# Environmental Policy Uncertainty and Sustainable Investing

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Sanjana Kadyan

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Adviser: Alan Finkelstein Shapiro

Uncertainty regarding implementation of environmental policies is a significant regulatory risk for investors and firms. Employing a monthly panel fixed-effects model (2010-2019) for firms of the Russell 3000 Index, I estimate that a rise in US environmental policy uncertainty is associated with higher stock price volatility and lower stock returns for firms belonging to sectors more exposed to environmental risks such as oil & gas and metals & mining. Vector Autoregressive model results also confirm similar adverse effects of environmental policy uncertainty on outcomes of energy sector-focused exchange traded funds (ETFs). These uncertainty shocks have spillover effects on other key sustainable markets as well. However, while environmental policy uncertainty matters for financial market outcomes of firms exposed to ESG risks, macroeconomic policy uncertainty matters more. This has implications of insufficient ESG-risk pricing in financial markets.

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## INTRODUCTION

Climate change is one of the most critical macroeconomic and financial policy challenges that countries are to face in the coming decades. While global investment needs to limit global warming to a 1.5$^{o}$ C pathway are estimated to be ranging from USD 3 trillion to USD 6 trillion per year until 2050, current global climate finance levels are at an insufficient USD 630 billion per year (IMF, 2022). It is, therefore, imperative to understand the barriers to mobilizing sustainable investment.

A 2021 global climate-finance survey of 861 sophisticated academicians and practitioners suggests regulatory risk to be the most important climate-related risk for investors and firms over the next five years (Stroebel and Wurgler 2021). Uncertainty regarding implementation of environmental regulations and policies severely complicates the valuation of long-term investments in sectors like energy and infrastructure. This may prevent capital from flowing into low-carbon sectors (Martinex-Diaz and Keenan 2020). Firms' expectations about future climate policy trajectories also influences their decisions about adopting green technologies (Basaglia et al. 2022), thereby having implications for climate mitigation.

Further, an abrupt implementation of ambitious climate policy after decades of delay could induce a cascading effect on investors' portfolios and have systemic implications for financial stability (Carney 2015, Battiston 2019, and Rudebusch 2021). Understanding investor behavior in response to policy uncertainty, therefore, has implications for building a robust and predictable environmental regulatory architecture (Goulder 2020).

In this paper, I estimate the effects of environmental and climate policy uncertainty on sustainable financial markets. To this end, I utilize Noailly et al. (2022)'s novel newspaper text-search based monthly index as a quantitative measure of US environmental policy uncertainty (EnvPU). Utilizing supervised machine learning methods on the text of news articles extracted from ten leading US newspapers, Noailly et al. (2022) construct the US environmental policy uncertainty index (EnvPU). The index represents the monthly share of environmental policy uncertainty articles over all environmental and climate policy articles, normalized to an average value of 100 over the 1990-2019 period. An increase in the EnvPU index, therefore, denotes a rise in prevailing US policy uncertainty amid ongoing discussions on environmental and climate policy.

To assess how sustainable financial markets respond to US environmental policy uncertainty shocks, I adopt two approaches. The first approach is a firm-level analysis whereby I exploit firm-level differences in exposure to environmental risks – measured by Environmental, Social and Governance (ESG) rating agencies – to estimate the effects of environmental policy uncertainty working through this channel. Employing a monthly panel fixed effects model over the January 2010 to March 2019 period for US firms on the Russell 3000 Index, I estimate if there is a stronger empirical association between US environmental policy uncertainty and financial outcomes for firms belonging to sectors more exposed to environmental risks compared to other firms.

To measure this exposure to environmental risks, I utilize information on sector-level Environmental Risk scores provided by leading Environmental, Social and Governance (ESG) rating agencies of the world. I provide more detail on these risk scores in Section 3. The idea of ESG-based investing first emerged in a 2006 United Nations Principles for Responsible

Investment (PRI) report and has become more salient for financial markets only in the last decade (Kell 2018, and Atkins 2020). Therefore, I focus my firm-level analysis from January 2010 onwards. The period of analysis also enables removing the potential endogenous effects of an unprecedented rise in general economic uncertainty during the Great Financial Crisis (GFC) of 2008.

Further, I assess potential spillover effects of environmental policy uncertainty in the United States, which is the second largest player in the global sustainable funds market after Europe, on financial outcomes of firms domiciled in the United Kingdom (UK), Germany and India. While the UK and the European Union (EU) members like Germany have made significant progress in developing domestic sustainable finance policies and markets, India is an emerging market in the context of global cooperation in green finance (International Institute of Green Finance (2021)). Understanding the transmission effects of uncertain US environmental policy across these markets will provide valuable information to policymakers for building domestic green finance development strategies.

My second empirical approach is to estimate a vector autoregression (VAR) for assessing the dynamic effects of environmental policy uncertainty on funds flowing into the energy sector, a sector most exposed to ESG risks. I estimate monthly VAR models for the US economy to examine the effect of an environment policy uncertainty shock on volatility and return of Energy sector focused Exchange Traded Funds (ETFs). Considering Oil & Gas ETFs and Clean Energy ETFs, the dynamic effects of these VAR models help understand whether financial outcomes in response to uncertain environmental policy depend on the nature of financial instrument and if investors respond differently to brown energy and green energy firms. The criteria for selection of these ETFs are based on their asset size, sector and country coverage and launch date of listing on a stock exchange to obtain the longest time series available. While Oil & Gas ETFs have existed on US stock exchanges since the early 2000s, ETFs providing coverage to the Clean Energy sector are a more recent phenomenon with the oldest such US-focused ETF launched in 2005.

Overall, I find that when US environmental policy uncertainty rises, domestic firms belonging to sectors that are most exposed to environmental risks, such as the oil & gas, metals & mining, and power generation sectors, witness higher stock price volatility and lower stock returns relative to less exposed firms. These firm-level uncertainty effects on stock price volatility are heterogenous by firm size, suggesting that the ability of firms to access own funds or to borrow from outside sources in the face of environmental policy uncertainty matters for sustainable investing outcomes. While small-cap and mid-cap US firms belonging to exposed sectors bear greater adverse effects of an environmental policy uncertainty shock, large-cap and mega-cap firms of such sectors experience volatility declines and lower return losses relative to smaller firms.

At the aggregate level, an increase in US environmental policy uncertainty growth is associated with greater price volatility and lower returns for Energy sector-focused Exchange Traded Funds. In line with firm-level effects by firm size, the volatility gains are higher for Energy ETFs with mid-cap and small-cap firm exposure relative to large-cap Energy ETFs.

Uncertainty about US environmental policy not only impacts domestic investors but also spillovers to the developed sustainable finance markets of UK and Germany, and emerging markets of India.

Similar to the effects on US firms, domestic firms on the London Stock Exchange belonging to environmentally risky sectors experience volatility gains and stock return losses in response to greater unpredictability about US environmental policy action. On the other hand, the volatility and returns effects of this shock on the German and Indian stock exchanges are mixed and potentially guided by the degree of advancement of green finance and clean transition in these economies.

Finally, while environmental policy uncertainty matters for financial outcomes of firms and ETFs exposed to environmental risks, general macroeconomic policy uncertainty matters more. Utilizing the Economic Policy Uncertainty Index of Baker, Bloom, and Davis (2016), I find that the firm-level volatility effect of a US environmental policy uncertainty shock is only $1/10^{th}$ of the size of the effect of a general economic policy uncertainty shock. Similarly, the rise in price volatility of Energy ETFs in response to higher macroeconomic policy uncertainty is 4 to 6 times the effect of an uncertain environmental policy regime. This has implications of insufficient climate-risk pricing by investors and necessitates work towards systematic accounting of sustainability criteria in financial markets.

The rest of the paper is organized as followed. Section 2 reviews the literature on the measurement of policy uncertainty and its impact on financial markets and the economy. Section 3 provides details about the data. Section 4 discusses the empirical strategy used in this study and provides the results. Section 5 concludes.

## II. LITERATURE REVIEW

Economic literature has highlighted the role of policy uncertainty in firms' investment decisions for a long time (Bernanke 1983, McDonald and Siegel 1986, Handley and Limão 2015, and Hasset and Metcalf 2019). However, systematic measurement of policy uncertainty, a fundamentally unobserved phenomenon, began only in the last decade. Baker, Bloom, and Davis (2016) developed a newspaper coverage frequency-based index of economic policy uncertainty and estimated its adverse effects on firm-level and aggregate investment for the US. More recently, new proxies of policy uncertainty have been developed for different policy domains, such as political risk (Hassan et al. 2019) and trade policy (Caldara et al. 2020).

However, theoretical, and empirical work in the domain of environmental policy uncertainty is still at a nascent stage. While Engle et al. (2020) developed proxies of regulatory climate risk to explore climate risk pricing in equity markets, Gavriilidis (2021) and Basaglia et al. (2021) employed the newspaper search strategy to build US climate policy uncertainty indices. Berestycki et al. (2022) extended this work to 12 other OECD countries with sub-indices also capturing the direction of climate policy uncertainty (that is, the acceleration or deceleration of decarbonization). The most recent work of Noailly et al. (2022) moves beyond dictionary-based news-search methods and utilizes supervised machine-learning to build a much broader US environmental and climate policy news and uncertainty index.

With quantitative measures of environmental policy uncertainty having been developed recently, emerging econometric contributions, while still limited, are helping to quantify the effects of this uncertainty on firm-level and aggregate outcomes. Employing a general equilibrium, production-based asset pricing model, Barnett (2020) estimates an accelerated oil extraction and a consequent fall in oil reserves, oil spot price and value of oil firms in response to risk and uncertainty of climate policy. Gavriilidis (2021) employs a Vector Autoregression methodology over the 2000-2020 period to find a strong and negative effect of US climate policy uncertainty (CPU) on aggregate and sectoral $CO_2$ emissions. On the other hand, Noailly et al. (2022) show an adverse macro effect of US environmental policy uncertainty (EPU) on low-carbon investments, specifically lower number of US cleantech venture capital deals and higher volatility of benchmark US clean energy exchange trade fund, PBW.

While these macro-level results offer useful evidence for the aggregate effects of environmental policy uncertainty, causal inference is challenging. To this end, Barnett (2020), Berestycki et al. (2022), and Noailly et al. (2022) provide evidence of the causal effects of environmental policy uncertainty on firm-level macroeconomic and financial outcomes. Using a global firm-level panel dataset (1990-2018) with industry-level carbon intensity as a proxy for exposure to climate policy risk, Berestycki et al. (2022) estimate a panel fixed effects model to estimate that more pollution-intensive firms experience higher implied stock price volatility and lower share prices, R&D efforts, and employment in response to environmental policy uncertainty. These effects are found to be stronger for larger and more capital-intensive firms. On the other hand, Noailly et al. (2022) provide evidence that environmental policy uncertainty is associated with a rise in stock market volatility of the greenest firms and lower low-carbon investment. Proxying climate policy exposure by model-predicted exposure to oil price shocks, Barnett (2020) employs cross-sectional regressions to estimate that in response to policy events that reduce the likelihood of future climate policy action, the most exposed sectors experience the largest increase in returns.

These quantitative measures have paved the way for new research on climate policy uncertainty. However, the conclusions of these studies are potentially dependent on the firm-level proxies of climate risk exposure as well as drivers of environmental policy uncertainty (Berestycki et al., 2022). Also, the predicted effects of environmental policy uncertainty may be different for green firms and brown firms (Barnett 2020).

I contribute to this literature by assessing the effects of environmental policy uncertainty on firm-level outcomes through the novel channel of firm-level exposure to Environmental, Social and Governance (ESG) risk, as measured by ESG rating agencies. Given the rise in the availability and salience of information on ESG risk in the last decade, this analysis provides useful information about how investors are absorbing ESG-related information in the face of policy uncertainty. Secondly, I contribute to the literature exploring the interactions between policy uncertainty, firm-level outcomes and financial leverage (Ballentine et al. 1993, and Kaya and Schildbach 2018) by identifying the relevance of firm size for stock outcomes in response to an environmental policy uncertainty shock. Finally, I complement the currently limited literature on the transmission effects of policy uncertainty shocks (Balcilar et al. 2020, and Londono, Ma, and Wilson 2021) by analyzing the same in the environmental policy domain.

## III. DATA AND DESCRIPTIVE STATISTICS

The data used in this study are from four main sources: (1) Noailly et al. (2022) (https://www.financingcleantech.com), (2) Baker, Bloom, and Davis (2016) (http://www.policyuncertainty.com), (3) ESG Ratings databases of S&P Global, MSCI and Bloomberg, and (4) Equity and Exchange Traded Fund (ETF) databases of Bloomberg and Morningstar Manager Research.

I retrieve newspaper-search based monthly indices of Environmental Policy Uncertainty (EnvPU) and Environmental Policy News (EnvP) for the United States from Noailly et al. (2022). Utilizing automated methods on the text of news articles extracted from ten leading US newspapers, Noailly et al. (2022) adopt a two-step procedure to construct the EnvP and EnvPU indices over the 1981-2019 period.[1] Firstly, the authors build a supervised machine learning algorithm to identify a sample of 80,045 newspaper articles about US environmental and climate policy from the total volume of 15 million news articles on the Dow Jones Factiva's platform. Scaling the monthly count of environmental and climate policy articles by the total monthly volume of news articles and normalizing it to an average value of 100 over the 1981-2019 period, the authors construct the US environmental policy index (EnvP). The EnvP index, shown in Figure 1, correctly captures crucial events in the history of US environmental policy, such as major UNFCCC climate change conferences, adoption of the 2001 National Energy Plan during George Bush's Presidency, Barack

[1] The list of newspapers includes New York Times, Washington Post, Wall Street Journal, Houston Chronicle, Dallas Morning News, San Francisco Chronicle, Boston Herald, Tampa Bay Times, San Jose Mercury News and San Diego Union Tribune (Noailly et. al. 2022).

Obama's signing of the Green New Deal into law in February 2009 and Donald Trump's announcement of withdrawal from the Paris agreement in June 2017.

The authors, subsequently, utilize a second supervised machine learning algorithm to identify policy uncertainty news within the subset of 80,045 environmental and climate policy news articles. Noailly et al. (2022) classify a set of 25,174 policy uncertainty related articles which specifically capture: a) policy shifts or reversal of environmental regulations, b) challenges in adoption and implementation of environmental policies such as political roadblocks, business resistance and legal issues, c) uncertainty about interpretation of rules, timing of adoption and enforcement and, d) other policies like trade disputes impacting clean markets. The authors consider articles as relevant only if they depict rising levels of current and future environmental and climate policy uncertainty and drop those articles which refer to past, declining or resolved policy uncertainty. To ensure that the environmental policy uncertainty index does not capture non-policy related uncertainty, the authors also exclude articles mentioning the uncertain impacts of climate change.

Finally, Noailly et al. (2022) construct the US environmental policy uncertainty index (EnvPU), as representing the monthly share of environmental policy uncertainty articles over all environmental and climate policy articles, normalized to an average value of 100 over the 1990-2019 period. An increase in the EnvPU index, therefore, denotes a rise in prevailing US policy uncertainty amid ongoing discussions on environmental and climate policy (EnVP). Figure 2 demonstrates a peaking of the EnvPU index at the end of 1995 when the US government momentously shut down for several weeks due to disagreements between Republican speaker

Newt Gingrich and then President Bill Clinton over cuts in environmental regulations and other spending programs. Uncertainty rose again in 2003 when the Senate rejected Bush administration's Energy Bill introduced in the early 2000s and courts blocked relaxations in pollution rules. While US environmental policy uncertainty declined 2004 onwards, it rose 40 per cent above its average level at the beginning of 2010s decade when the Senate called off Barack Obama's climate bill to cap carbon emissions. The EnvPU index skyrocketed again in 2017 and reached 60 per cent above average in the early months of Donald Trump's presidential tenure when there was heightened uncertainty regarding the extent of deregulation and replacement of existing environmental laws.

To assess the impact of US environmental policy uncertainty on sustainable financial markets, I adopt two approaches. The first approach is to investigate the effects of US environmental policy uncertainty on firm-level outcomes of 30-day realized stock price volatility and monthly stock return for publicly listed US firms on the Russell 3000 Index. The Russell 3000 Index measures the performance of the largest 3,000 US companies representing approximately 96% of the investable US equity market, as of the most recent reconstitution. I draw information on these firm-level outcomes from the Bloomberg equity database.

Employing a monthly panel fixed effects model over the January 2010 to March 2019 period, my identification strategy differentiates these firms by their exposure to uncertainty about environmental policy. Specifically, the model estimates whether firms with higher exposure to environmental policy uncertainty are more responsive to variations in this policy uncertainty. To measure this firm-level exposure, I utilize information on Standard & Poor Global's "ESG Risk Atlas". S&P Global is one of the leading Environmental, Social and Governance (ESG) rating agencies of the world. Its ESG Risk Atlas, published in July 2020, provides a global relative assessment of ESG risk exposures faced by sectors and regions.[2] Table 1 provides a description for all variables utilized in the firm-level analysis and Table 2 provides summary statistics.

Since such ESG-risk related information underlying the firm-level identification strategy has become salient in financial markets only in the last decade, I focus my firm-level analysis from January 2010 onwards. Additionally, general economic uncertainty tends to rise during economic activity downturns and fall during booms (Bloom, 2014). The chosen period of firm-level analysis (2010-2019), therefore, also enables removal of the potential endogenous effects of an unprecedented rise in global economic uncertainty during the Great Financial Crisis (GFC) of 2008.

S&P Global's ESG Risk Atlas comprises of three components: a) Sector Risk Scores (Environmental & Social), b) Regional Risk Scores and c) Governance Scores. Sector Risk Scores (Environmental) are a measure of the relative exposure of a GICS®-aligned sector to material environmental risks and opportunities. S&P Global Ratings captures the materiality of these risks across a sector's value chain by combining insights from their credit analysts located globally and from public assessments (such as those from the United Nations supported Principles for Responsible Investment, World Bank, World Health Organization, and Transparency

[2] Florence Devevey, Bruno Bastit, *Environmental, Social, And Governance: The ESG Risk Atlas: Sector And Regional Rationales And Scores* (S&P Global Ratings, 2020), https://www.spglobal.com/ratings/en/research/articles/200722-environmental-social-and-governance-the-esg-risk-atlas-sector-and-regional-rationales-and-scores-11582800.

International). Their sector-level analysis, denoted as Key Sustainability Factors for ESG Evaluations (KSFs), identify the most material environmental risks assessed in their ESG Evaluation.

The materiality of these risks across the industry's value chain are reflected in a weighting of four environmental factors. These factors are, a) greenhouse gas emissions, b) waste and pollution, c) water, and d) land use and biodiversity. The analysis also provides the quantitative and qualitative indicators used to assess a company's performance relative to its industry peers on each of these environmental factors.

Finally, the ESG Risk Atlas provides a weighted Sector Risk Score (Environmental) on a scale of 1-6 and allows comparisons between Global Industry Classification Standard (GICS) sub-industries. These sub-industry scores are subsequently averaged to provide sector-level scores for 24 GICS aligned sectors. A score closer to 1 represents a relatively low exposure of a GICS-aligned sector to environmental risks and a score closer to 6 represents higher exposure to these risks. Table 3 displays S&P Global's Environmental Risk Scores by GICS-aligned sectors.

I also control for financial variables impacting firm-level financial outcomes such as firm size (proxied by natural logarithm of market capitalization), profitability (proxied by return on assets) and leverage (total debt over total equity). Data on these indicators is drawn from the Bloomberg equity database.

To ensure robustness of the firm-level analysis, I also consider an alternative sector-level measure of exposure to environmental risk provided by another ESG rating agency MSCI. I utilize information on MSCI's "ESG Industry Risk Intensity Score" by GICS Sector from the agency's database issued in 2020.[3] MSCI's industry risk intensity methodology takes a bottom-up, data-driven approach to determine the relative magnitude of the ESG risks faced by different industries. Metrics such as carbon emissions, hazardous waste outputs, accident rates, product recalls, labor intensity, and perceived corruption prevalence are captured at the individual company business segment level and translated to a 1-10 decile score designed to allow comparisons between the 158 Global Industry Classification Standard (GICS) sub-industries. Table 4 displays MSCI's ESG Industry Risk Intensity score by 11 GICS-aligned sectors.

For further validity tests, I construct two additional exposure measures: a) greenhouse gas (GHG) intensity and, b) ESG ratings. I collate annual firm-level information, available from 2013 to 2023, on GHG intensity per unit of sales from the Bloomberg database. Greenhouse gas (GHG) intensity is calculated as metric tonnes of greenhouse gases in carbon dioxide equivalent (CO2e) emitted from direct operations per million of sales revenue in the company's reporting currency. I average the annual firm-level GHG intensity over these years to obtain the average GHG emissions intensity for every firm. Subsequently, I construct the exposure measure, the GHG emissions intensity for each two-digit sector as per GICS sector classification, by taking an average of the firm-level scores. Higher is the sector-level GHG emissions intensity, higher is the sector exposure

[3] Ankit Sayani, Bentley Kaplan, *Comparing Risk and Performance for Absolute and Relative ESG Scores An Empirical Analysis Using MSCI ESG Scores* (MSCI ESG Research LLC, 2020), https://www.msci.com/documents/10199/a645d4ff-b83e-426a-4636-e6fb81bbc599.

to environmental risk. Table 5 provides information on GHG Emissions Intensity per unit of sales by GICS-aligned sectors.

Typically, firms with lower ESG ratings, as per ESG rating methodologies, are more likely to be exposed to high ESG-related risk and are less successful in managing their exposure. Therefore, lower is the firm-level Environmental rating, higher is the firm’s exposure to environmental risk. To construct this exposure measure, I draw information on monthly Environmental ratings assigned to a firm by two ESG Ratings agencies, S&P Global and Bloomberg, both available on the Bloomberg ESG database. Information on firm-level monthly ESG metrics of both these agencies is available from 2015 onwards. Each firm’s exposure to environmental policy risk is measured by the Environmental rating assigned to it by the ESG rating agency. I average monthly firm-level Environmental ratings over time to obtain the exposure measure, the average Environmental rating for every firm. Table 1 provides definitions of both ratings and Table 6 provides information on these Environmental Ratings by GICS-aligned sectors.

To isolate the effect of US environmental policy uncertainty from uncertainty in macroeconomic and general economic policy in the firm-level and VAR analysis, I collate country-level data on general economic policy uncertainty indices for US, United Kingdom, Germany and India. I retrieve this data from Baker, Bloom, and Davis (2016) and http://www.policyuncertainty.com. Further, I collect data on additional macroeconomic controls from the Federal Reserve Bank of St. Louis database and Bloomberg database that may influence the valuation of firms belonging to sectors exposed to environmental risks. These include the monthly US Crude Oil West Texas Intermediate Cushing OK Spot Price growth and volatility, US Federal Funds effective rate, 30-day expected volatility of the U.S. stock market and return of Vanguard Total World Stock Index

Fund. Finally, I collect data on standard financial variables affecting firm-level financial outcomes such as market capitalization, return on assets and the ratio of total debt to total equity.

Europe is a global leader of the sustainable fund landscape with the most developed and diverse ESG market and contributes 83% of global sustainable fund assets (Morningstar 2022). EU member Germany and United Kingdom (UK) are leading sustainable finance hubs (International Institute of Green Finance 2021). These countries have shown commitment to sustainability through legislation and witnessed a rising share of sustainability funds to their net assets and market share in the European sustainable fund market (German Federal Ministry of Finance 2021, and HM Government 2023). On the other hand, India's rising sustainable debt issuance since 2016 and recent announcements of climate finance policies under the G20 Presidency, is helping it develop into an emerging player in the sustainable finance context (Robins 2023).

To assess potential spillover effects of environmental policy uncertainty in the United States, the second largest player in the global sustainable funds market, across the leading sustainable financial markets of UK and Germany, and India, a key emerging market in the context of climate financing, I collect data on the above-mentioned firm-level outcomes for all publicly-listed domicile companies on the Frankfurt Stock Exchange, London Stock Exchange, and India's BSE S&P 500 index. Tables 7(a-c) provide summary statistics of variables for each of these markets' firm-level analysis.

The second empirical approach uses a vector-autoregressive framework to study the dynamic relationship between environmental policy uncertainty and sustainable equity investment flowing into the Energy sector, a sector highly exposed to environmental risks (highest sector-level Environmental Risk Score). I collate financial outcomes on equity exchange traded funds (ETFs) providing exposure to firms belonging to the Energy sector. I consider US-focused and global Energy Sector Exchange Traded Funds (ETFs) covering the Oil & Gas and Clean Energy sub-sectors.

The upstream and downstream Oil & Gas sector is intrinsically exposed to environment risks associated with greenhouse gas emissions, pollution, and impact on biodiversity. While the oil exploration and production sub-sector is highly sensitive to long-term oil prices and the pace of a country's energy transition, the oil refineries sub-sector is exposed to significant environmental regulation and long-term trends of oil demand . The natural gas sector, which is a low carbon emitter relative to coal-fired power plants, is expected to serve as a key bridge for countries' energy transition policies until renewable/clean energy sectors are sufficiently developed. Clean energy investments, on the other hand, are exposed to land use risk and are significantly reliant on public policies for scaling up (Florence and Bastit, 2020). Given high exposure of the Oil & Gas and Clean Energy sectors to environmental risks, investments in these sectors, are therefore, primary candidates to be impacted by uncertainty in environmental policy.

Utilizing a global landscape of exchange traded funds (ETFs) provided by Morningstar Manager Research, Bloomberg, Vettafi, ETF.com and Financial Times Database, I identify five Energy ETFs: two Oil & Gas ETFs and three Clean Energy ETFs. These include US-focused ETFs such as Energy Select Sector SPDR® Fund (XLE), iShares U.S. Oil & Gas Exploration & Production ETF (IEO) and Invesco WilderHill Clean Energy ETF (PBW) launched on US stock exchanges.

To evaluate potential spillover effects of US environmental policy uncertainty on global financial markets, I also consider Energy ETFs focused on global markets such as Invesco Global Clean Energy ETF (PBD) and NORDEA 1: Global Climate and Environment Fund (NORDEA). My criteria for selection of these ETFs are based on their asset size, sector and country coverage and launch date of listing on a stock exchange to obtain the longest time series available. Table 8 provides a description of these ETFs. I draw monthly outcomes of 30-day realized price volatility and share price for these ETFs, from the Bloomberg database. While Oil & Gas ETFs like XLE and IEO have existed since the early 2000s, the first US-focused clean energy ETF, PBW, was launched in 2005.

In addition to macroeconomic controls utilized under the firm-level analysis, I also consider sector-relevant controls for the VAR analysis which are expected to be co-moving with the key Energy ETFs in question. These include the US natural gas price proxied by the Henry Hub Natural Gas Spot Price, return and volatility of the Russell 3000 Technology Index, S&P Global 1200 Industrials Sector Index and return of the iShares Global Industrials ETF drawn from the Bloomberg database. Table 9 provide summary statistics on all variables of the VAR analysis.

## IV. EMPIRICAL STRATEGY AND RESULTS

### IV.1 Firm Level Effects

I construct a monthly balanced panel dataset of US firms listed on the Russell 3000 Index (January 2010 to March 2019) to estimate the effects of US environmental policy uncertainty (EnvPU) on two firm-level outcomes: stock volatility and stock return. Following Baker, Bloom, and Davis (2016), my identification strategy relies on a differentiation of firms according to their exposure to environmental policy uncertainty. Specifically, I focus on estimating whether firms experiencing a higher exposure to environmental risk respond more to variations in environmental policy uncertainty.

I utilize a novel measure of firm-level exposure to environmental risk. I consider S&P Global's Sector Environmental Risk Scores as a measure of environmental risks across the value chain faced by 24 GICS-aligned sectors. If the firm operates in a GICS®-aligned sector, then its exposure measure equals the corresponding sector exposure measure. Therefore, firms operating in sectors with higher Environmental Risk Scores are assumed to be more exposed to environmental policy uncertainty. I use a sector-level average exposure measure as it may be a better proxy for the firm's ex ante exposure to uncertainty in environmental policy.

At the top end, firms operating in the Oil and Gas sector (incorporating subsectors from SIC 10101010-10102030) and Metals and Mining sectors (SIC 151040) have the highest Environmental Sector Risk Score of 6, as shown in Table 2. Other high exposure sectors are Agribusiness & Agricommodities, Chemicals, and Power generators (SIC 10102050: Coal &

Consumable Fuels, Independent Power Producers (SIC 55105010) and Renewable Electricity Generators (SIC 55105020). On the other hand, environmental risk exposures are low in the Services sector (including education services), Media, Non-Banking Financial Institutions (NBFIs) and Health Care.

I estimate the following equation:

$$y_{it} = \beta_1(\log(EnvPU_t) * \log(AvgExposure_j)) + \beta_2 X'_{it} + \gamma_i + \delta_t + \varepsilon_{it} \qquad (1)$$

where $y_{it}$ is the monthly realized volatility of stock price in natural log form (log ($Volatility_{it}$)) or the monthly stock return ($Return_{it}$) of a US domiciled firm $i$ on the Russell 3000 Index in month t. The period of analysis is from Jan 2010 to March 2019, $EnvPU_t$ is the monthly US environmental policy uncertainty index in time period t and $AvgExposure_j$ is the exposure measure, the Environmental Risk score (as part of the S&P Global's ESG Risk Atlas) for a GICS-aligned sector j.

Firm fixed effects ($\gamma_i$) allow controlling for structural and time-invariant differences in financial outcomes at the firm level. Month fixed effects ($\delta_t$) control for underlying unobservable common shocks impacting all firms. I use robust standard errors and cluster them at the firm level to counter concerns of serial correlation across observations for a firm.

Further, I include a vector of controls, $X_{it}$ that is comprised of the $EnvP_t$ index, which captures the volume of environmental policy news, so that I identify the effect of environmental policy uncertainty (second moment) for a given level of news coverage of environmental policy matters (first moment). Secondly, I control for another general measure of policy uncertainty, the

Economic Policy Uncertainty ($EPU_t$) index drawn from Baker, Bloom, and Davis (2016), to assess if environmental policy uncertainty informs us of anything different from general economic policy uncertainty. Third, I control for monthly volatility (or growth) in the price of crude oil proxied by the West Texas Intermediate ($WTI_t$) since fluctuations in oil prices potentially affect financial outcomes of firms operating in sectors more exposed to environmental risks. All these controls are interacted by the logged value of the exposure measure $AvgExposure_j$ in the key specification. Finally, I control for standard macroeconomic and financial variables that explain firm-level stock outcomes. These include the US federal funds rate ($FEFR_t$), 30-day expected volatility of the U.S. stock market ($VIX_t$), Vanguard Total World Stock Index Fund ($VT\_RETURN_t$), logged value of market capitalization ($FIRMSIZE_t$), return on assets ($ROA_t$) and the ratio of total debt to total equity ($LEVERAGE_t$).

Table 10 reports results for the estimated effects of US environmental policy uncertainty ($EnVPU_t$) on 30-day realized stock price volatility of firms on the Russell 3000 Index. My estimates of interest are stated in the first row with standard errors denoted in parentheses. Column (1) reports a basic specification that regresses logged 30-day realized stock price volatility on logged $EnVPU_t$ index and logged value of the exposure measure $AvgExposure_j$. Logged $EnVPU_t$ index is statistically significant at the 1 percent level, with a coefficient of 0.060 indicating that a 1 percent $EnVPU_t$ increase is associated with a 0.06 percent increase in firm-level realized stock volatility. The positive coefficient on the control variable $AvgExposure_j$ in Column (1) says that, conditional on logged $EnVPU_t$, average firm-level historical volatility is higher when firm-level logged value of exposure to environmental policy uncertainty $AvgExposure_j$ is higher. The coefficient on logged $EnVPU_t$ drops in magnitude as I add all controls in the specification under

Column (2), include firm fixed effects under Column (3) and both firm fixed effects and month fixed effects under Column (4). The logged value of $AvgExposure_j$ term drops out under Column (3) and Column(4), as it is collinear with the firm effects.

Now, implementing the identification strategy, I interact logged values of $EnVPU_t$ (second moment of environment policy) with the sector-level measure of exposure to environmental policy uncertainty i.e., logged value of $AvgExposure_j$. I add interactions of the controls ($EnVP_t, EPU_t, WTI_t$) with the exposure measure as additional variables. This specification tests if firms belonging to sectors with higher exposure to environmental risk are more responsive to movements in environmental policy uncertainty, on average and all else equal.

Column (5) reports the key result. The coefficient of 0.024 on the log($EnVPU_t$)*log($AvgExposure_j$) term suggests that for a firm with median exposure, that is, for a firm belonging to a sector with median Environmental risk score, a 1 percent increase in US environmental policy uncertainty over a given month leads to an increase of approximately 0.03 percent in historical realized volatility (0.024 x 1.098612 =0.026), on average and all else equal. This effect is significant at the 1 percent level and robust to including sector-month fixed effects (Column (6)), firm and quarter fixed effects (Column (7)), and firm and year fixed effects (Column (8)). Given that the dependent variable is 30-day historical stock price volatility, I consider two additional specifications, one where all explanatory variables are lagged by one period (Column (9)) and another where the lagged dependent variable is included (Column (10)). The effect of higher stock price volatility for exposed firms in response to environmental policy uncertainty is stable under these specifications as well. To put the coefficient under my key specification (Table

10 (Column 5)) into perspective, the monthly $EnVPU_t$ index rose on average by 2.65 log points from 2010 to 2018. Assuming a median exposure firm, this implies an estimated increase in realized stock volatility of approximately 0.1 percent (0.0265 x 0.03 x 1.098612 x 100) over this period.

On the other hand, for a firm belonging to a sector with median Environmental risk score, a 1 percent increase in US general economic policy uncertainty ($EPU_t$) over a given month leads to an increase of approximately 0.11 percent in historical realized volatility (0.198 x 1.098612 =0.108), on average and all else equal. From 2010 to 2018 the monthly $EPU_t$ index rose on average by 1.32 log points from 2010 to 2018. Assuming a median exposure firm, this implies an estimated increase in realized stock volatility of approximately 0.3 percent (0.0132 x 0.198 x 1.098612 x 100).

Therefore, a rise in environmental policy uncertainty is associated with a rise in monthly stock volatility of firms belonging to sectors more exposed to environmental risks such as Oil & Gas, Metals & Mining and Power Generators. However, this volatility effect is economically not significant. The effect of a rise in general policy uncertainty on firm-level stock price volatility of exposed firms is 3 times the effect of a rise in environmental policy uncertainty. General policy uncertainty shocks, therefore, matter more than environmental policy uncertainty shocks for realized stock volatility outcomes of firms belonging to sectors more exposed to environmental risks.

Observing the estimated effects of US environmental policy uncertainty ($EnVPU_t$) on the second firm-level outcome, monthly stock return of firms on the Russell 3000 Index, Column (5) of Table 11 reports the main result. For a firm belonging to a sector with median Environmental Risk score, a 1 percent increase in US environmental policy uncertainty over a given month leads to a decrease of 0.0002 percentage points in monthly stock returns ( (-)0.017) x 1.098612 x 0.01 =(-)0.018). The result is statistically significant at the 1 per cent level. Putting this coefficient in perspective, for a median exposure firm, this implies an estimated decrease in stock returns of approximately 0.0004 percentage points (0.0265 x 0.01 x (-0.017) x 1.098612 x 100) over the 2010-2018 period.

This stock return effect is opposite in sign but comparable in magnitude to general policy uncertainty effects on exposed firms. Also, it is robust to including alternative fixed-effects (Columns (6)-(8)), considering lagged explanatory variables (Column (9)) and including lagged dependent variable ((Column (10)).

In summary, a rise in environmental policy uncertainty is associated with rise in stock price volatility and fall in stock returns for firms more exposed to environmental risks, as measured by sector-level S&P Global's Environmental Risk Scores. For additional robustness checks, I consider alternative exposure measures for $AvgExposure_j$. Table 12 and Table 13 consider the baseline specification (Column 5 of Table 10 and 11) for alternative exposure measures and report the results for volatility and stock return regressions respectively. Firstly, I consider GICS sector-level averages of Environmental (E) ratings ($AvgEnvRating_j$) provided by two rating agencies: S&P Global and Bloomberg. As per the ESG ratings methodologies of these agencies, firms with lower Environmental (E) ratings are more exposed to environmental risks. I, therefore, construct

(1/log ($AvgEnvRating_j$)) as an alternative firm-level exposure measure. Table 12 (Column (2)) shows that the coefficient of the interaction term of logged values of $EnVPU_t$ with the firm-level exposure measures (1/log ($AvgEnvRating_j$)) has the expected positive sign and is statistically significant at the 1 percent level for the S&P Global rating exposure measure. However, the coefficient is close to zero for the Bloomberg rating measure (Table 12 (Column (1)), owing to small sample size.

For the stock return regressions (Table 13 (Column (1)), the coefficient on the S&P Global Ratings exposure measure has the expected negative sign as seen under my key specification result (Table 11 (Column(5)) and statistically significant at the 1 percent level. Again, owing to small sample size, the coefficient is close to zero for the Bloomberg rating measure (Table 13 (Column (2)). Secondly, I consider GICS sector-level greenhouse gas emissions intensity per unit of sales as an alternative exposure measure since sectors more exposed to environmental risks are expected to be more carbon-intensive. Column (3) of Table 12 and Table 13 reports that this measure's coefficients have the expected signs for both the volatility and stock return regressions and are statistically significant at the 5 per cent level and 1 per cent level respectively.

Thirdly, I consider sector-level Environmental Risk Scores provided by another ESG rating agency MSCI under Column (4) of these tables. This measure's coefficients also have the expected signs and are statistically significant at the 1 percent level for both the volatility and stock return specifications (Column (4) of Table 12 and Table 13). In sum, the effects of environmental policy uncertainty on volatility and stock returns of firms belonging to sectors more exposed to environment risks, as defined by sector-level S&P Global's Environmental Risk scores, are robust to alternative environmental risk exposure measures.

Policy uncertainty may compel firms to rely on their own funds for future investments, whereas other firms could seek financing via equity or bank borrowing (Ghosal and Loungani (2000)). Therefore, the effects of environmental policy uncertainty on financial outcomes of firms exposed to environmental risks may depend on the size of the firm and their consequent access to financing. To explore this empirically, I run separate regressions of the key specification under Column(5) of Tables 10 and 11 for small firms (denoted as micro-cap, small-cap and mid-cap firms) and large firms (denoted as large-cap and mega-cap firms) on the Russell 3000 Index.[4] Table 14 and Table 15 report the results.

Column (1) of Table 14 shows that small firms belonging to sectors exposed to higher environmental risk experience higher volatility in response to an environmental policy uncertainty shock, on average and all else equal. Specifically, for a small firm belonging to a sector with median Environmental Risk score, a 1 percent increase in US environmental policy uncertainty over a given month leads to an increase of approximately 0.04 percent (0.04 x 1.098612 =0.044) in volatility. This effect is statistically significant at the 1 percent level. On the other hand, large firms belonging to environmentally risky sectors experience lower volatility in response to an environmental policy uncertainty shock (Column (2) of Table 15). A large-cap firm belonging to

[4] Mega-Cap firms: market value of $200 billion or more, Large-Cap firms : market value between $10 billion and $200 billion, Mid-Cap firms: market value between $2 billion and $10 billion, Small-Cap firms: market value between $250 million and $2 billion, and Micro-Cap firms: market value of less than $250 million.

a sector with median Environmental Risk score experiences a decrease in volatility of approximately 0.02 percent ((-)0.021 x 1.098612 =0.023), potentially because of its ability to access financing more easily from markets in the face of environmental policy uncertainty.

Table 15 (Column (1)) shows that the stock return of a small firm falls by 0.0002 percentage points ((-)0.021 x 1.098612 x 0.01 =0.00023) in response to a 1 percent increase in environmental policy uncertainty, on average and all else equal. These small firm effects are statistically significant at the 1 percent level of significance. In contrast, large firms experience lower stock return losses in response to such a shock (Table 15 (Column (2)). These results suggest that the ability to seek financing matters for financial outcomes when exposed firms face environmental policy uncertainty.

### IV.1.1 Firm-level Spillover Effects of US Environmental Policy Uncertainty Shocks

United States is the second largest player in the global sustainable funds market after Europe. To assess if US environmental policy uncertainty shocks transmit beyond borders to developed sustainable markets of UK and Germany and emerging markets like India, I estimate the key specification under Equation 1 for each of these three markets with the dependent variable ($y_{it}$) being the natural logarithm of monthly realized volatility of stock price (log($Volatility_{it}$)) or the monthly stock return ($Return_{it}$) of domestic firms on the London Stock Exchange, Frankfurt Stock Exchange or Bombay Stock Exchange's S&P 500 Index from Jan 2010 to March 2019. While the key treatment coefficient $\beta_1$ remains the same, the vector of controls include US-level controls such as the US environmental policy news index ($EnvP_t$), country-level economic policy uncertainty control which is the UK (or Germany or India) Economic Policy Uncertainty Index ($EPU\_COUNTRY_t$) and crude oil price variable $WTI_t$ in volatility ($WTI\_VOL_t$) or growth form ($WTI\_RETURN_t$). All these controls are interacted by the logged value of the exposure measure $AvgExposure_j$, the Environmental Risk score (as part of the S&P Global's ESG Risk Atlas) for a GICS-aligned sector j. Finally, I control for additional global macroeconomic and country-level financial variables that explain firm-level stock outcomes. These include the US federal funds rate ($FEFR_t$), 30-day expected volatility of the U.K. FTSE 100 Index ($FTSE\_VIX_t$), Vanguard Total World Stock Index Fund return ($VT\_RETURN_t$), logged value of market capitalization ($FIRMSIZE_t$), return on assets ($ROA_t$) and the ratio of total debt to total equity ($LEVERAGE_t$).

Tables 16 to 21 report the key results for each of these countries' stock exchanges. In line with the effects on US firms, UK-domiciled firms listed on the London Stock Exchange and belonging to sectors more exposed to environmental risks experience higher stock price volatility and lower stock returns in response to a US environmental policy uncertainty shock. Specifically, a UK firm belonging to a sector with median environmental risk exposure experiences a rise in stock price volatility of 0.05 per cent (0.05 x 1.098612=0.054) (Table 16 Column (1)) and fall in stock returns of 0.0002 percentage points ((-)0.02 x 1.098612 x 0.01=0.0002) (Table 17 Column (1)) in response to a 1 per cent increase in uncertainty in US environmental policy.

On the other hand, German firms on the Frankfurt Stock Exchange and Indian BSE S&P 500 Index firms belonging to exposed sectors experience a gain in stock returns (Table 19 and Table 21 Column(1) in response to a US environmental policy uncertainty shock while the volatility results are mixed (Column(1) of Table 18 and Table 20). German firms of exposed sectors benefit on both fronts with higher stock returns and lower volatility in response to such a shock.

These heterogenous effects of delays in US climate policy action over the 2010-2019 period on firm-level stock price volatility and stock returns may be guided by each countries' policy progress in areas of green finance development, clean energy transition and coal-phase out. While UK is undertaking a relatively rapid coal-phase out plan by 2024, Germany's coal and gas dependence, particularly from Russia, has remained strong over the period of study (Brauers et al. (2020)).

As per World Economic Forum's Energy Transition Index (World Economic Forum, 2021), United Kingdom and France are the only major global economies to feature in the list of top 10 countries leading the energy transition in the last decade. While UK ranks 7$^{th}$ on the Energy Transition Index and has experienced one of the highest improvements in the top-10 positions of the index over the 2012-2021 decade, Germany and US rank lower at the 18$^{th}$ and 24$^{th}$ position respectively. India, an emerging country with rising energy demand, while registering the largest gains in rank improvements in energy transition in the last decade, has a low ETI rank of 87 in absolute terms. Given the delays in clean energy transition in countries like Germany and India relative to UK, investors seem to be internalizing an increase in likelihood of delays in US climate policy action as return seeking opportunities in the carbon-intensive German and Indian firms as compared to UK firms.

### IV.2 Aggregate Effects of US Environmental Policy Uncertainty

In this section, I characterize the dynamic relationship between environmental policy uncertainty and outcomes of Energy sector-focused Exchange Traded Funds (ETFs) using a monthly vector auto-regressive (VAR) framework. Unlike the firm-level fixed-effects analysis, causal inference from these VAR results is difficult given that environmental policy and policy uncertainty can respond to current and future economic conditions. However, the VAR framework helps assess the dynamic association between environmental policy uncertainty and aggregate financial outcome for firms belonging to a sector with the highest Environmental Score, that is energy.

Firstly, I focus on two key US-focused Oil & Gas ETFs and the benchmark Clean Energy ETF. These include the Energy Select Sector SPDR® Fund (XLE), iShares U.S. Oil & Gas Exploration & Production ETF (IEO) and Invesco WilderHill Clean Energy ETF (PBW). XLE is the oldest Oil & Gas Exploration & Production ETF listed on US financial markets since December 1998. This ETF provides exposure to US companies in the oil, gas and consumable fuel, energy equipment and services industries and effectively represents the energy sector of the S&P 500 Index. Similarly, IEO was launched in May 2006 and provides a sector view to the US Oil & Gas Exploration & Production sector. XLE and IEO are amongst the top-10 U.S. Oil & Gas Exploration & Production ETFs by assets under management with XLE holding the highest assets at USD 39.7 billion.[5] Both these ETFs have concentration issues for investors, as a few stocks account for big portions of the ETF's portfolio. On the other hand, PBW is the oldest US Clean Energy ETF and

[5] As per Vettafi ETF database, XLE's and IEO's AUM stand at USD 39,714 million and USD 728.21 million as on 21 April 2023 (https://etfdb.com/etfs/industry/oil--gas-exploration--production/)

was launched in 2005. It is composed of stocks of US companies engaged in the business of advancement of cleaner energy and conservation with heavy exposure in technology companies.

I consider two monthly outcomes of 30-day historical price volatility and return for these three funds. For each of these US-focused Energy ETFs, I construct a domestic monthly 7-variable VAR (p) (Lütkepohl, 2006) with each variable being dependent on its 'p' lagged values and the current and 'p' lagged values of the other 6 variables. In equation form, this structure is given by:

$$A_0 X_t = \Sigma_{i=1}^{p} A_i X_{t-i} + Re_t \qquad (2)$$

where $X_t$=[$EnvPU\_US_t$, $EnvP\_US_t$, $EPU\_US_t$, $WTI_t$, $SECTOR\_CONTROL_t$, $FEFR_t$, $ENERGY\_ETF_{t,}$]' is a 7 × 1 vector of observable and stationary time series variables of US Environmental and Policy Uncertainty Index ($EnvPU_t$) (Growth Rate), US Environmental Policy News Index ($EnvP_t$) (Growth Rate), US Economic Policy Uncertainty Index ($EPU\_US_t$) (Growth Rate), West Texas Intermediate crude oil prices ($WTI_t$), ETF-relevant sector control variable ($SECTOR\_CONTROL_t$), first difference of US Federal Funds Effective Rate ($FEFR_t$), and outcome of Energy ETF ($ENERGY\_ETF_{t,}$).

For the VAR models with volatility of Energy ETFs as the outcome variable, $ENERGY\_ETF_t$ takes the form of 30-day historical price volatility of the ETF ($ENERGY\_ETF\_VOL_{t,}$). West Texas Intermediate crude oil price variable ($WTI_t$) in these VAR models is also considered in its 30-day historical volatility form ($WTI\_VOL_t$). For the two US-focused Oil & Gas ETFs, XLE and IEO, the sector-level control variable relevant for these models is the US natural gas price proxied by Henry Hub Natural Gas Spot Price ($NATURAL\_GAS_t$) (Growth Rate). On the other hand, the sector-relevant control for technology sector focused US benchmark Clean Energy ETF, PBW, is the 30-day Historical Price Volatility of the Russell 3000 Technology Index ($TECH\_VOL_t$).

The ETF-return based VAR models for these 3 ETFs consider monthly growth in the closing stock price of these ETFs as the key outcome variable ($ENERGY\_ETF\_RETURN_t$). West Texas Intermediate crude oil price variable ($WTI\_RETURN_t$) and the sector-relevant control variable for PBW's share price growth VAR model ($TECH\_RETURN_t$) are also considered in their growth rate form.

To ensure stationarity, I transform the variables of policy uncertainty ($EnvPU\_US_t$, $EnvP\_US_t$, $EPU\_US_t$), West Texas Intermediate crude oil prices ($WTI_t$), ETF-relevant sector control ($SECTOR\_CONTROL_t$) and stock price of the ETF ($ENERGY\_ETF\_RETURN_t$) into their log first-differenced (growth rate) forms. On the other hand, the macroeconomic control variable $FEFR_t$ is first differenced. Finally, 30-day historical price volatility variables in any VAR model ($ENERGY\_ETF\_VOL_t$, $WTI\_VOL_t$ and $TECH\_VOL_t$) are stationary in their original form. Standard unit root test results of these variables are reported in Table 22.

To recover orthogonal shocks, I use the Cholesky ordering given above in the $X_t$ vector specification of Equation (2) for each of the six VAR models with the chosen optimal lag being one lag or two lags for each of these models, as provided by majority of the Information Criteria (amongst AIC, FPE, HQIC and BIC).

Figure 3 demonstrates that a one standard deviation shock to US environmental policy uncertainty growth is associated with a lagged increase in price volatility (a proxy for investment uncertainty) for the three US-focused Energy ETFs. Price volatility increases after a month for the two Oil & Gas ETFs, XLE and IEO, by 0.003 percentage points and 0.006 percentage points respectively. On the other hand, Clean Energy ETF PBW witnesses a higher increase of 0.01 percentage points in volatility after two months.

This potentially suggests that when the trajectory of environmental policy is uncertain, firms become unsure about future investments in the environmentally risky Energy sector. Again, the VAR results show that firm size matters for these outcomes. While PBW captures mid-cap and small-cap renewable energy stocks with weighted average market capitalization of USD 16.61 Bn, XLE and IEO are large-cap energy sector ETFs. This may explain why PBW witnesses a higher rise in volatility in response to an environmental policy uncertainty growth shock as compared to volatility gains for XLE and IEO.

These dynamic effects are, therefore, in line with the fixed effects model results by firm size for environmentally risky energy sector stocks. In terms of statistical significance, while the effect of environmental policy uncertainty on price volatility for the Clean Energy ETF PBW is statistically significant at the 68 per cent confidence interval for the 2$^{nd}$ lag, these effects are not significant for XLE and IEO for any lag, potentially owing to a short-time series.

Figure 4 plots the impulse response of monthly stock price returns of these US-focused Energy ETFs to an environmental policy uncertainty growth shock. A one standard deviation shock to US environmental policy uncertainty growth today is associated with a decrease in stock price returns of 0.008 percentage points per annum a month later for the two Oil & Gas ETFs, XLE and IEO. This return effect is statistically significant for XLE and IEO at the 90 per cent confidence interval at the 1st lag. Investors, therefore, withdraw investments from concentrated sector-focused Oil & Gas ETFs in the face of uncertain environmental policy. This is in line with firm-level effects of lower stock returns in response to an environmental policy uncertainty shock. On the other hand, benchmark Clean Energy ETF PBW witnesses a contemporaneous gain in returns of 0.01 percentage points per annum in response to the uncertainty shock followed by a return loss next month. However, this effect is statistically not significant at any lag.

To understand the economic significance of the effects of US environmental policy uncertainty on the volatility and return of these Energy ETFs, this effect is compared to that of US general economic policy uncertainty ($EPU\_US_t$) shock. Specifically, a one standard deviation shock to US economic policy uncertainty growth raises price volatility of US-focused Energy ETFs in the range of 0.02 to 0.04 percentage points per annum (Figure 5). On the other hand, all three ETFs experience return losses in the range of 0.025 to 0.04 percentage points per annum after one month in response to an economic policy uncertainty growth shock (Figure 6).

While the effects of general policy uncertainty on the volatility of an Energy ETF are 4 to 6 times the effect of an environmental policy uncertainty shock, the return effects are 3 to 4 times higher. These effects are also more persistent and statistically significant at the 95 per cent confidence interval. Therefore, the VAR models also show that while environmental policy uncertainty matters for investing outcomes of environmentally risky sectors like Energy, general economic policy uncertainty matters more.

To assess potential spillover effects of US environmental policy uncertainty on global sustainable financial markets, I now consider outcomes of 30-day historical price volatility and returns for two global Clean Energy ETFs majorly covering non-US firms. These include NORDEA 1: Global Climate and Environment Fund (NORDEA) and Invesco Global Clean Energy ETF (PBD). While NORDEA majorly captures clean energy firms of the developed regions of US (54.56 per cent), Developed Europe (21.73 per cent), Japan (7.43 per cent) and United Kingdom (6.58 per cent), PBD is more diverse in its coverage of both developed and emerging market firms (35.39 per cent for Developed Europe, 26.63 per cent for US, 10.57 per cent for China and 8.07 per cent for South Korea). [6]

The baseline monthly VAR specification for these global Clean Energy ETFs is the same as the domestic specification under Equation (2). The sector-relevant control ($SECTOR\_CONTROL_t$) for these industrials sector focused global Clean Energy ETFs, PBD and NORDEA 1, is the monthly return of iShares Global Industrial ETF ($ISHARES\_GLOBAL\_IND\_RETURN_t$) and S&P Global Industrial S&P Index ($SNP\_GLOBAL\_IND\_RETURN_t$) respectively. All series are stationary as demonstrated by standard unit root tests (Table 22). To recover orthogonal shocks, I use the same Cholesky ordering as given in the domestic VAR specification.

[6] As per Morningstar Research database for NORDEA 1 and PBD on 20 April 2023. (https://www.morningstar.co.uk/uk/funds and https://www.morningstar.com/etfs)

Figure 7 shows that in response to a one standard deviation shock to US environmental policy uncertainty growth, PBD and NORDEA 1 ETFs witness a contemporaneous decrease in price volatility of 0.01 percentage points and 0.001 percentage per annum respectively. After a month, the US and Europe-focused Clean Energy NORDEA 1 ETF becomes more volatile, in line with the effects for domestic ETF PBW. However, the more diverse PBD ETF continues to experience a decline in volatility after a month. This suggests that diversification of global Energy ETF portfolios matters for volatility outcomes in the face of US environmental policy uncertainty. In terms of returns (Figure 8), both PBD and NORDEA 1 ETF experience a contemporaneous gain in returns followed by losses next month in response to a US environmental policy uncertainty growth shock, like the effects on domestic PBW ETF.

These effects of environmental policy uncertainty on volatility and return of global Clean Energy ETFs are weak in magnitude and statistically not significant for any lag. Additionally, these effects are economically not significant relative to the spillover effects of US economic policy uncertainty. Specifically, a one standard deviation shock to US economic policy uncertainty growth raises price volatility of global Energy ETFs in the range of 0.02 to 0.035 percentage points per annum for four months after the shock (Figure 9). On the other hand, these ETFs experience losses in return in the range of 0.01 to 0.02 percentage points per annum for two months after the general economic policy uncertainty shock (Figure 10). The volatility effects are statistically significant at 1 per cent level of significance for both the ETFs while the return effects are statistically significant at 5 per cent level of significance.

I consider some robustness checks to my baseline VAR results, both for domestic and global Energy ETFs. News about environment policy uncertainty may potentially accumulate over months. Therefore, I test a VAR specification with 3-month backward looking moving-average transformation of the environmental policy uncertainty index (*EnvPU*$_t$) and environmental policy news index (*EnvP*$_t$) indices. A second robustness check considers a specification with only the main variables of interest, *EnvPU_US*$_t$ , *EnvP_US*$_t$ and *ENERGY_ETF*$_t$, in the same order. Thirdly, I restrict the baseline specification to the firm-level period of study from Jan 2010 to Mar 2019. I also consider another specification for the volatility VARs with 180-day historical price volatility (Growth Rate) as the key outcome variable. The impulse response results of our baseline VAR specification are broadly robust to these four VAR specifications as reported in Figure 11 and Figure 12. Finally, as a robustness check, I adopt an alternative Local Projections empirical specification:

$$
\begin{aligned}
\log(ENERGY_{ETF_{t+h}}) - \log(ENERGY_{ETF_t} \\
&= \alpha_h + \beta_h EnvPU_{US_t} + \delta_h(\log(ENERGY\_ETF_t) - \log(ENERGY\_ETF_{t-1})) \\
&+ Controls_t + \varepsilon_t \qquad (3)
\end{aligned}
$$

where h=0 to 12, $ENERGY\_ETF_t$ is the 30-day realized price volatility(or return) of ENERGY_ETF in period t, and $EnvPU\_US_t$ is the Growth Rate in Environmental and Policy Uncertainty Index. *EnvP*$_t$ is Growth Rate in US Environmental Policy News Index and $EPU\_US_t$ is Growth Rate in US Economic Policy Uncertainty Index. The control variables ($Controls_t$) are the same as utilized in each of the ETF's VAR specifications. Figure 11 and Figure 12 report values of the coefficient of $EnvPU_t$ ($\beta_h$) for each of the 13 regressions (h=0 to 12) for the five

Energy ETFs. While impulse responses under the Local Projections specification are higher in magnitude relative to the VAR impulse responses, the trends of rising volatility and falling returns in response to an uncertainty shock are similar.

## CONCLUSION

When US environmental policy uncertainty rises, domestic firms belonging to sectors that are most exposed to environmental risks, such as the Oil & Gas, Metals & Mining and Power Generation sectors, witness a rise in firm-level uncertainty, proxied by stock volatility and fall in stock returns.

The ability of these firms to access own funds or to borrow from outside sources in the face of environmental policy uncertainty matters for their stock outcomes. While liquidity-constrained small-cap and mid-cap US firms belonging to exposed sectors experience higher stock price volatility in response to an environmental policy uncertainty shock, large-cap and mega-cap firms of such sectors witness volatility declines. In terms of stock returns, US environmental policy uncertainty shocks are associated with greater losses for small firms relative to large firms.

At the aggregate level as well, an increase in US environmental policy uncertainty growth is associated with greater price volatility and lower returns for domestic Energy sector-focused Exchange Traded Funds. In line with firm-level effects by firm size, environmental policy uncertainty is associated with greater rise in volatility for Energy ETFs with small-cap and mid-cap exposure relative to large-cap Oil & Gas ETFs.

Uncertainty about US environmental policy not only impacts domestic investors but also spillovers to the developed sustainable finance markets of UK and Germany, and emerging markets of India. In line with the effects on US firms, domestic firms listed on the London Stock Exchange and belonging to environmentally risky sectors experience higher stock price volatility and lower stock returns in response to a decline in likelihood of US positive climate action. On the other hand, the firm-level stock price volatility and return effects on the German and Indian markets are heterogenous and potentially guided by the degree of advancement of green finance and clean transition in these economies.

Finally, I find that while environmental policy uncertainty matters for stock outcomes of firms and ETFs exposed to environmental risks, general or macroeconomic policy uncertainty matters more. The firm-level volatility effect of a US macroeconomic policy uncertainty shock is 3 times the size of the effect of an environmental policy uncertainty shock. Similarly, the rise in price volatility of Energy ETFs in response to higher macroeconomic policy uncertainty is 4 to 6 times the effect of an uncertain environmental policy regime. This potentially implies that investors of domestic and global sustainable financial markets behave similarly to those in traditional financial markets, and thereby internalize episodes of general policy uncertainty more than those of specific environmental policy. This has implications of insufficient climate-risk pricing in financial markets.

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## APPENDIX

## TABLES

**Table 1: Description of Variables**

| Variable | Description | Source |
|---|---|---|
| **Variables common to firm-level and VAR analysis** | | |
| EnVPU | Monthly US Environmental Policy Uncertainty Index (Average: 100 over 1990(M1) to 2019(M3)) | https://www.financingcleantech.com/ Noailly et al.(2022) |
| EnVP | Monthly US Environmental Policy News Index (Average: 100 over 1981 (M1) to 2019(M3)) | https://www.financingcleantech.com/ Noailly et al.(2021) |
| EPU_US | Monthly US Economic Policy Uncertainty Index | https://www.policyuncertainty.com Baker, Bloom, and Davis (2016) et al.(2016) |
| WTI | Monthly Crude Oil Spot Price, West Texas Intermediate Cushing Oklahoma: 30-day annualized historical volatility in price (WTI_VOL) and monthly closing stock price growth (WTI_RETURN) | Bloomberg |
| FEFR | Monthly US Federal Funds Effective Rate | Federal Reserve Bank of St. Louis database |
| **Variables specific to firm-level analysis** | | |
| Volatility | Firm-level 30-day annualized historical/realized volatility in stock prices | Bloomberg Equity database |
| Return | Monthly growth in firm-level closing stock price | |
| Sector-level S&P Global Env Risk Score | S&P Global's Environmental Risk Score by GICS Sector (Range from 0 (Lowest Exposure) to 6 (Highest Exposure) | S&P Global's ESG Risk Atlas, S&P Global ESG Research, 2020 |
| Sector-level MSCI Env Risk Score | MSCI'S ESG Industry Risk Intensity by GICS Sector | MSCI ESG Research, 2020 |
| Sector-level S&P Global Env Rating | S&P Global's Environmental Dimension Percentile Rank by GICS Sector (Ranges from 0(Lowest) to 100(Highest) | S&P Global ESG Database, Bloomberg |
| Sector-level Bloomberg Env Rating | Bloomberg ESG Environmental Pillar Score by GICS sector (Ranging from 0 to 10) | Bloomberg ESG database |
| Industry group-level GHG Emissions Intensity | Metric tonnes of greenhouse gases in carbon dioxide equivalent (CO2e) emitted from direct operations per million of sales revenue in the company's reporting currency (Calculated as Total GHG Emissions*1000 / Sales, or Total $CO_2$ Emissions*1000 / Sales) by GICS industry group | |

| | | |
|---|---|---|
| VIX | CBOE Volatility Index is a financial benchmark market estimate of expected volatility of the S&P 500 Index. | Bloomberg Equity database |
| FTSE_VIX | FTSE Implied Volatility Index Series that measure the implied volatility of the FTSE 100 index. | |
| FIRMSIZE | Firm-level monetary value of all outstanding shares stated in the pricing currency. Measure of corporate size. | |
| ROA | Firm-level indicator of how profitable a company is relative to its total assets, in percentage. (Calculated as: (Trailing 12M Net Income / Average Total Assets) * 100) | |
| LEVERAGE | Firm-level total debt divided by total shareholders' equity. (Calculated as: Short and Long Term Debt / Shareholders' Equity * 100) | |
| VT_RETURN | Vanguard Total World Stock Index Fund which seeks to track the market performance of large-, mid- and small-capitalization stocks of companies located around the world (FTSE Global All Cap Index) | Yahoo Finance |
| **Variables specific to VAR analysis** | | |
| ENERGY_ETF_VOL | 30-day annualized historical volatility in stock prices of Energy ETF (XLE, IEO, PBW, PBD, NORDEA 1) | Bloomberg Equity database |
| ENERGY_ETF_VOL_180 | 180-day annualized historical volatility in stock prices of Energy ETF (XLE, IEO, PBW, PBD, NORDEA 1) | |
| ENERGY_ETF_RETURN | Monthly growth in closing stock price of Energy ETF (XLE, IEO, PBW, PBD, NORDEA 1) | |
| NATURAL_GAS | Monthly growth in Henry Hub Natural Gas Spot Price Dollars per Million BTU,<br>Not Seasonally Adjusted | Federal Reserve Bank of St. Louis database |
| ISHARES_GLOBAL_IND_RETURN | Monthly Return of iShares Global Industrials ETF | www.ishares.com |
| SNP_GLOBAL_IND_RETURN | Monthly growth in S&P Global 1200 Industrials Sector Return Index | Bloomberg |

| | | |
|---|---|---|
| SNP_GLOBAL_IND_VOL | 30-day annualized historical volatility of S&P Global 1200 Industrials Sector Return Index | Bloomberg |
| RUSSELL3000_TECH_RETURN | Monthly growth in Russell 3000 Technology Index | Bloomberg |
| RUSSELL3000_TECH_VOL | 30-day annualized historical volatility of Russell 3000 Technology Index | Bloomberg |

**Table 2: Summary Statistics for Firm Level Analysis: United States**

| | count | mean | p50 | sd | min | max |
|---|---|---|---|---|---|---|
| Volatility | 203844 | 35.61 | 28.67 | 31.08 | 0.635 | 2164.3 |
| Return | 204969 | 0.00815 | 0.0108 | 0.121 | -6.174 | 9.107 |
| EnVPU | 310467 | 98.23 | 94.32 | 23.25 | 53.23 | 163.7 |
| EnVP | 310467 | 147.6 | 140.6 | 27.02 | 105.1 | 233.6 |
| EPU_US | 310467 | 140.1 | 130.5 | 43.47 | 63.88 | 284.1 |
| Sector-level S&P Global Env Risk Score | 310467 | 2.835 | 3 | 1.104 | 1.010 | 6 |
| Sector-level MSCI Global Env Risk Score | 310467 | 5.161 | 4 | 1.814 | 4 | 10 |
| Firm-level S&P Global Env Rating | 155844 | 32.65 | 27.28 | 20.16 | 0.0833 | 100 |
| Firm-level Bloomberg Env Rating | 75591 | 2.253 | 1.973 | 1.670 | 0.00459 | 8.014 |
| Industry group-level GHG Emissions Intensity | 310467 | 187.5 | 32.92 | 436.3 | 2.628 | 2516.8 |
| WTI_VOL | 310467 | 31.18 | 27.45 | 13.66 | 13.60 | 90.95 |
| FEFR | 310467 | 0.495 | 0.160 | 0.651 | 0.0700 | 2.410 |
| VIX | 310467 | 17.23 | 15.93 | 5.590 | 9.510 | 42.96 |
| FIRMSIZE | 206559 | 10223.3 | 1775.1 | 36312.6 | 0.00670 | 1099436 |
| ROA | 280211 | 0.0483 | 0.0522 | 0.0278 | -0.0609 | 0.112 |
| LEVERAGE | 293975 | 1.021 | 0.989 | 0.527 | 0.253 | 2.799 |
| *N* | 310467 | | | | | |

Notes: Table shows summary statistics for a balanced panel of 2797 publicly-listed companies of the Russell 3000 index on the US Stock Exchange from Jan 2010 to Dec 2019. These firms belong to 11 GICS aligned sectors, 68 industries and 153 subindustries. ROA and LEVERAGE variables are scaled down by a factor of 100 and measured at the Russell 3000 sectoral index level.

**Table 3: S&P Global's Environmental Risk Exposure scores by GICS aligned sector**

| **Sector Description** | **Environmental Risk Score** |
|---|---|
| Oil & Gas | 6 |
| Metals & Mining | 6 |
| Power Generation | 5 |
| Chemicals | 5 |
| Agribusiness and Agricommodities | 5 |
| Autos & Auto suppliers | 4 |
| Transportation | 4 |
| Oil & Gas Infrastructure | 4 |
| Materials | 4 |
| Real Estate | 3 |
| Utility Networks | 3 |
| Transportation Infrastructure | 3 |
| Telecom | 3 |
| Technology | 3 |
| Leisure | 3 |
| Consumer Goods | 3 |
| Retail | 3 |
| Capital Goods | 3 |
| Insurance | 3 |
| Banks | 3 |
| Health Care | 2 |
| Non-Banking Financial Institutions | 2 |
| Media | 1 |
| Services | 1 |
| **Median S&P Global Environmental Risk Exposure Score** | 3 |

Note: These **Environmental Risk Exposure scores** are provided by S&P Global under its ESG Risk Atlas and scored from 1 (lowest exposure) to 6 (highest exposure).

**Table 4: MSCI's Environmental Risk Exposure scores by GICS aligned sector**

| **Sector Description** | **Environmental Risk Score** |
|---|---|
| Energy | 10 |
| Materials | 9 |
| Communication Services | 7 |
| Industrials | 7 |
| Utilities | 7 |
| Consumer Staples | 5 |
| Consumer Discretionary | 4 |
| Financials | 4 |
| Healthcare | 4 |
| Information Technology | 4 |
| Real state | 4 |
| **Median MSCI Environmental Risk Exposure scores** | 5 |

Note: These **Environmental Risk Exposure scores** are provided by MSCI Rating Agency under and scored from 0 (lowest exposure) to 10 (highest exposure).

**Table 5: Bloomberg's Greenhouse Gas Emissions Intensity Per Unit of Sales by GICS aligned Industry Group**

| **Industry Group** | **GHG Emissions Intensity per unit of Sales** |
|---|---|
| Utilities | 2516.84 |
| Energy | 969.62 |
| Materials | 664.94 |
| Transportation | 539.06 |
| Automobiles & Components | 236.69 |
| Consumer Services | 155.79 |
| Commercial & Professional Services | 148.43 |
| Food, Beverage & Tobacco | 129.49 |
| Real Estate | 107.28 |
| Capital Goods | 69.65 |
| Semiconductors & Semiconductor Equipment | 65.59 |
| Telecommunication Services | 54.24 |
| Household & Personal Products | 49.51 |
| Food & Staples Retailing | 40.02 |
| Technology Hardware & Equipment | 38.24 |
| Consumer Durables & Apparel | 32.92 |
| Pharmaceuticals, Biotechnology & Life Sciences | 28.40 |
| Retailing | 24.85 |
| Health Care Equipment & Services | 18.58 |
| Media & Entertainment | 11.89 |
| Banks | 11.62 |
| Software & Services | 11.36 |
| Diversified Financials | 5.19 |
| Insurance | 2.63 |
| **Median GHG Emissions Intensity per unit of Sales by Industry Group** | 54.24 |

Note: The table reports averages of annual firm-level GHG Emissions Intensity per unit of sales from 2013 to 2023, further averaged at the GICS Industry Group level.

**Table 6: Average Environmental Ratings by 2-digit sector SIC code and Rating Agency**

| Sector Description | Sector Code | S&P Global Environmental Rating | Bloomberg Environmental Rating |
|---|---|---|---|
| Healthcare | 35 | 43.42 | 2.92 |
| Consumer Staples | 30 | 41.93 | 3.04 |
| Utilities | 55 | 38.81 | 3.41 |
| Consumer Discretionary | 25 | 34.48 | 1.69 |
| Communication Services | 50 | 33.67 | 2.76 |
| Information Technology | 45 | 32.59 | 2.45 |
| Materials | 15 | 31.93 | 3.28 |
| Real Estate | 60 | 29.63 | 1.57 |
| Financials | 40 | 29.54 | 1.09 |
| Industrials | 20 | 26.07 | 2.09 |
| Energy | 10 | 23.14 | 2.42 |
| **Median S&P Environmental Scores by SIC code** | | 32.59 | 2.45 |

Note: S&P Global Environmental Ratings (percentile ranks) are scored from 0 (Poorest) to 100 (Highest) while Bloomberg Environmental Ratings are scored from 0 (Poorest) to 10 (Highest)

**Table 7(a): Summary Statistics for Firm Level Analysis: London Stock Exchange, United Kingdom**

| | count | mean | p50 | sd | min | max |
|---|---|---|---|---|---|---|
| Volatility | 80373 | 34.92 | 25.87 | 32.66 | 0.137 | 684.6 |
| Return | 109285 | 0.000335 | 0 | 0.136 | -4.277 | 5.225 |
| EnVPU | 157065 | 98.23 | 94.32 | 23.25 | 53.23 | 163.7 |
| EnVP | 157065 | 147.6 | 140.6 | 27.02 | 105.1 | 233.6 |
| EPU_UK | 157065 | 156.8 | 140.6 | 76.31 | 62.34 | 558.2 |
| Sector-level S&P Global Env Risk Score | 121434 | 3.012 | 3 | 1.472 | 1.010 | 6 |
| Sector-level S&P Global Env Rating | 35520 | 52.09 | 51.47 | 21.58 | 2 | 100 |
| Sector-level Bloomberg Env Rating | 21201 | 2.568 | 2.361 | 1.642 | 0.00814 | 7.870 |
| Industry-level GHG Emissions Intensity | 120546 | 217.0 | 52.03 | 414.7 | 3.712 | 5383.5 |
| WTI_VOL | 158175 | 31.18 | 27.45 | 13.66 | 13.60 | 90.95 |
| WTI_RETURN | 158175 | 0.0881 | 0.978 | 7.803 | -21.88 | 24.77 |
| FEFR | 157065 | 0.495 | 0.160 | 0.651 | 0.0700 | 2.410 |
| FTSE_VIX | 158175 | 16.46 | 15.95 | 4.789 | 9.550 | 37.76 |
| FIRMSIZE | 87246 | 2252.9 | 77.08 | 10696.6 | 0.108 | 222492.5 |
| ROA | 57990 | -0.0195 | 0.0227 | 0.152 | -0.612 | 0.205 |
| LEVERAGE | 26796 | 0.580 | 0.361 | 0.664 | 0.00842 | 3.537 |
| *N* | 158175 | | | | | |

Notes: Table shows summary statistics for an unbalanced panel of 1418 publicly-listed companies on the London Stock Exchange from Jan 2010 to Dec 2019. These firms belong to 12 GICS aligned sectors, 69 industries and 136 subindustries. ROA and LEVERAGE variables are measured at the firm level, trimmed at the 5 percentile and 95 percentile level and scaled down by a factor of 100.

**Table 7(b): Summary Statistics for Firm Level Analysis: Frankfurt Stock Exchange, Germany**

| | count | mean | p50 | sd | min | max |
|---|---|---|---|---|---|---|
| Volatility | 58722 | 41.62 | 29.55 | 72.10 | 0.0740 | 3991.1 |
| Stock Price | 78588 | 6.399 | 4.214 | 22.90 | -95.92 | 333.3 |
| EnVPU | 84249 | 98.23 | 94.32 | 23.25 | 53.23 | 163.7 |
| EnVP | 84249 | 147.6 | 140.6 | 27.02 | 105.1 | 233.6 |
| EPU_GERMANY | 84249 | 169.6 | 160.8 | 63.02 | 65.22 | 454.0 |
| Sector-level S&P Global Env Risk Score | 62160 | 2.755 | 3 | 1.024 | 1.010 | 6 |
| Firm-level S&P Global Env Rating | 24531 | 45.25 | 44.03 | 23.36 | 2.207 | 100 |
| Firm-level Bloomberg Env Rating | 11655 | 2.949 | 2.737 | 1.661 | 0.0800 | 7.937 |
| WTI_VOL | 84249 | 31.18 | 27.45 | 13.66 | 13.60 | 90.95 |
| WTI_RETURN | 84249 | 0.0881 | 0.978 | 7.803 | -21.88 | 24.77 |
| FEFR | 84249 | 0.495 | 0.160 | 0.651 | 0.0700 | 2.410 |
| FIRMSIZE | 68590 | 3715.2 | 115.7 | 12318.5 | 0.0001000 | 130295.2 |
| ROA | 32655 | 0.0288 | 0.0342 | 0.0623 | -0.227 | 0.173 |
| LEVERAGE | 25695 | 0.734 | 0.515 | 0.703 | 0.0117 | 3.583 |
| VT_RETURN | 83490 | 0.00717 | 0.0107 | 0.0402 | -0.113 | 0.107 |
| *N* | 100344 | | | | | |

Notes: Table shows summary statistics for a balanced panel of 904 publicly-listed domestic firms on the Frankfurt Stock Exchange from Jan 2010 to Dec 2019. These firms belong to 11 GICS aligned sectors, 65 industries and 121 subindustries. ROA and LEVERAGE variables are measured at the firm level, trimmed at the 5 percentile and 95 percentile level, and scaled down by a factor of 100.

**Table 7(c): Summary Statistics for Firm Level Analysis: Bombay Stock Exchange, India**

| | count | mean | p50 | sd | min | max |
|---|---|---|---|---|---|---|
| Volatility | 41585 | 35.05 | 32.24 | 14.63 | 1.536 | 394.2 |
| Return | 41323 | 0.0124 | 0.00856 | 0.109 | -1.355 | 0.813 |
| EnVPU | 55611 | 98.23 | 94.32 | 23.25 | 53.23 | 163.7 |
| EnVP | 55611 | 147.6 | 140.6 | 27.02 | 105.1 | 233.6 |
| EPU_INDIA | 55611 | 169.6 | 160.8 | 63.02 | 65.22 | 454.0 |
| Sector-level S&P Global Env Risk Score | 55611 | 3.183 | 3 | 1.230 | 1.010 | 6 |
| Firm-level S&P Global Env Rating | 39072 | 38.42 | 33 | 24.49 | 3 | 100 |
| Firm-level Bloomberg | 15429 | 2.404 | 2 | 1.877 | 0.0400 | 7.380 |
| Env Rating | 55611 | 6.135 | 1.535 | 9.348 | 0.0240 | 24.71 |
| Sector-level GHG Emissions Intensity | 56166 | 31.18 | 27.45 | 13.66 | 13.60 | 90.95 |
| WTI_VOL | 56166 | 0.0881 | 0.978 | 7.803 | -21.88 | 24.77 |
| WTI_RETURN | 55611 | 0.495 | 0.160 | 0.651 | 0.0700 | 2.410 |
| FIRMSIZE | 41482 | 217843.6 | 58775.0 | 503929.3 | 120.3 | 8639957 |
| ROA | 55611 | 2.389 | 2.350 | 0.453 | 1.430 | 3.690 |
| LEVERAGE | 55611 | 1.287 | 1.271 | 0.0900 | 1.060 | 1.460 |
| VT_RETURN | 55664 | 0.00710 | 0.0105 | 0.0520 | -0.868 | 0.798 |
| *N* | 56166 | | | | | |

Notes: Table shows summary statistics for an unbalanced panel of 501 publicly-listed companies of BSE S&P 500 Index on the Bombay Stock Exchange from Jan 2010 to Dec 2019. These firms belong to 11 GICS aligned sectors, 59 industries and 108 subindustries. ROA and LEVERAGE variables are measured at the S&P BSE 500 Index level, trimmed at the 5 percentile and 95 percentile level. LEVERAGE variable is scaled down by a factor of 100.

**Table 8: Description of Energy Exchange Traded Funds**

| Energy ETF | Launch Date | Fund Domicile | Index tracked | Assets under Management | Top Countries Covered | Sectors Covered | Market Capitalization (Weighted Average) |
|---|---|---|---|---|---|---|---|
| **Oil & Gas ETFs** | | | | | | | |
| **Energy Select Sector SPDR® Fund (XLE)** | 12/16/1998 | US (NYSE Arca) | Energy Sector Index of S&P 500 | USD 39.71 Bn | US | Oil, Gas & Consumable Fuels: 90.56 % Energy Equipment & Services: 9.44 % | **Large Cap:** 98.08% Mid Cap: 1.83% Small Cap: 0.00% Micro Cap: 0.00% (USD 195.44 Bn) |
| **iShares U.S. Oil & Gas Exploration & Production ETF (IEO)** | 05/01/2006 | US (Cboe BZX formerly known as BAT) | Dow Jones U.S. Select Oil Exploration & Production Index | USD 728.21 Mn | US | Oil & Gas Exploration & Production: 69.16 % Oil & Gas Refining & Marketing & Transportation: 23.24 % Oil & Gas Storage & Transportation: 7.50 % | **Large Cap:** 77.62% Mid Cap: 19.55% Small Cap: 2.65% Micro Cap: 0.00% (USD 49.39 Bn) |
| **Clean Energy ETFs** | | | | | | | |
| **Invesco WilderHill Clean Energy ETF (PBW)** | 3/3/2005 | US | WilderHill Clean Energy Index (AMEX) | USD 683.49 Mn | US: 87.86% Canada: 5.87% China: 2.02% | Electronic Technology: 27.77% Producer Manufacturing: 18.73% Utilities: 12.23% Consumer Durables: 11.45% | **Large Cap:** 11.72% Mid Cap: 27.92% Small Cap: 37.67% Micro Cap: 22.8% (USD 16.61 Bn) |
| **Invesco Global Clean Energy ETF (PBD)** | 06/13/2007 | US (NYSE Arca) | WilderHill New Energy Global Innovation Index | USD 206.3 Mn | US: 29.22 % South Korea: 13.58 % China: 9.26 % | Producer Manufacturing: 28.40% Utilities: 24.89% Electronic Technology: 20.18% | Large Cap: 14.42% Mid Cap: 32.15% Small Cap: 41.56% Micro Cap: 11.75% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | | | | (USD 7.05 Bn) |
| **NORDEA 1: Global Climate and Environment Fund (NORDEA)** | 13/03/2008 | Luxembourg | - | 9,957.21 Mn EUR | US: 52.81%, Euro Zone: 18.64% Japan:6.92% UK:6.29% | Industrials: 32.7%, Technology: 20.98% Basic Materials: 16.07% and Consumer Cyclicals: 10.39% | Large Cap: 72.3% Mid Cap: 22% |

Source: Factsheets of respective ETFs, Morningstar Research, Bloomberg, ETF.com, Vettafi ETF database and Financial Times. Data as on Apr 23 2023.

**Table 9: Summary Statistics for Vector Autoregression Analysis**

| Variable | count | mean | p50 | sd | min | max |
|---|---|---|---|---|---|---|
| EnVPU | 351 | 100.00 | 96.05 | 25.52 | 44.91 | 174.6 |
| EnVPU_MA | 349 | 100.0 | 97.99 | 20.30 | 58.51 | 155.0 |
| EnVP | 459 | 100.00 | 86.11 | 44.56 | 39.70 | 258.6 |
| EnVP_MA | 457 | 99.84 | 83.82 | 41.81 | 42.67 | 207.2 |
| EPU_US | 231 | 123.4 | 112.5 | 47.09 | 44.78 | 284.1 |
| XLE_VOL | 243 | 0.244 | 0.218 | 0.131 | 0.0716 | 1.232 |
| XLE_VOL_180 | 239 | 0.253 | 0.239 | 0.109 | 0.124 | 0.746 |
| IEO_VOL | 155 | 0.303 | 0.253 | 0.179 | 0.118 | 1.382 |
| IEO_VOL_180 | 151 | 0.314 | 0.284 | 0.154 | 0.150 | 0.885 |
| PBW_VOL | 169 | 0.289 | 0.248 | 0.153 | 0.143 | 1.157 |
| PBW_VOL_180 | 165 | 0.400 | 0.278 | 0.393 | 0.175 | 1.944 |
| PBD_VOL | 141 | 0.250 | 0.207 | 0.168 | 0.0816 | 1.171 |
| PBD_VOL_180 | 138 | 0.265 | 0.215 | 0.147 | 0.0928 | 0.794 |
| NORDEA_VOL | 132 | 0.182 | 0.153 | 0.107 | 0.0688 | 0.810 |
| NORDEA_VOL_180 | 129 | 0.194 | 0.170 | 0.0918 | 0.0981 | 0.499 |
| XLE_RETURN | 243 | 0.00589 | 0.0101 | 0.0620 | -0.208 | 0.175 |
| IEO_RETURN | 154 | 0.00202 | 0.00953 | 0.0795 | -0.253 | 0.222 |
| PBW_RETURN | 168 | 0.00477 | 0.00650 | 0.156 | -0.408 | 1.655 |
| PBD_RETURN | 141 | -0.00462 | 0.00559 | 0.0842 | -0.430 | 0.196 |
| NORDEA_RETURN | 132 | 0.00505 | 0.00936 | 0.0529 | -0.220 | 0.187 |
| WTI_VOL | 312 | 0.358 | 0.327 | 0.157 | 0.136 | 1.282 |
| WTI_RETURN | 311 | 0.00346 | 0.0115 | 0.0914 | -0.395 | 0.311 |
| NATURAL_GAS | 266 | -0.000592 | -0.00292 | 0.134 | -0.473 | 0.477 |
| RUSSELL_TECH_VOL | 273 | 0.248 | 0.211 | 0.139 | 0.0721 | 0.794 |
| RUSSELL_TECH_RETURN | 272 | 0.00777 | 0.0125 | 0.0753 | -0.333 | 0.187 |
| ISHARES_GLOBAL_IND_RETURN | 150 | 0.656 | 1.100 | 5.159 | -21.28 | 16.49 |
| SNP_GLOBAL_IND_VOL | 243 | 0.151 | 0.132 | 0.0820 | 0.0417 | 0.611 |
| SNP_GLOBAL_IND_RETURN | 242 | 0.00500 | 0.0105 | 0.0502 | -0.241 | 0.154 |
| FEFR | 169 | 1.382 | 0.240 | 1.769 | 0.0700 | 5.260 |
| *N* | 459 | | | | | |

Notes: Table shows summary statistics for data on variables used in Vector Autoregressive analysis from January 1981 to March 2019. EnvPU_MA and EnvP_MA are three-month backward looking moving averages of EnvPU and EnvP index. See the notes under Table 1 for additional variable definitions. Volatility variables are scaled down by a factor of 100 to maintain similar scale of variables in the VAR specification.

**Table 10: Effects of US Environmental Policy uncertainty on monthly stock price volatility (30-day horizon) of firms on Russell 3000 Index**

| Dependent Variable: Log(Volatility) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | |
| Log(EnVPU) * Log(Avg Exposure) | | | | | **0.024**$^{***}$ | **0.028**$^{***}$ | **0.034**$^{***}$ | **0.022**$^{***}$ | **0.035**$^{***}$ | **0.028**$^{***}$ |
| | | | | | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.003) |
| Log(EnVP) * Log(Avg Exposure) | | | | | 0.044$^{***}$ | 0.032$^{***}$ | -0.012$^{**}$ | -0.010$^{*}$ | 0.120$^{***}$ | -0.020$^{***}$ |
| | | | | | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.004) |
| Log(EPU_US) * Log(Avg Exposure) | | | | | 0.099$^{***}$ | 0.093$^{***}$ | 0.074$^{***}$ | 0.073$^{***}$ | -0.030$^{***}$ | 0.070$^{***}$ |
| | | | | | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.003) |
| Log(WTI_VOL) * Log(Avg Exposure) | | | | | 0.111$^{***}$ | 0.111$^{***}$ | 0.115$^{***}$ | 0.126$^{***}$ | 0.037$^{***}$ | 0.074$^{***}$ |
| | | | | | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.003) |
| Log(Volatility)_ Lag | | | | | | | | | | 0.442$^{***}$ |
| | | | | | | | | | | (0.006) |
| Log(EnVPU) | 0.060$^{***}$ | 0.033$^{***}$ | 0.020$^{***}$ | 0.015$^{***}$ | | | | | | |
| | (0.007) | (0.005) | (0.005) | (0.005) | | | | | | |
| Log(EnVP) | | 0.011$^{*}$ | -0.005 | 0.053$^{***}$ | | | | | | |
| | | (0.006) | (0.005) | (0.005) | | | | | | |
| Log(EPU_US) | | 0.095$^{***}$ | 0.095$^{***}$ | 0.123$^{***}$ | | | | | | |
| | | (0.005) | (0.004) | (0.004) | | | | | | |
| Log(WTI_VOL) | | 0.127$^{***}$ | 0.122$^{***}$ | 0.120$^{***}$ | | | | | | |
| | | (0.005) | (0.004) | (0.004) | | | | | | |
| Log(Avg Exposure) | 0.019 | 0.022 | 0.000 | 0.000 | | | | | | |
| | (0.022) | (0.016) | (.) | (.) | | | | | | |
| log(VIX) | | 0.375$^{***}$ | 0.362$^{***}$ | 0.353$^{***}$ | 0.374$^{***}$ | 0.378$^{***}$ | 0.374$^{***}$ | 0.385$^{***}$ | 0.441$^{***}$ | 0.265$^{***}$ |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | (0.008) | (0.006) | (0.007) | (0.007) | (0.007) | (0.007) | (0.006) | (0.007) | (0.005) |
| Log(FEFR) | | 0.025$^{***}$ | 0.016$^{***}$ | 0.011$^{***}$ | 0.016$^{***}$ | 0.017$^{***}$ | 0.018$^{***}$ | -0.042$^{***}$ | 0.028$^{***}$ | 0.013$^{***}$ |
| | | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.005) | (0.002) | (0.001) |
| log(FIRMSIZE) | | -0.132$^{***}$ | -0.127$^{***}$ | -0.125$^{***}$ | -0.125$^{***}$ | -0.125$^{***}$ | -0.128$^{***}$ | -0.132$^{***}$ | -0.118$^{***}$ | -0.062$^{***}$ |
| | | (0.004) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.008) | (0.007) | (0.004) |
| ROA | | 0.057 | -0.494$^{**}$ | -0.470$^{**}$ | -0.276 | -0.253 | -0.296 | -0.526$^{**}$ | -0.272 | -0.100 |
| | | (0.262) | (0.217) | (0.218) | (0.213) | (0.215) | (0.213) | (0.214) | (0.207) | (0.124) |
| LEVERAGE | | -0.228$^{***}$ | 0.096$^{***}$ | 0.096$^{***}$ | 0.098$^{***}$ | 0.100$^{***}$ | 0.101$^{***}$ | 0.103$^{***}$ | 0.097$^{***}$ | 0.049$^{***}$ |
| | | (0.015) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.007) |
| Unit fixed-effects | No | No | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |
| Time fixed-effects | No | No | No | Month | Month | Sector-Month | Quarter | Year | Month | Month |
| *N* | 203844 | 180851 | 180851 | 180851 | 180851 | 180851 | 180851 | 180851 | 180128 | 178927 |
| adj. $R^2$ | 0.001 | 0.323 | 0.200 | 0.220 | 0.219 | 0.619 | 0.610 | 0.612 | 0.196 | 0.386 |

Standard errors in parentheses

The sample contains observations on 2797 firms on Russell 3000 Index from January 2010 to March 2019. The dependent variable corresponds to the natural logarithm of the 30-day realized volatility of stock prices. EnVPU refers to the value of US Environmental Policy Uncertainty index. Avg Exposure refers to S&P Global's Sector-level Average Environmental Risk Score as defined in Section 3. ROA and LEVERAGE variables are measured at the Russell 3000 sectoral index level and scaled down by a factor of 100. Column (9) specification has all independent variables lagged by one month while Column (10) specification includes a lagged dependent variable (Log(Volatility)_Lag). See the notes under Table 1 for additional variable definitions. Standard errors are robust and clustered at the firm level.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 11: Effects of US Environmental Policy uncertainty on monthly stock return of firms on the Russell 3000 Index**

| Dependent Variable: Return | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | | |
| Log(EnVPU)* Log(Avg Exposure) | | | | | **-0.017**$^{***}$ | **-0.007**$^{***}$ | **-0.011**$^{***}$ | **0.001** |
| | | | | | (0.002) | (0.002) | (0.002) | (0.002) |
| Log(EnVP) * Log(Avg Exposure) | | | | | 0.008$^{***}$ | -0.003 | -0.003 | -0.011$^{***}$ |
| | | | | | (0.002) | (0.002) | (0.002) | (0.003) |
| Log(EPU_US)* Log(Avg Exposure) | | | | | 0.016$^{***}$ | 0.017$^{***}$ | 0.014$^{***}$ | 0.006$^{***}$ |
| | | | | | (0.001) | (0.001) | (0.001) | (0.002) |
| Log(WTI_RETURN)* Log(Avg Exposure) | | | | | -0.002$^{***}$ | 0.000 | 0.002$^{***}$ | 0.003$^{***}$ |
| | | | | | (0.000) | (0.000) | (0.000) | (0.000) |
| Log(EnVPU) | -0.008$^{***}$ | -0.010$^{***}$ | -0.010$^{***}$ | -0.019$^{***}$ | | | | |
| | (0.001) | (0.002) | (0.002) | (0.002) | | | | |
| Log(EnVP) | | -0.006$^{***}$ | -0.002 | 0.012$^{***}$ | | | | |
| | | (0.002) | (0.002) | (0.002) | | | | |
| Log(EPU_US) | | 0.009$^{***}$ | 0.015$^{***}$ | 0.018$^{***}$ | | | | |
| | | (0.001) | (0.001) | (0.002) | | | | |
| Log(WTI_RETURN) | | 0.003$^{***}$ | 0.002$^{***}$ | -0.003$^{***}$ | | | | |
| | | (0.000) | (0.000) | (0.000) | | | | |
| Log(Avg Exposure) | -0.003$^{***}$ | 0.002$^{*}$ | 0.000 | 0.000 | | | | |
| | (0.001) | (0.001) | (.) | (.) | | | | |
| Log(FEFR) | | -0.003$^{***}$ | -0.008$^{***}$ | -0.006$^{***}$ | -0.006$^{***}$ | -0.007$^{***}$ | -0.007$^{***}$ | -0.002 |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.002) |
| log(FIRMSIZE) | | 0.003$^{***}$ | 0.022$^{***}$ | 0.022$^{***}$ | 0.021$^{***}$ | 0.022$^{***}$ | 0.021$^{***}$ | 0.027$^{***}$ |
| | | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| ROA | | -0.086$^{***}$ | -0.111$^{**}$ | -0.115$^{**}$ | -0.135$^{**}$ | -0.100$^{*}$ | -0.114$^{**}$ | -0.134$^{**}$ |
| | | (0.022) | (0.054) | (0.053) | (0.053) | (0.053) | (0.054) | (0.057) |
| LEVERAGE | | -0.004$^{***}$ | 0.001 | 0.001 | 0.000 | 0.001 | 0.001 | -0.001 |
| | | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| VT_RETURN | | 0.953$^{***}$ | 0.948$^{***}$ | 1.134$^{***}$ | 1.119$^{***}$ | 1.072$^{***}$ | 0.952$^{***}$ | 0.946$^{***}$ |
| | | (0.014) | (0.014) | (0.017) | (0.016) | (0.016) | (0.015) | (0.014) |
| Unit Fixed Effects | No | No | Firm | Firm | Firm | Firm | Firm | Firm |
| Time Fixed Effects | No | No | No | Month | Month | Sector-Month | Quarter | Year |
| $N$ | 204969 | 105896 | 105896 | 105896 | 105896 | 105896 | 105896 | 105896 |
| adj. $R^2$ | 0.000 | 0.085 | 0.093 | 0.106 | 0.106 | 0.102 | 0.092 | 0.097 |

Standard errors in parentheses

The sample contains observations on 2797 firms on Russell 3000 Index from January 2010 to March 2019. The dependent variable corresponds to monthly growth in closing stock price (Return). EnVPU refers to the value of US

Environmental Policy Uncertainty index. Avg Exposure refers to S&P Global's Sector-level Average Environmental Risk Score as defined in Section 3. ROA and LEVERAGE variables are measured at the Russell 3000 sectoral index level and scaled down by a factor of 100. See the notes under Table 1 for additional variable definitions. Standard errors are robust and clustered at the firm level.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 12: Robustness Checks for effects of US Environmental Policy Uncertainty on monthly stock price volatility (30-day horizon) on the Russell 3000 Index for alternative firm-level exposure specifications**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable: Log(Volatility)<br>Avg Exposure Specification: | Firm-level S&P Global Env Rating | Firm-level Bloomberg Env Rating | GHG Intensity risk measure | MSCI Sector-risk measure |
| Log(EnVPU) * Log(Avg Exposure) | **0.080*****$^{***}$ | **-0.000**$^{*}$ | **0.003**$^{**}$ | **0.010**$^{***}$ |
| | (0.021) | (0.000) | (0.001) | (0.003) |
| Log(EnVP) * Log(Avg Exposure) | 0.130$^{***}$ | -0.001$^{**}$ | 0.010$^{***}$ | 0.030$^{***}$ |
| | (0.020) | (0.000) | (0.001) | (0.003) |
| Log(EPU_US) * Log(Avg Exposure) | 0.296$^{***}$ | 0.001$^{***}$ | 0.024$^{***}$ | 0.073$^{***}$ |
| | (0.022) | (0.000) | (0.001) | (0.003) |
| Log(WTI_VOL) * Log(Avg Exposure) | 0.325$^{***}$ | 0.000 | 0.030$^{***}$ | 0.078$^{***}$ |
| | (0.017) | (0.000) | (0.001) | (0.003) |
| Log(VIX) | 0.379$^{***}$ | 0.582$^{***}$ | 0.376$^{***}$ | 0.356$^{***}$ |
| | (0.009) | (0.011) | (0.007) | (0.007) |
| Log (FEFR) | 0.015$^{***}$ | 0.049$^{***}$ | 0.018$^{***}$ | 0.013$^{***}$ |
| | (0.003) | (0.003) | (0.002) | (0.002) |
| Log(FIRMSIZE) | -0.126$^{***}$ | -0.110$^{***}$ | -0.125$^{***}$ | -0.124$^{***}$ |
| | (0.009) | (0.012) | (0.007) | (0.007) |
| ROA | -0.794$^{***}$ | -1.391$^{***}$ | -0.266 | -0.351 |
| | (0.249) | (0.310) | (0.214) | (0.216) |
| LEVERAGE | 0.097$^{***}$ | 0.125$^{***}$ | 0.096$^{***}$ | 0.097$^{***}$ |
| | (0.015) | (0.019) | (0.012) | (0.012) |
| Unit Fixed Effects | Firm | Firm | Firm | Firm |
| Time Fixed Effects | Month | Month | Month | Month |
| *N* | 110792 | 54806 | 180851 | 180851 |
| adj. $R^2$ | 0.601 | 0.570 | 0.618 | 0.619 |

Standard errors in parentheses

The sample contains observations on 2797 firms on Russell 3000 Index from January 2010 to March 2019. The dependent variable corresponds to the natural logarithm of the 30-day realized volatility of stock prices. EnVPU refers to the value of US Environmental Policy Uncertainty index. Column headings provide the form of Average Exposure considered for the specification as defined in Section 3. ROA and LEVERAGE variables are measured at the Russell 3000 sectoral index level and scaled down by a factor of 100. See the notes under Table 1 for additional variable definitions. Standard errors are robust and clustered at the firm level.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 13: Robustness Checks for effects of US Environmental Policy Uncertainty on monthly stock return of firms on the Russell 3000 Index for alternative firm-level exposure specifications**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent Variable: Return<br>Avg Exposure Specification | Firm-level S&P Global Env Rating | Firm-level Bloomberg Env Rating | GHG Intensity risk measure | MSCI Sector-risk measure |
| Log(EnVPU) * Log(Avg Exposure) | **-0.054*****$^{***}$ | **-0.000**$^{*}$ | **-0.005**$^{***}$ | **-0.012**$^{***}$ |
| | (0.007) | (0.000) | (0.001) | (0.001) |
| Log(EnVP) * Log(Avg Exposure) | 0.033$^{***}$ | -0.000$^{*}$ | 0.002$^{***}$ | 0.007$^{***}$ |
| | (0.011) | (0.000) | (0.001) | (0.002) |
| Log(EPU_US) * Log(Avg Exposure) | 0.053$^{***}$ | 0.000 | 0.005$^{***}$ | 0.011$^{***}$ |
| | (0.006) | (0.000) | (0.000) | (0.001) |
| Log(WTI_RETURN) * Log(Avg Exposure) | -0.004 | -0.000 | -0.001$^{***}$ | -0.002$^{***}$ |
| | (0.003) | (0.000) | (0.000) | (0.000) |
| VT_RETURN | 1.088$^{***}$ | 1.021$^{***}$ | 1.124$^{***}$ | 1.129$^{***}$ |
| | (0.022) | (0.024) | (0.017) | (0.017) |
| Log (FEFR) | -0.006$^{***}$ | -0.004$^{***}$ | -0.006$^{***}$ | -0.006$^{***}$ |
| | (0.001) | (0.001) | (0.000) | (0.000) |
| Log(FIRMSIZE) | 0.019$^{***}$ | 0.013$^{***}$ | 0.021$^{***}$ | 0.021$^{***}$ |
| | (0.001) | (0.002) | (0.001) | (0.001) |
| ROA | -0.067 | -0.023 | -0.131$^{**}$ | -0.121$^{**}$ |
| | (0.069) | (0.041) | (0.053) | (0.054) |
| LEVERAGE | 0.002 | -0.005$^{**}$ | 0.001 | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Unit Fixed Effects | Firm | Firm | Firm | Firm |
| Time Fixed Effects | Month | Month | Month | Month |
| *N* | 64624 | 31878 | 105896 | 105896 |
| adj. $R^2$ | 0.111 | 0.165 | 0.104 | 0.104 |

Standard errors in parentheses

The sample contains observations on 2797 firms on Russell 3000 Index from January 2010 to March 2019. The dependent variable corresponds to the monthly growth in closing stock price (Return). EnVPU refers to the value of US Environmental Policy Uncertainty index. Column headings provide the form of Average Exposure considered for the specification as defined in Section 3. ROA and LEVERAGE variables are measured at the Russell 3000 sectoral index level and scaled down by a factor of 100. See the notes under Table 1 for additional variable definitions. Standard errors are robust and clustered at the firm level.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 14: Effects of US Environmental Policy Uncertainty on 30-day realized stock price volatility of firms on the Russell 3000 Index by firm size**

| | (1) | (2) |
|---|---|---|
| Dependent Variable: Log(Volatility)<br>Firm size Specification: | Small firms | Large firms |
| Log(EnVPU) * Log(Avg Exposure) | **0.040*** ** | **-0.021*** ** |
| | (0.006) | (0.008) |
| Log(EnVP) * Log(Avg Exposure) | 0.057*** | 0.009 |
| | (0.006) | (0.008) |
| Log(EPU_US) * Log(Avg Exposure) | 0.096*** | 0.113*** |
| | (0.005) | (0.008) |
| Log(WTI_VOL) * Log(Avg Exposure) | 0.100*** | 0.140*** |
| | (0.005) | (0.006) |
| LOG_VIX | 0.331*** | 0.511*** |
| | (0.008) | (0.012) |
| Log (FEFR) | 0.011*** | 0.021*** |
| | (0.003) | (0.004) |
| Log(FIRMSIZE) | -0.137*** | -0.061*** |
| | (0.008) | (0.012) |
| ROA | -0.081 | -0.729** |
| | (0.264) | (0.365) |
| LEVERAGE | 0.096*** | 0.091*** |
| | (0.015) | (0.019) |
| Unit Fixed Effects | Firm | Firm |
| Time Fixed Effects | Month | Month |
| *N* | 133710 | 47141 |
| adj. $R^2$ | 0.198 | 0.316 |

Standard errors in parentheses

The sample contains observations on firms of the Russell 3000 Index from January 2010 to March 2019. The dependent variable corresponds to the natural logarithm of the monthly volatility of stock price. The two columns report results of the regression specification under Table 10 (Column 5) for small firms (Micro-Cap, Small-cap and Mid-cap firms) and large firms (Large-cap and Mega-Cap firms) on the Russell 3000 Index. Avg Exposure refers to S&P Global's Sector-level Average Environmental Risk Score. ROA and LEVERAGE variables are measured at the Russell 3000 sectoral index level and scaled down by a factor of 100. See the notes under Table 1 for additional variable definitions. Standard errors are robust and clustered at the firm level.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 15: Effects of US Environmental Policy Uncertainty on monthly stock return of firms on the Russell 3000 Index by firm size**

| | (1) | (2) |
|---|---|---|
| Dependent Variable: Return<br>Firm size Specification: | Small firms | Large firms |
| Log(EnVPU) * Log(Avg Exposure) | **-0.021*****  | **-0.008***** |
| | (0.002) | (0.002) |
| Log(EnVP) * Log(Avg Exposure) | 0.008** | 0.009*** |
| | (0.003) | (0.003) |
| Log(EPU_US) * Log(Avg Exposure) | 0.018*** | 0.008*** |
| | (0.002) | (0.002) |
| Log(WTI_RETURN) * Log(Avg Exposure) | -0.002*** | -0.001** |
| | (0.001) | (0.000) |
| Log (FEFR) | -0.006*** | -0.004*** |
| | (0.001) | (0.001) |
| Log(FIRMSIZE) | 0.023*** | 0.011*** |
| | (0.001) | (0.002) |
| ROA | -0.171** | -0.053 |
| | (0.075) | (0.048) |
| LEVERAGE | 0.002 | -0.003 |
| | (0.002) | (0.002) |
| VT_RETURN | 1.164*** | 0.992*** |
| | (0.020) | (0.024) |
| Unit Fixed Effects | Firm | Firm |
| Time Fixed Effects | Month | Month |
| *N* | 78512 | 27384 |
| adj. $R^2$ | 0.095 | 0.204 |

Standard errors in parentheses

The sample contains observations on firms of the Russell 3000 Index from January 2010 to March 2019. The dependent variable corresponds to the monthly growth in closing stock price (Return). The two columns report results of the regression specification under Table 11 (Column 5) for small firms (Micro-cap, Small-cap and Mid-cap firms) and large firms (Large-cap and Mega-cap firms) on the Russell 3000 Index. Avg Exposure refers to S&P Global's Sector-level Average Environmental Risk Score. ROA and LEVERAGE variables are measured at the Russell 3000 sectoral index level and scaled down by a factor of 100. See the notes under Table 1 for additional variable definitions. Standard errors are robust and clustered at the firm level.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 16: Effects of US Environmental Policy uncertainty on monthly stock price volatility (30-day horizon) of firms on London Stock Exchange**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable: Log(Volatility)<br><br>Avg Exposure Specification: | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Firm-level S&P Global Env Rating | Firm-level Bloomberg Env Rating | GHG Intensity risk measure |
| Log(EnVPU) * Log(Avg Exposure) | **$0.050^{***}$** | **$0.054^{***}$** | **0.025** | **$0.029^{*}$** | **-0.016** | **$0.037^{**}$** | **$0.158^{*}$** | **$0.002^{**}$** | **$0.018^{***}$** |
| | (0.020) | (0.019) | (0.016) | (0.016) | (0.021) | (0.016) | (0.095) | (0.001) | (0.005) |
| Log(EnVP)* Log(Avg Exposure) | 0.016 | 0.024 | 0.034 | 0.015 | $0.122^{***}$ | -0.031 | 0.170 | -0.000 | 0.003 |
| | (0.022) | (0.023) | (0.022) | (0.023) | (0.021) | (0.021) | (0.107) | (0.001) | (0.005) |
| Log(EPU_UK) * Log(Avg Exposure) | 0.015 | 0.000 | 0.010 | 0.008 | $0.070^{***}$ | $0.032^{**}$ | $0.135^{*}$ | $-0.002^{**}$ | 0.006 |
| | (0.017) | (0.017) | (0.016) | (0.015) | (0.016) | (0.013) | (0.079) | (0.001) | (0.004) |
| Log(WTI_VOL) * Log(Avg Exposure) | $0.072^{***}$ | $0.084^{***}$ | $0.086^{***}$ | $0.082^{***}$ | 0.002 | $0.042^{***}$ | $0.478^{***}$ | -0.001 | $0.023^{***}$ |
| | (0.017) | (0.016) | (0.016) | (0.017) | (0.016) | (0.012) | (0.080) | (0.001) | (0.004) |
| Log(Volatility)_Lag | | | | | | $0.399^{***}$ | | | |
| | | | | | | (0.013) | | | |
| log(FTSE_VIX) | $0.241^{***}$ | $0.227^{***}$ | $0.221^{***}$ | $0.253^{***}$ | $0.227^{***}$ | $0.154^{***}$ | $0.339^{***}$ | $0.503^{***}$ | $0.227^{***}$ |
| | (0.029) | (0.028) | (0.028) | (0.026) | (0.028) | (0.020) | (0.024) | (0.030) | (0.026) |
| Log(FEFR) | $-0.050^{***}$ | $-0.044^{***}$ | $-0.043^{***}$ | -0.005 | $-0.065^{***}$ | $-0.030^{***}$ | $-0.059^{***}$ | $-0.039^{*}$ | $-0.053^{***}$ |
| | (0.014) | (0.013) | (0.013) | (0.019) | (0.015) | (0.009) | (0.016) | (0.023) | (0.013) |
| log(FIRMSIZE) | $-0.061^{**}$ | $-0.064^{**}$ | $-0.064^{**}$ | $-0.083^{***}$ | $-0.084^{***}$ | $-0.036^{**}$ | -0.054 | -0.074 | $-0.052^{**}$ |
| | (0.026) | (0.026) | (0.026) | (0.027) | (0.023) | (0.016) | (0.033) | (0.045) | (0.026) |
| ROA | -0.153 | -0.154 | -0.150 | -0.155 | -0.159 | -0.086 | $-0.215^{*}$ | -0.220 | -0.150 |
| | (0.094) | (0.096) | (0.095) | (0.095) | (0.101) | (0.061) | (0.125) | (0.150) | (0.093) |
| LEVERAGE | -0.002 | -0.002 | -0.002 | -0.004 | -0.011 | -0.003 | -0.024 | -0.033 | -0.001 |
| | (0.020) | (0.021) | (0.021) | (0.021) | (0.020) | (0.013) | (0.022) | (0.025) | (0.020) |
| Unit Fixed Effects | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |
| Time Fixed Effects | Month | Sector-Month | Quarter | Year | Month | Month | Month | Month | Month |
| *N* | 16246 | 16246 | 16246 | 16246 | 16265 | 16204 | 9907 | 7251 | 16848 |
| adj. $R^2$ | 0.061 | 0.526 | 0.525 | 0.528 | 0.061 | 0.212 | 0.531 | 0.546 | 0.530 |

Standard errors in parentheses

The sample contains observations on 1418 publicly-listed domestic firms on London Stock Exchange from January 2010 to March 2019. The dependent variable corresponds to the natural logarithm of the 30-day realized volatility in stock price. Column headings provide the form of Average Exposure considered for the specification. Column (5)

specification has all independent variables lagged by one month while Column (6) specification includes a lagged dependent variable (Log(Volatility)_Lag). ROA and LEVERAGE variables are measured at the firm level, trimmed at the 5 percentile and 95 percentile level, and scaled down by a factor of 100. See the notes under Table 1 for additional variable definitions. Standard errors are robust and clustered at the firm level.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 17: Effects of US Environmental Policy uncertainty on monthly stock returns of domestic firms on the London Stock Exchange**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent Variable: Return<br><br>Avg Exposure Specification: | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Firm-level S&P Global Env Rating | Firm-level Bloomberg Env Rating | GHG Intensity risk measure |
| Log(EnVPU) * Log(Avg Exposure) | -0.020** | -0.023*** | -0.014* | -0.002 | -0.149*** | -0.001 | -0.006*** |
| | (0.008) | (0.008) | (0.007) | (0.009) | (0.028) | (0.000) | (0.002) |
| Log(EnVP)* Log(Avg Exposure) | 0.028*** | 0.019* | -0.000 | -0.007 | 0.149*** | -0.000 | 0.007*** |
| | (0.009) | (0.010) | (0.009) | (0.009) | (0.031) | (0.001) | (0.002) |
| Log(EPU_UK) * Log(Avg Exposure) | 0.005 | 0.008* | 0.006 | 0.001 | 0.028 | 0.000** | 0.002 |
| | (0.005) | (0.005) | (0.004) | (0.005) | (0.022) | (0.000) | (0.001) |
| Log(WTI_RETURN) * Log(Avg Exposure) | 0.002 | 0.001 | 0.000 | -0.000 | 0.020*** | -0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.005) | (0.000) | (0.000) |
| Log(FEFR) | 0.014*** | 0.015*** | 0.014*** | -0.003 | 0.010*** | 0.011*** | 0.014*** |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.003) | (0.003) | (0.004) |
| log(FIRMSIZE) | 0.041*** | 0.041*** | 0.042*** | 0.049*** | 0.020** | 0.023*** | 0.041*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.009) | (0.004) | (0.007) |
| ROA | 0.006 | 0.005 | 0.006 | 0.000 | 0.079*** | 0.055* | 0.008 |
| | (0.025) | (0.026) | (0.026) | (0.026) | (0.026) | (0.030) | (0.026) |
| LEVERAGE | -0.006 | -0.006 | -0.005 | -0.006 | 0.002 | 0.004 | -0.005 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.003) | (0.003) | (0.004) |
| VT_RETURN | 0.433*** | 0.462*** | 0.492*** | 0.520*** | 0.690*** | 0.768*** | 0.449*** |
| | (0.050) | (0.046) | (0.040) | (0.040) | (0.051) | (0.047) | (0.051) |
| Unit Fixed Effects | Firm | Firm | Firm | Firm | Firm | Firm | Firm |
| Time Fixed Effects | Month | Sector-Month | Quarter | Year | Month | Month | Month |
| *N* | 12401 | 12401 | 12401 | 12401 | 5902 | 4363 | 12698 |
| adj. $R^2$ | 0.052 | 0.063 | 0.054 | 0.062 | 0.176 | 0.193 | 0.065 |

Standard errors in parentheses

The sample contains observations on 1418 publicly-listed domestic firms on London Stock Exchange from January 2010 to March 2019. The dependent variable corresponds to the monthly growth in closing stock price (Return). Column headings provide the form of Average Exposure considered for the specification. ROA and LEVERAGE variables are measured at the firm level, trimmed at the 5 percentile and 95 percentile level, and scaled down by a factor of 100. See the notes under Table 1 for additional variable definitions. Standard errors are robust and clustered at the firm level.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 18: Effects of US Environmental Policy uncertainty on monthly stock price volatility (30-day horizon) of domestic firms on the Frankfurt Stock Exchange**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dependent Variable: Log(Volatility)<br><br>Avg Exposure Specification: | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Firm-level S&P Global Env Rating | Firm-level Bloomberg Env Rating |
| Log(EnVPU) * Log(Avg Exposure) | -0.046$^{***}$ | -0.045$^{***}$ | -0.039$^{***}$ | -0.025$^{*}$ | -0.032$^{**}$ | -0.026$^{**}$ | -0.219$^{***}$ | -0.025$^{**}$ |
| | (0.016) | (0.015) | (0.014) | (0.014) | (0.014) | (0.011) | (0.084) | (0.011) |
| Log(EnVP)* Log(Avg Exposure) | 0.130$^{***}$ | 0.125$^{***}$ | 0.101$^{***}$ | -0.004 | 0.198$^{***}$ | 0.029$^{**}$ | 0.618$^{***}$ | 0.028$^{**}$ |
| | (0.016) | (0.016) | (0.015) | (0.014) | (0.015) | (0.012) | (0.074) | (0.014) |
| Log(EPU_GER) * Log(Avg Exposure) | 0.069$^{***}$ | 0.065$^{***}$ | 0.051$^{***}$ | 0.061$^{***}$ | 0.022$^{**}$ | 0.050$^{***}$ | 0.312$^{***}$ | 0.013$^{**}$ |
| | (0.011) | (0.010) | (0.010) | (0.009) | (0.010) | (0.007) | (0.049) | (0.006) |
| Log(WTI_VOL) * Log(Avg Exposure) | 0.165$^{***}$ | 0.166$^{***}$ | 0.168$^{***}$ | 0.164$^{***}$ | 0.111$^{***}$ | 0.094$^{***}$ | 0.636$^{***}$ | 0.036$^{**}$ |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.009) | (0.006) | (0.082) | (0.015) |
| Log(Volatility)_Lag | | | | | | 0.497$^{***}$ | | |
| | | | | | | (0.010) | | |
| Log(FEFR) | -0.012$^{**}$ | -0.011$^{*}$ | -0.010$^{*}$ | -0.051$^{***}$ | -0.012$^{*}$ | -0.004 | -0.020$^{***}$ | -0.009 |
| | (0.006) | (0.006) | (0.006) | (0.015) | (0.006) | (0.003) | (0.006) | (0.006) |
| Log(FIRMSIZE) | -0.139$^{***}$ | -0.140$^{***}$ | -0.141$^{***}$ | -0.109$^{***}$ | -0.133$^{***}$ | -0.070$^{***}$ | -0.098$^{***}$ | -0.224$^{***}$ |
| | (0.019) | (0.019) | (0.019) | (0.023) | (0.019) | (0.010) | (0.018) | (0.029) |
| ROA | 0.130 | 0.125 | 0.137 | -0.002 | 0.131 | 0.042 | 0.067 | -0.077 |
| | (0.143) | (0.145) | (0.145) | (0.153) | (0.143) | (0.076) | (0.195) | (0.358) |
| LEVERAGE | 0.014 | 0.013 | 0.013 | 0.020 | 0.019 | 0.005 | 0.024 | -0.028 |
| | (0.020) | (0.020) | (0.020) | (0.019) | (0.019) | (0.011) | (0.025) | (0.027) |
| Unit Fixed Effects | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |
| Time Fixed Effects | Month | Sector-Month | Quarter | Year | Month | Month | Month | Month |
| $N$ | 22454 | 22454 | 22454 | 22454 | 22273 | 22445 | 13876 | 7913 |
| adj. $R^2$ | 0.091 | 0.495 | 0.491 | 0.511 | 0.066 | 0.316 | 0.445 | 0.389 |

The sample contains observations on 904 publicly-listed domestic firms on Frankfurt Stock Exchange from 2010M1 to 2019M3. The dependent variable corresponds to the natural logarithm of the monthly volatility in stock price. Column headings provide the form of Average Exposure considered for the specification. Column (5) specification has all independent variables lagged by one month while Column (6) specification includes a lagged dependent variable (Log(Volatility)_Lag). ROA and LEVERAGE variables are measured at the firm level, trimmed at the 5 percentile and 95 percentile level, and scaled down by a factor of 100. See the notes under Table 1 for additional variable definitions. Standard errors are robust and clustered at the firm level.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 19: Effects of US Environmental Policy uncertainty on monthly stock returns of domestic firms on the Frankfurt Stock Exchange**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable: Return<br><br>Avg Exposure Specification: | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Firm-level S&P Global Env Rating | Firm-level Bloomberg Env Rating |
| Log(EnVPU) * Log(Avg Exposure) | $0.023^{***}$ | $0.024^{***}$ | $0.021^{***}$ | $0.038^{***}$ | $0.072^{***}$ | 0.002 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.020) | (0.002) |
| Log(EnVP)* Log(Avg Exposure) | $-0.013^{**}$ | $-0.018^{***}$ | $-0.020^{***}$ | $-0.029^{***}$ | -0.037 | 0.004 |
| | (0.006) | (0.006) | (0.005) | (0.006) | (0.027) | (0.003) |
| Log(EPU_GER) * Log(Avg Exposure) | $-0.007^{**}$ | $-0.005^{*}$ | $-0.007^{***}$ | $-0.006^{**}$ | $-0.024^{*}$ | -0.002 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.014) | (0.002) |
| Log(WTI_RETURN) * Log(Avg Exposure) | $0.003^{***}$ | $0.002^{**}$ | 0.001 | 0.001 | 0.004 | -0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.004) | (0.000) |
| Log(FEFR) | $-0.007^{***}$ | $-0.007^{***}$ | $-0.006^{***}$ | $0.011^{***}$ | $-0.005^{***}$ | $-0.004^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.004) | (0.001) | (0.002) |
| Log(FIRMSIZE) | $0.018^{***}$ | $0.018^{***}$ | $0.018^{***}$ | $0.025^{***}$ | $0.012^{***}$ | $0.013^{**}$ |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.005) |
| ROA | 0.016 | 0.016 | 0.016 | 0.000 | 0.031 | -0.069 |
| | (0.032) | (0.033) | (0.032) | (0.032) | (0.055) | (0.105) |
| LEVERAGE | -0.001 | -0.001 | -0.001 | 0.001 | 0.001 | 0.005 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) | (0.008) |
| VT_RETURN | $0.584^{***}$ | $0.583^{***}$ | $0.603^{***}$ | $0.623^{***}$ | $0.770^{***}$ | $0.940^{***}$ |
| | (0.044) | (0.043) | (0.041) | (0.040) | (0.061) | (0.079) |
| Unit Fixed Effects | Firm | Firm | Firm | Firm | Firm | Firm |
| Time Fixed Effects | Month | Sector-Month | Quarter | Year | Month | Month |
| *N* | 11269 | 11269 | 11269 | 11269 | 6138 | 2743 |
| adj. $R^2$ | 0.074 | 0.088 | 0.082 | 0.097 | 0.123 | 0.161 |

Standard errors in parentheses

The sample contains observations on 904 publicly-listed domestic firms on Frankfurt Stock Exchange from January 2010 to March 2019. The dependent variable corresponds to the monthly growth in closing stock price (Return). Column headings provide the form of Average Exposure considered for the specification. ROA and LEVERAGE variables are measured at the firm level, trimmed at the 5 percentile and 95 percentile level, and scaled down by a factor of 100. See the notes under Table 1 for additional variable definitions. Standard errors are robust and clustered at the firm level.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 20: Effects of US Environmental Policy uncertainty on monthly stock price volatility (30-day horizon) of firms on BSE S&P 500 Index**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable: Log(Volatility)<br><br>Avg Exposure Specification: | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Firm-level S&P Global Env Rating | Firm-level Bloomberg Env Rating | GHG Intensity risk measure |
| Log(EnVPU) * Log(Avg Exposure) | $0.025^{***}$ | $0.022^{***}$ | $0.015^{**}$ | 0.001 | $0.026^{***}$ | 0.000 | 0.022 | 0.001 | $0.010^{***}$ |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.008) | (0.006) | (0.034) | (0.002) | (0.004) |
| Log(EnVP)* Log(Avg Exposure) | $0.040^{***}$ | $0.029^{***}$ | 0.006 | $-0.024^{***}$ | $0.023^{***}$ | $0.027^{***}$ | $0.162^{***}$ | 0.001 | -0.004 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.009) | (0.007) | (0.035) | (0.001) | (0.005) |
| Log(EPU_INDIA) * Log(Avg Exposure) | $0.011^{*}$ | $0.013^{**}$ | 0.002 | $0.046^{***}$ | $-0.027^{***}$ | 0.004 | $0.056^{**}$ | 0.000 | -0.004 |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.006) | (0.004) | (0.027) | (0.001) | (0.003) |
| Log(WTI_VOL) * Log(Avg Exposure) | $0.029^{***}$ | $0.031^{***}$ | $0.029^{***}$ | $0.029^{***}$ | $-0.012^{**}$ | $0.009^{***}$ | $0.112^{***}$ | 0.000 | $0.006^{**}$ |
| | (0.005) | (0.005) | (0.005) | (0.007) | (0.005) | (0.003) | (0.022) | (0.000) | (0.003) |
| Log(FEFR) | $-0.037^{***}$ | $-0.038^{***}$ | $-0.034^{***}$ | $-0.047^{***}$ | $-0.046^{***}$ | $-0.013^{***}$ | $-0.038^{***}$ | $-0.031^{***}$ | $-0.030^{***}$ |
| | (0.005) | (0.005) | (0.005) | (0.010) | (0.004) | (0.003) | (0.005) | (0.006) | (0.005) |
| Log(FIRMSIZE) | $-0.041^{***}$ | $-0.042^{***}$ | $-0.040^{***}$ | $-0.053^{***}$ | $-0.060^{***}$ | $-0.022^{***}$ | $-0.039^{***}$ | $-0.054^{***}$ | $-0.039^{***}$ |
| | (0.007) | (0.007) | (0.008) | (0.008) | (0.007) | (0.004) | (0.008) | (0.016) | (0.008) |
| ROA | $-0.064^{***}$ | $-0.073^{***}$ | $-0.047^{***}$ | $0.095^{***}$ | $-0.090^{***}$ | $-0.018^{**}$ | $-0.066^{***}$ | $-0.047^{**}$ | $-0.040^{***}$ |
| | (0.012) | (0.011) | (0.011) | (0.011) | (0.012) | (0.007) | (0.013) | (0.018) | (0.012) |
| LEVERAGE | 0.059 | 0.029 | 0.067 | $0.325^{***}$ | -0.039 | $0.100^{***}$ | 0.038 | 0.001 | $0.114^{***}$ |
| | (0.042) | (0.039) | (0.042) | (0.034) | (0.043) | (0.028) | (0.043) | (0.059) | (0.042) |
| Log(Volatility)_Lag | | | | | | $0.465^{***}$ | | | |
| | | | | | | (0.007) | | | |
| Unit Fixed Effects | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |
| Time Fixed Effects | Month | Sector-Month | Quarter | Year | Month | Month | Month | Month | Month |
| *N* | 40764 | 40764 | 40764 | 40764 | 40391 | 40672 | 33855 | 13654 | 40764 |
| adj. $R^2$ | 0.039 | 0.323 | 0.314 | 0.333 | 0.044 | 0.248 | 0.324 | 0.301 | 0.324 |

Standard errors in parentheses

The sample contains observations on 501 publicly-listed domestic firms on BSE S&P 500 Index of the Bombay Stock Exchange from January 2010 to March 2019. The dependent variable corresponds to the natural logarithm of the 30-day realized stock price volatility. Column headings provide the form of Average Exposure considered for the

specification. Column (5) specification has all independent variables lagged by one month while Column (6) specification includes a lagged dependent variable (Log(Volatility)_Lag). ROA and LEVERAGE variables are measured at the BSE S&P 500 index level. LEVERAGE variable is scaled down by a factor of 100. See the notes under Table 1 for additional variable definitions. Standard errors are robust and clustered at the firm level.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 21: Effects of US Environmental Policy uncertainty on monthly stock returns of firms on the BSE S&P 500 Index**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent Variable: Stock Return<br><br>Avg Exposure Specification: | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Sector-level S&P Global Env Risk Score | Firm-level S&P Global Env Rating | Firm-level Bloomberg Env Rating | GHG Intensity risk measure |
| Log(EnVPU) * Log(Avg Exposure) | **0.057$^{***}$** | **0.053$^{***}$** | **0.045$^{***}$** | **0.011$^{***}$** | **0.212$^{***}$** | **0.000** | **0.005$^{***}$** |
| | (0.003) | (0.003) | (0.002) | (0.003) | (0.011) | (0.001) | (0.002) |
| Log(EnVP)* Log(Avg Exposure) | -0.072$^{***}$ | -0.062$^{***}$ | -0.048$^{***}$ | -0.012$^{***}$ | -0.280$^{***}$ | -0.000 | -0.005$^{**}$ |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.018) | (0.001) | (0.002) |
| Log(EPU_INDIA) * Log(Avg Exposure) | -0.000 | -0.003$^{**}$ | -0.004$^{***}$ | -0.021$^{***}$ | -0.002 | 0.000 | 0.001$^{**}$ |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.006) | (0.000) | (0.001) |
| Log(WTI_RETURN) * Log(Avg Exposure) | 0.006$^{***}$ | 0.006$^{***}$ | 0.003$^{***}$ | 0.002$^{***}$ | 0.022$^{***}$ | -0.000 | 0.000$^{*}$ |
| | (0.001) | (0.001) | (0.000) | (0.000) | (0.003) | (0.000) | (0.000) |
| Log(FEFR) | 0.002$^{**}$ | 0.002 | -0.001 | -0.050$^{***}$ | 0.003$^{**}$ | 0.002 | 0.002$^{*}$ |
| | (0.001) | (0.001) | (0.001) | (0.003) | (0.001) | (0.002) | (0.001) |
| Log(FIRMSIZE) | 0.012$^{***}$ | 0.013$^{***}$ | 0.012$^{***}$ | 0.012$^{***}$ | 0.012$^{***}$ | 0.012$^{***}$ | 0.013$^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) |
| ROA | 0.036$^{***}$ | 0.039$^{***}$ | 0.026$^{***}$ | 0.026$^{***}$ | 0.039$^{***}$ | 0.017$^{***}$ | 0.023$^{***}$ |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.004) | (0.005) | (0.003) |
| LEVERAGE | 0.080$^{***}$ | 0.077$^{***}$ | 0.057$^{***}$ | -0.095$^{***}$ | 0.068$^{***}$ | 0.044$^{**}$ | 0.087$^{***}$ |
| | (0.014) | (0.013) | (0.014) | (0.013) | (0.015) | (0.019) | (0.014) |
| VT_RETURN | 0.487$^{***}$ | 0.450$^{***}$ | 0.444$^{***}$ | 0.181$^{***}$ | 0.491$^{***}$ | 0.567$^{***}$ | 0.561$^{***}$ |
| | (0.022) | (0.023) | (0.021) | (0.020) | (0.023) | (0.037) | (0.022) |
| Month Fixed Effects | Yes | No | No | No | Yes | Yes | Yes |
| *N* | 23895 | 23895 | 23895 | 23895 | 19819 | 7970 | 23895 |
| adj. $R^2$ | 0.087 | 0.076 | 0.046 | 0.106 | 0.087 | 0.069 | 0.070 |

Standard errors in parentheses

The sample contains observations on 501 publicly-listed domestic firms on BSE S&P 500 Index of the Bombay Stock Exchange from January 2010 to March 2019. The dependent variable corresponds to the monthly growth in closing stock price (Return). Column headings provide the form of Average Exposure considered for the specification. ROA and LEVERAGE variables are measured at the BSE S&P 500 index level. LEVERAGE variable is scaled down by a factor of 100. See the notes under Table 1 for additional variable definitions. Standard errors are robust and clustered at the firm level.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 22: Augmented Dickey Fuller Test Results for Vector Autoregressive Analysis**

| Variables | ADF Test Statistic (Z(t)) | MacKinnon approximate p-value for Z(t) | D-F critical value 1% | D-F critical value 5% | D-F critical value 10% |
|---|---|---|---|---|---|
| EnVPU_GROWTH | -27.52 | 0.000 | -3.452 | -2.876 | -2.57 |
| EnVP_GROWTH | -32.47 | 0.000 | -3.443 | -2.872 | -2.57 |
| EPU_US_GROWTH | -21.36 | 0.000 | -3.458 | -2.879 | -2.57 |
| XLE_VOL | -6.24 | 0.000 | -3.457 | -2.878 | -2.57 |
| IEO_VOL | -5.02 | 0.000 | -3.477 | -2.883 | -2.573 |
| PBW_VOL | -5.04 | 0.000 | -3.472 | -2.882 | -2.572 |
| NORDEA_VOL | -4.82 | 0.000 | -3.484 | -2.885 | -2.575 |
| PBD_VOL | -5 | 0.000 | -3.481 | -2.884 | -2.574 |
| XLE_RETURN | -17.87 | 0.000 | -3.457 | -2.878 | -2.57 |
| IEO_RETURN | -14.84 | 0.000 | -3.477 | -2.883 | -2.573 |
| PBW_RETURN | -13.78 | 0.000 | -3.472 | -2.882 | -2.572 |
| NORDEA_RETURN | -12.11 | 0.000 | -3.484 | -2.885 | -2.575 |
| PBD_RETURN | -11.8 | 0.000 | -3.481 | -2.884 | -2.574 |
| WTI_VOL | -7.85 | 0.000 | -3.451 | -2.876 | -2.57 |
| WTI_RETURN | -16.6 | 0.000 | -3.452 | -2.876 | -2.57 |
| NATURAL_GAS | -18.38 | 0.000 | -3.455 | -2.878 | -2.57 |
| RUSSELL3000_TECH_VOL | -6.22 | 0.000 | -3.455 | -2.877 | -2.57 |
| RUSSELL3000_TECH_RETURN | -17.68 | 0.000 | -3.455 | -2.877 | -2.57 |
| ISHARES_GLOBAL_IND_RETURN | -13.02 | 0.000 | -3.478 | -2.884 | -2.574 |
| SNP_GLOBAL_IND_VOL | -6.53 | 0.000 | -3.457 | -2.878 | -2.57 |
| SNPGLOBAL_IND_RETURN | -15.89 | 0.000 | -3.457 | -2.879 | -2.57 |
| FEFR_D | -5.7 | 0.000 | -3.487 | -2.885 | -2.575 |

Notes: Table shows Augmented Dickey Fuller Test Results for Vector Autoregressive Analysis. EnvPU_MA and EnvP_MA are three-month backward looking moving averages of EnvPU and EnvP index. See the notes under Table 1 for additional variable definitions. Volatility variables are scaled down by a factor of 100 to maintain similar scale of variables in the VAR specification. FEFR_D is the first differenced transformation of US Federal Funds Effective Rate.

## FIGURES

**Figure 1: Trends in US Environmental Policy Index**

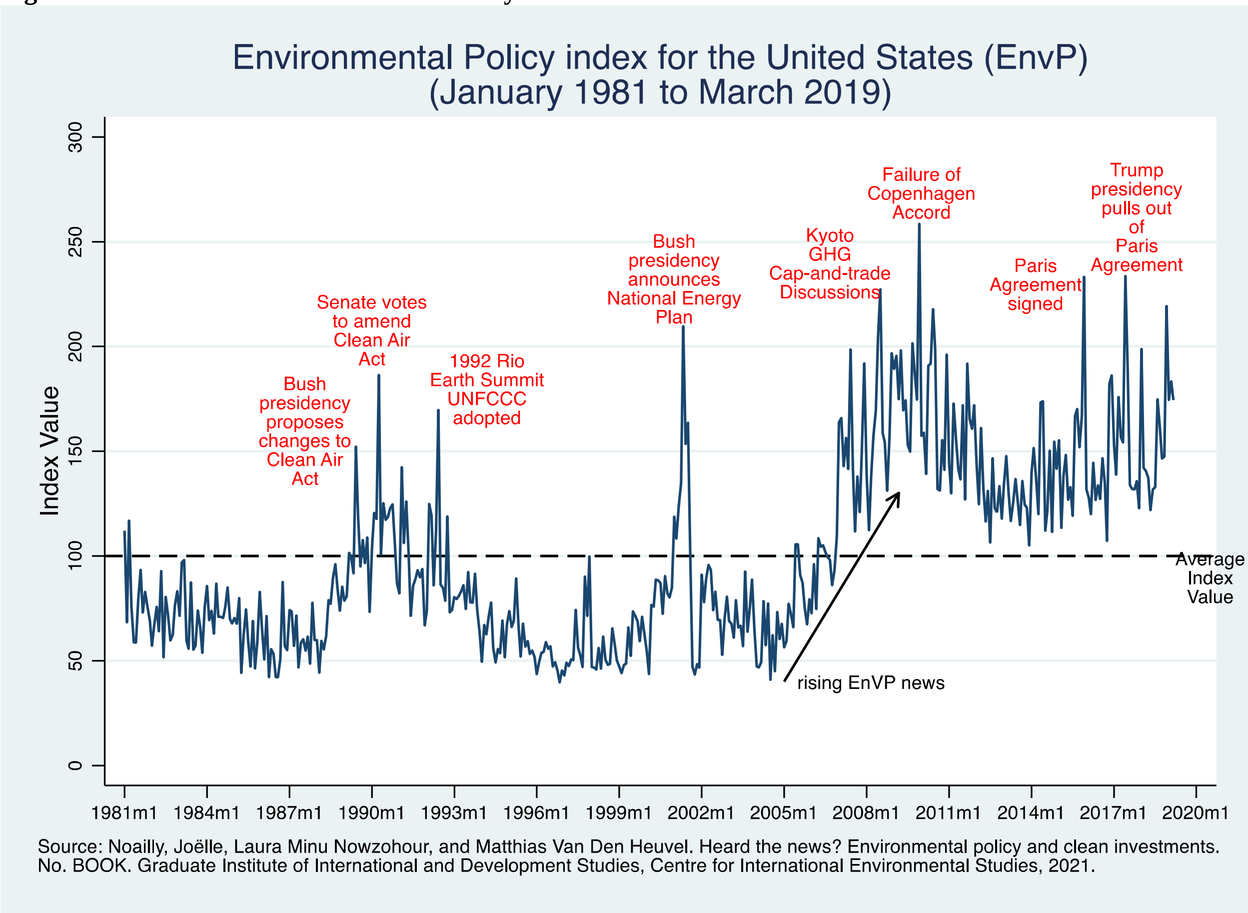
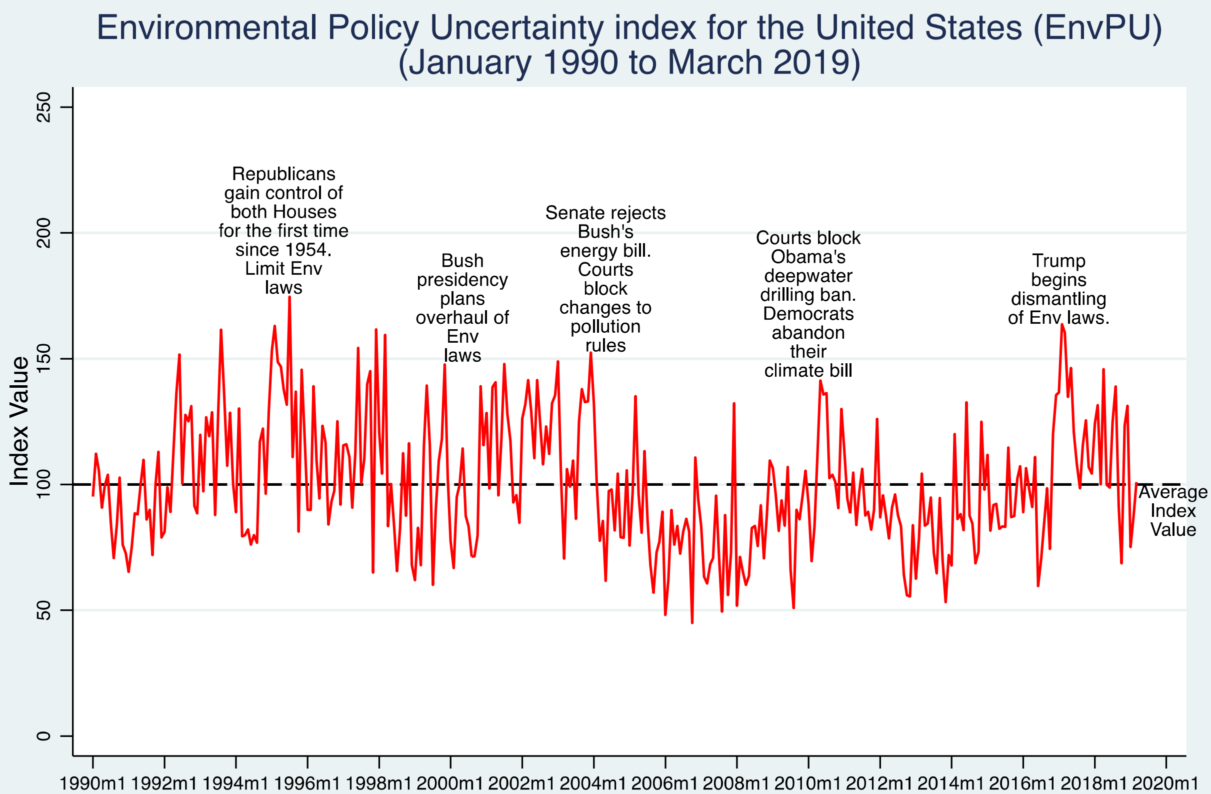
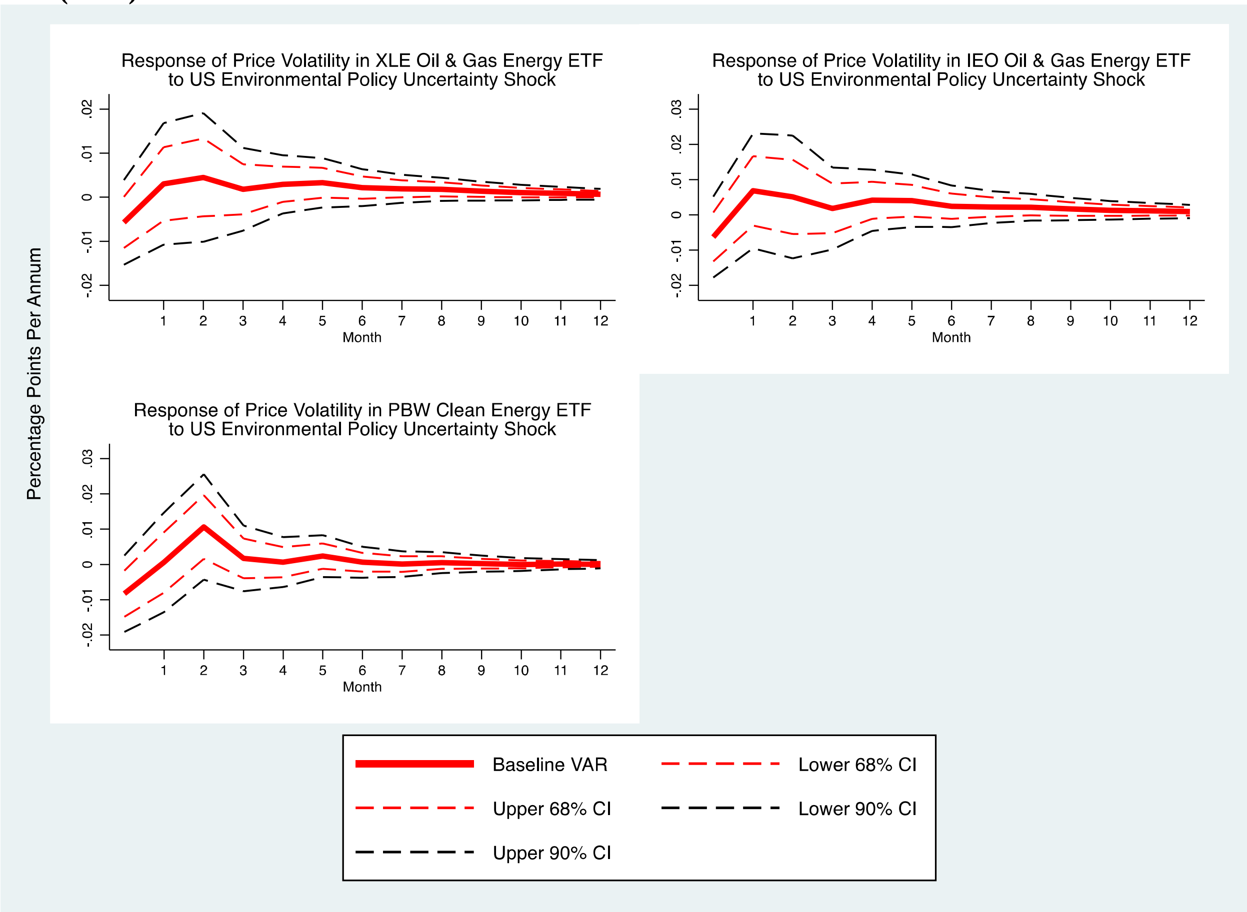


**Figure 2: Trends in US Environmental Policy Uncertainty Index**



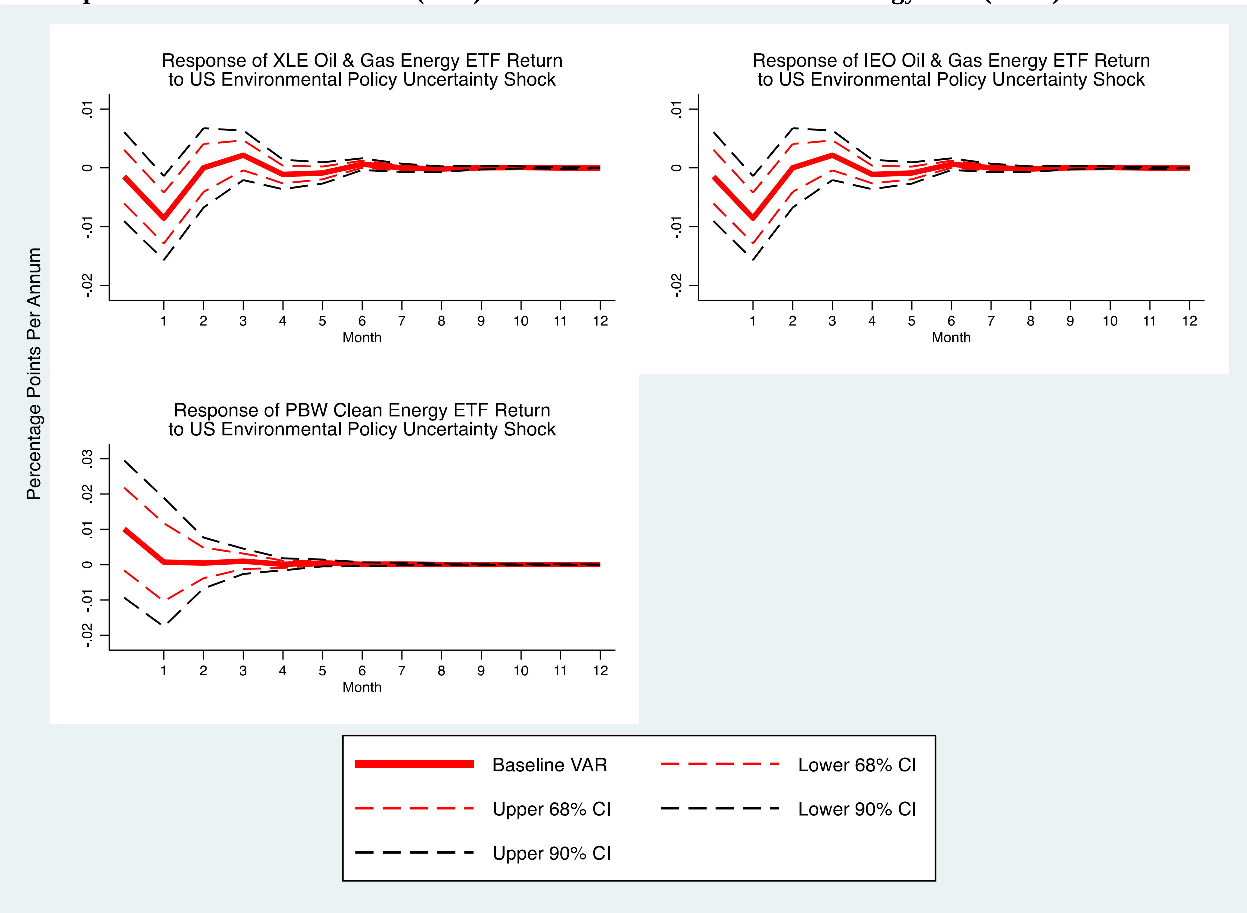

Source: Noailly, Joelle, Laura Nowzohour, and Matthias van den Heuvel. Does Environmental Policy Uncertainty Hinder Investments Towards a Low-Carbon Economy?. No. w30361. National Bureau of Economic Research, 2022.

**Figure 3: Estimated effects of a one standard deviation shock to US Environmental Policy Uncertainty growth on the 30-day historical price volatility of three US-focused Energy ETFs: Energy Select Sector SPDR® Fund (XLE), iShares U.S. Oil & Gas Exploration & Production ETF (IEO) and Invesco WilderHill Clean Energy ETF (PBW)**



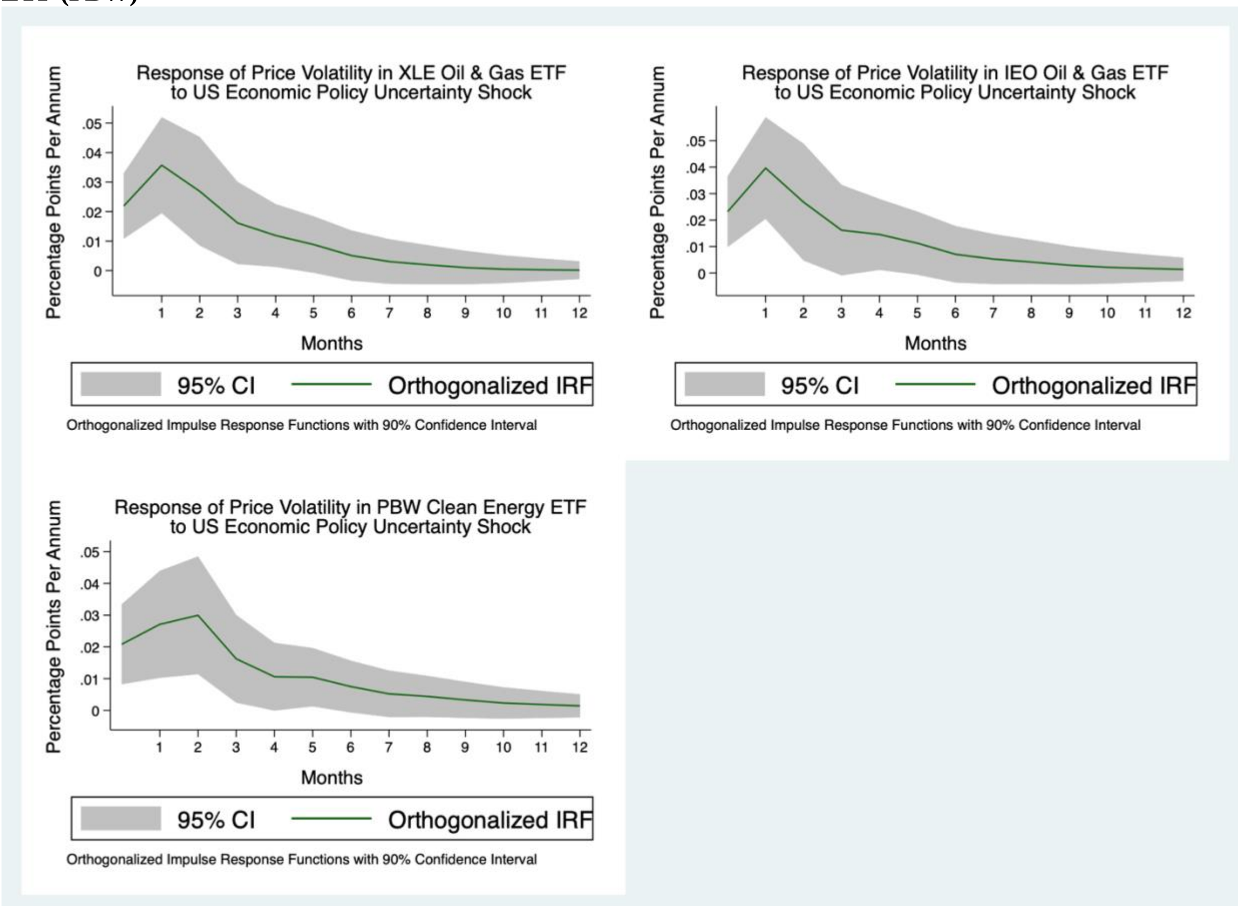

Note: Confidence intervals denote delta standard errors.
XLE: VAR (7) Model from 2005M5 to 2019M3 for 2 lags.
PBW: VAR (7) Model from 2005M3 to 2019M3 for 2 lags.
IEO: VAR (7) from 2006M6 to 2019M3 for 1 lag.

**Figure 4: Estimated effects of a one standard deviation shock to US Environmental Policy Uncertainty growth on the return of three US-focused Energy ETFs: Energy Select Sector SPDR® Fund (XLE), iShares U.S. Oil & Gas Exploration & Production ETF (IEO) and Invesco WilderHill Clean Energy ETF (PBW)**



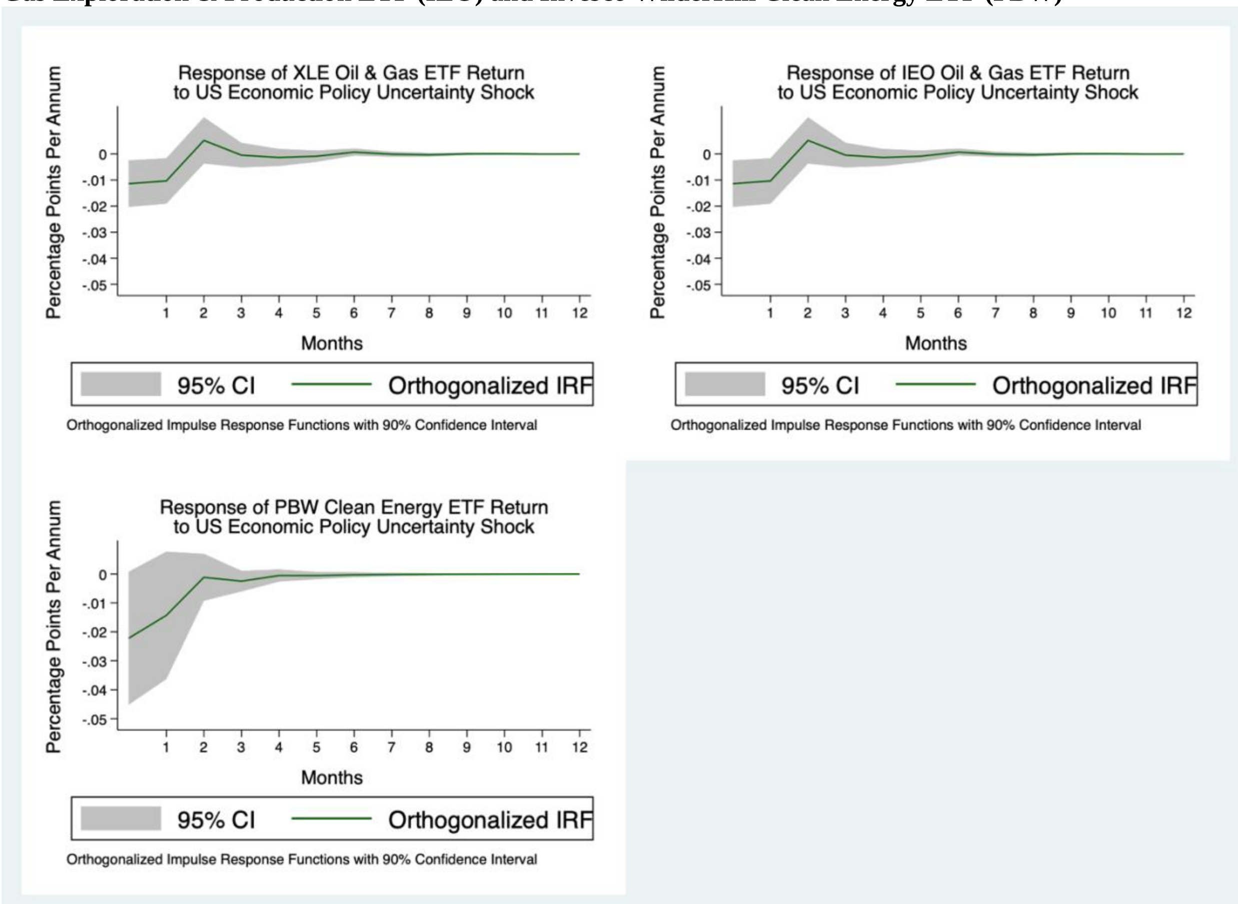

Note: Confidence intervals denote delta standard errors.
XLE: VAR (7) Model from 2005M5 to 2019M3 for 2 lags.
PBW: VAR (7) Model from 2005M5 to 2019M3 for 1 lag.
; IEO: VAR (7) from 2006M7 to 2019M3for 1 lag.

**Figure 5: Estimated effects of a one standard deviation shock to US Economic Policy Uncertainty growth on the 30-day historical price volatility of three US-focused Energy ETFs: Energy Select Sector SPDR® Fund (XLE), iShares U.S. Oil & Gas Exploration & Production ETF (IEO) and Invesco WilderHill Clean Energy ETF (PBW)**



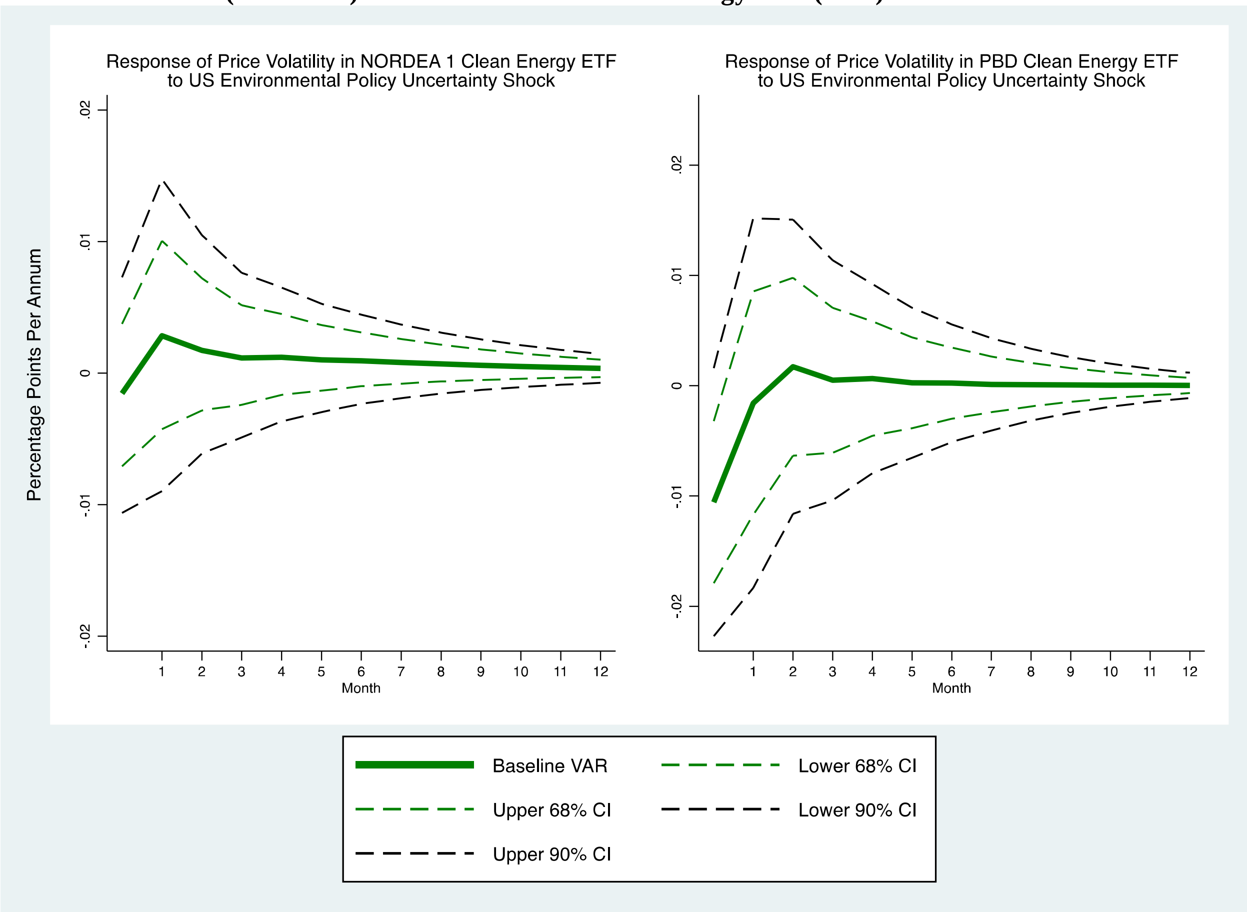

Note: Confidence intervals denote delta standard errors.
XLE: VAR (7) Model from 2005M5 to 2019M3 for 2 lags.
PBW: VAR (7) Model from 2005M3 to 2019M3.Model 2 lags.
IEO: VAR (7) from 2006M6 to 2019M3 for 1 lag.

**Figure 6: Estimated effects of a one standard deviation shock to US Economic Policy Uncertainty growth on the return of three US-focused Energy ETFs: Energy Select Sector SPDR® Fund (XLE), iShares U.S. Oil & Gas Exploration & Production ETF (IEO) and Invesco WilderHill Clean Energy ETF (PBW)**



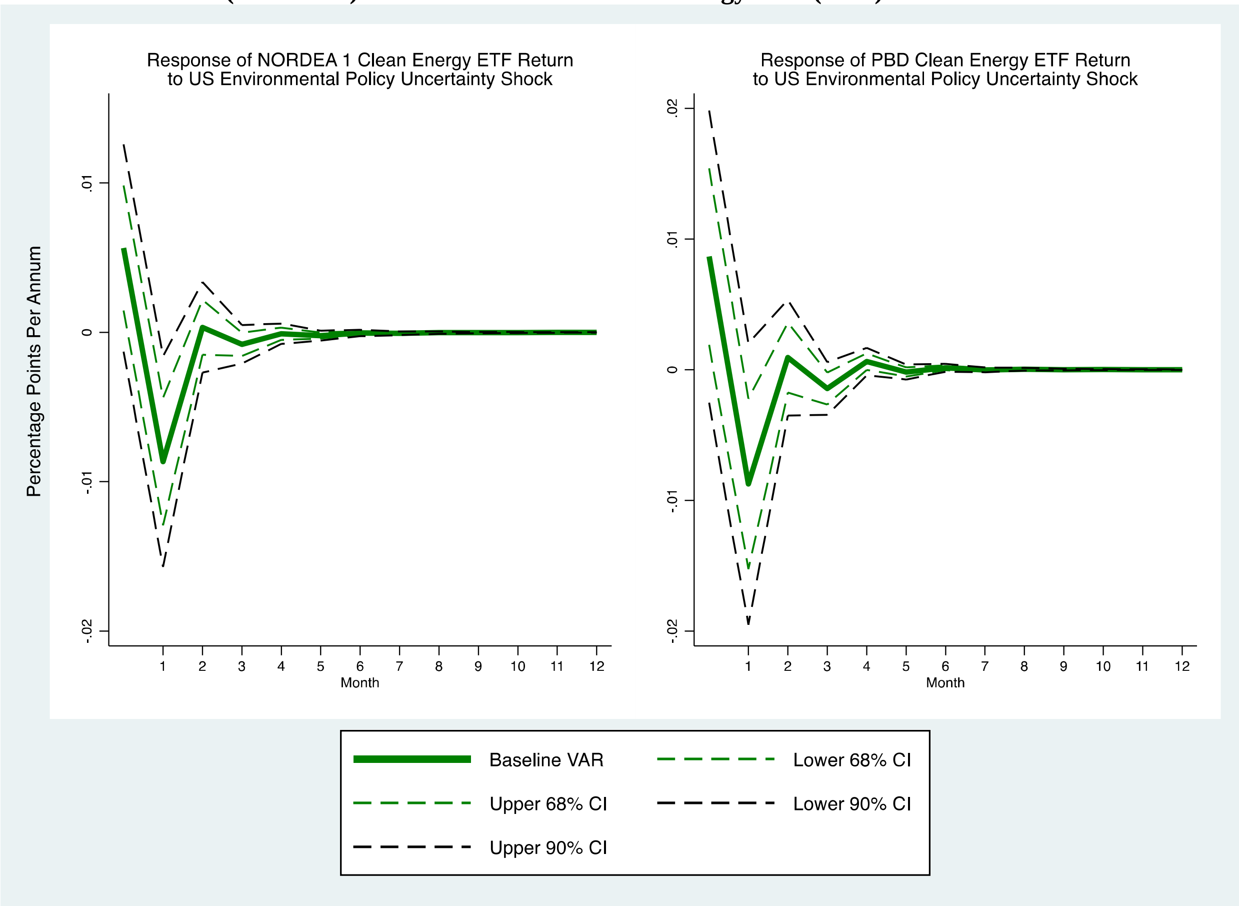

Note: Confidence intervals denote delta standard errors.
XLE: VAR (7) Model from 2005M5 to 2019M3 for 2 lags ;
PBW: VAR (7) Model from 2005M5 to 2019M3.Model 1 lag.
; IEO: VAR (7) from 2006M7 to 2019M3for 1 lag.

**Figure 7: Estimated impulse response of a one standard deviation shock to US Environmental Policy Uncertainty growth on the 30-day historical price volatility of two global Energy ETFs: 1: Global Climate and Environment Fund (NORDEA) and Invesco Global Clean Energy ETF (PBD)**



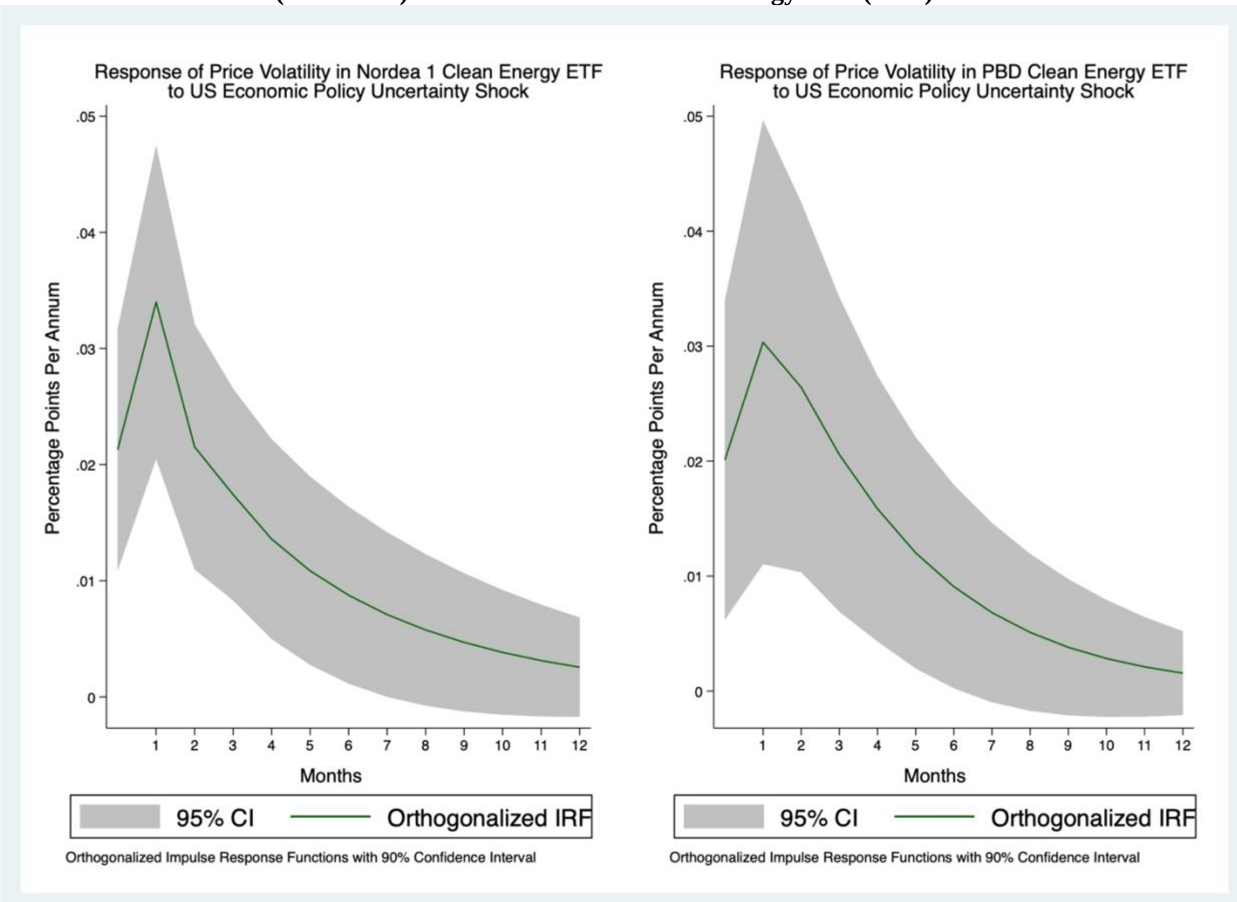

Note: Confidence intervals denote delta standard errors.
NORDEA 1: VAR (7) Model from 2008M5 to 2019M3 for 1 lag;
PBD: VAR (7) Model from 2007M8 to 2019M3 for 1 lag.

**Figure 8: Estimated impulse response of a one standard deviation shock to US Environmental Policy Uncertainty growth ($EnvPU\_US_t$) on the return of two global Energy ETFs: 1: Global Climate and Environment Fund (NORDEA) and Invesco Global Clean Energy ETF (PBD)**



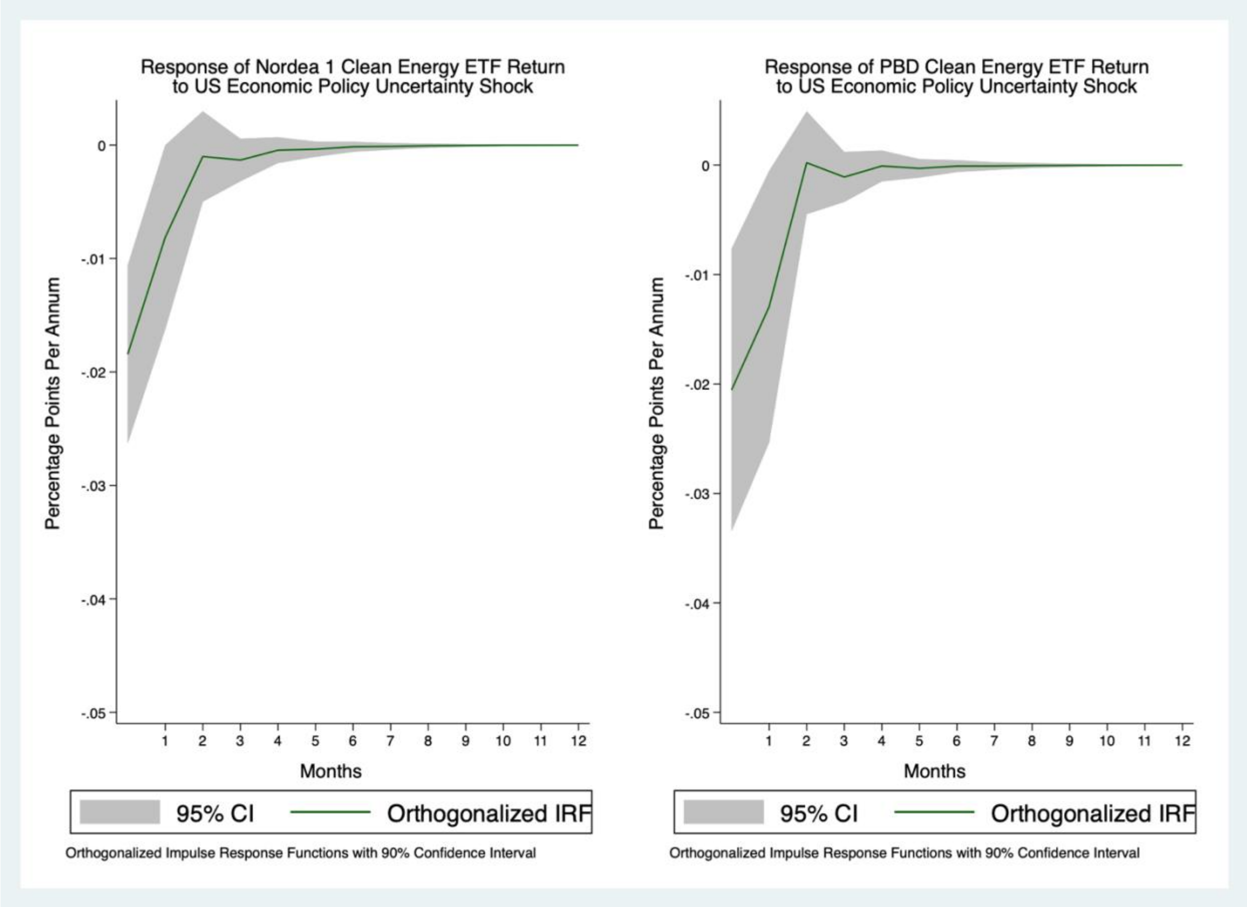

Note: Confidence intervals denote delta standard errors.
NORDEA 1: VAR (7) Model from 2008M5 to 2019M3 for 1 lag;
PBD: VAR (7) Model from 2007M8 to 2019M3 for 1 lag.

**Figure 9: Estimated effects of a one standard deviation shock to US Economic Policy Uncertainty growth ($EnvPU\_US_t$) on the 30-day historical price volatility of two global Energy ETFs: NORDEA 1: Global Climate and Environment Fund (NORDEA) and Invesco Global Clean Energy ETF (PBD)**



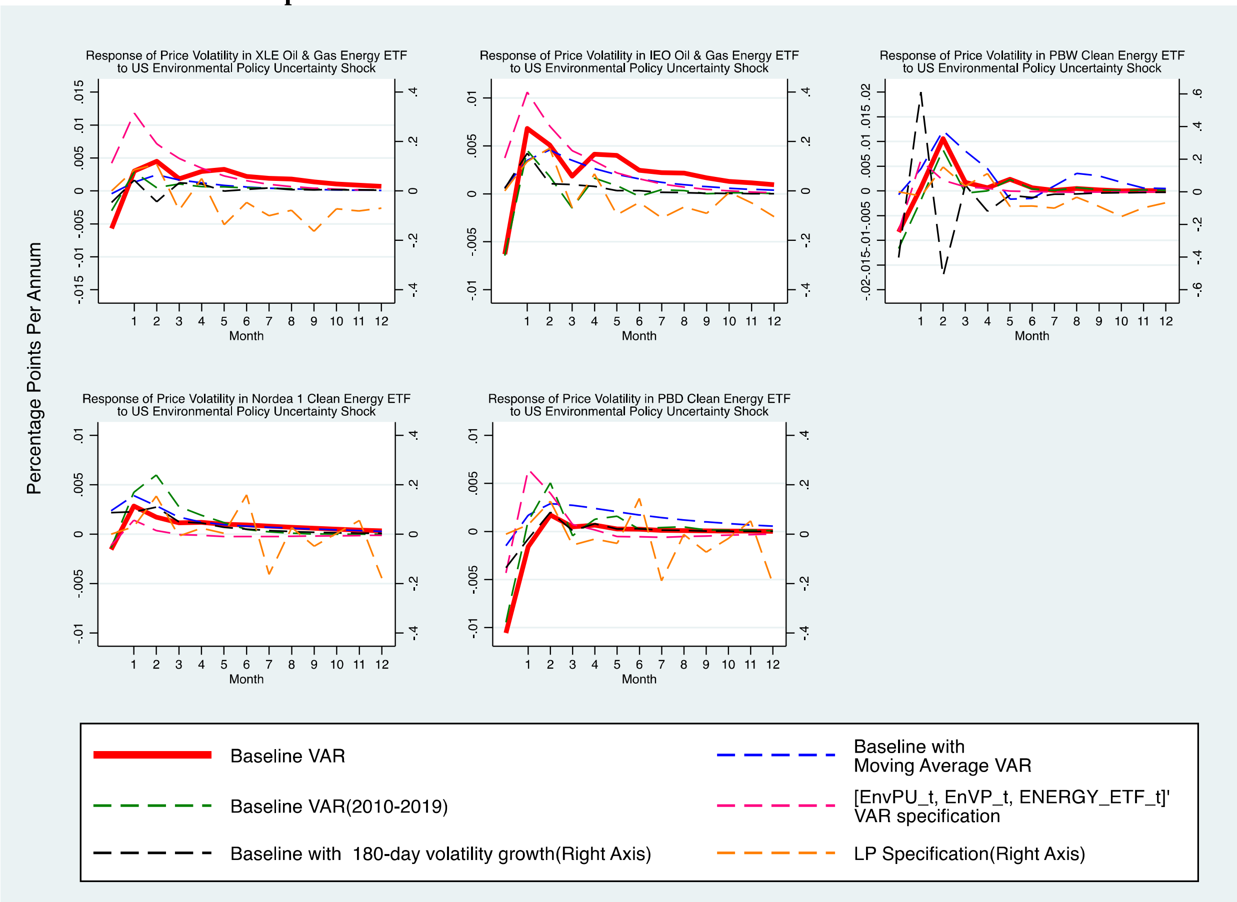

Note: Confidence intervals denote delta standard errors.
NORDEA 1: VAR (7) Model from 2008M5 to 2019M3 for 1 lag ;
PBD: VAR (7) Model from 2007M8 to 2019M3 for 1 lag.

**Figure 10: Estimated effects of a one standard deviation shock to US Economic Policy Uncertainty growth (EnvPU_US$_t$) on the return of two global Energy ETFs: NORDEA 1: Global Climate and Environment Fund (NORDEA) and Invesco Global Clean Energy ETF (PBD)**



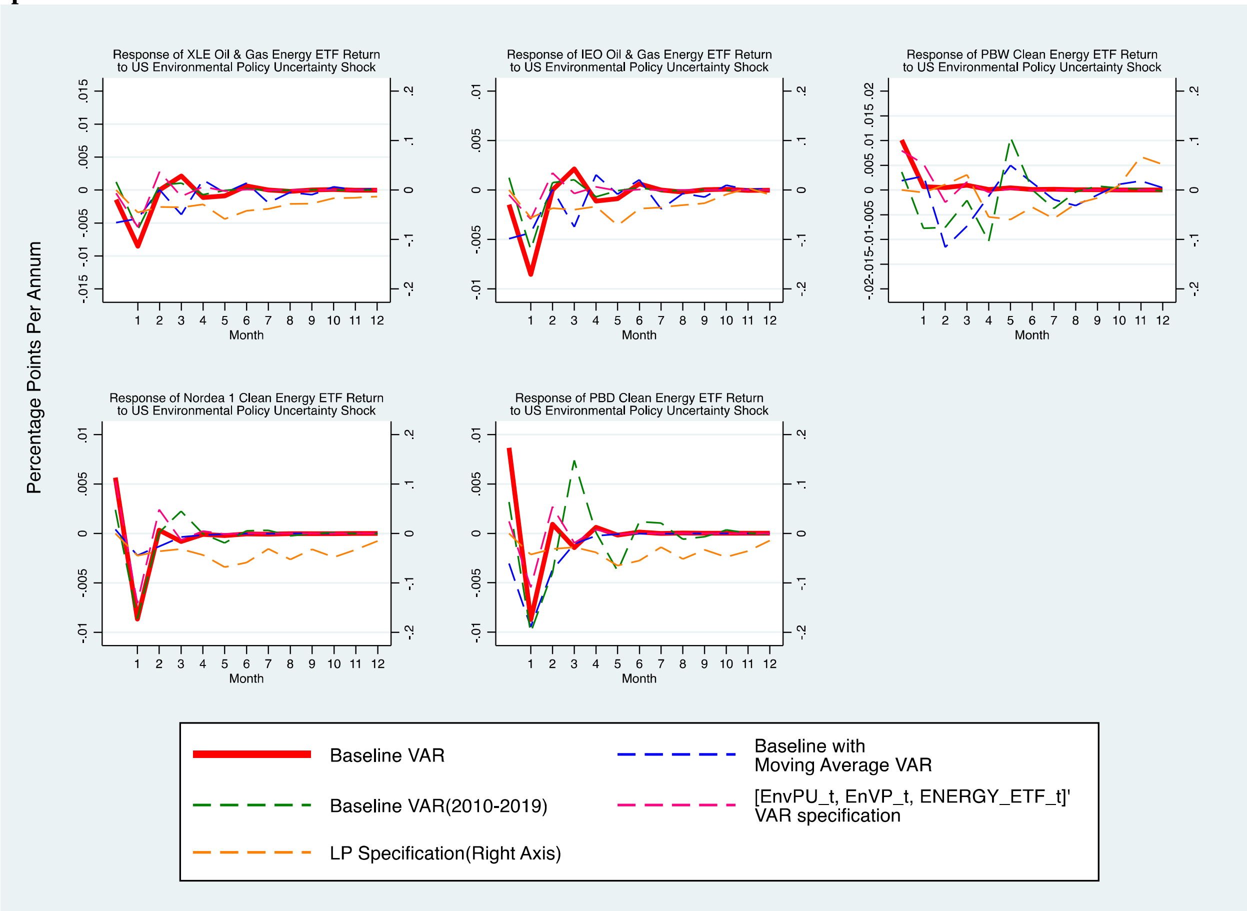

Note: Confidence intervals denote delta standard errors.
NORDEA 1: VAR (7) Model from 2008M5 to 2019M3 for 1 lag;
PBD: VAR (7) Model from 2007M8 to 2019M3 for 1 lag.

**Figure 11: Estimated impulse response of a one standard deviation shock to US Environmental Policy Uncertainty growth ($\text{EnvPU\_US}_t$) on the 30-day historical price volatility of US-focused and global Energy ETFs under alternative specifications.**




Note: Baseline VAR specifications:
XLE: VAR (7) Model from 2005M5 to 2019M3 for 2 lags;
PBW: VAR (7) Model from 2005M3 to 2019M3 for 2 lags;
IEO: VAR (7) from 2006M6 to 2019M3 for 1 lag.
NORDEA 1: VAR (7) Model from 2008M5 to 2019M3 for 1 lag ;
PBD: VAR (7) Model from 2007M8 to 2019M3 for 1 lag.

**Figure 12: Estimated impulse response of a one standard deviation shock to US Environmental Policy Uncertainty growth ($EnvPU\_US_t$) on the return of US-focused and global Energy ETFs under alternative specifications.**




Note: Baseline VAR specifications

XLE: VAR (7) Model from 2005M5 to 2019M3 for 2 lags.

PBW: VAR (7) Model from 2005M5 to 2019M3 for 1 lag.

IEO: VAR (7) from 2006M7 to 2019M3for 1 lag.

NORDEA 1: VAR (7) Model from 2008M5 to 2019M3 for 1 lag;

PBD: VAR (7) Model from 2007M8 to 2019M3 for 1 lag.

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