Investors might favour regions with stronger economic fundamentals, anticipating higher returns from such areas. Strong economic conditions in specific states can benefit particular industries such as real estate, retail, and services. This influence can affect portfolio sector allocations, making it advantageous to consider regional economic conditions when making investment decisions. Understanding state-level economic conditions helps investors manage risk exposures and optimize returns. Aligning portfolio strategies with regional economic trends can provide a strategic edge in maximizing performance.

In conclusion, state-level factors such as EPU_{States} and $ECON_{States}$ play a pivotal role in shaping portfolio returns. By incorporating these factors into asset pricing models, investors can better understand and navigate the risks and opportunities associated with regional economic variations. The findings underscore the necessity of a nuanced approach to modelling and interpreting the effects of economic conditions and policy uncertainty on portfolio performance. This approach not only enhances portfolio optimization but also supports more effective risk management in an increasingly complex economic landscape.

6 Robustness

In this section, we explore the influence of state-level climate risk factors - both physical and transition risks - to confirm the previous results that address the following research question: "How does the implementation of climate policies across diverse U.S. states influence national-level transition risks, and are these risks adequately reflected in market valuations of U.S. firms?". This approach demonstrates how these factors are priced in the cross-section of returns for U.S. energy sector firms, providing a realistic assessment of market valuation accuracy in relation to climate risk integration.

6.1 Comprehensive Climate Physical Risk Factor

We create a comprehensive climate physical risk indicator for 38 U.S. states from March 2000 to March 2023, we utilized a combination of temperature anomalies and the number of natural disasters occurring in each state on a monthly basis. The natural disaster data was sourced from the Federal Emergency Management Agency (FEMA) [2024] database, detailing the frequency and start dates of various natural disasters across 38 U.S. states.

[Figure 3 around here]

Figure 3 presents a heatmap illustrating the annual number of natural disasters for each state from 2000 to 2023. This visual representation allows us to observe trends and variations in the frequency of natural disasters across the states over the specified period. Notably, there has been a marked increase in the total number of natural disasters during the last decade, particularly in states such as Georgia, Illinois, Indiana, Kansas, and Maryland. This trend indicates a growing vulnerability and frequency of climate-related events in these regions.

The data highlights Texas as the leading state in terms of the total number of natural disasters, followed closely by Oklahoma and Missouri. These states have experienced a disproportionately high number of natural disasters, underscoring their susceptibility to climate extremes and the need for robust disaster preparedness and mitigation strategies.

We first processed the natural disaster data to aggregate the number of disasters by state and by month. Any months with no recorded disasters were assigned a value of zero to maintain the continuity of the dataset. Concurrently, temperature anomaly data was organized similarly by state and month to ensure alignment with the natural disaster data.

Normalization of the two datasets was then performed using min-max scaling, ensuring that each variable ranged from 0 to 1, which allowed for the combination of these two disparate datasets. Specifically, the number of natural disasters and temperature anomalies were normalized independently to facilitate their integration into a single composite indicator.

We calculated the climate physical risk score for each state and month by employing a weighted sum of normalized values, prioritizing the influence of natural disasters and temperature anomalies on physical climate risk. We assigned a weight of 0.7 to the normalized number of natural disasters, recognizing their immediate and severe impact, and a weight of 0.3 to the normalized temperature anomalies to account for their gradual yet significant effects. The resulting scores, which range from 0 to 100, quantify the level of climate physical risk, with higher scores indicating increased risk within a specific state during the given time period.

The final climate physical risk indicator provides a robust monthly measure of climate-related risks for each state, combining historical climatic deviations with the frequency of impactful natural events. This indicator serves as a valuable tool for assessing and comparing the climate-related risks faced by different states over the specified time period, aiding in the development of targeted mitigation and adaptation strategies.

Next, we delve into the risk premia associated with state-specific climate risk factors, as detailed in table 11. These estimated risk premia are derived using the methodology proposed by Giglio and Xiu [2021]. For each climate risk factor, we concentrate on the estimates of the market price of risk (λ) and the proportion of its time-series variation attributable to each of the latent factors.

[Table 11 around here]

The analysis covers a period of 277 months, utilizing 20 test portfolios to identify the target factor linked to each of the 38 distinct U.S. states. This comprehensive approach allows for a nuanced understanding of how climate risk factors impact state-specific risk premia and highlights the variation in the market price of risk across different states, using a maximum of 10 PCs as suggested by Giglio and Xiu [2021].

The analysis reveals that the R_g^2 values for individual factors generally increase with the inclusion of more principal components (PCs). This improvement signifies that additional PCs contribute significantly to explaining the variance in returns attributed to state-level climate anomalies. For example, in Alabama, the R_g^2 values for each factor rise from 0.035319 to 0.056144, underscoring the model's enhanced explanatory power with the incorporation of more PCs.

The variability in risk premia across states reflects the diverse impact of climate risks on portfolio performance. States like Arkansas, with a high FM risk premia of 6.5426 and a standard error of 0.6665, contrast sharply with Arizona, which presents a lower FM risk premia of 1.2232 with a standard error of 0.3451. This disparity highlights the different degrees of climate risk exposure across states, indicating that investors demand higher returns for greater perceived risks.

Moreover, the positive and statistically significant intercept values across all states and models suggest a consistent baseline return not captured by the risk factors alone. In Alabama, for instance, the intercept peaks at 0.0047 when utilizing 6 to 8 PCs, indicating a stable underlying return amidst varying climate risks.

The detailed state analysis, summarized in table 12, reinforces the pricing of climate risks into investment portfolios. Each state shows a positive and significant risk premium, such as California's 3.5048, reflecting its vulnerability to wildfires and droughts, and Illinois' 7.9214, highlighting the substantial returns demanded by investors for climate risks.

[Table 12 around here]

Nebraska and Minnesota exhibit exceptionally high-risk premia, pointing to the severe climate risks priced into their markets. Conversely, Wisconsin's significant risk premium of 8.6153 emphasizes the crucial role of climate risks in shaping investment returns in the state.

These findings confirm that climate risk factors are indeed priced into portfolio returns across various U.S. states, with investors requiring higher returns to compensate for these risks. The analysis also shows that portfolios with higher ESG scores, which indicate better environmental performance, tend to be less sensitive to climate risks, underscoring the importance of integrating

ESG factors into investment strategies.

Overall, the results reinforce previous findings that state-level climate risks significantly influence investment decisions, with substantial and positive risk premia indicating that investors recognize and price these risks into their portfolios. This state-specific analysis provides valuable insights for portfolio managers and investors, underscoring the importance of integrating comprehensive climate risk assessments and ESG considerations into investment processes to optimize risk-adjusted returns amid increasing climate variability. These findings align with the growing body of literature demonstrating that physical climate risk factors are systematically priced in financial markets.

For example, Jung et al. [2024] confirm that U.S. counties with high exposure to physical climate risks experience disproportionately larger declines in stock returns following severe natural disasters. However, a notable limitation of their research is its reliance on the extent to which the market itself prices climate risks, raising the question of whether equity market investors fully account for such risks. Our findings support their conclusions by providing evidence that physical risk factors, such as natural disasters and temperature anomalies, have measurable impacts on portfolio returns. This further substantiates the argument that equity markets indeed price physical climate risks, highlighting the necessity of factoring these risks into investment strategies as climate-related events become more frequent and severe.

6.2 Climate Policy Index

In this section, we analyse the risk premia linked to a novel risk factor quantifying climate transition risk, specifically focusing on climate policies adopted across various U.S. states. This analysis utilizes the climate policy index[14] proposed by Bergquist and Warshaw [2023a], which aggregates data from 25 individual policies to construct a comprehensive index reflecting state-level climate policy actions from 2000 to 2020. According with the authors (Bergquist and Warshaw [2023a]) this period marks a critical phase during which states enacted the majority of their climate-related policies, making it a focal point for our study.

The climate policy index illuminates variations in policy adoption and design across states, offering a richer perspective than single-policy analyses typically provide. By compiling a detailed dataset, Bergquist and Warshaw [2023a] captures nuances in the adoption and specific designs of 25 widely implemented policies aimed at reducing greenhouse gas emissions, promoting cleaner energy production, and enhancing energy efficiency across multiple states.

Due to data limitations, we constrain our analysis timeframe from March 2000 to December 2020. Given the annual nature of the indicator, we assume the same value for each month within a given year, under the reasonable assumption that climate policies do not change monthly at the U.S. state level. Our methodology, following Giglio and Xiu [2021], focuses on identifying statistically significant state climate transition risk factors. The statistically significant results of this comprehensive analysis are detailed in table 13, providing insights into how state-specific climate policies are factored into market valuations and the associated risk premia.

[14]The authors Bergquist and Warshaw [2023a] employ various types of policy data-ordinal, dichotomous, and continuous - as inputs for a Bayesian factor analysis model. This method is utilized to estimate the stringency of state climate policy regimes, which serves as the foundation for creating the climate policy index.

[Table 13 around here]

The analysis of the climate transition risk factor, which measures the impact of climate policies adopted in each state, reveals significant insights across various U.S. states. We focus on the risk premia, standard errors, cross-sectional R^2 values, and the suggested number of factors for each state (table 11). The findings highlight the importance and statistical significance of the climate transition risk factor in the economic landscape of these states.

For Alabama, the Fama-MacBeth (FM) risk premia estimate is 1.0328 with a standard error of 0.0729, indicating a strong and statistically significant risk premium. Using the three-pass method with four principal components (PCs), the risk premia estimate is 0.7799 with a higher standard error of 0.4464, reflecting greater variability. When increasing to ten PCs, the risk premia estimate is 0.8723 with a standard error of 0.4322. The cross-sectional R^2 values range from 0.2165 to 0.6992, with the R_g^2 values improving from 0.7817 to 0.9083 as more PCs are included, suggesting a robust model fit with additional PCs. The positive risk premia indicates that investors require compensation for exposure to climate transition risks in Alabama, reflecting the perceived economic impact of climate policies in this state.

Arkansas presents a similar scenario the FM risk premia is 0.8332 with a standard error of 0.0700. The three-pass method yields a risk premia of 0.8074 with a standard error of 0.4262 when using four PCs, and 0.6093 with a standard error of 0.3774 when using ten PCs. The R^2 values increase from 0.2165 to 0.6992, with R_g^2 values improving from 0.8411 to 0.9437, highlighting the model's robustness with more principal components. The positive risk premia for Arkansas indicates that investors perceive significant economic risks associated with the implementation of climate policies, requiring compensation for holding such investments.

For California, the FM risk premia estimate is 0.8166 with a standard error of 0.0752. The three-pass method with four PCs gives a risk premia of 0.6732 with a standard error of 0.4244, while with ten PCs, the estimate increases to 0.9173 with a standard error of 0.4144. The cross-sectional R^2 values improve from 0.2165 to 0.6992, with R_g^2 values ranging from 0.7480 to 0.8938, indicating a solid fit and the model's increasing explanatory power with more PCs. The positive risk premia in California reflect the state's aggressive climate policies and the significant economic adjustments required, thus leading investors to demand higher returns for these risks.

In Colorado, the FM risk premia is estimated at 0.7338 with a standard error of 0.0691. Using the three-pass method, the risk premia is 0.7567 with a standard error of 0.4388 when using four PCs, and 0.8280 with a standard error of 0.3682 when using ten PCs. The cross-sectional R^2 values range from 0.2165 to 0.6992, with R_g^2 values showing significant improvement from 0.8868 to 0.9630 as more PCs are incorporated, highlighting the increasing robustness of the model. The positive risk premia indicate that investors in Colorado also seek compensation for the economic uncertainties and adjustments related to climate transition policies.

In conclusion, these findings underscore the significant and variable impact of climate transition risks across different states, supporting our previous findings. The risk premia, as estimated by both the FM and three-pass methods (Giglio and Xiu [2021]), are generally positive and statistically significant, reflecting the importance of considering climate policies in economic risk assessments. The positive risk premia suggest that investors demand compensation for the increased risks associated

with climate transition policies, acknowledging the potential economic impacts and uncertainties introduced by these state-level initiatives. The increasing R^2 and R_g^2 values with additional PCs further confirm the robustness and explanatory power of the models, suggesting that incorporating more principal components can enhance the accuracy of the climate transition risk evaluations.

6.3 Firm Size and Sensitivity to State-Level Risks

As an additional robustness check, we aggregate U.S. firm returns by size instead of their ESG combined scores. This adjustment is motivated by the observation that smaller firms, due to their limited ability to reallocate operations across different states, are likely more sensitive to state-level risk factors and changes in environmental regulations. To construct size-based portfolios, we use the annual average market value (or market capitalization) of each firm, a widely recognized size metric in finance. This metric is computed as the mean market value of each firm across the entire sample period (2000–2023), providing a stable and representative measure of firm size. Firms are ranked based on their average market value and grouped into 40 portfolios using the `ntile()` function in RStudio, which ensures an even distribution of firms across portfolios.

Specifically, portfolios 1 to 20 consist of firms with the smallest market values (lowest standardized ranks), while portfolios 21 to 40 comprise firms with the largest market values (highest standardized ranks). The standardized rank for each firm is computed on a 0-1 scale within each date, ensuring consistency and comparability over time. This methodology ensures that each portfolio contains an approximately equal number of firms, except where ties in market value occur. By creating portfolios based on size, this approach enables us to investigate whether smaller firms exhibit greater sensitivity to state-level risk factors and regulatory changes compared to larger firms, providing deeper insights into the interaction between firm size and regional economic dynamics.

Table 11 reports the risk premia associated with U.S.-wide latent factors for the first 20 test portfolios, comprising smaller firms. These factors are measured as the ratio of each factor's eigenvalue to the sum of all eigenvalues from the sample covariance matrix of these portfolios. Similarly, Table 12 presents the risk premia estimates for test portfolios 21 to 40, which consist of larger firms. By comparing these tables, we gain valuable insights into how firms of different sizes respond to state-level risk factors and whether size amplifies or mitigates sensitivity to such risks. The first column in each table corresponds to the intercept, representing the zero-beta rate, while the subsequent columns detail the estimated risk premia for each principal component. For consistency, our analysis focuses on the first 10 principal components, capturing the most significant dimensions of variation in the data. The dataset spans 277 months, leveraging a total of 40 test portfolios to provide a robust framework for understanding the factor-driven variation in returns. These results allow us to explore whether firm size influences the extent to which U.S.-wide latent factors and state-level risks impact portfolio performance.

[Table 11 and Table 12 around here]

In general, small firms exhibit higher risk premia across most factors (Table 11 and Table 12), including climate risk factors, which can be particularly impactful for these firms. For instance, in the CPU model, the risk premium for small firms is 1.5724 under the Standard Fama-MacBeth Model and 0.3724 using the methodology of Giglio and Xiu (2021), whereas for larger firms, the corresponding values are 0.6649 and 0.2742, respectively. These findings suggest that smaller firms are more sensitive to climate risk factors, requiring a higher premium to compensate for the risks associated with climate change.

One reason for this heightened sensitivity is that smaller firms often have less flexibility to

reallocate their operations to states or regions with more favourable climate policies and lower associated risks. Unlike larger firms, which may have the resources and operational scale to diversify their locations and adapt to regions with fewer restrictions or more resilient infrastructure, small firms are more likely to be concentrated in areas with higher exposure to stringent climate policies. This lack of geographical diversification leaves them more vulnerable to regulatory changes and the potential economic consequences of climate-related risks, such as higher energy costs, stricter environmental regulations, or physical impacts from climate change.

Consequently, investors demand a higher premium from small firms to offset the risks of operating in more climate-sensitive regions, where the potential for policy changes and environmental disruptions may pose a significant financial burden. In contrast, larger firms, with greater resources to adapt and diversify, face relatively lower premiums, as their operations are less constrained by the climate-related risks that directly affect smaller, less flexible firms. This disparity highlights the disproportionate impact of climate risk on small firms, particularly those unable to easily relocate or adjust to the evolving regulatory landscape.

Additionally, smaller firms may be more sensitive to factors such as market risk (MKT), economic policy uncertainty (EPU_{US}) at the U.S. level, and other observed factors. In contrast, larger firms tend to exhibit risk premia that are either smaller or closer to zero for many of the Fama-French risk factors. For example, in the FF3 model, the market risk premium for small firms is -0.3094, whereas for larger firms, it is significantly higher at 1.9448. Moreover, the risk premia for SMB and HML are also more moderate for larger firms compared to those observed for small firms, further highlighting the differential sensitivity to these factors based on firm size.

Additionally, the risk premium associated with the PCI_{US} factor for small firms is estimated at 1.4894 (standard error: 0.0956), which is substantially higher than that for large firms (0.7807, standard error: 0.1009) according to the Standard Fama-MacBeth Model results. This significant difference suggests that the PCI_{US} factor explains more variation in returns for small firms than for large firms. These findings are consistent with the finance literature, which attributes higher risk premia for small firms to their greater exposure to macroeconomic risks and limited diversification compared to larger firms.

Using the methodology proposed by Giglio and Xiu [2021], the estimated risk premium for small firms is 0.3916 (standard error: 0.3133), while for large firms, it is 0.3792 (standard error: 0.2436). Although the magnitudes are comparable, the statistical significance of these estimates is limited due to high standard errors. The Three-Pass Regression Filter methodology thus shows smaller differences in risk premia between small and large firms. However, the lack of statistical significance in both cases highlights the limited explanatory power of the PCI_{US} factor in this framework. Interestingly, the R_g^2 values indicate that the PCI_{US} factor accounts for slightly more variation in returns for large firms than for small firms. This diminished statistical significance could reflect the challenges of capturing macroeconomic risk premia using latent factors for size-differentiated portfolios. Similar findings in the literature suggest that principal component or latent factor models are more effective in capturing broad market or economic risks rather than firm-specific variations tied to size.

Focusing on the responsiveness of portfolios to state-level economic risk factors, the analysis

reveals interesting dynamics. For instance, under the $ECON_{States}$ factor, small firms exhibit a risk premium of 0.5446, whereas larger firms display a higher risk premium of 1.0286. This indicates that larger firms require a greater premium to compensate for exposure to state-level economic conditions and policy uncertainties. The elevated risk premium for larger firms suggests they may be more sensitive to variations in economic performance.

This outcome could be attributed to the fact that larger firms typically operate across multiple states and regions, making them more exposed to the diverse and often conflicting economic and policy landscapes of different states. Their broader footprint means that adverse economic conditions or policy shifts in one state can have cascading effects across their operations, necessitating a higher premium to offset this increased vulnerability. Additionally, larger firms may face greater scrutiny and regulatory burdens at the state level, further amplifying their exposure to localized risks.

In contrast, smaller firms often operate within more localized or niche markets, which may insulate them from broader state-level economic fluctuations. Their narrower focus can mean they are less affected by the economic heterogeneity and policy differences across states, leading to a comparatively lower risk premium for state-level factors. This localized focus could also make small firms more agile and adaptable to specific regional conditions, reducing their perceived vulnerability to state-level economic and policy uncertainties.

These findings align with the existing literature, which highlights the localized nature of smaller firms. Small firms typically have a more concentrated geographic presence, often operating within specific states or regions, and may face greater operational and financial constraints when adapting to changes in state-level economic conditions or policy shifts. Furthermore, smaller firms may lack the resources and operational flexibility to quickly reallocate resources or adjust strategies across multiple states, making them more exposed to state-specific risks such as tax changes, regulatory adjustments, or regional economic downturns. In contrast, larger firms, often operating on a national or international scale, can diversify their operations and mitigate the adverse effects of localized risks, thereby reducing their sensitivity to state-level factors. This heightened responsiveness of small firms to state-level risk factors underscores the importance of considering firm size when assessing the broader implications of regional economic and policy fluctuations on financial performance.

In the case of EPU_{States}, smaller firms demonstrate a notably more negative risk premia (-1.0040), compared to the relatively modest negative risk premia of larger firms (-0.2782) under the Fama-MacBeth Model. This disparity highlights the heightened sensitivity of smaller firms to state-level economic policy uncertainty. The pronounced negative risk premia for smaller firms suggest that these firms are disproportionately impacted by fluctuations in state-level policy environments, likely due to their limited geographic diversification and resource constraints, which make them more vulnerable to localized economic and regulatory shifts.

Additionally, small firms exhibit a pronounced sensitivity to climate risk factors, as highlighted by the risk premium of 7.2464 for temperature anomalies at the state level in the small firms' portfolio. This significantly higher value, compared to the risk premium of 3.0963 for larger firms under the same model, underscores the heightened vulnerability of smaller firms to climate-related risks. When analysed using the Giglio and Xiu methodology, the disparity remains evident, with larger firms exhibiting a far smaller response to temperature anomalies, reflected in a risk premium

of just 0.1868 under the Three-Pass Regression Filter approach.

The heightened sensitivity of small firms to state-level temperature anomalies can be attributed to their limited ability to adapt to climate-related challenges. Smaller firms often lack the financial resources, operational flexibility, and scale to implement mitigation strategies, such as relocating operations, retrofitting facilities to withstand extreme weather, or investing in energy-efficient technologies. Additionally, their reliance on localized supply chains and markets amplifies their exposure to adverse climate events, as disruptions in a specific region can have a disproportionate impact on their operations and profitability.

Conversely, larger firms are better equipped to manage and mitigate climate risks. Their broader geographic footprint allows them to diversify operations across regions, reducing their reliance on any single location that might be adversely affected by temperature anomalies. Moreover, larger firms often have greater access to capital and expertise to implement climate resilience measures, such as renewable energy adoption, infrastructure investments, and advanced risk management practices. These advantages enable them to absorb climate-related shocks more effectively, resulting in a smaller risk premium for temperature anomalies.

These findings highlight the critical role of firm size in determining vulnerability to climate risk at the state level. Policymakers and stakeholders should consider these disparities when designing climate policies and support mechanisms. For instance, targeted subsidies or incentives for small firms to invest in climate resilience measures could help mitigate their disproportionate exposure to temperature anomalies. Similarly, improving access to financing for smaller firms to address climate-related challenges could play a key role in reducing their vulnerability and ensuring a more equitable adaptation to climate risks.

In conclusion, our analysis demonstrates that smaller firms are generally more susceptible to state-level factors and climate risks, such as temperature anomalies and climate policy uncertainty, compared to their larger counterparts. This heightened sensitivity is reflected in the significantly higher risk premia associated with these factors in the portfolios of smaller firms. By contrast, larger firms exhibit a more muted response to state-level factors, such as economic policy uncertainty (EPU_{States}) and economic conditions ($ECON_{States}$), indicating their relative resilience to localized economic and policy changes. Additionally, smaller firms display larger and more volatile market risk premia, as evidenced by factors such as SMB and HML. This suggests that their higher exposure to market fluctuations may stem from constraints in financial resources, limited diversification opportunities, and a greater reliance on local or regional markets. These characteristics make smaller firms more vulnerable to systemic shocks and economic disruptions.

The findings further highlight that state-level economic uncertainty and climate-related risks are particularly impactful for smaller firms. For example, the significantly higher risk premia for temperature anomalies at the state level suggest that smaller firms face greater challenges in mitigating and adapting to climate risks. In contrast, larger firms benefit from economies of scale, diversified operations, and greater access to resources, enabling them to absorb such risks more effectively.

6.4 Mimicking Portfolio Techniques:

In this research, we employ a robust econometric approach to hedge portfolio construction, drawing from standard asset pricing methods akin to those described by Engle et al. [2020]. Our central hypothesis posits that climate risk significantly influences asset markets, thereby enabling the creation of a well-diversified portfolio that isolates exposure to climate-related risk factors. This hedge portfolio, designed specifically for climate change shocks (CC_t), aims to exhibit unit exposure (β) to these shocks while remaining unexposed to other risk factors (v_t). This structure allows investors to adjust their climate risk exposure without altering their stance on other risk dimensions.[15]

Our analysis applies the mimicking portfolio technique to an initial set of 20 portfolios, organized based on their ESG combined scores. The focus here extends to crucial unobserved factors such as climate policy uncertainty (CPU_{US}), economic policy uncertainty (EPU_{US}), and economic conditions ($ECON_{US}$) at the national level, as well as state-specific risk factors like temperature anomalies ($Tanomalies$), economic policy uncertainty at the state level (EPU_{States}), and economic conditions at the state level ($ECON_{States}$). This methodological framework supports our primary investigation into the extent to which asset markets effectively price climate risk, particularly within the U.S. energy and highly energy dependent sectors, and examines the impact of diverse state-level climate policies on national transition risks and their reflection in market valuations.

Data compilation for this study included returns from these portfolios alongside various climate and other risk factors, with a particular emphasis on the CPU index. To ensure analytical consistency and comparability across different scales of data, we standardized all variables involved in the regression analysis. This standardization process is critical for addressing potential discrepancies that might arise from variable magnitude differences.

To discern the primary influences on portfolio returns variability, we implemented Principal Component Analysis (PCA). This method helped reduce data dimensionality while preserving essential variance components, with the top five principal components identified as capturing the most

[15] In this research, we employ a robust econometric approach to construct hedge portfolios, grounded in standard asset pricing methods similar to those outlined by Engle et al. [2020]. Our approach posits that climate risk significantly impacts asset markets, allowing us to build a diversified portfolio that selectively isolates climate-related risk exposure. Specifically, we aim to construct a hedge portfolio for climate change shocks CC_t with a unit exposure $\beta = 1$ to these shocks while remaining neutral to other risk factors v_t.

To achieve this, we first standardize portfolio returns R and risk factors F as follows:

$$R_{\text{scaled}} = \frac{R - \mu_R}{\sigma_R} \quad \text{and} \quad F_{\text{scaled}} = \frac{F - \mu_F}{\sigma_F},$$

where μ and σ represent the mean and standard deviation, respectively. Principal component analysis (PCA) is applied to R_{scaled} to decompose it as

$$R_{\text{scaled}} = U\Sigma V^\top.$$

The first p principal components (PCs) are then used to form the mimicking portfolios, calculated as $M = R_{\text{scaled}} V_{[:,1:p]}$. These mimicking portfolios are combined with the scaled risk factors in a single matrix,

$$C = \begin{bmatrix} M & F_{\text{scaled}} \end{bmatrix},$$

and further analyzed to isolate the climate risk factor. Finally, we regress each principal component PC_i on the combined components in C:

$$\text{PC}_i = \alpha + \beta_i \text{CombinedPC}_i + \epsilon,$$

where β_i quantifies the sensitivity of PC_i to each risk factor. For each PC, we compute the coefficient β_i, t-statistic, correlation, and mean return, ensuring the hedge portfolio's unit exposure to climate shocks while maintaining neutrality toward other risk dimensions. This structure thus allows investors to adjust their exposure to climate risk independently of other risk factors.

significant variations in portfolio returns.

In constructing the mimicking portfolios, we projected standardized portfolio returns onto these PCA loadings, ensuring that the portfolios mimicked the underlying factors reflected in the PCs. This alignment is crucial for facilitating a direct comparison in our regression analyses.

Subsequently, for each principal component, we conducted detailed regression analyses using the returns from the corresponding mimicking portfolios and each unobserved risk factor. These regressions were aimed at extracting relevant coefficients, t-statistics, correlations, and mean returns, providing a comprehensive view of how each risk factor influences portfolio performance. This thorough approach enhances our understanding of the dynamics at play in pricing climate-related risks within asset markets, offering critical insights for investors and policymakers navigating the complexities of climate change and investment strategy.

The analysis delineated in table 14 offers insightful revelations concerning the distinct relationships among principal components and their associated mimicking portfolios and the climate policy uncertainty (CPU_{US}) risk factor. For PCs 1, 2, and 3, the correlations are significantly positive, marking notable alignments with their respective mimicking portfolios. Specifically, PC1 manifests a robust correlation (0.7470) and a substantial coefficient of 1.6494, backed by a high T-statistic of 18.6356, which signifies a strong and statistically significant positive relationship. PC2 shows a meaningful but more moderate positive correlation of 0.3251, with a coefficient of 0.5876 and a T-statistic of 5.7017, suggesting a significant association. PC3 similarly displays a moderate positive correlation of 0.3078, with a coefficient of 0.4518 and a T-statistic of 5.3656, indicating a statistically noteworthy relationship.

[Table 14 around here]

Conversely, PC4 reveals a negative dynamic, characterized by a coefficient of -0.2920 and a T-statistic of -4.4630, indicating a statistically significant inverse relationship. The correlation of -0.2599 further supports this moderate negative association.

In stark contrast, PC5 exhibits a lack of significant association, marked by a negligible coefficient of -0.0467 and a T-statistic of -0.7336. The near-zero correlation of -0.0442 underscores the insignificance of this component in capturing the effects of its mimicking portfolio.

Statistically, PCs 1 through 4 demonstrate significance at conventional confidence levels (e.g., 5% significance level), whereas PC5 does not meet these criteria, illustrating its lack of statistical relevance.

Collectively, these findings corroborate the significant impact of climate policy uncertainty on the first four principal components, underscoring the crucial need to incorporate climate risk considerations into financial modelling and portfolio management. This analysis not only supports the methodology proposed by Giglio and Xiu [2021] but also affirms the relevance of climate transition risks within our research scope. The evidence provided thus addresses critical research questions concerning the adequacy of asset markets in accurately pricing climate risks, providing substantial insights for strategic portfolio adjustments and policy formulation.

Table 15 provides a detailed regression analysis, assessing the impact of economic policy uncertainty (EPU_{US}) in the U.S. on various principal components (PCs) used to construct mimicking portfolios. The analysis uncovers significant relationships and varying degrees of correlation across

the PCs, elucidating the influence of EPU_{US} on portfolio dynamics. PCs 1, 2, 3, and 5 meet the threshold for statistical significance at conventional levels (e.g., 5% significance level), with their T-statistics either surpassing 2 or dipping below -2. PC4, however, does not reach statistical significance, as indicated by a T-statistic near zero.

[Table 15 around here]

PC1 demonstrates a robust positive relationship with a coefficient of 0.9679 and a T-statistic of 7.6212, supported by a moderate correlation of 0.4176. This indicates a significant alignment between PC1 and its corresponding mimicking portfolio. PC2 presents a positive coefficient of 0.2222 with a T-statistic of 2.0542, although the correlation is relatively weak at 0.1229, suggesting a less pronounced but still statistically significant relationship.

Conversely, PC3 shows a notable negative relationship, with a coefficient of -0.4998 and a T-statistic of -6.0067, coupled with a moderate inverse correlation of -0.3406, highlighting significant adversarial impacts influenced by EPU_{US}. PC5 also exhibits a negative relationship, though weaker, with a coefficient of -0.1371 and a T-statistic of -2.1690. The correlation of -0.1297 further indicates a slight but significant inverse association.

Additionally, PC4 differs markedly, displaying an insignificant negative coefficient of -0.0230 and a T-statistic of -0.3392. The correlation of -0.0204 is minimal, suggesting no substantial impact of EPU_{US} on this principal component.

These findings elucidate that economic policy uncertainty in the U.S. significantly affects multiple principal components, impacting the financial modelling and portfolio management strategies. PCs 1, 2, 3, and 5, in particular, show how various dimensions of EPU_{US} influence portfolio returns, underscoring the need for comprehensive risk assessment and management practices in the face of economic uncertainty. This analysis aligns with and supports established financial theories, reinforcing the critical role of EPU_{US} in shaping investment outcomes and informing strategic decision-making in portfolio management.

Table 16 presents a comprehensive regression analysis that assesses the influence of the Economic Conditions ($ECON_{US}$) indicator on various principal components (PCs) within U.S. asset portfolios. This analysis provides valuable insights into the dynamic interactions between economic conditions and portfolio performance.

[Table 16 around here]

PC1 exhibits a strong and statistically significant positive relationship with a coefficient of 1.3348 and a T-statistic of 10.5169, supported by a moderate to strong correlation of 0.5356. This indicates a substantial alignment and responsiveness of PC1 to shifts in economic conditions. PC2 and PC3 both demonstrate statistically significant positive relationships with coefficients of 0.4233 and 0.2468, and T-statistics of 3.9958 and 2.8289, respectively. These PCs show weaker correlations (0.2342 for PC2 and 0.1682 for PC3), suggesting that while economic conditions influence these components, the impact is less pronounced compared to PC1. Additionally, PC4 presents a robust positive relationship with a coefficient of 0.8140 and a remarkable T-statistic of 17.4259, coupled with a strong correlation of 0.7244, underscoring a significant sensitivity to economic conditions.

PC5 contrasts with the other components, displaying a significant negative relationship. The coefficient of -0.1317 and a T-statistic of -2.0816, along with a weak inverse correlation of -0.1245,

indicate that PC5 inversely reacts to economic conditions, potentially offering diversification advantages within portfolio strategies.

The findings underscore the strong positive associations for most PCs highlight that economic health drives portfolio performance, whereas the negative relationship for PC5 suggests complexity and potential for strategic diversification. These insights confirm the critical role of economic conditions in shaping investment outcomes and underscore the necessity for sophisticated analysis techniques in capturing these effects within asset pricing models.

Table 17 details a regression analysis using Temperature Anomalies ($Tanomalies$) at the state level in the U.S. as a risk factor, revealing how these anomalies impact different principal components (PCs) in financial modeling. The analysis shows significant relationships for PCs 1, 2, 3, and 5, with PC1 exhibiting a particularly strong positive relationship, evidenced by a coefficient of 1.3853 and a T-statistic of 10.0809, alongside a correlation of 0.5195, suggesting a moderate to strong association with its mimicking portfolio. This implies that PC1 is considerably influenced by climate physical risks at the state level. Similarly, PC2 and PC5 display statistically significant positive relationships with coefficients of 0.3569 and 0.2523, respectively, albeit with weaker associations, indicating that these components are also affected by temperature anomalies but to a lesser extent.

[Table 17 around here]

Conversely, PC3 presents a robust positive coefficient of 1.0371 with a T-statistic of 16.5643 and a high correlation of 0.7067, indicating that temperature anomalies strongly influence this component. On the other hand, PC4 demonstrates a significant negative relationship, with a coefficient of -0.2320 and a T-statistic of -3.4991, suggesting an inverse association with temperature anomalies.

The statistical significance of these relationships across PCs 1, 2, 3, 4, and 5, underscores the importance of considering temperature anomalies in financial modeling and portfolio management. These findings indicate that state-level climate physical risks profoundly affect various aspects of portfolio returns, with both positive and negative impacts depending on the specific principal component. This nuanced influence highlights the need for sophisticated financial models that incorporate state-level climate risk measures to accurately capture their effects on investment portfolios, supporting the previous findings. The results from table 17 strongly advocate for the integration of these climate factors into portfolio strategies, enhancing the ability of investors to manage and hedge against climate-related risks effectively.

Table 18 details the regression analysis using economic policy uncertainty (EPU_{States}) at the state level in the U.S. as a risk factor, demonstrating how this uncertainty influences various principal components (PCs) in financial modelling. The analysis identifies significant relationships for PCs 1, 3, and 4, each exhibiting unique interactions with their respective mimicking portfolios. PC1 displays a positive relationship, with a coefficient of 0.6017 and a T-statistic of 4.5217, indicating a statistically significant influence of state-level EPU_{States}, albeit with a weak to moderate association suggested by a correlation of 0.2631. This result points to a moderate sensitivity of PC1 to fluctuations in economic policy uncertainty at the state level.

[Table 18 around here]

PC3 shows a weaker yet statistically significant positive relationship, marked by a coefficient of 0.2586 and a T-statistic of 2.9688, with a correlation of 0.1762. This suggests that PC3, while

influenced by state-level EPU_{States}, exhibits a lesser degree of sensitivity compared to PC1. In stark contrast, PC4 reveals a strong and significant negative relationship with EPU_{States}, as evidenced by a coefficient of -0.9154 and a T-statistic of -23.2978, coupled with a high negative correlation of -0.8147. This indicates that PC4 inversely responds to increases in state-level economic policy uncertainty, marking a substantial impact on this component of portfolio returns.

Conversely, PCs 2 and 5 show no statistically significant relationships with EPU_{States}. PC2, despite a coefficient of 0.1785 and a T-statistic close to significance at 1.6462, fails to demonstrate a meaningful relationship, as indicated by a very weak correlation of 0.0988. Similarly, PC5's minimal coefficient of 0.0043 and an almost negligible T-statistic of 0.0669 reflect an absence of influence from state-level EPU_{States} on this component.

The overall findings from table 18 underscore the differential impact of state-level economic policy uncertainty on various components of portfolio returns. PCs 1, 3, and 4 are notably affected, with PC1 and PC3 experiencing positive impacts and PC4 a significant negative influence, indicating diverse responses within the portfolio to changes in economic policy uncertainty. These results highlight the importance of incorporating state-level EPU_{States} measures into financial models and portfolio management strategies, as they significantly affect portfolio dynamics. The varied relationships also suggest that state-level EPU_{States} influences different aspects of portfolio returns, affirming the need for nuanced approaches to managing economic policy uncertainty in investment strategies.

Lastly, table 19 provides a detailed regression analysis focusing on the Economic Conditions Indicator ($ECON_{States}$) at the state level in the U.S. and its effect on principal components (PCs) within portfolio returns. The analysis reveals varied influences of state-level economic conditions on different components, highlighting significant relationships for most PCs, except PC3.

[Table 19 around here]

The findings indicate a strong and statistically significant positive relationship between PC1 and its mimicking portfolio, marked by a coefficient of 1.2638 and a T-statistic of 9.9375, suggesting that economic conditions have a substantial impact on this component. The correlation coefficient of 0.5140 reflects a moderate to strong association, confirming that PC1 is highly responsive to changes in state-level economic conditions.

Similarly, PC2 exhibits a statistically significant positive relationship with a coefficient of 0.4472 and a T-statistic of 4.2351, alongside a moderate correlation of 0.2474. This suggests that PC2, while less influenced than PC1, still significantly responds to economic conditions at the state level.

Conversely, PC3 shows an insignificant relationship, underscored by a coefficient of -0.1659 and a T-statistic of -1.8869, with a weak correlation of -0.1131. This indicates that PC3 is not significantly affected by state-level economic conditions, which might be due to its sensitivity to other unmeasured factors.

PC4 demonstrates a strong positive relationship with state-level economic conditions, evidenced by a coefficient of 0.8631 and a T-statistic of 19.8919, with a strong correlation of 0.7681. This shows that PC4 is significantly influenced by economic dynamics at the state level, reflecting a substantial impact on this component. In contrast, PC5 presents a negative relationship, although statistically significant, with a coefficient of -0.1773 and a T-statistic of -2.8212, and a weak to

moderate negative correlation of -0.1677. This suggests that PC5 inversely reacts to improvements in economic conditions, which might offer diversification benefits within a broader investment strategy.

Overall, the results from table 19 underscore the significant influence of state-level economic conditions on several principal components, particularly PC1, PC2, and PC4, with PC1 and PC4 showing strong positive impacts and PC5 displaying a negative relationship. These findings suggest that economic conditions at the state level should be considered critical factors in portfolio management, influencing various components of portfolio returns. The presence of both positive and negative relationships across different PCs highlights the complex and varied impact of economic conditions on investment returns, affirming the necessity for nuanced financial modelling and strategic portfolio adjustments to optimize returns in light of state-specific economic environments.

7 Conclusions

In this research, we examined the risk premia in U.S. firms using the methodology proposed by Giglio and Xiu [2021]. Our primary objective is to assess the efficacy with which asset markets account for climate risk, specifically emphasizing the aspect of climate transition risk. We aim to determine whether the proactive responses of U.S. firms to climate-related challenges are adequately reflected in market valuations. A key aspect of our research is integrating a U.S. state-level climate change indicator into our model, acknowledging the varying capacities of U.S. states to respond to the federal policy void. From our perspective this necessitated a nuanced approach to risk measurement.

Our analysis revealed several key implications essential for understanding portfolio performance and making informed investment decisions. Firstly, the statistical significance of all coefficients, including intercepts and risk premia, across the models confirms the robustness and reliability of our estimates, enhancing confidence in the findings' validity and applicability.

Secondly, robust statistical metrics such as R_g^2 and stable intercepts across varying principal component levels within each model bolster the accuracy of the results. Higher levels of principal components generally improve model fit and refine risk premia estimates, indicating a thorough analysis framework. The coherence of results is evident in consistent trends across different model specifications, reinforcing the reliability of the estimation procedures employed.

While each model and risk factor present distinct impacts on portfolio performance, the overall coherence and accuracy of the findings underscore their relevance in financial modelling and empirical finance. The comprehensive use of the three-pass methodology proposed by Giglio and Xiu [2021] with varying principal components provides a holistic understanding of the influences of risk factors on investment portfolios, offering valuable insights for investment strategies and risk management practices.

Our analysis using the three-pass methodology with varying numbers of principal components highlights the nuanced impacts of each model and risk factor on the test portfolios, aligning with established principles in financial modelling and empirical finance. The stability and consistency of intercepts across different models and principal component levels provide a reliable baseline for understanding expected returns. Concurrently, the varying risk premia estimates highlight the diverse influences of factors such as climate policy uncertainty (CPU_{US}), economic policy uncertainty (EPU_{US}), and economic conditions indicator ($ECON_{US}$) on portfolio performance. The CPU factor reflect market-wide risk perceptions related to climate policies, influencing portfolio returns accordingly in the United States. Economic policy uncertainty (EPU) factor reveal how firms with diverse environmental, social, and governance (ESG) profiles respond differently to policy unpredictability, affecting their market performance. Lastly, economic conditions indicator (ECON) factor underscores the impact of broader economic health on firm profitability and, consequently, portfolio outcomes. These insights align with economic theories and provide a practical framework for investors and policymakers to evaluate and manage portfolio risks effectively.

Additionally, the Giglio and Xiu [2021] methodology offers valuable insights into the pricing of risk at the state level, demonstrating that incorporating additional principal components consistently enhances model fit and explanatory power. This underscores the importance of capturing

unobserved factors in asset pricing. The distinct risk-return profiles observed for state level temperature anomalies ($Tanomalies$), economic policy uncertainty (EPU_{States}), and economic conditions indicator ($ECON_{States}$) provide crucial information for both policymakers and investors regarding regional economic dynamics.

Our findings align with existing literature that emphasizes the significant impact of environmental factors on economic outcomes. The strong and significant risk premia indicate that temperature anomalies are indeed priced in the cross-section of returns, suggesting significant implications for portfolio performance, particularly in climate-sensitive sectors. The variability and positive nature of the risk premia imply that assets in lower ESG-ranked portfolios require higher compensation for bearing temperature anomaly risks. In contrast, higher ESG-ranked portfolios might exhibit lower sensitivity to these risks, reflecting better risk management practices. The mixed and sometimes insignificant risk premia for EPU_{States} suggest that while economic policy uncertainty has some effect on returns, it is not consistently priced across all portfolios. This factor has moderate implications for performance, and its impact may vary based on other market conditions. Lastly, the generally positive and somewhat significant risk premia for $ECON_{States}$ indicate that economic conditions are priced to some extent, though not as strongly as temperature anomalies. This factor has moderate implications, especially for regionally focused investments.

From a policy perspective, our findings advocate for the integration of comprehensive state-level climate risk assessments in investment decisions. Policymakers and investors should consider these insights to tailor their strategies, enhancing resilience and optimizing returns in the face of climate-related uncertainties. Additionally, the evident pricing of climate risks and the significant role of state-level economic conditions in shaping market valuations underscore the need for policies that support transparent and consistent climate-related disclosures. Such measures would improve the accuracy of risk assessments and foster more informed investment decisions.

One of the significant challenges encountered in this research was the scarcity of detailed state-level climate risk measures, particularly those related to transition risks driven by differing climate policies across U.S. states. Our study highlighted the diversity in climate policy enactment across states, underscoring the need for more granular risk assessments. For future research, it would be beneficial to develop a refined climate transition risk measure at the state level. This could be achieved by employing text-analysis techniques to extract data from the National Conference of State Legislatures and various state-level newspapers. Such an approach would enhance the granularity of our analysis, allowing for a more nuanced understanding of how state-specific climate policies impact financial markets. This would not only fill a significant gap in current research but also provide investors and policymakers with critical tools for better assessing and managing climate-related risks in their decision-making processes.

Future research in the area of climate risk could focus on exploring the frequency dynamics of climate-related factors, such as temperature anomalies, extreme weather events, and environmental changes, which often exhibit seasonal patterns or variations across different time frequencies (e.g., quarterly, annual, or multi-year cycles). These temporal fluctuations suggest that climate risks may impact portfolios differently depending on the time horizon being observed. For instance, industries like agriculture, energy, and insurance might be more profoundly affected by seasonality risks, such

as temperature fluctuations or extreme weather events, during specific periods of the year.

Additionally, a focus on frequency-specific climate risk factors could reveal distinct risk exposures that are currently unobserved in traditional asset pricing models. Risks that appear subtle on an aggregate level might exhibit significant volatility or impact when examined at different time scales, such as short-term daily fluctuations versus long-term annual trends. For example, while temperature anomalies may seem mild on an annual scale, their seasonal volatility could introduce higher-frequency risks that existing models fail to capture. To address these dynamics, future research could employ frequency-domain analysis techniques, such as wavelet or spectral analysis, which are designed to decompose time series data into their frequency components. This would allow researchers to investigate how climate risk exposures vary across different time horizons. Seasonal factor models or time-frequency models could also be explored to account for shifting risk exposures over different periods.

Some potential research questions include: "How does climate risk vary across different frequencies (e.g., seasonal, annual)?"; "Is there a seasonality effect in climate-related risk factors, and how does it affect portfolio returns?"; and "Can previously unobserved frequency-specific climate risks be identified, and do they provide additional explanatory power in asset pricing models?".

Incorporating frequency-specific climate risk factors represents a promising avenue for future research. Given the cyclical nature of many climate-related phenomena, analyzing these dynamics could offer deeper insights into how climate risks are priced into financial markets. Additionally, it could lead to the development of more sophisticated models that capture previously overlooked risks, contributing significantly to the growing field of climate finance.

In conclusion, the results underscore the importance of incorporating state-level factors such as temperature anomalies, economic policy uncertainty, and economic conditions into investment strategies. While temperature anomalies demonstrate strong pricing and significant implications for portfolio performance, economic policy uncertainty and economic conditions exhibit more varied impacts that require careful consideration in portfolio management decisions. These findings highlight the relevance of regional perspectives in enhancing resilience and capturing value in increasingly complex financial markets. Investors should consider these insights to optimize risk-adjusted returns and capitalize on diverse market opportunities, particularly in regions experiencing significant climate impacts or economic fluctuations.

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A Appendix

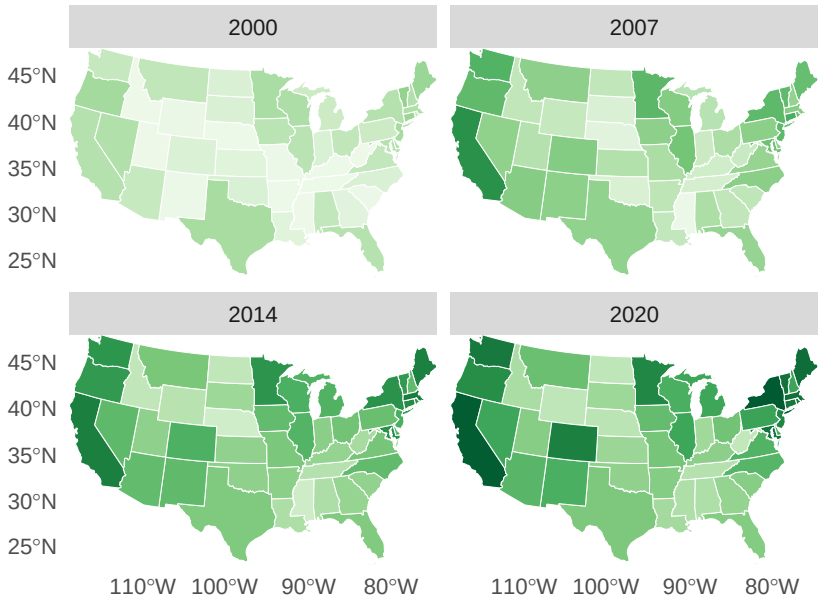


Figure 1: **State Climate Policy, 2000–2020.** The map illustrates the number and strength of climate policies enacted by each state from 2000 to 2020. States are shaded in varying shades of green to indicate their climate policy activity, with darker greens representing states that have implemented a greater number of robust climate policies, and lighter greens representing states with fewer and less stringent policies. This visualization was created using the R package Tigris and is based on spatial data provided by the US Census Bureau. Source: Bergquist and Warshaw [2023a]

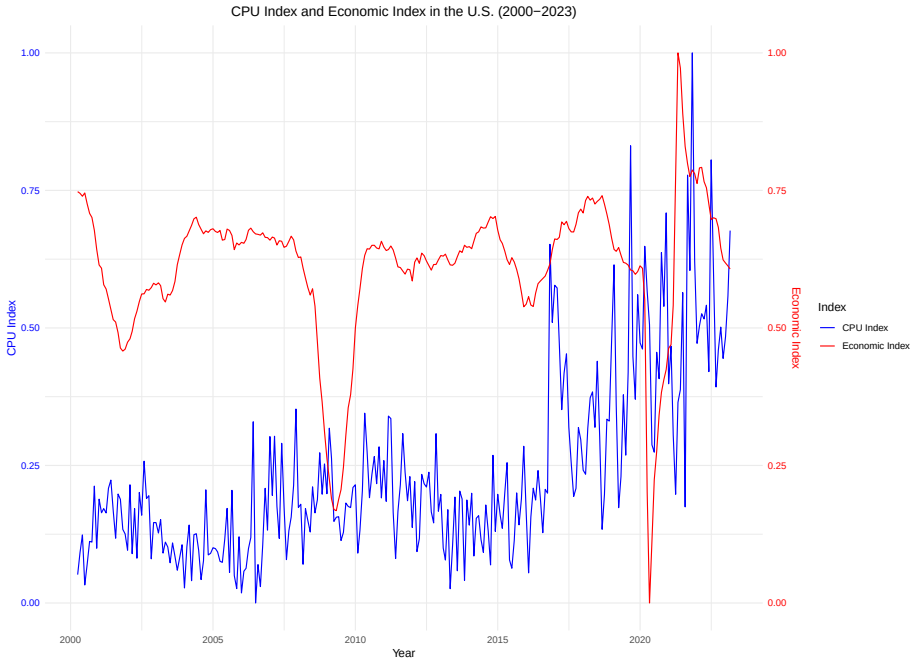


Figure 2: **Comparative Analysis of Climate Policy Uncertainty (CPU) and U.S. Economic Index Indicators (2000-2023).**

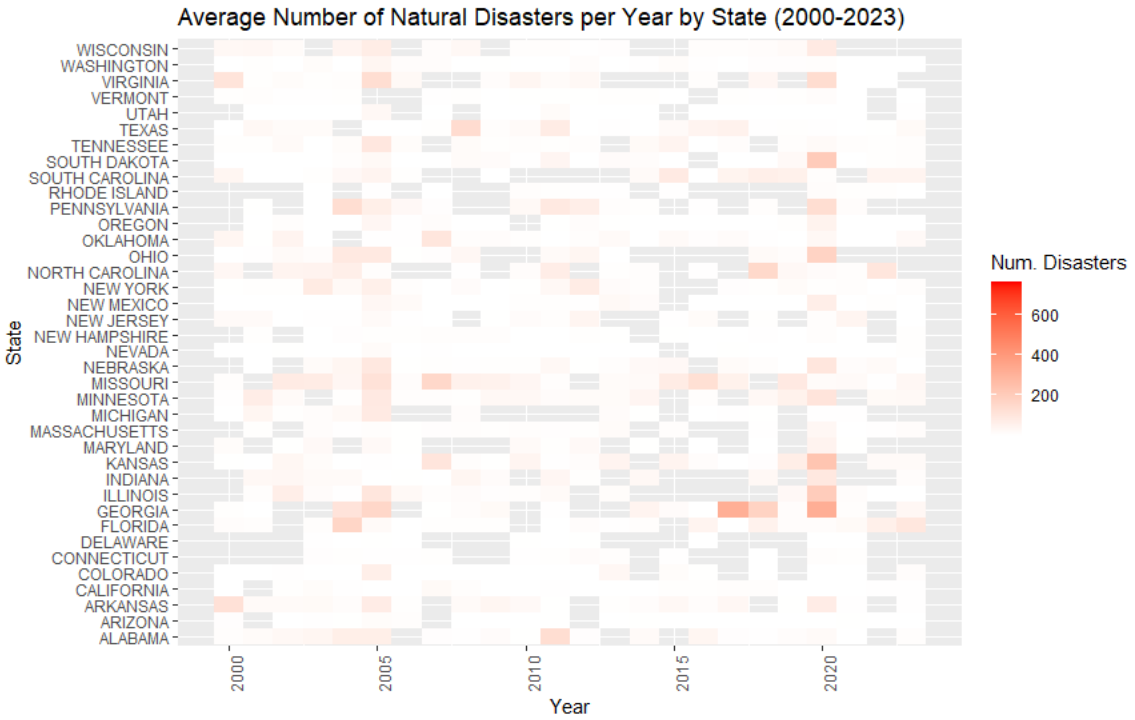


Figure 3: **Cumulative number of natural disasters across all 38 U.S. states throughout the entire period from 2000 to 2023.** Source: Federal Emergency Management Agency (FEMA) [2024]

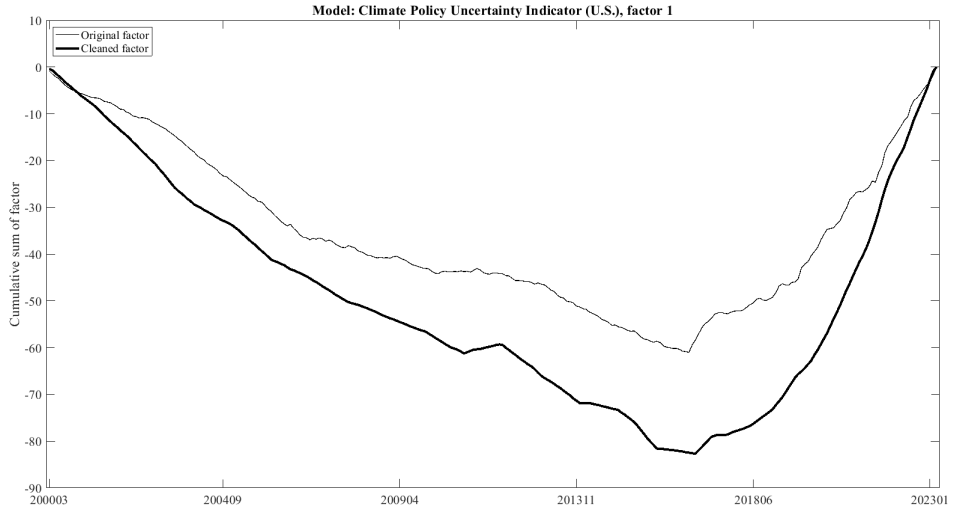


Figure 4: **Cumulative sum of the Climate Policy Uncertainty Index (CPU_{US}) factor in the U.S.** The cleaned factor (thick line) smooths out the noise from the original factor (thin line), showing a clearer trend of the cumulative impact of climate policy uncertainty on portfolio returns from 2000 to 2023.

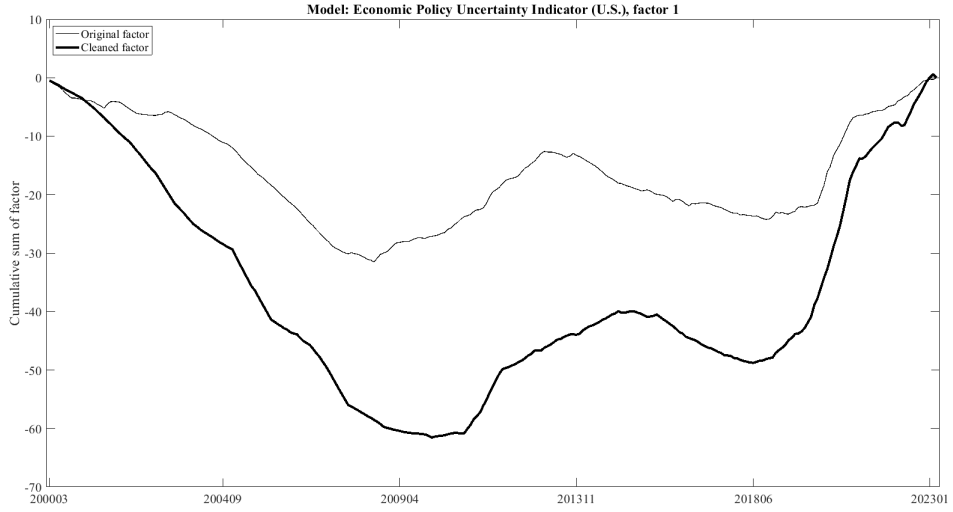


Figure 5: **Cumulative sum of the Economic Policy Uncertainty Indicator (EPU_{US}) factor in the U.S.** The graph compares the original factor (thin line) with the cleaned factor (thick line), illustrating the long-term cumulative impact of economic policy uncertainty on portfolio performance from 2000 to 2023.

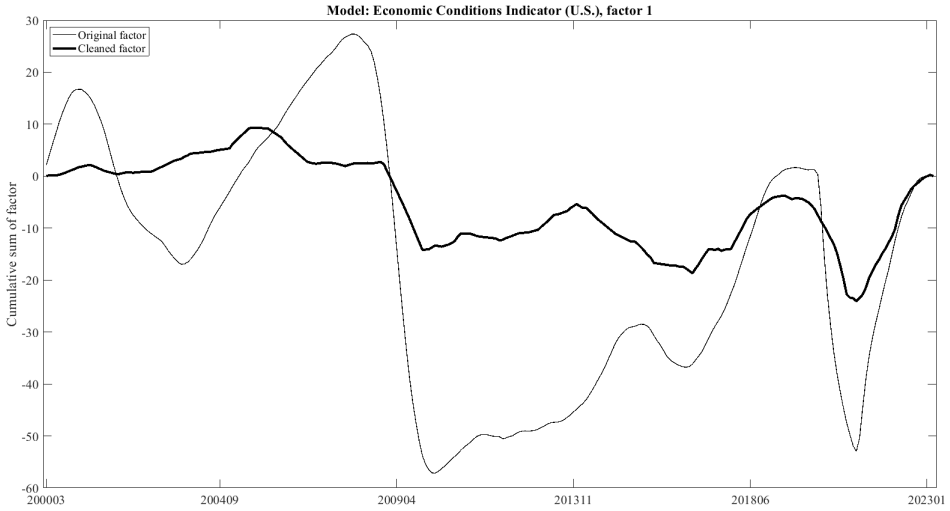


Figure 6: **Cumulative sum of the Economic Conditions Indicator ($ECON_{US}$) factor in the U.S.** The graph compares the original factor (thin line) with the cleaned factor (thick line), illustrating the long-term cumulative impact of economic policy uncertainty on portfolio performance from 2000 to 2023.

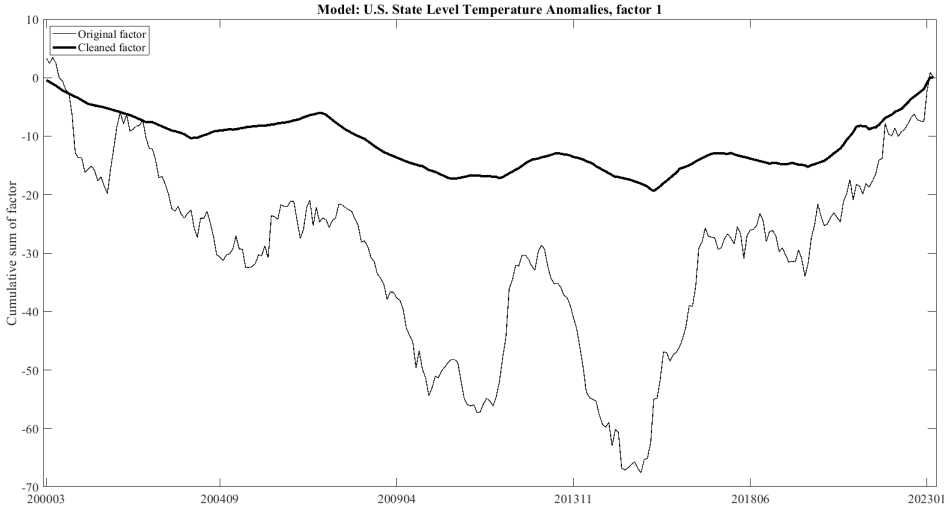


Figure 7: **Cumulative sum of the Temperature Anomalies ($Tanomalies$) factor at the U.S. state level.** The graph depicts the original factor (thin line) and the cleaned factor (thick line), highlighting the influence of temperature anomalies on portfolio returns over time, from 2000 to 2023.

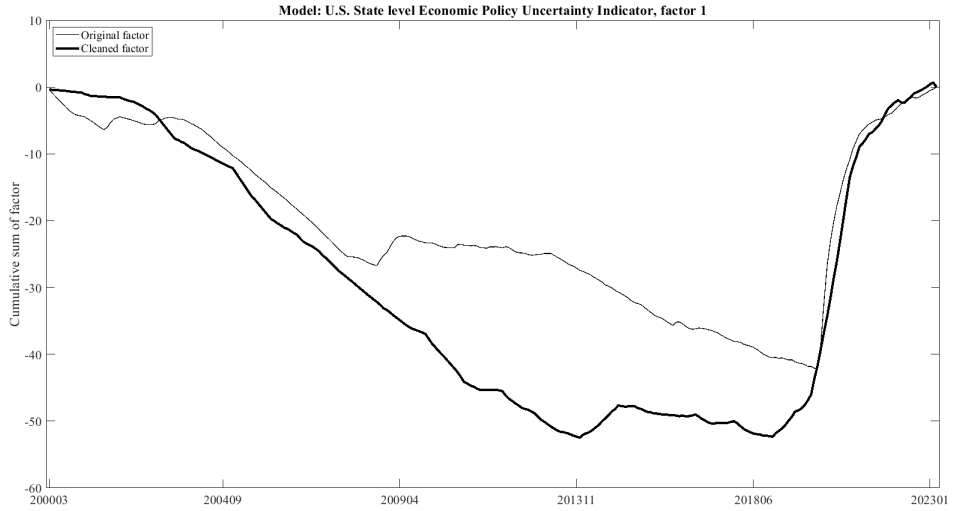


Figure 8: **Cumulative sum of the Economic Policy Uncertainty Indicator (EPU_{States}) factor at the U.S. state level.** The original factor (thin line) and cleaned factor (thick line) are shown, demonstrating the cumulative effect of state-level economic policy uncertainty on portfolio returns from 2000 to 2023.

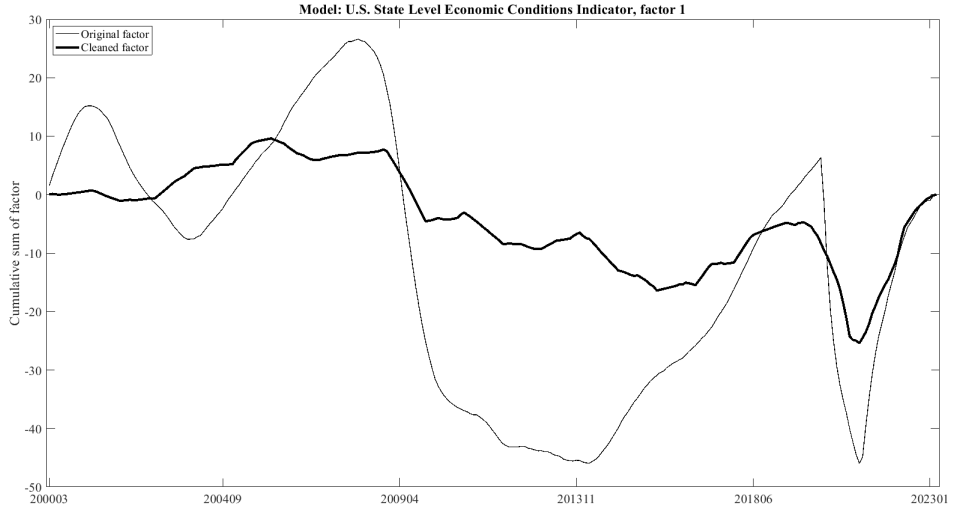


Figure 9: **Cumulative sum of the Economic Conditions Indicator ($ECON_{States}$) factor at the U.S. state level.** This figure compares the original factor (thin line) with the cleaned factor (thick line), indicating the cumulative impact of economic conditions on portfolio performance from 2000 to 2023.

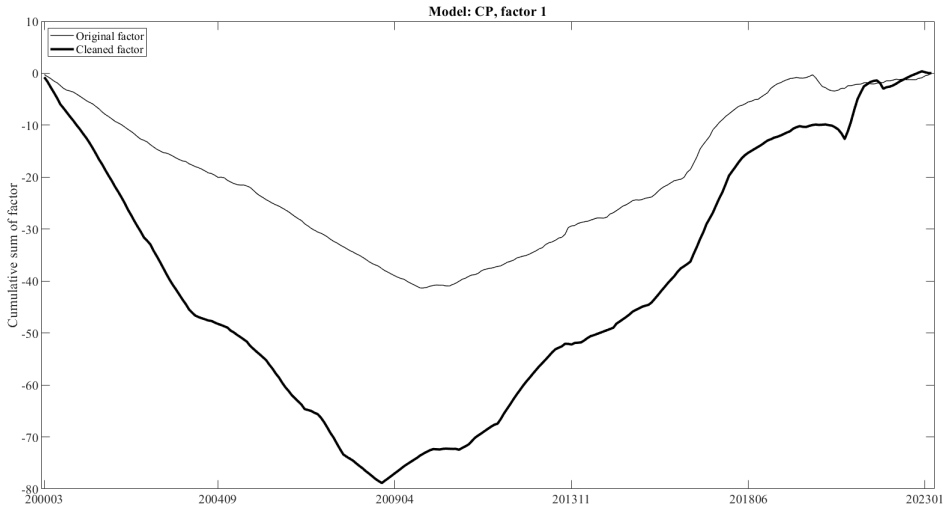


Figure 10: **Cumulative sum of the Partisan Conflict Index (PCI_{US}) factor in the U.S.** This figure compares the original factor (thin line) with the cleaned factor (thick line), indicating the cumulative impact of partisan conflict index on portfolio performance from 2000 to 2023.

Table 1: **Summary Statistics for Each Portfolio**. The table displays the mean, median, standard deviation (Std), skewness, and kurtosis for each of the 20 portfolios.

Portfolio	Mean	Median	Std	Skewness	Kurtosis
1	-0.00058	0.00277	0.00914	-3.00706	12.09511
2	-0.00271	-0.00074	0.00601	-2.27479	7.74854
3	-0.00006	0.00320	0.00805	-1.89154	5.42329
4	-0.00551	-0.00576	0.00443	-1.18158	5.25230
5	-0.00200	-0.00059	0.00687	-1.82763	6.22540
6	0.00320	0.00473	0.00453	-2.63679	9.75205
7	0.00368	0.00462	0.00311	-2.86280	12.16327
8	0.00324	0.00416	0.00355	-2.67488	10.34106
9	0.00291	0.00382	0.00297	-1.78696	7.03519
10	0.00341	0.00372	0.00279	-1.44525	7.17214
11	0.00316	0.00256	0.00315	0.72460	3.47799
12	0.00533	0.00478	0.00291	0.55989	2.68634
13	0.00493	0.00422	0.00284	1.63249	6.37019
14	0.00488	0.00474	0.00207	0.01187	2.71403
15	0.00447	0.00462	0.00241	-0.17981	1.88071
16	0.00411	0.00416	0.00188	0.01936	2.87962
17	0.00459	0.00462	0.00183	-0.20774	3.28810
18	0.00389	0.00371	0.00200	-0.28105	2.69274
19	0.00516	0.00530	0.00214	-0.04998	2.15857
20	0.00624	0.00614	0.00149	0.01044	2.20012

Name	Frequency	Period	Code
Adjusted Close Price	Daily	2000/03/01 – 2023/03/01	P
Cumulative Returns	Monthly	2000/03 - 2023/03	R
Total Market Portfolio Return (in excess of the risk-free rate)	Monthly	2000/03 - 2023/03	MKT
Size Premium (Small minus Big)	Monthly	2000/03 - 2023/03	SMB
Value Premium (High minus Low)	Monthly	2000/03 - 2023/03	HML
Operating Profitability (Robust minus Weak)	Monthly	2000/03 - 2023/03	RMW
Investment (Conservative minus Aggressive)	Monthly	2000/03 - 2023/03	CMA
U.S. States Economic Index Indicator	Monthly	2000/03 - 2023/03	ECON_States
U.S. Wide Economic Index Indicator	Monthly	2000/03 - 2023/03	ECON_US
Climate Policy Uncertainty Index Indicator (U.S. Wide)	Monthly	2000/03 - 2023/03	CPU_US
Climate Policy Index Indicator at U.S. State level	Monthly	2000/03 - 2020/12	CPI_States
Economic Policy Uncertainty Indicator at U.S. State level	Monthly	2000/03 - 2023/03	EPU_States
Economic Policy Uncertainty Indicator at U.S. Wide level	Monthly	2000/03 - 2023/03	EPU_US
Temperature Anomaly at U.S. State level	Monthly	2000/03 - 2023/03	TAnomalies
Natural Disasters at U.S. State level	Monthly	2000/03 - 2023/03	Natural_US
Partisan Conflict Index (U.S. Wide)	Monthly	2000/03 - 2023/03	PCI_US

Table 2: **Data Description and Respective Codes.**

Table 3: **Risk Premia for Observed and Unobserved Factors.** *Notes: This table presents the intercept, risk premia (λ), zero-beta variance, and the variance of risk premia for both observed and unobserved factors, following the methodology proposed by Giglio and Xiu [2021]. The factors CPU_{US}, EPU_{US}, $ECON_{US}$, Tanomalies, EPU_{States}, and $ECON_{States}$ are standardized.*

Factors	Intercept	Risk Premia	Zero-Beta Variance	Risk Premia Variance
CPU (for $\hat{p} = 10$)	0.0045	0.1063	0.0000	0.2000
FF3 - MKT (for $\hat{p} = 10$)	0.0045	-0.0099	0.0000	0.1426
FF3 - SMB (for $\hat{p} = 10$)	0.0045	0.1761	0.0000	0.1673
FF3 - HML (for $\hat{p} = 10$)	0.0045	0.2774	0.0000	0.2139
EPU_US (for $\hat{p} = 10$)	0.0045	0.0723	0.0000	0.4404
ECON_US (for $\hat{p} = 10$)	0.0045	-0.0574	0.0000	0.3185
PCI_US (for $\hat{p} = 10$)	0.0045	-0.3114	0.0000	0.3664
FF5 - MKT (for $\hat{p} = 10$)	0.0045	-0.0099	0.0000	0.1426
FF5 - SMB (for $\hat{p} = 10$)	0.0045	0.1744	0.0000	0.1687
FF5 - HML (for $\hat{p} = 10$)	0.0045	0.2774	0.0000	0.2138
FF5 – RMW (for $\hat{p} = 10$)	0.0045	-0.1612	0.0000	0.2005
FF5 - CMA (for $\hat{p} = 10$)	0.0045	0.3254	0.0000	0.2142
Tanomalies (for $\hat{p} = 10$)	0.0045	0.1422	0.0000	0.1188
EPU_States (for $\hat{p} = 10$)	0.0045	0.2241	0.0000	0.1065
ECON_States (for $\hat{p} = 10$)	0.0045	0.1700	0.0000	0.1140

Table 4: **Comparison of Standard Fama-MacBeth (FM) Model Estimates for U.S.-Wide Risk Factors and Giglio and Xiu (2021) Methodology Estimates.** This table presents the estimated intercepts and risk premia, along with their standard errors, for the CPU_{US}, EPU_{US}, $ECON_{US}$, and PCI_{US} factors. The results are derived from the Fama-MacBeth two-pass regression method. The results are shown for the four models, along with the goodness-of-fit measure R_g^2 for each factor.

Model	**Standard FM**			**Giglio and Xiu (10 PCs)**			
	Intercept	**Risk Premia**	**Std. Error**	**Intercept**	**Risk Premia**	**Std. Error**	R_g^2
CPU_{US}	0.0037	0.9555	0.0856	0.0045	0.1063	0.2000	0.5941
EPU_{US}	0.0035	1.6015	0.1395	0.0045	0.0723	0.2917	0.4404
$ECON_{US}$	0.0040	2.6936	0.2288	0.0045	-0.0574	0.3477	0.3185
PCI_{US}	0.0032	1.8075	0.1659	0.0045	-0.3114	0.3664	0.5283

Table 5: **Comparison of Standard Fama-MacBeth (FM) Model and Giglio and Xiu (2021) Methodology for Fama-French Risk Factors**. This table compares the estimated intercepts, risk premia, and standard errors from the Fama-MacBeth (FM) model and the Three-Pass Regression Filter (3PRF) methodology by Giglio and Xiu (2021). Results are shown for both the Fama-French three-factor (FF3) and five-factor (FF5) models. The risk factors include MKT (market), SMB (small minus big), HML (high minus low), RMW (robust minus weak), and CMA (conservative minus aggressive).

Model	**Factor**	**Standard FM**			**Giglio and Xiu (10 PCs)**		
		Intercept	**Risk Premia**	**Std. Error**	**Intercept**	**Risk Premia**	**Std. Error**
FF3	MKT	0.0042	5.0783	0.3428	0.0045	-0.0099	0.1426
	SMB		0.3206	0.5436		0.1761	0.1673
	HML		9.9083	0.4243		0.2774	0.2139
FF5	MKT	0.0040	4.9465	0.3094	0.0045	-0.0099	0.1426
	SMB		2.3935	0.3798		0.1744	0.1687
	HML		6.3616	0.2597		0.2774	0.2138
	RMW		-2.9438	0.2569		-0.1612	0.2005
	CMA		8.4491	0.4919		0.3254	0.2142

Table 6: **Comparison of Standard Fama-MacBeth (FM) Model and Giglio and Xiu (2021) Methodology for U.S. State-Level Risk Factors**. This table compares the estimated intercepts, risk premia, and standard errors from the Standard Fama-MacBeth (FM) model and the Giglio and Xiu methodology (using 10 PCs) for U.S. state-level risk factors: Tanomalies, EPU_{States}, and $ECON_{States}$.

Model	**Factor**	**Standard FM**			**Giglio and Xiu (10 PCs)**		
		Intercept	**Risk Premia**	**Std. Error**	**Intercept**	**Risk Premia**	**Std. Error**
State-Level	Tanomalies	0.0039	4.2121	0.3479	0.0045	0.1422	0.046413
	EPU_States	0.0032	1.5217	0.1469	0.0045	0.2241	0.47737
	ECON_States	0.0041	2.8582	0.2292	0.0045	0.1700	0.32505

Table 7: **Three-Pass Methodology and Standard Fama-MacBeth (FM) Results for 38 States**. This table presents the empirical results using the Three-Pass Regression Filter (3PRF) and the Standard FM methodology for 38 U.S. states, using four and 10 principal components (PCs) as suggested factors. The table shows the intercepts and risk premia for both methodologies, along with the R_g^2 for 10 PCs.

State	Intercept (FM)	FM Risk Premia	Intercept (Three-Pass)	Risk Premia (4 PCs)	Risk Premia (10 PCs)	R^2g (10 PCs)
Alabama	0.0032 (0.0001)	3.5432 (0.3912)	0.0045 (0.0006)	-0.0348 (0.0990)	-0.0687 (0.1759)	0.056144
Arizona	0.0026 (0.0001)	1.2232 (0.3451)	0.0045 (0.0006)	-0.0838 (0.1169)	-0.0352 (0.2181)	0.088512
Arkansas	0.0033 (0.0001)	6.5426 (0.6665)	0.0045 (0.0006)	0.0213 (0.0887)	-0.0461 (0.1929)	0.025927
California	0.0033 (0.0001)	3.5048 (0.3154)	0.0045 (0.0006)	-0.0082 (0.1325)	0.1335 (0.2252)	0.12245
Colorado	0.0026 (0.0001)	3.0184 (0.4854)	0.0045 (0.0006)	-0.0674 (0.1018)	0.0057 (0.2009)	0.058119
Connecticut	0.0039 (0.0000)	3.4534 (0.2780)	0.0045 (0.0006)	0.1755 (0.0862)	0.1376 (0.1951)	0.068999
Delaware	0.0036 (0.0001)	3.9384 (0.3548)	0.0045 (0.0006)	0.0673 (0.0836)	0.0149 (0.1811)	0.05785
Florida	0.0036 (0.0001)	2.4611 (0.2313)	0.0045 (0.0006)	0.0354 (0.1081)	-0.0276 (0.1753)	0.11631
Georgia	0.0029 (0.0001)	2.9765 (0.4117)	0.0045 (0.0006)	-0.0692 (0.1052)	-0.1988 (0.1904)	0.069509
Illinois	0.0034 (0.0001)	7.9214 (0.7056)	0.0045 (0.0006)	0.0136 (0.0854)	0.0496 (0.1729)	0.020549
Indiana	0.0033 (0.0001)	6.3605 (0.6406)	0.0045 (0.0006)	0.0007 (0.0836)	-0.0369 (0.1815)	0.022326
Kansas	0.0035 (0.0001)	13.2899 (0.9664)	0.0045 (0.0006)	0.0262 (0.0826)	0.1740 (0.1771)	0.013465
Maryland	0.0036 (0.0001)	3.9366 (0.3540)	0.0045 (0.0006)	0.0641 (0.0874)	0.0396 (0.1831)	0.054086
Massachusetts	0.0040 (0.0000)	3.1338 (0.2503)	0.0045 (0.0006)	0.1951 (0.0844)	0.1709 (0.1908)	0.074477
Michigan	0.0037 (0.0001)	5.9018 (0.4925)	0.0045 (0.0006)	0.0353 (0.0900)	0.1202 (0.1797)	0.036951
Minnesota	0.0030 (0.0001)	10.4652 (0.6934)	0.0045 (0.0006)	0.0055 (0.0794)	0.1800 (0.1989)	0.035742
Missouri	0.0031 (0.0001)	8.4247 (0.7034)	0.0045 (0.0006)	0.0342 (0.0917)	0.0993 (0.1815)	0.026001
Nebraska	0.0035 (0.0001)	10.5453 (0.7400)	0.0045 (0.0006)	0.0174 (0.0850)	0.2506 (0.1837)	0.032221
Nevada	0.0028 (0.0001)	5.0350 (0.4361)	0.0045 (0.0006)	-0.0394 (0.1286)	0.1515 (0.2179)	0.10041
New Hampshire	0.0041 (0.0000)	3.5899 (0.2800)	0.0045 (0.0006)	0.1997 (0.0860)	0.1583 (0.1996)	0.064409
New Jersey	0.0038 (0.0000)	3.6784 (0.3068)	0.0045 (0.0006)	0.1275 (0.0867)	0.1188 (0.1839)	0.060971
New Mexico	0.0027 (0.0001)	3.3317 (0.4822)	0.0045 (0.0006)	-0.0777 (0.1133)	-0.0741 (0.2065)	0.057634
New York	0.0039 (0.0000)	5.4023 (0.4395)	0.0045 (0.0006)	0.0945 (0.0830)	0.0396 (0.1895)	0.03351
North Carolina	0.0032 (0.0001)	3.1731 (0.3488)	0.0045 (0.0006)	-0.0377 (0.0952)	-0.0066 (0.1801)	0.059031
Ohio	0.0034 (0.0001)	4.8174 (0.4737)	0.0045 (0.0006)	-0.0018 (0.0861)	-0.0136 (0.1760)	0.028758
Oklahoma	0.0035 (0.0001)	7.2914 (0.6098)	0.0045 (0.0006)	0.0597 (0.0966)	0.0739 (0.1962)	0.030511
Oregon	0.0029 (0.0001)	5.2903 (0.4210)	0.0045 (0.0006)	-0.0476 (0.1417)	0.3072 (0.2464)	0.12052
Pennsylvania	0.0036 (0.0001)	4.9061 (0.4322)	0.0045 (0.0006)	0.0503 (0.0835)	0.0380 (0.1795)	0.033448
Rhode Island	0.0039 (0.0000)	3.0597 (0.2462)	0.0045 (0.0006)	0.1900 (0.0850)	0.1747 (0.1883)	0.079058
South Carolina	0.0035 (0.0001)	3.7742 (0.3788)	0.0045 (0.0006)	0.0177 (0.0862)	-0.0364 (0.1865)	0.05614
South Dakota	0.0032 (0.0001)	9.9079 (0.6530)	0.0045 (0.0006)	0.0004 (0.0871)	0.3127 (0.2041)	0.047601
Tennessee	0.0035 (0.0001)	5.0632 (0.4860)	0.0045 (0.0006)	0.0402 (0.0869)	-0.0060 (0.1871)	0.032152
Texas	0.0030 (0.0001)	5.5146 (0.6271)	0.0045 (0.0006)	-0.0259 (0.0822)	0.0108 (0.1117)	0.023316
Utah	0.0027 (0.0001)	4.7893 (0.4728)	0.0045 (0.0006)	-0.0532 (0.1128)	0.0616 (0.2148)	0.083185
Vermont	0.0041 (0.0000)	4.0776 (0.3111)	0.0045 (0.0006)	0.2008 (0.0884)	0.1361 (0.1986)	0.057901
Virginia	0.0032 (0.0001)	4.1208 (0.4397)	0.0045 (0.0006)	-0.0174 (0.0943)	-0.0427 (0.1776)	0.036368
Washington	0.0030 (0.0001)	5.3935 (0.4186)	0.0045 (0.0006)	-0.0324 (0.1389)	0.3612 (0.2520)	0.12505
Wisconsin	0.0032 (0.0001)	8.6153 (0.6810)	0.0045 (0.0006)	-0.0005 (0.0840)	0.1339 (0.1887)	0.03615

Table 8: **Summary of Three-Pass Methodology and Standard FM Results for 38 U.S. States**

State	Intercept (FM)	FM Risk Premia	Intercept (Three-Pass)	Risk Premia (10 PCs)	R^2g (10 PCs)
Alabama	0.0032	3.5432	0.0045	-0.0687	0.0561
Arizona	0.0026	1.2232	0.0045	-0.0352	0.0885
Arkansas	0.0033	6.5426	0.0045	-0.0461	0.0259
California	0.0033	3.5048	0.0045	0.1335	0.1225
Colorado	0.0026	3.0184	0.0045	0.0057	0.0581
Connecticut	0.0039	3.4534	0.0045	0.1376	0.0690
Delaware	0.0036	3.9384	0.0045	0.0149	0.0579
Florida	0.0036	2.4611	0.0045	-0.0276	0.1163
Georgia	0.0029	2.9765	0.0045	-0.1988	0.0695
Illinois	0.0034	7.9214	0.0045	0.0496	0.0205
Indiana	0.0033	6.3605	0.0045	-0.0369	0.0223
Kansas	0.0035	13.2899	0.0045	0.1740	0.0135
Maryland	0.0036	3.9366	0.0045	0.0396	0.0541
Massachusetts	0.0040	3.1338	0.0045	0.1709	0.0745
Michigan	0.0037	5.9018	0.0045	0.1202	0.0370
Minnesota	0.0030	10.4652	0.0045	0.1800	0.0357
Missouri	0.0031	8.4247	0.0045	0.0993	0.0260
Nebraska	0.0035	10.5453	0.0045	0.2506	0.0322
Nevada	0.0028	5.0350	0.0045	0.1515	0.1004
New Hampshire	0.0041	3.5899	0.0045	0.1583	0.0644
New Jersey	0.0038	3.6784	0.0045	0.1188	0.0610
New Mexico	0.0027	3.3317	0.0045	-0.0741	0.0576
New York	0.0039	5.4023	0.0045	0.0396	0.0335
North Carolina	0.0032	3.1731	0.0045	-0.0066	0.0590
Ohio	0.0034	4.8174	0.0045	-0.0136	0.0288
Oklahoma	0.0035	7.2914	0.0045	0.0739	0.0305
Oregon	0.0029	5.2903	0.0045	0.3072	0.1205
Pennsylvania	0.0036	4.9061	0.0045	0.0380	0.0334
Rhode Island	0.0039	3.0597	0.0045	0.1747	0.0791
South Carolina	0.0035	3.7742	0.0045	-0.0364	0.0561
South Dakota	0.0032	9.9079	0.0045	0.3127	0.0476
Tennessee	0.0035	5.0632	0.0045	-0.0060	0.0322
Texas	0.0030	5.5146	0.0045	0.0108	0.0233
Utah	0.0027	4.7893	0.0045	0.0616	0.0832
Vermont	0.0041	4.0776	0.0045	0.1361	0.0579
Virginia	0.0032	4.1208	0.0045	-0.0427	0.0364
Washington	0.0030	5.3935	0.0045	0.3612	0.1251
Wisconsin	0.0032	8.6153	0.0045	0.1339	0.0362

Table 9: **Three-Pass Procedure Methodology Results for Selected States**. This table presents the empirical results from the Standard Fama-MacBeth (FM) methodology and the Three-Pass Regression Filter (3PRF) methodology for selected U.S. states. The estimates include intercepts and risk premia, with standard errors in parentheses. The results are shown for models using 4 and 10 principal components (PCs), along with the R_g^2 values for each factor.

Model	Alabama	Arizona	Arkansas	California	Illinois	Wisconsin
Standard FM (estimate - standard error)						
Intercept	0.0032	0.0026	0.0033	0.0033	0.0034	0.0032
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
FM risk premia	3.5432	1.2232	6.5426	3.5048	7.9214	8.6153
	(0.3912)	(0.3451)	(0.6665)	(0.3154)	(0.7056)	(0.6810)
Three-Pass (estimate - standard error)						
Using 4 PCs						
Intercept	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Risk premia	-0.0348	-0.0838	0.0213	-0.0082	0.0136	-0.0005
	(0.0990)	(0.1169)	(0.0887)	(0.1325)	(0.0854)	(0.0840)
R_g^2 for each factor	0.0353	0.0249	0.0129	0.0706	0.0079	0.0048
Using 10 PCs						
Intercept	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Risk premia	-0.0687	-0.0352	-0.0461	0.1335	0.0496	0.1339
	(0.1759)	(0.2181)	(0.1929)	(0.2252)	(0.1729)	(0.1887)
R_g^2 for each factor	0.0561	0.0885	0.0259	0.1225	0.0205	0.0361

Table 10: **Climate Transition Risk Factor Analysis by State (2000-2020)**. This table presents the empirical results for the standard Fama-MacBeth (FM) methodology and the Three-Pass Regression Filter (3PRF) methodology, using 4 and 10 principal components (PCs). The intercepts, risk premia, and R_g^2 values are reported with their standard errors in parentheses.

Model	Alabama	Arizona	Arkansas	California	Colorado
Standard FM (estimate - standard error)					
Intercept	0.0032	0.0026	0.0033	0.0033	0.0034
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Risk premia	1.0328	0.8495	0.8332	0.8166	0.7338
	(0.0729)	(0.0711)	(0.0700)	(0.0752)	(0.0691)
Three-Pass (estimate - standard error)					
Using 4 PCs					
Intercept	0.0045	0.0045	0.0045	0.0045	0.0045
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Risk premia	0.7799	0.7743	0.8074	0.6732	0.7567
	(0.4464)	(0.4525)	(0.4262)	(0.4244)	(0.4388)
R_g^2 for each factor	0.7817	0.8467	0.8411	0.7480	0.8868
Using 10 PCs					
Intercept	0.0045	0.0045	0.0045	0.0045	0.0045
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Risk premia	0.8723	0.7250	0.6093	0.9173	0.8280
	(0.4322)	(0.3729)	(0.3774)	(0.4144)	(0.3682)
R_g^2 for each factor	0.9083	0.9334	0.9437	0.8938	0.9630

Table 11: **Comparison of Risk Premia for Observed and Latent Factors for Portfolios of Small Firms.** *Notes: This table compares the estimated intercepts, risk premia, and standard errors obtained from the Standard Fama-MacBeth (FM) model and the Three-Pass Regression Filter methodology proposed by Giglio and Xiu. The analysis includes both observed and latent factors, with results based on 10 principal components. Additionally, the R_g^2 values for each factor are provided for the Three-Pass Regression Filter methodology.*

Model	**Factor**	**Standard FM**			**Giglio and Xiu (10 PCs)**			$\mathbf{R_g^2}$
		Intercept	**Risk Premia**	**Std. Error**	**Intercept**	**Risk Premia**	**Std. Error**	
CPU	-	0.0034	1.5724	0.0965	0.0032	0.3724	0.2771	0.5604
FF3	MKT	-0.0012	-0.3094	0.3332	0.0032	0.2670	0.1596	0.0506
	SMB		2.9543	0.3578		0.1987	0.1772	0.0285
	HML		-3.7215	0.2467		-0.4875	0.2013	0.1178
FF5	MKT	-0.0012	-1.3807	0.3216	0.0032	0.2670	0.1596	0.0506
	SMB		1.7671	0.3603		0.1905	0.1730	0.0278
	HML		-2.1182	0.2576		-0.4877	0.2013	0.1178
	RMW		-2.9884	0.2255		-0.3842	0.2189	0.1381
	CMA		-3.1161	0.1927		-0.6587	0.2142	0.1498
EPU_US	-	0.0010	0.7616	0.1029	0.0032	-0.0844	0.3073	0.3313
ECON_US	-	0.0010	0.3660	0.1137	0.0032	-0.2404	0.2891	0.3293
Tanomalies	-	0.0040	7.2464	0.2943	0.0032	0.2298	0.1797	0.0542
EPU_States	-	-0.0014	-1.0040	0.1055	0.0032	-0.0001	0.2763	0.3354
ECON_States	-	0.0010	0.5446	0.1146	0.0032	-0.2575	0.2737	0.3426
PCI_US	-	0.0010	1.4894	0.0956	0.0032	0.3916	0.3133	0.4435

Table 12: **Comparison of Risk Premia for Observed and Latent Factors for Portfolios of Larger Firms.** *Notes: This table compares the estimated intercepts, risk premia, and standard errors obtained from the Standard Fama-MacBeth (FM) model and the Three-Pass Regression Filter methodology proposed by Giglio and Xiu. The analysis includes both observed and latent factors, with results based on 10 principal components. Additionally, the R_g^2 values for each factor are provided for the Three-Pass Regression Filter methodology.*

Model	**Factor**	**Standard FM**			**Giglio and Xiu (10 PCs)**			$\mathbf{R_g^2}$
		Intercept	**Risk Premia**	**Std. Error**	**Intercept**	**Risk Premia**	**Std. Error**	
CPU	-	0.0056	0.6649	0.0890	0.0059	0.2742	0.1870	0.5470
FF3	MKT	0.0058	1.9448	0.3693	0.0059	-0.0232	0.0893	0.0372
	SMB		-1.7213	0.3421		-0.0609	0.1045	0.0384
	HML		0.7474	0.2099		0.0271	0.1368	0.1059
FF5	MKT	0.0057	1.7602	0.3617	0.0059	-0.0232	0.0893	0.0372
	SMB		-2.1089	0.3310		-0.0662	0.1030	0.0383
	HML		0.9840	0.2081		0.0270	0.1368	0.1058
	RMW		-0.0328	0.2416		0.0152	0.1555	0.1195
	CMA		0.4966	0.2450		-0.0382	0.1264	0.0851
EPU_US	-	0.0055	0.4146	0.1211	0.0059	-0.1967	0.2619	0.5096
ECON_US	-	0.0059	0.9147	0.1118	0.0059	0.3156	0.2380	0.5474
Tanomalies	-	0.0055	3.0963	0.3239	0.0059	0.1868	0.1148	0.0661
EPU_States	-	0.0055	0.4382	0.1253	0.0059	-0.2782	0.2548	0.5006
ECON_States	-	0.0060	1.0286	0.1131	0.0059	0.4215	0.2501	0.5006
PCI_US	-	0.0054	0.7807	0.1009	0.0059	0.3792	0.2436	0.4986

Table 13: **Regression Results of Principal Components on Mimicking Portfolios and Climate Policy Uncertainty (CPU_{US}) in the U.S.**
Notes: This table presents the regression coefficients, T-statistics, correlations, and mean returns for the first five principal components. The results provide insights into the relationship between principal components derived from mimicking portfolios and the Climate Policy Uncertainty index.

PC	**Coefficient**	**T-Statistic**	**Correlation**	**Mean-Return**
1	1.6494	18.6356	0.7470	-4.4262e-17
2	0.5876	5.7017	0.3251	2.6393e-16
3	0.4518	5.3656	0.3078	-1.0725e-16
4	-0.2920	-4.4630	-0.2599	-8.5088e-17
5	-0.0467	-0.7336	-0.0442	9.1633e-17

Table 14: **Regression Results of Principal Components on Mimicking Portfolios and Economic Policy Uncertainty (EPU_{US}) in the U.S.**
Notes: This table presents the regression coefficients, T-statistics, correlations, and mean returns for the first five principal components. These results provide insights into the relationship between principal components derived from mimicking portfolios and the Economic Policy Uncertainty index in the U.S.

PC	Coefficient	T-Statistic	Correlation	Mean-Return
1	0.9679	7.6212	0.4176	-4.4262e-17
2	0.2222	2.0542	0.1229	2.6393e-16
3	-0.4998	-6.0067	-0.3406	-1.0725e-16
4	-0.0230	-0.3392	-0.0204	-8.5088e-17
5	-0.1371	-2.1690	-0.1297	9.1633e-17

Table 15: **Regression Results of Principal Components on Mimicking Portfolios and Economic Conditions Indicator ($ECON_{US}$) in the U.S.**
Notes: This table presents the regression coefficients, T-statistics, correlations, and mean returns for the first five principal components. The analysis explores the relationship between principal components derived from mimicking portfolios and the Economic Conditions Indicator at the national level in the U.S.

PC	Coefficient	T-Statistic	Correlation	Mean-Return
1	1.3348	10.5169	0.5356	-4.4262e-17
2	0.4233	3.9958	0.2342	2.6393e-16
3	0.2468	2.8289	0.1682	-1.0725e-16
4	0.8140	17.4259	0.7244	-8.5088e-17
5	-0.1317	-2.0816	-0.1245	9.1633e-17

Table 16: **Regression Results of Principal Components on Mimicking Portfolios and Temperature Anomalies ($Tanomalies$) in U.S. States**
Notes: This table presents the regression coefficients, T-statistics, correlations, and mean returns for the first five principal components. These results highlight the relationship between principal components derived from mimicking portfolios and temperature anomalies across various U.S. states.

PC	Coefficient	T-Statistic	Correlation	Mean-Return
1	1.3853	10.0809	0.5195	-4.4262e-17
2	0.3569	3.3411	0.1975	2.6393e-16
3	1.0371	16.5643	0.7067	-1.0725e-16
4	-0.2320	-3.4991	-0.2065	-8.5088e-17
5	0.2523	4.0741	0.2386	9.1633e-17

Table 17: **Regression Results of Principal Components on Mimicking Portfolios and Economic Policy Uncertainty (EPU_{States}) at State Level**
Notes: This table presents the regression coefficients, T-statistics, correlations, and mean returns for the first five principal components. The findings illustrate the relationship between principal components derived from mimicking portfolios and the Economic Policy Uncertainty index at the state level in the U.S.

PC	Coefficient	T-Statistic	Correlation	Mean-Return
1	0.6017	4.5217	0.2631	-4.4262e-17
2	0.1785	1.6462	0.0988	2.6393e-16
3	0.2586	2.9688	0.1762	-1.0725e-16
4	-0.9154	-23.2978	-0.8147	-8.5088e-17
5	0.0043	0.0669	0.0040	9.1633e-17

Table 18: **Regression Results of Principal Components on Mimicking Portfolios and Economic Conditions Indicator ($ECON_{States}$) at State Level**
Notes: This table presents the regression coefficients, T-statistics, correlations, and mean returns for the first five principal components. The analysis explores the relationship between principal components derived from mimicking portfolios and the Economic Conditions Indicator at the state level in the U.S.

PC	Coefficient	T-Statistic	Correlation	Mean-Return
1	1.2638	9.9375	0.5140	-4.4262e-17
2	0.4472	4.2351	0.2474	2.6393e-16
3	-0.1659	-1.8869	-0.1131	-1.0725e-16
4	0.8631	19.8919	0.7681	-8.5088e-17
5	-0.1773	-2.8212	-0.1677	9.1633e-17