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Effect of Climate Policy Uncertainty on the Relationship between Investor Sentiment and Metals and Mining Industry Index Returns: Time-Varying Granger Causality Approach

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Abstract

Recognizing the substantial contribution of the metals and mining (M&M) industry to climate change and global warming, it is anticipated that investor sentiments will exert influence over investment decisions, potentially affecting the stock prices of firms within this sector. Furthermore, uncertainties, particularly surrounding climate change policies, significantly shape investor behavior. This study endeavors to investigate the role of uncertainty in elucidating the relationship between investor sentiment and stock prices, focusing specifically on returns from the metals and mining sector index, which is highly related to climate change. Employing innovative rolling window and recursive evolving methodologies, we analyze the time-varying Granger causality from climate policy uncertainty to the dynamic conditional correlation between investor sentiment and returns on the M&M sector and the S&P 500 indices. Our findings demonstrate a notable increase in correlations between the M&M sector index returns and investor sentiment over time, highlighting nuanced responses within the metals and mining industry compared to the broader market. Additionally, our results reveal that climate policy uncertainty significantly influences the correlation between M&M index returns and investor sentiment, particularly following the Paris Climate Accords, suggesting heightened emotional investor responses during periods of increased policy uncertainty. However, this impact does not uniformly extend to the broader market, underscoring the sector-specific effects of policy uncertainties. These insights emphasize the importance for company stakeholders, managers, and investors to consider fluctuations in consumer confidence and policy uncertainties, recognizing the varying impacts across sectors to inform strategic decision-making.

1. Introduction

The debate on the relationship between investor sentiment and asset prices dates back to De Long et al. (1990), which presents that investors are trading based on their sentiment. However, as the pain from a loss has a greater influence than joy

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from the gain on investors, individuals act differently in different market states (see Kahneman and Tversky, 1979; Desroches and Gosselin, 2002; Gino et al., 2012; Ugurlu-Yildirim et al., 2021). In particular, an uncertain political environment impacts investor sentiment and financial markets. In this paper, we aim to delve into the relationship between these variables.

This study centers its attention on the Metals and Mining industry for specific reasons. While the literature extensively addresses uncertainties in economic policies, there is a growing focus on the environmental implications of policy uncertainties. This shift in emphasis is attributed to the increasingly evident effects of climate change and global warming, which have become more noticeable to individuals in recent times. Liu et al. (2020) provide insights into how alterations in policy environments affect diverse companies in distinct ways. What stands out is the significant disparity in how policy changes, particularly those related to climate change, affect companies in various industries. Among these industries, the mining sector stands out as highly relevant to climate change, facing potential damage from the regularity and severity of extreme climate events (Pearce, 2019) and potential increases in tensions between the public and the mining sector (Vigya and Daniel, 2013). Furthermore, changes in climate change policies have repercussions on mineral resources' supply and demand, with a strong focus on the mining industry due to its substantial carbon emissions and environmental pollution (Sun et al., 2020). The metals and mining sector is traditionally characterized by substantial capital requirements and long-term projects, requiring a methodical approach from initial exploration to eventual closure. Complexity arises from extensive infrastructure needs and uncertainties tied to subsoil conditions, ore deposit quality, and size. Additionally, investments in this sector tend to be irreversible, leading firms to adopt rigorous risk assessments within a stringent capital allocation framework. Consequently, these companies are more susceptible to macroeconomic fluctuations (Rumokoy et al., 2023). According to a recent survey conducted by E&Y (2023), executives in the metals and mining sector worldwide have identified climate change as one of the top three risks confronting their businesses during times of global conflict and uncertainty. From this perspective, this study aims to investigate the dynamic conditional correlation between investor sentiment and the metals and mining (M&M) sector index returns and whether uncertainty in climate policy has a part in explaining this relationship by employing the novel time-varying Granger causality approach. To ascertain whether the M&M sector exhibits behavior distinct from the overall market, our study also examines the relationship between these variables and S&P 500 index returns.

Our paper mainly has two stages of analysis. In the first stage, we derive the time-varying conditional correlation series between index prices and investor sentiment using the DCC-GARCH (1,1) model. De Long et al. (1990) claim that individuals trade according to their sentiments, and they offer an asset-pricing model in which these not-fully rational investors put additional non-diversifiable risk on the assets priced in equilibrium. Aligned with De Long et al. (1990), various empirical studies have explored the influence of investor sentiment on stock prices, utilizing diverse proxies such as the risk appetite index (Baek et al., 2005), volatility premium, initial returns on IPO, market turnover (Baker et al., 2012), Gallup investor survey, and University of Michigan survey (Greenwood and Shleifer, 2014). These studies reveal a positive correlation between investor sentiment and stock prices, persisting across both short and long-term horizons. Given the M&M industry's recognition as a significant contributor to climate change and global warming, it is anticipated that investor sentiments will wield sway over their investment choices. These decisions, in turn, hold the potential to impact the stock prices of firms within the metals and mining sector. In this respect, this study contributes to this strand of the literature by presenting whether the time-varying correlation between investor sentiment and the returns on the M&M sector index and S&P 500 index display different patterns.

Although presenting the direct correlation between investor sentiment and the mining industry index price is important, explaining the underlying reasons for this correlation is even more essential. In that matter, we further investigate whether the dynamic correlation between sentiment and M&M sector index prices is affected by climate policy uncertainty by employing time-varying Granger causality analysis in the second stage. Kahneman and Tversky (1979) have posited that investors exhibit distinct behaviors across different market conditions. They argue that the distress stemming from losses tends to influence investors more significantly than the joy derived from gains. This discourse has gained further depth through studies suggesting that sentiment affects asset prices asymmetrically in both favorable and unfavorable market circumstances, primarily due to short sale constraints (Grinblatt and Keloharju, 2009; Ugurlu-Yildirim et al., 2021). Consequently, research endeavors investigating the intricate relationship between uncertainty and sentiment have assumed considerable significance in recent decades. We add to this strand of the literature by showing the impact of climate policy uncertainty on the relationship between investor sentiment and index returns.

Our paper makes a twofold contribution of significance. Firstly, we employ a novel methodology originally developed by Shi et al. (2018). This innovative approach, known as the time-varying Granger causality analysis, affords us the capability to discern shifts in causal relationships during specific temporal intervals or on particular dates. Secondly, we augment the existing body of scholarly literature by elucidating the influence of climate policy uncertainty on the dynamic correlation between investor sentiment and stock market performance.

This paper proceeds as follows. Section two details the relevant literature. Section three presents the data and methodology employed in this paper. The fourth section discusses the empirical results. Section five concludes this paper.

2. Literature Review

Our paper primarily delves into two distinct areas of research. The first one explores the connection between investor sentiment and the stock market, while the second delves into how policy uncertainty influences this relationship.

The studies demonstrate that investors are influenced not only by rational sentiment but also by irrational sentiment or external factors. Sometimes, they might base their investment decisions on personal beliefs, even in the absence of a rational foundation for those beliefs. Due to these sensitivities, unanticipated shifts in investor sentiment can exert a substantial impact on stock returns (Baker and Wurgler, 2006; Black, 1986; De Long et al., 1990; Kumar and Lee, 2006; Sayim, 2013). Due to the absence of directly observable indicators measuring investor sentiment, several prior empirical studies use consumer confidence indices as substitutes for investor sentiment (Schmeling, 2009). Fisher and Statman (2003) find positive correlations between consumer confidence measures and a direct assessment of investor sentiment compiled by the American Association of Individual Investors during the period from 1987 to 2000. Qui and Welch (2006) make a clear differentiation between validating investor sentiment proxies via the UBS/Gallup investor sentiment survey and examining the correlations of these measures with the financial market series. Based on their findings, they propose a consensus that consumer confidence meets the criteria as a valid proxy for investor sentiment. Chen (2015) defines consumer confidence as the perception of consumers regarding the economic climate. While a high degree of confidence indicates optimism for the economic future, a low degree of confidence implies pessimism for the economic prospects and future income. Therefore, if consumers are pessimistic about the future, they are inclined to raise their precautionary savings and reduce their consumption (Gelpler et al., 2007). Research on investor sentiment and its impact on the stock market primarily encompasses two key aspects: the overall effect and the cross-sectional effect. The former involves examining how market sentiment influences the entire stock market as a whole, while the latter focuses on understanding how market sentiment differentially affects various stock categories. Studies on the overall effect typically investigate the influence of investor sentiment on market returns (De Long et al., 1990; Dash and Maitra, 2018; Lao et al., 2018) and the majority of these findings tend to support a notable correlation between investor sentiment and financial asset prices (Niu et al., 2021).

While research on investor sentiment primarily concentrates on the stock market, there has been limited exploration into how investor sentiment influences the returns of specific industries. Traditionally, the metals and mining industry is known for its capital-intensive nature, involving long-term projects that demand a systematic approach from mine exploration to exit. This complexity arises from the extensive infrastructure requirements in developing a mine, along with uncertainties related to subsoil conditions, ore body grade, and dimensions. Consequently, companies in this industry adhere to a stringent capital allocation framework, necessitating rigorous investment decisions and a thorough examination of project risks (Rumokoy et al., 2023). Another notable characteristic is the industry's high integration into the global economy, making firms more susceptible to macroeconomic volatility (Jefferis, 2014). Huang et al. (2014) show that in bearish market conditions, the influence of investor sentiment on the stock returns of resource-based industries like nonferrous metals and petrochemicals is notably pronounced, whereas it becomes inconsequential when the stock market is bullish. This phenomenon may be attributed to resource-based industries where investors tend to increase their investments in resource stocks to mitigate risks, thus making these stocks more resilient to market fluctuations. Consequently, the significance of investor sentiment on these stocks is more pronounced during bearish markets while becoming inconsequential in bullish ones. Rumokoy et al. (2023) present a negative and significant impact of the VIX, a widely used measure of market risk and investor sentiment, on investments in Australian metals and mining firms. The findings indicate that firms are inclined to decrease their investments when the VIX rises. A higher VIX signifies growing uncertainty among investors and market participants about market conditions, often leading to reduced investor confidence and a decline in demand for equities and other riskier assets, including firm stocks. In times of market uncertainty and increased risk, creditors may adopt conservative lending practices, restricting access to funding and elevating borrowing costs. This, in turn, may diminish metals and mining firms' capacity to invest in Capital Expenditure (CapEx) projects as they face challenges in securing necessary funding for their operations. Pearce et al. (2011) demonstrate that mining operations are influenced by the 'politics of climate change,' encompassing public perception of a company's dedication to tackling climate change and the formulation of government regulations governing Greenhouse Gas (GHG) emissions. Likewise, Hardy et al. (2023) present that the sentiment conveyed in financial reports from U.S. mining companies has predictive value for the returns of specific base metals, precious metals, and fuel commodities. Bessec and Fouquau (2022) add to the expanding body of literature utilizing media text to capture investor sentiment and explore its impact on financial markets, revealing a negative effect in the energy and materials sectors, particularly in chemicals and metals. The current media emphasis on environmental issues has heightened public awareness and incentivized economic actors to adopt more environmentally friendly practices, impacting financial markets as well. Notably, the observed negative impact is prominent in energy, chemicals, and metals, suggesting that investors perceive these activities as environmentally harmful. This study enhances the existing body of research by examining how the relationship between investor sentiment and M&M sector index returns changes over time, and whether this relationship exhibits variations compared to the broader market.

Another strand of the literature that our paper relates to is the impact of uncertainty on the stock market. The literature on uncertainty is closely tied to risk exposure and behavioral responses in uncertain times. Knight (1948) defines uncertainty as the inability to predict future events, leading to reduced economic expectations as it intensifies. This is supported by Friedman's (1957) "permanent income hypothesis," where current consumption depends on anticipated future income, resulting in increased caution and reduced spending during heightened uncertainty. Modigliani (1986) reinforces this idea with the "life cycle hypothesis," indicating that an uncertain economic environment leads to decreased or delayed consumption. Leland (1968) shows that uncertainty in future income encourages savings. Keynes (1936) emphasizes emotional decision-making, termed "animal spirits," affecting confidence. Gulen and Ion (2016) note that firms delay investments during uncertain times, especially amidst rising political instability, impacting risk perception. Such political uncertainty leads to emotional decision-making, negatively affecting investor sentiment and consumption (Sims et al., 2012; Svensson et al., 2017).

Although the literature on the relationship between uncertainty and financial markets is massive, the studies on the link between CPU and financial markets are scant. The exploration of relationships between CPU and financial markets is gradually expanding, with Lamperti et al. (2021) highlighting that fund allocation between brown and green assets plays a crucial role in the possibility of transitioning towards sustainability. The capital-intensive sectors are particularly susceptible to policy uncertainties, impacting the income stream derived from irreversible investments. The prospective control of emissions emerges as a critical risk affecting the economic viability of sector investments, a concern that policy aims to address and regulate (Fuss et al., 2008). Climate policies, which aim to restrict greenhouse gas emissions from fossil energy consumption, can profoundly influence the supply and demand dynamics of crude oil and natural gas, thereby impacting their prices in the international market (Guo et al., 2022). Bouri et al. (2021) present the initial empirical proof that CPU significantly influences the performance of green energy stocks in comparison to brown energy stocks. They conclude that these results emphasize the predictive value of CPU for the price dynamics of both green and brown energy equities, underscoring its sway on investors' inclinations towards green energy stocks (Bouri et al., 2021). Ren et al. (2023) explore the bidirectional causality between CPU and traditional energy sources (oil, coal, natural gas), as well as green markets (clean energy, green bonds, carbon trading), using the time-varying Granger test. The study observes that elevated CPU levels stimulate green investment and innovations in clean energy research and development, leading to a reduction in carbon emissions (Ren et al., 2023; Kuzemko et al., 2020). The role of CPU may be heterogeneous and time-varying, as demonstrated by Hoang (2022), who identifies a positive impact on R&D investment for general firms but a significant negative impact on high emitters adopting a "wait-and-see" strategy in response to environmental policy changes. Supporting Hoang (2022), Guo et al. (2022) employ TVP-VAR-SV models to scrutinize the nonlinear effects of CPU, financial speculation, economic activity, and the US dollar exchange rate on the global prices of crude oil and natural gas, respectively. Their outcomes revealed that the time-varying impact of CPU on energy prices shifts significantly from positive to negative over time, and financial speculation exerts opposite effects on oil and gas prices. Zeng et al. (2022) identify the CPU index's strong predictive value for the volatility of the carbon-neutral concept index, surpassing the China Economic Policy Uncertainty (CEPU) index when the market experiences high volatility. In another study, Liu and Wang (2017) argued that CPU significantly affects short-term behaviors and activities of energy-intensive industries. In terms of the impact of CPU on the mining industry, the literature is even more limited. Studies, including Ford et al. (2010), Pearce et al. (2011), and Odell et al. (2018), highlight that the mining industry is highly vulnerable to climate change, especially considering that mining facilities were originally constructed with the assumption of a stable climate. Beyond direct climate change impacts, mining companies face exposure to shifts in the political economy context they operate. Climate change can trigger alterations in legal settings, policies, market conditions, and stakeholder attitudes toward mining activities (Klein et al., 2022; Odell et al., 2018). By employing the Fama-MacBeth regression methodology, Hsu et al. (2023) demonstrate the adverse effect of CPU on the mining industry is vast. Likewise, Ren et al. (2022) uncover a significant nonlinear impact of CPU on enterprise investment, with substantial negative effects on the mining industry and significantly positive effects on electricity, heat, gas, water, and other industries.

Uncertainty holds a significant role in shaping consumer buying decisions by influencing risk perception (Lee et al., 2019; Carter and Moital, 2018). While some studies suggest that investor sentiment primarily mirrors prevailing economic conditions (Throop, 1992; Carroll et al., 1994), an alternative perspective draws from the concept of "animal spirits," proposing that individual choices can be influenced by psychological factors beyond economic variables (Desroches and Gosselin, 2002). Katona (1975) underscores two primary factors affecting consumer spending: the willingness to consume and the ability to do so. Among these, the willingness to make purchases is not solely determined by reactions to economic indicators but can also be shaped by non-economic events like wars or political crises. Psychological theory, centered on uncertainty, suggests that a decline in confidence can reduce consumption, even in the absence of an income decrease (Desroches and Gosselin, 2002). Acemoglu and Scott (1994) support this view, highlighting the adverse impact of uncertainty on consumption willingness.

While evidence regarding sentiment indexes explaining consumption behavior is somewhat limited when major economic variables are considered, these indexes often diverge from macroeconomic indicators. Therefore, sentiment can significantly explain individual consumption patterns during critical political and economic events (Garner, 1991; Throop, 1992). High economic and political turmoil periods are linked to consumer confidence volatility, indicating substantial fluctuations can profoundly impact consumption. Although Roberts and Simon (2001) dispute sentiment's predictive power for consumption, Desroches and Gosselin (2002) stress its importance in forecasting consumption during high-uncertainty periods. They support prior research, including Garner (1991) and Throop (1992), by asserting that confidence indexes are valuable indicators of consumption, even when controlling for other consumption-affecting variables. Notably, studies investigating investor sentiment's effectiveness during high-uncertainty periods are relatively scarce, with most focusing on predefined periods such as wars or crises. Therefore, we aim to add the literature on uncertainty, sentiment, and the stock market by examining how the correlation between sentiment and the M&M sector index prices is influenced by uncertainties in climate policy.

3. Data and Methodology

In this section, we display the dataset and the methodology that we employ in our empirical analysis.

3.1 Data

We aim to explore the dynamic conditional correlation between investor sentiment and the M&M sector index returns and the time-varying causality from CPU to this correlation. Additionally, we will illustrate the dynamic correlation between sentiment and S&P 500 index returns, and examine the influence of CPU on this relationship. This analysis will help us determine if the M&M industry exhibits distinct characteristics. Our dataset consists of monthly data spanning from June 2006 to August 2022. The choice of the initial date for our sample period is based on data availability for the S&P Metals and Mining Selected Industry Index.

We utilize the first differences of logarithmic S&P Metals and Mining Selected Industry Index prices, referred to as ΔLM, as our metric for tracking metals and mining industry index returns. Additionally, we employ the first differences of logarithmic S&P 500 index prices, denoted as ΔLSP, to gauge overall stock market index returns. Both sets of data have been sourced from the investing.com website.

In line with existing literature, we utilize the first differences of the logarithmic form of the University of Michigan's Index of Consumer Sentiment, ΔCSI, as a proxy for investor sentiment. Although the consumer sentiment index primarily indicates households' perceptions of economic activities tied to macroeconomic conditions while investor sentiment indices like Baker and Wurgler's (2006) reflect investors' perspectives on the overall stock market (Chung et al., 2012), numerous prior research endeavors exploring investor sentiment have employed the University of Michigan Consumer Sentiment Index, as evidenced by studies such as Ludvigson (2004), Lemmon and Portniaguina (2006), Bergman and Roychowdhury (2008), and Shen et al. (2017). The consumer sentiment index is a preferred choice for an investor sentiment proxy due to several factors. Firstly, it is highly regarded by both economists and individual investors, as it provides valuable insights into the stock market, and as it reflects the beliefs of the general public, it aligns well with the perspectives of less informed investors (Shleifer, 2000; Charoenrook, 2006). This index is constructed through a monthly phone survey involving over 500 respondents. MICS effectively captures the confidence levels of US consumers regarding current and future economic conditions. An increase in MICS values signifies a reduced sensitivity to economic shocks, as demonstrated in prior research (Ugurlu-Yildirim et al., 2021; Guo et al., 2017). Consumer confidence indexes play a crucial role in assessing individual risk perceptions and are a valuable tool in this regard.

In order to proxy for the uncertainty in climate policies, the natural logarithmic form of the Climate Policy Uncertainty Index, LCPU, is employed. Gavriilidis (2021) constructed this textual-based index to calculate the changes in the environmental policies executed by the government. We aim to present whether the uncertain policy regarding the environment affects the correlation between investor sentiment and the M&M sector and S&P 500 index prices.

In the literature, it has been shown that the Producer Price Index (PPI) is one of the major macroeconomic variables that influences stock prices (see Flannery and Protopapadakis, 2002; Sirucek, 2012). PPI assesses the increase in costs of production factors essential for producing goods consumed by the population. The computation of these indices constitutes the primary measures used to evaluate inflation in a country and it is an indicator of inflation at the wholesale level (Vilcu, 2015). Fluctuations in raw material prices impact intermediate and final product prices, ultimately influencing consumer prices (Clark, 1995). Moreover, any rise in the PPI translates into the Consumer Price Index (CPI) and may significantly impact the economy's long-term growth (Khan et al., 2018). Therefore, the first difference of the natural logarithmic transformation of the producer price index of the total mining industry, hereafter ΔLPPI, is employed as a control variable to account for the influence of inflation and general economic conditions on stock prices (see Sirucek, 2012; Vilcu, 2015; Anggraeni and Irawan, 2018). The data is obtained from the Federal Reserve Bank of St. Louis Economic Research Division.

It is worthwhile to note that all variables are utilized in the logarithmic form to decrease heteroscedasticity and nonnormality. Descriptive statistics of all variables are presented in Table 1, and their graphical demonstrations are portrayed in Figure 1. As Figure 1 shows, none of the variables, except LCPU, has a trend or seasonality. LCPU, on the other hand, has a trend starting after 2015, most likely after the Paris

Climate Accords, which was signed in December 2015 and entered into force in November 2016.

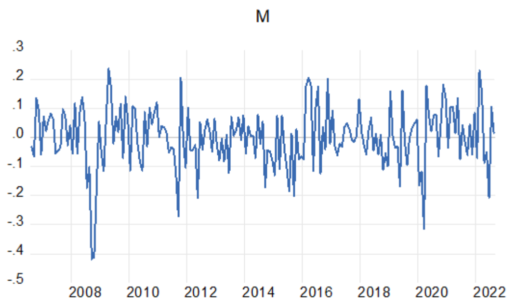
Table 1 Descriptive Statistics

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*	*Skewness*	*Kurtosis*
ΔLM	193	0.000	0.105	-0.418	0.237	-0.653	4.786
ΔLSP	193	0.006	0.045	-0.186	0.119	-0.818	4.644
ΔCSI	193	-0.002	0.057	-0.216	0.128	-0.692	4.257
ΔLPPI	193	5.303	0.204	4.792	5.897	0.161	2.722
LCPU	193	4.780	0.457	3.338	6.019	0.217	2.780

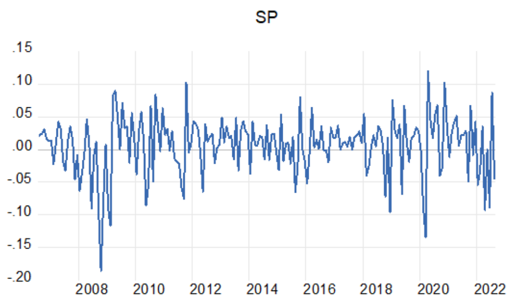
Notes: Table 1 shows the descriptive statistics of the variables in use. ΔLM, ΔLSP, ΔCSI, ΔLPPI, and LCPU refer to the first difference of the logarithmic transformation of the S&P Metals and Mining Selected Industry index price, S&P 500 index price, University of Michigan's Index of Consumer Sentiment, producer price index of the total mining industry, and the logarithmic transformation Climate Policy Uncertainty index, respectively.

Figure 1 Historical ΔLM, ΔLSP, ΔCSI, CPU, and ΔLPPI

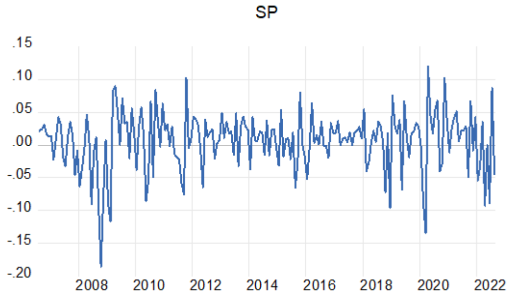
(a)



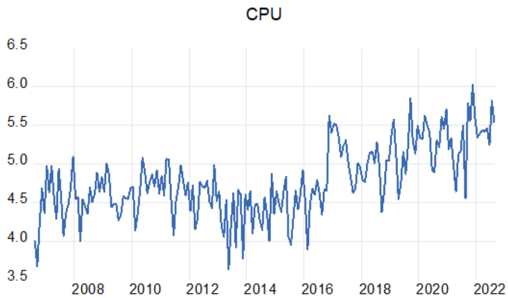
(b)



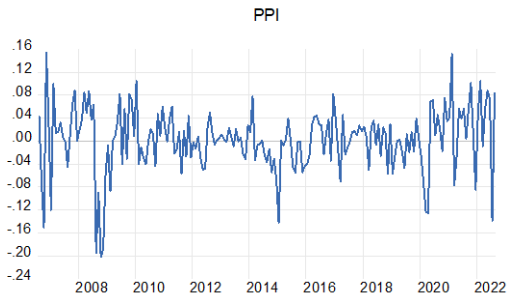
(c)



(d)



(e)



Notes: ΔLM, ΔLSP, CSI, CPU, and ΔLPPI refer to the first difference of the natural log of the Metals & Mining Selected Industry index price, the first difference of the natural log of the S&P 500 index price, the first difference log of the University of Michigan's Index of Consumer Sentiment, Climate policy uncertainty index, and the producer price index of the total mining industry, respectively.

To find the order of integrations of the variables, we employ augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests (see Dickey and Fuller, 1979; Phillips and Perron, 1988). Table 2 presents the results of the unit root tests of variables used in the analysis. All variables are integrated of order 0, in other words, they are all stationary.

Table 2 Unit Root Test Results (Levels)

Variable		*ADF*	*PP*
ΔLM		-8.147***	-12.133***
ΔCSI		-12.255***	-13.700***
ΔLPPI	*Intercept*	-5.624***	-11.572***
ΔLSP		-13.150***	-13.174***
LCPU		-4.303***	-6.212***

Notes: Table 2 shows the unit-root test results for the levels of the variables in use. ΔLM, ΔLSP ΔCSI, ΔLPPI, and LCPU refer to the log difference of S&P Metals and Mining Selected Industry index price, the log difference of S&P 500 index price, the log difference of the University of Michigan's Index of Consumer Sentiment, log difference of producer price index of the total mining industry, and the natural logarithmic transformation of the Climate Policy Uncertainty index, respectively. ADF and PP indicate Dickey-Fuller and Phillips-Perron, respectively. Superscripts *** and ** signify significance at 1% and 5%, respectively.

3.2 Methodology

3.2.1. DCC Model

The DCC-GARCH approach developed by Engle (2002) models time-varying correlation and volatility dynamics. DCC-GARCH model proposes a two-stage approach. In the first stage, model parameters are estimated by utilizing GARCH specification and in the second stage dynamic correlations are estimated. In the study, dynamic correlations between investor sentiment and the M&M sector index and dynamic correlation between investor sentiment and S&P 500 index returns are captured by utilizing the DCC-GARCH approach. The mean and variance equations of the GARCH (1, 1) model developed by Bollerslev (1986) are specified as follows;

$$y_t = \theta_0 + \varepsilon_t \text{ where } \varepsilon_t = z_t \sigma_t \quad (1)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (2)$$

where z_t should be generally normally distributed with zero mean and variance one (Sorensen, 2005), σ_t^2 denotes conditional variance; ω is the constant term representing the long-term average variance; α_1 and β_1 are the ARCH and GARCH parameters, which shows the short-term impact of past shocks on volatility and the persistence of volatility, respectively. For stationarity, the following conditions should be met: $\omega > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\alpha_1 + \beta_1 < 1$.

$$\boldsymbol{H_t} = D_t R_t D_t \quad (3)$$

$$\boldsymbol{D_t} = diag(h_{11t}^{1/2}, \dots, h_{33t}^{1/2}) \quad (4)$$

$$\boldsymbol{R_t} = diag(q_{11t}^{-1/2}, \dots, q_{33t}^{-1/2}) Q_t diag(q_{11t}^{-1/2}, \dots, q_{33t}^{-1/2}) \quad (5)$$

where H_t denotes the *3 x 3* conditional covariance matrix, R_t indicates the conditional correlation matrix, and D_t is the *3 x 3* diagonal matrix of time-varying standard deviations on the diagonal.

$$\boldsymbol{Q_t} = (1 - a - b)\bar{P} + a(\xi_{t-1}\acute{\xi}_{t-1}) + b(Q_{t-1}) \tag{6}$$

where Q_t is a *3 x 3* symmetric positive definite matrix; a and b are the scalars which should provide the condition $a + b < 1$ for the model stability; $\bar{P}$ is the *3 x 3* unconditional correlation matrix of the standardized residuals of ξ_t.
The dynamic conditional correlation estimator between investor sentiment, producer price index of the total mining industry, and index returns is displayed below;

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{8}$$

3.2.2. Time-Varying Granger Causality

This study aims to reveal the time-varying Granger causality association among investor sentiment, climate policy uncertainty, producer price index, and metals and mining industry index returns by employing the rolling window and recursive expanding (evolving) algorithms introduced by Shi et al. (2018, 2020). The lag-augmented VAR (LA-VAR) procedure which provides size stability (Toda and Yamamoto, 1995; Dolado and Lütkepohl, 1996) is adopted to detect the time-varying causality relationships between the CPU index and the dynamic correlations obtained from the DCC model. Thus, y_1 denotes the dynamic correlation series obtained from the first step of the analysis while y_2 denotes CPU specified by the following equations;

$$y_{1t} = \alpha_{10} + \alpha_{11}t + \sum_{i=1}^{k+d}\beta_{1i}y_{1t-i} + \sum_{i=1}^{k+d}\mu_{1i}y_{2t-i} + \varepsilon_{1t} \tag{9}$$

where t is a time trend, k is the lag order of the VAR model, and ε_{it} are the error terms. d denotes the maximum order of integration in the VAR system. The non-causality from y_{2t} to y_{1t} describes that the conditional past values of y_{1t} cannot be predicted by the lagged values of y_{2t} in the model (Shi et al., 2020). Thus, the null hypothesis of Granger non-causality from y_{2t} to y_{1t} is tested by utilizing the Wald Test as follows;

$$H_0\colon \mu_{11} = \cdots = \mu_{1k} = 0 \tag{10}$$

LA-VAR model is specified in the following matrix form

$$y_t = \boldsymbol{\Gamma}\tau_t + \boldsymbol{\Phi}x_t + \boldsymbol{\Psi}z_t + \varepsilon_t \tag{11}$$

where $\Gamma = (\gamma_0, \gamma_1)_{nx(q+1)}$, $\tau_t = (1,t)'_{2x1}$, $x_t = (y'_{t-1;\ldots,}y'_{t-k})'_{nkx1}$, $z_t = (y'_{t-k-1;\ldots,}y'_{t-k-d})'_{ndx1}$, $\Phi = (J_{1,\ldots,}J_k)_{nxnk}$, and $\Psi = (J_{k+1,\ldots,}J_{k+d})_{nxnd}$. The null hypothesis of Granger non-causality is exhibited by the Wald test restrictions;

$$H_0\colon \boldsymbol{R}\theta = 0 \tag{12}$$

$$W = \left(\boldsymbol{R}\hat{\theta}\right)^{'}\left[\boldsymbol{R}\left(\hat{\Omega} \otimes (X'QX)^{-1}\boldsymbol{R}^{'}\right)\right]^{-1}\left(\boldsymbol{R}\hat{\theta}\right) \tag{13}$$

where R is $m\ x\ n^2k$ matrix, $\hat{\theta} = vec(\Theta)$which denotes the raw vectorization of the OLS estimator $\hat{\theta} = Y^{'}QX(X^{'}QX)^{-1}$, $\hat{\Omega} = T^{-1}\hat{\varepsilon}'\hat{\varepsilon}$ and $\otimes$ represents the Kronecker product. The Wald statistic asymptotically distributed X_m^2 under the null hypothesis and m represents the number of restrictions (Toda and Yamamoto, 1995; Dolado and Lütkepohl, 1996; Shi et al., 2020).
The Wald statistics are derived from the Granger causality tests by utilizing subsamples of the data. By using fractional samples f_1 and f_2 for starting and ending points, $f_w=f_2-f_1$, the Wald statistic is calculated based on the LA-VAR procedure denoted by $W_{f_1}^{f_2}$ where T denotes the total number of observations. Let, $\tau_1 = \lfloor f_1T \rfloor$, $\tau_2 = \lfloor f_2T \rfloor$, and $\tau_0 = \lfloor f_0T \rfloor$ be the minimum number of observations that enable to estimation of the VAR system. In the rolling window procedure (Swanson, 1998), the regression window size is fixed. The starting point τ_1 runs from 1 to $T- \tau_0+1$, and the ending point $\tau_2 = \tau_1 + \tau_0 -1$. For the recursing evolving window procedure (Phillips et al., 2015a, 2015b), the endpoint of the regression is considered as $\tau_2 = \{\tau_0, \ldots, T\}$ while the starting of the regression is τ_1 rather than keeping a fixed distance, and the supremum of Wald statistic is given (Shi et al., 2018, 2020; also see Hammoudeh et al., 2020);

$$SW_f(f_0) = \frac{sup}{(f_1, f_2)\in \hat{0}, f_2=f}\{W_{f_2}(f_1)\} \tag{14}$$

where $\hat{0} = \{(f_1, f_2): 0 < f_0 + f_1 \leq f_2 \leq 1 \ and\ 0 \leq f_1 \leq 1 - f_0\}$,

The test statistics are specified in Equation (15) for the rolling window procedure;

$$\hat{f}_e = \frac{inf}{f\in[f_0,1]}\{f: W_f(f - f_0) > cv\} \quad and$$
$$\hat{f}_f = \frac{inf}{f\in[\hat{f}_e,1]}\{f: W_f(f - f_0) < cv\} \tag{15}$$

The test statistics are specified in Equation (16) for the recursive evolving procedure;

$$\hat{f}_e = \frac{inf}{f\in[f_0,1]}\{f: SW_f(f_0) > scv\} \quad and$$
$$\hat{f}_f = \frac{inf}{f\in[\hat{f}_e,1]}\{f: SW_f(f_0) < scv\} \tag{16}$$

where $\hat{f}_e$ and $\hat{f}_f$ represent the estimated first chronological observations whose test statistics are respectively higher or smaller than the critical values for the beginning and ending points of the causal relationship. Also, cv and scv denote the critical values associated with the W_f and SW_fstatistics, respectively (Shi et al., 2018).

4. Empirical Results

4.1. DCC Model Tests

Our study mainly consists of two stages. In the first stage, the dynamic correlation between investor sentiment and the M&M sector index is tested by employing the DCC-GARCH (1,1) model. Then, in order to investigate whether the M&M sector shows a different character than the market, we find the time-varying correlation between S&P 500 index returns and investor sentiment. The estimation results of the mean and variance equation of the GARCH (1,1) model are displayed in Table 3. The presence of statistically significant parameters suggests the existence of conditional heteroscedasticity. GARCH and ARCH parameters are denoted by β_h and χ, respectively, with GARCH parameters surpassing short-term ARCH parameters, indicating a notable impact of long-term volatility. Moreover, all β_h values are statistically significant, suggesting market momentum across all equity indices and highlighting the potential significance of conditional heteroscedasticity on equity returns. Diagnostic tests using 10 and 20 lags reveal no significant issues at the 1% level.

Table 3 Mean and Variance Equation Results

	DLNSPMM	*DLNSP500*
	Mean Equation	
Constant	0.0082	0.0086***
	Variance Equation	
β_0	0.0023**	0.0002
χ	0.2994***	0.2693***
β_h	0.5131***	0.6622***
Q(10)	0.758	0.504
Q(20)	0.948	0.282
SR(10)	0.471	0.638
SR(20)	0.748	0.708
ARCH(10)	0.9729	0.2611
ARCH(20)	0.4586	0.9112

Notes: Table 3 presents the estimation of coefficients within the mean and variance equations of the GARCH (1,1) model, with index returns as the dependent variables. Alongside the model outcomes, the table displays the p-values for the Ljung–Box Q statistics and ARCH LM test statistics with 10 and 20 lags. The term "SR" indicates squared residuals. Significance levels, denoted by *,**, and *** signify significance at the 10%, 5%, and 1% levels, respectively. The parameters χ and βh denote the ARCH and GARCH parameters, respectively.

The results of DCC-GARCH (1,1) models are shown in Table 4. The a_i^2 parameters reflect how past standardized shocks influence the present dynamics, while the b_i^2 parameters signify the influence of past dynamics on the current ones. Table 4 Panel A reveals that in the estimation in which the M&M sector index returns are used, all parameters are statistically significant. The fulfillment of the requisite conditions demonstrates the stability of the employed model, thus confirming its adequacy for interpreting the results and elucidating the interconnected dynamics. Conversely, in Table 4 Panel B, we observe that although the parameter b_i^2 holds statistical significance, the parameter a_i^2 does not. This finding suggests that previously standardized shocks do not exert a significant influence on the current dynamics within the model that examines the correlation between ΔLSP, ΔCIS, and ΔLPPI. Nevertheless, it is worth noting that in both models, the stability conditions, as expressed by $a_i^2 + b_i^2 < 1$, are satisfied.

Table 4 Estimation Results of DCC Models

	Panel A: ΔLM (Dependent variable)		
	a_i^2	b_i^2	Log Likelihood
Coefficient	-0.0251	1.0009	1.3508
Standard Error	0.0078	0.0042	
z-statistics	-3.2232	236.9784	
p-value	0.0013	0.0000	
	Panel B: ΔLSP (Dependent variable)		
	a_i^2	b_i^2	Log Likelihood
Coefficient	0.0075	0.7947	1.6282
Standard Error	0.0220	0.2847	
z-statistics	0.3391	2.7916	
p-value	0.7345	0.0052	

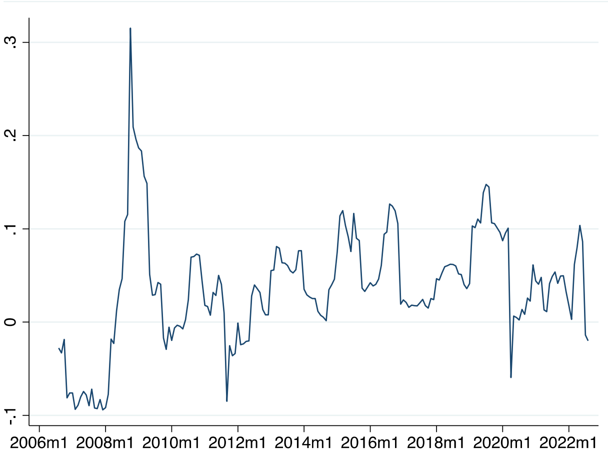
Notes: The estimation of coefficients of the DCC models. ai2 shows the impact of past standardized shocks on the current dynamics, bi2 shows the impact of lagged dynamics on the current dynamics. ΔLM and ΔLSP first difference of the natural log of Metals & Mining Selected Industry index price, and SP500 index price, respectively.

Figure 2 and Figure 3 illustrate the dynamic correlations among variables, revealing a noticeable trend of increasing correlations between ΔLM and ΔCIS throughout the years. This finding is in line with Døskeland and Pedersen (2016) who conducted a natural experiment among individual investors in an online bank and demonstrated that environmental concerns play a role in investment decisions, albeit financial motives remain predominant. Another significant finding is that the correlation between the M&M sector index returns and investor sentiment, as well as the correlation between the S&P 500 index returns and investor sentiment, generally tends to move inversely, increasing when the other decreases. When we compare the graphs in Panel A of Figure 2 and Figure 3, it becomes apparent that one graph shows an increase in correlation during periods when the other depicts a decrease. This observation indicates that the M&M industry responds differently to investor sensitivity compared to the overall market. This finding also indicates that the feelings of consumers on the economic future influence the metals and mining sector index returns, particularly after an increase in the attention of people on climate change with the execution of the Paris Climate Accord in 2016. In that manner, our paper supports Bessec and Fouquau (2022) that show a negative impact of media text capturing investor sentiment in energy and materials sectors, particularly chemicals and metals, underscoring heightened public awareness of environmental issues and its impact on financial markets. Moreover, these findings align with the findings of Hardy et al. (2023) that demonstrate sentiment expressed in financial reports from U.S. mining companies predicts returns of specific base metals, precious metals, and fuel commodities. Presenting a significant impact of sentiment on index returns adds to the studies, including Otoo (1999), Fisher and Statman (2003), Greenwood and Shleifer (2014), and Ugurlu-Yildirim (2021) that present investor sentiment has a direct impact on stock prices.

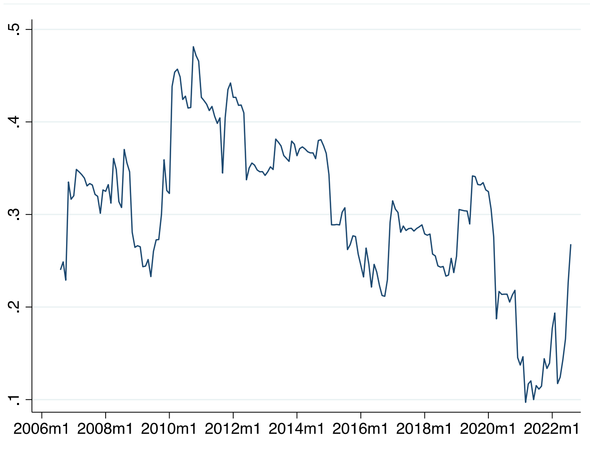
When we examine Figure 2-b, which illustrates the changing correlations between ΔLM and ΔLPPI in years, we observe that the correlation diminishes throughout time, particularly after 2015. The decreased correlation after the Paris Climate Accord suggests that with a binding agreement between countries about climate change and increased attention of people on climate change, the decisions of the consumer are affected by psychological factors, which cannot be inferred from economic variables, which is in line with the "animal spirits" concept (Desroches and Gosselin, 2002). While the correlation was mainly from a macroeconomic indicator, namely the producer price index that is highly correlated with world oil prices before 2015; feelings of consumers started to influence the index returns in the S&P Metals and Mining industry after 2015. Conversely, we do not discern a similar pattern in the correlation between ΔLSP and ΔLPPI, reinforcing our conclusion that the M&M industry exhibits distinct behavior compared to the market.

Figure 2 Dynamic Conditional Correlation (DCC) Series Graphs

(a) ΔLM- ΔCSI



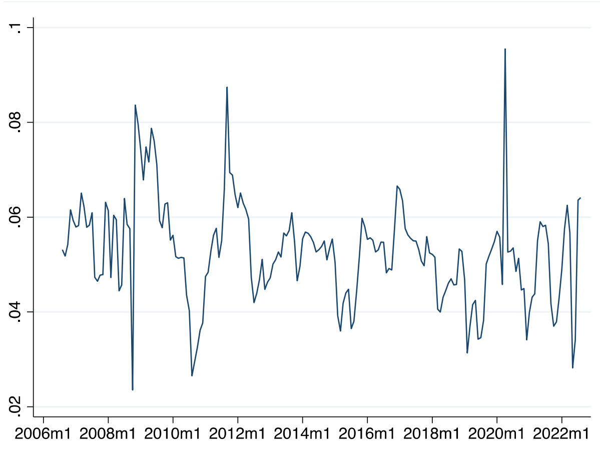
(b) ΔLM- ΔLPPI



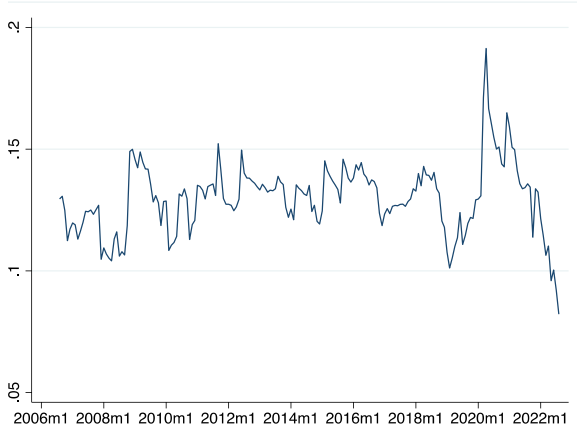
Notes: Dynamic correlation series derived from the DCC model. ΔLM-CSI, ΔLM- ΔLPPI are correlations between two related variables. ΔLM, ΔCSI, and ΔLPPI refer to the first difference of the natural log of Metals & Mining Selected Industry index price, the first difference of the natural log of the University of Michigan's Index of Consumer Sentiment, and the producer price index of the total mining industry, respectively.

Figure 3 Dynamic Conditional Correlation (DCC) Series Graphs

(a) ΔLSP - ΔCSI



(b) ΔLSP - ΔLPPI



Notes: Dynamic correlation series derived from the DCC model. ΔLSP -ΔCSI and ΔLSP -ΔLPPI are correlations between two related variables. ΔLSP, ΔCSI, and ΔLPPI refer to the first difference of the natural log of the S&P 500 index price, the first difference of the natural log of the University of Michigan's Index of Consumer Sentiment, and the producer price index of the total mining industry, respectively.

4.2 Time-Varying Granger Causality Analysis

After finding the DCC series between related variables, we investigate whether there is a causal relationship between climate policy uncertainty and these series. In this approach, before running the test, the number of lags to be added to the model, denoted by p, and the order of integration of the variables, denoted by d, are required to be detected. To find the order of integrations of the variables, we employ augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests (see Dickey and Fuller, 1979; Phillips and Perron, 1988). As can be seen from Table 2, we reject the null hypothesis that proposes the existence of unit root in levels, all variables used in this step are integrated of order 0. Therefore, d is accepted as 0.

Then, the number of lags to be included in the model is obtained. Table 5 shows the lag order selection criteria. As Akaike Information Criteria (AIC) suggests using 3 lags for both of the models, we get the time-varying causality from the VAR model with *p* equals 3.

Table 5 Estimation Results of the Lag Order Selection

Panel A: DCCMCSI-LCPU							
Lag	***LL***	***LR***	***df***	***p***	***FPE***	***AIC***	***HQIC***
0	142.0240			0.0010	0.0008	-1.4817	-1.4678
1	333.9910	383.9300	4	0.0000	0.0001	-3.4708	-3.4291
2	341.8430	15.7030	4	0.0030	0.0001	-3.5116	-3.4421*
3	346.9320	10.1800*	4	0.0380	0.0001*	-3.5231*	-3.4258
4	347.9870	2.1100	4	0.7160	0.0001	-3.4919	0.3669
Panel B: DCCSPCSI-CPU							
Lag	***LL***	***LR***	***df***	***p***	***FPE***	***AIC***	***HQIC***
0	471.4540				0.0000	4.9678	-4.9539
1	572.0890	201.2700	4	0.0000	0.0000	-5.9904	-5.9487
2	581.5910	19.0050*	4	0.0010	0.0000	-6.0486	-5.9791*
3	586.0850	8.9868	4	0.0610	0.0000*	-6.0538*	-5.9565
4	587.6200	3.0706	4	0.5460	0.0000	-6.0277	-5.9027

Notes: The estimation of the lag order selection analysis. DCCMCSI, DCCSPCSI and LCPU refer to the DCC series between ΔLM and ΔCSI, the DCC series between ΔLSP and ΔCSI, and the natural log of Climate Policy Uncertainty, respectively. LL, LR, FPE, AIC, HQIC refer to log-likelihood, sequential modified LR test statistic, Final Prediction Error, Akaike's Information criterion, Hannan-Quinn information criterion, respectively.

The Wald-test results of the time-varying causality analysis between the DCC series between ΔLM and ΔCSI, hereafter DCCMCSI, and LCPU and DCC series between ΔLM and ΔCSI, hereafter DCCMCSI, and LCPU, and DCC series between ΔLSP and ΔCSI, hereafter DCCSPCSI, and LCPU based on the rolling window (RO) and recursive expanding (RE) methods are in Table 6. The findings for the entire sample presented in Table 6- Panel A show that we reject the null hypothesis of no Granger causality from LCPU to DCCMCSI at a 1 percent significance level for both rolling window and recursive evolving algorithms. Therefore, both the rolling window and the recursive expanding Wald test results indicate that there is a significant causality from LCPU to the dynamic correlation between S&P Metals and Mining Selected Industry index prices and investor sentiment for the period between July 2006 and August 2022. On the other hand, there is a causality from climate policy uncertainty to DCCSPCSI only at the 5 percent significance level.

Table 6 Wald Test Results

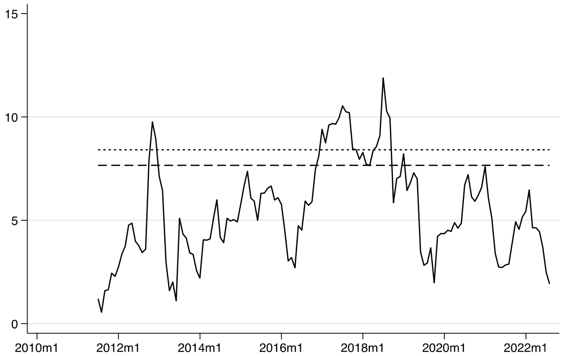
Panel A- Causality to: DCCMCSI		
Causality from:	***Max Wald RO***	***Max Wald RE***
	11.884***	12.541***
CPU	*8.408*	*8.971*
	(11.489)	(11.598)
Panel B- Causality to: DCCSPCSI		
Causality from:	***Max Wald RO***	***Max Wald RE***
	14.769**	14.769**
CPU	*7.323*	*7.429*
	(15.098)	(15.317)

Notes: Table 6-Panel A shows the Wald test results for the analysis in which DCCMCSI is the dependent variable, and Table 6- Panel B shows the Wald test results for the analysis in which DCCSPCSI is the dependent variable. RO and RE refer to Rolling and Recursive Expanding, respectively. Lag lengths are determined by Akaike Information Criterion (AIC). DCCMCSI, DCCSPCSI, and LCPU refer to the DCC series between ΔM and ΔCSI, the DCC series between ΔLSP and ΔCSI, and the natural log of Climate Policy Uncertainty, respectively. Numbers in italics and parenthesis show the 95th percentile and 99th percentile of test statistics, respectively. Superscripts *** and ** signify significance at 1% and 5%, respectively.

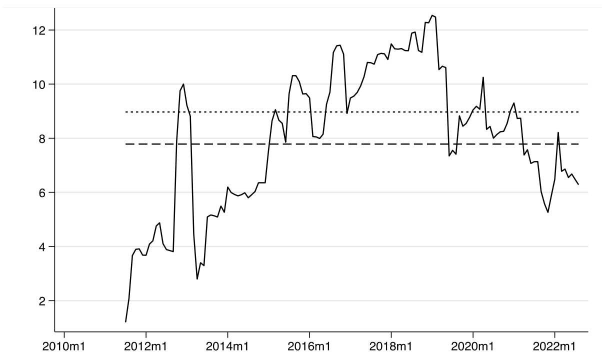
In Figure 4, the causality from climate policy uncertainty to the dynamic correlation between the S&P Metals and Mining industry index and investor sentiment through the sample period is illustrated. Parts (a) and (b) show the Rolling and the Recursive Expanding Wald test results for DCCMCSI caused by LCPU, respectively. Both techniques indicate that there is a significant causality, especially after the Paris Climate Accords. The significant impact is more persistent when we employ a RE approach, which reveals the best finite sample performance among the time-varying causality techniques (see Shi et al., 2018). Table 6 and Figure 4 indicate that an increase in political uncertainty makes investors act according to their emotions instead of economic indicators; therefore, the correlation between sentiment and the M&M sector index returns is influenced by LCPU. Our result put empirical evidence to the literature on the psychological approach to consumption. Periods of heightened economic or political uncertainty often lead to increased volatility in consumer confidence, potentially impacting consumption levels. Consumption is not solely determined by economic factors but also by individuals' confidence in their future financial circumstances, according to psychological theory. Uncertainty, whether present or anticipated, is the primary driver of consumer behavior, with a decline in confidence potentially causing reduced consumption independent of income fluctuations (Katona, 1975; Desroches and Gosselin, 2002). This finding resonates well with Pearce et al. (2011) who illustrate how mining operations are influenced by the 'politics of climate change,' encompassing both public perception of a company's dedication to addressing climate change and government regulations regarding GHG emissions. Moreover, our findings partly support previous literature, including Garner (1991), Throop (1992), and Desroches and Gosselin (2002), which show that while the sentiment is irrelevant during regular times, it is a helpful indicator of consumption and saving attitudes during the times of political and economic uncertainty.

Figure 4 Time-Varying Causality from LCPU to DCCMCSI

(a)



(b)

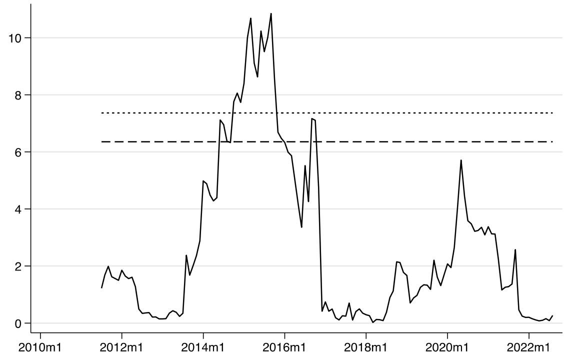


Notes: (a) shows the Rolling Wald test results for DCCMCSI caused by CPU, (b) shows the Recursive Expanding Wald test results for DCCMCSI caused by CPU. DCCMCSI and CPU refer to the DCC series between ΔLM and ΔCSI, and the natural log of Climate Policy Uncertainty, respectively. (--) and (..)depict 90th and 95th percentiles of bootstrapped test statistics, respectively.

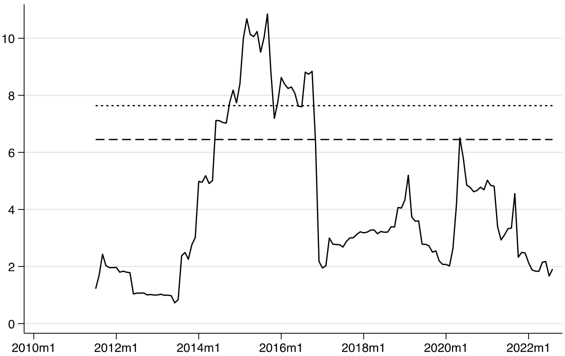
Unlike Figure 4, Figure 5 demonstrates that for most of the time period examined, there is no causality from LCPU to DCCSPCSI. The only period we observe a significant causality from climate policy uncertainty to the dynamic correlation between investor sentiment and S&P 500 index returns is a time span around the 2016 Paris Climate Accords. This finding indicates that during periods only when there is substantial market interest in climate change, CPU has an impact on the relationship between investor sentiment and index returns.

Figure 5 Time-Varying Causality from LCPU to DCCSPCSI

(a)



(b)



Notes: (a) shows the Rolling Wald test results for DCCSPCSI caused by CPU, (b) shows the Recursive Expanding Wald test results for DCCSPCSI caused by CPU. DCCSPCSI and LCPU refer to the DCC series between ΔLSP and ΔCSI, and the natural log of Climate Policy Uncertainty, respectively. (--) and (..)depict 90th and 95th percentiles of bootstrapped test statistics, respectively.

5. Conclusions

This paper addresses an important issue that emerged in the literature, which is the relationship between consumer sentiment, policy uncertainty, and stock markets. Our study offers the dynamic relationship between metals and mining industry index returns and consumer sentiment throughout time and how this time-varying correlation differs from the overall market. Then, the part of the climate policy uncertainty in enlightening this correlation is analyzed by a novel approach, time-varying causality based on the rolling window and recursive expanding methods, to show the causality from climate policy uncertainty to the metals and mining industry index and S&P index returns.

Although the connection between consumer sentiment and stock returns is rich literature, exploring the impact of uncertainty on this relationship is rather new. Our results add to this literature by showing a notable increase in correlations between the M&M sector index and investor sentiment over time. Interestingly, the correlation between M&M sector index returns and investor sentiment typically moves inversely to that of the S&P 500 index returns, indicating differing responses of the M&M industry and the broader market to investor sentiment. Then, we explore the causality drivers and find that climate policy uncertainty notably influences the correlation between M&M index returns and investor sentiment, particularly after the Paris Climate Accords. This suggests that increased policy uncertainty leads individuals to base their investments more on emotions than economic fundamentals, strengthening sentiment's impact on stock prices, particularly in climate-sensitive industries like metals and mining.

This paper has valuable implications for investors, policymakers, and firms. Understanding that the M&M sector shows a notable increase in correlations with investor sentiment over time highlights the sector's sensitivity to market sentiment. This awareness can help investors gauge how sentiment-driven factors might impact M&M stocks more significantly compared to other sectors. Moreover, recognizing that the correlation between M&M sector index returns and investor sentiment moves inversely to that of the S&P 500 index returns suggests that M&M stocks may provide diversification benefits. Investors could use this understanding to diversify their portfolios and reduce overall risk. Additionally, the finding that climate policy uncertainty notably influences the correlation between M&M index returns and investor sentiment underscores the importance of monitoring regulatory developments. Investors can benefit by staying informed about policy changes and understanding their potential impacts on sentiment and stock prices in climate-sensitive industries like metals and mining. Another implication is that investors may adjust their strategies by incorporating sentiment analysis alongside traditional fundamental analysis. This could involve monitoring sentiment indicators, sentiment trends, and sentiment shifts that affect M&M stocks.

Firms in the M&M sector can benefit from the insights provided in this study in several ways, influencing their strategic and operational behavior. Recognizing the notable increase in correlations between the M&M sector index and investor sentiment over time helps firms understand the market dynamics affecting their stock prices. This awareness allows firms to anticipate and respond to sentiment-driven fluctuations in their stock prices more effectively. Secondly, acknowledging that the correlation between M&M sector index returns and investor sentiment moves inversely to that of the broader S&P 500 index suggests that M&M firms may experience different market reactions compared to firms in other sectors. This understanding can guide firms in crafting sector-specific investor relations strategies and communication approaches that resonate with investor sentiment. Moreover, the finding that climate policy uncertainty notably influences the correlation between M&M index returns and investor sentiment highlights the importance of monitoring and addressing regulatory developments. Firms can benefit by staying proactive in understanding policy changes, assessing their potential impacts on sentiment and stock prices, and adjusting their strategic priorities accordingly. Additionally, given that increased policy uncertainty leads investors to base their decisions more on emotions than economic fundamentals, M&M firms can enhance their investor engagement strategies. This may involve providing clearer communication on how the firm is navigating regulatory uncertainty, its sustainability initiatives, and its resilience to policy changes. Transparent communication can help mitigate negative sentiment and build investor confidence. Lastly, understanding the implications of sentiment-driven stock price movements encourages M&M firms to adopt long-term sustainability and resilience strategies. This may involve diversifying operations, investing in green technologies, and fostering stakeholder relationships that support sustainable development goals. These efforts can enhance the firm's attractiveness to investors and mitigate volatility in stock prices during uncertain periods.

Finally, the finding of the significant impact of climate policy uncertainty on the correlation between investor sentiment and the stock market presents valuable insights to policymakers by emphasizing the importance of consistent and clear climate policies, especially in climate-sensitive industries. Policymakers should try to offer transparency and stability in climate policies to mitigate the potential adverse effects of uncertainty on investor behavior.

REFERENCES

Acemoglu D, Scott A (1994): Consumer Confidence and Rational Expectations: Are Agents' Beliefs Consistent with the Theory? *Economic Journal,* 104(422):1–19.

Anggraeni D, Irawan T (2018): Causality Analysis of Producer Price Index (PPI) and Consumer Price Index (CPI) in Indonesia. *Jurnal Ekonomi dan Kebijakan Pembangunan*, 7(1): 60-77.

Baek IM, Bandopadhyaya A, Du C (2005): Determinants of Market-Assessed Sovereign Risk: Economic Fundamentals or Market Risk Appetite? *Journal of International Money and Finance,* 24:533–548.

Baker M, Wurgler J (2006): Investor Sentiment and the Cross-Section of Stock Returns. *Journal of Finance*, 61(4):1645-1680.

Baker M, Wurgler J, Yuan Y (2012): Global, Local and Contagious Investor Sentiment. *Journal of Financial Economics,* 104(2):272–287.

Bergman N, Roychowdhury S (2008): Investor Sentiment and Corporate Disclosure. *Journal of Accounting Research*, 46:1057–1083.

Bessec M, Fouquau J (2022): Green Attention in Financial Markets: A Global Warning. *Annals of Economics and Statistics*, 148:29-64.

Black F (1986): Noise. *Journal of Finance*, 41(3):529-543.

Bouri E, Iqbal N, Klein T (2022): Climate Policy Uncertainty and the Price Dynamics of Green and Brown Energy Stocks*.* *Finance Research Letters*, 47:102740.

Carroll C, Fuhrer J, Wilcox D (1994): Does Consumer Sentiment Forecast Household Spending? If so, Why? *The American Economic Review,* 84(5):1397-1408.

Carter H, Moital M (2018): A Taxonomy of Event Participants Based on Risk and Security Perceptions. *Journal of Hospitality and Tourism Insights,* 1(4):325-339.

Charoenrook A (2005): *Does Sentiment Matter?* Working Paper. Vanderbilt University, Nashville, TN, USA, pp. 1–44.

Chen MH (2015): Understanding the Impact of Changes in Consumer Confidence on Hotel Stock Performance in Taiwan. *International Journal of Hospitality Management,* 50: 55.

Chung S, Hung C, Yeh C (2012): When Does Investor Sentiment Predict Stock Returns? *Journal of Empirical Finance*, 19:217–240.

Clark T (1995): Do Producer Prices Lead Consumer Prices? *Federal Reserve Bank of Kansas City Economic Review*, 80:25-39.

Dash SR, Maitra D (2018), "Does Sentiment Matter for Stock Returns? Evidence from Indian Stock Market Using Wavelet Approach", Finance Research Letters, Vol. 26, pp. 32-39.

De Long JB, Shleifer A, Summers LH, Waldmann RJ (1990): Noise Trader Risk in Financial Markets. *Journal of Political Economy*, 98(4):703–738.

Desroches B, Gosselin MA (2002): *The Usefulness of Consumer Confidence Indexes in the United States,* Bank of Canada Working Paper No. 2002-22.

Dickey DA, Fuller WA (1979): Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association,* 74:427-431.

Dolado JJ, Lütkepohl H (1996): Making Wald Tests Work for Cointegrated VAR Systems. *Economic Review,* 15:369–386.

Døskeland T, Pedersen LJT (2016): Investing with Brain or Heart? A Field Experiment on Responsible Investment. *Management Science*, 62:1632–1644.

Engle R (2002), 'Dynamic Conditional Correlation - a Simple Class of Multivariate GARCH Models', Journal of Business and Economic Statistics, 20:339–50.

Ernst & Young (2023): *Top 10 Business Risks and Opportunities for Mining and Metals in 2023*. Available at: https://assets.ey.com/content/dam/ey-sites/ey-com/en_gl/topics/mining-metals/ey-top-10-business-risks-and-opportunities-for-mining-and-metals-in-2023.pdf.

Fisher KL, Statman M (2003): Consumer Confidence and Stock Returns. *Journal of Portfolio Management,* 30(1):115–127.

Flannery MJ, Protopapadakis A (2002): Macroeconomic Factors Do Influence Aggregate Stock Returns. *The Review of Financial Studies*, 15(3):751–782.

Ford JD, Pearce T, Prno J, Duerden F, Berrang Ford L, Beaumier M, Smith T (2010): Perceptions of Climate Change Risks in Primary Resource Use Industries: A Survey of the Canadian Mining Sector. *Regional Environmental Change*, 10:65–81.

Friedman M (1957): *A Theory of the Consumption Function*, Princeton University Press, Princeton.

Fuss S, Szolgayova J, Obersteiner M, Gusti M (2008): Investment under Market and Climate Policy Uncertainty. *Applied Energy*, 85:708-721.

Garner CA (1991): Forecasting Consumer Spending: Should Economists Pay Attention to Consumer Confidence Surveys? Federal Reserve Bank of Kansas City, *Economic Review* (May/June): 57–71.

Gavriilidis K (2021): *Measuring Climate Policy Uncertainty*. Available at SSRN. https://ssrn.com/abstract=3847388.

Gino F, Brooks AW, Schweitzer ME (2012): Anxiety, Advice, and the Ability to Discern: Feeling Anxious Motivates Individuals to Seek and Use Advice. *Journal of Personality and Social Psychology,* 102(3):497–512.

Greenwood R, Shleifer A (2014): Expectations of Returns and Expected Returns. *The Review of Financial Studies,* 27(3):714–746.

Grinblatt M, Keloharju M (2009): Sensation Seeking, Over-Confidence, and Trading Activity. *The Journal of Finance,* 64(2): 549–578.

Gulen H, Ion M (2016): Policy Uncertainty and Corporate Investment. *Review of Financial Studies,* 29(3):523-564.

Guo H, Hung CHD, Kontonikas A (2017): *Investor Sentiment Regimes, Monetary Policy Shocks, and Stock Price Reaction*. Retrieved from http://sfm.finance.nsysu.edu.tw/25thSFM/php/Papers/CompletePaper/081-369845438.pdf.

Guo J, Long S, Luo W (2022): Nonlinear Effects of Climate Policy Uncertainty and Financial Speculation on the Global Prices of Oil and Gas. *International Review of Financial Analysis*, 83:102286.

Hammoudeh S, Ajmi AN, Mokni K (2020): Relationship between Green Bonds and Financial and Environmental Variables: A Novel Time-Varying Causality. *Energy Economics*, 92:104941.

Hardy N, Ferreira T, Quinteros MJ, Magner NS (2023): "Watch Your Tone!": Forecasting Mining Industry Commodity Prices with Financial Report Tone. *Resources Policy*, 86:104251.

Hoang K (2022): How Does Corporate R&D Investment Respond to Climate Policy Uncertainty? Evidence from Heavy Emitter Firms in the United States. *Corporate Social Responsibility and Environmental Management*, 29:936-949.

Hsu PH, Li K, Tsou CY (2023): The Pollution Premium. *The Journal of Finance*, 78:1343-1392.

Huang C, Yang X, Yang X, Sheng H (2014): *Mathematical Problems in Engineering:* 545723.

Jefferis, K. (2014): Macroeconomic Management in a Mineral-Rich Economy. *Policy Note*, 14:0105.

Kahneman D, Tversky A (1979): Prospect Theory: An Analysis of Decision Under Risk. *Econometrica,* 47(2):263–291.

Katona G (1975): *Psychological Economics.* New York: Elsevier Scientific Publishing Company.

Keynes J (1936): *The General Theory of Employment, Interest and Money*, Harcourt and Brace, New York, NY.

Khan K, Chi-Wei S et. al. (2018): Producer Price Index and Consumer Price Index : Causality in Central and Eastern European Countries. *Ekonomický časopis*, 66(4):367 - 395.

Klein J, Kayhkö J, Rasanen A, Groundstroem F, Eilu P (2022): Climate Risk Perception, Management, and Adaptation in the Nordic Mining Sector. *The Extractive Industries and Society*, 10: 101092.

Knight F (1948): *Risk, Uncertainty and Profit*, London School of Economics and Political Science, New York, NY.

Kocaarslan B, Soytas U, Sarı R, Ugurlu E (2019): The Changing Role of Financial Stress, Oil Price, and Gold Price in Financial Contagion among US and BRIC Markets. *International Review of Finance,* 19:541-574.

Kumar A, Lee CM (2006): Retail Investor Sentiment and Return Comovements. *Journal of Finance*, 65(5):2451-2485.

Kuzemko C, Bradshaw M, Bridge G, Goldthau A, Jewell J, Overland I, Scholten D, Graaf TV, Westphal K (2020): Covid-19 and the Politics of Sustainable Energy Transitions. Energy *Research and Social Sciences*, 68:101685.

Lamperti F, Bosetti V, Roventini A, Tavoni M, Treibich T (2021): Three Green Financial Policies to Address Climate Risks. *Journal of Financial Stability*, 54:100875.

Lee JH, Mustapha A, Hwang J (2019): Enhancing Ethnic Restaurant Visits and Reducing Risk Perception: The Effect of Information and Protection Motivation. *Journal of Hospitality and Tourism Insights,* 2(4):341-357.

Leland H (1968): Saving and Uncertainty: The Precautionary Demand for Saving. *Quarterly Journal of Economics,* 82(3): 465-473.

Lemmon M, Portniaguina E (2006): Consumer Confidence and Asset Prices: Some Empirical Evidence. *The Review of Financial Studies*, 19:1499–1529.

Liu R, He L, Liang X, Yang X, Xia Y (2020): Is There Any Difference in the Impact of Economic Policy Uncertainty on the Investment of Traditional and Renewable Energy Enterprises? A Comparative Study Based on Regulatory Effects. *Journal of Cleaner Production* 255:120102.

Liu W, Wang Z (2017): The Effects of Climate Policy on Corporate Technological Upgrading in Energy Intensive Industries: Evidence from China. *Journal of Cleaner Production*, 142:3748–3758.

Lao J, Nie H, Jiang Y (2018): Revisiting the Investor Sentiment–Stock Returns Relationship: A Multi-Scale Perspective Using Wavelets. *Physica A*, 499:420-427.

Ludvigson S (2004): Consumer Confidence and Consumer Spending. *Journal of Economic Perspectives*, 18:29–50.

Modigliani F (1986): Life Cycle, Individual Thrift, and the Wealth of Nations. *Science,* 234:704-712.

Niu H, Lu Y, Wang W (2021): Does Investor Sentiment Differently Affect Stocks in Different Sectors? Evidence from China. *International Journal of Emerging Markets.*

Odell SD, Bebbington A, Frey KE (2018): Mining and Climate Change: A Review and Framework for Analysis. *The Extractive Industries and Society*, 5:201–214.

Otoo MW (1999): *Consumer Sentiment and the Stock Market*. FEDS Working Paper, 99-60. Federal Reserve Board, Washington, DC.

Pearce TD, Ford JD, Prno J et al. (2011): Climate Change and Mining in Canada. *Mitigation and Adaptation Strategies for Global Change*, 16:347–368.

Pearce TD, Ford JD, Prno J, Duerden F, Pittman J, Beaumier M, Berrang-Ford L, Smit B (2019): Climate Change and Mining in Canada. *Mitigation and Adaptation Strategies for Global Change,* 16:347-368.

Phillips PCB, Perron P (1988): Testing for a Unit Root in Time Series Regression. *Biometrika,* 75(2):335–346.

Phillips PC, Shi S, Yu J (2015a): Testing for Multiple Bubbles: Limit Theory of Real-Time Detectors. *International Economic Review*, 56:1079-1134.

Phillips PC, Shi S, Yu J (2015b): Testing for Multiple Bubbles: Historical Episodes of Exuberance and Collapse in the S&P 500. *International economic review*, 56:1043-1078.

Qiu LX, Welch I (2006): *Investor Sentiment Measures*. Available at SSRN: https://ssrn.com/abstract=589641.

Ren X, Shi Y, Jin C (2022): Climate Policy Uncertainty and Corporate Investment: Evidence from the Chinese Energy Industry. *Carbon Neutrality*, 1:1–11.

Ren X, Li J, He F, Lucey B (2023): Impact of Climate Policy Uncertainty on Traditional Energy and Green Markets: Evidence from Time-Varying Granger Tests. *Renewable and Sustainable Energy Reviews*, 173:113058.

Roberts I, Simon J (2001): *What Do Sentiment Surveys Measure?* Research Discussion Paper, Economic Research Reserve Bank of Australia.

Rumokoy LJ, Omura A, Roca E (2023): Geopolitical Risk and Corporate Investment in the Metals and Mining Industry: Evidence from Australia. *Pacific-Basin Finance Journal,* 79:101991.

Sayim M, Morris PD, Rahman H (2013): The Effect of US Individual Investor Sentiment on Industry-Specific Stock Returns and Volatility. *Review of Behavioral Finance,* 5(1):58-76.

Schmeling M (2009): Investor Sentiment and Stock Returns: Some International Evidence. *Journal of Empirical Finance,* 16:394–408.

Shen J, Yu J, Zhao S (2017): Investor Sentiment and Economic Forces. *Journal of Monetary Economics,* 86:1-21.

Shi S, Phillips PC, Hurn S (2018): Change Detection and the Causal Impact of the Yield Curve. *Journal of Time Series Analysis,* 39:966–987.

Shi S, Hurn S, Phillips PC (2020): Causal Change Detection in Possibly Integrated Systems: Revisiting the Money-Income Relationship. *Journal of Financial Economics,* 18(1):158–180.

Shleifer A (2000): *Inefficient Markets: An Introduction to Behavioral Finance*. Oxford University Press, Inc., New York.

Sims ER, Barsky RB, Sims ER (2012): Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence. *The American Economic Review,* 102(4):1343-1377.

Sirucek M (2012): *Macroeconomic Variables and Stock Market: US Review*. MPRA Paper: 39094, University Library of Munich, Germany.

Sun Y, Yang Y, Huang N, Zou X (2020): The Impacts of Climate Change Risks on Financial Performance of Mining Industry: Evidence from Listed Companies in China. *Resources Policy,* 69:101828.

Svensson H, Albæk E, Van Dalen A, De Vreese C (2017): The Impact of Ambiguous Economic News on Uncertainty and Consumer Confidence. *European Journal of Communication,* 32(2): 85-99.

Swanson NR (1998): Money and Output Viewed Through a Rolling Window. *Journal of monetary Economics*, 41: 455-474.

Throop AW (1992): Consumer Sentiment: Its Causes and Effects. Feder. Reserve Bank San Franc. *Economic Review,* 1:35–60.

Toda HY, Yamamoto T (1995): Statistical Inference in Vector Autoregressions with Possibly Integrated Processes. *Journal of Econometrics,* 66:225–250.

Ugurlu-Yildirim E, Kocaarslan B, Ordu-Akkaya BM (2021): Monetary policy uncertainty, investor Sentiment, and US Stock Market Performance: New Evidence from Nonlinear Cointegration Analysis. *International Journal of Financial Analysis,* 26:1724-1738.

Vigya S, Daniel MF (2013): In Situ Adaptation to Climatic Change: Mineral Industry Responses to Extreme Flooding Events in Queensland, Australia. *Society and Natural Resources,* 26:1252–1267.

Vilcu, R.C. (2015): Inflation by Producer Price Index – Predictive Factor for Inflation by Consumer Price Index? The case of Romania. *Romanian Statistical Review Supplement, Romanian Statistical Review*, 63(2):22-37.

Yang, C., and Gao, B. (2014): The Term Structure of Sentiment Effect in Stock Index Futures Market. *The North American Journal of Economics and Finance,* 30:171–182.

Zeng, Q., Ma, F., Lu, X., & Xu, W. (2022). Policy Uncertainty and Carbon Neutrality: Evidence from China. *Finance Research Letters*, 47:102771.