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Air Pollution and Stock Returns – Extensions and International Perspective

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Abstract: This study strengthens the conclusion reached recently in the literature documenting (Levy and Yagil, 2011) the negative relationship between air pollution and stock returns. For the US capital market, this relationship persists even when controlling for other variables such as the January or Monday anomalies, or seasonal and meteorological effects. In both the US and Canada, the negative impact of air pollution on stock returns is stronger for pollution-related companies. Finally, this negative relationship exists not just in the US and Canada, but also in three other selected countries (each from a different continent): the Netherlands, China and Australia.

JEL Classifications: I10, G14

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I. Introduction

A recent study by Levy and Yagil (2011), hereafter LY, has empirically documented the Pollution Effect - a negative relationship between air pollution and stock returns for the US capital market. In their conclusions they speculate about whether pollution-related companies are more heavily penalized by the stock market's participants when air pollution becomes unhealthy. In addition, they suggest extending the investigation to other countries. Their results also raise the question as to whether the negative impact of air pollution on stock returns still holds when accounting for meteorological effects documented in the literature in the context of stock returns. Finally, they did not examine whether the relationship also holds for a lagged pollution variable as well.

Levy and Yagil (2011) describe the sequential chain of events as follows. Air pollution has a depressing effect on mood. Mood, in turn, has an impact on decision making, one type of which is investment in stocks. Accordingly, LY first cite studies, such as those by Schiffman et al. (1995) and Lundberg (1996), documenting the negative effects of air pollution on mood. Next, they present studies, such as those by Slovic and Peters (2006), and Pennings and Garcia (2009), establishing the relationship between mood and decision making. Finally, they review studies in financial economics, such as those mentioned above, that have investigated the relationship between mood-related meteorological variables and stock returns.

Given this gap in our knowledge, this study investigates several questions about the negative relationship between air pollution and stock returns: (1) Does this relationship hold when other meteorological effects (reviewed below) are considered?; (2) Is the relationship stronger for pollution-related corporations?; and (3) Is the relationship present in countries other than the US?

The literature documents an empirical relationship between meteorological factors and stock returns. These factors include cloud cover (Saunders, 1993), weather (Chang et al., 2008), temperature (Cao and Wei, 2005), summer/winter seasonality or the May to October effect (Bouman and Jacobson, 2002), amount of daylight and seasonal affective disorder, SAD, (Kamstra et al., 2000; Kamstra, 2003), and lunar cycles (Yuan et al., 2005). Jacobsen and Marquering's (2008) findings reconfirm the relationship between stock returns and summer/winter seasonality, SAD and temperature. Underlying all of these studies is the perception that these meteorological factors can affect the mood of investors, which in turn, can affect market returns.

Other papers, however, find that meteorological variables have no effect. Loughran and Schultz (2004) find little evidence that cloudy weather in the city in which a company is based affects its returns. Pardo and Valor (2003) investigate the possible relationship between weather and market index returns in the context of the Spanish market. They find that weather variables, such as hours of sunshine and humidity levels, have no influence on stock prices.

Kramer and Runde (1997) try to replicate the findings in Saunders (1993) using German data and do not find any systematic relationship between sunshine and stock returns.

In this paper we extend Levy and Yagil (2011) as well as Jacobsen and Marquering (2008) in order to determine whether the pollution effect has any additional explanatory power over the weather variables with respect to stock returns. Our data indicate that the frequency of polluted days is higher in the summer than in the winter. By controlling for these weather-related variables, we will demonstrate whether air pollution has any additional impact on stock returns.

Given this brief scientific background, the objective of this study is threefold. First, we investigate whether the negative relationship between air pollution and stock returns in the US documented by LY is robust with respect to other meteorological effects. Second, we examine whether this relationship is stronger for pollution-related corporations. Third, we document the potential presence of such a relationship in an international context.

The structure of this study is organized as follows. Section 2 introduces the Air Quality Index (AQI) and related hypotheses. Section 3 describes the methodology and data. Section 4 discusses the main results, and the last section concludes the study.

II. The Air Quality Index and Derived Hypotheses

A. The Air Quality Index

The US Federal Environmental Protection Agency (EPA) uses the Air Quality Index (AQI) for reporting daily air quality. It indicates the levels of air pollution and the health issues that may be of concern as a result of these levels. The purpose of the AQI is to assess what local air quality means to public health. The scale ranges from 0 to 500. The higher the AQI value, the greater the danger to public health. AQI values between 1 to 100 are defined by the EPA as Good (or Moderate), while higher values between 101 to 500 are defined by the EPA as Unhealthy (broken down into different levels of unhealthiness). Thus, in this study AQI levels up to 100 will be called Good, while levels exceeding 100 will be called Unhealthy.

In Canada, the AQI is published by the Canadian Ministry of Environment. The ministry defines AQI levels of 0 to 49 as Very Good, Good or Moderate, while levels exceeding 49 are defined as Poor or Very Poor. Accordingly, in this study, AQI levels up to 49 are defined as Good, while those exceeding 49 are defined as Unhealthy.

The air quality indices for the other countries in the sample are presented later.

B. The Hypotheses

This study tests three hypotheses. The first two are similar to those postulated by Levy and Yagil (2011), and the third is a new hypothesis suggested here. The hypotheses draw upon the earlier studies mentioned in the introduction section, which found a relationship between (a) air pollution and mood, and (b) mood and stock returns.

Hypothesis 1 (H1) posits that stock market returns are negatively related to air quality. This hypothesis was empirically verified by LY. This paper extends LY's study and tests H1 using the data of countries other than the US. In addition, we apply a more comprehensive regression analysis to the US data in order to examine whether, aside from other meteorological variables, air pollution is negatively related to stock returns.

According to Hypothesis 2 (H2), also suggested by LY, air pollution may even affect local traders investing in securities exchanges located far from the polluted area. Hypothesis 2 implies that air pollution in New York, for instance, may affect not only trading on the NYSE, but also trading on other securities exchanges located far from New York that is conducted by traders in New York. In order to test this hypothesis, LY chose another stock exchange which, like the NYSE, was also located in the US. In contrast, the distant stock exchange used in our study is located outside the US.¹

Hypothesis 3 (H3) posits that the negative relationship between air pollution and stock returns may be stronger for pollution-related companies than for other companies. Potential factors that may contribute to a stronger relationship include (1) a negative market attitude towards polluting companies; (2) the fact that the employees in such companies are closer to the pollution source, which may reduce their productivity; and (3) the fact that such companies are more vulnerable to air pollution-related lawsuits.

The three hypotheses presented above are tested in the following sections.

III. Methodology and Data

A. Methodology

As in LY, the methodology selected will mainly be based on t-tests and regression analysis. The t-tests will measure the difference between the Good sample and the Unhealthy sample in terms of the mean return or proportion of positive-return days. The regression analysis will be used to investigate the relationship between air pollution and stock returns more directly by controlling for potentially relevant variables.

Following prior related studies, we use a t-test for two sample means for testing the statistical significance of the return difference between the two categories – the sample of trading days on which the AQI level is Good and the sample of trading days when the AQI level is Unhealthy. For robustness purposes, we also use a second t-test, the t-test for two sample proportions, for testing the difference between the proportion of positive-return days in the Good sample and the corresponding proportion in the Unhealthy sample. The sample means t-test is given by:

$$t_{means} = (\bar{r}_{Good} - \bar{r}_{Unhealthy}) / (\sigma_{Good}^2 / n_{Good} + \sigma_{Unhealthy}^2 / n_{Unhealthy})^{1/2}, \quad (1)$$

where $\bar{r}$ and σ^2 are the mean and variance, respectively, of the daily stock rate of return, and n is the number of trading days.

The t-test for the two sample proportions is:

$$t_{proportions} = (P_{Good} - P_{Unhealthy}) / [P_{Good}(1 - P_{Good}) / n_{Good} + P_{Unhealthy}(1 - P_{Unhealthy}) / n_{Unhealthy}]^{1/2}, \quad (2)$$

where P stands for the proportion of positive-return days and n is the number of trading days.

The relationship between air pollution and stock returns can also be investigated by estimating the following regression equation:

$$r_t = \beta_0 + \beta_1 Polut_t + e_t, \quad (3)$$

where r_t is the rate of return for day t, $Polut_t$ represents the pollution effect measured here by two alternative variables – AQI and AQL. AQI is measured by the original numerical values, while AQL is a dummy variable carrying the value of 1 for Unhealthy days and 0 for Good days, β_0 and β_1 are the OLS coefficients, e is the error term, and n is as defined above. If air pollution has a negative impact on returns, according to H1, β_1 will be negative.

To control for potentially confounding effects, many earlier related studies incorporated the meteorological variables and first-order auto-correlation in returns into relationship equations such as that expressed by Eq. (3). Such studies include those of Edmans *et al.* (2007) on sports, the lunar study of Yuan *et al.* (2006), Cao and Wei (2005) on temperature, Kamstra *et al.* (2003) on Seasonal Affective Disorder (SAD), Garrett, Kamstra and Kramer's (2005) winter blues study and Saunders' (1993) weather study. In addition, a time-lagged pollution effect will be included in the regression equation. Accordingly, the following equation can be estimated:²

$$r_t = \beta_0 + \beta_1 Polut_t + \beta_2 Polut_{t-1} + \beta_3 r_{t-1} + \beta_4 Monday_t + \beta_5 January_t + \beta_6 Lunar_t + \beta_7 Cloud_t + \beta_8 Summer_t + \beta_9 SAD_t + \beta_{10} Temp_t + e_t, \quad (4)$$

where t and t-1 denote the current and lagged time period, respectively; r and Polut are as defined above; Monday and January are dummy variables representing the two corresponding anomalies established in the literature; Lunar, Cloud and Summer are dummy variables carrying the value of 1, respectively, for full moon, cloudy days and summer (i.e., May to October), and 0 otherwise; SAD is seasonal affective disorder and Temp is the temperature level. The pollution variable is expected to be negatively related to stock returns; that is, $\beta_1(Polut_t) < 0$, and if there is no pollution lag effect, $\beta_2(Polut_{t-1}) = 0$, where, for notational convenience, the variable name corresponding to the beta value is given in the parenthesis. The impact of the other variables in Eq. (4) has been examined widely in the literature and their expected signs are as follows (e.g., Jacobsen and Marquering, 2008): $\beta_3(r_{t-1}) = 0$; $\beta_4(Monady_t) < 0$; $\beta_5(January_t) > 0$; $\beta_6(Lunar_t) > 0$; $\beta_7(Cloud_t) < 0$; $\beta_8(Summer_t) < 0$; $\beta_9(SAD_t) > 0$ and $\beta_{10}(Temp_t) < 0$.

Jacobsen and Marquering (2008) found that Summer, SAD and Temp are strongly correlated, and suggest that only one of them should be used in the regression equation to represent the seasonal effect. Therefore, in the equation

below the variable “Season” denotes all three of these variables. Similarly, if $Polut_t$ and $Polut_{t-1}$ are strongly correlated (a possibility tested in the subsequent section), they will be included separately in two equations. Consequently, Eq. (4) reduces to:

$$r_t = \beta_0 + \beta_1 Polut_t + \beta_2 r_{t-1} + \beta_3 Monday_t + \beta_4 January_t + \beta_5 Lunar_t + \beta_6 Cloud_t + \beta_7 Season_t + e_t \quad (5)$$

Before estimating Eq. (5), to reduce a potential problem of multicollinearity, simple correlations will be applied to all independent variables to exclude the estimation of an equation containing two highly correlated variables. Such variables will be included in two separate estimated equations.

In addition, in order to test for potential heteroskedasticity, we use the Breusch-Pagan test. Furthermore, due to the assumption that the error term (e_t) in Eqs. (4) and (5) follows a Generalized Autoregressive Conditional Heteroskedastic (GARCH) process (Bollerslev, 1986), we re-estimate Eq. (5) using the following GARCH (1,1) Equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 e_{t-1}^2 \quad , \quad (6)$$

where σ_t^2 and σ_{t-1}^2 are Periods t and $t-1$'s variances in the security return, and α_0 , α_1 , α_2 are the GARCH model coefficients.

In order to determine which model selection method is best, we use three selection methods – the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) (also known as the Schwarz Information Criterion) and the Hannan-Quinn Information Criterion (HQC). These three criteria have been used in the literature for ranking models by their level of fit. The model having the lowest AIC, BIC or HQC value is ranked best.

Finally, to test for a possible lagged relationship between air pollution and stock returns, the following version of Eq. (4) is estimated:³

$$r_t = \beta_0 + \beta_1 Polut_t + \beta_2 Polut_{t-1} + e_t \quad , \quad (7)$$

where $Polut$ is measured by AQI and AQL, defined above, and t denotes the time period.

The estimation of Eqs. (5), (6) and (7) will be applied to various stock indices of different stock exchanges noted below.

B. The Data

To make the results in this study compatible with those of Levy and Yagil (2011), and given the additional statistical tests conducted here, our sample for the US is identical to that of Levy and Yagil (2011). The data for the other countries in the sample are provided later in Section 4.4.

We use daily data taken from the stock returns on the following stock exchanges: the NYSE, the AMEX, the NASDAQ, Philadelphia (PHLX) and Toronto. The stock market indices employed are the following: the Dow Jones Industrial Average (DJIA), the Standard and Poor's 500 (S&P 500), the NASDAQ Composite Index, the Amex Composite Index and the Toronto Stock Exchange (TSX) Composite Index. We begin here with the US and Canada. In Section 4.4 we will briefly examine the relationship between air pollution and stock returns for other countries as well.

The US AQI data has been taken from LY. The sample time period begins on January 1, 1997 and ends on June 30, 2007.⁴ Information on the AQI in Toronto can be found at <http://www.airqualityontario.com>. Due to data availability, our sample period for Toronto's AQI is January 1, 2005 to June 30, 2007.

Descriptive statistics of the daily AQI during the sample period are presented in the following section. Accordingly, daily data have been gathered for the other variables investigated in this study. Note that daily (rather than weekly or monthly) data are used in numerous related studies such as those of Edmans *et al.* (2007), Yuan *et al.* (2006), Cao and Wei (2005), Kamstra *et al.* (2000 and 2003) and Saunders (1993).

The AQI sample in our study refers to the county closest to the stock exchange. The closest county is defined as the county having the shortest mean distance between the monitoring stations located throughout the county and the stock exchange. Accordingly, Kings County is the closest to the NYSE. The distance between the monitoring

stations located in Kings County and the NYSE ranges between one and four miles with a mean station distance of roughly three miles⁵. For the PHLX, the closest county is Delaware County, and for the TSX the closest county is Downtown Toronto.

In order to test Hypothesis 2, we examined the impact of air pollution in New York on stock returns on the TSX.

To test Hypothesis 3, which posited a potentially stronger negative relationship between air pollution and the returns of pollution-related stocks, we selected three indices that could be described as pollution-related indices. One is provided by the Dow Jones Company, and the other two are available on the PHLX and the TSX. These three indices are the Dow Chemical, the Oil Service Sector Index on the PHLX, and the Capped Energy Index on the TSX.

The regression analysis requires additional data on the following variables: phases of the moon, cloudy days, SAD and temperature. As in Yuan *et al.* (2005), we obtained the lunar calendar from Life-Cycles-Destiny.com (<http://www.life-cycles-destiny.com/dw/moon-phases-eclipse-2002-2003-2004-2005.htm>). This website provides a table that documents the date and time (Greenwich Mean Time) of the four phases of the moon for the period from 1861 to 2020.

As in other studies (e.g., Kamstra *et al.*, 2003; Cao and Wei, 2005; and Jacobsen and Marquering, 2008), the SAD equals the number of night hours minus 12 for the trading days in the fall and winter, and zero otherwise. Data on the daily sunrise and sunset hours were taken from the USNO's (U.S. Naval-Observatory) site (http://aa.usno.navy.mil/data/docs/rs_oneyear.php).

We have measured the Cloud variable by two alternative related variables – Fog and Rain. As noted in the next section, these two variables were found to be highly correlated in our sample. Consequently, they were included separately in two versions of the regression Eq. (5) to represent the cloud variable. Data about fog, rain and temperature were taken from the National Climatic Data Center's website (<http://www.ncdc.noaa.gov/oa/ncdc.html>). Both the fog and rain variables are measured as dummy variables carrying the value of 1 on foggy or rainy days, and 0 on other days.

C. The AQI Statistics

For the county in New York State closest to the NYSE, the AQI includes 2,594 trading days. In 37 of them, the AQI level was Unhealthy. Appendix A includes the dates of the 37 days. For Philadelphia, our sample includes 2,600 trading days. In 43 of them, the AQI level was Unhealthy. The AQI findings for Toronto include 717 daily values, of which 12 were Unhealthy.

IV. Results

The discussion about the results is organized as follows. Section 4.1 analyzes the impact of meteorological effects on the relationship between air pollution and stock returns obtained through a regression analysis applied to the US sample. Section 4.2 presents the findings for Hypothesis 1 and 2 in the Canadian capital market using the TSX data. Section 4.3 discusses the findings for Hypothesis 3 applied to both US and Canadian pollution-related stock indices. Finally, Section 4.4 presents the international evidence supporting these hypotheses.

A. Meteorological Effects and the Air Pollution-Stock Returns Relationship

A1 Regression Analysis of the US Sample

This section provides a more extensive regression analysis than in LY's original study of the relationship between air pollution and stock returns. To reduce a potential problem of multicollinearity in the multi regression equation, a simple correlation matrix was first constructed for the following variables: the lagged return (r_{t-1}), the AQI, the

lagged AQI (AQI_{t-1}), the AQL, the lagged AQL (AQL_{t-1}), Monday, January, Lunar, Summer, SAD, Temperature (Temp), Fog and Rain. The variables r , AQI and AQL are measured as in the preceding subsection, and Temp is the average daily temperature level reported in degrees Fahrenheit. SAD is measured as the number of night hours minus 12 for the trading days during fall and winter, and zero otherwise.

The following six dummy variables receive the value of 1 when they meet the following criteria and are 0 otherwise. Monday is 1 when day t is the trading day following a weekend; January equals 1 for trading days occurring during January; Lunar is 1 for trading days that are three days before the full moon day, a full moon day and three days after the full moon day. Summer is 1 for trading days occurring during May to October. Rain is 1 if during the day rain had fallen, and Fog is 1 if during the day fog appeared.

The correlation matrix of the explanatory variables is presented in Table 1. The table demonstrates that both AQI and AQL, whether lagged or not, are strongly and positively correlated (at a significance level of 1%). Therefore,

only one of the two variables – AQI or AQL -- will be included in the regression equation. As documented by Jacobsen and Marquering (2008), the following three seasonal variables – Summer, SAD and Temperature -- are strongly correlated (at the 1% significance level). January is also strongly statistically correlated with the three seasonal variables. Thus, in accordance with the suggestion of Jacobsen and Marquering (2008), we will investigate the impact of each of these four variables separately. Finally, the Fog and Rain variables were also found to be strongly correlated and hence will be examined separately.

Consequently, 16 regression equations have been estimated as follows. Regressions 1-8 are for the AQI, while 9-16 are for the AQL pollution dummy variable. Fog is in regressions 1-4 and 9-12, while Rain is in 5-8 and 13-16. Finally, each of the four sets contains four regressions that include the four seasonal variables separately – Summer, SAD, Temperature and January. The regression results for one of these four sets – the AQI and Fog set -- are presented in Table 2. The results for the remaining three sets will be discussed briefly later.

Table 1: Correlation Matrix of the Simple Correlations between Selected Variables, January 1, 1997 – June 30, 2007

	AQI	AQI _{t-1}	AQL	AQL _{t-1}	r _{t-1}	Monday	January	Lunar	Summer	SAD	Temp	Fog	Rain
AQI	1.00												
AQI _{t-1}	0.588 ***	1.00											
AQL	0.436 ***	0.29 ***	1.00										
AQL _{t-1}	0.237 ***	0.406 ***	0.316 ***	1.00									
r _{t-1}	-0.05 ***	-0.049 ***	-0.016 ***	-0.036 **	1.00								
Monday	-0.021 ***	-0.1 ***	-0.033 **	-0.035 **	-0.005	1.00							
January	-0.011 ***	0.0003 ***	-0.037 **	-0.034 **	-0.011	-0.021	1.00						
Lunar	-0.003 ***	-0.001 ***	0.003 ***	0.007 ***	-0.002	-0.001	0.003	1.00					
Summer	0.078 ***	0.067 ***	0.101 ***	0.089 ***	-0.025	-0.004	-0.304 ***	0.008	1.00				
SAD	-0.039 **	-0.031 *	-0.072 ***	-0.067 ***	0.026 *	-0.005	0.469 ***	-0.006	-0.611 ***	1.00			
Temp	0.204* **	0.207 ***	0.168 ***	0.145 ***	-0.03 *	0.002	-0.391 ***	-0.004	0.777 ***	-0.651 ***	1.00		
Fog	0.066 ***	0.125 ***	0.032 *	0.026 *	-0.025	-0.014	0.017	-0.01	0.057 ***	-0.048 ***	0.077 ***	1.00	
Rain	-0.074 ***	0.029 *	-0.033 **	0.0004 *	-0.013	-0.032 *	-0.038 **	0.002	0.043 **	-0.069 ***	0.088 ***	0.535 ***	1.00

The table 1 presents the simple correlation coefficients (ρ_{ij}) between two given variables for the following possible explanatory variables in Eq. (4), where Polt is represented by AQI and AQL and Cloud is represented by Fog and Rain. The notation is as follows. AQI_t is the current Air Quality Index; AQI_{t-1} is the lagged AQI; AQL_t is a

dummy variable carrying the value of 1 for Good days and 0 for Unhealthy days; AQL_{t-1} is the lagged AQL; r_{t-1} is the lagged daily return on the S&P 500 Index; SAD is Seasonal Affective Disorder; Temp is the average daily Temperature; The following six variables are dummy variables: Monday, January, Lunar, Summer, Rain and Fog. The correlation matrix in this table demonstrates that both AQI and AQL, whether lagged or not, are strongly and positively correlated. The three seasonal variables – Summer, SAD and Temp - are strongly correlated with each other, and they are also strongly correlated with the January variable. Finally, Fog and Rain are also strongly correlated. The symbols ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

The table2 demonstrates the regression results of one of Eq. (5)'s versions. The first, second and third value for each of the four regressions represent, respectively, the OLS coefficient value on the first line of the table, its t-statistic on the second line, and the significance level on the third line. The seasonal variable is measured by Summer, SAD, Temp and January corresponding respectively to Regressions 1, 2, 3 and 4 in the table. The number of observations is 2,615 days. The central finding in the table is the statistically significant ($\alpha < 2\%$) impact of the AQI variable on

the returns of the S&P 500 Index. The other variables were not found to be statistically significant. The findings for the Breusch-Pagan test indicate that the errors are not homoscedastic.

Table 2: Regression Results of the Relationship between the S&P 500 Index Daily Return and Selected Explanatory Variables, January 1, 1997 – June 30, 2007

Regression	1	2	3	4
Intercept	0.0015 2.75 0.0060	0.0011 1.98 0.0472	0.0018 2.13 0.0306	0.0013 2.54 0.0107
AQI_t	-0.00003 -2.4 0.0161	-0.00003 -2.44 0.0147	-0.00002 -2.30 0.0233	-0.00003 -2.48 0.0150
r_{t-1}	-0.0255 -1.31 0.1920	-0.0257 -1.31 0.1889	-0.0254 -1.30 0.3473	-0.0251 -1.28 0.3530
Monday	0.0001 0.28 0.8124	0.0001 0.25 0.8051	0.0001 0.24 0.8140	0.0001 0.24 0.8164
Lunar	0.0002 0.33 0.7409	0.0002 0.33 0.7408	0.0002 0.32 0.7457	0.0002 0.32 0.7443
Fog	-0.0001 -0.11 0.9095	-0.0001 -0.11 0.9147	-0.0001 -0.12 0.9086	-0.0001 -0.16 0.8727
Season	-0.0004 -0.95 0.3422	0.0003 1.22 0.2226	-0.0000 -0.69 0.4856	0.0001 0.08 0.9345
Breusch-Pagan test	117.17	115.25	108.41	105.39
Akaike	-8.9544	-8.9547	-8.9543	-8.9541
Hannan-Quinn	-8.9487	-8.9490	-8.9486	-8.9484
Schwarz	-8.9387	-8.9390	-8.9386	-8.9384

The dependent variable in Table 2 is the daily return on the S&P500 Index, and the independent variables are as

follows: AQI, the lagged daily return on the S&P 500 Index (r_{t-1}), Monday, Lunar, Fog and one of the following four seasonal variables -- Summer, SAD, Temperature and January -- each in one of the four regressions in this set. The central finding in the table is the statistically significant ($\alpha < 2\%$) negative impact of the AQI on stock returns. In fact, the AQI in this 4-regression set emerged as the only significant variable. While the direction of the impact of Lunar, Fog and the seasonal variables -- Summer, SAD and Temperature -- is generally consistent with those of Yuan et al. (2005), Cao and Wei (2005), Kamstra et al. (2003) and Saunders (1993), the impact is not statistically significant.⁶

The findings in Table 2 above for the January and r_{t-1} variables are in line with Bouman and Jacobsen's (2002) conclusion that one advantage of using stock market indices is that they exhibit less autocorrelation and are less influenced by the January effect anomaly, which is closely related to the small-firm effect. Note that recent empirical studies of market anomalies have found that the Monday and January effects are not statistically significant

Essentially very similar results are obtained when the AQI is replaced with the AQL pollution dummy variable, and when Fog is replaced with Rain. In other words, in all 16 regressions, the only statistically significant variables are the pollution variables - AQI and AQL; both are significant at $\alpha < 2\%$. As implied by Table 2, the significance level of the AQI variable in the four regressions, reported in Table 2, ranges between 1.47% and 2.33%.

As indicated by Table 2, the values of the three information criteria -- AIC, BIC and HQC -- are very similar both to each other and across all four equations -- 1 to 4 in the table. Specifically, the value for both AIC and BIC is -8.95,

while for HQC it is -8.94. These findings imply that none of the four equations is superior to the others. This result is consistent with Jacobson and Marquering's (2008) conclusion that all three seasonal variables – Summer, SAD and Temperature -- produce the same result. The finding is also consistent with the high simple correlation values (reported in Table 1) between these three seasonal variables as well as the January effect. As stated above, the test results from all four equations demonstrate the statistical significance of the pollution variable and the non-significance of the other variables.

We also conducted a Breusch-Pagan test on the data. Its values for all four equations in Table 2 indicate that the regression errors are not homoskedastic. We therefore re-estimated Eq. (5) using a GARCH (1,1) model, as described by Eq. (6) above. The estimation results of Eq. (6) for the four equations in Table 2, not shown here, are very similar to the OLS results in Table 2.

For all four GARCH equations, the values of the information criteria – AIC, BIC and HQC -- are -9.00, -8.99 and -8.98, respectively. Given this similarity across the four equations, the estimation results for only the fourth equation is given below:

$$\begin{aligned}
 r_t &= \beta_0 + \beta_1 AQL_t + \beta_2 r_{t-1} + \beta_3 Monday_t + \beta_4 Lunar_t + \beta_5 Fog_t + \beta_6 Season_t + e_t \\
 &= \begin{matrix} 0.0016 & -0.00003AQL_t & -0.0257r_{t-1} & +0.00002Monday_t & +0.0004Lunar_t \\ (2.80) & (-2.48) & (-1.16) & (0.04) & (0.70) \end{matrix} \\
 &\quad +0.0001Fog_t \quad +0.0002Season_t \quad + e_t \\
 &\quad (0.12) \quad (0.25)
 \end{aligned} \tag{8}$$

The GARCH estimates are

$$\begin{aligned}
 \sigma_t^2 &= \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 e_{t-1}^2 \\
 &= 0.0001 + 0.1603\sigma_{t-1}^2 + 0.1348e_{t-1}^2 \\
 &\quad (8.98) \quad (2.58) \quad (6.40)
 \end{aligned} \tag{9}$$

and the Maximum Likelihood value is 8,069, where all three GARCH coefficients -- α_0 , α_1 and α_2 -- are statistically significant. The notation is as defined before, and the t-statistic appears in the parenthesis.

These estimation results, like those for the OLS results in Table 2, once again validate the significance of the pollution variable and the non-significance of the other variables.

We have also estimated simple regression equations for the daily return and each of the independent variables. As in the multi regressions, in the simple regressions, the only variable that emerged as statistically significant is the pollution variable – AQI and AQL. Finally, we obtained results similar to those for the S&P 500 Index reported above for the other three indices – the DJIA, the NASDAQ Composite and the AMEX Composite.

A2. Testing for the Time-Lagged Impact of Air Pollution

Underlying Eq. (5) is the assumption of a no-time lagged relationship between air pollution and stock returns. The findings reported above suggest that such a relationship exists. To investigate whether the previous day's pollution level is also related to the current day's stock return, we estimated the following equation, accompanied by the findings for the S&P 500 Index:

$$\begin{aligned}
 r_t &= \beta_0 + \beta_1 AQL_t + \beta_1 AQL_{t-1} + e_t \\
 &= \begin{matrix} 0.0004 & -0.0043 & -0.0019 \\ (1.85) & (-2.20) & (-0.87) \end{matrix}
 \end{aligned} \tag{10}$$

where all variables are as defined before, the t-statistic is in parenthesis and the number of days is 2,615. These findings demonstrate that the impact on stock returns of the lagged pollution variable, like that of the current-time variable, is negative but not statistically significant. Similar results are obtained when AQL is replaced with AQI, and when the other stock indices are used.

A3. Implications for Risk Aversion

The findings in this study imply that there might be a chain linking air pollution, mood, decision making and risk taking. For example, based on their experiments, Leith and Baumeister (1996) conclude that bad moods cut short the rational consideration of options and foster risk taking by impairing self regulation instead of by altering subjective utilities. Using three experiments, Constans and Mathews (1993) also find a relationship between mood and the subjective risk of future events.

Thus, a bad mood due to air pollution can change the risk premium. In their study of the SAD effect, Garret *et al.* (2005) argue that the SAD effect may well be a consequence of changes in risk aversion over time.

The psychological studies reviewed in Section I imply that the mood effects of air pollution can be expressed as aggression and hopelessness. Thus, the investor may exhibit a higher degree of risk taking, or, equivalently, a lower degree of risk aversion. As a result, the risk premium becomes lower. Consequently, the collective change in risk aversion might be related to the lower stock returns on Unhealthy days documented in this study.

B. Air Pollution and Stock Returns in Canada

LY confirmed Hypotheses 1 and 2 for the US capital market. This section will examine whether these two hypotheses also hold for the Canadian capital market. The main findings are summarized in Table 3. These findings indicate that while the mean daily stock return on the TSX composite index during Good days is positive (0.08%), during Unhealthy days it is negative. Specifically, this negative return amounts to -0.33%, which is four times larger (in absolute terms) than the corresponding return during Good days. The daily Unhealthy minus Good (UMG) return gap amounts to -0.4% and is statistically significant at 7.8%. These findings partially support H1 regarding the negative relationship between air pollution and stock returns.

H2 states that local air pollution may affect local traders not only with respect to their local trading, but also in terms of their trading on securities exchanges located far from the polluted local area. The findings on the second line in Table 3 indicate that on Good (Unhealthy) days in New York, the daily return on the TSX composite index is 0.04% (-0.31%). The resulting Unhealthy Minus Good (UMG) return difference is -0.35% and is significant at 1%. These findings imply that air pollution in New York not only adversely affects trading on the NYSE, but also trading on distant exchanges such as the TSX. These findings are similar to those of LY with respect to the PHLX being the distant exchange and support H2.

The findings on lines 3 and 4 of Table 3 indicate that the pollution effect exists not only in terms of return differences, but also in terms of the proportion of the differences in positive-return days between Good days and Unhealthy days. Specifically, while this proportion amounts to 0.56 on Good days, it falls to 0.40 on Unhealthy days. As implied by the t-test presented in Eq. 2, this proportion difference is significant at 15%. However, as shown on line 4 of Table 3, for the New York pollution case, the proportion gap between Unhealthy and Good days for the TSX is statistically negative at the 6% level. These findings for the TSX are consistent with LY's findings regarding both the NYSE and PHLX. In other words, there is a pollution effect present in terms of both returns and proportion of positive-return days.

Table 3: Mean Daily Stock Returns and Proportion of Positive Return Days in the TSX by the AQI Level in Toronto and New York

	Good	Unhealthy	UMG	α (%)
TSX Returns (%)	0.08	-0.33	-0.41*	7.8
TSX Returns By NY Pollution (%)	0.04	-0.31	-0.35***	1
TSX Proportion	0.56	0.40	-0.16	15
TSX Proportion By NY Pollution	0.56	0.43	-0.13	6

For the Toronto Stock Exchange (TSX) Composite Index, the table shows the mean percentage daily return for Good and Unhealthy days as well as the Unhealthy Minus Good (UMG) return difference and its significance level (α). TSX Proportion denotes the proportion of positive-return days by daily AQI level. The symbol NY Pollution denotes the relationship between air pollution in New York and returns on the TSX. The t-tests are given by Eqs. (1) and (2).

C. Some Additional International Evidence

Though this study focuses on the US and Canada, some indication about the relationship between air pollution and stock returns is provided here for additional selected countries. However, air pollution data for countries other than the US and Canada are more difficult to gather.

To provide an international perspective, we selected one country from each of the following three continents – Europe, Asia and Australia. For Europe, we chose the Netherlands because it houses the headquarters of the largest stock exchange in Europe – the Euronext. For Asia, we selected China due to the size of both the country and the Chinese economy. Finally, we included Australia in the international sample. The stock exchanges corresponding to the selected countries on these three continents are the Amsterdam Euronext, Hong Kong and Sydney. The stock return indices selected for these countries are the AEX Index for Amsterdam, the Hang Seng Index for Hong Kong and the S&P ASX200 for Sydney.

While an air quality index is available for Sydney and Hong Kong, we found no such index for Amsterdam. Instead, information about several pollutants was available for Amsterdam. We selected the particular matter pollution measurement (PM10) – the pollutant for which the largest number of observations was available.

As with the US and Canada, here too, the air pollution index has been divided into two distinct categories – Good and Unhealthy -- corresponding to the AQL dummy variable used for the US and Canada. The Environmental Protection Department (EPD) in Hong Kong defines the "Very high" level of its air pollution index as Unhealthy. The Environmental Protection Agency (EPA) in Australia has three levels in its Air Pollution Index – Low, Medium and High – the last of which we characterized as Unhealthy. For Amsterdam, the European standard used by the European Environmental Agency (EEA) was employed, and a level exceeding $75 \mu\text{g}/\text{m}^3$ (in 24 hours) for the pollutant selected was defined as Unhealthy. As with the US and Canadian samples, the sample time period for the three countries ends on June 30, 2007. The start date, however, varies due to data availability, resulting in a number of observations of 1,242, 1,366 and 1,110 days for Amsterdam, Hong Kong and Sydney, respectively.⁷

For each country, the mean value of the daily return on Good days (given by the country's stock index) was computed and compared to the corresponding value on Unhealthy days. A t-test was then applied to the Good minus Unhealthy return difference, and the results appear in Table 5. The main findings for the US and Canada reported in the preceding tables are also reintroduced in Table 5 for comparative purposes.

The table presents the mean daily percentage rate of return on Good days (r_{Good}) and Unhealthy days ($r_{\text{Unhealthy}}$), as well as the Unhealthy Minus Good return difference (r_{UMG}). Table 5 demonstrates that the UMG for each of the three countries is negative and statistically significant at 2.36%, 3.38% and 8.72% for Amsterdam, Hong Kong and Sydney, respectively. These findings are similar to those for the US and Canada reported in the previous sections.

Eq. (3) has been also estimated for each of the three countries. The significance level of the $\beta_1(\text{Polut}_t)$ OLS coefficient in Eq. (3) is provided in Table 5, where Polut is defined as the Air Quality Level (AQL). These regression results indicate that, as in the American and Canadian cases, the relationship between air pollution and stock returns is negative at significance levels of 0.56%, 9.7% and 8.9% for Amsterdam, Hong Kong and Sydney, respectively.

Like the findings for the stock exchanges in New York and Toronto reported above, these findings for the stock exchanges in Amsterdam, Hong Kong and Sydney once again demonstrate that the relationship between air pollution and stock returns is negative.

Table 4: Mean Stock Returns of Pollution-Related Indices by the Daily Air Quality Index (AQI) Levels in New York, Philadelphia, and Toronto for 1997 - 2007 (in percent)

	Good	Unhealthy	UMG
By the Local Pollution:			
New York: Dow Chemical	0.06	-0.46	0.52**
Philadelphia: PHLX Oil Service Sector Index	0.11	-0.75	0.86*
Toronto: TSX Capped Energy Index	0.12	-0.57	0.69***
By the New York Pollution:			
Philadelphia: PHLX Oil Service Sector Index	0.09	-0.56	0.65**
Toronto: TSX Capped Energy Index	0.09	-0.53	0.61***

The table shows the mean daily return on three pollution-related indices by the local pollution level in three cities, New York, Philadelphia, and Toronto, as well as by the New York pollution level. The symbols ***, **, and *

denote statistical significance at the 1%, 5%, and 10% levels, respectively. As noted before, the sample period for Toronto is shorter.

D. Some Additional International Evidence

Though this study focuses on the US and Canada, some indication about the relationship between air pollution and stock returns is provided here for additional selected countries. However, air pollution data for countries other than the US and Canada are more difficult to gather.

To provide an international perspective, we selected one country from each of the following three continents – Europe, Asia and Australia. For Europe, we chose the Netherlands because it houses the headquarters of the largest stock exchange in Europe – the Euronext. For Asia, we selected China due to the size of both the country and the Chinese economy. Finally, we included Australia in the international sample. The stock exchanges corresponding to the selected countries on these three continents are the Amsterdam Euronext, Hong Kong and Sydney. The stock return indices selected for these countries are the AEX Index for Amsterdam, the Hang Seng Index for Hong Kong and the S&P ASX200 for Sydney.

While an air quality index is available for Sydney and Hong Kong, we found no such index for Amsterdam. Instead, information about several pollutants was available for Amsterdam. We selected the particular matter pollution measurement (PM10) - the pollutant for which the largest number of observations was available.

As with the US and Canada, here too, the air pollution index has been divided into two distinct categories - Good and Unhealthy -- corresponding to the AQL dummy variable used for the US and Canada. The Environmental Protection Department (EPD) in Hong Kong defines the "Very high" level of its air pollution index as Unhealthy. The Environmental Protection Agency (EPA) in Australia has three levels in its Air Pollution Index – Low, Medium and High – the last of which we characterized as Unhealthy. For Amsterdam, the European standard used by the European Environmental Agency (EEA) was employed, and a level exceeding $75 \mu\text{g}/\text{m}^3$ (in 24 hours) for the pollutant selected was defined as Unhealthy. As with the US and Canadian samples, the sample time period for the three countries ends on June 30, 2007. The start date, however, varies due to data availability, resulting in a number of observations of 1,242, 1,366 and 1,110 days for Amsterdam, Hong Kong and Sydney, respectively.⁷

For each country, the mean value of the daily return on Good days (given by the country's stock index) was computed and compared to the corresponding value on Unhealthy days. A t-test was then applied to the Good minus Unhealthy return difference, and the results appear in Table 5. The main findings for the US and Canada reported in the preceding tables are also reintroduced in Table 5 for comparative purposes.

The table presents the mean daily percentage rate of return on Good days (r_{Good}) and Unhealthy days ($r_{\text{Unhealthy}}$), as well as the Unhealthy Minus Good return difference (r_{UMG}). Table 5 demonstrates that the UMG for each of the three countries is negative and statistically significant at 2.36%, 3.38% and 8.72% for Amsterdam, Hong Kong and Sydney, respectively. These findings are similar to those for the US and Canada reported in the previous sections.

Eq. (3) has been also estimated for each of the three countries. The significance level of the $\beta_1(\text{Polut}_t)$ OLS coefficient in Eq. (3) is provided in Table 5, where Polut is defined as the Air Quality Level (AQL). These regression results indicate that, as in the American and Canadian cases, the relationship between air pollution and stock returns is negative at significance levels of 0.56%, 9.7% and 8.9% for Amsterdam, Hong Kong and Sydney, respectively.

Like the findings for the stock exchanges in New York and Toronto reported above, these findings for the stock exchanges in Amsterdam, Hong Kong and Sydney once again demonstrate that the relationship between air pollution and stock returns is negative.

The table 5 presents the daily percentage rate of return (r) for Good days (r_{Good}), Unhealthy days ($r_{\text{Unhealthy}}$) and the Unhealthy Minus Good return difference, as well as its significance level for Amsterdam (the Netherlands), Hong Kong (China) and Sydney (Australia). The main findings for the US and Canada reported in the preceding tables are reintroduced in this table for comparative purposes. The stock indices are the AEX Index for Amsterdam, the Hang Seng Index for Hong Kong and the S&P ASX200 for Sydney. For Hong Kong and Sydney the sample time period ends on June 30, 2007, while for Amsterdam it ends on December 31, 2006. In addition, the starting date varies according to data availability. The findings indicate that the Good minus Unhealthy return difference is positive and statistically significant at 2.36%, 3.38% and 8.72%, for Amsterdam, Hong Kong and Sydney, respectively. The

"Pollution regressor sig. level" at the bottom of the table corresponds to the significance level of $\beta_1(\text{Polut}_t)$ OLS coefficient in Eq. (3): $r_t = \beta_0 + \beta_1 \text{Polut}_t + e_t$, where Polut is defined as the Air Quality Level (AQL).

Table 5: Air Pollution and Stock Returns for Selected Countries

	USA	Canada	Netherlands	China	Australia
$r_{\text{Good}} (\%)$	0.04	0.08	0.03	0.06	0.07
$r_{\text{Unhealthy}} (\%)$	-0.45	-0.3	-1.08	-0.09	-0.21
$r_{\text{Unhealthy Minus Good Mean}} (\%)$	-0.49	-0.41	-1.11	-0.15	-0.28
Sig. level (%)	0.7	7.8	2.36	3.38	8.72
Number of days	2,945	717	1,242	1,366	1,093
Pollution regressor sig. level (%)	0.50	0.69	0.56	9.7	8.9

V. Summary and Conclusions

This study addresses several research questions. First, it investigates whether the negative relationship between air pollution and stock returns (found by Levy and Yagil (LY), 2011) also holds when meteorological variables are considered. Second, the study examines whether this negative relationship also holds for a country such as Canada that is economically and geographically close to the United States. Third, the study tests whether this negative relationship is stronger for pollution-related companies in both the US and Canada. Finally, the study also examines whether other countries on different continents also experience falling stock prices when air pollution levels rise. To investigate the first question, we added three additional explanatory variables that LY had not considered—the effects of the phases of the moon, cloud cover and seasons. The last of these factors consists of three variables—summer, SAD and temperature. According to the literature, there is a strong correlation among these three variables, so we considered their potential impact separately.

Our regression results indicate a statistically significant negative impact of air pollution on stock returns. The direction of the impact of the remaining explanatory variables – phases of the moon, cloud cover and seasons (summer, SAD and temperature) -- is generally consistent with the corresponding findings in the literature. Their predictive power, however, beyond that of the pollution variable, is weak and limited. We obtained similar using different stock indices, such as the S&P 500, the DJIA, the NASDAQ Composite or the AMEX. Furthermore, the findings are essentially unchanged whether the pollution variable is measured as the AQI or as a dummy variable.

With regard to the second research question, data from the Canadian capital market support LY's H1 and H2. Specifically, air pollution in Toronto has a negative relationship to stock returns on the Toronto Stock Exchange (TSX). Furthermore, in line with H2, we found that air pollution in New York not only adversely affects trading on the NYSE, but also trading on a distant exchange such as the TSX.

Stronger support for H1 and H2 is also evident in the finding that air pollution has a negative effect on returns in pollution-related companies – as suggested by the third research question represented by H3. The return difference between Unhealthy and Good days is statistically higher for the Dow Chemical, the PHLX Oil Index and the TSX Energy Index than for the ordinary composite stock indices in the NYSE, PHLX and TSX.

With respect to the last research question, we establish empirically that the negative relationship between air pollution and stock returns not only holds for the US and Canada, but also for each of the other three countries selected from Europe, Asia and Australia. For the Amsterdam AEX Index, Hong Kong Hang Seng Index and Sydney S&P ASX200 Index we found that the Unhealthy-Good return difference is statistically negative. In addition, the relationship between air pollution and stock returns for these three countries' stock indices⁸ is negative at significance levels ranging from 0.56% to 9.7%.

In sum, the overall findings of this study appear consistent with the evidence reported in psychological studies that air pollution has a negative impact on behavior and decision making. Establishing that the decisions of stock traders worldwide may be affected by air pollution levels, even those in areas far away from the exchanges on which these traders do business, has profound implications for the world of investment.⁹

VI. Footnotes

1. In LY's study, the stock market chosen outside New York is the Philadelphia Stock Exchange (PHLX). In this study, we use the Toronto Stock Exchange (TSX). Though both exchanges are electronic markets and can receive orders from any part of the world, it seems reasonable that due to the close economic and political

relationship between the US and Canada, as well as the relatively short geographical distance between both exchanges (both markets are located on the east coast), NYSE traders may generally account for a relatively large share of the TSX's trading volume. Studies indicate (see, e.g., Hau and Rey, 2008) that US traders account for about half of the trading in the Canadian stock market.

2. As stated in the introduction, this study extends both LY (2011) and Jacobsen and Marquering (2008). Like numerous prior studies, the latter also incorporates the Monday and January effects into the return regression. While studies have found that these effects are related to stock returns in numerous countries, the magnitude of these effects has become weaker in recent years (see, e.g., Brusa *et al.*, 2003).
3. As indicated above, Eq. (7) is a short version of Eq. (4). However, to focus solely on the time-lagged impact of air pollution, we have estimated Eq. (7) separately. We discuss the findings in Section 4.1.2.
4. In selecting the AQI, our purpose has been to adopt an air quality index that is constructed and reported by the US EPA. According to the EPA, the AQI indicates the level of air pollution and health issues associated with these levels, thereby helping us delineate the relationship between air quality and health.
5. While there are several monitoring stations in each county, the U.S. EPA publishes the AQI daily data for the county level only – not for individual monitoring stations. Compared to Kings County, the distance between the monitoring stations located in New York County and the NYSE ranges between 1 and 8 miles with a mean distance of roughly 5 miles. Thus, Kings County is closer to the NYSE than New York County.
6. It can be argued, alternatively, that if a coefficient is not statistically different from zero, its sign is irrelevant.
7. The web sites of the relevant government environmental agencies for the Netherlands, Australia and China are respectively: <http://www.eea.europa.eu/>, <http://www.epa.nsw.gov.au> and <http://www.epd-asg.gov.hk/>.
8. To be compatible with the literature, the current study, like all prior similar studies, uses stock indices. The extension to individual stocks may be an extension that is worth pursuing.
9. LY (2011) have already shown that the air pollution effect is economically exploitable. Specifically, they demonstrate that an AQI-based investment strategy yields a much higher return than a simple buy and hold policy.

VII. References

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Appendix A. The Unhealthy Days in Kings County and the Corresponding S&P Return

NO.	Date	AQI Level	S&P Return (%)
1	11/2/1999	106	-0.47
2	10/27/2000	156	1.11
3	12/11/2000	107	0.75
4	5/3/2001	106	-1.49
5	5/4/2001	110	1.44
6	6/13/2001	120	-1.13
7	6/14/2001	103	-1.75
8	6/28/2001	101	1.25
9	8/6/2001	119	-1.14
10	8/7/2001	116	0.33
11	8/9/2001	107	-0.01
12	8/10/2001	115	0.57
13	4/17/2002	108	-0.20
14	6/26/2002	108	-0.27
15	7/2/2002	109	-2.12
16	7/8/2002	131	-1.22
17	7/9/2002	147	-2.47
18	7/12/2002	152	-0.64
19	7/18/2002	117	-2.70
20	7/19/2002	104	-3.84
21	8/13/2002	116	-2.17
22	6/26/2003	135	1.08
23	6/27/2003	146	-0.97
24	8/13/2003	109	-0.64
25	8/21/2003	101	0.30
26	8/22/2003	116	-1.02
27	10/9/2003	123	0.48
28	5/12/2004	118	0.17
29	5/13/2004	104	-0.08
30	6/8/2004	107	0.15
31	6/9/2004	109	-0.95
32	7/22/2004	128	0.27
33	8/20/2004	101	0.65
34	7/19/2005	104	0.67
35	7/26/2005	109	0.17
36	9/13/2005	109	-0.75
37	5/31/2007	108	0.03

Unhealthy" in our study includes two AQI categories: "Unhealthy Sensitive" and "Unhealthy."