Air Pollution, Mood and Stock Return in Romania

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Abstract

Considered one of the major threats of our times for the human species, air pollution was proven to have multiple psychological, social and economic effects. In the last two decades, the relationship between air pollution and the stock market was analysed mainly for the Chinese stock market, with very few papers oriented towards other markets. The present paper tries to fulfil this gap by exploring this relationship for the Romanian stock market. The main results show that relative pollution values (mainly PM10) and pollution awareness impact stock returns in Bucharest Stock Market, in line with the assumption of the Mood Maintenance Hypothesis.

Key words: pollution, mood misattribution, risk aversion, stock returns
J.E.L. classification : D91, E44, E71, G41

1. Introduction

Classical finance theory seems unable to explain why individuals continue to have irrational attitudes about investment decisions. If the investors were as self-interested, rational and utility maximisers as the theory say, there would be fewer speculative bubbles, panic, herd behaviour and financial crises. The truth is that the ability of the human mind to understand and process large amounts of data is limited. Confronted with thousands of daily information, the brain often uses heuristics and relies on less rational reasoning.

According to the risk-as-feelings hypothesis, feeling, emotions and mood play a very important role in the financial decision, being responsible for generating behaviours responses far away from rational ones (Loewenstein et al. 2001). Since stock pricing represents a trade-off between benefits and costs (benefits represented by the future cash net flows and costs represented by the associated risks) mood, more precisely mood misattribution usually affects decision-making. According to the *mood–as–information theory,* developed by Schwarz (1990), people tend to take decisions depending on their mood, even when the source of their mood state is unrelated to those specific decisions: *mood misattribution.* On the one hand, individuals in a bad mood are more pessimistic about their future perspective profits than those in a neutral or positive mood and on the other hand, risk aversion is also proved to be influenced by mood. Even if various limits to arbitrage exist, equities remain occasionally mispriced, so a small group of investors influenced by mood may generate specific patterns in stock markets. (Lucey and Dowling, 2005).

Mood and changes if mood influences decision-making through cognitive evaluation and risk-taking channels.

Individuals in a good mood tend to have greater creativity, ingenuity, and efficiency in solving multi-attribute decision problems (Pham, 2007), but they are prone to rely on stereotypes and judgmental heuristics and have a higher propensity to optimism and overconfidence biases (Barberis and Thaler, 2003). On the other side, sad individuals tend to rely less on scripts and stereotypes and trigger a more systematic, data-driven form of reasoning (Schwarz, 2002) but anger and disgust seems to encourage the use of heuristic rather than systematic processing (Triedens and Linton, 2001).

The link between mood and risk-taking may be explained in the framework of the Affect Diffusion Model (AIM) proposed by Forgas (1995) and the Mood Maintenance Hypothesis (MMH) proposed by Isen, Nygren, & Ashby (1998).

The AIM model suggests that individuals in bad moods have a more pessimistic view of the future, perceive the situation as riskier and have a lower propensity toward risk. Individuals in a positive affective state have a more optimistic view, perceive a safer environment and are tempted to take more risks. The AIM key assumption is that the mood influence on risk-taking and decision is more influential in driving evaluation and responses if the situation is more complex and unanticipated. A key element in the correlation between mood and risk-taking is the reaction to the news in different psychological states. For instance, the individual's response to bad news differs according to the initial affective state. If the individual has a pleasant, happy day, the influence of bad news may be limited but exacerbated if the individual is already in a bad mood. So, our mood in case of bad news influences our response but also the level of response.

The MMH is pretty different and, at first look, irreconcilable with AIM. The core of MMH is that no matter the current mood, the main goal of any individual is to achieve and maintain well-being. According to this desiderate, the individual in a good mood attempt to avoid risky situations to preserve the positive affective state. In case of a bad mood, the individual is more prone to choose a risky situation hoping that the potential positive result would be able to lift his spirit.

One may wonder how to reconcile these hypotheses since they seem quite the opposite. The main point is that individuals are pretty different, so we cannot say that two individuals will act precisely the same in similar circumstances. Various factors influence the relationship between mood and risky behaviour as age, gender, genetic heritage, personality traits and endocrine system functioning. Chou, Lee and Ho (2007) found an effect of positive and negative mood on risk-taking tendency according to *age*, in the line of AIM. It seems that extreme events produce greater brain reactions than similar magnitude positive events in younger adults, but in older adults, cognitive functioning and positive emotion play a more critical role. In terms of *gender*, Fehr-Duda et al.(2011), based on a laboratory experiment, demonstrated that women in elated mood are more prone to take more risks because they are tempted to weigh more optimistically the probabilities opposite to men who, even in a positive state, tend to apply rational decision criteria. Risk attitude is proven to be also influenced by the presence of certain types of *genes* (Kuhnen and Chiao., 2009). Consequently, the same mood, either positive or negative, may affect two individuals with different genetic heritage differently. Recent studies conducted in Neuroeconomics show that a higher *testosterone level* determines a reduction of fear and anxiety, decreases the risk-aversion and increases the frequency of higher offers (Eisenegger et al., 2010), except in the case of increased market volatility that generates a higher level of *cortisol* associated with a higher risk-aversion. *Personality* influences the relationship between mood, risk aversion, and behaviours. Neurotic individuals prefer to engage in risky behaviour to cope with negative mood states (in line with MMH). Still, extrovert individuals will take more risks due to a positive mood (in line with AIM). In both cases, impulsivity is a catalyst for the connection between mood and risk attitude since it increases the probability that a neurotic individual will take more risks due to a negative mood. (Cooper, Agocha, and Sheldon, 2000).

Since mood has a non-equivocal impact on risk aversion, one could conclude that the variables influencing mood could also impact risk aversion and capital markets returns. Several studies in the last decade analyse the correlation between air pollution, mood and stock returns, mainly in the Chinese stock market, American, Italian and Turkish markets. From our knowledge, there is no study to asses this relation for the Romanian capital marker, so this study is aimed to fill this gap.

The paper is structured as follows: the second part is dedicated to the previous literature that assesses the psychological, social and economic impact of air pollution; the third part details the used data and methodology, the fourth part includes the main results, and the last part concludes.

2. Literature review. Psychological, social and economic effects of air pollution

Air pollution represents the most significant environmental threat to public health, responsible for approximately 9 million deaths per year, corresponding to one in six deaths worldwide (Fuller et al., 2022).

Air pollution consists of a mixture of particulate matter ($PM_{2.5}$, PM_{10}), gases such as carbon monoxide (CO), ozone (O_3), sulphur dioxide (SO_2), nitrogen dioxide (NO_2), organic compounds and metals and it is usually measured and reported with the help of composite indexes: Air Pollution Index(API) and Air Quality Index (AQI). The most widely studied pollutants in the literature are $PM_{2.5}$ and PM_{10} (a comprehensive review of pollution's main psychological, social and economic effects may be found in Lu, 2020).

The recent literature shows that severe air pollution may heavily impact health. $PM_{2.5}$ alone is proven to reduce global life expectancy by approximately one year in 2019 (Vos et al.,2020). The primary diseases associated with $PM_{2.5}$ air pollution are lung diseases, stroke, heart disease and cancer, diabetes, and mental problems.

On a psychological level, air pollution is associated with a decrease in well-being and happiness, increased annoyance, anxiety, substance abuse, suicide and prevalence of mental disorders such as depression, schizophrenia and autism (Lu, 2020).

Air pollution harms cognitive functioning, from prenatal development, childhood and youth to young and old adults. Exposure to air pollutants reduces the capacity of red cells' hemoglobin to oxygenate the brain and other organs leading to deficits in attention, memory, math ability, verbal and non-verbal intelligence, visuo-construction or concentration, increased prevalence for cognitive biases (Schikowski et al., 2015). Considering the negative impact of pollution on cognitive performance, several studies proved that decision-making quality is also affected if the air is not clean. For instance, Chew et al. (2021) found that when the pollution level is accentuated, individuals have a higher risk aversion, and ambiguity aversion and are more impatient in decisions. Also, due to air pollution, the disposition bias (predisposition to sell winners' assets and keep losers) is exacerbated (Huang, Xu and Yu, 2020).

Stock investments are cognitively demanding decisions, so it is not surprising that recent literature found a significant correlation between air quality and trading behaviour in stock markets. The most important studies that address this issue are summarised in the following table:

Table no. 1. Published studies on the stock return effects of the air pollution

Authors	Stock markets	Timespan	Variable for pollution	Main results
Lepori (2008)	Milan Stock Exchange	January 2, 1980, to May 19, 2006	PM, NO_2, and SO_2 daily average values- computed based on hourly data from 5 am through 6 pm.	The results show a negative relationship between air pollution concentrations and demand in stock markets. This relation is channelled on one side by the increased bodily cortisol levels associated with the increased air pollution that reduces the investor's risk appetite. Conversely, poor air quality affects investors' moods, making them more risk-averse.
Levy and Yagil (2011)	NYSE, AMEX, NASDAQ and the stock exchange in Philadelphia	January 1, 1997 to June 30, 2007	Dummy variable based on the daily values of the AQI carrying the value of 1 for Good days and 0 for Unhealthy days.	The results proved that air pollution negatively affects stock returns for all four stock exchanges, even after controlling for other variables. The exchange distance from the polluted areas matters since the relationship becomes weaker as the distance increases.
Demir and Ersan (2016)	Istanbul Stock Exchange	2008 to 2013	Particulate matter PM_{10} and lagPM_{10}	The authors found a negative relationship between the lag of air pollution and stock returns in Istanbul, Ankara and Izmir, dominant Turkish people regarding investments.
Heyes, Neidell, and Saberian (2016)	New York Stock Exchange	January 2000 to November 2014	Particulate matter $PM_{2.5}$	A strong negative relationship between pollution and stock returns was found at the day level and intraday. The connection is mediated by the changes in risk appetite induced by pollution.

Li and Peng (2016)	Shanghai and Shenzhen Stock Exchanges	January 2005 to 31 December 2014	AQI daily values	The results show a negative relationship between air pollution and stock returns and a two-day-lagged positive relationship over the period. The effect seems weaker for companies that protect air quality, but the authors did not find a more substantial effect for polluting companies.
Wu et al.(2018)	Chinese stock market	December from 2014 to 2016	AQI daily values	The main conclusion is that pollution starts to negatively influence the stock yield (the study includes stocks from the most polluting industries) after the AQI passes the threshold of 300.
Wu, Hao, and Lu (2018)	Shanghai and Shenzhen Stock Exchanges	December 1, 2013 to December 31, 2015	AQI daily values	The authors find a strong relationship between air pollution and stock pricing of locally headquartered firms, mainly manifested in low returns and turnovers and high illiquidity due to the home bias.
Wu and Lu (2020)	1656 firms listed on Shanghai and Shenzhen Stock Exchanges	January 2014 to December 2017	A daily firm-level individual investor mood index based on AQI weighted with daily search volume for each firm and city considered, using Baidu Index.	A bad mood induced by poor air quality seems to increase risk aversion and determine individual investors to buy fewer stocks, lowering stocks' returns and liquidity. This relationship was not found in the institutional investor's case.
Wu, Chou and Lu (2020)	Chinese A-share market	December 2013 to December 2016	A firm-level measure of fund-manager mood determined by air pollution based on the average air quality in the areas where open-end funds managers are located, weighted by their portfolio holdings.	The results show that the depressed fund-managers mood also determines negative stock returns and a decrease in liquidity during the most polluted days.
Xu, Wang, and Tu, (2021)	Shanghai Stock Exchange	March 1, 2013, to December 30, 2016	Daily average $PM_{2.5}$ and air pollution awareness using the related searches on the Baidu search engine.	The authors point out that the current day's air conditions and consecutive days significantly affect the stock returns through people's awareness of air pollution.
Jiang et al.(2021)	Shenzhen Exchange	2005-2019.	API for 2005-2012 and air quality index AQI for 2014-2019	The main findings support the idea that high air pollution significantly and Shenzhen stock returns, especially in the bullish market phases.
Nguyen, and Pham, (2021)	NYSE, AMEX and NASDAQ	January 1980 to December 2016	A monthly AQI for each metro area is computed based on the daily values of the AQI.	The authors analysed 16 capital market anomalies and concluded that long-short returns of anomalies are stronger following high rather than low pollution periods because air pollution intensifies cognitive biases.
Liu et al. (2021)	China's A-share market	January 1, 2016 to September 2, 2020	AQI daily values	The results show that polluting enterprises receive more attention on trading days when increased investors' attention will directly reduce their stock prices, except when stock markets show an upward trend or frequently fluctuate when this effect is not visible.

Dong et al.(2021)	Shenzhen Stock Exchange	2009–2015	API and AQI	The authors document a negative relationship between air pollution during the visits made by investment analysts, mutual/hedge fund managers, reporters and individual investors and subsequent earnings forecasts.
Kiihamäki, Korhonen, and Jaakkola (2021)	47 stock exchanges all over the world	2004-2019, with different study periods across the considered cities	Daily $PM_{2.5}$	The main results of the study show that, on average, a 10 µg/m3 increase in PM2.5 reduces same-day returns by 1.2 per cent (with a stronger correlation in the areas with the lower average PM2.5 concentration and lower stock capitalisation). The second effect is on market volatility since the same decline in air quality seems to increase stock market volatility by 0,2 per cent.
Li et al.(2021)	Chinese stock market	2007–2015	Daily AQI for 247 cities where the investment accounts analysed are opened.	The authors found that air pollution significantly increases the tendency to sell winning assets while holding onto losing assets after analysing 773,198 investment accounts open in one of the most significant mutual funds in Shanghai.
Ming Lee, Ling and Tan (2022)	Malaysian stock market	5 July 2019 to 8 April 2022	AQI daily values	Air pollution (both same-day and lagged ones) seems to affect some of the analysed sectors: finance, property, construction, healthcare, technology, energy, utilities, and consumer sectors, but the impact varies across the industries and market conditions.
Guo, Wei and Huang (2022)	China Stock Market	June 24, 2016, to November 7, 2018	AQI daily values for the 104 cities where the investor sample was located	Based on an analysis of individual transaction data, the authors show that air pollution reduces investors' propensity to buy and increases their tendency to sell. The effect seems stronger for less experienced investors and those who live in very polluted cities.
Xu (2022)	*Chinese stock market*	*Dec. 2013 to Apr. 2018*	AQI and concentrations of various pollutants: $PM_{2.5}$ and PM_{10}, SO_2, CO, NO_2, and O_3.	Aside from the decrease in stock returns generated by the increase in pollution found also in other papers, the authors see a significant mediation effect between air pollution and the stock market (first, air pollution affects stock returns, and then stock returns mediate the impact of air pollution on trading volume on the following day)

Source: author's compilation

3. Research methodology

The majority of studies conducted in this area use the Chinese stock market, considering, on the one side, that China has struggled a lot in the last decades with the air pollution problem and, on the other side, that the market is driven in large proportion by individual investors. The present study addresses the same issue for the Romanian capital market. Even if we do not expect such a strong correlation due to the smaller level of pollution and lower individual investors' participation in the Bucharest Stock Exchange, we expect air pollution to exercise some effects on the stock returns. Similar to other stock markets, home bias (Wu, Hao and Lu, 2018) would determine investors to prefer trading on the domestic market, so the influence of the foreign investors, exposed to other air quality conditions, may be neglected.

In this study, we have used a twofold approach.

First, we tested the impact of primary pollutants on daily returns from 23 October 2020 to 14 October 2022. The air pollution data refer to the daily values of the most significant pollutants ($PM_{2.5}$, PM_{10}, O_3, NO_2, SO_2). Air quality data were compiled from https://aqicn.org/city/bucharest and transformed into relative values. For the market return, we have used daily BET (daily closing values of BET are provided by the Bucharest Stock Exchange: www.bvb.ro) transformed into daily returns ($BETR_t$) using the following formula:

$$\text{BETR}_{t=}\frac{(BET_t - BET_{t-1})}{BET_{t-1}} (1)$$

Daily returns and pollution levels were matched and we eliminated the days where either air quality or BET values were missing. In total, our sample consists of 471 observations.

To avoid spurious results, the Augmented Dickey-Fuller test and Phillips- Perron were performed, and the results show that all series are stationary.

The central hypothesis is that air pollution (through one or several pollutants) will have an impact on the stock returns, channelled by mood misattribution, either in a negative sense (according to the AIM hypothesis) or in a positive sense (according to the MMH hypothesis). The proposed model is OLS, in line with the large part of the previous research included in Table 1:

$\text{BETR}_t = c + \beta_1 BETR_{t-1} + \beta_2 PM_{10\,(t)} + \beta_3 PM_{2.5(t)} + \beta_4 O_{3(t)} + \beta_5 NO_{2(t)} + \beta_6 SO_{2(t)}$ (2)

where c- intercept

$\beta_1 \ldots . \beta_6$ -importance coefficients

$PM_{2.5}$, PM_{10}, O_3, NO_2, SO_2-relative daily values of pollutants

We have used the previous rate of return as a control variable. We decided not to use variables for different calendar anomalies such as the January effect, the Turn of the month effect, and the Monday effect because, on the one side, our sample is relatively short, and for instance, a dummy variable for the January effect would lead to no results. On the other side, due to missing data in terms of pollution, we had to adjust the sample very much and missed some important observations in terms of return to account for the Turn of the month effect or Monday effect. The last motivation was that all those effects were proven to diminish in turmoil times, and since our sample is focused on the COVID era, we expected the market to be too volatile for these anomalies.

The second approach used as the independent variable the air pollution awareness (idea present in Wu and Lu, 2020; Xu, Wang and Tu, 2021). Individuals' perception of air pollution increases their anxiety and depression since perceiving air pollution will determine people to reduce outdoor. The time spent outside and physical activities are very important for a good affective state (as we have seen in the introduction, the connection between air pollution and stock return is channelled by mood misattribution through risk aversion). As a proxy for air pollution awareness, we have used the weekly number of searches in Google Trends for a couple of key terms as air pollution, air quality, smog, mist ("poluarea aerului", "calitatea aerului", "smog", "ceata") and in the end, after testing the model we choose the first syntax to determine the variable awareness. For market returns, we have used the weekly BET returns (BETWR) computed with a similar formula used for daily one but using the weekly closing values for BET provided by https://tradingeconomics.com/romania/stock-market. The data spans between 12 October 2017 and 30 October 2022, raising 258 observations. We hypothesise that both current and previous air pollution awareness would have an impact on weekly returns.

The proposed model is:

$\text{BETWR}_t = c + \beta_1\, awarness_t + \beta_2\, awarness_{t-1}$ (3)

where c- intercept

β_1, β_2 -importance coefficients

4. Findings

After testing the first model specifications, we obtained the following results, starting from the initial model and eliminating the statistically non-significant variables one by one. Similar to Demir and Ersan (2016), we also tested the influence of one-day lag pollution in the last model.

Table no. 2 Results based on the first approach

Independent variables	**Model 1 coefficients**	**Model 2 coefficients**	**Model 3 coefficients**	**Model 4 coefficients**	**Model 5 coefficients**	**Model 6 coefficients**
c	0,000261 (0,000477)					
$BETR_{t-1}$	0,115720** (0,046195)	0,116427** (0,046141)	0,110455** (0,046341)	0,111273** (0,046303)	0,112622** (0,046211)	0,110502** (0,045872)
$PM_{10(t)}$	0,000731 (0,001280)	0,000742 (0,001278)				
$PM_{2.5(t)}$	0,000136 (0,001023)	0,000208 (0,001014)	-0,00660 (0,000910)			
$O_{3(t)}$	0,000748 (0,000942)	0,000829 (0,000930)	0,000589 (0,000931)	0,000535 (0,000928)		
$NO_{2(t)}$	0,0000053 (0,000966)	0,000139 (0,000953)	0,000359 (0,000887)	0,000349 (0,000886)	0,000288 (0,000879)	
$SO_{2(t)}$	-0,000819 (0,001191)	-0,000746 (0,001183)	-0,000621 (0,001145)	-0,000598 (0,001144)	-0,000587 (0,001143)	
$PM_{10(t-1)}$						0,001934* (0,001094)
R-squared	0,019473	0,015823	0,013891	0,012770	0,012060	0,017761
Adjusted R-squared	0,003418	0,004961	0,005353	0,006374	0,007802	0,017621
No. of observations	471	471	471	471	471	471

Note: In the table *** stands for statistically significant at 1%, ** stands for statistically significant at 5%, * stands for statistically significant at 10%, and the standard deviation is in ().

Source: author's computation

As one may notice, except for the last model, the pollution variable does not seem to have any statistically significant impact on stock returns in this period. It is not unexpected considering the market's very high volatility and the recession's start. The only model with a statistically significant impact of the lagged relative value of PM_{10} on the daily return is the last one, but the direction is not the expected one. In the majority of the previous studies, air pollution has a negative impact on stock returns. Here, it seems that even though the influence is relatively small, the air pollution with PM_{10} determines an increase in stock returns. This kind of direction may be justified either by a prevalence toward an attitude in line with MMH or by the fact that being visible pollution (particles PM10 are quite large, so their increase may be distinguishable), investors are more prone to limit outdoor activities, have more time to asses investment alternatives and, due to the COVID crises, maybe also more resources to spend since the consumption was contracted.

The results from the second approach are included in the following table.

Table no. 3 Results based on the second approach

Independent variables	Model 1 coefficients	Model 2 coefficients	Model 3	Model 4
c	0,002764 (0,002720)			
$awareness_t$	0,000186 (0,000106)	0,000242* (0,0000091)	0,000141* (0,0000079)	
$awarness_{t-1}$	-0,000258 (0,000106)	-0,000203** (0,0000091)		0,0000082 (0,000008)
R-squared	0,031082	0,027160	0,008396	0,000440
Adjusted R-squared	0,023483	0,023360	0,008396	0,000440
No. of observations	258	258	258	258

Note: In the table *** stands for statistically significant at 1%, ** stands for statistically significant at 5%, * stands for statistically significant at 10%, and the standard deviation is in ().

Source: author's computation

Looking at the result, one may notice that the direction of the influence seems to be the same (see model 3). Current pollution awareness seems to increase stock market returns even if, again, the influence is relatively small and the statistical significance is not very large. The lagged awareness seemed initially influential when included in the same model as the current one but using it alone in model 4 proved insignificant.

5. Conclusions

The COVID crisis, combined with the energy crisis from the last months, managed to drag the world economy into recession. The turmoil times analysed in the present paper are characterised by fear and irrational behaviour that is often hard to include in a particular theory. Personality traits are changing; the mood oscillates a lot, and, as a result, the appetite for risky investments is also affected.

Contrary to our initial expectations, based on the previous literature, air pollution from Bucharest seems to have a very small positive effect on stock returns traded on the Bucharest Stock Exchange, somehow in line with the assertion of the Mood Maintenance Hypothesis. According to this hypothesis, individuals in bad moods will take more risks in an attempt to use the potential success to lift their spirits. The direction is the same for the relative level of pollution and pollution awareness.

The study results have to be interpreted with caution. The sample is small; we had to deal with many missing values, which created some limitations. Some future research using a larger dataset may generate more reliable results.

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