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Ambient particulate air pollution and daily stock market returns and volatility in 47 cities worldwide

Simo-Pekka Kiihamäki¹, Marko Korhonen² & Jouni J. K. Jaakkola^{1,3,4✉}

We studied globally representative data to quantify how daily fine particulate matter (PM_{2.5}) concentrations influence both daily stock market returns and volatility. Time-series analysis was applied on 47 city-level environmental and economic datasets and meta-analysis of the city-specific estimates was used to generate a global summary effect estimate. We found that, on average, a 10 µg/m³ increase in PM_{2.5} reduces same day returns by 1.2% (regression coefficient: - 0.012, 95% confidence interval: - 0.021, - 0.003) Based on a meta-regression, these associations are stronger in areas where the average PM_{2.5} concentrations are lower, the mean returns are higher, and where the local stock market capitalization is low. Our results suggest that a 10 µg/m³ increase in PM_{2.5} exposure increases stock market volatility by 0.2% (regression coefficient 0.002, 95% CI 0.000, 0.004), but the city-specific estimates were heterogeneous. Meta-regression analysis did not explain much of the between-city heterogeneity. Our results provide global evidence that short-term exposure to air pollution both reduces daily stock market returns and increases volatility.

Ambient air pollution has currently dramatic effects on public health and economy worldwide. The World Health Organization estimated that ambient air pollution accounts for 4.2 million deaths per year due to stroke, heart disease, lung cancer and chronic respiratory diseases (https://www.who.int/health-topics/air-pollution#tab=tab_2). Ambient air pollution comprises a complex mixture of components potentially harmful to health, but fine particulate matter (PM_{2.5}) is considered to be the driver of health effects. A recent epidemiologic study, conducted in 672 cities or regions in 42 countries worldwide, provides quantitative estimates of the effects of short-term exposure to fine particulate matter on total mortality and mortality from cardiovascular and respiratory diseases¹. An increase of 10 µg/m³ in the 2-day moving average of PM_{2.5} concentration was related to a 0.68% (95% CI 0.59, 0.77) increase in daily all-cause mortality, 0.55% (0.45, 0.66) increase in cardiovascular mortality and 0.74% (0.53, 0.95) increase in respiratory mortality.

Deryugina et al.² assessed overall health effects of PM_{2.5} exposure in the United States and estimated the economic costs of PM_{2.5} exposure. They estimated accounting for age and sex that a 1 µg/m³ increase in PM_{2.5} causes the loss of 2.99 life-years per million beneficiaries over 3 days. Using a conventional value of \$100,000 per life-year³ results in a cost of 299,000 per million beneficiaries. Mortality effects represents a tip of the iceberg in the overall health effects and the overall economic costs are likely to be vast. Thus, many countries have taken action to regulate the air pollution levels, which has led to improvements in air quality, especially in the wealthier countries.

In addition to causing morbidity and mortality, exposure to air pollution is also linked to different types of psychological, economic and social effects⁴. During the last three decades, researchers have tried to assess how different environmental phenomena affect stock prices and returns⁵. A popular and widespread explanation for the potential effects is that certain environmental factors may have a negative effect on the mood of the investors^{6,7}. Additionally, there is recent evidence that short term exposure to air pollution can hinder cognitive performance⁸, which could influence the behavior of the investors as well.

The hypothesized relation between air pollution and volatility is more complex than the relation between air pollution and stock returns. Several competing theories have been developed on how environmental factors may influence stock market volatility via the mood pathway, which are discussed by Symeonidis et al.⁹ Worsening of mood (increases in air pollution) can cause more disagreement between the investors and the market valuation, which may then lead to increased volatility¹⁰⁻¹². Whereas according to other studies, a better mood (decreases

¹Center for Environmental and Respiratory Health Research, Faculty of Medicine, University of Oulu, Oulu, Finland. ²Department of Economics, Oulu Business School, University of Oulu, Oulu, Finland. ³Finnish Meteorological Institute, Helsinki, Finland. ⁴Biocenter Oulu, University of Oulu, Oulu, Finland. ✉email: jouni.jaakkola@oulu.fi

| Author(s) | Pub. year | Cities | Study period | Pollutant(s) | Covariates | Methods | Results |
|----------------|-----------|---|-----------------|--|---|---------------------------------------|---|
| Levy and Yagil | 2011 | New York, Philadelphia | 01/1997–06/2007 | AQI as binary classification | Monday, January, lag1 returns | OLS, t-test | Significant negative effect for unhealthy AQI days |
| Levy and Yagil | 2013 | New York, Philadelphia, Toronto, Amsterdam, Sydney, Hong Kong | 01/1997–06/2007 | AQI | lag1 returns, Monday, full moon, fog, season | OLS | Significant negative effect for an increase in AQI |
| Lepori | 2016 | Milan | 01/1989–05/2006 | PM ₁₀ , lag1 and 3dMA | lag1–2 returns, SAD, fall, fullmoon, newmoon, Monday, tax, temperature, rain, month | Binary logit | Significant negative effect on centralized market returns. Stronger effects for 3dMA. Found the effects for NO _x and SO ₂ as well |
| Li and Peng | 2016 | Shanghai, Shenzhen | 01/2005–12/2014 | AQI | Humidity, wind speed, SAD, Monday, January, lag1 returns, lags 1–2 for AQI | OLS | Significant negative effect only for time period 2010–2014. Noticed a rebound effect with lag2 AQI |
| Heyes et al. | 2016 | New York | 01/2000–11/2014 | PM _{2.5} | lag1–2 returns, temperature, dew point, precipitation, wind speed, air pressure, cloud cover, O ₃ , CO, day of the week, tax dummy, year-by-week | OLS | Significant negative effect (– 0.0171) for a unit increase of PM _{2.5} . Various additional sensitivity and robustness checks |
| He and Liu | 2018 | Shanghai | 02/2005–03/2017 | AQI | Temperature, humidity, wind speed, precipitation, cloud cover, SAD, Monday, January, lag1 return | OLS | Found no relationship between air quality and the stock returns |
| Wu et al. | 2018 | 33 Chinese cities | 12/2013–12/2015 | AQI, PM _{2.5} , PM ₁₀ , SO ₂ , CO, NO ₂ , O ₃ | lag1 returns, SAD, humidity, temperature, air pressure, visibility, wind speed, cloud cover, 30-day average return, Monday, month | Cross-sectional panel data regression | Observed a significant negative effect between air pollution and stock returns |
| An et al. | 2018 | Chinese national aggregate | 01/2014–12/2015 | AQI | Investor sentiment | OLS, GARCH | Found a statistically significant relationship between air quality and returns, but not between air quality and volatility |

Table 1. Characteristics of the previous studies on the relation between daily air pollution levels and stock returns and volatility.

in air pollution) may lead to increased trading volumes which would also lead to increased volatility^{13,14}. A third theory relies on the assumption that returns and volatility are inversely correlated¹⁵, and therefore if air pollution decreases returns, it should simultaneously increase the volatility.

In this study we focused on how daily PM_{2.5} concentrations affect stock market returns and volatility. The main focus of the previous literature has been on the associations between daily air pollution concentrations and stock returns^{16–23}. Somewhat surprisingly, the relationship between air pollution levels and stock volatility has only been assessed in three research articles^{16,19,23}. The results are somewhat controversial; studies focusing on Europe and North America have found that increases in daily air pollution levels decrease stock returns^{18–21}, whereas studies with Chinese data have not reported such an association^{17,22}. Table 1 summarizes the results, methods and geospatial coverage of the previous studies.

Furthermore, there are not enough studies to generalize the results globally or to explain the differences in associations between market locations. Our aim was to fill this gap in knowledge by using data from 47 stock exchange cities around the globe. We tested the following hypotheses:

Hypothesis 1 Increases in the levels of daily PM_{2.5} concentrations decrease daily stock returns.

Hypothesis 2 Increases in the levels of daily PM_{2.5} concentrations increase daily stock volatility.

We applied regression models for each city individually. The volatilities of the stock indices were modeled with GJR-GARCH(1,1) method, which has been developed for accounting for asymmetric shocks²⁴. In addition to traditional time-series analysis methods, we applied random effects meta-analysis²⁵, which has been rarely used in economics but more commonly in environmental epidemiology^{1,26}, to summarize the global effects of air pollution on stock returns and volatility.

Results and discussion

Associations between daily PM_{2.5} concentrations and stock returns. Our main results are presented in Fig. 1, where the effect estimates are based on Eq. (2) presented in “Methods” section. The effect estimates, and their 95% confidence intervals, are presented for each city individually. The results are in line with our hypothesis that investors exposure to PM_{2.5} would lead to decreased stock returns. The summary effect estimate for PM_{2.5} based on 47 city specific estimates is -0.012 (95% confidence interval $-0.021, -0.003$), which is statistically significant at the 5% level. The effect estimate corresponds to an average 1.2% reduction in stock returns per a $10 \mu\text{g}/\text{m}^3$ increase in PM_{2.5}. A rather substantial amount of heterogeneity can be observed when comparing the results of individual cities ($I^2 = 48.64\%$).

We quantified the effects with different lags (see Appendix figures A2–A5) and found that the effect persisted when applying a 2-day moving average. Epidemiological research suggests that air pollutants have distributed lag effects on health over subsequent days²⁷ which is also backed by the results of Lepori et al.¹⁹ who found that the association was stronger when applying a 3-day moving average instead of the index day concentration. In our sample, the 2-day and 3-day moving averages provided similar summary effect estimates, 2-day: -0.009 ($-0.018, -0.000$); 3-day: -0.012 ($-0.025, 0.001$), as the index day with some differences in individual cities. The other lagged patterns did not produce significant results, which implies that the PM_{2.5} effect on investors has a rather short induction period. In addition to the shorter lags, we tested the individual cities for a 30 lag-day cumulative association. The long-term cumulative effects were not significant across the board.

Besides the overall pooled effect estimate, we present all the city-specific effect estimates which are somewhat similar to the corresponding estimates observed in the previous studies. Similarly to both Li and Peng²² and He and Liu¹⁷ we did not observe any significant effect in Shanghai. However, in our case, the effect estimate is of similar size as the pooled effect; -0.007 (95% confidence interval: $-0.026, 0.013$). Lepori¹⁹ used a 3-day average PM₁₀ concentration as a predictor, and observed that the Italian stock market returns were 2% less likely to be positive when PM₁₀ levels rose by $10 \mu\text{g}/\text{m}^3$. While not directly comparable, our estimate has a positive sign, which implies that returns in Milan have been higher on days with higher PM_{2.5} levels. The estimate, however, is not statistically significant which could be related to a small sample size; our sample for Milan only covers a short 1-year time span.

Finally, if we compare the present results from New York City, -0.051 ($-0.146, 0.044$), with those from Heyes et al.¹⁸ who estimated a coefficient of -0.0171 for $1 \mu\text{g}/\text{m}^3$, we can notice some difference. The previous studies^{20,21} also found a statistically significant relationship in New York, whereas we did not. In fact, the point estimate presented by Heyes is over 3 times larger than ours. This is a slight surprise, since we used highly similar methods and data as was used in the article by Heyes et al.¹⁸. The main difference between the analyses, that we could think of, is the time span. Their study period reaches from 2000 up to 2014, while our data sample ranges between 2007 and 2019.

In order to understand the variation of the effects over time, we split the data into four five-year strata and analyzed them as shorter periods (Appendix figures A6–A9). Due to most of the data being from the last five years, we believe that assessing the summary estimates for each period is not meaningful. However, we observed some interesting patterns that further underlines that studying the phenomenon with a large geographical and temporal scope is important. For example, the effect estimates for Athens and Helsinki are close to 0 and statistically insignificant when using the full data sample, whereas these cities have a highly significant negative coefficient in the 2011–2015 and 2016–2019 samples respectively.

We studied also the role of traffic emissions as potential confounders of the association between PM_{2.5} and stock returns. In addition to PM_{2.5}, traffic emissions include other pollutants. We did not have direct information on traffic emissions or volumes, but we used NO₂ as an indicator of traffic emissions in the European cities. Inclusion of NO₂ in the models did not influence the pooled effect estimates (see Appendix figures A10 and A11). The summary effect estimate for the European cities was 25% stronger than in the full sample.

Associations between daily PM_{2.5} concentrations and volatility. The results for the volatility models are presented in Fig. 2. The summary effect estimate (0.002 per $10 \mu\text{g}/\text{m}^3$ increase in PM_{2.5}, 95% CI $0.000, 0.004$) indicated that PM_{2.5} concentration increases the stock market volatility, but there was substantial heterogeneity between the city-specific effect estimates ($I^2 = 88.22\%$). From the GJR-GARCH parameter estimates we found that the leverage term γ was positive (36 out of 47) with no statistical significance (35 out of 47) in most of the locations (See Appendix Table A2). Only Ulaanbaatar had a statistically significant negative γ term. This means that, in the majority of the locations, negative shocks have more impact on volatility than positive shocks²⁸.

The effect estimate for New York City was the largest at 0.199 ($0.151, 0.247$) which represents a rather substantial 22% increase in volatility when the PM_{2.5} rose by $10 \mu\text{g}/\text{m}^3$. The magnitude of the estimate for New York City was much larger than those of any other cities. The difference could not be attributed to geographical areas as the other North American city, Toronto, ended up with the second highest negative estimate. Additionally, there were four European cities (Oslo, London, Brussels, and Lisbon) where the effect estimate was considerably large and statistically significant at the 95% level.

The observed heterogeneity is not that surprising. In fact, Symeonidis et al.⁹ used a similar approach to model the effects of weather conditions on stock market volatility using a cross-sectional data that contained multiple cities as well. Their results have, similarly, a wide amount of variance between the results of individual cities. One possible explanation is that other underlying features related to the population could modify the effects of environmental factors on investor behavior. For example, the level of internationalization of the stock market, reliance on technology (such as algorithmic trading), or cultural features of the affected traders, could influence how the decreased mood or risk-aversion manifests on the stock market.

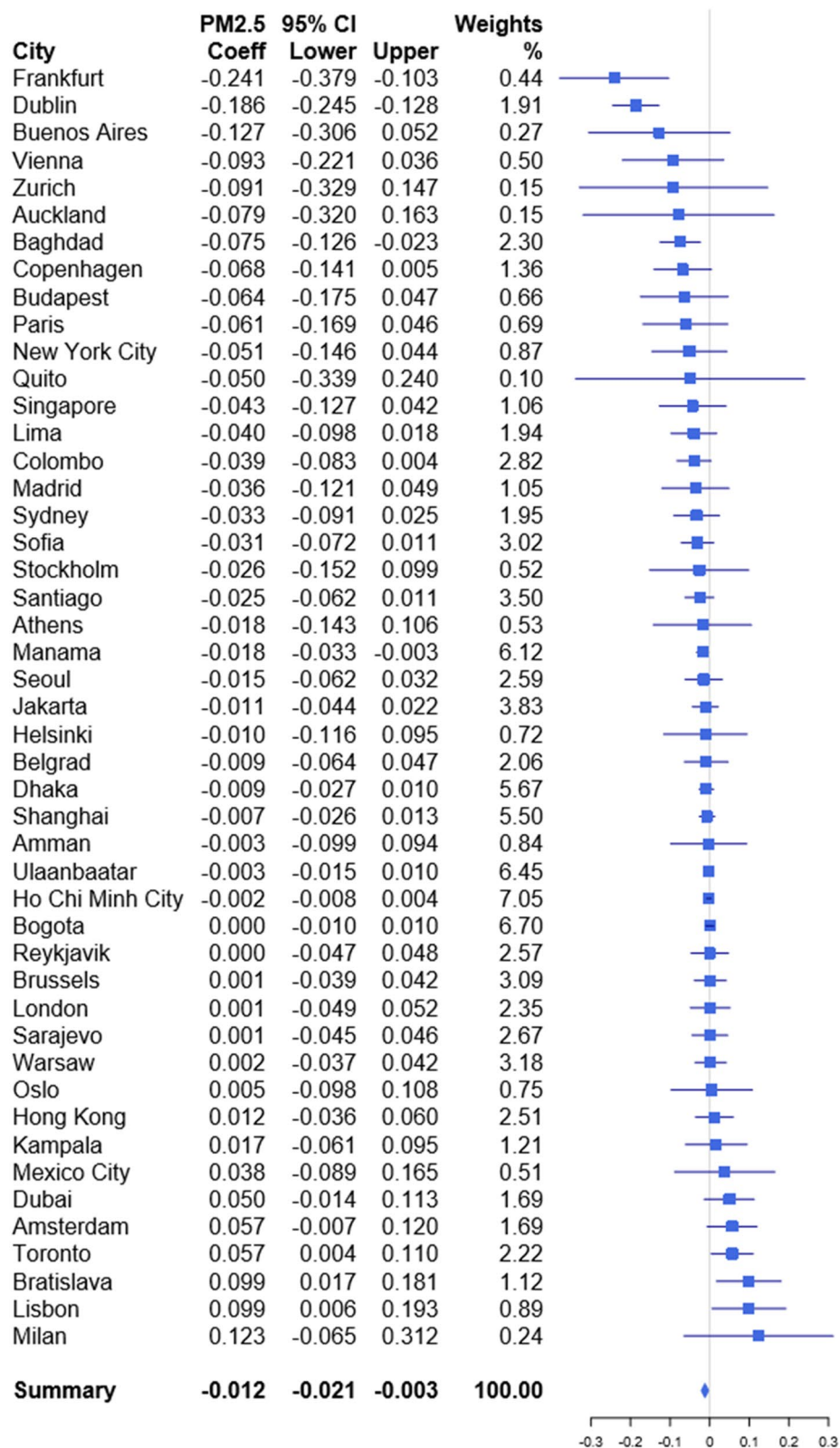


Figure 1. Regression coefficients and 95% confidence intervals for the association between 10 $\mu\text{g}/\text{m}^3$ increase in daily $\text{PM}_{2.5}$ concentration and stock index returns.

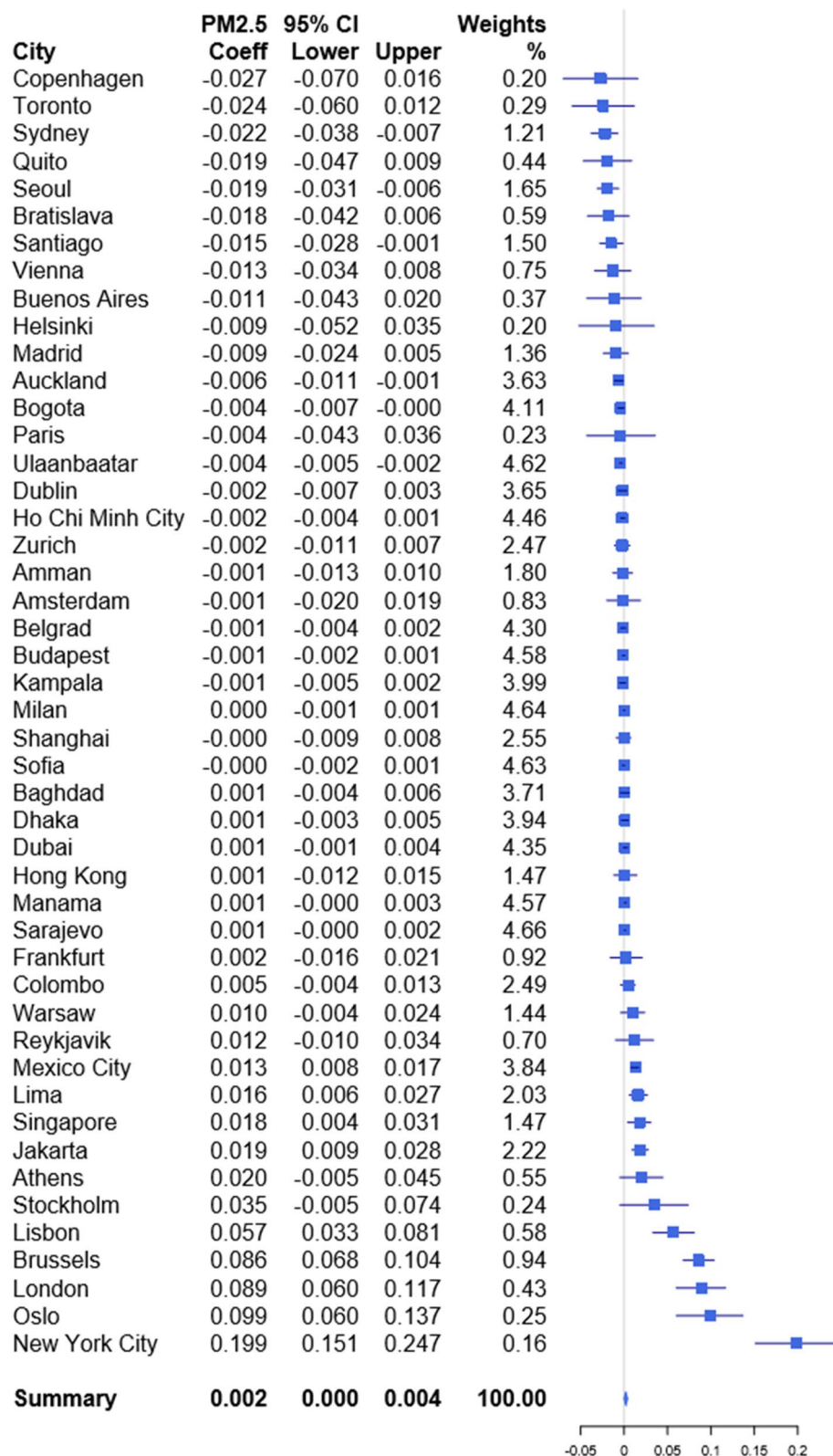


Figure 2. Regression coefficients and 95% confidence intervals for the association between 10 µg/m³ increase in daily PM_{2.5} concentration and stock index volatility.

We adjusted for traffic emissions as a potential confounder also for the association between PM_{2.5} and stock market volatility by adding NO₂ as an indicator of traffic-related emissions into the model (see Appendix figures A12 and A13). Interestingly, the summary effect estimate for the European cities decreased from 0.008 (95% CI 0.003, 0.012) in the unadjusted model to 0.004 (95% CI 0.000, 0.008) in the model adjusting for NO₂. These findings indicate some confounding by NO₂, but show an independent effect of PM_{2.5}. It is also worth noting that the effect estimate for Europe only is significantly higher than the global summary effect estimate.

Determinants of between-city heterogeneity in effect estimates for returns and volatility. We observed significant between-city variability in the effect estimates of our main regression analyses. The physiological effects of PM_{2.5} exposure on humans should be consistent everywhere. We believe that some other type of phenomena might explain the differences in the city-specific results. An easy explanation would be, that the PM_{2.5} measurements do not describe accurately enough the exposure on those who are trading the stocks. For example, internet has made reaching the various stock markets from farther distances relatively easy and thus the proportion of international traders might be large enough to offset any effects of local air pollution concentrations. Furthermore, the amount of international trading at the stock markets may vary strongly, and thus be a significant source of the observed heterogeneity. Unfortunately, we were unable to attain relevant data for quantifying the phenomenon, or to locate where the majority of the traders participate the stock trading from.

In order to explain the differences in the city-specific estimates, we applied meta-regression on the results. The key explanatory variables tested for these analyses were study period (start year, end year, length of time span), the mean, range and interquartile-range of PM_{2.5} concentration and daily returns, market capitalization of the stock market, and geographic location based on continents, and Köppen climate classification. The market capitalization was dichotomized as:

< 100 billion = 0.

> = 100 billion = 1.

The limited number of cities and rather large deviance between the city-specific regression estimates creates some issues for the meta-regression. The relatively small number of independent observations (N = 47) limits the power of the analyses. Similarly, the available degrees of freedom within the model does not allow fitting many explanatory variables simultaneously.

The best fitting meta-regression model for the returns models (I² of 54.16%) included mean returns, mean PM_{2.5} concentrations (µg/m³), and the market cap dummy as predictors. The mean concentration of PM_{2.5} provided an estimate of 0.0005 (95% CI 0.0000, 0.0010) per a 10 µg/m³ increase in PM_{2.5}, which would suggest that the effect of PM_{2.5} on daily returns is stronger in locations where the concentrations are lower on average. If we assume that the exposure–response function for the phenomenon is S shaped, it would be plausible that a short-term increase in PM_{2.5} concentrations would have a smaller effect in locations where the average concentrations are already high.

Furthermore, the meta-regression estimate for the mean daily return was also significant with a coefficient of – 0.4928 (– 0.7832, – 0.2024), which would suggest that the effect is stronger in markets where the returns are higher on average. The estimate for the market cap dummy was not significant even at 10% level, but the coefficient 0.0170 (– 0.0066, 0.0407) suggests that the negative effect of air pollution might be stronger in locations where the market capitalization is smaller. This could indicate that the level on internationalization of the smaller stock exchanges is also smaller, and therefore the effect of local air pollution would also be stronger.

We attempted to apply meta-regression on the volatility models as well. However, our predictors did not seem to catch much of the heterogeneity. The I² statistic remained consistently at very high levels. The best fitting model (I² = 88.22%) included only the mean daily returns with an estimate of – 0.0440 (– 0.0855, – 0.0025). The results imply that the PM_{2.5} effect on volatility is lower in stock exchanges where the returns are higher on average.

The previous studies have focused mainly on individual cities, and at most only tested the models in a couple of additional locations. In this study we have presented that the effects vary between time and space, which was also noted by Li and Peng²². Focusing on a single or a handful of cities may provide results that are only relevant in the studied location and only during the specific time span of the study. Therefore, generalizing or drawing conclusions from such results can be misleading. By using long temporal and wide geospatial coverage we increased the credibility of the results and provided evidence that the studied associations between daily PM_{2.5} concentrations and stock returns/volatility exist on a global scale, even if their observed magnitude may vary between time and place.

Conclusions

This study presents a major contribution to economics by expanding the geographic coverage of the studies related to the association between air pollution exposure and stock market returns and volatility. We believe that these findings are also of significant importance in environmental health on providing indirect evidence that short-term exposure to air pollution can have substantial effects on mood and human cognitive functions, which in turn affects investor behavior.

The results of our global assessment on the effects of PM_{2.5} on stock market returns provide evidence that on average, a 10 µg/m³ increase PM_{2.5} concentration decreases the daily returns by 1.2%. Furthermore, we show that these associations are stronger in areas where the average PM_{2.5} concentrations are lower, the mean returns are higher, and where the local stock market capitalization is low.

Additionally, we present evidence that increases in the PM_{2.5} levels also influence the stock market volatility. The latter results are notably heterogenous and can not be generalized in a global scale. Regardless of the lack of generalizability, the findings further strengthen the hypothesis that air pollution influences investors' behavior.

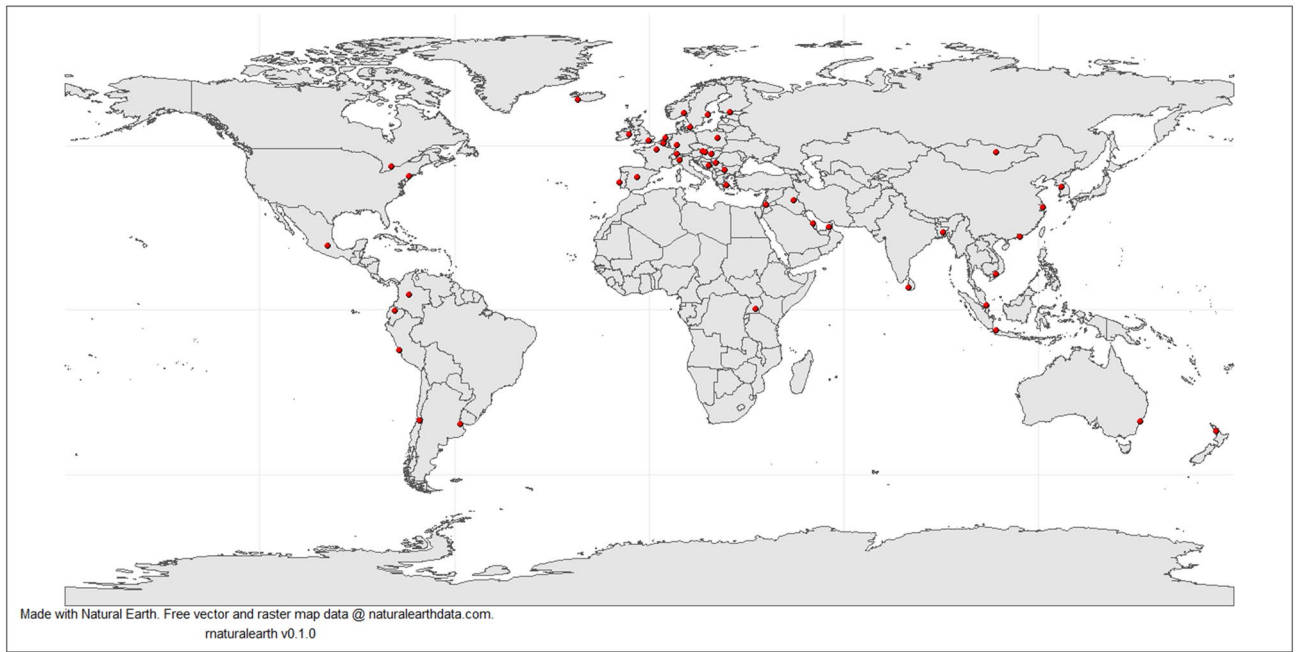


Figure 3. Geographical coverage of the study.

Additional research on the causal mechanisms is still needed as we do not yet know why the investor behavior changes along variations in the levels of air pollution. The current study could also be expanded to cover additional stock market related responses such as trading volumes, and a wider set of factors for explaining the observed heterogeneity.

Methods

Data. Our aim was to assess globally the effects of air pollution on stock markets. There are 144 stock exchanges worldwide. Investing.com, to our knowledge, has the largest inventory of the exchanges and the indices traded in each of them. In order to get a global geospatial coverage for the study, we searched their locations and filtered out all major indices. This generated a list of 88 cities representing the stock market capitals of their respective regions.

After attaining a wide range of possible cities, we identified the coordinate points of the stock exchanges and searched for air quality data from as close to the coordinate point as possible. We found daily air pollutant concentration measurements for 54 of the 88 cities in total. Out of these cities, 47 contained a sufficient amount of $PM_{2.5}$ measurements to be included in the analysis. The geospatial coverage of the study is illustrated in Fig. 3. The data sources for all air quality monitoring stations are provided in the supplementary material (Metadata spreadsheet). Most of the cities where air quality measurements could not be found were located in Asia and Africa. Finally, we downloaded matching meteorological data for the respective locations from the NOAA GSOD database (<https://data.noaa.gov/dataset/dataset/global-surface-summary-of-the-day-gsod>).

Since we cannot assess the empirical relation between stock returns and $PM_{2.5}$ on the days they were not measured, we omitted all days where either one of the values was missing. The total number of observations was 47 928, the time spans for each city ranged between 1 and 19 years and the median time span was 4 years. Table 2 presents the mean (sd) for the main interest variables daily returns and $PM_{2.5}$ concentrations, as well as the time span covered in the data.

Imputation. A preliminary investigation revealed that the meteorological variables contained a significant amount of missing data, which can be seen from Fig. 4. Most of the missing data were seemingly at random. We, however, identified also larger sections of consecutive missing values. Apparently, certain weather parameters of interest had not been measured in all cities during the study periods. In order to assess the research question while accounting for the weather-related confounding effects, we decided to impute the missing values in order to keep the number of observations at good levels. We assumed that the meteorological phenomena were non-linearly correlated with each other. Therefore, we performed a multiple imputation using the CART (Classification and Regression Training) method from MICE package for R.

Model and feature selection. Based on previous literature, we identified a wide set of variables that could be used in the regression models. First, we tried several different ways of capturing temporal variations in the data. Similarly to Heyes et al.¹⁸, we found that including week of year and day of week dummies was an effective method for accounting for non-linearities in the temporal trends. In addition, we followed a common practice in

| City | Study period | Returns, mean (sd) | PM _{2.5} , mean (sd) |
|------------------|--------------|--------------------|-------------------------------|
| Amman | 2019–2019 | – 0.028 (0.213) | 23.273 (6.181) |
| Amsterdam | 2013–2018 | 0.011 (0.976) | 14.549 (9.434) |
| Athens | 2016–2019 | 0.076 (1.300) | 19.174 (9.414) |
| Auckland | 2017–2019 | 0.088 (0.549) | 6.869 (1.990) |
| Baghdad | 2019–2019 | – 0.004 (0.460) | 36.807 (18.471) |
| Belgrad | 2016–2019 | 0.052 (0.535) | 23.209 (18.957) |
| Bogota | 2016–2019 | 0.035 (0.724) | 17.789 (28.483) |
| Bratislava | 2017–2019 | 0.038 (0.946) | 16.089 (10.675) |
| Brussels | 2006–2019 | 0.008 (1.230) | 21.264 (13.904) |
| Budapest | 2019–2019 | 0.055 (0.743) | 14.006 (9.354) |
| Buenos Aires | 2015–2019 | 0.192 (2.098) | 16.138 (9.961) |
| Colombo | 2017–2019 | – 0.014 (0.419) | 28.368 (14.391) |
| Copenhagen | 2004–2018 | 0.012 (1.291) | 13.280 (6.346) |
| Dhaka | 2016–2019 | 0.053 (0.601) | 77.646 (56.423) |
| Dubai | 2018–2019 | 0.037 (0.758) | 48.351 (26.022) |
| Dublin | 2019–2019 | 0.143 (0.878) | 10.086 (8.102) |
| Frankfurt | 2017–2019 | 0.034 (0.858) | 9.838 (6.194) |
| Helsinki | 2005–2017 | 0.021 (1.415) | 9.523 (5.704) |
| Ho Chi Minh City | 2016–2019 | 0.070 (0.934) | 41.448 (68.312) |
| Hong Kong | 2011–2019 | – 0.008 (1.115) | 27.096 (14.899) |
| Jakarta | 2015–2019 | 0.026 (0.779) | 44.702 (17.018) |
| Kampala | 2017–2019 | 0.042 (0.796) | 57.362 (18.132) |
| Lima | 2016–2019 | 0.040 (0.757) | 33.268 (13.482) |
| Lisbon | 2010–2019 | – 0.041 (1.199) | 13.325 (7.470) |
| London | 2001–2019 | 0.013 (1.145) | 13.790 (8.310) |
| Madrid | 2004–2005 | 0.048 (0.690) | 21.385 (9.579) |
| Manama | 2016–2019 | 0.026 (0.414) | 57.305 (25.026) |
| Mexico City | 2012–2014 | – 0.018 (0.818) | 29.528 (9.250) |
| Milan | 2018–2018 | – 0.062 (1.059) | 21.019 (13.142) |
| New York City | 2007–2019 | 0.023 (1.190) | 9.568 (5.681) |
| Oslo | 2010–2019 | 0.055 (1.186) | 9.982 (6.273) |
| Paris | 2011–2018 | 0.042 (1.212) | 14.784 (11.747) |
| Quito | 2016–2019 | 0.059 (0.458) | 17.219 (5.099) |
| Reykjavik | 2006–2019 | 0.004 (0.962) | 7.496 (9.020) |
| Santiago | 2009–2019 | 0.039 (0.861) | 27.782 (14.417) |
| Sarajevo | 2016–2019 | – 0.018 (0.723) | 27.657 (21.552) |
| Seoul | 2015–2019 | 0.005 (0.770) | 23.301 (13.176) |
| Shanghai | 2011–2017 | 0.033 (1.421) | 47.740 (40.938) |
| Singapore | 2016–2019 | 0.021 (0.713) | 16.043 (7.527) |
| Sofia | 2019–2019 | – 0.083 (0.453) | 19.906 (18.548) |
| Stockholm | 2004–2007 | 0.028 (0.976) | 14.216 (6.587) |
| Sydney | 2015–2019 | 0.018 (0.814) | 7.278 (7.113) |
| Toronto | 2004–2017 | 0.017 (1.109) | 7.458 (6.227) |
| Ulaanbaatar | 2015–2019 | 0.036 (1.057) | 96.620 (116.081) |
| Warsaw | 2009–2019 | – 0.023 (1.164) | 28.810 (16.801) |
| Vienna | 2017–2019 | 0.039 (0.896) | 14.844 (11.220) |
| Zurich | 2019–2019 | 0.111 (0.592) | 9.041 (6.081) |

Table 2. Characteristics of the 47 stock market cities included in the present study.

stock-related predictions and included 1- and 2-day lagged returns as predictors to account for autocorrelation in the dependent variable.

We defined stock returns as: $RET_t = (\ln(P_t) - \ln(P_{t-1})) * 100$, where P_t is the closing price of the city's corresponding stock index on day t . Then, we formulated the following baseline (1) model:

$$RET_t = \beta_0 + \beta_1 PM_{2.5,t} + \beta_2 RET_{t-1} + \beta_3 RET_{t-2} + \beta_4 woy_t + \beta_5 dow_t \quad (1)$$

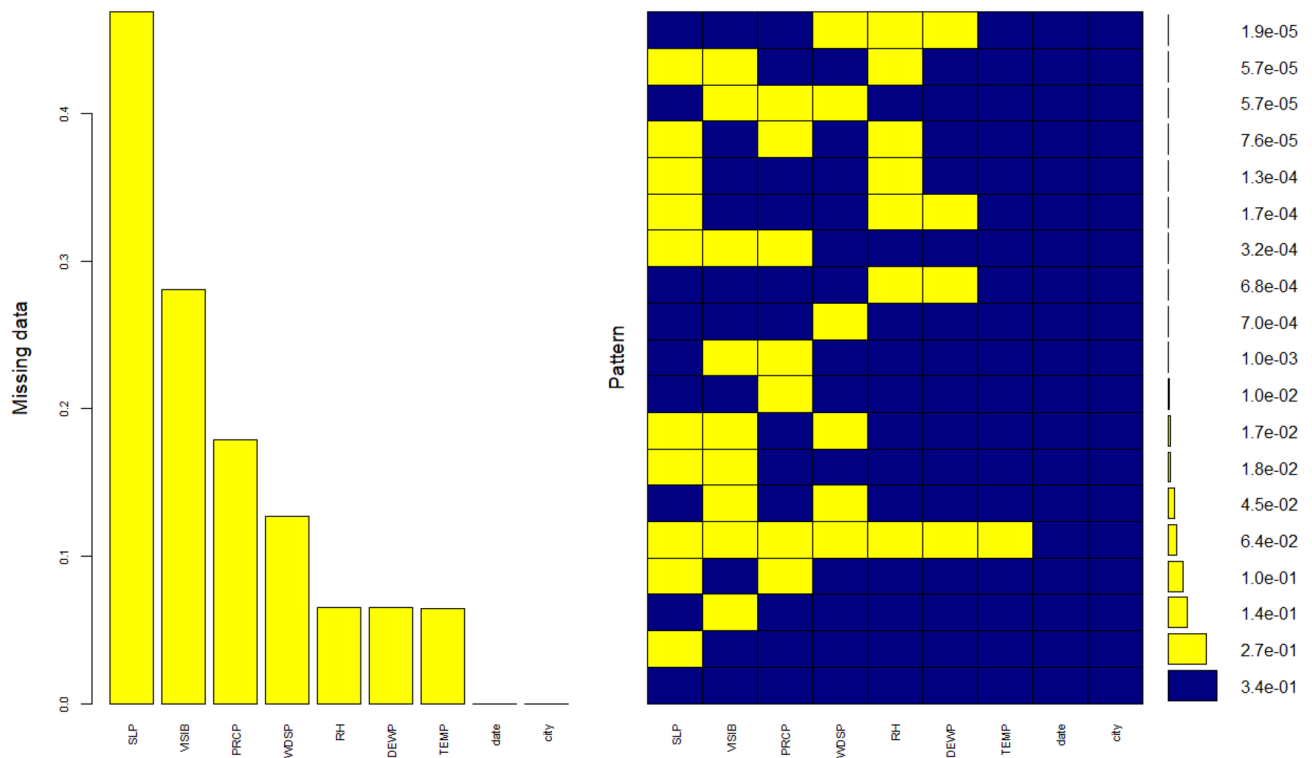


Figure 4. Patterns of missing data.

where RET_t denotes the daily return on day t and is defined as, $PM_{2.5}$ the daily concentration, and woy and dow representing the week of year and day of week dummies respectively.

To systematically elaborate on the role of the remaining set of variables, we formed a grid containing each combination of them. Then we added each combination together with the fixed baseline model and iterated an OLS regression for each city with each combination. This approach proved to be efficient for testing the effects and importance of each individual variable and it also served as a test of sensitivity for the relation of main interest. Some variables, such as relative humidity and lunar cycle indicators, were excluded since they did not improve the model and had significant collinearity with other included variables. Furthermore, we explored the lagged associations of $PM_{2.5}$ and the stock returns and concluded, that the effect was strongest when using the index day values.

Final model specifications. The final model (2) was then constructed based on both earlier literature and rigorous experimentation with the data. The final model:

$$RET_t = \beta_0 + \beta_1 PM_{2.5,t} + \beta_2 RET_{t-1} + \beta_3 RET_{t-2} + \beta_4 woy_t + \beta_5 dow_t + \beta_6 PRCP_t + \beta_7 WDSP_t + \beta_8 SLP_t + \beta_9 VISIB_t + \beta_{10} TEMP_bins_t + \beta_{11} DEWP_bins_t + \beta_{12} SAD + \varepsilon_t, \quad (2)$$

where PRCP, WDSP, SLP, and VISIB denote precipitation, wind sed, sea level pressure, and visibility respectively. These meteorological variables were treated as continuous. SAD denotes the daylength in hours, and is treated as a continuous variable in the models. Temperature (TEMP_bins) and dew point (DEWP_bins) were treated as dummy bins, each bin having a width of 2.5 °C to account for non-linearities, a method adopted from the article by Heyes et al.¹⁸. Finally, the Newey-West standard errors ε_t were applied to adjust for arbitrary serial correlation within the models. In the sensitivity analyses of the European cities, we assessed potential confounding by traffic emissions by fitting daily NO_2 concentrations into the models.

gjrGARCH volatility model. Next, we moved on to test the effects of air pollution on stock market volatility. For this analysis, we implemented a 3-step GJR-GARCH regression in order to accurately define the volatility and to explain how the environmental factors influence it. First, in order to account for the independent effects in the mean model, we took the residuals from the final returns model (2). Second, we applied a GJR-GARCH(1,1) model on the residuals to model the stock volatilities. Third, once we had obtained the volatilities, we performed an OLS regression using the volatilities as the dependent variable.

The volatility can then be defined as follows:

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1}) \varepsilon_{t-1}^2 - 1 + \beta \sigma_{t-1}^2,$$

where the I_{t-1} indicator function is:

$$I_{t-1}(\varepsilon_{t-1}) = \varepsilon_{t-1} \text{ for } \varepsilon_{t-1} > 0 \text{ and } I_{t-1}(\varepsilon_{t-1}) = 0 \text{ otherwise}$$

A GJR type of GARCH model was selected because it can account for asymmetric nature of the volatility²⁴ and can be flexibly fit on different datasets. It has also been used for similar studies by, for example, Symeonidis et al.⁹ and Dowling and Lucey²⁹.

Global estimation via meta-analysis. In order to capture the global effects, we used a similar approach as Liu et al.¹ who studied the effects of particulate matter on mortality in 652 cities. Essentially, the regression models were performed individually for each city, and finally summarized using a random effects meta-analysis²⁵. In this manner, we were able to account for heterogeneity between the cities. Finally, we interpret the summary-effect estimate as a generalized global average effect. We chose this method over panel-regression since we expect there to be significant amount of between-city heterogeneity. A panel regression model assumes that the temporal and meteorological factors have equal effects in different cities. We argue that by allowing the confounders and temporal trends to flexibly adjust individually for each city, the results for the effect of main interest will be more valid. In the sensitivity analyses, we elaborated the role of traffic emissions as a potential confounder by fitting NO₂ concentrations in the models.

Data availability

The imputed data set for replicating the results presented in the article is available at Mendeley [<https://doi.org/10.17632/z8t3s8btvx.1>]. Additionally, the sources of data for each individual city are described in the included metadata file.

Code availability

Code for the analyses is available from Mendeley [<https://doi.org/10.17632/z8t3s8btvx.1>] along with the data.

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Author contributions

Study design (S.P.K, M.K, J.J.K.J); data collection (S.P.K); data analysis (S.P.K, M.K); writing of manuscript (S.P.K); data interpretation and editing of manuscript (S.P.K, M.K, J.J.K.J); comments and discussion on the manuscript (M.K, J.J.K.J).

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to J.J.K.J.

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