Environmental Stressors, Mood, and Investment Decisions: Evidence from Ambient Air Pollution

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Abstract

The evidence produced in the fields of medicine and psychology is employed to build a behavioral hypothesis according to which daily increases in the ambient levels of air pollution would be expected to negatively affect agents' moods, in turn inducing them to reduce their demand for risky stocks and, ultimately, depressing equity returns. Such a conjecture is tested using a natural experiment provided by a stock market institutional change. Contrary to the predictions of traditional asset pricing theories, the empirical results seem to confirm the existence of a "mood effect" that is essentially attributable to the traders physically located in the city that hosts the Stock Exchange. The findings turn out to be robust to the use of alternative pollution proxies, estimation frameworks, and sets of control variables. An instrumental variables estimation procedure is also implemented to address some potential issues of endogeneity, and provides further support for the hypothesis under investigation. From a larger perspective, the findings also represent a challenge to the Efficient Market Theory, as it is shown that there exist some unexploited profitable trading strategies based on public air pollution data.

Keywords: Air pollution; Mood misattribution; Stock returns; Milan stock exchange; Market efficiency; Behavioral finance; Weather effect; Calendar anomalies

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There's so much pollution in the air now that if it weren't for our lungs there'd be no place to put it all

- Robert Orben

It has long been suspected that some environmental stimuli have the power to affect moods. For example, background music has long been in use in retail stores and offices, allegedly to elicit certain desired behaviors or attitudes among shoppers or employees (Milliman, 1982; Bruner, 1990). Indeed, marketing researchers have been investigating for decades how the store environment can be manipulated so as to influence consumer purchases (Turley and Milliman, 2000). More recently, this kind of effort has found a sound theoretical justification in the psychological literature, whose findings tend to support the view that the emotional state experienced at the time of making a choice can bias the decision-making process (e.g. Schwartz and Clore, 1983; Johnson and Tversky, 1983; Schwartz, 1990; MacLeod and Campbell, 1992; Mann, 1992; Isen and Labroo, 2003).

Applying this same line of reasoning to the field of finance is tempting for two reasons. First, showing that investment decisions can be influenced by mood patterns triggered by some environmental stressors would support the claims of behavioral finance advocates, according to whom some psychological forces play a role in determining the equilibrium prices that prevail in the financial markets (Thaler, 1993). Second, the computations required for making investment decisions are typically complex, abstract, and involve risk, which are precisely the attributes that are believed to induce people to rely more heavily on their emotions when making a choice (Forgas, 1995).

The present paper intends to give a contribution to this strand of literature by investigating whether air pollution, through the adverse impact it is believed to have on people's physical and psychological spheres, is able to exert a depressing influence on investment decisions and, ultimately, on stock returns. Such a research question has been stimulated by some promising findings that have emerged in the field of behavioral finance, and the specific hypothesis that undergoes empirical testing has been strictly built upon the evidence produced in the disciplines of medicine and psychology. As such, the results can hardly fall under the criticism of data snooping.

The empirical analysis is conducted using data from the Italian stock market[1]. Two are the main reasons that led to this choice. First, Milan, which hosts the corresponding Stock Exchange, appears to be among the cities that have been suffering the most from the air pollution phenomenon, at least within the industrialized countries (The New York Times, 1989; International Herald Tribune, 2007). Second, the MSE underwent a major institutional change in the middle of the 1990's, which provides a natural experiment that can shed light on the hypothesis under investigation (e.g., Pardo and Valor, 2003). In particular, trading at the MSE switched from an open outcry system to a computerized and decentralized one. If air pollution was an effective mood proxy and mood had an influence on portfolio decisions, then daily air pollution measured in the city of Milan should exhibit a significant (negative) relationship with Italian stock returns only during the era in which trading would physically take place on the floor of the MSE.

After controlling for well-known calendar anomalies, behavioral variables, and international economic shocks, the empirical analysis produces results that are indeed consistent with the hypothesis under scrutiny, for daily air pollution concentrations are estimated to have a significant negative correlation with stock returns during the sub-period in which trading was centralized, whereas no connection is detected after the trading switch. Furthermore, the lag structure of the air pollution effect appears to mimic the evidence generated by medical and psychiatric studies, as changes in air pollution levels (proxied by particulate matter) are estimated to have both a contemporaneous and a lagged relationship with equity returns.

The results turn out to be robust to the use of alternative air pollution proxies (nitrogen oxides, sulfur dioxide), estimation frameworks (GARCH, OLS, Logit), and sample choices.

[1] The expressions "Italian stock market" and "Milan Stock Exchange" (MSE) will be used interchangeably throughout the paper, as the city of Milan hosts the main (and now sole) Italian stock exchange.

A potential endogeneity problem arises due to the links that air pollution has with economic activity on the one hand and social costs on the other hand. Though several clues, as discussed later, suggest that the detected air pollution effect is not caused by these links, an instrumental variables estimation is carried out in order to identify more precisely the influence that pollution has on investment decisions. More specifically, three lagged meteorological variables are employed as instruments: wind speed, atmospheric pressure, and rainfall. Empirically, these variables show a high correlation with the endogenous variable and moreover, it seems very reasonable to believe that they do not have any systematic relationship with either current economic activity or equity returns. As a result, we think that the empirical findings, which confirm the outcomes of the previous steps, are indeed consistent with a causal impact of air pollution on mood, portfolio decisions and, ultimately, on stock returns.

These results are remarkable on two grounds. First, by reinforcing the findings of similar investigations, they bring a challenge to the paradigm that has been dominating economic analysis, according to which only purely economic factors play a role in asset pricing. Second, they constitute an anomaly when interpreted in light of the Efficient Market Theory, as the study reveals the existence of some unexploited profitable trading strategies based on past (and public) air pollution data.

Future research efforts may want to extend this framework to other financial markets, especially those that still operate through open outcry trading systems. The use of experimental data seems quite problematic in this particular setting, but alternative environmental stressors could be employed successfully maintaining a similar approach.

The rest of the paper is organized as follows. Section I discusses the mechanisms through which investment decisions are conjectured to be affected by some psychological factors, and comments on the empirical evidence produced so far. Section II gives on overview of the air pollution phenomenon and section III examines the effects it has been found to exert on the human body and psyche. Section IV puts forward the behavioral hypothesis that will be tested, and section V describes the data. Section VI explores some potential sources of endogeneity, and the empirical analysis is conducted in section VII, which also contains a battery of robustness checks. Section VIII investigates the implications that the findings have in light of the Efficient Market Theory. Section IX concludes.

I. Environment, Affective State, and Decision-Making

In the last ten years or so, finance researchers have begun to investigate a subject that has been attracting marketing experts' attention for decades. The question of whether and how the store environment can be used to affect the time and money that consumers spend in the store, obviously, has always been of interest to retailers. The concept of "store atmospherics", introduced by Kotler (1973-1974), refers precisely to "the effort to design buying environments to produce specific emotional effects in the buyer that enhance his purchase probability". From a theoretical viewpoint, this kind of endeavor can find validation, for example, in the work of Byrne and Clore (1970), who maintain that "affect elicited by a stimulus conditions behavior and attitudes toward other stimuli merely associated with it". In other words, the emotional state experienced at the time a decision is being made is likely to condition the decision itself (Isen et al., 1978; Frijda, 1988; Forgas, 1995; Loewenstein, 2000), for emotions are believed to regulate thought and inform judgment and cognitive evaluations (Damasio, 1994; Loewenstein et al., 2001). Many emotions are believed to have emerged as useful responses from evolutionary conditioning (Frank, 1988; LeDoux, 1996), and help individuals economize on information processing, as "emotion allows people to transcend the details, prioritize, and focus on the decision to be made" (Ackert et al., 2003). Interestingly, psychologists posit that the same rules of thumb (or heuristics) that regularly help people make decisions, might occasionally lead them astray. When mood works as a "source of information" to individuals, it might influence their choices even in those circumstances when the source of the mood state does not have anything to do with the decision being made, i.e. a mechanism of "mood misattribution" may be at work (Schwartz and Clore, 1983; Schwartz, 1990).

Such a hypothesis can find support, for instance, in several studies on consumer behavior. Product choice, purchase intentions, behavior traits, and actual purchases have all been shown to be partly affected by factors such as in-store music, ambient scent and illumination (Milliman, 1982; McElrea and Standing, 1992; Areni and Kim, 1993; Gulas and Bloch, 1995; North and Hargreaves, 1996; 1997; 1998; Summers and Hebert, 2001). These findings appear to be hard to reconcile with the rationality assumption typically evoked by economists.

It seems therefore natural to wonder whether these fascinating results can be extended so as to encompass a broader set of human decisions and a wider definition of environment. This is exactly where finance researchers come into play. Indeed, one of the strands of literature spawned by the growth of behavioral finance, at the end of the 1990's, has started to show a keen interest in the relationship between investor mood and investment decisions[2]. Broadly speaking, behavioral finance advocates claim that, contrary to the view of the paradigm that has dominated economic analysis (labeled by Shiller (2006) as "neoclassical finance"), several psychological factors play a role in the mental process that originates people's investment decisions and, as such, these same factors could be successfully incorporated into asset pricing models (e.g., Kahneman and Tversky, 1979; Kahneman and Riepe, 1998). More narrowly, the strand of literature previously mentioned has focused on trying to identify some environmental variables that might act as mood proxies for large groups of investors, the rationale being that changes in the environment may trigger mood changes and, ultimately, have an impact on investment decisions through, for example, the mood misattribution mechanism. The seminal contribution in this area can be traced back to Saunders (1993), who, employing the percentage cloud cover in New York city as a proxy for investor mood, observes that such an explanatory variable exhibits a significant relationship with the returns of three global indices of the U.S. stock market. These results have been challenged by some subsequent investigations (Pardo and Valor, 2003; Keef and Roush, 2003; Tufan and Hamarat, 2004; Loughran and

[2] For an excellent review, see Lucey and Dowling (2005a).

Schultz, 2004; Lucey and Dowling, 2005a; Goetzmann and Zhu, 2005), yet some supporting evidence has also been produced (Hirshleifer and Shumway, 2003; Chang et al., 2006).

Along similar lines, alternative environmental factors have been used as proxies in an attempt to capture some collective mood-swing patterns. These include temperature (Keef and Roush, 2003; Cao and Wei, 2005; Chang et al., 2006), humidity (Pardo and Valor, 2003; Chang et al., 2006), rain and snow (Hirshleifer and Shumway, 2003), wind (Keef and Roush, 2003), and seasonal light cycle (Kamstra et al., 2003). The findings are encouraging for behavioral finance proponents and, from a larger perspective, also suggest that empirical work in this area should be deeply rooted into some underlying psychological/medical hypotheses in order to produce reliable results.

This is precisely the goal of the present investigation. Particular care is paid in the next few sections to the shaping of a behavioral hypothesis that is strictly built upon medical and psychological findings and is subsequently tested empirically. Here the focus will be on ambient air pollution, which, indeed, can be considered as one of the most critical environmental stressors to which individuals are exposed, and has been deemed responsible for a broad spectrum of physical and psychological effects on human beings. Based on the evidence offered in the relevant literature, it will be possible to identify an unequivocal hypothesis according to which daily increases in air pollution concentrations can be expected to cause increased psychological distress (i.e., a mood deterioration) and, in turn, a reduced demand in the stock market. It is therefore conjectured that, *ceteris paribus*, air pollution should have a negative marginal effect on equity returns. The empirical analysis, carried out in the following sections, indeed seems to produce results that are highly consistent with such an interpretation. The first step now will consist in presenting an overview of the air pollution phenomenon and of its consequences.

II. Ambient Air Pollution: Taxonomy and Sources

Air pollution is an umbrella term that refers to the presence of unhealthy particles and gases in the atmosphere that may endanger the health of humans, animal life, plants, and may even damage objects such as statues and buildings[3]. In this paper, most of the analysis is centered upon one specific constituent of air pollution, i.e. Particulate Matter (PM). Yet some attention is also devoted to the examination of the role played by nitrogen oxides (NO_x) and sulfur dioxide (SO_2). Several reasons have contributed to this choice; first, as the following sections will show, most epidemiological, toxicological and psychological studies have focused on these compounds, especially on PM. Second, data about daily concentrations of these pollutants in Milan and neighboring cities are readily available and reliable. Third, though these three pollutants are somewhat related to each other, as discussed later, their emission into the atmosphere originates from rather different sources, which will allow us to address more convincingly some potential issues of endogeneity.

PM consists of "a complex mixture of solid and liquid particles of organic and inorganic substances suspended in the air" (WHO, 2003). These suspended particles may vary in composition, size, and origin, and are generally classified by their aerodynamic diameter. Total Suspended Particulates (TSP) include all airborne particles. PM_{10} refers to particles with an aerodynamic diameter less than 10 μm (micrometers). $PM_{2.5}$ is used for particles with a diameter less than 2.5 μm. PM can either be directly emitted into the air (primary PM) or be formed secondarily (secondary particulate) in the atmosphere from gaseous precursors, mainly SO_2, NO_x, ammonia, and non-methane volatile organic compounds (WHO, 2006). The largest particles typically consist of wind-blown dust from agricultural processes, mining operations, uncovered soil, and unpaved roads. Road dust caused by traffic is also a critical contributor to this category. Additional inputs come from mould spores, plant and insect parts, and pollen grains. Smaller particles (diameter less than 2.5 μm) are largely formed from gases, whereas the smallest ones are formed by nucleation from heavy

[3] See Colls (2002) for an introduction to air pollution.

metals, elemental carbon, organic carbon, sulfates, and nitrates (WHO, 2003). According to WHO (2006) the major share of TSP emissions at the European level is estimated to originate from "the combustion of solid fuels in small stoves in the residential and commercial sectors, followed by industrial emissions from energy combustion and manufacturing processes and from agricultural activities".

Residence time in the atmosphere is a key factor in determining the travel distance of air pollutants. The residence time of PM in the atmosphere may vary from 1-2 days to 4-6 days, depending mainly on the size and chemical composition of the particles (WHO, 2006). The larger particles are more easily deposited and normally travel less than 6 miles from their place of origination. Yet, dust storms may transport them for over 600 miles. Primary fine particles can travel up to 1200-1800 miles, which implies that pollutants emitted in one region can affect PM concentrations in adjacent regions and even in neighboring countries.

The symbol NO_x is used to represent the total concentration of nitric oxide (NO) plus nitrogen dioxide (NO_2). NO reacts with the oxygen in air to form nitrogen dioxide (Cotton et al., 1999). Although there are natural sources of NO_x (e.g., volcanic action, forest fires), the combustion of fossil fuels is the major contributor in European urban areas (WHO, 2003). Traffic, in particular, represents the major anthropogenic source of NO_x, followed by stationary sources such as power plants, domestic heating, furnaces and boilers. As a result, NO_x is a good indicator of automotive emissions, which also makes it a proxy for other unmeasured pollutants emitted by vehicles (Samakovlis et al., 2004). Additionally, NO_x is "a precursor for a number of harmful secondary air pollutants, including nitric acid, the nitrate part of secondary inorganic aerosols and photo oxidants" (WHO, 2003).

Outdoor SO_2 is the main product from the combustion of sulfur compounds. The most important natural sources of SO_2 are volcanoes, forest fires, and oceans. As far as anthropogenic emissions are concerned, they can be mainly tracked back to residential heating, power plants, smelting of metals, paper manufacture and, residually, traffic (ARPA, 2003). Beyond being part of air pollution *per se*, sulfur dioxide and nitrogen oxides also play a role in the acid rain phenomenon, as they mix with water vapor in the atmosphere and then fall to earth as rain, snow and mist (McCormick, 1989).

Human beings are exposed to air pollution by inhalation and through contact with the skin and the eyes (Oehme et al., 1996). Though people spend the majority of their time indoors, WHO (2006) maintains that outdoor concentrations of air pollutants, typically measured through monitoring networks, are representative of population exposure.

Throughout the paper, PM, NO_x, and SO_2 will be merely regarded as proxies for air pollution, keeping in mind that the impact they may be found to have on mood, investment decisions and, ultimately, on equity returns might originate from a mixture of pollutants[4].

III. Human Reaction to Air Pollution

A. Physiological Effects

Air pollution has been the core of a massive number of neuro-toxicological and epidemiological studies[5]. Short-term and long-term exposures to ambient air pollution have been linked to a wide variety of acute and chronic health effects, respectively, ranging from slight irritation symptoms to restricted activity and to death (American Thoracic Society, 2000; WHO, 2001). A partial list of health outcomes, arranged in order of severity, is shown in Figure 1 in the form of a pyramid. Such a shape is meant to emphasize that, though the most serious effects are confined to a relatively small fraction of the population, some minor symptoms and physical distress are estimated to be experienced by a huge number of people.

Figure 1 approximately here

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[4] The investigations conducted in the fields of epidemiology and toxicology have not been very successful yet at isolating the health effects of individual pollutants, for toxins are normally present in the atmosphere in the form of mixtures. The issue is further enhanced by the fact that combinations of different air pollutants are conjectured to give rise to dynamic chemical reactions and generate synergistic effects (Samakovlis et al., 2004). Additionally, any given chemical might interfere with the absorption or detoxification of some other substances (Oehme et al., 1996).

[5] See WHO (2003) for a detailed list of references.

A.1. Morbidity and Mortality

PM appears to be the most widely investigated factor, and there is growing evidence pointing at PM as a dangerous contaminant *per se* (WHO, 2006). The research conducted in this area has detected a broad spectrum of short-term effects, ranging from lung inflammatory reactions and respiratory symptoms to increases in hospital admissions and mortality rates (Ostro et al., 1995; Dockery and Pope, 1996; Pope, 1996; Cropper et al., 1997; Daniels et al, 2000; Chay and Greenstone, 2003; Peng et al., 2004; Peng et al., 2005; Maynard et al., 2007). Similarly, long-term exposure has been associated with rises in cardiovascular diseases and reduced life expectancy (Ostro, 1994; Brunekreef, 1997; Abbey et al., 1999; Panyacosit, 2000; Pope et al., 2002). Focusing on morbidity rates, for example, Ostro and Rothschild (1989), using US data from the Health Interview Survey, maintain that there exists a short-term positive association between fine particulate and "both minor restrictions in activity and respiratory conditions severe enough to result in work loss and bed disability in adults". Taking a closer look at Italian data, Michelozzi et al. (1998), using a sample covering the period 1992-1995, find that a 10 $\mu g/m^3$ increase in TSP in Rome is estimated to generate a concurrent 0.4% increase in total daily mortality. A comparable relationship (at lag 0 and 1) is detected by Biggeri et al. (2001) using daily data about PM_{10} from eight Italian cities, and by Le Tertre et al. (2005) with regard to the city of Milan.

The picture does not change substantially when it comes to NO_x, which is also believed to have relevant effects on morbidity and mortality rates, both in the short- and in the long-term (Love et al., 1982; Sexton et al., 1983; Koenig et al., 1987; Folinsbee, 1992; Salome et al., 1996; Strand et al., 1997; Morgan et al., 1998; Blomberg et al., 1999; Erbas and Hyndman, 2001; Samakovlis et al., 2004; Schildcrout et al., 2006). In their study on Italian data, Michelozzi et al. (1998) estimate that a 10 $\mu g/m^3$ increase in NO_2 (at lag 1 and 2) produces a 0.3%-0.4% increase in total daily mortality, the impact being stronger on those people living in the city center. An analogous representation emerges from the investigations on Italian data conducted by Biggeri et al. (2001) and Fusco et al. (2001), the latter finding that total respiratory hospital admissions are significantly correlated with same-day levels of NO_2.

Moving to the third air pollutant under investigation, sulfur dioxide (SO_2), there exists an extensive body of research documenting its adverse influence on respiratory symptoms, cardiovascular diseases, and premature mortality (Chinn et al., 1981; Krzyzanowsli and Wojtymiak, 1982; Bates and Sizto, 1983; Schwartz et al., 1988; Derriennic et al., 1989; Ponka, 1990; Schwartz et al., 1991; Ostro, 1994, Sunyer et al., 1996; Wong et al., 2002; Low et al., 2006; Chen et al., 2007). Among the investigations on Italian data, a significant association between daily SO_2 levels and some relevant health outcomes has been found, for example, by Ciccone et al. (1995), Vigotti et al. (1996), and Cadum et al. (1999).

A.2. Threshold Concentrations

A crucial question is whether there exists a threshold below which no effects of air pollution on human health are to be anticipated. With regard to PM, the World Health Organization conducted a review study with the specific purpose of giving an answer to such a question, concluding that "most epidemiological studies on large populations have been unable to identify a threshold concentration below which ambient PM has no effect on mortality and morbidity. It is likely that within any large human population, there is a wide range in susceptibility so that some subjects are at risk even at the low end of current concentrations" (WHO, 2006). A similar rationale induced the World Health Organization to state that "there is no evidence for a threshold for NO_2" (WHO, 2006).

More uncertainty surrounds the third pollutant under observation, SO_2. In the 2005 update of its air quality guidelines, the World Health Organization, after giving emphasis to the finding that sulfur dioxide "was significantly associated with daily mortality in 12 Canadian cities with an average concentration of only 5 $\mu g/m^3$", claims that, if there were some significant SO_2 thresholds, they "would have to be very low" (WHO, 2005).

A.3. Cortisol Levels

Among the direct physiological effects of air pollution, one turns out to be particularly intriguing in the current context. Several studies conducted on animals and human subjects have documented that urban air pollutants may trigger increases in bodily cortisol levels (Dorow et al., 1983; Raff et al., 1985; Hsieh et al., 1992; Etkina and Etkina, 1995; Tomei et al., 2003; Nowakowicz-Debek et al., 2004). Cortisol is a hormone produced by the adrenal cortex, and is believed to play "a central role in the physiological and behavioral response to a physical challenge or psychological stressor" (Coates and Herbert, 2008). Several psychological studies suggest that there exists a negative relationship between cortisol levels and risk taking behavior (Rosenblitt et al., 2001). In particular, individuals who experience high cortisol levels are believed to be less likely to engage in sensation seeking behaviors (Mazur, 1995; Netter et al., 1996; Wang et al., 1997), where sensation seeking is defined as "pursuing and taking risks in order to experience a variety of new sensations" (Zuckerman, 1979). Taking a closer look at the realm of financial markets, such a conjectured shift in risk preferences is indeed consistent with the findings of Coates and Herbert (2008), who experimentally measured the daily levels of such a hormone in a sample of male financial traders under real working conditions.

In the present framework, the evidence just discussed can now be employed to propose the first channel through which air pollution is hypothesized to affect investment decisions (Figure 2). More specifically, increases in air pollution concentrations are believed to cause increases in bodily cortisol levels, which in turn are conjectured to intensify agents' risk aversion and, ultimately, reduce demand in the stock market and compress equity returns[6]. The second channel, which is more psychological in nature, will be discussed in a subsequent section.

[6] This is, of course, a conjecture. The exact underlying mechanisms are left for investigation to others, such as environmental toxicologists and experimental psychologists.

B. Psychological Effects: Mood Deterioration

Apart from its well documented biophysical effects, air pollution has also been found to have an impact on human mental and emotional health (see Figure 2). Meertens and Swaen (1997) even claim that the latter might often be of greater importance to well-being than the former. Perceived effects, such as annoyance, have been detected in numerous studies (e.g., Forsberg et al., 1997; Klaeboe et al., 2000; Danuser, 2001; Rotko et al., 2002). Peper (1999) states that human beings exposed to neurotoxins "may exhibit alterations in cognitive and affective functioning, and report a wide range of subjective symptoms", a point of view that is shared by numerous other investigations (e.g., Weiss, 1983; Evans and Cohen, 1987; Schottenfeld, 1992). Among the symptoms, feelings of fatigue, low mood and exhaustion have shown a significant association with air quality (Sagar et al., 2007). Indeed, air pollution can represent "a major stressful stimulus to exposed persons and can lead to a variety of emotional, mental and physical changes not only by direct toxic effects", for an indirect cognitive mediation can also play a role "in terms of a negative appraisal of pollutants" (Bullinger, 1990). In the words of Lundberg (1996), environmental toxins can generate "symptoms compatible with anxiety and depression, among them cognitive and behavioral changes".

Figure 2 approximately here

Bullinger (1989), using multivariate time-series analysis on German data, estimates that daily increases in air pollution concentrations (SO_2) have a contemporaneous and lagged negative effect (up to lag 4) on emotional well-being, measured in terms of mood and perceived stress. Similarly, Evans et al. (1988), investigating a sample of Los Angeles residents, find a modest yet significant relationship between ambient photochemical oxidants and anxiety symptoms[7]. Along the same lines, Zeidner and Schechter (1988), and Chattopadhyay et al. (1995), using Israeli and Indian cross-sectional data, respectively, claim that exposure to acute levels of ambient air pollution is responsible for heightened levels of anxiety, depression, and tension.

According to the evidence uncovered by some epidemiological studies, the effects of environmental toxins can also penetrate into the psychiatric sphere. More specifically, after controlling for meteorological variables and other confounders, PM, NO_2, and other photochemical oxidants appear to have a positive association with the incidence of psychiatric emergencies (Strahilevitz et al., 1979; Briere et al., 1983; Rotton and Frey, 1984).

It should not be surprising that physical and emotional health appear to be intertwined. In his theoretical work on mood, Morris (2000) asserts that the fundamental function of the mood system is "to regulate goal-directed behavior in such a way as to maintain a balance between the availability of goal-relevant resources and the perceived level of demands for them". In his interpretation, goal-relevant resources include factors such as health, skills, and money, whereas demands for these resources originate from goals that people set. The author then claims that mood changes can be initiated by environmental events that modify people's perceived demands and/or resources, the implication being that "mood will deteriorate when available resources are perceived as inadequate to meet active demands".

When applied to the current context, Morris' theory suggests that events such as daily increases in air pollution levels, by having a negative impact on physical health (i.e., a goal-relevant resource), can indirectly provoke a mood deterioration. Such a view finds support in numerous empirical studies (e.g., Aneshensel et al., 1984; Livneh and Antonak, 1994; Maier and Watkins, 1998; Cohen et al., 1999; Rasul et al., 2002; Baker, 2006). Eckenrode (1984), for instance, investigating the causes of short-term mood changes in a sample of women, concludes that the most important direct determinants are concurrent daily stressors and physical symptoms, alongside previous levels of psychological well-being. In brief, pain and

[7] The class of photochemical oxidants for the most part consists of ozone, nitrogen dioxide, and peroxyacyl nitrates (WHO, 1979).

discomfort produced by the symptoms of physical impairment are very likely to play a role in worsening mood (Rasul et al., 2002).

IV. Air Pollution, Mood, and Investment Decisions

It has been argued in a previous section that air pollution may exercise an influence on portfolio decisions via the role played by bodily cortisol (first channel, see Figure 2). As anticipated, the second channel proposed here builds upon evidence put forward in the fields of psychology and medicine which argues, on the one hand, that people's decisions are influenced by their mood and, on the other hand, that variations in air pollution levels can affect people's mood.

Numerous experimental studies show that, contrary to the axioms of expected utility theory, people in a positive (negative) mood tend to be more optimistic (pessimistic) and use probability estimates biased toward positive (negative) outcomes, which ultimately makes them more (less) risk seeking, all else equal (Johnson and Tversky, 1983; Kavanagh and Bower, 1985; Mayer et al., 1992; Wright and Bower, 1992; Constans and Matthews, 1993; Mittal and Ross, 1998; Fehr-Duda et al., 2006; Kliger and Levy, 2003, 2008). In other words, bad (good) mood causes people to systematically distort their probability weighting functions and, therefore, it affects their decisions involving risk. MacLeod and Campbell (1992) suggest that this effect may be mediated by the so-called "availability heuristic" proposed by Kahneman and Tversky (1973), according to which individuals "tend to base their estimates of the frequency or future probability of a given class of events on the ease with which instances of such events can be brought to mind". Indeed, the two authors find that mood changes "selectively facilitate the recall of personal memories that are emotionally congruent" with the new mood state and, as a result, the perceived probability of future negative (positive) events is higher in the low (high) mood condition. These results are also consistent with the findings of Kliger and Levy (2003, 2008), who, by extracting risk preferences from option prices, show that investors increase (decrease) their subjective probabilities of adverse events when they are in a bad (good) mood condition[8].

Based on the evidence just presented, it is therefore hypothesized that increases in air pollution concentrations cause mood deteriorations and, in turn, induce agents to be more pessimistic and employ probability estimates biased toward adverse outcomes when making investment decisions. Ultimately, this effect will induce agents to prefer safer assets over risky stocks, reducing demand in the stock market, and decreasing equity returns, *ceteris paribus*.

The two channels discussed here embody two effects that are expected to work in the same direction, and yield an unambiguous testable hypothesis. In order for the empirical evidence to be consistent with the interpretation portrayed here, in a reduced-form model one should observe a negative relationship between air pollution concentrations and stock returns. The goal of the present investigation is precisely to test such a linkage. Keeping in mind the medical and psychological literature cited above, the data will be inspected for both simultaneous and lagged effects[9].

It is useful to remark that, given the existence of limits to arbitrage (e.g., Barberis and Thaler, 2001), for this air pollution effect to leave any trace of evidence in the pattern of stock returns it may be sufficient that only a subset of agents suffer from the above-mentioned mood fluctuations (Lucey and Dowling, 2005a). A necessary condition, however, is that agents do not realize that their decisions are driven by changes in their moods (Mehra and Sah, 2002).

[8] It should be pointed out that a few experimental studies in the field of psychology have detected the opposite effect, i.e. a positive incidental mood has been found to increase risk aversion. These results have been justified based on the so-called mood maintenance hypothesis, according to which individuals in a good mood would tend to behave more cautiously because both their monetary investment and their current mood condition are at stake when making a decision involving risk (Isen and Geva, 1987; Isen and Labroo, 2003). Au et al. (2003) reconcile the two conflicting predictions about the impact of mood on people's risk preferences by arguing that which of the two effects dominates depends on the circumstances. In particular, "in ambiguous situations where probabilities are not given explicitly" (e.g. real investment decisions in financial markets) the priming effect of mood can be expected to dominate, and a positive (negative) mood will encourage (discourage) risk taking behavior. Such an interpretation indeed finds support in the outcomes of the authors' foreign exchange market experiment. As a result, and also based on the findings of Kliver and Levy (2003; 2008) mentioned above, in the present context (which deals with real decisions in real financial markets) the priming effect of mood can be expected to dominate, and it seems reasonable to conjecture that a negative (positive) mood will increase (decrease) risk aversion.

[9] In particular, the time-series studies examined here have revealed a lag structure that typically ranges between 1 and 5 days.

Interestingly, the lag structure potentially embedded in the air pollution effect also generates an opportunity to put to test the Efficient Market Theory, according to which past data (e.g., lagged pollution levels) contain no useful information for predicting future stock returns.

The Italian stock exchange, located in Milan, seems to represent an especially suitable setting for performing these tests. First, as shown below, during the period under observation air pollution reached high levels numerous times in the city of Milan and, as such, its inhabitants are likely to have been appreciably affected by it. Second, the Milan Stock Exchange moved from a floor trading system to a computerized and decentralized one at the beginning of the 1990's; this event provides a natural experiment that can give more strength to the empirical results.

V. Data

A. Air Pollution Proxies

Ambient air pollution concentrations are typically measured through a network of monitoring stations[10]. Given the goal of the present study and the potential issues of endogeneity discussed below, one would like to employ a measure of air pollution that is highly representative of population exposure near the Milan Stock Exchange (where traders were physically located) and, at the same time, is very unlikely to be systematically associated with overall economic activity in Italy. In particular, ideally, this measure should exhibit no systematic connection with the emissions caused by industrial activities that are strictly related to companies listed on the Italian stock market. This would make air pollution an exogenous factor when explaining the behavior of Italian stock returns.

[10] According to the guidelines set by the Italian Environmental Protection Agency (APAT, 2004), monitors are classified according to their type/purpose (Background, Industrial, Roadside), the area in which they are located (Urban, Suburban, Rural), and the characteristics of that same area (Residential, Commercial, Industrial, Agricultural).

In the city of Milan, over the period under consideration, data about PM have been recorded by three monitors[11]. Given the characteristics of these monitors, their proximity to the Milan Stock Exchange, and the purpose of the present analysis, only the data generated by one of these stations have been employed in the study[12]. It is worth to stress that the measurements made by such a monitor are representative of population exposure in the area that precisely encircles the MSE.

Hourly data about PM, NO_x, and SO_2 ambient concentrations, as measured by such a monitoring station, from January 1, 1980 through May 19, 2006, have been obtained from ARPA Lombardia[13]. Particulate matter is measured as TSP from 01/01/1980 through 02/13/1998, and as PM_{10} thereafter[14]. All concentrations are measured in terms of $\mu g/m^3$. Daily average values have then been calculated using hourly data from 5am through 6pm[15].

Figure 3 approximately here

Figure 3 allows a graphical inspection of the PM data[16]. Summary statistics are displayed in Table I. TSP data have also been collected from monitors located in fourteen other cities within Lombardy[17].

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[11] One monitor (Roadside/Urban/Residential-Commercial) is located in Liguria Street, 1.9 miles South of the MSE. A second monitor (Roadside/Urban/Residential-Commercial) is located in De Vincenti Street, 2.2 miles North-West of the MSE. The third monitor (Background/Urban/Residential) is located in Juvara Street, 1.9 miles North-East of the MSE. According to APAT (2004), roadside monitors are meant to measure the air pollution mainly caused by traffic emissions coming from neighboring streets; the concentrations they record are representative of areas whose radius generally does not exceed a few hundred yards. Industrial-type monitors are used to quantify the air pollution mainly emitted by close industrial sites; the concentrations they track are representative of areas whose radius is generally less than 100 yards. Background stations normally represent overall city-wide exposure more closely than do roadside sites. In particular, background-urban-residential stations are employed to monitor air pollution levels within large urban areas. The measurements they make are not directly influenced by nearby traffic or industrial activities, and are meant to track air pollution mainly generated within the urban area under observation (APAT, 2004); significant contributions might also come from outside that area, due to pollutants being transported in the atmosphere. Typically, the ambient concentrations these monitors record are representative of areas whose radius does not exceed 3 miles.

[12] This is the monitoring station located in Juvara Street.

[13] http://www.arpalombardia.it/qaria/default.asp. ARPA Lombardia is the Regional Environmental Protection Agency that manages the network of monitoring stations in Lombardy, which is the Italian region in which Milan is located.

[14] Since the conversion rate between these two measures is not necessarily stable over time, it has been chosen not to employ the PM_{10} data in the empirical analysis, thus reducing the sample period under investigation.

[15] When more than three hourly observations were missing, a missing daily value was assigned.

[16] The figure shows that quite a few observations are missing. Nevertheless, this should not be regarded as a matter of concern. First, the missing observations can be safely considered as purely random in the context of the current analysis.

Table I approximately here

Figure 4 provides some details about the contribution that different sources make to the emissions of PM, NO_x, and SO_2 in the Province of Milan. As far as particulate matter (TSP) is concerned, road transport (i.e., traffic) is responsible for the largest amount of emissions, followed by residential and commercial heating, and combustion in manufacturing industry (ARPA Lombardia, 2001; 2002; 2003a; 2003b; 2003c; 2006). Even greater appears to be the role of traffic in the release of nitrogen oxides, whereas energy production and heating are the main factors to blame for the emissions of sulfur dioxide.

Figure 4 approximately here

B. Equity Returns and Control Variables

Stock returns for the Italian market have been computed using daily closing values of three MSE global indices, i.e., MIB Storico, Comit, and Datastream Italy-market, from January 2, 1980 through May 19, 2006[18]. Figure 5 allows a graphical examination of the equity data, whereas the summary statistics are reported in Table II. Similarly, the daily returns of the German and U.S. markets have been calculated using the Datastream Germany-market index and the S&P500 index, respectively.

Figure 5 approximately here

Second, the period covered by the air pollution data appears to be quite extended, the result being that a few thousand daily observations turn out to be available for estimation purposes.

[17] These include all the cities, within Lombardy, for which TSP data are available starting from, at least, the beginning of 1991.

[18] Adopting the standard approach, daily stock returns have been calculated as the logarithmic difference between any two consecutive closing values, i.e., $r_t = \ln P_t - \ln P_{t-1}$, where P_t and P_{t-1} are the daily closing values of a given MSE index on trading day t and $t-1$, respectively. All data have been collected from Datastream; the Datastream codes for the indices mentioned above are ITMHIST, MILANBC, and TOTMKIT, respectively.

Table II approximately here

To control for well-known calendar anomalies, a *Monday* dummy has been created, taking the value of 1 on Mondays and 0 otherwise (e.g., Gibbons and Hess, 1981; Ko et al., 1997). Also, a *Tax* dummy has been constructed, being assigned the value of 1 over the first seven days of January (e.g., Branch, 1977; Dyl, 1977).

The other control variables employed in the econometric analysis come from disparate sources[19]. Daily data about temperature and rain in Milan have been obtained from ARPA Lombardia[20].The Seasonal Affective Disorder (SAD) effect has been calculated according to the methodology proposed by Kamstra et al. (2003)[21]. Following Krivelyova and Robotti (2003), a variable that captures temporary disturbances of the Earth's magnetosphere has been obtained from the National Geophysical Data Center in Boulder, Colorado[22]. Since the authors suggest that the influence of geomagnetic storms on stock returns may be a lagged one, a dummy variable *Geostorm* has been constructed, taking the value of 1 on the three days following the geomagnetic index being above 6. Finally, to control for the alleged behavioral effects of the lunar cycle (Yuan et al., 2006), data about the lunar phases, obtained from NASA, have been employed to create a *FullMoon* dummy variable taking the value of 1 up to three days before and after each Full Moon date and 0 otherwise[23]. Analogously, a *NewMoon* dummy has been constructed, being assigned the value of 1 up to three days before and after each New Moon date.

[19] These are the behavioral variables that are typically included in this stream of literature.
[20] http://www.arpalombardia.it/meteo/meteo.asp. Daily temperature values, in Celsius degrees, are computed as the mean of maximum and minimum daily temperatures. Rain is measured in mm. Both time series begin on January 2, 1989.
[21] More specifically, the SAD effect is assumed to be captured by two variables: a *Fall* dummy variable, taking the value of 1 from September 21 through December 20 of each year and 0 otherwise, and a *SAD* variable that measures the (normalized) number of hours of night in Milan. The SAD variable takes the value of 0 from March 21 through September 20.
[22] http://www.ngdc.noaa.gov/stp/GEOMAG/kp_ap.shtml. Unlike the authors, here it has been chosen to use the C9 index as a proxy for geomagnetic activity. This index gives a qualitative estimate of the overall level of geomagnetic activity according to a scale that ranges from 0 (quiet) to 9 (highly disturbed). The estimation has also been carried out employing the Ap index used by the authors; no difference has been detected in the results.
[23] http://sunearth.gsfc.nasa.gov/eclipse/phase/phase2001gmt.html.

VI. Possible Issues of Endogeneity

Before turning to the econometric analysis, it seems useful to explore some potential sources of endogeneity. Since overall air pollution, at the country level, is clearly connected with a country's economic activity (factor 1) and also generates some social costs (factor 2) through the externalities it creates, if one wanted to accurately measure the alleged behavioral effect of pollution on stock returns, then these two factors should be controlled for. Sadly, as the present study employs daily data, no good proxies seem to exist for this purpose. Nevertheless, several approaches can be adopted to tackle this problem.

Standard economic theory suggests that, on a global scale, both economic activity and the social costs associated with air pollution are likely to exhibit a connection with stock returns. As far as the first factor is concerned, it seems the case that large amounts of pollutants are emitted into the air through the use of materials and fuel inputs in the industry and service sectors. Ignoring for a moment the elements that govern the dispersion of pollutants in the atmosphere (e.g., meteorological phenomena), it seems safe to assert that the air pollution levels recorded in a given area are associated with economic activity in that area. For instance, if one focused upon an entire country, e.g. Italy, then unexpected changes in overall economic activity in Italy would be assumed to both generate unexpected changes in overall air pollution concentrations and have an impact on the Italian stock market[24]. In particular, one would expect to observe a (probably positive) contemporaneous relationship between unexpected positive changes in air pollution levels (meaning augmented economic activity) and stock returns. In such a setting, failing to statistically control for economic activity would cause the estimator of the (alleged) pollution effect to be biased.

Secondly, as anticipated, airborne contaminants are also known for having a negative feedback onto economic activity via the social costs (externalities) they generate. These costs take the form of premature mortality (WHO, 2006), reduced productivity, work loss, and "restricted activity days" due to the health

[24] Alternatively, one could conjecture that, since many aspects of a country's economic activity cannot be observed on a daily basis (e.g. industrial production, energy consumption), traders use air pollution daily data to infer information about overall economic activity.

effects of pollution (Ostro, 1983; Hausman et al., 1984; Ostro and Rothschild, 1989; Zuidema and Nentjes, 1997; Östblom and Samakovlis, 2004), and damage to the agricultural sector (Henderson, 1996; Spash, 1997; Murphy et al., 1999). Hansen and Selte (1997), for instance, find that ambient concentrations of PM have a significant relationship with daily sick-leaves in Oslo, Norway. At the country level, computations made for some European nations have revealed that the overall costs generated by air pollution are currently high, ranging between 0.1% and 1% of GNP (OECD, 1994). As a result, standard economic theory suggests that unexpected increases in a country's air pollution levels could have a negative impact on stock returns through the unexpected social costs they produce. Which effect dominates (whether factor 1 or 2) is mainly an empirical question, and is likely to depend on the particular situation considered.

What really matters here is that air pollution, unlike some other environmental stressors analyzed in the behavioral finance literature (e.g., Saunders, 1993; Kamstra et al., 2003; Hirshleifer and Shumaway, 2003), cannot be treated *a priori* as a purely exogenous factor when explaining the behavior of stock returns. Greater care is needed here to make sure that the results do not suffer from endogeneity. To address this issue, as partly anticipated, the empirical strategy will involve (1) a scrupulous geographical selection of the air pollution measures, (2) the use of a natural experiment, and (3) an instrumental variables estimation.

VII. Empirical Analysis

A. Particulate Matter and Stock Returns: a Natural Experiment

As previously mentioned, the Italian stock market provides a favorable setting for the purpose of testing whether investment decisions can be influenced by the mood changes triggered environmental stressors. This is because the MSE experienced an institutional change at the beginning of the 1990's, the shift being from a floor trading system to a computerized and decentralized one. The transformation process was over by April 15, 1994, when no more shares were traded through the open outcry system[25].

This institutional revolution provides a "natural experiment" (e.g., Pardo and Valor, 2003): (1) until April 15, 1994, traders were physically present on the trading floor located in Milan and, as such, their exposure to air pollution was accurately tracked by the monitoring station employed in the current study. If the behavioral hypothesis constructed in the previous sections was correct, then, during this period, air pollution concentrations should be expected to be a good agent mood proxy and, thus, exhibit a negative relationship with Italian stock returns. On the other hand, after April 15, 1994, since traders began to operate remotely from many other places, characterized by dissimilar environmental conditions, air pollution levels in Milan should not be any longer a good proxy for agent mood; as such, no association between pollution and Italian equity returns should be expected during this second era[26]. Also, (2) if the relationship between pollution levels and stock returns was spurious (i.e., caused by an omitted variable, such as economic activity or the social costs generated by air pollution), then one would expect to find the same statistical evidence in both sub-periods[27].

As a result, documenting a negative relationship between air pollution and Italian stock returns during the first era and the breaking of such a link in correspondence of the institutional change mentioned above would provide evidence in support of the hypothesis under investigation.

[25] More specifically, the transition process began on November 25, 1991, when 5 companies' shares started to be traded through the computerized system. Another 5 companies' shares were moved on 01/16/1992, 25 on 05/18/1992, 4 on 04/19/1993, 41 on 07/16/1993, 73 on 12/16/1993, 26 on 01/17/1994, and 225 on 04/15/1994 (Pia, 1997).

[26] In fact, such a restriction can be loosened a bit as, undoubtedly, after the system switch some traders kept operating from structures situated in Milan. As a result, for the argument to work it would be sufficient that the air pollution effect observed during the second era, if present, was "weaker" than during the first one.

[27] Unless, of course, the linkage between the omitted variable and Italian stock returns disappeared at the end of the first era. This issue will be discussed later.

B. Basic Model

A careful examination of Figure 5 and Table II shows that the distributions of the equity returns under scrutiny are affected by excess kurtosis and volatility clustering. As such, a GARCH specification has been deemed as the most appropriate to conduct the empirical analysis (Engle, 1982; Bollerslev, 1986). In particular, the following model has been estimated using the Huber-White sandwich robust estimator of variance (Huber, 1967; White, 1980):

$$\begin{aligned} r_t &= \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} + \mu_{PM_k} PM_{t-k} + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t + \gamma_{FullMoon} FullMoon_t + \\ &\quad + \gamma_{NewMoon} NewMoon_t + \gamma_{Monday} Monday_t + \gamma_{Tax} Tax_t + \varepsilon_t \end{aligned} \tag{1}$$

$$\varepsilon_t = z_t \sigma_t \qquad\qquad z_t \sim iid\ (0,1)$$

$$\sigma_t^2 = \delta + \gamma \varepsilon_{t-1}^2 + \phi \sigma_{t-1}^2$$

where r_t represents the daily return of a given MSE index between time t-1 and time t, PM_{t-k} measures the daily ambient concentration of particulate matter (TSP) in Milan at time t-k, and the remaining variables have the meaning previously specified. A flexible number of lagged returns has been added to each regression, when statistically significant, to purge the time series of equity returns from any intrinsic autocorrelations.

All the coefficient estimates, for the case of k equal to 1, are reported in Table III. Table IV, instead, collects only the estimated marginal effects of the air pollution proxy for values of k up to 5. Focusing on the first sub-period, 1980-1994, the MIB index provides strong evidence of a negative relationship between particulate matter and stock returns, for the coefficients on the proxy are negative and statistically different from zero, at least at the 10% level, from lag 0 up to 4. For example, Table III suggests that a 10 μg/m^3 increase in the level of TSP is estimated to reduce the following day's equity returns by 1 basis point. The evidence is somewhat weaker for the Comit index, given that the air pollution proxy is statistically significant at lag 1 (p-value 0.04) and partially significant at lag 0 and 2. When considering the Datastream index, marginal significance is reached only at lag 1 (p-value 0.13). It is worth to emphasize that all the coefficients exhibit the (negative) expected sign.

Table III and Table IV approximately here

Based on the medical and psychological literature cited in the previous sections, it is speculated that the effects of a prolonged exposure to high levels of air pollution might, to some extent, add to each other. To test this hypothesis, a variable PM_{Mean_t} is constructed and assigned a value equal to the mean of the PM concentrations observed during the previous five days (i.e., from *t-1* through *t-5*). Model [1] has been re-estimated using such a pollution proxy and the relevant coefficients are reported in the last row of Table IV. The picture that emerges is highly supportive of the hypothesis under investigation, especially when considering the MIB and Comit indices (the sign of the coefficient on the pollution variable is negative, and standard statistical significance is achieved). Marginal evidence is also reached in the case of the third index (p-value 0.11).

Moving to the second sub-period (1994-1998), as conjectured, no evidence of a significant impact of particulate matter on stock returns is found at any lag (see Table IV). The coefficients generally show a negative sign, yet statistical significance is never even approached. As such, it can be concluded that these preliminary estimates are consistent with the behavioral hypothesis under study, suggesting that further scrutiny should be granted.

Some attention must also be paid to the remaining explanatory variables in model [1]. As Table III shows, the estimates from both sub-periods corroborate the SAD effect advanced by Kamstra et al. (2003), for the coefficient on the SAD variable is positive and the one on the *Fall* dummy is negative, as suggested by the authors. Solid statistical significance is reached across the three market indices. Same reasoning applies to the Monday effect, which appears to be even stronger in the second sub-sample, whereas the *Tax* dummy does not turn out to have any remarkable explicative power. More difficult to interpret is the role played by the lunar cycle, since the estimates seem to either contradict the findings of Yuan et al. (2006) and Dichev and Janes (2003) (i.e., the coefficient on the *NewMoon* dummy is negative) or provide no evidence at all[28].

C. Controlling for Meteorological Factors

Some recent studies in the field of behavioral finance have shown that certain environmental variables, supposedly acting as proxies for investor mood, display an association with stock returns. These include temperature (Keef and Roush, 2003; Cao and Wei, 2005; Chang et al., 2006), rain (Lucey and Dowling, 2005b), and geomagnetic storms (Krivelyova and Robotti, 2003). At the same time, a number of connections between weather and air pollution concentrations have been established in the meteorological literature (e.g., Campbell and Gipps, 1975; Mossetti et al., 2005). To avoid the risk of obtaining biased estimators, it is therefore essential to add more controls to model [1], which becomes:

$$
\begin{aligned}
r_t = {} & \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} + \mu_{PM_{Mean}} PM_{Mean_t} + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t + \gamma_{FullMoon} FullMoon_t + \\
& + \gamma_{NewMoon} NewMoon_t + \gamma_{Monday} Monday_t + \gamma_{Tax} Tax_t + \gamma_{Temp} Temp_t + \gamma_{Rain} D_t^{Rain} + \\
& + \gamma_{Geostorm} Geostorm_t + \varepsilon_t
\end{aligned} \tag{2}
$$

$$\varepsilon_t = z_t \sigma_t \qquad\qquad z_t \sim iid\ (0,1)$$

$$\sigma_t^2 = \delta + \gamma \varepsilon_{t-1}^2 + \phi \sigma_{t-1}^2$$

[28] It may be worth to mention that Lucey and Dowling (2005b) found a similar "paradoxical" result when studying Italian data.

where D_t^{Rain} is a dummy that takes the value of 1 if a positive amount of rain has fallen in Milan at time t, $Temp_t$ is the average temperature in Milan on day t, and $Geostorm_t$ is a dummy that captures disturbances of the Earth's magnetosphere. The remaining variables are self-explanatory[29].

Table V approximately here

The coefficients obtained estimating model [2] are collected in Table V. The marginal effects of the air pollution proxy (average PM concentration between day *t-1* and day *t-5*) are again negative and highly statistically significant across the three equity indices when the first sub-period is analyzed[30]. In absolute value, the size of the pollution effect turns out to be even greater than in model [1]: for example, focusing on the MIB index, a 10 μg/m^3 increase in the average PM level over the previous five days is estimated to lower the following day's Italian stock returns by 3 basis points. Such an impact appears to be economically significant, as the mean and standard deviation of the PM_{Mean_t} variable during the first half of the 1990's are approximately 85 μg/m^3 and 40 μg/m^3, respectively.

As expected, the mood effect cannot be detected any longer after the transformation of the Italian stock exchange in 1994. Qualitatively, the other explanatory variables exhibit patterns that are similar to the ones reported in Table III. No support is found in favor of the conjecture that wants rain and geomagnetic activity to be good proxies for investor mood[31].

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[29] It should be noted here that the available data for these weather series cover a shorter time span and, therefore, their inclusion into the regression equation generates a shrinkage of the sample.

[30] Model [2] has also been estimated using PM_{t-k} as the pollution proxy. Across the three indices, and for k ranging from 0 through 5, the coefficient on such a variable has always turned out to be negative and highly statistically significant. As such, for brevity, only the results referring to PM_{Mean_t} are reported in Table V.

[31] Different is the case of the temperature variable, for this factor exhibits a seasonal behavior that tracks very closely the length of the day (i.e., the SAD variable). In many occurrences, these last two controls turn out to be jointly statistically significant yet individually insignificant. It appears very challenging to empirically identify the contribution that is individually attributable to each of them, if any.

D. Controlling for International Economic Shocks

Up to this point, no explicit economic/financial factor has been employed in the analysis. It is natural to wonder whether the results discussed in the previous sections are robust to the inclusion of some variables that are able to capture the stream of economic news flowing into financial markets. Given the frequency of the data used here, adopting a direct approach seems quite impractical. Instead, the strategy employed to tackle this issue will consist in inserting into model [2] the returns of two international stock market indices, i.e. the S&P500 and a global index of the German market. The goal is to use these indices to indirectly capture (at least some of) the unexpected economic shocks that occurred daily over the period covered by the present investigation. In particular, the German index is expected to incorporate more closely European-specific shocks, whereas the S&P500 is employed to capture global shocks[32]. Also, the inclusion of these two international indices should purge the time series of Italian stock returns from those seasonal patterns that are common to other international markets. The following model has been fitted by maximum likelihood:

$$\begin{aligned} r_t = \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} + \mu_{PM_{Mean}} PM_{Mean_t} + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t + \gamma_{FullMoon} FullMoon_t + \\ + \gamma_{NewMoon} NewMoon_t + \gamma_{Monday} Monday_t + \gamma_{Tax} Tax_t + \gamma_{Temp} Temp_t + \gamma_{Rain} D_t^{Rain} + \\ + \gamma_{Geostorm} Geostorm_t + \gamma_{Germany} Germany_t + \gamma_{USA} USA_{t-1} + \varepsilon_t \end{aligned} \quad (3)$$

$$\varepsilon_t = z_t \sigma_t \qquad\qquad z_t \sim iid\ (0,1)$$

$$\sigma_t^2 = \delta + \gamma \varepsilon_{t-1}^2 + \phi \sigma_{t-1}^2$$

[32] Obviously, Italian-specific news plays an important role in shaping Italian stock returns. However, the potential omitted-variable issue attributable to the occurrence of country-specific shocks is addressed in some other sections of this paper, especially through the natural experiment examined in section A and the instrumental variables estimation that will be discussed in section G.

where $Germany_t$ represents the returns of the German market and USA_{t-1} represents the returns of the U.S. market[33].

Table VI approximately here

The estimates are collected in Table VI, and clearly show that a strong positive correlation exists between the returns of the Italian stock market and the U.S. and German returns. Yet, the evidence regarding the air pollution effect is left untouched. The coefficients on the regressor under observation are once again negative across the three indices, and the null hypothesis of no relationship with Italian equity returns can be rejected at very high confidence levels.

As it should be expected, some control variables are now less statistically significant than they were in model [2], their temporal pattern being the same (or similar) across the three stock markets whose returns are included in the regression equation (e.g., Monday effect, lunar cycle, SAD effect).

Model [3] has also been estimated by OLS (using Newey-West adjusted standard errors) and adopting a LOGIT specification[34]. In both cases the results are qualitatively similar to the ones described above, and the evidence turns out to be highly consistent with the behavioral hypothesis under scrutiny (i.e., the coefficient on the air pollution proxy is always negative and statistically significant when the first sub-sample is analyzed, whereas it is not distinguishable from zero when it comes to the second sub-sample). As such, overall, the findings appear to be robust to the addition of alternative sets of controls and to alternative estimation frameworks.

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[33] The latter is included with a lag because the American markets terminate their daily operations at least six hours after trading in Milan has already come to an end, the implication being that the S&P500 index on day *t* incorporates some economic news that is absorbed by the Italian equity indices on the following trading day. This is, of course, a basic specification, as the goal here is not to fully describe the spillover effects among these three markets, which may be much more complex.

[34] The estimates are not reported here for brevity; they are available from the author.

E. Alternative Air Pollution Proxies

As emphasized during the literature review, medical research has been hesitant in attributing specific health effects to individual pollutants, for most epidemiological studies have to deal with complex mixtures of environmental toxins whose specific (and synergistic) effects are not yet completely understood. Therefore, it appears interesting to test whether the air pollution effect, detected in the previous sections using PM as an indicator, is robust to the use of alternative pollution proxies.

Second, daily data about ambient concentrations of nitrogen oxides and sulfur dioxide in Milan are available for a longer time span than PM, their time series extending up to 2006.

Third, employing a set of different proxies may help shed light on the potential endogeneity issue previously mentioned. As shown in section V, the direct emissions of PM, NO_x, and SO_2, in the Province of Milan, can be credited to rather dissimilar sets of sources. While the major contributor to the emissions of TSP and NO_x is road transport, residential heating systems and power plants take the lion's share when it comes to SO_2. Showing that air pollution in Milan, independently of its sources, is systematically connected with Italian stock returns is an important step towards proving that the results illustrated in the previous sections are not spurious, and that the behavioral hypothesis tested in this paper is indeed supported by the facts.

Table VII and Table VIII approximately here

Following this line of reasoning, model [3] has been fitted replacing PM with either NO_x or SO_2. The relevant coefficients are contained in Table VII and VIII[35]. Focusing on the first sub-sample (1989-1994), the lag structure exhibited by the air pollution effect when NO_x is used as a proxy is somewhat similar to the one discussed for PM, though the statistical significance of the individual lags is more limited.

[35] Only the marginal effects of the air pollution proxies are reported in these two tables. The patterns characterizing the control variables are virtually the same as the ones shown in Table VI.

The size of the marginal effect is estimated to reach its maximum around lag 3 and 4, which is reasonable if one considers that NO_x also contributes to the formation of secondary PM in the atmosphere, a process that may take a few days. A variable $NO_{x_t}^{Mean}$ has also been constructed to test whether a protracted exposure to high levels of air pollution may generate effects that add up to each other. It has been assigned a value equal to the average NO_x ambient concentration between day *t-1* and day *t-4*. As shown in Table VII, the estimated marginal effect of this variable conforms to the evidence collected so far, though in the case of the MIB index the statistical relevance is only marginal. Quantitatively, a one standard deviation increase in the mean level of NO_x over the previous four days is estimated to reduce the following day's stock returns by approximately 8 basis points. As such, the magnitude of this effect is comparable to what has been found using PM as a proxy. Once again, when the second sub-period (1994-2006) is examined, the air pollution effect seems to disappear.

The picture that emerges when sulfur dioxide is employed as a proxy turns out to be similar. When individual lags are used, the statistical evidence is quite solid for the Datastream and MIB indices, in the latter case extending up to the third lag[36]. Based on the same rationale stated above, a variable that measures the average ambient concentration of SO_2 over the previous few days (three in this case) is constructed, and its marginal effect on equity returns is assessed. The corresponding sign happens to be negative, as expected, and the null hypothesis of no effect can be rejected, at least at the 10% confidence level, across the three market indices. Also, the size of the estimated pollution effect is equivalent to the outcomes obtained using the other two proxies, for a one standard deviation increase in the average SO_2 level, computed over the previous three days, is expected to decrease stock returns by approximately 10 basis points.

[36] In the second sub-period (1994-2006), the coefficient on the SO_2 variable turns out to be marginally statistically significant at lag 2. Given the considerable evidence previously discussed, it seems the case that this single piece of evidence can hardly substantiate a decisive argument to refute the hypothesis under scrutiny.

F. Further Robustness Checks

A possible critique to the natural experiment proposed here is that the institutional change in the trading system of the Milan Stock Exchange might not be the only relevant event that took place between the two eras analyzed here. In other words, one might conjecture that the air pollution effect seems to disappear after April 14, 1994 because the correlation between stock returns and air pollution experienced an alteration for reasons unrelated to the institutional change mentioned above. Examining Table I and Figure 3, it is indeed possible to notice that air pollution concentrations generally decreased between the end of the 1980s and the end of the 1990s. Such an abatement seems to be attributable to several factors: (1) the introduction of European emission standards that set progressively lower limits for exhaust emissions of new vehicles sold in E.U. member states, (2) technological improvements, (3) the renovation of residential and commercial heating systems, (4) the moving of some industrial firms[37].

Table IX approximately here

A reasonable strategy to tackle the issues created by the (potential) existence of unobserved (possibly relevant) structural breaks consists in reducing the length of the two sub-periods employed in the natural experiment. As the two sub-samples shrink toward the switch date, the probability that the disappearance of the air pollution effect after April 14, 1994 has been caused by factors other than the transformation of the Milan Stock Exchange should diminish accordingly. Based on this intuition, model [3] has been re-estimated using alternative samples, and the results are reported in Table IX. Though the statistical significance of the effect is somewhat reduced when the first sub-period shrinks, the coefficients remain negative and the null hypothesis of no relationship between air pollution in Milan and Italian stock returns can always be rejected at standard confidence levels (at least in the case of the Comit and MIB

[37] http://www.arpalombardia.it/qaria/doc_EvoluzioneAnni.asp. These factors are mentioned by ARPA Lombardia on its web site, which was accessed on July 10, 2007.

indices). Similarly, reducing the second sub-sample does not have any notable impact on the picture depicted thus far as, once again, no evidence of a connection between air pollution and equity returns can be found. Given these empirical patterns, it seems unlikely that some structural change, other than the trading system switch at the MSE, is responsible for the observed breaking of the link between the two variables of interest.

One might still wonder, though, whether the inability to detect an air pollution effect after April 14, 1994 is due to the fact that air pollution concentrations are lower, on average, in the second sub-period. In principle, lower levels of environmental toxins may imply that the physical/psychological discomfort experienced by people is not severe enough to affect their mood and their decision-making process. If this was the case, then no trace evidence of an air pollution effect would be found by the econometrician in the second era. Contrary to this argument, however, is the medical literature cited in section III, according to which no specific threshold has been identified below which the adverse influence of PM on the human body ceases to work. In order to give an empirical answer to this issue, model [3] has also been re-estimated using the first difference of the pollution proxy, as follows

$$\begin{aligned} r_t = \alpha &+ \sum_{j=1}^{P} \beta_j r_{t-j} + \mu\, \Delta PM_{Mean_t} + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t + \gamma_{FullMoon} FullMoon_t + \\ &+ \gamma_{NewMoon} NewMoon_t + \gamma_{Monday} Monday_t + \gamma_{Tax} Tax_t + \gamma_{Temp} Temp_t + \gamma_{Rain} D_t^{Rain} + \\ &+ \gamma_{Geostorm} Geostorm_t + \gamma_{Germany} Germany_t + \gamma_{USA} USA_{t-1} + \varepsilon_t \end{aligned} \tag{4}$$

$$\varepsilon_t = z_t \sigma_t \qquad\qquad z_t \sim iid\ (0,1)$$

$$\sigma_t^2 = \delta + \gamma \varepsilon_{t-1}^2 + \phi \sigma_{t-1}^2$$

where ΔPM_{Mean_t} represents the change in the variable PM_{Mean_t} between time *t-1* and time *t*. The results, not reported here for brevity, are qualitatively very similar to the ones presented for model [3]. As expected, the coefficient on the pollution proxy is negative and statistically significant (at least at the 5% level) across the three market indices in the first sub-period (1989-1994), whereas no evidence is found when the second sub-period (1994-1998) is analyzed. These estimates, therefore, suggest that the mood effect is at work even at low air pollution concentrations (i.e., concentration changes have an impact independently of the air pollution level outstanding), which refutes the conjecture according to which the disappearance of such an effect, in the second era, would be attributable to air quality improvements.

Yet another route is worth of exploration. In principle, not only stock returns but also their variance might be influenced by the environmental stressor under scrutiny here. To examine this possible further link, the pollution proxy has been inserted into the conditional variance equation of model [3], giving origin to the following GARCH model:

$$\begin{aligned} r_t &= \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} + \mu_{PM_{Mean}} PM_{Mean_t} + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t + \gamma_{FullMoon} FullMoon_t + \\ &+ \gamma_{NewMoon} NewMoon_t + \gamma_{Monday} Monday_t + \gamma_{Tax} Tax_t + \gamma_{Temp} Temp_t + \gamma_{Rain} D_t^{Rain} + \\ &+ \gamma_{Geostorm} Geostorm_t + \gamma_{Germany} Germany_t + \gamma_{USA} USA_{t-1} + \varepsilon_t \end{aligned} \qquad (5)$$

$$\varepsilon_t = z_t \sigma_t \qquad\qquad z_t \sim iid\ (0,1)$$

$$\sigma_t^2 = \delta + \eta PM_{Mean_t} + \gamma \varepsilon_{t-1}^2 + \phi \sigma_{t-1}^2$$

where all the variables have the same meaning as previously illustrated. When the estimates for the MIB and Comit indices are evaluated, the null hypothesis of no connection between air pollution and the variance of equity returns cannot be rejected at standard confidence levels (the p-values equal 0.39 and 0.17, respectively). Moving to the Datastream index, a negative and statistically significant marginal effect is observed (p-value 0.01), implying that increases in pollution concentrations appear to be associated with reduced variability of returns. Though this individual finding, *per se*, seems to have no obvious interpretation, taken together these outcomes suggest that the negative impact that air pollution is estimated to have on stock returns cannot be attributed to an increase in objective risk (i.e., in the variance of returns) caused by the former.

G. Instrumental Variables Estimation

Up to this point, several methods/justifications have been proposed in an attempt to show that the air pollution proxies employed in the empirical analysis are not endogenous: (1) the daily concentration data are taken from a sole monitor located in the city of Milan, and are merely representative of human exposure around the Milan Stock Exchange (few squared miles), which means they are very unlikely to represent a global measure of air pollution in the Italian peninsula[38]; (2) a natural experiment, based on an institutional change experienced by the Italian stock market, has shown that the air pollution effect can only be detected over the period in which traders would physically gather on the floor of the MSE; (3) the main source of PM in Milan is road traffic, which is unlikely to have an unambiguous and systematic link with overall Italian economic activity; (4) the estimated air pollution effect exhibits a complex lag structure, implying that current modifications in the ambient concentration of a given air pollutant will also have an impact on stock returns in the near future; on the other hand, if both daily air pollution levels and stock returns were driven by concurrent economic activity (i.e., pollution is endogenous), then only a contemporaneous relationship between pollution and returns should be detected; (5) assuming for a moment that air pollution was indeed an endogenous variable, standard finance theory suggests that only unexpected changes in economic activity and, in turn, unexpected changes in daily air pollution levels, should be correlated with equity returns; in other words, only the unexpected component of air pollution should be useful in determining the direction of stock returns. Nevertheless, this line of reasoning appears to be refuted by the evidence discussed so far (i.e., it is the actual air pollution level in Milan, not just its unexpected component, that exhibits a systematic relationship with Italian equity returns).

[38] Table X shows the pair-wise correlation between PM daily concentrations in Milan and in a set of neighboring cities (see Figure 6 for a geographical representation). The figures demonstrate that air pollution patterns can be very dissimilar even when considering any two cities in close proximity (few miles away from each other). This further proves how the concentrations recorded by the monitor located in Milan are representative of a very small area and cannot even be thought of as representing a provincial measure.

Figure 6 approximately here

Table X approximately here

This said, identifying a link of causality is always challenging, and all the feasible techniques should be explored. The results proposed here would surely become more solid if good instruments for air pollution were employed. Luckily, a careful examination of the forces at work in this setting reveals that the instruments can be derived from a "natural" experiment. Indeed, this appears to be one of the cases in which it is possible to exploit the forces through which Nature has generated an environment somewhat similar to a randomized experiment. As it is well understood, ambient air pollution is deeply affected by meteorological conditions (e.g., Campbell and Gipps, 1975; Mossetti et al., 2005). As such, a set of meteorological parameters can turn out to be helpful when employed as instruments. In particular, our instruments will include: (1) wind speed, (2) atmospheric pressure, and (3) rainfall, all measured in the city of Milan.

The intuition behind this identification strategy is straightforward. While high wind speed, low pressure, and heavy rain in Milan all contribute to reduce air pollution concentrations in that city (Campbell and Gipps, 1975; Mossetti et al., 2005), one can hardly maintain that they also directly affect overall Italian economic activity. Similarly, there seems to be no theoretical justification for believing that lagged values of these meteorological variables should have any systematic relationship with Italian stock returns[39]. For these reasons, we believe that it is realistic to take these variables as exogenous. The first-stage regression equation is the following:

$$PM_t = \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} + \sum_{k=2}^{3} \lambda_k Wind_{t-k} + \sum_{k=2}^{3} \pi_k \, Pressure_{t-k} + \sum_{k=2}^{3} \psi_k Rain_{t-k} + controls + \varepsilon_t \tag{6}$$

[39] It has been chosen to use lagged values because, in principle, these environmental factors might work as mood proxies and, thus, have a contemporaneous relationship with equity returns. However, the following should be kept in mind: (1) no study has thus far documented a link between atmospheric pressure and stock returns; (2) the estimates produced by fitting model [3] have shown that rainfall has no relationship with returns; (3) model [3] has also been estimated including contemporaneous wind speed as a regressor, yet no marginal effect on equity returns has been found.

where $Wind_{t-k}$ measures wind speed in Milan on day t-k, $Pressure_{t-k}$ captures the atmospheric pressure in Milan on day t-k, and the remaining variables are self-explanatory. The first-stage estimates confirm that these instruments have high explanatory power for current PM, as across the three stock market indices it is possible to reject the null hypothesis that their coefficients are jointly equal to zero at confidence levels far below 1%. As such, the weak instruments problem illustrated by Bound et al. (1995) does not seem to apply here[40].

Table XI approximately here

Table XI collects the second-stage estimates, which, once again, tell a consistent story and confirm what has been documented in the previous sections. When the first sub-sample is used, all three market indices display an air pollution effect that is both statistically significant and economically relevant. In particular, a one standard deviation increase in the current PM ambient concentration is estimated to reduce stock returns by approximately 0.2%. No statistical significance is achieved, instead, when the second sub-period is analyzed.

Taken as a whole, we believe that our empirical methodology provides robust evidence of a relationship between air pollution and stock returns, which is consistent with the hypothesis according to which some psychologically relevant (yet economically neutral) factors play a role in the process that generates investment decisions. More specifically, one can speculate that this empirical relationship is mediated by the role that mood is believed to play in decision making and, in particular, in portfolio decisions. Also, in line with the findings of Goetzmann and Zhu (2005), the natural experiment described in section A effectively suggests that such a mood effect mainly passes through the traders physically located in the city that hosts the Stock Exchange.

[40] The results are robust to the use of alternative lag structures.

VIII. Mood Effect and Efficient Market Theory

The evidence produced by the present empirical analysis appears to be intriguing on two grounds. First, it represents a conundrum in light of the paradigm that dominates economic analysis, as it suggests that some forces, other than economic ones, contribute to shape equilibrium prices in the financial markets. Second, it poses a challenge to the Efficient Market Theory, as it insinuates that some publicly available past information (i.e., air pollution levels) is helpful for predicting future stock returns.

Though the latter finding is appealing *per se*, in order to determine whether this truly constitutes a "market anomaly", one needs to demonstrate that it is possible to construct some profitable trading strategy using air pollution data. Several routes could be explored here. The easiest approach that comes to mind consists in creating an air pollution index (API) that generates buying/selling signals when a given threshold concentration is crossed. To keep things simple, the focus here will be on selling signals, though this framework could be straightforwardly extended to purchases as well. In particular, an indicator is constructed according to the following specification:

$$API_t = \begin{cases} 1, \text{ if } PM_{Mean_t} \geq 180\ \mu\text{g/m}^3 \quad \text{or} \quad NOx_{Mean_t} \geq 650\ \mu\text{g/m}^3 \quad \text{or} \quad SO2_{Mean_t} \geq 180\ \mu\text{g/m}^3 \\ 0, \text{ otherwise} \end{cases}$$

where all the variables have the meaning previously illustrated, and the threshold values have been chosen so that they are approximately equal to the sum of the mean and standard deviation of the corresponding variables[41]. When the API index assumes value 1, it obviously indicates that air quality has been remarkably low over the previous few days (high-pollution state), so that, *ceteris paribus*, a poor

[41] Mean and standard deviation have been computed using the relevant data from January 2, 1989 to April 14, 1994. It must be noticed that the results, discussed below, are robust to the choice of the threshold values. Based on random experimentation, it can be safely said that the range within which each of the three pollution proxies generates valuable signals is relatively large, so that a huge set of profitable combinations can be built.

performance of the Italian stock market should be expected[42]. In other words, a selling signal is generated. The portfolio could then be bought back when the API index takes on again value 0 (low-pollution state).

To verify the validity of this strategy, the following GARCH model has been fitted using data from the first sub-sample (1989-1994):

$$
\begin{aligned}
r_t &= \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} + \mu_{API} API_t + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t + \gamma_{FullMoon} FullMoon_t + \\
&\quad + \gamma_{NewMoon} NewMoon_t + \gamma_{Monday} Monday_t + \gamma_{Tax} Tax_t + \gamma_{Temp} Temp_t + \gamma_{Rain} D_t^{Rain} + \\
&\quad + \gamma_{Geostorm} Geostorm_t + \gamma_{Germany} Germany_t + \gamma_{USA} USA_{t-1} + \varepsilon_t
\end{aligned} \tag{7}
$$

$$
\varepsilon_t = z_t \sigma_t \qquad\qquad z_t \sim iid\ (0,1)
$$

$$
\sigma_t^2 = \delta + \gamma \varepsilon_{t-1}^2 + \phi \sigma_{t-1}^2
$$

The estimates, reported in Table XII, indeed reveal that poor air quality, as captured by the API index, is systematically associated with lower-than-average stock returns[43]. An inspection of the three market indices suggests that, on average, the marginal effect on returns equals –0.25%. As such, even if transaction costs are taken into account, the empirical regularities exploited by this strategy seem to be strong enough to grant (institutional) investors an excess return over a simple buy-and-hold strategy[44]. In other words, given the existence of unexploited profitable trading strategies based on air pollution data, the air pollution effect appears to qualify as a market anomaly. Future research endeavors may be directed toward testing whether this violation of the efficient market theory can be detected in other stock markets that, nowadays, still employ open outcry trading systems.

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[42] It should be noticed that the value that the API index will take on day *t* is already known on day *t-1*, as the three pollution proxies on which the index is based are constructed using data from time *t-1* through *t-5*.

[43] Regression equation [7] has also been estimated using a Logit specification. The outcomes, reported in Table XIII, suggest that the probability that stock returns turn out to be positive is reduced by approximately 10% when the API index takes value 1. For comparison purposes, it can be said that such a value is greater than the "Monday effect" estimated through the same framework.

[44] For a discussion about the magnitude of transaction costs, see Krivelyova and Robotti (2003).

Table XII and Table XIII approximately here

IX. Conclusion

This paper provides a contribution to the debate on behavioral finance. On the one hand, advocates of traditional asset pricing theories maintain that investors are able to isolate the relevant economic variables, process them in a fully rational way, and incorporate them into the price of securities. On the other hand, detractors argue that investment decisions, just like many other types of human decisions, are influenced by a set of biases that are inherently part of the way people's mental processes develop. More specifically, psychologists have found evidence that the emotional state (i.e., mood) experienced at the time of making a decision is able to affect the decision being made even if the source of the former is unrelated to the latter (so-called mood misattribution). Following this line of reasoning, behavioral finance researchers have started to analyze whether collective mood swings, triggered for example by some environmental factors, can alter investment decisions and generate some detectible patterns in the time series of equity returns.

The present investigation has focused on air pollution and on its role as an environmental stressor. Based on the evidence produced in the fields of medicine and psychology, it has been argued that daily increases in ambient air pollution may increase bodily cortisol levels, in turn making individuals less risk seeking (first channel). Moreover, increased air pollution concentrations are believed to deteriorate agents' mood, in turn distorting their probability estimates of future events, making them more risk averse and inducing them to shy away from risky assets (second channel). The two effects work in the same direction, and are conjectured to give rise to a negative relationship between air pollution concentrations, demand in the stock market, and ultimately equity returns, *ceteris paribus*.

Such a hypothesis has been tested empirically using data from the Milan Stock Exchange, and exploiting a natural experiment provided by an institutional change in trading system. The evidence appears to be highly consistent with the hypothesis under investigation, and supports the view that some psychologically-relevant yet economically-neutral factors indeed play a role in shaping portfolio decisions. The findings also constitute a puzzle when interpreted in light of the Efficient Market Theory, as public past data about air pollution seem to represent valuable information for predicting future stock returns.

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Table I

Summary Statistics - Air Pollution and Environmental Variables

Table I displays a number of summary statistics that describe the sample. For each variable, summary statistics are reported for two sub-samples, the first one (upper row) covering the period when trading at the Milan Stock Exchange was centralized, and the second one (lower row) referring to the era in which trading was computerized and decentralized. The variable described as *C9 Index* measures the intensity of disturbances of the Earth's magnetosphere (i.e. geomagnetic storms), and ranges from 0 (quiet) to 9 (highly disturbed). All the other variables have been measured daily by a monitor located in the city of Milan, Italy.

Variable	Period	Mean	Standard deviation	Min	Max	Skewness	Kurtosis
PM (μg/m^3)	01/02/1980-04/14/1994 (2731 obs)	122.25	80.55	6.28	679.86	1.77	7.69
	04/15/1994-02/13/1998 (919 obs)	56.32	20.21	5.13	148.77	.70	3.80
NO_x (μg/m^3)	01/02/1980-04/14/1994 (2317 obs)	342.48	309.00	19.07	2592	2.45	10.62
	04/15/1994-05/19/2006 (2976 obs)	204.31	166.31	28.57	1501	2.48	11.42
SO2 (μg/m^3)	01/02/1980-04/14/1994 (2159 obs)	141.69	187.44	0	1311	2.47	10.31
	04/15/1994-05/19/2006 (2899 obs)	16.94	18.08	.44	163.36	2.10	9.15
Temp (C°)	01/02/1989-04/14/1994 (1083 obs)	14.07	7.78	-4.60	29.80	.07	1.89
	04/15/1994-05/19/2006 (3009 obs)	14.36	7.83	-4.80	32.00	.03	1.88
Rain (mm)	01/02/1989-04/14/1994 (1035 obs)	2.23	7.97	0	122.20	7.73	86.91
	04/15/1994-05/19/2006 (3037 obs)	2.55	8.23	0	212	8.49	155.15
C9 Index	01/02/1980-04/14/1994 (3550 obs)	3.25	2.11	0	9	.24	2.01
	04/15/1994-05/19/2006 (3059 obs)	2.57	2.12	0	9	.58	2.29
Wind (m/s)	01/02/1989-04/14/1994 (979 obs)	1.44	.57	.39	4.25	1.10	4.98
	04/15/1994-05/19/2006 (3006 obs)	1.66	.59	.20	6.09	1.61	8.42
Pressure (hPa)	01/02/1989-04/14/1994 (1077 obs)	1005.37	7.89	977.21	1027.28	-.07	3.31
	04/15/1994-05/19/2006 (2984 obs)	1001.55	7.35	969.58	1023.60	-.13	3.24

Table II

Summary Statistics – Stock Returns

Table II displays a number of summary statistics that describe the time series of stock returns used in the analysis. For each variable, summary statistics are reported for two sub-samples, the first one (upper row) covering the period when trading at the Milan Stock Exchange was centralized, and the second one (lower row) referring to the era in which trading was computerized and decentralized. Comit, Datastream Italy-market, and MIB are global indices of the Italian stock market. Datastream Germany-market is a global index of the German stock market, and S&P500 is a global index of the U.S. stock market. Equity returns are expressed in percentage points.

Variable	Period	Mean	Standard deviation	Min	Max	Skewness	Kurtosis
Comit index	01/02/1980-04/14/1994 (3550 obs)	.064	1.41	-14.85	8.30	-.84	12.95
	04/15/1994-05/19/2006 (3059 obs)	.026	1.19	-8.47	6.22	-.53	6.54
Datastream Italy-market index	01/02/1980-04/14/1994 (3607 obs)	.072	1.42	-9.84	9.18	-.37	9.09
	04/15/1994-05/19/2006 (3073 obs)	.024	1.27	-7.79	6.90	-.18	5.94
MIB index	01/03/1985-04/14/1994 (2285 obs)	.056	1.31	-10.31	6.88	-.62	8.96
	04/15/1994-05/19/2006 (3056 obs)	.027	1.19	-8.48	6.22	-.54	6.55
S&P500 index	01/02/1980-04/14/1994 (3470 obs)	.039	1.02	-22.89	8.71	-3.47	82.78
	04/15/1994-05/19/2006 (2978 obs)	.036	1.08	-7.11	5.57	-.11	6.58
Datastream Germany-market index	01/02/1980-04/14/1994 (3550 obs)	.033	0.96	-12-14	5.91	-1.12	17.86
	04/15/1994-05/19/2006 (3059 obs)	.023	1.18	-7.21	5.48	-.37	5.98

Table III
Air Pollution and Stock Return – A Natural Experiment (Basic Model)

This table displays the results of estimating model [1]. The left-hand side of the table contains the coefficient estimates produced using the first sub-sample of data, covering the period when trading at the Milan Stock Exchange was centralized. The right-hand side shows the estimates generated using the second sub-sample, which refers to the era in which trading was computerized and decentralized. The air pollution proxy employed is the ambient concentration of Particulate Matter (PM) at lag 1. Stock returns are expressed in percentage points. P-values are in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively.

	Centralized Market			Decentralized Market		
	Comit *01/02/1980-04/14/1994*	Datastream *01/02/1980-04/14/1994*	MIB *01/03/1985-04/14/1994*	Comit *04/15/1994-02/13/1998*	Datastream *04/15/1994-02/13/1998*	MIB *04/15/1994-02/13/1998*
α	.136*** (0.003)	.132** (0.011)	.179*** (0.001)	.054 (0.630)	.020 (0.859)	.043 (0.695)
β_1	.250*** (0.000)	.284*** (0.000)	.286*** (0.000)	.134*** (0.002)		.145*** (0.001)
β_2		-.115*** (0.000)	-.105** (0.032)			-.082* (0.081)
β_3		.055* (0.078)	.067** (0.043)			.075* (0.089)
$\mu_{PM_{t-1}}$	-.00063** (0.027)	-.00052 (0.129)	-.00099*** (0.008)	-.00049 (0.807)	.00037 (0.853)	-.00034 (0.863)
γ_{SAD}	.068*** (0.003)	.064*** (0.007)	.057* (0.051)	.087** (0.019)	.095** (0.022)	.088** (0.022)
γ_{Fall}	-.122* (0.055)	-.176*** (0.005)	-.151* (0.064)	-.190* (0.077)	-.236* (0.056)	-.189* (0.082)
$\gamma_{FullMoon}$	.009 (0.870)	-.008 (0.889)	-.039 (0.547)	.096 (0.268)	.110 (0.249)	.117 (0.193)
$\gamma_{NewMoon}$	-.109** (0.036)	-.127** (0.017)	-.104* (0.090)	.013 (0.893)	.013 (0.902)	.016 (0.857)
γ_{Monday}	-.131** (0.016)	-.091* (0.097)	-.113* (0.085)	-.218** (0.021)	-.249** (0.017)	-.238** (0.013)
γ_{Tax}	-.094 (0.535)	-.113 (0.517)	-.027 (0.901)	-.101 (0.709)	-.028 (0.943)	-.092 (0.736)
Log pseudo-likelihood	-4399.1	-4516.2	-2746.793	-1421.9	-1463.5	-1414.2
Obs	2730	2772	1743	920	923	917
Gaps	295	296	223	29	29	29

Table IV
Air Pollution and Stock Return – Basic Model (Alternative Lag Structures)

This table displays the results of estimating model [1] using alternative lag structures of the air pollution proxy, Particulate Matter (PM). The left-hand side of the table contains the coefficient estimates produced using the first sub-sample of data, covering the period when trading at the Milan Stock Exchange was centralized. The right-hand side shows the estimates generated using the second sub-sample, which refers to the era in which trading was computerized and decentralized. Each row refers to a different version of model [1], where the difference arises from the type of lag applied to the pollution proxy. The first row contains the estimated coefficient on the air pollution proxy at lag 0, whereas in the following rows alternative lags of the pollution proxy are employed, from 1 through 5. In the last row, the pollution proxy employed is the mean of the PM levels recorded between day *t-5* and day *t-1*. Equity returns are expressed in percentage points. P-values are in parenthesis below the corresponding coefficients. The number of lagged returns included in each estimated equation is shown in brackets. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively.

	Centralized Market			Decentralized Market		
	Comit *01/02/1980-04/14/1994*	Datastream *01/02/1980-04/14/1994*	MIB *01/03/1985-04/14/1994*	Comit *04/15/1994-02/13/1998*	Datastream *04/15/1994-02/13/1998*	MIB *04/15/1994-02/13/1998*
μ_{PM_t}	-.00043 (0.124) [3]	-.00035 (0.335) [3]	-.00076** (0.033) [3]	-.00009 (0.961) [3]	.00116 (0.598) [0]	-.00027 (0.891) [3]
$\mu_{PM_{t-1}}$	-.00063** (0.027) [1]	-.00052 (0.129) [3]	-.00099*** (0.008) [3]	-.00049 (0.807) [3]	.00037 (0.853) [0]	-.00034 (0.863) [3]
$\mu_{PM_{t-2}}$	-.00049 (0.103) [3]	-.00017 (0.591) [2]	-.00061* (0.080) [3]	-.00149 (0.419) [3]	-.00138 (0.506) [0]	-.00136 (0.461) [3]
$\mu_{PM_{t-3}}$	-.00043 (0.169) [3]	-.00026 (0.435) [3]	-.00066* (0.080) [3]	-.00029 (0.878) [3]	.00086 (0.689) [0]	-.00038 (0.841) [3]
$\mu_{PM_{t-4}}$	-.00036 (0.246) [3]	.00012 (0.673) [3]	-.00070* (0.074) [2]	.00205 (0.267) [3]	.00161 (0.423) [0]	.00207 (0.261) [3]
$\mu_{PM_{t-5}}$	-.00035 (0.249) [3]	-.00014 (0.625) [3]	-.00041 (0.289) [3]	-.00156 (0.38) [3]	-.00132 (0.471) [0]	-.00164 (0.356) [3]
$\mu_{PM_{Mean}}$	-.00068** (0.032) [3]	-.00056 (0.113) [3]	-.00087** (0.021) [2]	-.00006 (0.979) [3]	.00051 (0.852) [0]	-.00009 (0.972) [3]

Table V

Air Pollution and Stock Return - Controlling for Meteorological Conditions

This table displays the results of estimating model [2]. The left-hand side of the table contains the coefficient estimates produced using the first sub-sample of data, covering the period when trading at the Milan Stock Exchange was centralized. The right-hand side shows the estimates generated using the second sub-sample, which refers to the era in which trading was computerized and decentralized. The air pollution proxy employed is the mean level of Particulate Matter (PM) recorded between day *t-5* and day *t-1*. Compared to model [1], three weather proxies are included as controls, i.e. temperature, rain, and geomagnetic storms. Stock returns are expressed in percentage points. P-values are in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively.

	Centralized Market			Decentralized Market		
	Comit	Datastream	MIB	Comit	Datastream	MIB
	01/02/1989-04/14/1994	*01/02/1989-04/14/1994*	*01/02/1989-04/14/1994*	*04/15/1994-02/13/1998*	*04/15/1994-02/13/1998*	*04/15/1994-02/13/1998*
α	.430**	.443**	.439**	-.005	.026	-.001
	(0.011)	(0.017)	(0.010)	(0.981)	(0.909)	(0.996)
β_1	.295***	.267***	.306***	.155***		.154***
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
β_2	-.097*		-.112**	-.080*		-.081*
	(0.053)		(0.025)	(0.086)		(0.082)
$\mu_{PM_{Mean}}$	-.00287***	-.00263***	-.00304***	-.00032	.00012	-.00034
	(0.000)	(0.001)	(0.000)	(0.899)	(0.965)	(0.894)
γ_{SAD}	.066	.032	.076	.111**	.109*	.109**
	(0.172)	(0.579)	(0.137)	(0.043)	(0.072)	(0.046)
γ_{Fall}	-.253***	-.262***	-.263***	-.227**	-.255*	-.226**
	(0.010)	(0.011)	(0.010)	(0.044)	(0.053)	(0.045)
$\gamma_{FullMoon}$	-.157**	-.116	-.163**	.142	.156	.142
	(0.042)	(0.170)	(0.040)	(0.114)	(0.108)	(0.117)
$\gamma_{NewMoon}$	-.169**	-.151*	-.164*	.023	.034	.023
	(0.042)	(0.077)	(0.051)	(0.804)	(0.729)	(0.803)
γ_{Monday}	-.099	-.153*	-.117	-.243***	-.267***	-.250***
	(0.233)	(0.064)	(0.168)	(0.008)	(0.007)	(0.007)
γ_{Tax}	-.090	-.012	-.086	-.054	.060	-.049
	(0.759)	(0.967)	(0.772)	(0.855)	(0.901)	(0.869)
γ_{Temp}	-.007	-.008	-.006	.002	.001	.002
	(0.329)	(0.311)	(0.393)	(0.772)	(0.885)	(0.795)
γ_{Rain}	-.007	-.011	-.009	-.027	-.077	-.023
	(0.919)	(0.889)	(0.893)	(0.727)	(0.345)	(0.766)
$\gamma_{GeoStorm}$	.033	.040	-.015	-.068	-.212	-.076
	(0.658)	(0.622)	(0.840)	(0.701)	(0.195)	(0.665)
Log pseudo-likelihood	-1475.6	-1519.5	-1476.3	-1458.1	-1506.6	-1456.4
Obs	975	984	961	951	955	948
Gaps	35	35	35	5	5	5

Table VI

Air Pollution and Stock Returns - Controlling for International Economic Shocks

This table displays the results of estimating model [3] using the first sub-sample of data, which refers to the period when trading at the Milan Stock Exchange was centralized. The air pollution proxy employed is the mean level of Particulate Matter (PM) recorded between day *t-5* and day *t-1*. Compared to model [2], two international stock market indices are included as controls, i.e. Datastream Germany-market and S&P500. Stock returns are expressed in percentage points. P-values are in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively.

	Centralized Market		
	Comit *01/02/1989-04/14/1994*	Datastream *01/02/1989-04/14/1994*	MIB *01/02/1989-04/14/1994*
α	.356** (0.026)	.345* (0.051)	.364* (0.028)
β_1	.230*** (0.000)	.185*** (0.000)	.239*** (0.000)
β_2	-.144*** (0.000)	-.071* (0.075)	-.154*** (0.000)
β_3	.077** (0.026)		.076** (0.034)
$\mu_{PM_{Mean}}$	-.00251*** (0.000)	-.00291*** (0.000)	-.00284*** (0.000)
γ_{SAD}	.027 (0.549)	.036 (0.448)	.038 (0.425)
γ_{Fall}	-.163* (0.062)	-.230** (0.019)	-.175* (0.061)
$\gamma_{FullMoon}$	-.092 (0.244)	-.056 (0.477)	-.079 (0.323)
$\gamma_{NewMoon}$	-.109 (0.163)	-.111 (0.151)	-.094 (0.227)
γ_{Monday}	-.061 (0.425)	-.091 (0.241)	-.065 (0.401)
γ_{Tax}	.025 (0.935)	.205 (0.418)	.021 (0.946)
γ_{Temp}	-.004 (0.520)	-.003 (0.660)	-.003 (0.624)
γ_{Rain}	-.074 (0.293)	-.045 (0.546)	-.080 (0.260)
$\gamma_{GeoStorm}$	.011 (0.873)	.026 (0.739)	-.035 (0.619)
$\gamma_{Germany}$	.518*** (0.000)	.498*** (0.000)	.540*** (0.000)
γ_{USA}	.166*** (0.000)	.177*** (0.000)	.168*** (0.000)
Log pseudo-likelihood	-1326.5	-1383.6	-1323.1
Obs	952	960	937
Gaps	53	54	54

Table VII

Air Pollution and Stock Returns – Alternative Proxy (NO_x)

This table displays the results of estimating model [3] using Nitrogen Oxides (NO_x), instead of Particulate Matter (PM), as a proxy for air pollution. The left-hand side of the table contains the marginal effects of air pollution estimated using the first sub-sample of data, which covers the period when trading at the Milan Stock Exchange was centralized. The right-hand side shows the estimates generated using the second sub-sample, which refers to the era in which trading was computerized and decentralized. Each row refers to a different version of model [3], where the difference arises from the type of lag applied to the pollution proxy. The first row contains the marginal effect of the air pollution proxy at lag 0, whereas in the following rows alternative lags of the pollution proxy are employed, from 1 through 5. In the last row, the pollution proxy employed is the mean of the NO_x levels recorded between day *t-4* and day *t-1*. Equity returns are expressed in percentage points. P-values are in parenthesis below the corresponding coefficients. The number of lagged returns included in each estimated equation is shown in brackets. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively.

	Centralized Market			Decentralized Market		
	Comit *01/02/1989-04/14/1994*	Datastream *01/02/1989-04/14/1994*	MIB *01/02/1989-04/14/1994*	Comit *04/15/1994-05/19/2006*	Datastream *04/15/1994-05/19/2006*	MIB *04/15/1994-05/19/2006*
μ_{NOx_t}	-.00003 (0.864) [2]	.00010 (0.562) [1]	.00001 (0.980) [2]	-.00001 (0.980) [1]	-.00005 (0.670) [0]	.00001 (0.997) [1]
$\mu_{NOx_{t-1}}$	-.00008 (0.651) [3]	-.00025 (0.161) [1]	-.00010 (0.588) [3]	.00001 (0.901) [1]	.00003 (0.791) [0]	.00001 (0.899) [1]
$\mu_{NOx_{t-2}}$	-.00021 (0.166) [3]	-.00019 (0.221) [1]	-.00022 (0.174) [3]	.00007 (0.556) [1]	-.00004 (0.706) [0]	.00007 (0.554) [1]
$\mu_{NOx_{t-3}}$	-.00023 (0.140) [3]	-.00028* (0.074) [1]	-.00025 (0.113) [3]	.00002 (0.879) [1]	-.00003 (0.787) [0]	.00004 (0.766) [1]
$\mu_{NOx_{t-4}}$	-.00031* (0.050) [2]	-.00034** (0.032) [1]	-.00030* (0.074) [2]	.00005 (0.675) [1]	.00001 (0.908) [0]	.00006 (0.658) [1]
$\mu_{NOx_{t-5}}$	-.00021 (0.132) [2]	-.00021 (0.167) [1]	-.00019 (0.212) [2]	.00003 (0.773) [1]	-.0001 (0.273) [0]	.00004 (0.720) [1]
$\mu_{Nox_{Mean}}$	-.00033* (0.081) [3]	-.00039** (0.034) [2]	-.00030 (0.136) [3]	.00003 (0.855) [1]	-.00009 (0.531) [0]	.00003 (0.833) [1]

Table VIII

Air Pollution and Stock Returns – Alternative Proxy (SO_2)

This table displays the results of estimating model [3] using Sulfur Dioxide (SO_2), instead of Particulate Matter (PM), as a proxy for air pollution. The left-hand side of the table contains the marginal effects of air pollution estimated using the first sub-sample of data, covering the period when trading at the Milan Stock Exchange was centralized. The right-hand side shows the estimates generated using the second sub-sample, which refers to the era in which trading was computerized and decentralized. Each row refers to a different version of model [3], where the difference arises from the type of lag applied to the pollution proxy. The first row contains the marginal effect of the air pollution proxy at lag 0, whereas in the following rows alternative lags of the pollution proxy are employed, from 1 through 5. In the last row, the pollution proxy employed is the mean of the SO_2 levels recorded between day *t-3* and day *t-1*. Equity returns are expressed in percentage points. P-values are in parenthesis below the corresponding coefficients. The number of lagged returns included in each estimated equation is shown in brackets. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively.

	Centralized Market			Decentralized Market		
	Comit *01/02/1989-04/14/1994*	Datastream *01/02/1989-04/14/1994*	MIB *01/02/1989-04/14/1994*	Comit *04/15/1994-05/19/2006*	Datastream *04/15/1994-05/19/2006*	MIB *04/15/1994-05/19/2006*
μ_{SO2_t}	-.00096 (0.176) [2]	-.00129* (0.093) [2]	-.0011462 (0.082) [3]	-.00089 (0.498) [1]	-.0014838 (0.248) [0]	-.00092 (0.479) [1]
$\mu_{SO2_{t-1}}$	-.00108 (0.172) [2]	-.00151** (0.043) [2]	-.0012364 (0.084) [3]	-.00107 (0.399) [1]	-.0019136 (0.130) [0]	-.00092 (0.461) [1]
$\mu_{SO2_{t-2}}$	-.00094 (0.212) [2]	-.00191** (0.011) [2]	-.0011984 (0.083) [3]	-.00217* (0.080) [1]	-.0022128* (0.094) [1]	-.00206* (0.090) [1]
$\mu_{SO2_{t-3}}$	-.00111 (0.123) [2]	-.00106 (0.180) [1]	-.0011885 (0.074) [3]	-.00001 (0.992) [1]	-.0003191 (0.812) [0]	.00021 (0.865) [1]
$\mu_{SO2_{t-4}}$	-.00095 (0.223) [2]	-.00089 (0.293) [1]	-.0008177 (0.258) [3]	.00129 (0.317) [1]	.0005473 (0.695) [0]	.00128 (0.320) [1]
$\mu_{SO2_{t-5}}$	-.00034 (0.630) [2]	-.00085 (0.323) [1]	-.0006407 (0.338) [3]	.00078 (0.541) [1]	-.0005863 (0.667) [0]	.00077 (0.536) [1]
$\mu_{SO2_{Mean}}$	-.00138* (0.099) [2]	-.00186** (0.022) [1]	-.00152* (0.053) [3]	-.00140 (0.330) [1]	-.0019175 (0.211) [0]	-.00119 (0.401) [1]

Table IX
Air Pollution and Stock Returns – Alternative Sub-Periods

This table displays the results of estimating model [3] using smaller sub-samples. The air pollution proxy employed is the mean level of Particulate Matter (PM) recorded between day *t-5* and day *t-1*. The left-hand side of the table contains the marginal effects of the air pollution proxy estimated using alternative subsets of the first sub-sample of data, which covers the period when trading at the Milan Stock Exchange was centralized; each row contains the air pollution effect estimated from a different subset of data. The right-hand side shows the marginal effects of the air pollution proxy estimated using alternative subsets of the second sub-sample of data, which refers to the era in which trading was computerized and decentralized. Equity returns are expressed in percentage points. P-values are in parenthesis below the corresponding coefficients. The number of lagged returns included in each estimated equation is shown in brackets. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively.

	Centralized Market				Decentralized Market		
	Comit	Datastream	MIB		Comit	Datastream	MIB
01/02/1989-04/14/1994	-.0025*** (0.000) [3]	-.0029*** (0.000) [2]	-.0028*** (0.000) [3]	*04/15/1994-13/02/1998*	-.00176 (0.383) [1]	-.00024 (0.922) [0]	-.00177 (0.379) [1]
01/02/1990-04/14/1994	-.0022*** (0.003) [3]	-.0025*** (0.001) [2]	-.0024*** (0.004) [3]	*04/15/1994-12/31/1996*	.00101 (0.729) [1]	.00198 (0.566) [0]	.00096 (0.742) [2]
01/02/1991-04/14/1994	-.0021* (0.069) [2]	-.0020* (0.084) [2]	-.0021* (0.086) [2]	*04/15/1994-12/29/1995*	-.00270 (0.535) [1]	-.00105 (0.834) [0]	-.00285 (0.517) [2]
01/02/1992-04/14/1994	-.0027* (0.061) [2]	-.0021 (0.142) [1]	-.0027* (0.068) [2]				

Table X

Air Pollution Cross-City Correlation Matrix

This table displays estimated cross-city air pollution correlation coefficients for a sample of cities located in Lombardy, the Italian region whose capital is Milan. The air pollution proxy employed in the computations is Particulate Matter (PM). The first column contains the names of the cities in which PM daily concentrations have been measured by background monitors. The second column indicates the distance between a given city and the monitoring station located in the city of Milan. The third column specifies the province in which each given city is located.

City	Distance from Milan (km)	Province	Mil	Per	Rho	Agr	Vil	Inz	Cass	Leg	Nib	Fil	Cast	Tur	Var	Casn
Milan	-	Milan	♦													
Pero	11	Milan	0.73	♦												
Rho	14.5	Milan	0.41	0.80	♦											
Agrate	15	Monza	0.43	0.63	0.63	♦										
Villasanta	16	Monza	0.36	0.64	0.69	0.67	♦									
Inzago	21	Milan	0.65	0.83	0.54	0.61	0.57	♦								
Cassano	23	Milan	0.56	0.84	0.68	0.59	0.51	0.86	♦							
Legnano	27	Milan	0.50	0.78	0.73	0.72	0.60	0.70	0.65	♦						
Nibionno	30	Lecco	0.72	0.78	0.51	0.57	0.50	0.76	0.73	0.60	♦					
Filago	31	Bergamo	0.69	0.75	0.45	0.55	0.52	0.73	0.67	0.57	0.76	♦				
Castano	34	Milan	0.70	0.83	0.60	0.53	0.61	0.74	0.63	0.71	0.82	0.76	♦			
Turbigo	37	Milan	0.59	0.72	0.69	0.48	0.44	0.73	0.62	0.67	0.58	0.56	0.78	♦		
Varese	48	Varese	0.51	0.35	0.13	0.09	0.08	0.40	0.24	0.27	0.47	0.35	0.46	0.24	♦	
Casnigo	60	Bergamo	0.64	0.70	0.31	0.49	0.41	0.74	0.64	0.54	0.78	0.65	0.70	0.60	0.48	♦
Colico	72	Lecco	0.48	0.46	0.31	0.45	0.46	0.37	0.39	0.42	0.40	0.57	0.54	0.39	0.32	0.40

Table XI
Air Pollution and Stock Returns – Instrumental Variables Estimation

This table reports the coefficients and significance levels from the instrumental variables estimation. The left-hand side of the table contains the coefficient estimates produced using the first sub-sample of data, covering the period when trading at the Milan Stock Exchange was centralized. The right-hand side shows the estimates generated using the second sub-sample, which refers to the era in which trading was computerized and decentralized. The air pollution proxy employed in the computations is the contemporaneous concentration of Particulate Matter (PM). The instruments are wind speed, atmospheric pressure, and rainfall, all of which employed with a lag, as specified in model [6]. Equity returns are expressed in percentage points. P-values are in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively.

	Centralized Market			Decentralized Market		
	Comit *01/02/1989-04/14/1994*	Datastream *01/02/1989-04/14/1994*	MIB *01/02/1989-04/14/1994*	Comit *04/15/1994-02/13/1998*	Datastream *04/15/1994-02/13/1998*	MIB *04/15/1994-02/13/1998*
α	.377 (0.145)	.339 (0.208)	.366 (0.174)	.435 (0.275)	.559 (0.187)	.398 (0.324)
β_1	.226*** (0.000)	.147*** (0.001)	.226*** (0.000)	.102*** (0.006)		.099*** (0.008)
β_2	-.121*** (0.000)	-.069* (0.077)	-.120*** (0.000)			
μ_{PM_t}	-.0052** (0.025)	-.0043* (0.081)	-.0055** (0.024)	-.0096 (0.163)	-.0102 (0.177)	-.0088 (0.211)
γ_{SAD}	.105 (0.104)	.089 (0.181)	.127* (0.073)	.105* (0.080)	.116* (0.098)	.099* (0.100)
γ_{Fall}	-.329** (0.013)	-.299** (0.015)	-.353** (0.012)	-.092 (0.393)	-.157 (0.211)	-.087 (0.417)
$\gamma_{FullMoon}$	-.088 (0.350)	-.097 (0.331)	-.076 (0.428)	.240*** (0.006)	.274*** (0.004)	.246*** (0.005)
$\gamma_{NewMoon}$	-.029 (0.751)	-.020 (0.837)	-.019 (0.841)	.021 (0.794)	.031 (0.736)	.016 (0.837)
γ_{Monday}	-.101 (0.365)	-.178 (0.106)	-.124 (0.293)	-.235*** (0.010)	-.349*** (0.001)	-.243*** (0.007)
γ_{Tax}	-.323 (0.384)	-.221 (0.582)	-.354 (0.343)	-.019 (0.948)	-.227 (0.525)	-.008 (0.978)
γ_{Temp}	.0003 (0.967)	-.001 (0.925)	.002 (0.792)	.003 (0.677)	-.0002 (0.983)	.003 (0.715)
γ_{Rain}	.037 (0.668)	.065 (0.462)	.027 (0.767)	-.169* (0.069)	-.169* (0.087)	-.159* (0.089)
$\gamma_{GeoStorm}$	.109 (0.250)	.074 (0.466)	.071 (0.469)	-.130 (0.486)	-.282 (0.122)	-.124 (0.509)
$\gamma_{Germany}$	.539*** (0.000)	.563*** (0.000)	.556*** (0.000)	.807*** (0.000)	.612*** (0.000)	.809*** (0.000)
γ_{USA}	.170*** (0.002)	.153*** (0.005)	.180*** (0.001)	.051 (0.339)	-.011 (0.836)	.050 (0.347)
Obs	744	752	733	856	859	853

Table XII

A Test of the Efficient Market Theory Using an Air Pollution Index (GARCH model)

This table displays the results of estimating model [7] using the first sub-sample of data, which refers to the period when trading at the Milan Stock Exchange was centralized. The air pollution index (API) is a binary variable constructed based on lagged concentrations of Particulate Matter (PM), Nitrogen Oxides (NO_x), and Sulfur Dioxide (SO_2). Loosely speaking, the API index takes value 1 when air quality has been relatively poor during the past few days. According to the trading strategy discussed in section VIII, when this happens a selling signal is produced. Equity returns are expressed in percentage points. P-values are in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively.

	Centralized Market		
	Comit *01/02/1989-04/14/1994*	Datastream *01/02/1989-04/14/1994*	MIB *01/02/1989-04/14/1994*
α	.122 (0.401)	.078 (0.607)	.102 (0.493)
β_1	.234*** (0.000)	.182*** (0.000)	.241*** (0.000)
β_2	-.139*** (0.000)		-.148*** (0.000)
β_3	.076** (0.028)		.076** (0.034)
μ_{API}	-.222** (0.027)	-.289*** (0.003)	-.245** (0.019)
γ_{SAD}	.047 (0.318)	.056 (0.249)	.060 (0.222)
γ_{Fall}	-.135 (0.113)	-.181* (0.062)	-.143 (0.110)
$\gamma_{FullMoon}$	-.083 (0.289)	-.040 (0.606)	-.080 (0.317)
$\gamma_{NewMoon}$	-.106 (0.183)	-.101 (0.185)	-.098 (0.219)
γ_{Monday}	-.066 (0.384)	-.099 (0.201)	-.074 (0.334)
γ_{Tax}	.050 (0.865)	.266 (0.230)	.056 (0.853)
γ_{Temp}	-.003 (0.653)	-.001 (0.861)	-.002 (0.795)
γ_{Rain}	-.078 (0.266)	-.050 (0.500)	-.084 (0.242)
$\gamma_{GeoStorm}$	-.009 (0.888)	-.004 (0.957)	-.049 (0.493)
$\gamma_{Germany}$	.505*** (0.000)	.473*** (0.000)	.522*** (0.000)
γ_{USA}	.161*** (0.000)	.176*** (0.000)	.171*** (0.000)
Log pseudo-likelihood	-1341.5	-1400.9	-1338.8
Obs	963	971	948
Gaps	54	55	55

Table XIII

A Test of the Efficient Market Theory Using an Air Pollution Index (LOGIT model)

This table displays the results of estimating equation [7] using a LOGIT model. The coefficients that appear in the table are marginal effects, i.e. they show the estimated impact that each variable has on the probability of observing a positive return. The estimation is based on the first sub-sample of data, which refers to the period when trading at the Milan Stock Exchange was centralized. The air pollution index (API) is a binary variable constructed based on lagged concentrations of Particulate Matter (PM), Nitrogen Oxides (NO_x), and Sulfur Dioxide (SO_2). Loosely speaking, the API index takes value 1 when air quality has been relatively poor during the past few days. According to the trading strategy discussed in section VIII, when this happens a selling signal is produced. Equity returns are expressed in percentage points. P-values are in parenthesis below the corresponding coefficients. One, two, and three asterisks denote statistical significance at the ten, five, and one percent level, respectively.

	Centralized Market		
	Comit *01/02/1989-04/14/1994*	Datastream *01/02/1989-04/14/1994*	MIB *01/02/1989-04/14/1994*
β_1	.150*** (0.000)	.100*** (0.004)	.158*** (0.000)
μ_{API}	-.092* (0.082)	-.109** (0.035)	-.118** (0.026)
γ_{SAD}	.032 (0.227)	.022 (0.408)	.040 (0.143)
γ_{Fall}	-.083* (0.085)	-.063 (0.183)	-.099** (0.042)
$\gamma_{FullMoon}$	-.058 (0.185)	-.061 (0.158)	-.048 (0.285)
$\gamma_{NewMoon}$	-.048 (0.257)	-.108 (0.009)	-.049 (0.254)
γ_{Monday}	-.089** (0.035)	-.052 (0.219)	-.083* (0.054)
γ_{Tax}	.079 (0.602)	.161 (0.245)	.068 (0.664)
γ_{Temp}	-.001 (0.703)	-.001 (0.774)	-.001 (0.753)
γ_{Rain}	-.005 (0.900)	-.017 (0.650)	-.007 (0.853)
$\gamma_{GeoStorm}$	-.006 (0.892)	-.002 (0.969)	-.009 (0.833)
$\gamma_{Germany}$	.155*** (0.000)	.166*** (0.000)	.154*** (0.000)
γ_{USA}	.118*** (0.000)	.104*** (0.000)	.127*** (0.000)
Log pseudo-likelihood	-596.8	-605.3	-583.9
Obs	963	971	948

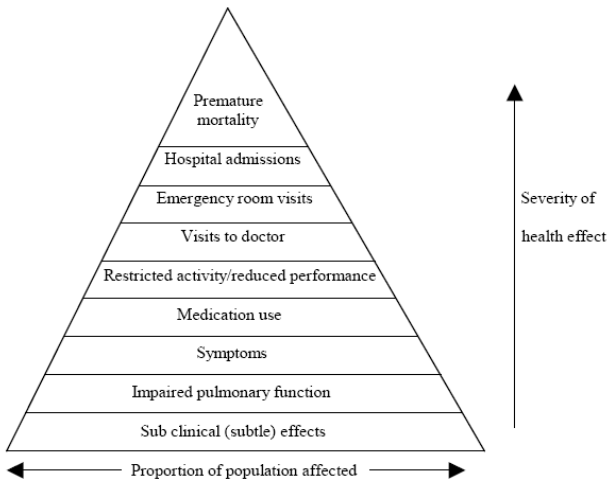


Figure 1. Air pollution health effects pyramid, from WHO (2001).

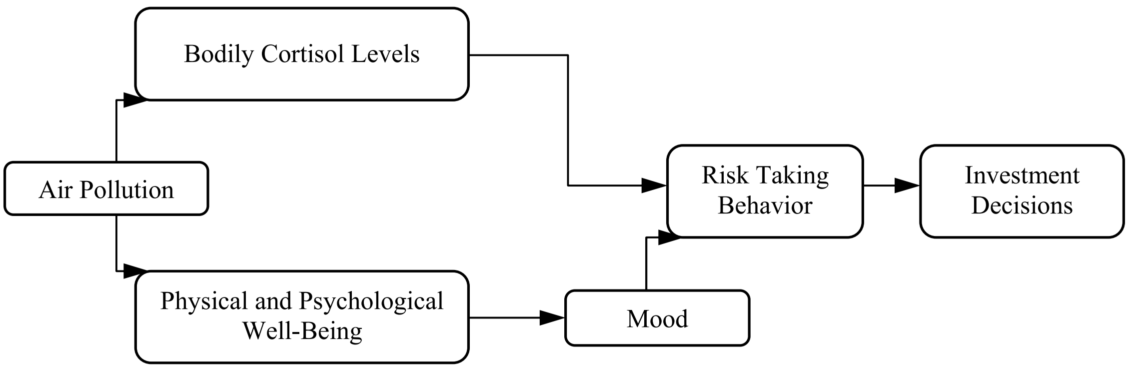


Figure 2. Channels that mediate the impact of air pollution on investment decisions.

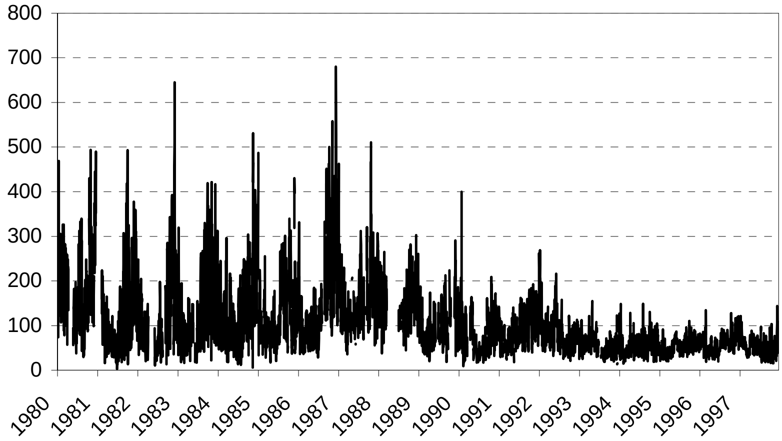
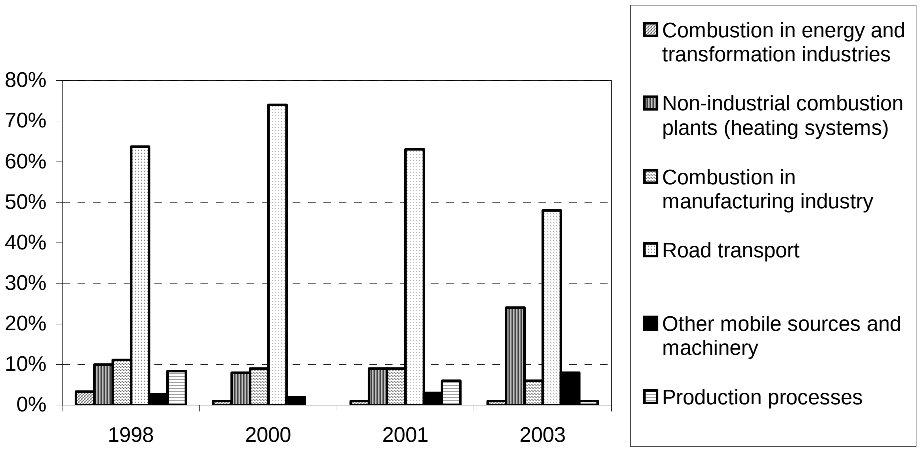
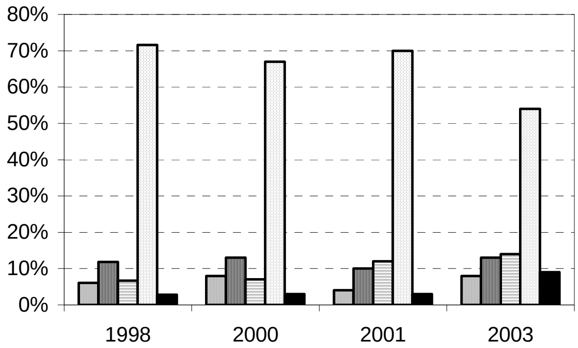


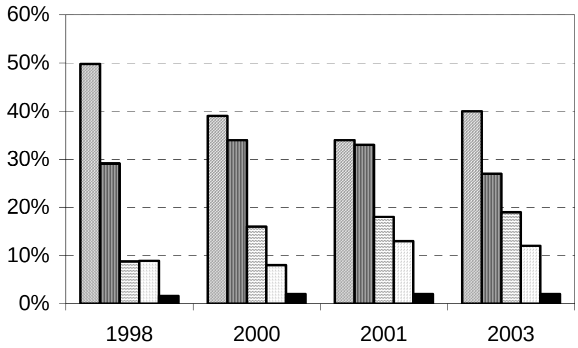
Figure 3. Daily ambient concentrations ($\mu g/m^3$) of particulate matter (TSP) in Milan.



Panel (a). Total Suspended Particulate.



Panel (b). Nitrogen oxides (NO_x).



Panel (c). Sulfur dioxide (SO_2).

Figure 4. Main sources of air pollution emissions in the Province of Milan (percentage contribution). The data are taken from ARPA Lombardia (2001; 2002; 2003a; 2003b; 2003c; 2006).

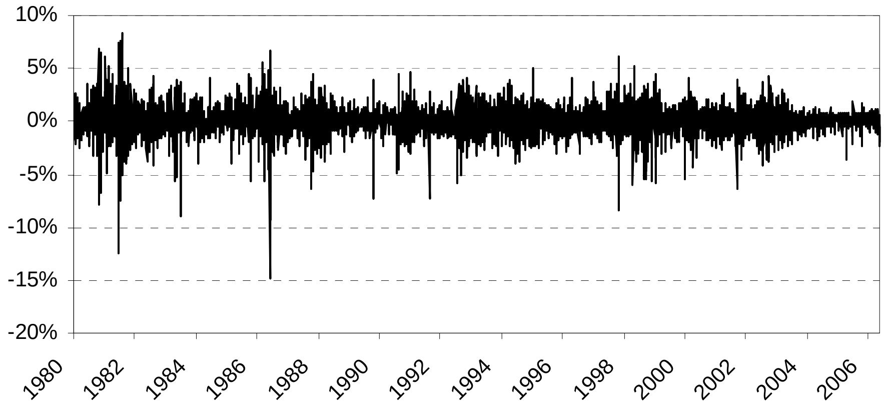


Figure 5. Daily equity returns of the Italian stock market (Comit index).

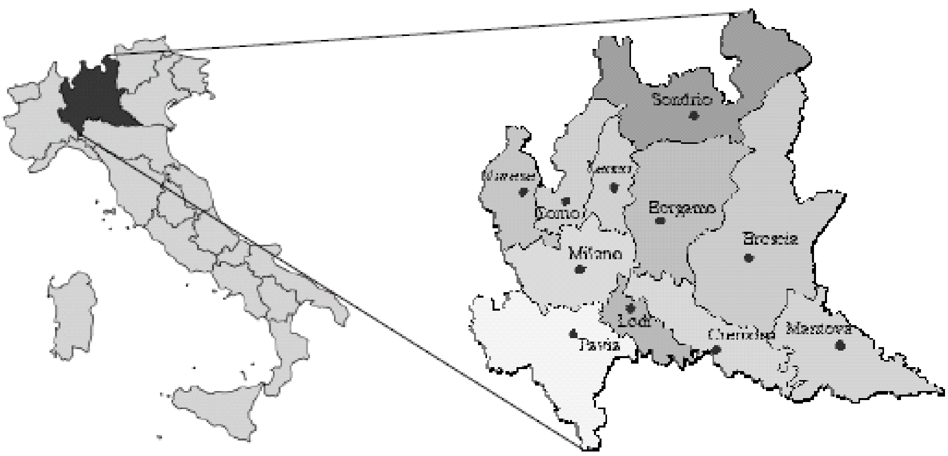


Figure 6. This picture gives a graphical representation of the location of Milan within Italy (left) and Lombardy (right).