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Research article

Monetary policy shocks and sectoral heterogeneity in clean energy markets

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ABSTRACT

Clean energy transitions are central to achieving global sustainability goals, yet their progress depends partly on how macroeconomic forces shape green financial markets. This paper investigates the impact of US monetary policy shocks on nineteen clean energy stock indices from 2010 to 2023. Using panel factor models and structural Bayesian VARs, we identify a significant common factor that explains up to 60% of the sectoral variation. However, sectoral responses are heterogeneous: energy storage, green IT, and wind stocks react positively, while smart grid, green building, and transportation stocks respond negatively to monetary policy shocks. These results indicate that monetary policy can shift resources toward specific clean energy sectors but also reveal the vulnerability of other sectors to financial conditions, creating potential barriers to achieving environmental objectives.

1. Introduction

Global investment in clean energy sectors is growing rapidly in response to escalating environmental challenges, which have broader social and economic implications. At the COP29 climate summit, world leaders, policymakers, and academics emphasise the need for decisions that enable the scaling up of finance and investment for climate action; otherwise, the trajectory of the Paris Agreement would be impossible to achieve. To get on track for global net-zero emissions, energy transition, and grid investment must average $5.6 trillion annually between 2025 and 2030 (Bloomberg New Energy Finance, 2025). Indeed, more than public finance is required. Hence, the private sector plays a pivotal role in mobilising trillions of funds towards clean investment in this vital transition as part of coordinated environmental management efforts to align financial systems with sustainability goals (Saharti et al. 2025).

As far as firms in the clean production sectors are concerned, scaling up investment to meet growing demand is essential to mitigate the adverse effects of climate change and to foster energy transition (Anastasiou et al. 2024). However, investment barriers, such as high upfront costs, are a significant obstacle to deterring such projects (Campiglio, 2016; Nasreen et al. 2020; Emodi et al. 2022). Equity and debt markets often provide firms with access to external financing as a remedy to raise capital. Such markets enable firms to grow, develop, and invest in clean energy projects through the issuance of clean energy stocks and green bonds (Ferrari and Nispi Landi, 2023). Consequently, the growth in the clean energy market has been gaining momentum globally as an appealing investment destination – in comparison to brown energy assets – especially for responsible and impact investors due to its essential role and innovation in steering the economic system towards decarbonisation and delivering tangible environmental outcomes through reduced carbon footprints and sustainable renewables (Saeed et al. 2021; El Khoury et al. 2024).

A vast majority of scholars and policy practitioners believe this transition is feasible through investing in climate solutions and redirecting economic resources to low-carbon productive sectors. However, the empirical literature raises a host of complex questions about the role of central banks in achieving climate change objectives and supporting financial stability for effective environmental management at both national and global scales. While policies promoting clean energy investment are of great concern for the macroeconomy, they still warrant further exploration in the empirical literature, particularly regarding the implementation of monetary policy tools, as Hu et al. (2024b) have argued. In this framework, we examine the relationship between US monetary policy and clean energy stocks, highlighting its impact on the pathway to net-zero emissions. Properly evaluating this intersection appears critical amid the recent surge in global inflation and various geopolitical events that have disrupted the global energy markets.

Moreover, following the 2008 crisis and until the 2022 inflation spikes, interest rates have been trending downward, reaching historically low levels, thereby constraining the effectiveness of monetary policy. In response, the US Federal Reserve, like other central banks, resorted to unconventional measures to increase money supply and

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stimulate the economy (Sleibi et al. 2023).[1] However, after the COVID-19 pandemic and the reduction in soaring inflation, central banks in major economies have changed their stance to monetary tightening by increasing interest rates (DiLeo, 2023; Jiang et al. 2023). Additionally, firms struggle to accumulate capital in a high-interest-rate environment due to the high cost of financing. In this context, some authors have shown that monetary tightening slows economic activity and negatively affects firms' stock prices. As a result, investments in the stock markets become less appealing (Miranda-Agrippino and Rey, 2020; Laine, 2023; Maurer and Nitschka, 2023).[2]

Consequently, examining the reaction of clean energy stocks to the stance of monetary policy has a particular significance for the literature on firms' investment opportunities in the clean energy sector and the wider macroeconomy. This research direction is important for three reasons: First, clean energy investment, where energy transition and grid investments require mobilising trillions of funds, has become a critical factor in fighting climate change, achieving meaningful decarbonisation, and promote renewables – all of which are central to strategic environmental protection aimed at balancing ecological goals with economic growth (Doğan et al. 2020; Jiang et al. 2025). Second, investors consider clean energy equities as critical inputs when making portfolio allocation decisions and determining the cost of capital, thereby affecting the overall flow of funds. Hence, it serves as an essential benchmark for assessing investors' risk and return preferences in the clean energy sector and the broader economy following monetary policy decisions (Xia et al. 2019; Ciner et al. 2023). Third, the US monetary policy plays a dominant role in global financial markets, influencing trade, asset prices, commodity prices, and other macroeconomic fundamentals within the US, with potential spillover effects on other economies (Anzuini et al. 2013; Bauer and Neely, 2014; Miranda-Agrippino and Rey, 2020). In parallel, climate change can have significant macroeconomic effects, whether through physical impacts or transition impacts (Lamperti et al. 2021). These effects concern monetary policymakers and have consequences that need to reconsider climate change in the context of the price stability mandate, as well as considering climate risks and environmental management objectives as inputs in central banks' macroeconomic models and forecasting toolkits (Campiglio et al. 2018; Dafermos et al. 2018; Kahn et al. 2021; Ahmad and Satrovic, 2023).

Furthermore, our main contribution lies in our approach of modelling clean energy stock indices and their responses to monetary policy. One notable feature of these indices is their tendency to comove over time, albeit with some heterogeneity (Pham, 2019; Gil-Alana et al. 2023; Nasir and He, 2023; El Khoury et al. 2024). Other scholars relate the comovement of stock indices to the interdependence and interconnectedness between different sectors (Wu, 2019; Li et al. 2024). Nevertheless, when considering model construction using panel data, Sul (2019) argues that comovement, or cross-sectional dependence, among different units (clean energy stock indices in our case) is usually due to unobserved common factor(s) that can be interpreted as a common shock to the system of indices. Failing to account for common factors may yield biased or inconsistent estimates in panel regressions. Therefore, in the first step of our analysis, we apply the Bai and Ng (2004) Panel Analysis of Nonstationarity in Idiosyncratic and Common components (hereafter PANIC) method to uncover the potential underlying factor structure of the panel data and determine how significant the impact of the common shocks is on individual indices at the sectoral level.[3] Using monthly data from 2010 to 2023, our results reveal significant cross-sectional dependence and a common factor that explains up to 60% of the variation in clean energy stock indices.

Additionally, the influence of the common factor exhibits a substantial degree of heterogeneity across sectors and subsectors, with some indices demonstrating a significantly greater sensitivity to the common factor than others. In the second step, we estimate a structural Bayesian Vector AutoRegression (BVAR) model to identify monetary policy shocks and study their effects on both the common factor component and the indices' idiosyncratic components after filtering out the effects of common shocks. Our findings suggest that monetary policy shocks have a positive, statistically significant impact on the common factor. Furthermore, the heterogeneous behaviour remains evident in the sector-specific responses to monetary policy shocks, even after accounting for the effects of the common factor, suggesting the presence of sector-specific effects. To the best of our knowledge, this modelling strategy is novel to the empirical literature on monetary policy and sectoral clean energy investment.

The remainder of the paper runs as follows. Section two summarises the relevant literature. Section three presents the data. Section four describes the empirical methods. Section five reveals the empirical findings, and finally, Section six concludes.

2. Literature review

The existing literature highlights the importance of monetary policy decisions and financial regulation in mobilising capital towards low-carbon sectors to achieve a sustainable economy. As argued by Campiglio (2016), these interventions aim to steer economic resources towards clean energy investments to reduce emissions. In this vein, central banks must continue exploring and designing effective policies that incentivise green investments.

On the theoretical side, Dafermos et al. (2018) develop an ecological macroeconomic model to analyse how monetary policy can mitigate financial distress caused by climate change. They argue that green quantitative easing (QE) programs, i.e., expanding central banks' balance sheets via purchases of green corporate bonds, lower yields and reduce borrowing costs for firms investing in green projects. Therefore, green QE programs can reduce climate-induced financial instability. However, they argue that these policies alone cannot prevent substantial global warming. Ferrari and Nispi Landi (2023) combine a dynamic stochastic general equilibrium (DSGE) framework with an environmental model to study the transmission channel of green asset purchases (QE) from non-polluting firms. While green QE aims to reduce emissions, the authors underscore the importance of shifting investments from "brown" to "green" bonds within such programs to achieve optimal impact. Such findings are also confirmed by Giovanardi et al. (2023). Addressing the pressing need to understand the interplay between

[1] Such a toolbox includes various forms of liquidity support, large-scale asset purchases or quantitative easing, and forward guidance, all aimed at influencing real output and inflation (Kapetanios et al., 2012; Gambacorta et al., 2014).

[2] Both recent and earlier research provide extensive evidence that monetary policy can influence stock prices, particularly the reactions of stocks within the same sector (see, e.g., Ehrmann and Fratzscher (2004). The traditional view in the literature states that the present value of a stock equals the sum of expected earnings or dividends discounted to the present, with the present value inversely related to the discount rate (Williams, 1938; Campbell, 1991). For instance, if the Federal Reserve raises the policy rate (monetary tightening), this typically leads to a quick and noticeable decline in the stock market (Miranda-Agrippino and Rey, 2020; Gupta et al., 2023; Maurer and Nitschka, 2023). In this framework, the impact of monetary policy on the stock market operates through several channels, including the wealth effect on consumption spending, where stock price changes influence consumer confidence and expenditure, and the balance sheet effect on investment spending, where changes in firms' valuations affect their investment decisions, among other mechanisms (Bernanke and Kuttner, 2005).

[3] In the context of our empirical strategy, the presence of common factors among the stock market indices can be a result of a strong correlation among different sectors and subsectors of clean energy stocks. As argued by Sleibi et al. (2023), such a factor structure can be due to common regulatory requirements, for example, the central bank's monetary policy actions.

monetary policy and climate-related systemic risk, Hu et al. (2024b) pioneer an approach that combines a forward-looking climate stress-testing framework with a financial network model. Their findings, derived from a China-specific low-carbon transition scenario, demonstrate the potential of targeted reductions in the required reserve ratio to mitigate systemic risk while simultaneously spurring green lending of firms operating in low-carbon sectors. Another study by Chan (2020) addresses how central banks mitigate environmental degradation by changing interest rates. Using DSGE models to analyse monetary and carbon policies, they argue that increasing the nominal interest rate lowers household consumption and aggregate output, thereby reducing both the inflation rate and carbon emissions.

In the context of empirical research and ongoing debates about effective climate change mitigation strategies, Ni and Ruan (2023) investigate the effects of unconventional monetary policy on carbon emissions, primarily in the zero-lower-bound environment. Using the multi-period difference-in-difference method on panel data from 45 counties from 2007 to 2019, they find that the negative interest rate policy significantly reduces CO2 emissions through the exchange rate channel. Mbassi et al. (2023) empirically examine whether the inflation targeting within the monetary policy framework matters for environmental pollution. In a sample of 47 countries from 1980 to 2017, the authors employed both parametric and nonparametric approaches and argue that inflation targeting reduces total greenhouse gas emissions in both developed and emerging economies. They also suggest that the nexus between inflation targeting and pollution is indirect, passing through financial instability, inflation volatility, and economic growth. Focusing on the US, Hashmi et al. (2022) employ an autoregressive distributed lag approach to examine the relationship between the real interest rate, a proxy for monetary policy, and renewable energy from 1960 to 2020. Their results indicate that a contractionary monetary policy has a negative impact on renewable energy consumption in both the long- and short-run. Additionally, the authors discuss three potential channels for this result: the portfolio rebalances, signalling, and exchange rate channels. The first proposes that an upsurge in real interest rates discourages demands for goods and services, while the second channel expounds that a surge in interest rates transmits a common signal to market participants that the rate will remain high in the future. In both channels, individuals decrease the consumption of renewable energy. The third channel notes depreciation of the US dollar following monetary tightening, which discourages the import of renewable energy products, thereby reduces their consumption.

Furthermore, Chishti et al. (2021) examine the impact of monetary policy on carbon emissions in BRICS countries from 1985 to 2014. Using various long- and short-run methods, they argue that an expansionary monetary policy worsens environmental quality while a contractionary monetary policy improves it. Focusing on ASEAN countries, Mughal et al. (2021) demonstrate that contractionary (expansionary) monetary policy reduces (enhances) CO2 emissions over the period from 1990 to 2019. Similar results are confirmed by Qingquan et al. (2020), who study the relationship between monetary policy and environmental pollution in 14 Asian economies. Using panel least squares from 1990 to 2014, with real interest rates as a proxy for monetary policy, the authors find that an expansionary monetary policy has a positive impact on CO_2 emissions.

Another domain of recent research related to our work examines the nexus between clean energy stocks and other macroeconomic fundamentals. For instance, Ciner et al. (2023) study a large set of possible predictors of clean energy stock returns during the COVID-19 period. They find a significant impact from a set of explanatory variables, including small-company stocks, interest rates (measured by corporate and high-yield bond yields), and equities from emerging markets. On the other hand, the authors discover no influence from the oil market, highlighting distinct dynamics in financial markets during the pandemic. Some scholars focus on oil and clean energy prices together. In this vein, Tiwari et al. (2023) employ cross-quantile analysis to investigate the interdependence between clean and brown energy market returns, as measured by different oil price benchmarks. The authors find a weak dependence and coherence between clean and dirty energy markets, stressing the importance of reducing fossil fuel consumption in investment decisions for the renewable energy sector. On the contrary, Cao and Xie (2023) quantify the time-varying dependence between crude oil futures and clean energy stock markets. Using quantile regressions, the findings reveal a positive dependence between crude oil and energy markets, with a stronger influence at lower quantiles than at higher ones. Similar results are supported by Dawar et al. (2021), which uses quantile regression to examine oil prices and clean energy stock indices from 2005 to 2019. The authors demonstrate that oil price shocks have a strong impact on stock indices at lower quantiles; however, this impact tends to decrease at upper quantiles, i.e., during bearish market periods. Further, the authors explain that such practices are common for investors when hedging against fluctuations in oil prices. This occurs when market conditions lead to low or negative stock returns, which explains the shift towards clean energy investment in response to negative oil price shocks.

Moreover, Pham (2019) examines whether stocks in clean energy sectors respond differently to oil price shocks. Using data on clean energy indices from 2010 to 2018 and several multivariate GARCH models, the author finds that the relationship between oil prices and clean energy stocks varies over subsectors of the clean energy stock market. This finding also highlights the heterogeneous responses of clean energy subsectors to shocks in oil prices.

Other recent work investigates the connectedness among clean energy stocks, climate policy uncertainty, fossil fuel and technology sectors, see, e.g., Farid et al. (2023), Rao et al. (2023), Su and Zhao (2023), Umar et al. (2022), Pham (2021), Zhao (2020), and Maghyereh et al. (2019), among others.

Based on this literature review, empirical research on the effects of monetary policy on clean energy stocks is limited. Given this context and the rising trend of clean energy investments, along with recent interest rate changes aimed at controlling inflation, this paper assesses the effects of US monetary policy shocks across different clean energy sectors and subsectors, while accounting for unobserved common factors within the clean energy indices.

3. Data

To answer our research question on the impact of monetary policy shocks on clean energy stocks, we combine sector-level stock index data with macroeconomic variables to identify US monetary policy shocks.

Following several scholars, we utilise the NASDAQ OMX Green Economy Family as a benchmark for the clean energy market.[4] Compared to other measures of clean energy stocks, this index offers multiple indices that track sustainable companies operating in the clean energy sector (Pham, 2019). We collect data on nineteen indices categorised into five major groups: Advanced Materials, Bio/Clean Fuels, Energy Efficiency, Renewable Energy, and the broader Green Economy Index. We extract monthly data from *the LSEG Workspace* database, covering the period from October 2010 to October 2023. The monthly data correspond to the closing price of each index at the end of the month; this approach is applied consistently across all variables used in

[4] The NASDAQ OMX Green Equity Family indices are a complete set of environmental indices comprised of companies working to enhance economic development based on reducing carbon usage. These family indices have been popularly used in the literature on clean energy finance. For example, Tiwari et al. (2023); El Khoury et al. (2024), Ciner et al. (2023), Chen et al. (2022), Hammoudeh et al. (2021) and Pham (2019), among others.

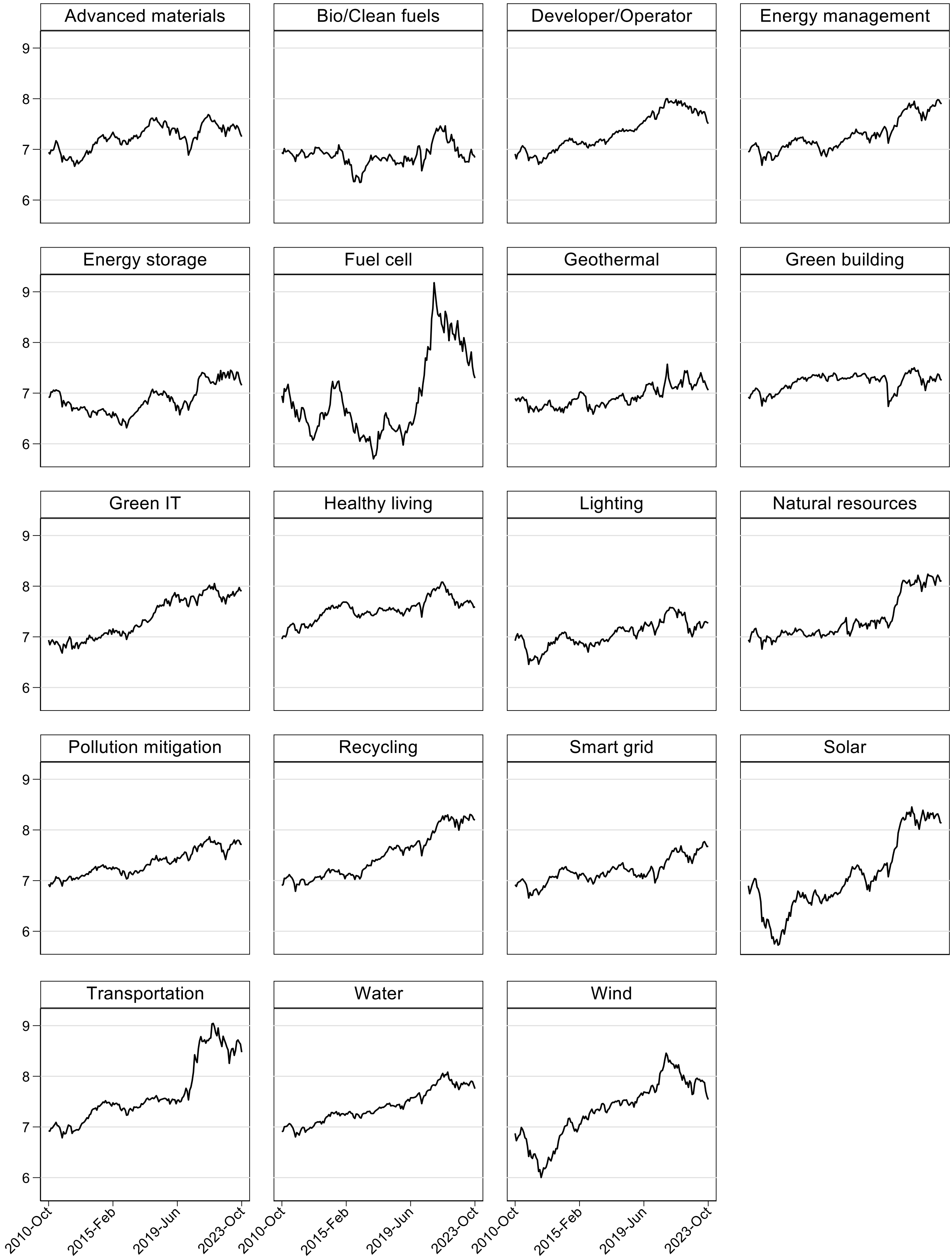

Fig. 1. Time series plots of the nineteen clean energy indices in the sample over the period October 2010 to October 2023 ($N = 19$, $T = 157$). Each index is shown in natural logarithmic form.

the analysis. Fig. 1 displays the series for each index.[5]

We further gather specific variables for the same period and frequency to identify the US monetary policy shocks. These variables, plotted in Fig. 2, are commonly used in monetary policy literature, including real GDP, the consumer price index, and the volatility index (VIX). Additionally, we follow Sleibi et al. (2023) and Conti (2017) and use the shadow rate of Wu and Xia (2016) to capture the Fed's unconventional monetary policy actions and to account for the Zero Lower Bound (ZLB). The shadow rate is more responsive to policy actions than the Federal Funds Rate (FFR) and has the desirable feature of taking negative values during periods of monetary loosening.[6]

4. Empirical methodology

We follow a two-step empirical strategy to examine the impact of US monetary policy shocks on clean energy stock indices. First, we investigate whether the stock indices exhibit significant comovement driven by an unobserved common factor. To do this, we utilise the PANIC method to extract the common factor and separate the common effects from index-specific components. Second, we employ a Bayesian Vector Autoregression (BVAR) model with zero and sign restrictions, incorporating the shadow interest rate and controls, to identify exogenous monetary policy shocks. Subsequently, we estimate the effects of these shocks on the components of the clean energy stock index identified in the first stage.

4.1. PANIC analysis

Using the Bai and Ng (2004) PANIC approach, we investigate the presence of common factors.[7] This choice endeavours to model non-stationarity in a panel time series data (Y_{it}) by assessing to what extent non-stationarity is due to a common factor or an idiosyncratic (index-specific) component. We fit a factor model to the data as follows:

$$Y_{it} = \alpha_i + \lambda_i F_t + \varepsilon_{it}. \tag{1}$$

where α_i is the fixed effects component, λ_i is an $r \times 1$ vector of factor loadings, F_t is an $r \times 1$ vector of common factors, ε_{it} is an idiosyncratic or index-specific component, $i = 1, .., 19$ and $t = 1, .., 157$.[8] To ensure stationarity and obtain consistent estimates, the factor representing the shared dynamics within the data is first estimated by differencing the data in levels. Subsequently, the first principal component, which has the largest common variance, is extracted from the differenced data. Finally, the component is reintegrated back to the levels to obtain the factor estimates.

After disentangling the panel data into two components, the PANIC method also enables the examination of their statistical properties by identifying the source of the unit root using both univariate and panel unit root tests.[9][10]

4.2. Benchmark specification

To analyse the effects of US monetary policy shocks on clean energy stock indices, we augment these series into a structural VAR and estimate it using Bayesian methods. Structural VARs have been extensively employed to identify the effects of monetary policy in both early and recent research; see, e.g., Sleibi et al. (2023), Conti (2017), Gambacorta et al. (2014), Bernanke et al. (2005), Christiano et al. (1999), among others. Using BVAR estimates provides valuable insights into how monetary policy shocks affect both the common factor and the idiosyncratic components of stock indices.

The following Equation is our benchmark VAR:

$$Z_t = \delta + A(L)Z_{t-1} + B\varepsilon_t. \tag{2}$$

where Z_t is a vector of endogenous variables, δ is a vector of intercepts, $A(L)$ is a lag polynomial with the VAR slope coefficients, and B is the contemporaneous impact matrix of mutually uncorrelated shocks ε_t. The vector of endogenous variables Z_t comprises five variables: real output, consumer prices, implied stock market volatility (VIX), and the shadow rate. We further add to the above parsimonious specification the common factor series of stock indices estimated in Section 4.1.

4.3. Identification of monetary policy shocks

We identify exogenous structural shocks as positive shocks to the shadow rate, i.e., monetary tightening. To isolate these shocks, we refer to the identification process introduced by Arias et al. (2018), where we impose zero and sign restrictions on the contemporaneous matrix of B in Eq. (1). The assumptions we follow are found in the common and recent literature on identifying monetary policy shocks using the same approach, namely, Gambacorta et al. (2014), Boeckx et al. (2017), Sleibi et al. (2023). First, we assume that output and consumer prices respond with a lag to shocks in the shadow rate. This assumption helps isolate aggregate supply and demand shocks from monetary policy innovations and is plausible for monetary VAR models using monthly data. In contrast, the shadow rate is allowed to respond contemporaneously to shocks in both output and prices.

Second, we distinguish between policy-driven changes and endogenous responses resulting from financial distress. In doing so, we assume that an increase in the shadow interest rate, i.e., a contractionary monetary policy, can raise the VIX index, which captures market risk and uncertainty. The conventional view we follow in imposing this restriction holds that contractionary policy increases the cost of borrowing and potentially reduces investors' liquidity and confidence, thereby increasing financial market uncertainty and ultimately leading to higher VIX values.

Finally, since adding the common factor of clean energy stock indices is new to the literature and to allow the data to speak, we leave the common factor's response unrestricted. Our identification scheme is

[5] The clean energy index data are only available since in October 2010. To ensure a balanced panel for the empirical analysis, all macroeconomic variables are aligned to the same period.

[6] Updates to the Wu and Xia shadow rate were suspended after March 2022, when the FOMC raised the Federal Funds Rate (FFR) above 0–0.25%. As the shadow rate closely tracks the effective Federal Funds rate in such periods, the latter is used as a substitute thereafter.

[7] This approach of extracting the common factor out of the panel data has been used in previous studies; see, for example, Sleibi et al. (2023) on private credit, Byrne et al. (2012) on interest rates and Byrne et al. (2013) on commodity prices.

[8] The factor loading is allowed to be index-specific to observe any heterogeneous impacts of the common factor on each clean energy sector.

[9] We follow different information criteria, namely, Bai and Ng (2002), Onatski (2010), and Ahn and Horenstein (2013), to identify the number of unobserved common factors.

[10] We are interested in examining the effects of monetary policy on both components. The common factor represents the common driving force of the data, and the idiosyncratic component represents index-specific information after removing the common factor.

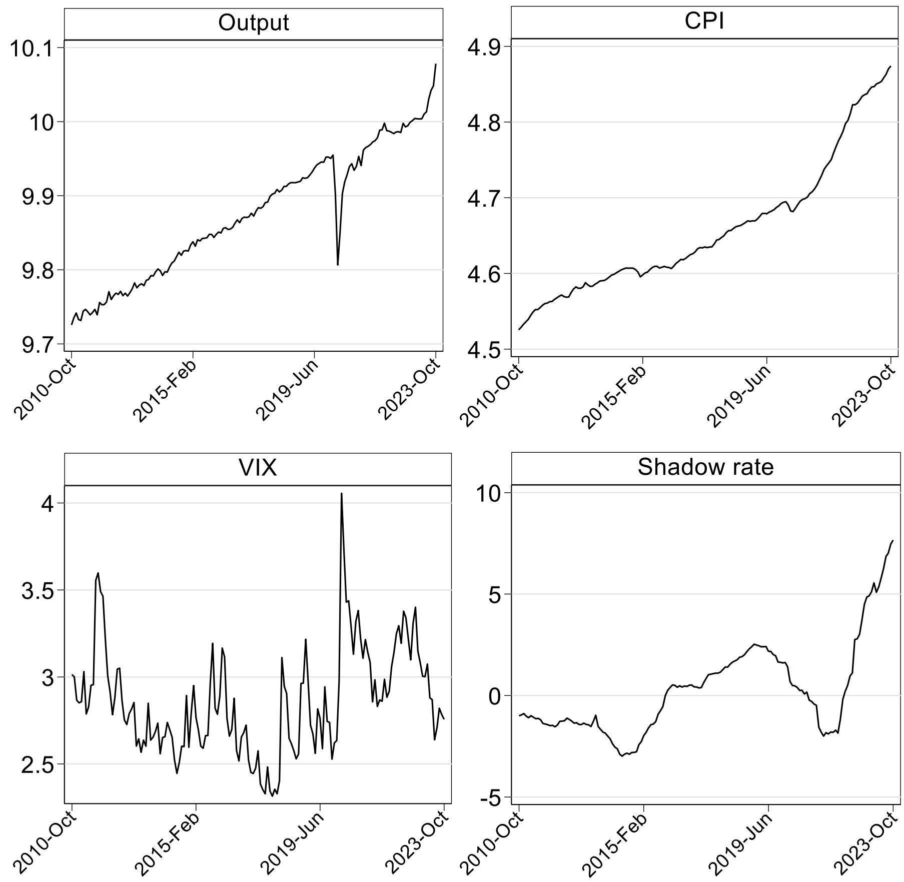

Fig. 2. Time-series plots of the macroeconomic variables (real output, consumer price index (CPI), VIX, and the shadow rate) used in the BVAR estimation over the period October 2010 to October 2023 ($T = 157$). All variables are shown in natural logarithmic form, except for the shadow rate, which is expressed in percentage terms.

Table 1
Structural identification of monetary policy shocks.

Output	Prices	VIX	Shadow rate	Common factor
0	0	+	+	?

Notes: "+" and "0" indicate a positive restriction and no immediate response to the shock, respectively. "?" indicates an unrestricted response of the variable. All restrictions are implemented on impact and the following month.

summarised in Table 1.[11]

5. Results

In the first part of the analysis, we examine whether the indices of clean energy stocks are persistent over time and feature a pervasive factor structure. We begin by assessing the stationarity of the panel of nineteen indices using Hadri (2000), Choi (2001), and Im et al. (2003) panel unit root tests. All tests are applied at the level of each series and indicate no rejection of the null of non-stationarity at standard significance levels.[12] Based on the presence of a unit root, we further employ the Pesaran (2015) CD test to determine whether the panel of clean energy stock indices exhibits weak or strong cross-correlation. Table 2 presents the results of the CD test for three samples; Panel A covers the full sample period, i.e., October 2010–October 2023; Panel B covers the period just before the COVID-19 pandemic, i.e., October 2010–December 2019, while Panel C focuses solely on the period January 2020–October 2023.[13] The null hypothesis is rejected for each panel, indicating that the panel data of clean energy stock indices exhibit a strong dependence with a degree of correlation, $|\widehat{\overline{\rho}_{ij}}| = 65\%$, on average.

The presence of high correlation and strong CSD within clean energy stock indices raises concerns about the unobserved common factors influencing the stocks of clean energy sectors. This finding motivates the choice of the PANIC approach to account for these components, allowing for a robust analysis of the effects of monetary policy on both the common factor and the index-specific components of the indices.

[11] The identification of monetary policy shocks in the baseline BVAR specification relies on zero and sign restrictions, which are invariant to variable ordering. In the subsequent analysis, where we estimate individual BVAR models for each index, we adopt a recursive (Cholesky) identification scheme with a specific causal ordering: the monetary policy shock variable (extracted from the baseline structural model) is placed first, followed by the corresponding index-specific component. This ordering assumes that monetary policy shocks are contemporaneously exogenous to the indices, consistent with standard practice in the monetary transmission literature (e.g., Christiano et al., 1999; Assenmacher-Wesche and Gerlach, 2008; Sleibi et al., 2020).

[12] These results are not reported for brevity but are available upon request.

[13] As argued by Ciner (2021), during the COVID-19 pandemic, the financial market dynamics have been altered. Thereby, the rationale for dividing the sample period into two additional sub-samples is to check the reliability of our results, specifically during the global pandemic.

Table 2
Cross-sectional dependence tests of clean energy stock indices.

Panel A			Panel B			Panel C		
CD test	$\widehat{\rho_{ij}}$	$\lvert\widehat{\rho_{ij}}\rvert$	CD test	$\widehat{\rho_{ij}}$	$\lvert\widehat{\rho_{ij}}\rvert$	CD test	$\widehat{\rho_{ij}}$	$\lvert\widehat{\rho_{ij}}\rvert$
121.6***	0.743	0.743	74.23***	0.539	0.60	53.69***	0.605	0.605

Notes: This table presents Pesaran (2015) CD test statistics. Panels A, B, and C represent sample periods for October 2010–October 2023, October 2010–December 2019, and January 2020–October 2023, respectively, for the cohort of indices. *** denotes significance at the 1% level. $\widehat{\rho_{ij}}$ denotes the average pairwise correlation coefficient over cross-sections $\lvert\widehat{\rho_{ij}}\rvert$ denotes the average absolute pairwise correlations.

5.1. Factor analysis

Using the PANIC approach, we present the statistical properties of the panel of clean energy indices. The strength of this method lies in assessing data stationarity and uncovering the heterogeneous impact of the common factor across indices. We proceed by allowing up to four factors and estimate the optimal number using the criteria outlined in Section 4.1. Table 3 displays the eigenvalue ratios for each factor, indicating the extent to which each common factor explains the panel of indices. It also presents the unit root test statistics for both the common factor and the idiosyncratic components, as well as the recommended number of common factors based on each information criterion.

The results, presented across the full sample and two subsamples, provide evidence for the dominant role of the first common factor, which is significant and accounts for up to 60% of the variation in our data.[14] Further, the null of a unit root cannot be rejected for the majority of the common factors across different samples. This result indicates that non-stationarity is due to pervasive common factors, confirming their significant role in explaining the panel data of indices. Fig. 3 displays the first common factor extracted using the PANIC method. Interestingly, the estimated factor exhibits noticeable declines during major US QE episodes, particularly in 2010 and 2020, despite QE's conventional association with rising asset prices. This pattern likely reflects the fact that the common factor captures comovement among clean energy indices rather than their price levels. During QE, liquidity injections and lower risk premia affect sectors differently, as investor reallocation depends on sector-specific fundamentals such as technological maturity, capital intensity, and sensitivity to long-term interest rates (Gertler and Karadi, 2013). As a result, sectoral responses may diverge, leading to reduced comovement even when aggregate prices rise. This heterogeneous response is consistent with the portfolio rebalancing and signalling channels of QE (Gagnon et al., 2011; Joyce et al., 2012).

Unlike existing literature on clean energy stocks, we evaluate the significance of this factor and examine its impact on individual clean energy stock indices. Table 4 presents the percentage of the overall variance in each index explained by the factor.[15] The empirical results reveal sectoral heterogeneity in clean energy market integration, with the common factor importance ranging from 27.35% to 83.74% across the nineteen indices. This heterogeneity reflects a distinctive “core-periphery” structure in clean energy stock markets, aligning with existing literature on renewable energy sector characteristics and financial market integration. The sectors exhibiting the highest common factor dominance - water (83.74%), energy management (82.82%), recycling (78.92%), smart grid (74.96%), and green building (70.21%) - are primarily infrastructure-heavy, utility-adjacent sectors that require substantial capital investments and exhibit long asset lifecycles. This finding demonstrates that capital-intensive renewable energy sectors show greater sensitivity to common shocks such as macroeconomic conditions and financial market developments, with their high comovement resembling traditional utility investments where shared exposure to interest rate sensitivity and regulatory coordination makes them particularly responsive to systematic financial conditions (Schmidt et al. 2019; Bauer et al. 2025).

In contrast, the sectors with the lowest common factor influence, i.e., fuel cell (34.30%) and geothermal (27.35%), exhibit relatively weak exposure to the common factor; hence, they represent emerging, highly specialised technologies that remain largely decoupled from broader clean energy market dynamics. The fuel cell sector's idiosyncratic behaviour likely reflects its technology-specific development trajectory, niche market applications, and dependence on company-specific partnerships in the hydrogen economy (Ho et al. 2014; Wilberforce et al. 2016). In the same vein, geothermal energy's extremely low common factor influence reflects its highly location-specific and resource-dependent nature, with project success contingent on geological conditions and limited geographic expansion opportunities (McBride et al. 2025).

The moderate common factor influence observed in established sectors, such as solar (58.67%), wind (52.05%), green IT (52.88%), and transportation (56.57%), among others, presents a sensitivity to aggregate clean energy comovements; however, with substantial sector-specific variations. This balanced exposure pattern reflects the fact that such sectors are central to clean energy transitions and thus align with broader market trends. They are also subject to sector-specific drivers, such as supply chain disruptions and geopolitical events affecting specific resources.

While there is some heterogeneity in the responses of each clean energy stock index to the common factor, our findings also suggest that the influence of the non-stationary common factor is prevalent across the cohort of indices. These findings, in summary, support the literature on financial contagion and interdependence between sectoral stock market indices (Yarovaya et al. 2022; Li et al. 2024). Building on this result, our next step aims to assess the extent to which US monetary policy affects the pervasiveness of clean energy stocks, proxied by the common factor.[16]

5.2. Monetary policy and the common factor

Having identified the common factor of the clean energy stock indices and delineated their properties -specifically, the distinction between common and idiosyncratic components - this section investigates the relationship between US monetary policy shocks and the common element of the nineteen indices. Based on the standard lag-length selection criteria, the BVAR model includes three lags of the endogenous variables, estimated over the sample period November 2010 to October 2023, with prior and posterior distributions belonging to the Normal-

[14] All information criteria suggest one common factor. As a result, we proceed with the analysis, focusing only on the first common factor.

[15] This ratio is calculated as the standard deviation of the original series to the standard deviation of the index-specific component (i.e., $\sigma(\Delta Y_{it})/\ \sigma(\Delta\varepsilon_{it})$ from Eq. (1)). It takes the value of one if the index is completely dominated by the common factor.

[16] At a later stage, we alternate our measure of stock market indices by examining the effects of monetary policy on another component of the indices, namely, the idiosyncratic component ε_{it}.

Table 3
PANIC analysis on clean energy stock indices.

Sample	Factor	ε_{it}	IC_1	IC_2	IC_3	ON	ER	GR
2010–2023	−3.543**, −2.469, −1.449, −3.947*** [0.601, 0.059, 0.047, 0.038]	5.962***	1	1	1	1	1	1
2010–2019	−3.203*, −2.316, −2.145, −1.687 [0.606, 0.053, 0.045, 0.041]	4.307***	1	1	1	1	1	1
2020–2023	−2.927, −2.785, −2.763, −3.505** [0.633, 0.076, 0.058, 0.037]	5.689***	1	1	1	1	1	1

Notes: This table presents the statistical properties of the clean energy stock indices using the PANIC method. This test applies unit root tests to the common factor series and panel unit root tests to the set of idiosyncratic components. The panel data set spans October 2010 to October 2023 ($N = 19$, $T = 157/111/45$). Each index series is log-transformed, demeaned, and standardised. Eigenvalues are in square brackets [.]. */**/*** indicate rejection of the null hypothesis of a unit root at the 10/5/1 percent significance levels, respectively. The information criteria of Bai and Ng (2004) are denoted as IC_1, IC_2, and IC_3. Onatski's (2010) method is denoted as ON. Ahn and Horenstein's (2013) method is denoted as ER and GR, respectively.

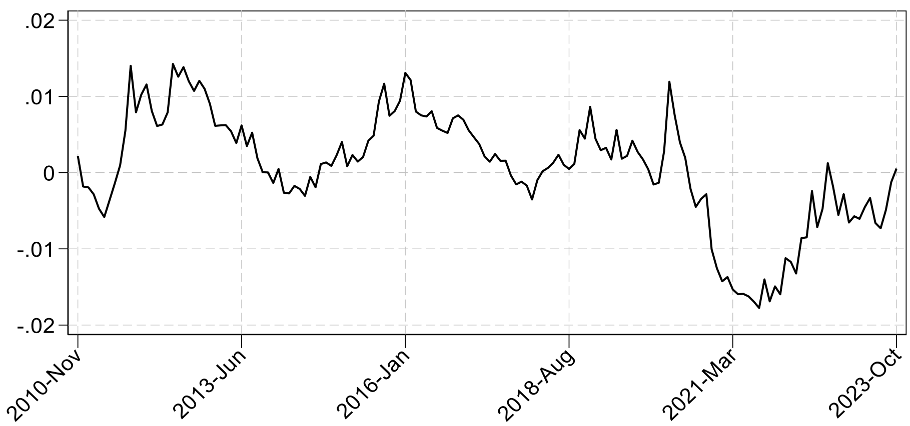

Fig. 3. Estimated common factor extracted from the nineteen clean energy stock indices using the PANIC decomposition over the period November 2010 to October 2023. The series is monthly, and the total number of observations is $T = 156$ due to differencing.

Table 4
The common factor importance for individual indices.

Advanced Materials Index	68.69%
Bio/Clean Fuels Index	46.60%
Energy Management Index	82.82%
Energy Storage Index	60.69%
Green IT Index	52.88%
Smart Grid Index	75.96%
Developer/Operator Index	57.54%
Fuel Cell Index	34.30%
Geothermal Index	27.35%
Solar Index	58.67%
Wind Index	52.05%
Green Building Index	70.21%
Lighting Index	63.79%
Natural Resources Index	45.48%
Pollution Mitigation Index	69.76%
Recycling Index	78.92%
Transportation Index	56.57%
Water Index	83.74%
Healthy Living Index	56.88%

Notes: This table examines the degree to which the first common factor explains the variation in each clean energy stock market index. The panel data set spans October 2010 to October 2023 for the nineteen indices ($N = 19$, $T = 157$) using differenced and standardised data.

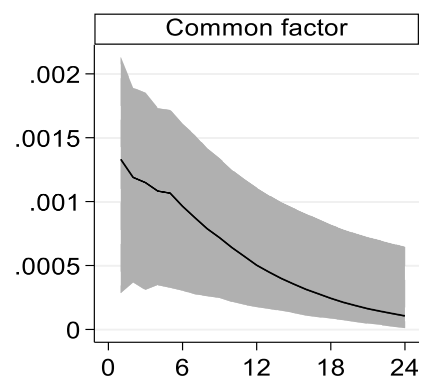

Fig. 4. Solid line represents the median IRFs, capturing the response of the first common factor following a shock in the shadow rate variable. Shaded areas depict the 68% confidence intervals.

Wishart family.

In Fig. 4, we present the impulse response functions, which show that a positive monetary policy shock, i.e., monetary tightening, increases the common factor by 0.14% on impact. This response gradually declines and then dies out at longer horizons over the specified period. This finding also aligns with the literature on the stock market's instant reaction to policy (Li et al. 2010; Challe and Giannitsarou, 2014). Furthermore, our results complement those of Sleibi et al. (2023), who argue that monetary policy tightening decreases the comovement of firms' debt. Bridging our study with theirs, we argue that during monetary easing, i.e., low interest rates, firms can access the debt market by issuing bonds or borrowing from financial intermediaries to fund new or existing projects. Hence, an increase in debt comovement. However, during monetary tightening, stock prices become cheaper (through the discount rate channel), creating an opportunity for investors to purchase stocks, thereby increasing the comovement of stock market indices.

To broaden our understanding of the model's implications, we present the findings of the other variables included in the BVAR specification. Fig. 5 indicates that the contractionary monetary policy shock is characterised by an increase in the shadow rate of about 1.75%, which gradually fades out after six months. The responses of output and prices indicate that the economy slows down following an increase in the shadow rate. Finally, a contractionary monetary policy shock leads to a significant rise in the VIX index, which lasts for less than 12 months. All

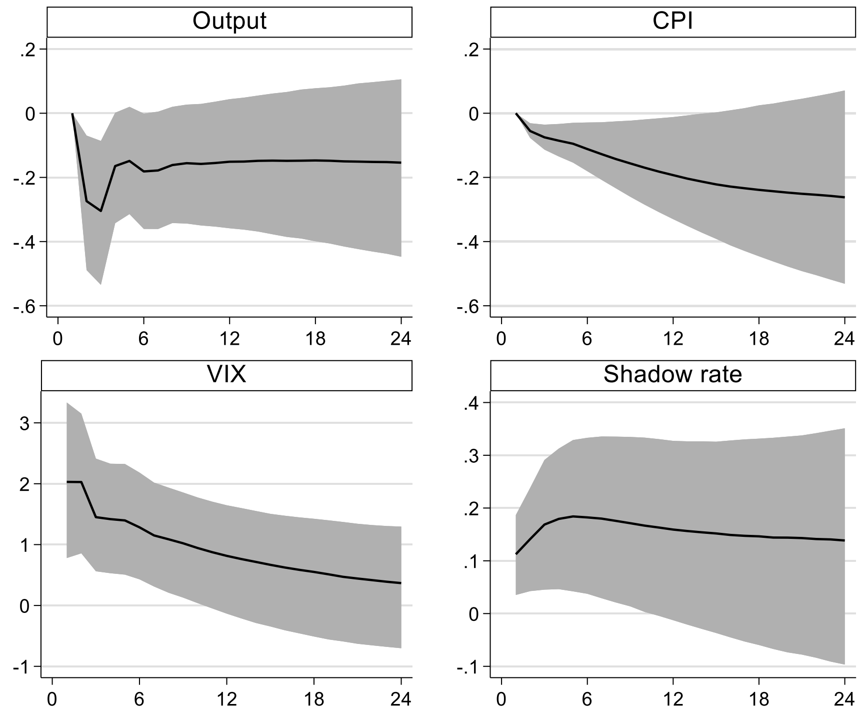

Fig. 5. Solid lines represent the median IRFs, capturing the response of each variable in the baseline specification following a shock in the shadow rate variable. Shaded areas depict the 68% confidence intervals.

responses are correctly signed, i.e., in line with the literature and the imposed sign restrictions.

5.3. Monetary policy and index-specific shocks

In this section, we take an additional step to uncover potential heterogeneity in the response of clean energy to monetary policy surprises by focusing on individual indices, particularly the idiosyncratic element of Eq. (1) in Section 4.1, i.e., the index-specific components or shocks (ε_{it}) of the panel of indices (Y_{it}) after estimating and removing the common factor (F_t). Similar to the analysis presented in Section 5.2, we employ a bivariate BVAR model that includes the monetary policy shocks variable (extracted from the baseline structural model with the other macroeconomic variables) and the index-specific component.

We estimate nineteen separate BVAR specifications while replacing the index-specific shocks each time (ε_{it}). For readability, we group the results into three categories. The first group in Fig. 6 shows indices with positive, significant responses, suggesting sectors that may benefit from tighter monetary conditions and potentially attract reallocated investment flows. These are: green IT, energy storage, developer/operator, geothermal, solar, wind, and natural resources indices. The second group in Fig. 7 presents the indices with negative and significant responses, indicating sectors that may face financing headwinds under contractionary monetary policy. These are: bio/clean fuel, smart grid, energy management, healthy living, green building, water, and transportation indices. The third group in Fig. 8 presents the indices' responses, which are insignificant (either positive or negative), suggesting relative insulation from monetary policy shocks. This group includes advanced material, recycling, fuel cell, pollution mitigation, and lighting indices.

Moreover, the asymmetric responses are also evident within each group. For instance, the impact of monetary policy shocks is more pronounced on energy storage and wind indices, with a positive effect of up to 0.175% on each index that persists throughout the entire period. However, the impact on the solar index is short-lived, reaching only 0.1% for the first two months after the shock. Similar heterogeneous impacts are found in indices with negative responses. Notably, the smart grid and transportation indices respond remarkably, decreasing by −0.165% and −0.175%, respectively, for the entire period. In contrast, the impact on energy management and bio/clean fuel indices is short-lived, lasting only for the first two months. This distinction between persistence and transience is critical for environmental policy design and management, as sectors with prolonged sensitivity may require targeted financial instruments or a supportive policy framework to maintain investment momentum.

Interestingly, Pham (2019) argues that energy management and bio/clean fuel stocks are the most influenced by oil price fluctuations, while wind, geothermal, and fuel cell stocks demonstrate the weakest connection. This result may indicate that monetary policy shocks have less influence on sectors most closely tied to movements in fossil fuel prices, and vice versa. However, caution is warranted for two reasons: (i) Pham (2019) uses the returns of each clean energy stock index instead of price levels, does not distinguish between common and idiosyncratic components of the data, and consequently does not consider the role of the common factor; (ii) the author uses only eleven indices, whereas ours includes nineteen.

5.4. Economic interpretation and policy implications

The heterogeneous responses of green finance sectors to monetary policy tightening can be understood through established monetary transmission channels, revealing how sectoral characteristics interact with financial conditions to produce divergent outcomes. The positive response of renewable energy production sectors (solar, wind, geothermal) and related infrastructure (energy storage, developer/operator) reflect several complementary mechanisms rooted in portfolio rebalancing theory. Following Bernanke and Kuttner (2005), contractionary monetary policy often triggers a "flight-to-quality," in which investors reallocate capital toward sectors with stronger fundamentals and clearer growth prospects. Additionally, these renewable energy sectors have established themselves as technologically mature industries with faster project cycles and predictable cash flows from long-term

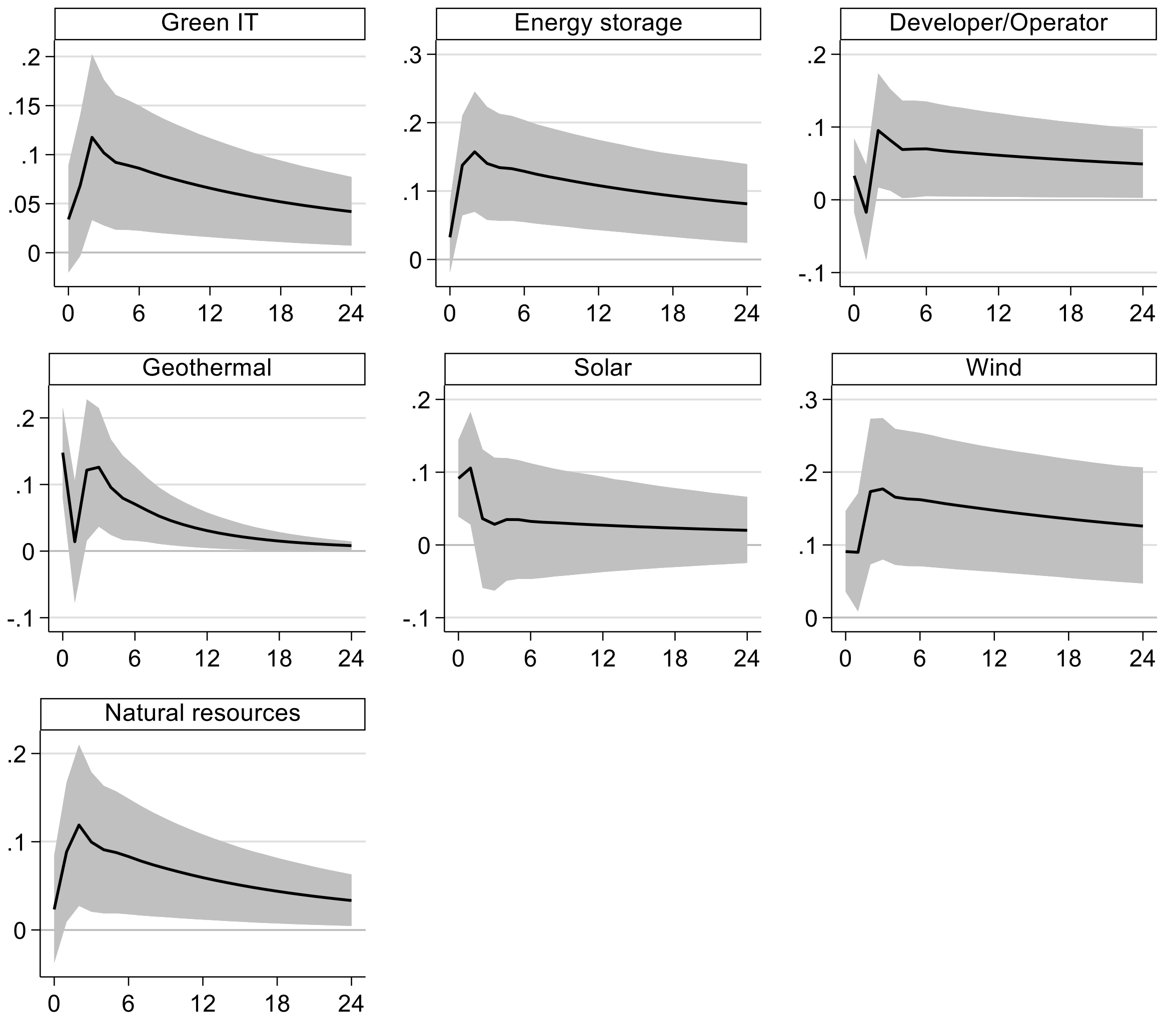

Fig. 6. Solid lines represent the median IRFs, capturing indices with positive responses following a shock in the shadow rate variable. Shaded areas depict the 68% confidence intervals.

purchase agreements (PPAs), making them attractive defensive investments during periods of monetary tightening (Polzin et al. 2015; Pástor et al. 2022). Additionally, tighter monetary conditions create a competitive advantage through what Caballero and Hammour (1994) describe as a "cleansing effect". Energy production sectors, particularly solar and wind, have achieved significant cost competitiveness with fossil fuels, making them less vulnerable to higher financing costs compared to nascent technologies (IRENA, 2023). This cost advantage becomes more pronounced when higher interest rates increase the financing burden on less efficient competitors, potentially accelerating market share gains for renewable energy producers. The positive response of these sectors may also reflect expectations that monetary tightening often coincides with fiscal policy support for strategic sectors. Historical evidence suggests that during periods of economic uncertainty, governments tend to accelerate infrastructure spending in growth sectors like renewable energy (Mazzucato and Semieniuk, 2017; Yuen and Yuen, 2024; Tørstad et al. 2025). The Inflation Reduction Act of 2022 exemplifies this pattern, prioritizing climate investments even during a period of monetary tightening.

The negative responses observed in bio/clean fuels, smart grid, energy management, and related sectors align with the traditional monetary transmission mechanism through the cost of capital and credit channels. These sectors are characterized by high capital requirements and long development cycles, making them particularly vulnerable to interest rate increases through the cost of capital channel (Kashyap and Stein, 1995). Bio/clean fuels and smart grid technologies require substantial upfront R&D investments and infrastructure development, with uncertain and distant cash flows that are heavily discounted when interest rates rise (Popp et al. 2011). As Gertler and Gilchrist (1994) argue, smaller and more leveraged firms in emerging green technology sectors face tighter financial constraints during contractionary monetary policy, as sectors like energy management and green building often comprise smaller companies with limited access to capital markets, making them more dependent on bank financing that becomes more expensive and scarce during monetary tightening (De Haas and Popov, 2019). Furthermore, several sectors in this group have significant exposure to discretionary consumer spending, where monetary tightening reduces consumer purchasing power and delays discretionary investments in energy efficiency upgrades and sustainable products, following the standard consumption channel of monetary policy (Christiano et al. 1999).

The insignificant responses of advanced materials, recycling, fuel cells, pollution mitigation, and lighting sectors suggest structural characteristics that provide relative insulation from monetary policy shocks through regulatory-driven demand and market diversification. These sectors often benefit from regulatory mandates and compliance requirements that are relatively insensitive to monetary policy actions. Pollution mitigation and recycling, for example, are driven by environmental regulations and waste management requirements that remain stable regardless of interest rate levels (Porter and van der Linde, 1995;

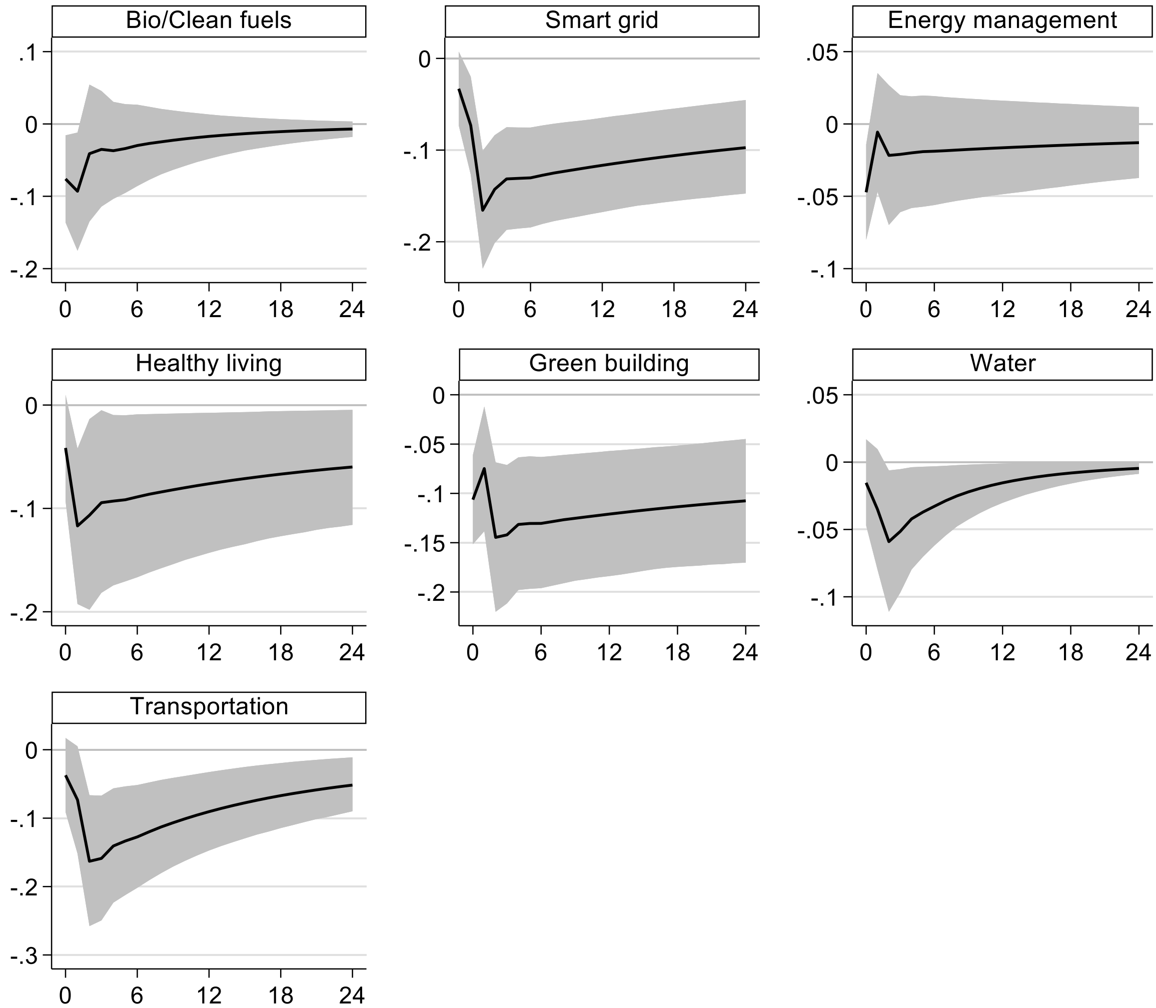

Fig. 7. Solid lines represent the median IRFs, capturing indices with negative responses following a shock in the shadow rate variable. Shaded areas depict the 68% confidence intervals.

Tumu et al. 2023; Hu et al. 2024a). This regulatory foundation provides a floor for demand that insulates these sectors from the cyclical effects of monetary policy. Additionally, advanced materials and lighting sectors serve diverse end markets beyond clean energy, including traditional industrial applications, thereby reducing their sensitivity to clean energy-specific investment cycles. LED lighting, for instance, has achieved widespread adoption across multiple sectors, creating stable demand patterns and reducing its dependence on green investment flows (Sandén and Hillman, 2011). Fuel cells represent a unique case of a technology in transition, where an insignificant response may reflect a balancing of negative financing effects with positive fundamental developments, as applications in industrial and transportation sectors begin to benefit from regulatory support and a competitive advantage.

These heterogeneous responses ultimately reflect the varying degrees of integration between green finance sectors and financial markets, with important implications for both policy coordination and investment strategy. More mature sectors (renewable energy production) demonstrate characteristics of established industries that can benefit from portfolio rebalancing effects, while emerging sectors (bio/clean fuels, smart grid) remain more vulnerable to financing conditions (Jacobsson and Bergek, 2011). Furthermore, the results highlight potential conflicts between monetary and climate policies: monetary tightening may support mature renewable energy sectors through quality-flight effects, while simultaneously constraining financing for emerging clean technologies crucial to environmental management, particularly for comprehensive decarbonisation. These findings support the importance of coordinated policy design that accounts for sectoral heterogeneity in green finance (Campiglio et al., 2018). For investors, these findings suggest that green finance portfolios exhibit significant internal diversification during monetary policy cycles, with heterogeneous responses providing natural hedging opportunities within sustainable investment strategies.

5.5. *Robustness checks*

We ensure the reliability of our findings through a battery of robustness checks, which involve altering our specifications using different approaches. Regarding the PANIC method, we estimate the common factor over various time horizons and end the sample before the COVID-19 period, as presented in Section 5.1. We further use daily rather than monthly data on the stock indices and then compute the common factor. We find that all information criteria, based on daily data, consistently recommend a single common factor. Regardless of whether daily or monthly observations are employed, the common factor series of both exhibit high correlation (above 96% on average).

We further assess the robustness of our results by examining changes in sample composition through the exclusion of indices where the common factor exhibits a dominant influence (i.e., those in which the common factor explains more than 75% of the variance in any individual index). This sensitivity analysis reveals no significant alterations

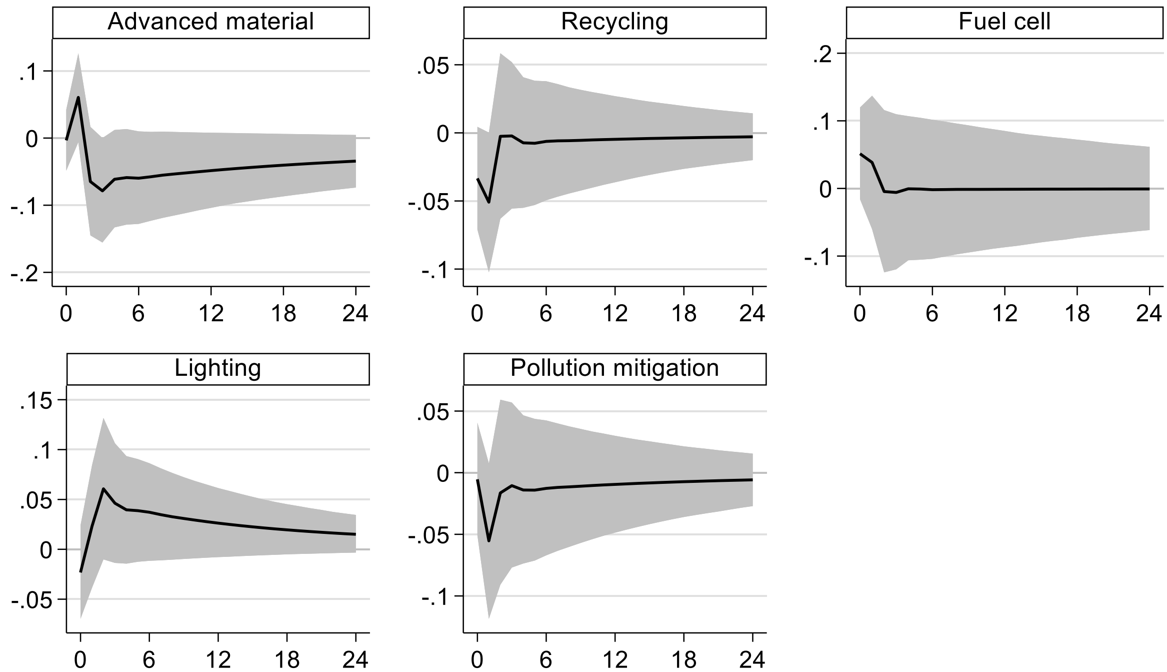

Fig. 8. Solid lines represent the median IRFs, capturing indices with insignificant responses following a shock in the shadow rate variable. Shaded areas depict the 68% confidence intervals.

to the estimated common factor structure.

To explore the sensitivity of our results to lag length specification, we estimate a BVAR with lag orders of 1, 2, and 4 months. We also estimate the BVAR over different time horizons that correspond to those used in the PANIC approach. Additionally, we estimate monetary policy shocks using the Federal Reserve's total assets as an alternative monetary policy indicator, rather than the shadow rate. In all cases, the results remain qualitatively unaffected.[17]

To further examine the sources of heterogeneity across clean energy stock indices, we conduct an additional robustness analysis by incorporating oil prices into our framework.[18] We re-estimate nineteen individual BVAR models, each including the spot WTI crude oil price and a specific clean energy index with the same lag length as before. Following a recursive (Cholesky) identification scheme, oil prices are ordered first, allowing them to affect clean energy indices contemporaneously but not vice versa. The results reveal substantial heterogeneity in sectoral responses to oil price shocks, which can be classified into three distinct groups. First, five sectors shown in Fig. 9 are: bio/clean fuels, energy management, smart grid, green building, and pollution mitigation, exhibit positive, statistically significant responses, consistent with substitution effects in which higher oil prices enhance the competitiveness of clean energy alternatives (Kumar et al., 2012; Sadorsky, 2012).[19] Second, five sectors shown in Fig. 10 are: developer/operator, solar, wind, lighting, and water, display negative and statistically significant responses, likely reflecting input-cost pressures and heightened sensitivity to increases in the discount rate associated with inflationary pressures from rising oil prices (Bondia et al., 2016; Henriques and Sadorsky, 2008). Third, the remaining nine sectors shown in Fig. 11, namely advanced materials, energy storage, green IT, fuel cell, geothermal, natural resources, transportation, recycling, and healthy living, show statistically insignificant responses, suggesting that offsetting mechanisms or sector-specific factors dominate over oil price considerations (Ferrer et al., 2018; Reboredo et al., 2017). These findings reinforce our main conclusion that clean energy stock indices exhibit considerable heterogeneity in their response patterns, partly due to varying sensitivities to oil price shocks.

6. Conclusion

This study examines the transmission of US monetary policy shocks to clean energy financial markets by analyzing nineteen clean energy sector indices spanning October 2010 to October 2023. Our research addresses a critical gap in the literature by examining how monetary policy affects the emerging clean finance sector, a topic of particular relevance given the recent period of monetary tightening and the growing importance of sustainable finance in capital markets. Using the Panel Analysis of Nonstationarity in Idiosyncratic and Common components (PANIC) methodology, we find that clean energy stock indices exhibit a dominant common factor structure, with a single common factor accounting for up to 60% of cross-sectional variation. This finding demonstrates significant comovement within the clean energy sector, while also revealing substantial heterogeneity in individual sector exposures to this common factor. The factor structure ranges from highly integrated sectors, with factor loadings exceeding 80%, to more idiosyncratic sectors, with loadings below 30%, indicating diverse degrees of systemic risk exposure across clean energy sectors. We further advance the analysis by estimating a structural Bayesian VAR specification, which reveals that monetary policy shocks generate significant responses in clean energy markets through two distinct channels. First, the common factor responds positively to monetary tightening, suggesting that contractionary policy enhances comovement across clean energy sectors. Second, with important implications for investment and policy, we document pronounced heterogeneity in how individual sectors respond to monetary policy shocks after controlling for common factor exposure. Specifically, seven sectors, including renewable energy production (solar, wind, and geothermal), green IT, energy storage, developer/operator, and natural resources, show positive responses to

[17] The empirical results of the alternative specifications are available upon request.

[18] We would like to thank an anonymous reviewer for this suggestion.

[19] These results are consistent with Pham (2019), who finds that the bio/clean fuels and energy management sectors exhibit the strongest connections with oil prices.

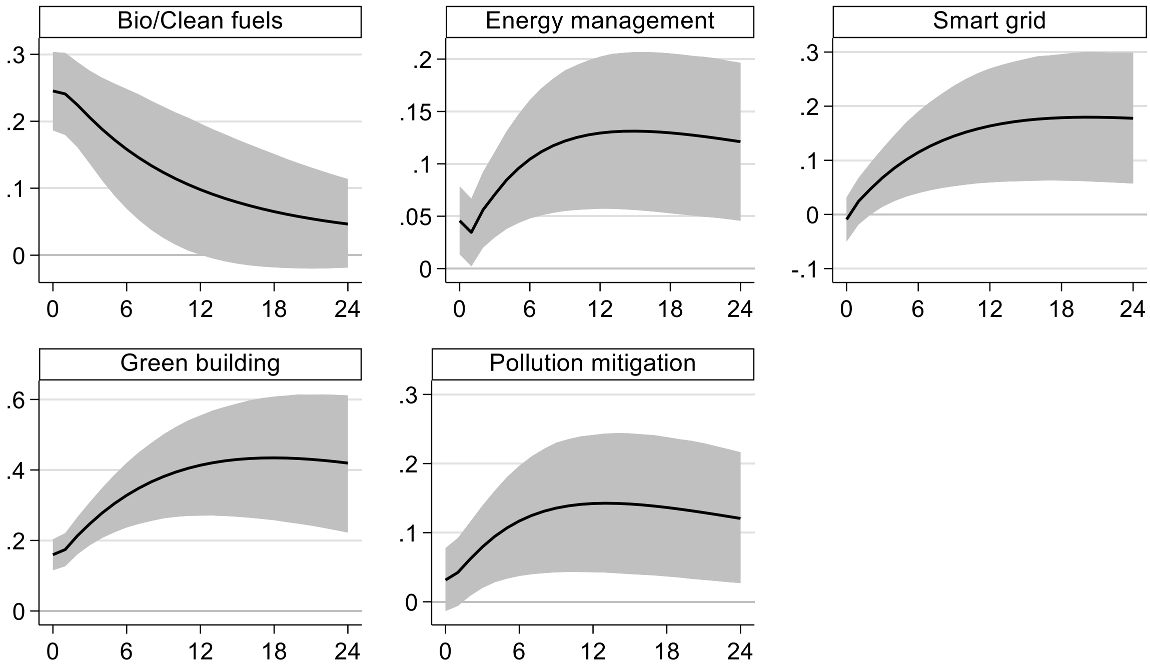

Fig. 9. Solid lines represent the median IRFs, capturing indices with positive responses in the baseline specification following a shock in the oil price variable. Shaded areas depict the 68% confidence intervals.

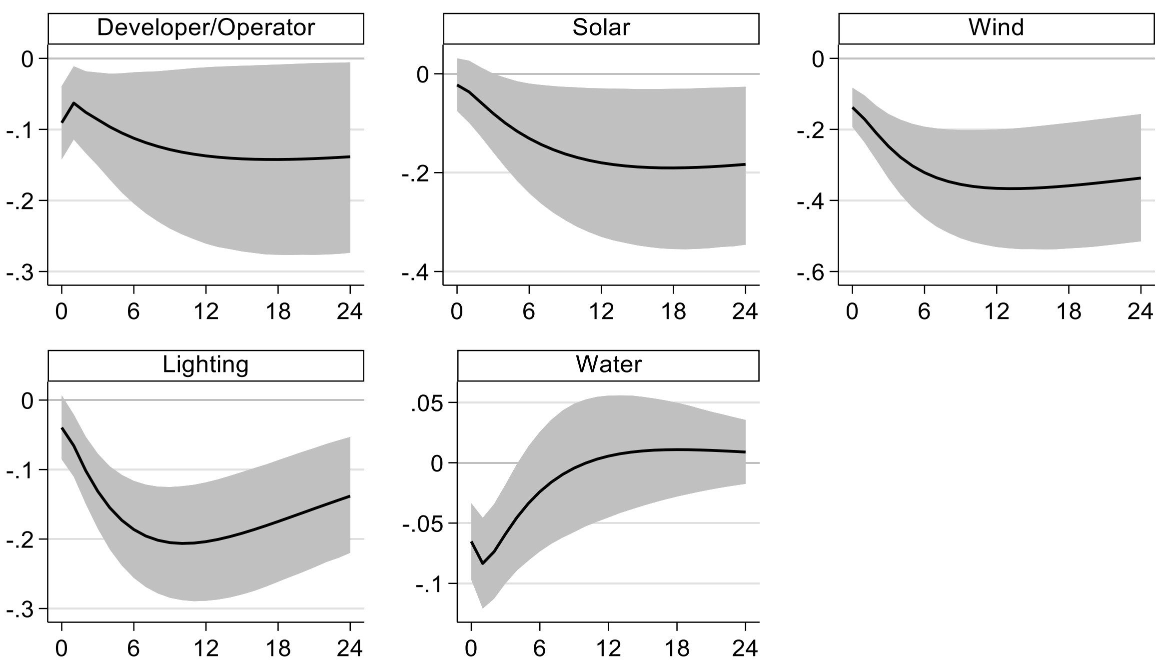

Fig. 10. Solid lines represent the median IRFs, capturing indices with negative responses in the baseline specification following a shock in the oil price variable. Shaded areas depict the 68% confidence intervals.

monetary tightening. In comparison, seven other sectors, including bio/clean fuels, smart grid, energy management, healthy living, green building, water, and transportation, demonstrate significant negative responses. Five sectors show statistically insignificant responses, suggesting relative insulation from monetary policy transmission.

These heterogeneous responses reflect fundamental differences in sector characteristics, including capital intensity, market maturity, regulatory support, and financing structures. These results demonstrate that sectors with positive responses benefit from flight-to-quality dynamics and competitive advantages during monetary tightening. In contrast, sectors with negative responses incur higher financing costs and experience reduced investment in capital-intensive, early-stage technologies. The insulated sectors benefit from regulatory-driven demand and diversified revenue streams, providing stability across monetary policy cycles.

Our results reveal potential conflicts between monetary and climate policies, where contractionary monetary policy may simultaneously support mature renewable energy sectors while constraining financing for emerging clean technologies. This underscores the importance of integrating climate considerations into the central bank's policy toolkit

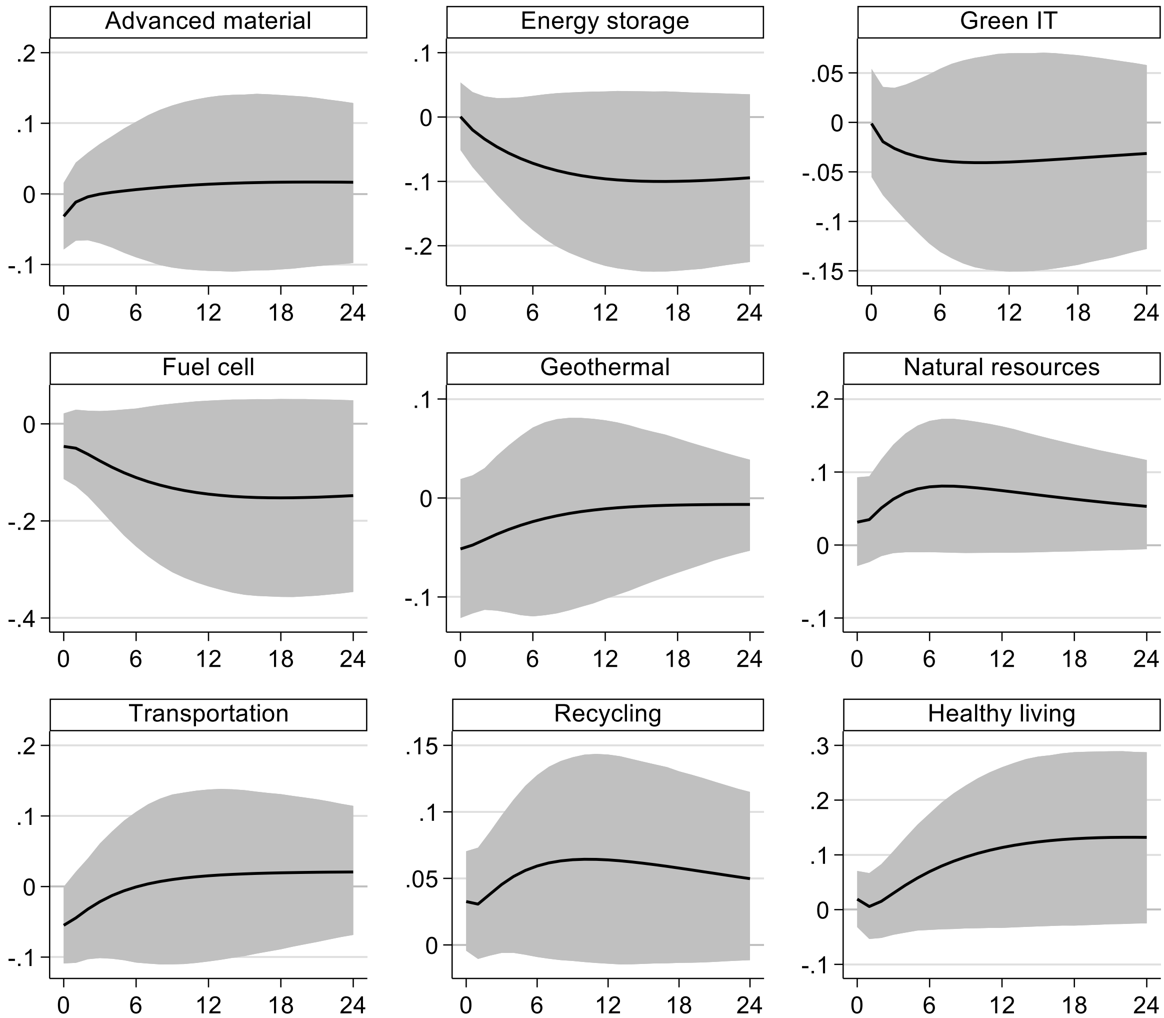

Fig. 11. Solid lines represent the median IRFs, capturing indices with insignificant responses in the baseline specification following a shock in the oil price variable. Shaded areas depict the 68% confidence intervals.

and coordinating these efforts with fiscal interventions, such as subsidies, loan guarantees, or innovative financing mechanisms to support vulnerable sectors during periods of monetary tightening. Such policy coordination becomes particularly critical given the urgency of climate action and the need for sustained investment across all clean energy sectors.

While our study provides valuable insights, future research can expand in several directions. First, investigating the macroeconomic and policy determinants of the common factor could provide further evidence of the systematic risk sources in clean energy markets. Second, examining how global factors and international policy coordination affect sector-specific responses would enhance understanding of cross-border transmission mechanisms. Third, extending the analysis to include corporate fundamentals and micro-level firm characteristics could illuminate the mechanisms driving sectoral heterogeneity. In addition, future research could explore the role of fiscal policy, such as subsidies, tax incentives, and public investment programs, in shaping the dynamics of clean energy markets. Ultimately, examining the interplay among monetary policy, climate policy, and macroprudential regulation can inform optimal policy coordination frameworks that facilitate the energy transition while preserving financial stability.

Declaration of competing interest

The author declares that there is no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The author do not have permission to share data.

References

Ahmad, M., Satrovic, E., 2023. How does monetary policy moderate the influence of economic complexity and technological innovation on environmental sustainability? The role of green central banking. Int. J. Finance Econ. 1.

Ahn, S.C., Horenstein, A.R., 2013. Eigenvalue ratio test for the number of factors. Econometrica 81, 1203–1227.

Anastasiou, D., Ballis, A., Guizani, A., Kallandranis, C., Lakhal, F., 2024. Monetary policy impact on sustainability: analyzing interest rates and corporate carbon emissions. J. Environ. Manag. 368, 122119.

Anzuini, A., Lombardi, M.J., Pagano, P., 2013. The impact of monetary policy shocks on commodity prices. Int. J. Central Banking.

Arias, J.E., Rubio-Ramírez, J.F., Waggoner, D.F., 2018. Inference based on structural vector autoregressions identified with sign and zero restrictions: theory and applications. Econometrica 86, 685–720.

Assenmacher-Wesche, K., Gerlach, S., 2008. Monetary policy, asset prices and macroeconomic conditions: a panel-VAR study (No. 149). NBB Working Paper.

Bai, J., Ng, S., 2002. Determining the number of factors in approximate factor models. Econometrica 70, 191–221.

Bai, J., Ng, S., 2004. A panic attack on unit roots and cointegration. Econometrica 72, 1127–1177.

Bauer, M.D., Neely, C.J., 2014. International channels of the Fed's unconventional monetary policy. J. Int. Money Finance 44, 24–46.

Bauer, M.D., Offner, E.A., Rudebusch, G.D., 2025. Green stocks and monetary policy shocks: evidence from Europe. Eur. Econ. Rev. 177, 105044.

Bernanke, B.S., Boivin, J., Eliasz, P., 2005. Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. Q. J. Econ. 120, 387–422.

Bernanke, B.S., Kuttner, K.N., 2005. What explains the stock market's reaction to federal reserve policy? J. Finance 60, 1221–1257.

Bloomberg New Energy Finance (BNEF), 2025. Energy transition investment trends 2025. Bloomberg.

Boeckx, J., Dossche, M., Peersman, G., 2017. Effectiveness and transmission of the ECB's balance sheet policies. Int. J. Central Banking 13, 297–333.

Bondia, R., Ghosh, S., Kanjilal, K., 2016. International crude oil prices and the stock prices of clean energy and technology companies: Evidence from non-linear cointegration tests with unknown structural breaks. Energy 101, 558–565.

Byrne, J.P., Fazio, G., Fiess, N., 2012. Interest rate comovements, global factors and the long end of the term spread. J. Bank. Finance 36, 183–192.

Byrne, J.P., Fazio, G., Fiess, N., 2013. Primary commodity prices: comovements, common factors and fundamentals. J. Dev. Econ. 101, 16–26.

Caballero, R.J., Hammour, M.L., 1994. The cleansing effect of recessions. Am. Econ. Rev. 1350–1368.

Campbell, J.Y., 1991. A variance decomposition for stock returns. Econ. J. 101, 157–179.

Campiglio, E., 2016. Beyond carbon pricing: the role of banking and monetary policy in financing the transition to a low-carbon economy. Ecol. Econ. 121, 220–230.

Campiglio, E., Dafermos, Y., Monnin, P., Ryan-Collins, J., Schotten, G., Tanaka, M., 2018. Climate change challenges for central banks and financial regulators. Nat. Clim. Change 8, 462–468.

Cao, G., Xie, F., 2023. The asymmetric impact of crude oil futures on the clean energy stock market: based on the asymmetric variable coefficient quantile regression model. Renew. Energy 218, 119303.

Challe, E., Giannitsarou, C., 2014. Stock prices and monetary policy shocks: a general equilibrium approach. J. Econ. Dynam. Control 40, 46–66.

Chan, Y.T., 2020. Are macroeconomic policies better at curbing air pollution than environmental policies? A DSGE approach with carbon-dependent fiscal and monetary policies. Energy Policy 141, 111454.

Chen, Y., Zhu, X., Chen, J., 2022. Spillovers and hedging effectiveness of non-ferrous metals and sub-sectoral clean energy stocks in the time and frequency domains. Energy Econ. 111, 106070.

Chishti, M.Z., Ahmad, M., Rehman, A., Khan, M.K., 2021. Mitigations pathways towards sustainable development: assessing the influence of fiscal and monetary policies on carbon emissions in BRICS economies. J. Clean. Prod. 292, 126035.

Choi, I., 2001. Unit root tests for panel data. J. Int. Money Finance 20, 249–272.

Christiano, L.J., Eichenbaum, M., Evans, C.L., 1999. Monetary policy shocks: what have we learned and to what end? Handb. Macroecon. 1, 65–148.

Ciner, C., 2021. Stock return predictability in the time of COVID-19. Finance Res. Lett. 38, 101705.

Ciner, C., Kosedag, A., Lucey, B., 2023. Predictors of clean energy stock returns: an analysis with best subset regressions. Finance Res. Lett. 55, 103912.

Conti, A.M., 2017. Has the FED fallen behind the curve? Evidence from VAR models. Econ. Lett. 159, 164–168.

Dafermos, Y., Nikolaidi, M., Galanis, G., 2018. Climate change, financial stability and monetary policy. Ecol. Econ. 152, 219–234.

Dawar, I., Dutta, A., Bouri, E., Saeed, T., 2021. Crude oil prices and clean energy stock indices: lagged and asymmetric effects with quantile regression. Renew. Energy 163, 288–299.

De Haas, R., Popov, A., 2019. European Central Bank; Working Paper Series 2318.

DiLeo, M., 2023. Climate policy at the bank of England: the possibilities and limits of green central banking. Clim. Policy 23, 671–688.

Doğan, B., Balsalobre-Lorente, D., Nasir, M.A., 2020. European commitment to COP21 and the role of energy consumption, FDI, trade and economic complexity in sustaining economic growth. J. Environ. Manag. 273, 111146.

Ehrmann, M., Fratzscher, M., 2004. Taking stock: monetary policy transmission to equity markets. J. Money Credit Bank. 36, 719–737.

El Khoury, R., Alshater, M.M., Li, Y., Xiong, X., 2024. Quantile time-frequency connectedness among G7 stock markets and clean energy markets. Q. Rev. Econ. Finance 93, 71–90.

Emodi, N.V., Wade, B., Rekker, S., Greig, C., 2022. A systematic review of barriers to greenfield investment in decarbonisation solutions. Renew. Sustain. Energy Rev. 165, 112586.

Farid, S., Karim, S., Naeem, M.A., Nepal, R., Jamasb, T., 2023. Comovement between dirty and clean energy: a time-frequency perspective. Energy Econ. 119, 106565.

Ferrari, A., Nispi Landi, V., 2023. Whatever it takes to save the planet? Central banks and unconventional green policy. Macroecon. Dyn. 1–26.

Ferrer, R., Shahzad, S.J.H., López, R., Jareño, F., 2018. Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. Energy Econ. 76, 1–20.

Gagnon, J., Raskin, M., Remache, J., Sack, B., 2011. The financial market effects of the federal Reserve's large-scale asset purchases. Int. J. Central Banking 7 (1), 3–43.

Gambacorta, L., Hofmann, B., Peersman, G., 2014. The effectiveness of unconventional monetary policy at the zero lower bound: a cross-country analysis. J. Money Credit Bank. 46, 615–642.

Gertler, M., Gilchrist, S., 1994. Monetary policy, business cycles, and the behavior of small manufacturing firms. Q. J. Econ. 109, 309–340.

Gertler, M., Karadi, P., 2013. QE 1 vs. 2 vs. 3...: a framework for analyzing large-scale asset purchases as a monetary policy tool. Int. J. Central Banking 9 (S1), 5–53.

Gil-Alana, L.A., Infante, J., Martín-Valmayor, M.A., 2023. Persistence and long run comovements across stock market prices. Q. Rev. Econ. Finance 89, 347–357.

Giovanardi, F., Kaldorf, M., Radke, L., Wicknig, F., 2023. The preferential treatment of green bonds. Rev. Econ. Dynam. 51, 657–676.

Gupta, R., Nel, J., Nielsen, J., 2023. US monetary policy and BRICS stock market bubbles. Finance Res. Lett. 51, 103435.

Hadri, K., 2000. Testing for stationarity in heterogeneous panel data. Econom. J. 3, 148–161.

Hammoudeh, S., Mokni, K., Ben-Salha, O., Ajmi, A.N., 2021. Distributional predictability between oil prices and renewable energy stocks: is there a role for the COVID-19 pandemic? Energy Econ. 103, 105512.

Hashmi, S.M., Syed, Q.R., Inglesi-Lotz, R., 2022. Monetary and energy policy interlinkages: the case of renewable energy in the US. Renew. Energy 201, 141–147.

Henriques, I., Sadorsky, P., 2008. Oil prices and the stock prices of alternative energy companies. Energy Econ. 30, 998–1010.

Ho, J.C., Saw, E.-C., Lu, L.Y.Y., Liu, J.S., 2014. Technological barriers and research trends in fuel cell technologies: a citation network analysis. Technol. Forecast. Soc. Change 82, 66–79.

Hu, L., Ouyang, X., Zhou, Z., 2024a. Synergistic effects of pollutant control: evidence from China's sulfur dioxide emission control policy. Energy Econ., 107457

Hu, X., Zhu, B., Zhou, H., 2024b. Impact of low-carbon monetary policies on climate-related systemic risk: evidence from China. J. Clean. Prod. 434, 139858.

Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. J. Econom. 115, 53–74.

IRENA, 2023. Renewable energy statistics 2023. International Renewable Energy Agency.

Jacobsson, S., Bergek, A., 2011. Innovation system analyses and sustainability transitions: contributions and suggestions for research. Environ. Innov. Soc. Transit. 1, 41–57.

Jiang, E.X., Matvos, G., Piskorski, T., Seru, A., 2023. Monetary Tightening and US Bank Fragility in 2023: Mark-To-Market Losses and Uninsured Depositor Runs? National Bureau of Economic Research Working Paper Series No. 31048.

Jiang, Y., Ather Bukhari, A.A., Ather Bukhari, W.A., Khamdamov, S.-J., 2025. Integrating green finance and energy transitions for decarbonization: policy pathways to achieve COP-29 goals in E7 economies. J. Environ. Manag. 382, 125217.

Joyce, M., Miles, D., Scott, A., Vayanos, D., 2012. Quantitative easing and unconventional monetary policy–an introduction. Econ. J. 122 (564), F271–F288.

Kahn, M.E., Mohaddes, K., Ng, R.N.C., Pesaran, M.H., Raissi, M., Yang, J.-C., 2021. Long-term macroeconomic effects of climate change: a cross-country analysis. Energy Econ. 104, 105624.

Kapetanios, G., Mumtaz, H., Stevens, I., Theodoridis, K., 2012. Assessing the economy-wide effects of quantitative easing. Econ. J. 122, F316–F347.

Kashyap, A.K., Stein, J.C., 1995. The impact of monetary policy on bank balance sheets. In: Carnegie-Rochester Conference Series on Public Policy. Elsevier, pp. 151–195.

Kumar, S., Managi, S., Matsuda, A., 2012. Stock prices of clean energy firms, oil, and carbon markets: A vector autoregressive analysis. Energy Econ. 34, 215–226.

Laine, O.-M., 2023. Monetary policy and stock market valuation. Int. J. Central Banking 19, 365–416.

Lamperti, F., Bosetti, V., Roventini, A., Tavoni, M., Treibich, T., 2021. Three green financial policies to address climate risks. J. Financ. Stabil. 54, 100875.

Li, G., Shen, Z.Y., Song, M., Wei, W., 2024. Exploring the interconnectedness of China's new energy and stock markets: a study on volatility spillovers and dynamic correlations. Int. Rev. Econ. Finance 89, 471–484.

Li, Y.D., İşcan, T.B., Xu, K., 2010. The impact of monetary policy shocks on stock prices: evidence from Canada and the United States. J. Int. Money Finance 29, 876–896.

Maghyereh, A.I., Awartani, B., Abdoh, H., 2019. The comovement between oil and clean energy stocks: a wavelet-based analysis of horizon associations. Energy 169, 895–913.

Maurer, T.D., Nitschka, T., 2023. Stock market evidence on the international transmission channels of US monetary policy surprises. J. Int. Money Finance 136, 102866.

Mazzucato, M., Semieniuk, G., 2017. Public financing of innovation: new questions. Oxf. Rev. Econ. Pol. 33, 24–48.

Mbassi, C.M., Hyoba, S.E.C., Shahbaz, M., 2023. Does monetary policy really matter for environmental protection? The case of inflation targeting. Res. Econ. 77, 427–452.

McBride, M., Helmeci, D., Goh, D., Mangalmurti, D., 2025. Unlocking Global Geothermal Energy: Pathways to Scaling International Deployment of Next-Generation Geothermal.

Miranda-Agrippino, S., Rey, H., 2020. US monetary policy and the global financial cycle. Rev. Econ. Stud. 87, 2754–2776.

Mughal, N., Kashif, M., Arif, A., Guerrero, J.W.G., Nabua, W.C., Niedbała, G., 2021. Dynamic effects of fiscal and monetary policy instruments on environmental pollution in ASEAN. Environ. Sci. Pollut. Control Ser. 28, 65116–65126.

Nasir, R.M., He, F., 2023. Do clean energy stocks and sub-sectors hedge China economic policy uncertainty: new evidence from wavelet analysis. J. Clean. Prod. 429, 139385.
Nasreen, S., Tiwari, A.K., Eizaguirre, J.C., Wohar, M.E., 2020. Dynamic connectedness between oil prices and stock returns of clean energy and technology companies. J. Clean. Prod. 260, 121015.
Ni, J., Ruan, J., 2023. Does negative interest rate policy impact carbon emissions? Evidence from a quasi-natural experiment. J. Clean. Prod. 422, 138624.
Onatski, A., 2010. Determining the number of factors from empirical distribution of eigenvalues. Rev. Econ. Stat. 92, 1004–1016.
Pástor, Ľ., Stambaugh, R.F., Taylor, L.A., 2022. Dissecting green returns. J. Financ. Econ. 146, 403–424.
Pesaran, M.H., 2015. Testing weak cross-sectional dependence in large panels. Econom. Rev. 34, 1089–1117.
Pham, L., 2019. Do all clean energy stocks respond homogeneously to oil price? Energy Econ. 81, 355–379.
Pham, L., 2021. How integrated are regional green equity markets? Evidence from a cross-quantilogram approach. J. Risk Financ. Manag.
Polzin, F., Migendt, M., Täube, F.A., von Flotow, P., 2015. Public policy influence on renewable energy investments—A panel data study across OECD countries. Energy Policy 80, 98–111.
Popp, D., Hascic, I., Medhi, N., 2011. Technology and the diffusion of renewable energy. Energy Econ. 33, 648–662.
Porter, M.E., van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. J. Econ. Perspect. 9, 97–118.
Qingquan, J., Khattak, S.I., Ahmad, M., Ping, L., 2020. A new approach to environmental sustainability: assessing the impact of monetary policy on CO2 emissions in Asian economies. Sustain. Dev. 28, 1331–1346.
Rao, A., Lucey, B., Kumar, S., Lim, W.M., 2023. Do green energy markets catch cold when conventional energy markets sneeze? Energy Econ. 127, 107035.
Reboredo, J.C., Rivera-Castro, M.A., Ugolini, A., 2017. Wavelet-based test of comovement and causality between oil and renewable energy stock prices. Energy Econ. 61, 241–252.
Sadorsky, P., 2012. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Econ. 34, 248–255.
Saeed, T., Bouri, E., Alsulami, H., 2021. Extreme return connectedness and its determinants between clean/green and dirty energy investments. Energy Econ. 96, 105017.
Saharti, M., Saeed, A., Chaudhry, S.M., Nasir, M.A., 2025. Lending relationships of firms for a just transition. Eur. Financ. Manag. 31, 1195–1216.
Sandén, B.A., Hillman, K.M., 2011. A framework for analysis of multi-mode interaction among technologies with examples from the history of alternative transport fuels in Sweden. Res. Pol. 40, 403–414.
Schmidt, T.S., Steffen, B., Egli, F., Pahle, M., Tietjen, O., Edenhofer, O., 2019. Adverse effects of rising interest rates on sustainable energy transitions. Nat. Sustain. 2, 879–885.
Sleibi, Y., Casalin, F., Fazio, G., 2020. Bank-specific shocks and aggregate leverage: empirical evidence from a panel of developed countries. J. Financ. Stabil. 49, 100743.
Sleibi, Y., Casalin, F., Fazio, G., 2023. Unconventional monetary policies and credit comovement in the Eurozone. J. Int. Financ. Mark. Inst. Money 85, 101779.
Su, X., Zhao, Y., 2023. What has the strongest connectedness with clean energy? Technology, substitutes, or raw materials. Energy Econ. 128, 107169.
Sul, D., 2019. Panel Data Econometrics: Common Factor Analysis for Empirical Researchers. Routledge.
Tiwari, A.K., Trabelsi, N., Abakah, E.J.A., Nasreen, S., Lee, C.C., 2023. An empirical analysis of the dynamic relationship between clean and dirty energy markets. Energy Econ. 124.
Tørstad, V., Stankovic, T., Nahm, J., Urpelainen, J., Hovi, J., 2025. Macroeconomic crises and green recovery spending: introducing the CLIMREC dataset. npj Climate Action 4, 18.
Tumu, K., Vorst, K., Curtzwiler, G., 2023. Global plastic waste recycling and extended producer responsibility laws. J. Environ. Manag. 348, 119242.
Umar, M., Farid, S., Naeem, M.A., 2022. Time-frequency connectedness among clean-energy stocks and fossil fuel markets: comparison between financial, oil and pandemic crisis. Energy 240, 122702.
Wilberforce, T., Alaswad, A., Palumbo, A., Dassisti, M., Olabi, A.G., 2016. Advances in stationary and portable fuel cell applications. Int. J. Hydrogen Energy 41, 16509–16522.
Williams, J.B., 1938. The Theory of Investment Value. MA: Harvard University Press, Cambridge.
Wu, F., 2019. Sectoral contributions to systemic risk in the Chinese stock market. Finance Res. Lett. 31, 386–390.
Wu, J.C., Xia, F.D., 2016. Measuring the macroeconomic impact of monetary policy at the zero lower bound. J. Money Credit Bank. 48, 253–291.
Xia, T., Ji, Q., Zhang, D., Han, J., 2019. Asymmetric and extreme influence of energy price changes on renewable energy stock performance. J. Clean. Prod. 241, 118338.
Yarovaya, L., Brzeszczyński, J., Goodell, J.W., Lucey, B., Lau, C.K.M., 2022. Rethinking financial contagion: information transmission mechanism during the COVID-19 pandemic. J. Int. Financ. Mark. Inst. Money 79.
Yuen, T.H.A., Yuen, W.K.T., 2024. Public investment on renewable energy R&D projects: the role of geopolitical risk, and economic and political uncertainties. Energy Econ. 138, 107837.
Zhao, X., 2020. Do the stock returns of clean energy corporations respond to oil price shocks and policy uncertainty? J. Econ. Struct. 9, 53.