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THREE ESSAYS ON BEHAVIORAL FINANCE

By

Gabriele M. Lepori

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ABSTRACT

THREE ESSAYS ON BEHAVIORAL FINANCE

By

Gabriele M. Lepori

This dissertation consists of three empirical essays that explore whether and how financial decision-making is influenced by some psychological factors that do not have a direct economic relevance. The hypotheses proposed here and the results obtained bring a challenge to the accuracy of the paradigm that has been dominating the theory of asset pricing, according to which investors' decisions are exclusively shaped by economic variables. Second, they represent a puzzle when interpreted in light of the Efficient Market Hypothesis.

The first essay investigates the relationship between investor mood and investment decisions. The evidence produced in the fields of psychology and behavioral finance is employed to construct a hypothesis according to which daily changes in the marginal investor's emotional state, caused by changes in ambient air pollution, would be expected to have an impact on aggregate demand in the stock market, ultimately affecting equity returns in a predictable fashion. Such a behavioral hypothesis is tested by means of a natural experiment allowed by an institutional change experienced by the Milan Stock Exchange in the middle of the 1990's. Interestingly, the empirical results do seem to provide support to such a conjecture, and the "mood effect" detected here turns out to be

robust to the use of alternative air pollution proxies, estimation methods, and sets of controls. It is also shown that, despite the predictions of the efficient market theory, there exist some unexploited profitable trading strategies based on air pollution data.

The second essay extends the Seasonal Affective Disorder (SAD) hypothesis to the foreign exchange market. According to medical evidence, seasonal changes in the length of the day produce corresponding changes in human mood, which in turn is conjectured to play a role in the process that governs investment decisions. Such a framework appears to generate some neat predictions in terms of exchange rate dynamics, which are then tested using weekly data on six currencies vis-à-vis the Australian Dollar. The empirical analysis is conducted using an LSTR model, the underlying idea being that the exchange rate moves between two regimes that arise out of the divergence between the seasonal daylight cycles of the northern and southern hemispheres. The findings, in this case, only provide weak evidence in support of the hypothesis under investigation.

In the third essay, an empirical investigation is conducted to determine whether investment decisions can be affected by superstition. After discussing the mechanisms through which superstitions are conjectured to originate, the analysis focuses on a set of superstitious beliefs that, according to folkloristics, can be expected to be held by large groups of people. The behavioral hypothesis that arises out of this context is then tested using daily data from the U.S. stock market, and the outcomes seem to be consistent with the view that superstition can indeed affect investment choices. Moreover, it appears to be possible to profitably exploit some of the empirical regularities that superstitious beliefs cause in the time series of equity returns.

ACKNOWLEDGMENTS

No researcher works in a vacuum. We are all influenced by others, and good research takes a network of knowledge. This work was made possible by the contributions that, directly or indirectly, came from many people.

First, I would like to thank Professor Richard T. Baillie for serving as my advisor through the stages of my graduate school experience. His fruitful advice and kind support are enormously appreciated. Indeed, the origins of this dissertation can be precisely traced back to some early ideas that I developed when I was a student in his classes.

I am also highly indebted to Professors Geoffrey Booth, Raoul Minetti, and Emma Iglesias, whose detailed comments and suggestions greatly improved the quality of the analyses presented here. Similarly, I wish to thank Professor Michael Conlin for the insights he gently shared with me about the mechanics of human decision-making.

Thanks to the former director of the economics graduate program, Professor Thomas Jeitschko, for believing in my English proficiency, and to the current director, Professor Paul Menchik, for giving me the opportunity to gain precious teaching experience.

I am also happy to say that this long journey was made more enjoyable by the encouragement that came on the one hand from my fellow doctoral students, especially Makoto, Sanders, Simon, and Vincent, and on the other hand from the residents of Owen Hall, particularly Alex, Chia-Yu, Harrison, Jay, Jorge, Lan, and Tatsuya.

I want to express the deepest thank to my family, without which none of this would have been achievable.

Last, I want to thank the advocates of orthodox finance and economics for the research stimuli with which they have so far provided me. Heterodox approaches like the one proposed here would probably lose much of their appeal, in my eyes, if there was not a *status quo* to be challenged.

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Air Pollution, Investor Mood, and Financial Choices:

Evidence from the Milan Stock Exchange

1.1. Introduction

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 belief that the feelings experienced at the time of making a choice can bias the decision-making process through a mechanism of "mood misattribution" (Schwartz and Clore, 1983; Schwartz, 1990; Mann, 1992).

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 essay 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 which 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 mining.

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 an institutional change in the middle of the 1990's, which allows for 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 buying/selling decisions, then daily air pollution measured in

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

the city of Milan, should exhibit a significant relationship with 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 increases in air pollution levels are estimated to have a significant negative effect on stock returns during the sub-period in which trading was centralized, whereas no effect 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 current changes in air pollution concentrations (proxied by particulate matter) are estimated to influence equity returns concurrently and in the following few days.

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.

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 stock returns. 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, I think that the empirical findings, which confirm the outcomes of the previous steps, do provide solid evidence of a causal impact of air pollution on investment decisions and ultimately, on stock returns.

These results are remarkable on two grounds. First, 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 chapter is organized as follows. Section 1.2 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 1.3 gives on overview of the air pollution phenomenon and section 1.4 examines the effects it has been found to exert on the human body and psyche. Section 1.5 puts forward the behavioral hypothesis that will be tested, and section 1.6 describes the data. Section 1.7 explores some potential sources of endogeneity, and the empirical analysis is conducted in section 1.8, which also contains a battery of robustness checks. Section 1.9 investigates the implications that the findings have in light of the Efficient Market Theory. Section 1.10 concludes.

1.2. Environment, Affective State, and Human Decisions

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). What is intriguing here is the idea that mood works as a "source of information" to individuals, and it influences their choices even when the source of the mood state does not have anything to do with the decision being made, i.e. it is believed that a mechanism of "mood misattribution" may be at work in people's minds (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). The existence of such links appears hard to justify unless one is willing to somewhat loosen the definition of rational decision-making.

It seems therefore natural to wonder whether these fascinating findings 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, where such a connection has been typically interpreted as being mediated by the "mood misattribution" mechanism[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

[2] For an excellent review on the role of the mood misattribution framework applied to a behavioral finance context, see Hirshleifer and Shumway (2003), and Lucey and Dowling (2005a).

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 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 detectible 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) and wind (Keef and Roush, 2003). It should be said, however, that only a few of these studies appear to have been rigorously constructed upon some specific hypothesis produced in the fields of medicine and/or psychology. One of the most intriguing analyses in this area can be attributed to Kamstra et al. (2003), who empirically test whether the well-known Seasonal Affective Disorder (SAD) phenomenon, caused by the seasonal variation in the length of the day, is responsible for at least part of the seasonal pattern that stock returns typically exhibit. Their findings are encouraging for behavioral finance proponents, and, from a larger perspective, their work also suggests that, in order to be considered solid, empirical evidence in this field needs to be deeply rooted into some underlying psychological/medical hypothesis.

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 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 the level of air pollution are believed to be associated with increased psychological distress (i.e., mood deterioration) and, in turn, with 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.

1.3. Air Pollution: Taxonomy and Origins

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 essay, 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, daily data about the levels of these pollutants in Milan and neighboring cities are readily accessible 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, dimension, and origin, and are generally categorized according to their aerodynamic diameter. Total Suspended Particulates (TSP) include all airborne particles. PM_{10} refers to particles with an aerodynamic diameter less than 10 μm

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

(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 produced 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 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.

Before moving to the existing evidence about the human response to air pollution, it is important to emphasize that 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). Throughout the essay, 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 investment decisions and, ultimately, on equity returns might originate from a mixture of pollutants.

1.4. Physiological and Psychological Reactions to Air Pollution

1.4.1. Physiological Effects

Air pollution has been the core of a massive number of neuro-toxicological and epidemiological investigations[4]. Short-term and long-term exposures to ambient air pollution have been connected with 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). Though the most severe effects are confined to a relatively small portion of the population, a huge number of people is believed to experience at least some minor symptoms and some form of physical distress.

1.4.1.1. Morbidity and Mortality

PM appears to be the most widely studied factor, and there is increasing 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.,

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

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 produce 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. 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).

1.4.1.2. Heart Rate

Among the direct effects of air pollution on the cardiovascular system, one turns out to be particularly relevant in light of the current context. Numerous recent investigations have documented the existence of a positive link between daily/hourly rises in air pollution levels and augmented heart rate (Peters et al., 1999; Pope et al., 1999; Dockery, 2001; Magari et al., 2001; Lagorio et al., 2003; Gong et al., 2004; Liu et al., 2007). For example, Dockery et al. (1999) find that "increased pulse rate, as well as the odds of having a pulse rate 5 or 10 beats per minute above normal" are significantly associated with exposure to PM on the previous 1 to 5 days. Similarly, studying a sample of middle aged healthy individuals living in a metropolitan area in France, Ruidavets et al. (2005) claim that there exists a positive and contemporaneous connection between daily levels of NO_2 and SO_2 and resting heart rate. Furthermore, the authors show that such an impact can be noticed even at low concentration levels of these pollutants.

These findings are critical here because heart rate changes, as we will see later, are also associated with the onset of feelings of anxiety and fear (i.e., heightened anxiety is linked to augmented heart rate). The fact that heart rate is connected both with air pollution, on the one hand, and with affective arousal, on the other hand, might foster a phenomenon of mood misattribution. Such a line of reasoning will be developed in depth in section 1.4.2.3.

1.4.1.3. 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).

1.4.2. Psychological Influence

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 1.1).

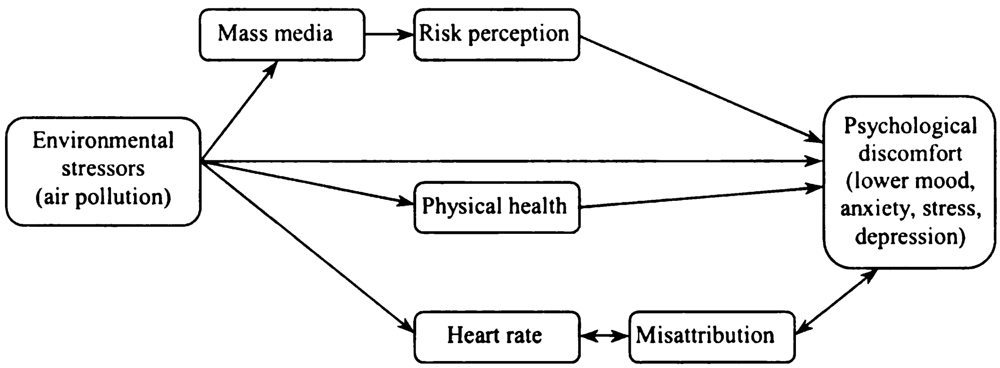

Figure 1.1 Direct and indirect effects of air pollution on psychological well-being.

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".

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[5]. 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

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

psychiatric emergencies (Strahilevitz et al., 1979; Briere et al., 1983; Rotton and Frey, 1984).

1.4.2.1. Risk Perception

Among the indirect effects that air pollution can exert on mental health, two channels have received particular attention. The first channel deals with the links between beliefs, risk perception, and mental discomfort (Figure 1.1). Lazarus and Folkman (1984) argue that the health consequences of an (environmental) stressor, such as a pollutant, depend on the appraisal of the threat (perceived risk) and of the personal resources to deal with it. Within such a framework, not only air pollution *per se*, but also people's beliefs about air pollution, through their influence on risk perception, are expected to have an impact on human psychological well-being. In this regard, Lima (2004), studying a sample of individuals living near an incinerator, finds that risk perception, together with the interaction between risk perception and environmental annoyance created by air pollution, "significantly increase the prediction of psychological symptoms", i.e., anxiety, depression, and stress. Lercher et al. (1995), analyzing the relationship between perceived air quality and psychosomatic symptoms in a sample of adults in Tyrol, Austria, argue that poorly rated air quality is significantly associated with low mood and feelings of fatigue and exhaustion, though an analogous link could not be established with actual air quality. Lima (2004) suggests that risk perception "amplifies the effects of annoyance, as it introduces a suggestion of danger to environmental changes", in turn inducing people to pay more attention to such changes as they can be perceived as potentially harmful.

Her empirical results show that the "suspicion of threat", *per se*, can produce heightened levels of annoyance and, ultimately, more extensive symptoms of psychological irritation.

These findings are supported by another strand of literature that shows how the release of "sham" airborne chemicals, totally innocuous *per se*, can trigger perceptions of somatic change and illness through a process of symptom misinterpretation (MacGregor and Fleming, 1996). It has been found, for instance, that symptom reporting is amplified by the release of unfamiliar or unpleasant (innocuous) odors (Smith et al., 1978; Knasko, 1993; Dalton et al., 1997; Chen and Haviland-Jones, 1999; Dalton, 1999; Jones et al., 2000), and even by the presence of "imaginary" pollutants/odors (O'Mahoney, 1978; Knasko et al., 1990; Lange and Fleming, 2005).

In the context of the present investigation, such a line of reasoning is relevant because not only individuals inhale neurotoxins from the environment in which they live, for they also receive information from the mass media and their interpersonal networks about air pollution daily ambient concentrations and the risks it spawns (Coleman, 1993; Morton and Duck, 2001; Frewer et al., 2002; Wakefield and Elliott, 2003). In this sense, the mass media may work as what Kasperson et al. (1988) call "risk amplification stations". Indeed, it is reasonable to believe that media coverage of air pollution is increasing in the levels of pollution itself: sudden and sharp rises in the ambient levels of some neurotoxins are likely to cause increased volumes of information, the use of "sensational" headlines, and more frequent debates which, ultimately, can be expected to amplify risk perception among the public. If one believes in the framework proposed above, the implication is that daily increases in air pollution concentrations can be thought of as having both a direct negative impact on physical health and an indirect negative influence, modulated by risk perception, in terms of psychological discomfort, i.e., anxiety and stress.

1.4.2.2. Physical Health and Emotional State

The second indirect channel has do to with the interconnection existing between physical and emotional health. 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". In his opinion, mood changes then affect how individuals think, what they feel like doing, and how optimistic/pessimistic they are (e.g., "when mood is bad, goal-directed activity seems less likely to succeed and so we are more inclined to put off a task or lower our aspiration level"). 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 deterioration of mood.

Such a view can find 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 changes in mood 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. Pain and discomfort produced by the symptoms of physical impairment are very likely to play a role in worsening mood (Rasul et al., 2002).

1.4.2.3. Anxiety, Heart Rate, and Mood Misattribution

It is believed that exposure to physical and psychological stressors induces the autonomic nervous system to produce physiological arousal (Levenson, 2003), and an increased heart rate is characteristic of such a state of arousal (Appelhans and Luecken, 2006). Experiencing heightened autonomic activity, such as a heart rate acceleration, in response to a situation or event "can serve as a somatic cue that one is encountering a potentially difficult or dangerous situation" (Hastings et al., 2007). An extensive body of research has documented the existence of a positive correlation between anxiety and cardiovascular activity, measured in terms of heart rate (Behnke et al., 1974; Behnke and Beatty, 1981; Mezzacappa et al., 1997; Abel and Larkin, 1990; Calvo et al., 1996; Roth et al., 1996; Breivik et al., 1998; Georgiades et al., 2000; McCarthy and Goffin, 2004). Analogously, pulse rate appears to reveal a good correspondence to self-reported fear (Lang et al., 1970; Lang, 1971; Sartory et al., 1977).

As it has been previously argued, affective states (feelings or mood) contain information that individuals employ for the assignment of meaning or relevance to the situation. Nonetheless, if one embraces the mood misattribution theory, then what follows is the view that human beings may often attribute arousal or feelings to the wrong sources (e.g., Ross, 1977). In the present context, the mood misattribution framework may operate as follows (see Figure 1.1): (1) when dealing with investment decisions, instead of correctly attributing their increased anxiety and heart rate to increases in air pollution levels, people may mistakenly ascribe them to an increased perceived riskiness of their portfolio of assets and/or to an augmented perceived uncertainty about the economy's future prospects[6] (e.g., Hirshleifer and Shumway, 2003; Kamstra et al., 2003; Lucey and Dowling, 2005a); (2) if this was the case, then people's affective state would play a role in shaping their financial decisions (i.e., increased anxiety and heart rate would likely lead investors to shy away from risky stocks and prefer safer assets[7]). This is, of course, a conjecture. The exact underlying mechanisms are left for investigation to others, such as experimental psychologists.

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[6] Hirshleifer and Shumway (2003), Kamstra et al. (2003), and Lucey and Dowling (2005a), for example, discuss a similar mechanism, though referring to different environmental factors.

[7] This line of reasoning (i.e., the higher the level of anxiety, the lower the demand for risky stocks) is suggested, for example, by Kamstra et al. (2000).

1.5. Air Pollution, Mood Misattribution, and Investment Decisions

As it should be clear by now, the hypothesis advanced and tested in this essay builds upon research from psychology and medicine which argue, 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. Figure 1.1 summarizes the channels, discussed in the previous sections, through which pollution is believed to exert an impact on psychological well-being. What needs to be emphasized here is that all the causal relationships discussed above point to the same direction, i.e., all of them suggest a negative influence of poor air quality on emotional state. An extensive review of the relevant literature has also shown that both contemporaneous and lagged (negative) effects can possibly be produced. In the case of the latter, the time-series studies examined here have revealed a lag structure that typically ranges between 1 and 5 days.

Applying the mood misattribution framework to the present setting appears to yield an unambiguous testable hypothesis. The key idea in that framework is that "mood tends to inform decisions even when the cause of the mood is unrelated to the decision being made" (Lucey and Dowling, 2005a). *Ceteris paribus*, (1) if increases in the level of air pollution cause market participants to experience lower mood, greater anxiety, and augmented heart rate and (2) investors attribute such affective changes to the wrong source (e.g., perceived riskiness of their portfolios, pessimism about future developments of the economy), then (3) their investment decisions will turn out to be influenced by a factor that, *per se*, is economically irrelevant. For instance, following the reasoning hinted at by Kamstra et al. (2000), greater subjective anxiety could be expected to induce agents to prefer safer assets over risky stocks. In turn, all else equal, this would lower demand in the equity market, pushing down stock returns. In one word, if the previous conjecture was valid, then in a reduced-form model one would expect to observe a negative relationship between air pollution concentrations and stock returns. The goal of the present investigation is precisely to empirically 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.

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).

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 offers the chance to make use of a natural experiment that can give more strength to the empirical results.

1.6. Data

1.6.1. Air Pollution Proxies

Ambient air pollution concentrations are typically measured through a network of monitoring stations[8]. 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 coming from businesses 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.

In the city of Milan, over the period under consideration, data about PM have been recorded by three monitors[9]. Given the characteristics of these monitors, their

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[8] 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).

[9] 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

proximity to the Milan Stock Exchange, and the purpose of the present analysis, only one station has been judged as suitable for providing the data[10]. It is worth to stress that the measurements made by such a monitor are representative of population exposure in a small area that precisely encircles the MSE.

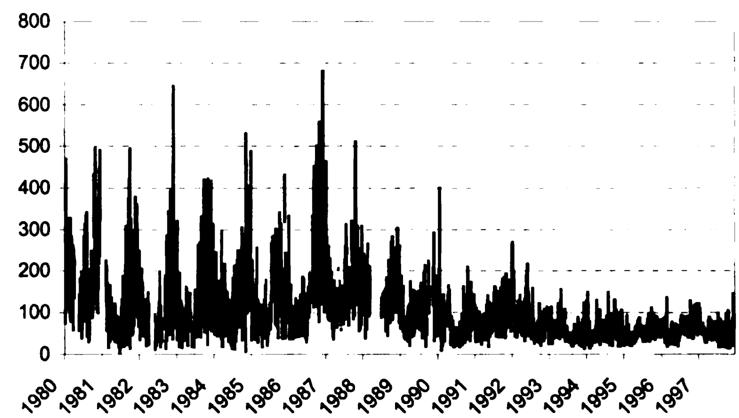

Figure 1.2 Daily ambient concentrations ($\mu g/m^3$) of particulate matter (TSP) in Milan.

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 acquired from ARPA Lombardia[11]. Particulate matter is measured as TSP from

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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.

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

[11] 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.

01/01/1980 through 02/13/1998, and as PM_{10} thereafter[12]. 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[13].

Figure 1.2 allows a graphical inspection of the PM data[14]. Summary statistics are displayed in Table 1.1. TSP data have also been collected from monitors located in fourteen other cities within Lombardy[15].

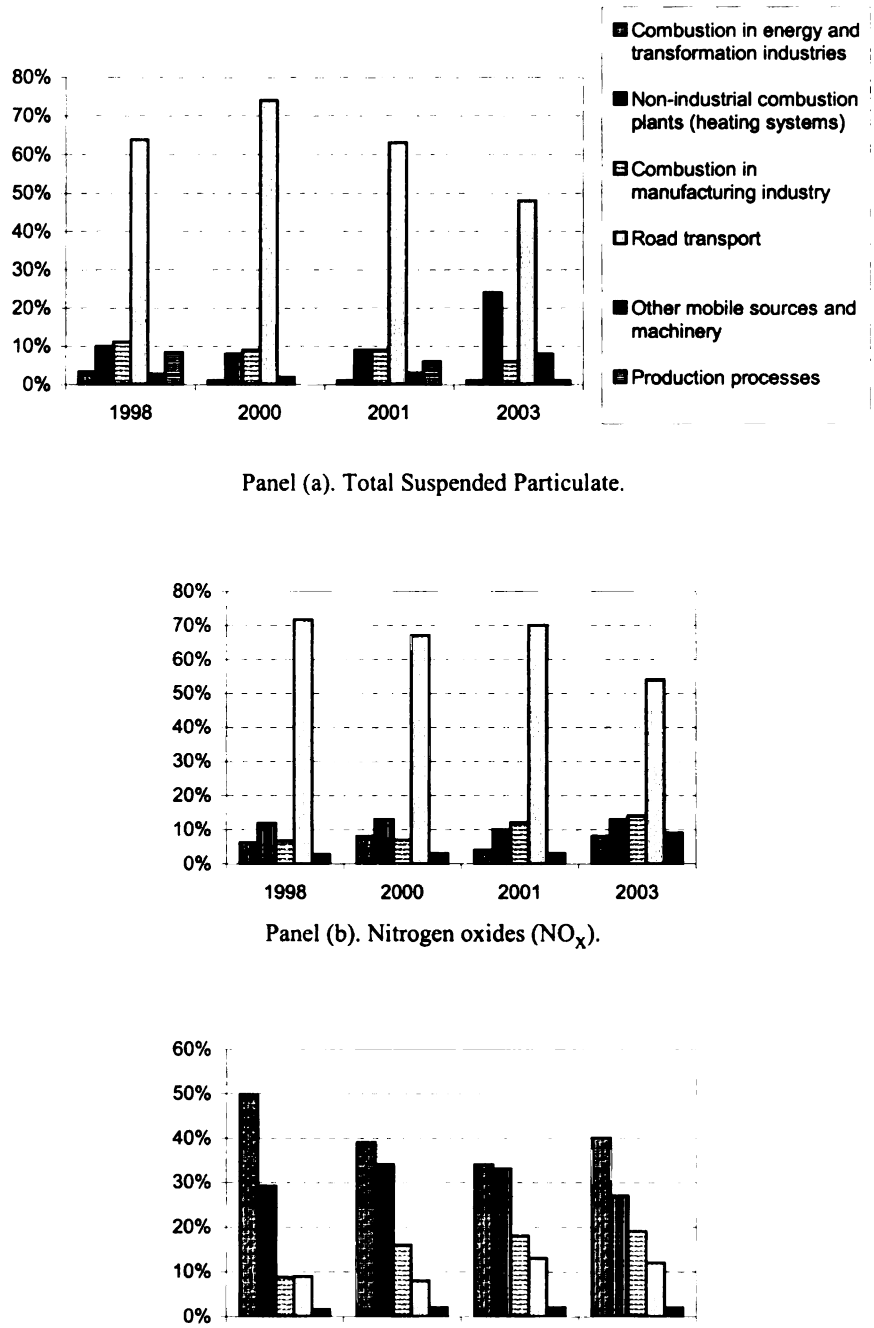
Figure 1.3 provides some details about the contribution that different sources make to the emissions of PM, NO_x, and SO_2 in the Province of Milan. As far as particulate matter (TSP) is concerned, road transport (i.e., traffic) is responsible for the largest amount of emissions, followed by residential 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.

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

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

[14] 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. 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.

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



Panel (a). Total Suspended Particulate.

Panel (b). Nitrogen oxides (NO_X).

Panel (c). Sulfur dioxide (SO_2).

Figure 1.3 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).

1.6.2. 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[16]. Figure 1.4 allows a graphical examination of the equity data, whereas the summary statistics are reported in Table 1.2. 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.

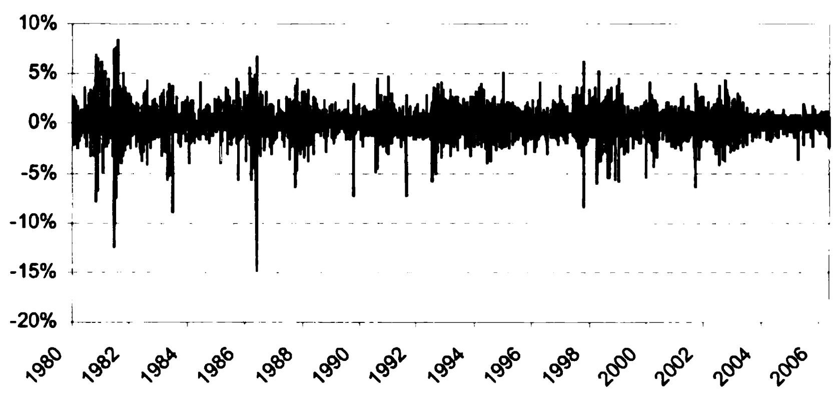


Figure 1.4 Daily equity returns of the Italian stock market (Comit index).

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;

[16] Adopting the standard approach, daily stock returns have been calculated as the logarithmic difference between any two consecutive 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.

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[17]. Daily data about temperature and rain in Milan have been obtained from ARPA Lombardia[18].The Seasonal Affective Disorder (SAD) effect has been calculated according to the methodology proposed by Kamstra et al. (2003)[19]. 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[20]. As 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[21]. Analogously, a *NewMoon* dummy has been constructed, being assigned the value of 1 up to three days before and after each New Moon date.

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[17] These are the behavioral variables that are typically included in this stream of literature.

[18] 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.

[19] 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.

[20] 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.

[21] http://sunearth.gsfc.nasa.gov/eclipse/phase/phase2001gmt.html.

1.7. 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[22]. 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 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

[22] 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.

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.

1.8. Empirical Examination

1.8.1. Particulate Matter and Equity 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 by some environmental stressor. 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[23].

This institutional revolution allows for a "natural experiment" (e.g., Pardo and Valor, 2003) to be conducted as follows: (1) one needs to consider that, 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

[23] 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).

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[24]. 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[25].

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

1.8.2. Basic Model

A careful examination of Figure 1.4 and Table 1.2 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 maximizing the Gaussian density function and using robust standard errors (Huber, 1967; White, 1980):

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[24] 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.

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

$$r_t = \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} + \mu_{t-k}^{PM} PM_{t-k} + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t +$$
$$+ \gamma_{FullMoon} FullMoon_t + \gamma_{NewMoon} NewMoon_t + \qquad (1.1)$$
$$+ \gamma_{Monday} Monday_t + \gamma_{Tax} Tax_t + \varepsilon_t$$

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

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

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 1.3. Table 1.4, 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 1.3 suggests that a 10 $\mu g/m^3$ 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.

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_t^{Mean} 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 [1.1] has been estimated again using such a pollution proxy and the relevant coefficients are reported in the last row of Table 1.4. 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 1.4). 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 [1.1]. As Table 1.3 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. It may be worth to mention that Lucey and Dowling (2005b) found a similar "paradoxical" result when studying Italian data.

1.8.3. 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 [1.1], which becomes:

$$r_t = \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} + \mu_{Mean}^{PM} PM_t^{Mean} + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t +$$
$$+ \gamma_{FullMoon} FullMoon_t + \gamma_{NewMoon} NewMoon_t + \gamma_{Monday} Monday_t + \qquad (1.2)$$
$$+ \gamma_{Tax} Tax_t + \gamma_{Temp} Temp_t + \gamma_{Rain} D_t^{Rain} + \gamma_{Geostorm} Geostorm_t + \varepsilon_t$$

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

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

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[26].

The coefficients obtained estimating model [1.2] are collected in Table 1.5. 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[27]. In absolute value, the size of the pollution effect turns out to be even greater than in model [1.1]: for example, focusing on the MIB index, a 10 $\mu g/m^3$ 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

[26] It should be noted here that, due to the time span covered by the available data for these weather series, their inclusion into the regression equation generates a shrinkage of the sample data.
[27] Model [1.2] 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_t^{Mean} are reported in Table 1.5.

impact appears to be economically significant, as the mean and standard deviation of the PM_t^{Mean} variable, during the first half of the 1990's, were approximately 85 $\mu g/m^3$ and 40 $\mu g/m^3$, respectively.

As expected, the effect cannot be detected any longer after the transformation of the Italian stock exchange in 1994. Qualitatively, the other explanatory variables exhibit patterns similar to the ones reported in Table 1.3. No support is found in favor of the conjecture that wants rain and geomagnetic activity to be good proxies for investor mood. 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.

1.8.4. Controlling for International Economic News

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 the 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 [1.2] 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[28]. 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 quasi-maximum likelihood:

$$
\begin{aligned}
r_t = \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} + \mu_{Mean}^{PM} PM_t^{Mean} + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t + \\
+ \gamma_{FullMoon} FullMoon_t + \gamma_{NewMoon} NewMoon_t + \gamma_{Monday} Monday_t + \\
+ \gamma_{Tax} Tax_t + \gamma_{Temp} Temp_t + \gamma_{Rain} D_t^{Rain} + \gamma_{Geostorm} Geostorm_t + \\
+ \gamma_{Germany} Germany_t + \gamma_{USA} USA_{t-1} + \varepsilon_t
\end{aligned}
\tag{1.3}
$$

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

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

where $Germany_t$ represents the returns of the German market and USA_{t-1} alludes to the returns of the U.S. market. 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

[28] 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 essay, especially through the natural experiment examined in section 1.8.1 and the instrumental variables estimation that will be discussed in section 1.8.7.

incorporates some economic news that is absorbed by the Italian equity indices on the following trading day[29].

The estimates are collected in Table 1.6, 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 [1.2], 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 [1.3] has also been estimated, in turn, by OLS (using Newey-West adjusted standard errors) and adopting a LOGIT specification[30]. 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.

---

[29] 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.

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

1.8.5. 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 generated by the existence of a link between economic activity and pollution. As shown in section 1.6, the direct emissions of PM, NO_x, and SO_2 produced 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 essay is indeed supported by the facts.

Following this line of reasoning, model [1.3] has been fitted replacing PM with either NO_X or SO_2. The relevant coefficients are contained in Table 1.7 and 1.8[31]. 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. 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 some 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 is assigned a value equal to the average NO_X ambient concentration between day *t-1* and day *t-4*. As shown in Table 1.7, 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 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

[31] 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 1.6.

Datastream and MIB indices, in the latter case extending up to the third lag[32]. 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 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.

1.8.6. 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 during the period analyzed. 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 1.1 and Figure 1.2, it is indeed possible to notice that air pollution levels 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

[32] A critical point should be highlight here, though. When analyzing 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 can hardly substantiate a decisive argument to refute the hypothesis under scrutiny.

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[33].

One 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, 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 [1.3] has been re-estimated using alternative samples, and the results are reported in Table 1.9. 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 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 the fact that air pollution concentrations have been lower, on average, during the second sub-period. In principle, lower levels of

[33] 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.

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 should be found in the time series of stock returns in the second era. Contrary to this argument, however, is the medical literature cited in section 1.4.1.3, 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 the problem, model [1.3] has also been re-estimated using the first difference of the pollution proxy, as follows

$$\begin{aligned} r_t = {} & \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} + \mu \ \Delta PM_t^{Mean} + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t + \\ & + \gamma_{FullMoon} FullMoon_t + \gamma_{NewMoon} NewMoon_t + \gamma_{Monday} Monday_t + \\ & + \gamma_{Tax} Tax_t + \gamma_{Temp} Temp_t + \gamma_{Rain} D_t^{Rain} + \gamma_{Geostorm} Geostorm_t + \\ & + \gamma_{Germany} Germany_t + \gamma_{USA} USA_{t-1} + \varepsilon_t \end{aligned} \tag{1.4}$$

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

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

where ΔPM_t^{Mean} represents the change in the variable PM_t^{Mean} between time *t-1* and time *t*. The results, not reported here for brevity, are qualitatively very close to the ones discussed for model [1.3]. 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 produced when the second sub-period (1994-1998) is analyzed. These estimates, therefore, suggest that the air pollution effect is at work even at low concentrations (i.e., concentration changes matter independently of the air pollution level outstanding), which refutes the conjecture according to which its disappearance, 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 potential further link, the pollution proxy has been inserted into the conditional variance equation of model [1.3], giving origin to the following GARCH model:

$$
\begin{aligned}
r_t = {} & \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} + \mu_{Mean}^{PM} PM_t^{Mean} + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t + \\
& + \gamma_{FullMoon} FullMoon_t + \gamma_{NewMoon} NewMoon_t + \gamma_{Monday} Monday_t + \\
& + \gamma_{Tax} Tax_t + \gamma_{Temp} Temp_t + \gamma_{Rain} D_t^{Rain} + \gamma_{Geostorm} Geostorm_t + \\
& + \gamma_{Germany} Germany_t + \gamma_{USA} USA_{t-1} + \varepsilon_t
\end{aligned}
\tag{1.5}
$$

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

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

where all the variables have the same meaning 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 the fact that the former generates an increase in objective risk (i.e., in the variance of returns).

1.8.7. Instrumental Variables Estimation

Up to this point, several methods/justifications have been used 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[34]; (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 when traders would physically

[34] Table 1.10 shows the pair-wise correlation between PM daily concentrations in Milan and in a set of neighboring cities. The data 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.

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 its unexpected component, that exhibits a systematic relationship with Italian equity returns).

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 necessary to overcome the potential endogeneity issue 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 subset of the latter 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[35]. For these reasons, we believe that it is realistic to take these variables as exogenous. The first-stage regression equation is the following

$$\begin{aligned} PM_t &= \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} + \sum_{k=2}^{3} \lambda_k Wind_{t-k} + \sum_{k=2}^{3} \pi_k Pressure_{t-k} + \\ &+ \sum_{k=2}^{3} \psi_k Rain_{t-k} + Controls + \varepsilon_t \end{aligned} \tag{1.6}$$

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

[35] 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 documented a link between atmospheric pressure and stock returns; (2) the estimates produced by fitting model [3] have shown that rainfall has no effect on 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.

explanatory power for current PM, as across the three stock market indices it is possible to reject the null hypothesis that their six 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[36].

Table 1.11 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 causal effect of air pollution on 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 regularity appears to be caused by what could be defined as a "mood effect". Also, in line with the findings of Goetzmann and Zhu (2005), the natural experiment described in section 1.8.1 effectively suggests that such a mood effect mainly passes through the traders physically located in the city that hosts the Stock Exchange.

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

1.9. Air Pollutants, Mood, 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:

$$API_t = \begin{cases} 1, \text{ if } PM_t^{Mean} \geq 180\ \mu g/m^3 \text{ or } NO_{x,t}^{Mean} \geq 650\ \mu g/m^3 \text{ or } SO_{2,t}^{Mean} \geq 180\ \mu g/m^3 \\ 0, \text{ otherwise} \end{cases}$$

where the variables have the same 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[37]. 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 performance of the Italian stock market should be expected[38]. 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):

$$
\begin{aligned}
r_t = \alpha + \sum_{j=1}^{P} \beta_j r_{t-j} &+ \mu_{API} API_t + \gamma_{SAD} SAD_t + \gamma_{Fall} Fall_t + \\
&+ \gamma_{FullMoon} FullMoon_t + \gamma_{NewMoon} NewMoon_t + \gamma_{Monday} Monday_t + \\
&+ \gamma_{Tax} Tax_t + \gamma_{Temp} Temp_t + \gamma_{Rain} D_t^{Rain} + \gamma_{Geostorm} Geostorm_t + \\
&+ \gamma_{Germany} Germany_t + \gamma_{USA} USA_{t-1} + \varepsilon_t
\end{aligned}
\tag{1.7}
$$

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

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

[37] 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.

[38] 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*.

The estimates, reported in Table 1.12, indeed reveal that poor air quality, as captured by the API index, is expected to significantly reduce stock returns[39]. 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[40].

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.

[39] Regression equation [1.7] has also been estimated using a Logit specification. The outcomes, reported in Table 1.8, 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.

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

1.10. Concluding Remarks

This essay 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 stocks. 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 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 medical and psychological fields, it has been conjectured that daily increases in the ambient concentration of air pollution are able to deteriorate agents' mood and induce them to decrease their demand for risky stocks, ultimately lowering equity returns, *ceteris paribus*. Such a hypothesis has been tested empirically using data from the Milan Stock Exchange, and exploiting a natural experiment allowed by the occurrence of an institutional change in the way trading was conducted in the Italian stock market. The evidence appears to be consistent with the hypothesis under investigation, and supports the view that some psychologically-relevant yet economically-neutral factors indeed play a role in shaping investment 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.

Table 1.1 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 ($\mu g/m^3$)	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 ($\mu g/m^3$)	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
SO_2 ($\mu g/m^3$)	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 1.2 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 1.3 Air Pollution and Stock Return – A Natural Experiment (Basic Model)

This table displays the results of estimating model [1.1] by quasi-maximum likelihood and using robust standard errors. 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	Datastream	MIB	Comit	Datastream	MIB
	01/02/1980-04/14/1994	*01/02/1980-04/14/1994*	*01/03/1985-04/14/1994*	*04/15/1994-02/13/1998*	*04/15/1994-02/13/1998*	*04/15/1994-02/13/1998*
α	.136***	.132**	.179***	.054	.020	.043
	(0.003)	(0.011)	(0.001)	(0.630)	(0.859)	(0.695)
β_1	.250***	.284***	.286***	.134***		.145***
	(0.000)	(0.000)	(0.000)	(0.002)		(0.001)
β_2		-.115***	-.105**			-.082*
		(0.000)	(0.032)			(0.081)
β_3		.055*	.067**			.075*
		(0.078)	(0.043)			(0.089)
μ_{t-1}^{PM}	-.00063**	-.00052	-.00099***	-.00049	.00037	-.00034
	(0.027)	(0.129)	(0.008)	(0.807)	(0.853)	(0.863)
γ_{SAD}	.068***	.064***	.057*	.087**	.095**	.088**
	(0.003)	(0.007)	(0.051)	(0.019)	(0.022)	(0.022)
γ_{Fall}	-.122*	-.176***	-.151*	-.190*	-.236*	-.189*
	(0.055)	(0.005)	(0.064)	(0.077)	(0.056)	(0.082)
$\gamma_{FullMoon}$	.009	-.008	-.039	.096	.110	.117
	(0.870)	(0.889)	(0.547)	(0.268)	(0.249)	(0.193)
$\gamma_{NewMoon}$	-.109**	-.127**	-.104*	.013	.013	.016
	(0.036)	(0.017)	(0.090)	(0.893)	(0.902)	(0.857)
γ_{Monday}	-.131**	-.091*	-.113*	-.218**	-.249**	-.238**
	(0.016)	(0.097)	(0.085)	(0.021)	(0.017)	(0.013)
γ_{Tax}	-.094	-.113	-.027	-.101	-.028	-.092
	(0.535)	(0.517)	(0.901)	(0.709)	(0.943)	(0.736)
Ln (L)	-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 1.4 Air Pollution and Stock Return – Basic Model (Alternative Lag Structures)
This table displays the results of estimating model [1.1] using alternative lag structures of the air pollution proxy, Particulate Matter (PM). The model has been estimated by quasi-maximum likelihood and using robust standard errors 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 [1.1], 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	Datastream	MIB	Comit	Datastream	MIB
	01/02/1980-04/14/1994	*01/02/1980-04/14/1994*	*01/03/1985-04/14/1994*	*04/15/1994-02/13/1998*	*04/15/1994-02/13/1998*	*04/15/1994-02/13/1998*
μ_t^{PM}	-.00043	-.00035	-.00076**	-.00009	.00116	-.00027
	(0.124)	(0.335)	(0.033)	(0.961)	(0.598)	(0.891)
	[3]	[3]	[3]	[3]	[0]	[3]
μ_{t-1}^{PM}	-.00063**	-.00052	-.00099***	-.00049	.00037	-.00034
	(0.027)	(0.129)	(0.008)	(0.807)	(0.853)	(0.863)
	[1]	[3]	[3]	[3]	[0]	[3]
μ_{t-2}^{PM}	-.00049	-.00017	-.00061*	-.00149	-.00138	-.00136
	(0.103)	(0.591)	(0.080)	(0.419)	(0.506)	(0.461)
	[3]	[2]	[3]	[3]	[0]	[3]
μ_{t-3}^{PM}	-.00043	-.00026	-.00066*	-.00029	.00086	-.00038
	(0.169)	(0.435)	(0.080)	(0.878)	(0.689)	(0.841)
	[3]	[3]	[3]	[3]	[0]	[3]
μ_{t-4}^{PM}	-.00036	.00012	-.00070*	.00205	.00161	.00207
	(0.246)	(0.673)	(0.074)	(0.267)	(0.423)	(0.261)
	[3]	[3]	[2]	[3]	[0]	[3]
μ_{t-5}^{PM}	-.00035	-.00014	-.00041	-.00156	-.00132	-.00164
	(0.249)	(0.625)	(0.289)	(0.38)	(0.471)	(0.356)
	[3]	[3]	[3]	[3]	[0]	[3]
μ_{Mean}^{PM}	-.00068**	-.00056	-.00087**	-.00006	.00051	-.00009
	(0.032)	(0.113)	(0.021)	(0.979)	(0.852)	(0.972)
	[3]	[3]	[2]	[3]	[0]	[3]

Table 1.5 Air Pollution and Stock Return - Controlling for Meteorological Conditions

This table displays the results of estimating model [1.2] by quasi-maximum likelihood and using robust standard errors. 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 [1.1], 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)
μ_{Mean}^{PM}	-.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)
Ln (L)	-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 1.6 Air Pollution and Stock Returns - Controlling for International Economic Shocks
This table displays the results of estimating model [1.3] using the first sub-sample of data, which refers to the period when trading at the Milan Stock Exchange was centralized. The model has been estimated by quasi-maximum likelihood and using robust standard errors. 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 [1.2], 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	Datastream	MIB
	01/02/1989-04/14/1994	*01/02/1989-04/14/1994*	*01/02/1989-04/14/1994*
α	.356**	.345*	.364*
	(0.026)	(0.051)	(0.028)
β_1	.230***	.185***	.239***
	(0.000)	(0.000)	(0.000)
β_2	-.144***	-.071*	-.154***
	(0.000)	(0.075)	(0.000)
β_3	.077**		.076**
	(0.026)		(0.034)
μ^{PM}_{Mean}	-.00251***	-.00291***	-.00284***
	(0.000)	(0.000)	(0.000)
γ_{SAD}	.027	.036	.038
	(0.549)	(0.448)	(0.425)
γ_{Fall}	-.163*	-.230**	-.175*
	(0.062)	(0.019)	(0.061)
$\gamma_{FullMoon}$	-.092	-.056	-.079
	(0.244)	(0.477)	(0.323)
$\gamma_{NewMoon}$	-.109	-.111	-.094
	(0.163)	(0.151)	(0.227)
γ_{Monday}	-.061	-.091	-.065
	(0.425)	(0.241)	(0.401)
γ_{Tax}	.025	.205	.021
	(0.935)	(0.418)	(0.946)
γ_{Temp}	-.004	-.003	-.003
	(0.520)	(0.660)	(0.624)
γ_{Rain}	-.074	-.045	-.080
	(0.293)	(0.546)	(0.260)
$\gamma_{GeoStorm}$	.011	.026	-.035
	(0.873)	(0.739)	(0.619)
$\gamma_{Germany}$	.518***	.498***	.540***
	(0.000)	(0.000)	(0.000)
γ_{USA}	.166***	.177***	.168***
	(0.000)	(0.000)	(0.000)
Ln (L)	-1326.5	-1383.6	-1323.1
Obs	952	960	937
Gaps	53	54	54

Table 1.7 Air Pollution and Stock Returns – Alternative Proxy (NO_X)

This table displays the results of estimating model [1.3] using Nitrogen Oxides (NO_X), instead of Particulate Matter (PM), as a proxy for air pollution. The model has been estimated by quasi-maximum likelihood and using robust standard errors. 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 [1.3], 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	Datastream	MIB	Comit	Datastream	MIB
	01/02/1989-04/14/1994	*01/02/1989-04/14/1994*	*01/02/1989-04/14/1994*	*04/15/1994-05/19/2006*	*04/15/1994-05/19/2006*	*04/15/1994-05/19/2006*
	-.00003	.00010	.00001	-.00001	-.00005	.00001
μ_t^{NOx}	(0.864)	(0.562)	(0.980)	(0.980)	(0.670)	(0.997)
	[2]	[1]	[2]	[1]	[0]	[1]
	-.00008	-.00025	-.00010	.00001	.00003	.00001
μ_{t-1}^{NOx}	(0.651)	(0.161)	(0.588)	(0.901)	(0.791)	(0.899)
	[3]	[1]	[3]	[1]	[0]	[1]
	-.00021	-.00019	-.00022	.00007	-.00004	.00007
μ_{t-2}^{NOx}	(0.166)	(0.221)	(0.174)	(0.556)	(0.706)	(0.554)
	[3]	[1]	[3]	[1]	[0]	[1]
	-.00023	-.00028*	-.00025	.00002	-.00003	.00004
μ_{t-3}^{NOx}	(0.140)	(0.074)	(0.113)	(0.879)	(0.787)	(0.766)
	[3]	[1]	[3]	[1]	[0]	[1]
	-.00031*	-.00034**	-.00030*	.00005	.00001	.00006
μ_{t-4}^{NOx}	(0.050)	(0.032)	(0.074)	(0.675)	(0.908)	(0.658)
	[2]	[1]	[2]	[1]	[0]	[1]
	-.00021	-.00021	-.00019	.00003	-.0001	.00004
μ_{t-5}^{NOx}	(0.132)	(0.167)	(0.212)	(0.773)	(0.273)	(0.720)
	[2]	[1]	[2]	[1]	[0]	[1]
	-.00033*	-.00039**	-.00030	.00003	-.00009	.00003
μ_{Mean}^{NOx}	(0.081)	(0.034)	(0.136)	(0.855)	(0.531)	(0.833)
	[3]	[2]	[3]	[1]	[0]	[1]

Table 1.8 Air Pollution and Stock Returns – Alternative Proxy (SO_2)

This table displays the results of estimating model [1.3] using Sulfur Dioxide (SO_2), instead of Particulate Matter (PM), as a proxy for air pollution. The model has been estimated by quasi-maximum likelihood and using robust standard errors. 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 [1.3], 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_t^{SO2}	-.001 (0.176) [2]	-.001* (0.093) [2]	-.001 (0.082) [3]	-.001 (0.498) [1]	-.001 (0.248) [0]	-.001 (0.479) [1]
μ_{t-1}^{SO2}	-.001 (0.172) [2]	-.002** (0.043) [2]	-.001 (0.084) [3]	-.001 (0.399) [1]	-.002 (0.130) [0]	-.001 (0.461) [1]
μ_{t-2}^{SO2}	-.001 (0.212) [2]	-.002** (0.011) [2]	-.001 (0.083) [3]	-.002* (0.080) [1]	-.002* (0.094) [1]	-.002* (0.090) [1]
μ_{t-3}^{SO2}	-.001 (0.123) [2]	-.001 (0.180) [1]	-.001 (0.074) [3]	-.00001 (0.992) [1]	-.0003 (0.812) [0]	.0002 (0.865) [1]
μ_{t-4}^{SO2}	-.001 (0.223) [2]	-.001 (0.293) [1]	-.001 (0.258) [3]	.001 (0.317) [1]	.001 (0.695) [0]	.001 (0.320) [1]
μ_{t-5}^{SO2}	-.0003 (0.630) [2]	-.001 (0.323) [1]	-.001 (0.338) [3]	.001 (0.541) [1]	-.001 (0.667) [0]	.001 (0.536) [1]
μ_{Mean}^{SO2}	-.001* (0.099) [2]	-.002** (0.022) [1]	-.002* (0.053) [3]	-.001 (0.330) [1]	-.002 (0.211) [0]	-.001 (0.401) [1]

Table 1.9 Air Pollution and Stock Returns – Alternative Sub-Periods

This table displays the results of estimating model [1.3] using smaller sub-samples. The model has been estimated by quasi-maximum likelihood and using robust standard errors. 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	-.003*** (0.000) [3]	-.003*** (0.000) [2]	-.003*** (0.000) [3]	04/15/1994-13/02/1998	-.002 (0.383) [1]	-.0002 (0.922) [0]	-.002 (0.379) [1]
01/02/1990-04/14/1994	-.002*** (0.003) [3]	-.003*** (0.001) [2]	-.002*** (0.004) [3]	04/15/1994-12/31/1996	.001 (0.729) [1]	.002 (0.566) [0]	.001 (0.742) [2]
01/02/1991-04/14/1994	-.002* (0.069) [2]	-.002* (0.084) [2]	-.002* (0.086) [2]	04/15/1994-12/29/1995	-.003 (0.535) [1]	-.001 (0.834) [0]	-.003 (0.517) [2]
01/02/1992-04/14/1994	-.003* (0.061) [2]	-.002 (0.142) [1]	-.003* (0.068) [2]				

Table 1.10 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	Milan	Pero	Rho	Agrate	Villasanta	Inzago	Cassano
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
Filago	31	Bergamo	0.69	0.75	0.45	0.55	0.52	0.73	0.67
Castano	34	Milan	0.70	0.83	0.60	0.53	0.61	0.74	0.63
Turbigo	37	Milan	0.59	0.72	0.69	0.48	0.44	0.73	0.62
Varese	48	Varese	0.51	0.35	0.13	0.09	0.08	0.40	0.24
Casnigo	60	Bergamo	0.64	0.70	0.31	0.49	0.41	0.74	0.64
Colico	72	Lecco	0.48	0.46	0.31	0.45	0.46	0.37	0.39

City	Distance from Milan (km)	Province	Legnano	Nibionno	Filago	Castano	Turbigo	Varese	Casnigo
Milan	-	Milan							
Pero	11	Milan							
Rho	14.5	Milan							
Agrate	15	Monza							
Villasanta	16	Monza							
Inzago	21	Milan							
Cassano	23	Milan							
Legnano	27	Milan	♦						
Nibionno	30	Lecco	0.60	♦					
Filago	31	Bergamo	0.57	0.76	♦				
Castano	34	Milan	0.71	0.82	0.76	♦			
Turbigo	37	Milan	0.67	0.58	0.56	0.78	♦		
Varese	48	Varese	0.27	0.47	0.35	0.46	0.24	♦	
Casnigo	60	Bergamo	0.54	0.78	0.65	0.70	0.60	0.48	♦
Colico	72	Lecco	0.42	0.40	0.57	0.54	0.39	0.32	0.40

Table 1.11 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 [1.6]. Equity returns are expressed in percentage points. P-values based on robust standard errors 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	.377	.339	.366	.435	.559	.398
	(0.145)	(0.208)	(0.174)	(0.275)	(0.187)	(0.324)
β_1	.226***	.147***	.226***	.102***		.099***
	(0.000)	(0.001)	(0.000)	(0.006)		(0.008)
β_2	-.121***	-.069*	-.120***			
	(0.000)	(0.077)	(0.000)			
μ_t^{PM}	-.0052**	-.0043*	-.0055**	-.0096	-.0102	-.0088
	(0.025)	(0.081)	(0.024)	(0.163)	(0.177)	(0.211)
γ_{SAD}	.105	.089	.127*	.105*	.116*	.099*
	(0.104)	(0.181)	(0.073)	(0.080)	(0.098)	(0.100)
γ_{Fall}	-.329**	-.299**	-.353**	-.092	-.157	-.087
	(0.013)	(0.015)	(0.012)	(0.393)	(0.211)	(0.417)
$\gamma_{FullMoon}$	-.088	-.097	-.076	.240***	.274***	.246***
	(0.350)	(0.331)	(0.428)	(0.006)	(0.004)	(0.005)
$\gamma_{NewMoon}$	-.029	-.020	-.019	.021	.031	.016
	(0.751)	(0.837)	(0.841)	(0.794)	(0.736)	(0.837)
γ_{Monday}	-.101	-.178	-.124	-.235***	-.349***	-.243***
	(0.365)	(0.106)	(0.293)	(0.010)	(0.001)	(0.007)
γ_{Tax}	-.323	-.221	-.354	-.019	-.227	-.008
	(0.384)	(0.582)	(0.343)	(0.948)	(0.525)	(0.978)
γ_{Temp}	.0003	-.001	.002	.003	-.0002	.003
	(0.967)	(0.925)	(0.792)	(0.677)	(0.983)	(0.715)
γ_{Rain}	.037	.065	.027	-.169*	-.169*	-.159*
	(0.668)	(0.462)	(0.767)	(0.069)	(0.087)	(0.089)
$\gamma_{GeoStorm}$	.109	.074	.071	-.130	-.282	-.124
	(0.250)	(0.466)	(0.469)	(0.486)	(0.122)	(0.509)
$\gamma_{Germany}$	.539***	.563***	.556***	.807***	.612***	.809***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_{USA}	.170***	.153***	.180***	.051	-.011	.050
	(0.002)	(0.005)	(0.001)	(0.339)	(0.836)	(0.347)
Obs	744	752	733	856	859	853

Table 1.12 A Test of the Efficient Market Theory Using an Air Pollution Index (GARCH model) This table displays the results of estimating model [1.7] using the first sub-sample of data, which refers to the period when trading at the Milan Stock Exchange was centralized. The model has been estimated by quasi-maximum likelihood and using robust standard errors. 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 1.9, 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	Datastream	MIB
	01/02/1989-04/14/1994	*01/02/1989-04/14/1994*	*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)
Ln (L)	-1341.5	-1400.9	-1338.8
Obs	963	971	948
Gaps	54	55	55

Table 1.13 A Test of the Efficient Market Theory Using an Air Pollution Index (LOGIT model)
This table displays the results of estimating equation [1.7] 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 1.9, 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_I	.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)
Ln (L)	-596.8	-605.3	-583.9
Obs	963	971	948

Chapter 2

Is There a SAD Foreign Exchange Market Cycle?

Evidence From an LSTR Model

2.1. Introduction: SAD Effect and Seasonal Stock Market Cycles

The empirical literature on asset pricing and investor mood has recently discovered an interesting link between stock returns and the so-called Seasonal Affective Disorder (SAD) effect. According to Kamstra et al. (2003), there exists a stock market cycle caused by the interaction between modifications in people's medical/psychological conditions and their decision-making process. The authors maintain that investors' degree of risk aversion can be affected by a set of psychological factors related to the mood realm (i.e. depression and anxiety), which in turn can be altered by some environmental cues. The specific variable considered in their analysis is the seasonal daylight cycle, which is believed to be responsible for the winter blues phenomenon and its more severe manifestation, i.e. SAD.

The framework advanced by Kamstra et al. suggests that, as investor mood progressively deteriorates during the fall (due to a diminished number of hours of daylight), market participants become increasingly risk averse and tend to shy away from risky stocks, *ceteris paribus*. In the winter, as the number of hours of daylight gradually increases, investor mood gets back to normal and, during the adjustment process, the market participants experience a decrease in their degree of risk aversion, which in turn leads them to be more aggressive in terms of portfolio choices. As such, all else equal, the demand for risky stocks is expected to increase during the winter, until the SAD effect eventually disappears, presumably at the onset of the Spring.

In the time series of stock returns of several major equity markets the authors find some empirical regularities which indeed appear to be consistent with the previous interpretation, i.e. stock returns are lower than average in the fall and higher than average in the winter, their magnitude being correlated with the seasonal variation in the length of the night. Based on their findings it seems possible to construct a set of trading strategies that take advantage of the differences in the daylight cycles that characterize countries located at different latitudes, ultimately earning an "excess return" over a simple global diversification strategy.

The rest of the chapter is organized as follows. Section 2.2 extends the SAD framework to the foreign exchange market. Section 2.3 puts forward the testable hypothesis that emerges, and section 2.4 describes the model that is employed in the empirical investigation. Section 2.5 illustrates the data and results of the econometric analysis are discussed in section 2.6. Section 2.7 concludes.

2.2. SAD and Exchange Rate Dynamics

To my knowledge, the analysis contained in this chapter represents the first attempt to extend the SAD framework to the foreign exchange market. It seems a natural step though, as the first question that comes to mind is whether the empirical regularities that the SAD effect generates in several countries' stock markets can spill over into the dynamics of those same countries' exchange rates.

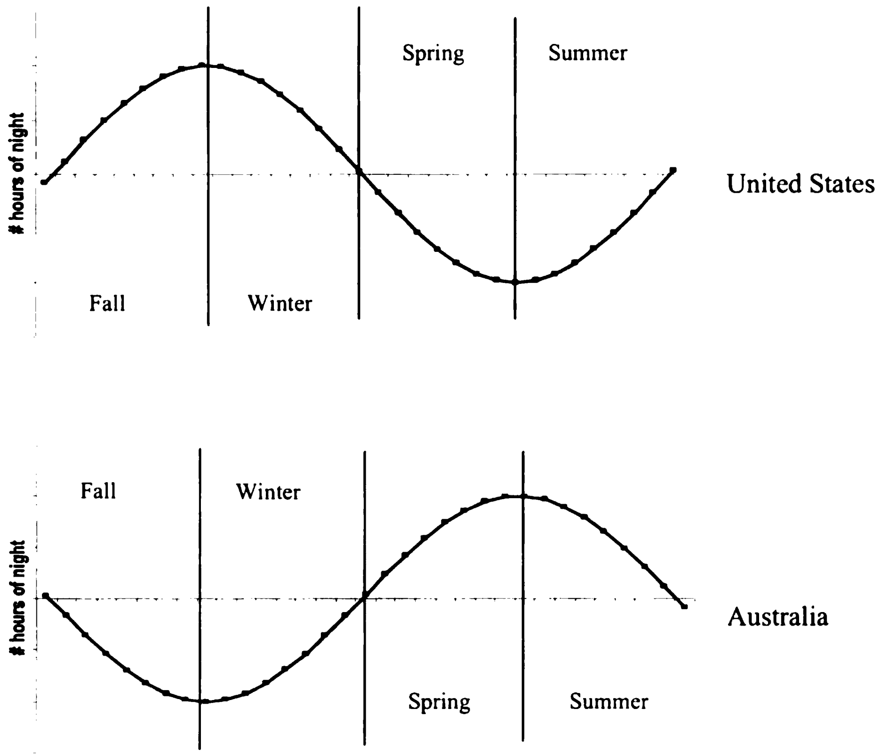

Figure 2.1 Daily hours of night in the United States and Australia (seasons refer to the northern hemisphere).

In particular, since the seasonal daylight cycles in the northern and southern hemispheres are out of sync, one would wonder if their corresponding SAD cycles could produce a periodic pattern in the rate of exchange between the currencies of any two countries located in opposite hemispheres.

The story goes as follows. Here we focus for simplicity on the exchange rate between U.S. dollars and Australian dollars, where the latter acts as the numeraire. First, as shown in Figure 2.1, the length of the night reaches its peak in Sydney six months after it has done so in New York. Second, according to the medical literature discussed by Kamstra et al. (2003), SAD is assumed to strike in the fall and fade away in the winter, whereas it is believed that in the spring and in the summer people are not affected at all by such a medical condition.

Combining these two facts together yields an interesting outcome in terms of exchange rate behavior, if one believes in the SAD hypothesis proposed by Kamstra et al. (2003). When Americans enter the fall, SAD hits the United States, whereas no change takes place in Australia. As such, Americans are assumed to become increasingly risk averse and shy away from risky stocks. The original conjecture advanced in this essay is that American investors not only reduce their demand for domestic stocks, *ceteris paribus*, but also decrease their demand for any foreign stocks, among which Australian stocks. If this is the case, then in the foreign exchange market one should observe a decrease in the supply of U.S. dollars (Americans now need fewer Australian dollars to buy their desired amount of Australian stocks), which would be expected to cause an increase in the equilibrium value of the exchange rate (i.e. an appreciation of the US dollar), all else equal. Such an adjustment process is depicted in Figure 2.2.

As the season changes and Americans enter the winter, SAD fades away in the United States and, again, no relevant event occurs in Australia (which is now in the summer). It follows that Americans progressively move back to exhibiting their standard degree of risk aversion, increasing their holdings of risky stocks during the adjustment process, all else equal. As in the previous case, my conjecture is that their increased demand for stocks not only falls onto domestic equity but also on foreign equity, among which Australian stocks. If this intuition is correct, then in the foreign exchange market one should observe an expansion in the supply of U.S. dollars, *ceteris paribus*, and ultimately a fall in the exchange rate (i.e. a depreciation of the U.S. dollar).

Analogous reasoning applies when Americans enter the spring and the summer, so that Australians enter the fall and the winter, respectively.

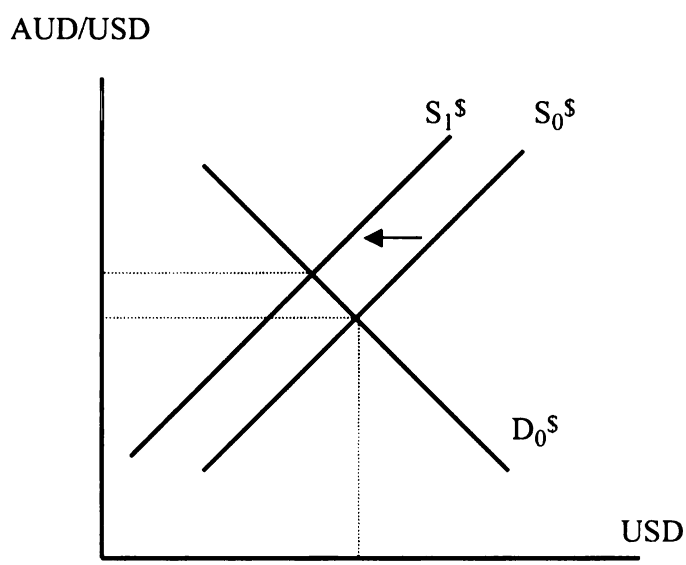

Figure 2.2 Fall in the United States. The SAD effect causes the US dollar to appreciate.

2.3. Hypothesis Under Investigation

Overall, such a framework puts forward an unambiguous testable hypothesis. The exchange rate between U.S. dollars and Australian dollars is expected to exhibit a seasonal pattern: the U.S. dollar should appreciate in the summer and in the fall and depreciate in the winter and in the spring, all else equal.

More generally, the rate of exchange between the currencies of any two countries located in opposite hemispheres should exhibit such a behavior, whereas this pattern should not appear when one considers the currencies of any two countries located in the same hemisphere (or at least at similar latitudes). Also, the appreciation/depreciation process should be a function of the daylight cycle and be more acute for countries that are further apart in terms of latitude.

2.4. An LSTR Model for the Exchange Rate

One possible way to tackle the issues raised by the hypothesis discussed in the previous section is to assume that the exchange rate seasonally moves between two distinct regimes. In one regime (which covers summer and fall), due to the seasonal pattern of the SAD effect, the currency of the country in the northern hemisphere is expected to experience an excess demand and therefore appreciate against the currency of the country in the southern hemisphere. In the other regime (winter and spring), the timing of the SAD cycle is such that the same currency is expected to experience an excess supply and thus depreciate.

One may also conjecture that there is no abrupt shift between the two regimes discussed above. Instead, the exchange rate may smoothly move from one to the other, the transition process being governed by the difference between the seasonal daylight cycles in the two hemispheres.

Following such a line of reasoning, a Logistic Smooth Transition Regression (LSTR) model seems the most appropriate to conduct the empirical investigation. More precisely, the following model will be employed in the econometric analysis

$$\Delta s_{t+1} = [\alpha_1 + \beta_1(f_t - s_t)] \cdot [1 - G(z_t, \gamma, c)] + [\alpha_2 + \beta_2(f_t - s_t)] \cdot G(z_t, \gamma, c) + u_{t+1} \qquad (2.1)$$

where Δs_{t+1} is the rate of appreciation (depreciation) of a currency, s_t is the logarithm of the spot exchange rate (measured in terms of units of a southern hemisphere's country's currency per one unit of a northern hemisphere's country's currency), f_t is the forward exchange rate, and u_{t+1} is the disturbance term. *G(.)* is a logistic transition function

$$G(z_t, \gamma, c) = \left(1 + \exp\left(-\gamma\left(\frac{z_t - c}{\sigma_{z_t}}\right)\right)\right)^{-1} \qquad \text{with } \gamma > 0 \qquad (2.2)$$

where z_t is the transition variable, σ_{zt} is the standard deviation of z_t, γ is the transition speed parameter, and c is the threshold between the two regimes.

The forward premium is included in the regression equation mainly as a control variable. As it will be argued later, from a theoretical viewpoint it is not obvious whether its impact on the dependent variable should be different across the two regimes. Nor is it obvious whether the SAD framework highlighted here imposes some other kind of restrictions on β_1 and β_2. The next section will discuss in more detail how the transition variable has been constructed.

2.4.1. Transition Variable

As previously mentioned, the transition process between the two regimes is likely to be associated with the seasonal daylight patterns in the two hemispheres. An initial inspection of Figure 2.1 may lead one to think that the daily difference between the length of the night in the two countries under observation represents a suitable transition variable.

Nevertheless, as Figure 2.3 reveals, the variable just described follows a pattern that is not entirely consistent with the shift between the summer-fall regime and the winter-spring regime. More accurately, the daily difference in the length of the night between, for example, United States and Australia reaches an annual peak at the end of the northern hemisphere fall and a trough at the end of the northern hemisphere spring.

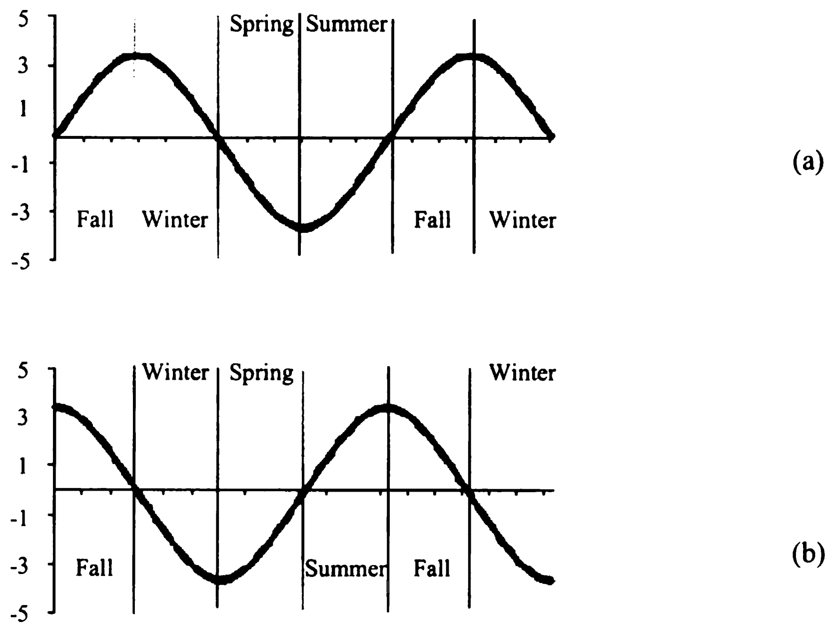

Figure 2.3 Difference in the daily number of hours of night between United States and Australia (panel a) and transition variable (panel b). Note: seasons refer to the northern hemisphere.

This drawback can be easily fixed by shifting the whole time series of such a variable three months forward, so that it reaches an annual maximum at the end of the northern hemisphere summer (i.e., in the middle of the summer-fall regime) and a yearly minimum at the end of the northern hemisphere winter (i.e., in the middle of the winter-spring regime), as shown in Figure 2.3. The resulting variable is employed in model [2.1] as the transition variable z_t.

2.4.2. Interpretation of the Parameters

Once the transition variable has been determined, it becomes relatively straightforward to clarify the meaning of model [2.1] and identify the predictions generated by the SAD framework in terms of restrictions on the parameters of the model. The transition function reaches a maximum when the transition variable reaches its yearly maximum at the end of the northern hemisphere summer, so that the summer-fall regime represents the upper regime in model [2.1], whereas the winter-spring regime represents the lower regime.

As a result, if the Uncovered Interest Rate Parity (UIP) condition held (i.e. $\alpha=0$ and $\beta=1$ in the following model),

$$\Delta s_{t+1} = \alpha + \beta \left(f_t - s_t\right) + u_{t+1} \tag{2.3}$$

then one would expect α_1 to be negative and α_2 to be positive in model [2.1], given that the currency of a country in the southern hemisphere is expected to appreciate against the currency of a country in the northern hemisphere during the (northern) winter-spring period and depreciate during the (northern) summer-fall period, that is

$$\alpha_1 < 0 \ , \ \alpha_2 > 0 \tag{2.4}$$

Given the overwhelming evidence about the empirical failure of the UIP (e.g. Maynard and Phillips, 2001; Baillie and Kilic, 2006), it might also be possible to make the previous prediction less stringent.

On the other hand, it appears to be more complex determining whether the SAD framework also yields some neat predictions in terms of the parameters β_1 and β_2. At this point of the analysis, I do not see any particular reason for the slope parameter to be consistently different across the two seasonal regimes. Nevertheless, an interesting implication could be derived if the data sample at hand was divided into two sub-samples, one containing those observations for which the forward premium is positive and the other one containing the observations for which the forward premium is negative. The parameters may differ systematically according to the following rule

$$\text{If } (f_t - s_t) \begin{cases} > 0, & \text{then} \quad \beta_1 < \beta_2 \\ < 0, & \text{then} \quad \beta_1 > \beta_2 \end{cases} \tag{2.5}$$

The reasoning is the following. Consider again the example about the rate of exchange between U.S. dollars and Australian dollars. When the forward premium is positive, the Australian dollar is expected to depreciate and such a rate of depreciation might be augmented when the event happens to take place in the upper regime (northern summer-fall), because that is the regime in which the SAD effect is already forcing the Australian dollar towards a depreciation. If the event took place in the lower regime (northern winter-spring), instead, the SAD effect would be driving the Australian dollar in the opposite direction, thus lowering the extent of its depreciation. As a result, one may conjecture that, given a positive forward premium, β_1 should be smaller than β_2. Analogous reasoning applies when the forward premium is negative, the difference being that in such a scenario the inequality sign would be reversed.

Though mentioned here, this hypothesis is not tested directly. Instead, it is left for future investigations that may have the benefit of having to deal with larger samples. As the next section will show, the present work is based on a relatively small sample of currencies and covers a relatively short time span.

2.5. Data

The data set used in the empirical analysis contains weekly data on spot exchange rates for the currencies of the U.S. Dollar (UD), Euro (EU), UK Pound (UK), Swiss Franc (SF), Japanese Yen (JY), and Canadian Dollar (CD) vis-à-vis the Australian Dollar (AD). This data set has been constructed using the daily data provided by the Federal Reserve Bank of St. Louis (noon buying rates in New York city for cable transfers payable in foreign currencies), and covers the period 01/02/1998 through 04/11/2007[41].

Weekly data on LIBOR rates for the above currencies have been obtained from the British Bankers' Association and have then been employed to construct the time series of forward exchange rates for the these same currencies[42]. A simple visual inspection of the data, not reported here, reveals that the UIP does not hold, on average, for the currencies considered here.

The transition variable has been constructed for each exchange rate and for the relevant time period starting from the corresponding countries' daylight cycles, and according to the formulas presented by Kamstra et al. (2003) for the SAD effect. In particular, the difference in the length of the night for each pair of countries has been adjusted, as discussed in section 2.4.1, to obtain the final transition variable used in the regressions.

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[41] The only exception is the Euro currency, for which the available time series starts at the beginning of January, 1999.
[42] http://www.bba.org.uk/bba/jsp/polopoly.jsp?d=103.

2.6. Empirical Results

The results from estimating model [2.3] by maximum likelihood are collected in Table 2.1. Excluding the case of the Japanese Yen, the coefficient β is always estimated to be negative, even though statistical significance is never achieved. The time series analyzed here, therefore, seem to exhibit the typical properties documented in the literature about the forward premium puzzle.

The estimated coefficients for the LSTR in model [2.1] are reported in Table 2.2. Overall, the results do not provide strong evidence is support of the hypothesis under investigation. For the Euro, UK Pound, Japanese Yen, α_1 is indeed estimated to be negative, whereas α_2 is estimated to be positive, but the corresponding standard errors are relatively high, and one cannot confidently reject the null hypothesis that these two coefficients are jointly equal to zero. In the case of the U.S. Dollar, Swiss Franc and Canadian Dollar, the first parameter is estimated to be positive and in two instances it turns out to be even greater than the second one; yet, once again, the null hypothesis that the two parameters do not statistically differ from zero cannot be rejected.

In terms of transition between regimes, the best results have been obtained for the Swiss Franc, UK Pound and Japanese Yen, as their estimated transition functions appear to be satisfactorily smooth. Euro, Canadian Dollar and U.S. Dollar, on the other hand, present an extremely abrupt switch between regimes, which raises serious doubts about the adequacy of the model employed here.

It should be kept in mind that the evidence provided here is based on a sample that contains a single southern hemisphere's country's currency, i.e. the Australian Dollar. Future investigations should extend the data set and include at least the currencies of New Zealand and South Africa. Also, weekly data are likely to incorporate a relevant amount of noise, which suggests that future analyses should also be based on lower frequency data.

2.7. Concluding Remarks

This analysis contained in this chapter represents a first attempt to extend the SAD framework (developed by Kamstra et al., 2003) to the foreign exchange market. From a theoretical perspective, the SAD theory appears to generate some neat and testable predictions in terms of exchange rate dynamics. In particular, during the (northern hemisphere) winter and spring, the currency of any country located in the northern hemisphere is anticipated to experience an excess supply and depreciate against the currency of any country located in the southern hemisphere. The opposite is expected to happen during the (northern hemisphere) summer and fall.

A Logistic Smooth Transition Regression model has been chosen to investigate such a phenomenon, the underlying idea being that the two time periods discussed above (winter-spring and summer-fall) constitute tow separate regimes through which the exchange rate smoothly moves while being affected by the differences between the daylight cycles of the two countries considered.

The empirical results, overall, appear weak and do not provide solid evidence in support of the initial hypothesis. Such an empirical failure might have been caused, at least in part, by the short time span covered by the available data (a little more than four hundred weekly observations) and by the inclusion into the sample of only one southern hemisphere's country's currency.

Table 2.1 Forward premium anomaly regressions

HCC standard errors are in parenthesis below the corresponding parameter estimates. For the US Dollar the sample has been reduced to the more recent three years of observations[43].

$\Delta s_{t+1} = \alpha + \beta\ (f_t - s_t) + u_{t+1}$

	UD	EU	UK	SF	JY	CD
α	0.001	0.003	0.0002	0.005	-0.004	0.0001
	(0.002)	(0.003)	(0.001)	(0.004)	(0.009)	(0.001)
β	-2.595	-6.681	-0.014	-6.754	3.877	-0.154
	(5.219)	(4.923)	(4.458)	(4.744)	(9.102)	(3.294)
Obs.	142	274	434	434	432	434

Table 2.2 Results from Restricted LSTR UIP regressions (*c* = *0*)

HCC standard errors are in parenthesis below the corresponding parameter estimates. For the US Dollar the sample has been reduced to the more recent three years of observations (see footnote 43). The threshold parameter *c* is set to zero in all regressions.

$$\Delta s_{t+1} = [\alpha_1 + \beta_1 (f_t - s_t)] \cdot [1 - G(z_t, \gamma, c)] + [\alpha_2 + \beta_2 (f_t - s_t)] \cdot G(z_t, \gamma, c) + u_{t+1}$$

where $G(z_t, \gamma, c) = \left(1 + \exp\left(-\gamma(z_t - c)/\sigma_{z_t}\right)\right)^{-1}$

	UD	EU	UK	SF	JY	CD
α_1	0.001	-0.001	-0.0004	0.00003	-0.021	0.002
	(0.003)	(0.004)	(0.001)	(0.004)	(0.012)	(0.002)
β_1	-1.153	-0.762	-0.456	-1.219	20.103	-3.978
	(7.507)	(7.318)	(5.821)	(5.526)	(12.404)	(4.967)
α_2	0.0003	0.007	0.001	0.011	0.016	-0.002
	(0.003)	(0.003)	(0.001)	(0.007)	(0.015)	(0.002)
β_2	-4.254	-12.580	0.216	-12.462	-15.289	3.604
	(7.071)	(6.431)	(6.893)	(8.459)	(14.501)	(4.328)
γ	81.93	211.13	18.68	11.65	23.93	527.85
	(19.45)	(33.51)	(13.32)	(4.05)	(4.63)	(15.70)
Obs.	142	274	434	434	432	434

[43] When using the whole US Dollar sample, the transition function would not converge, so the sample size was repeatedly reduced until a reasonable estimate was obtained.

Chapter 3

Superstition and Investment Decisions

3.1. Introduction

As mentioned in the previous chapter, the research carried out in the field of behavioral finance has discovered a rich collection of cognitive and emotional biases that affect investors' decision-making process (e.g. Shleifer, 1999; Hirshleifer, 2001).

This chapter aims at contributing to such a stream of financial literature by exploring whether and how investment decisions can be influenced by superstitious beliefs. Numerous investigations conducted in the social sciences, in particular in the fields of psychology and sociology, have produced some evidence in support of the view that superstition can influence individuals' attitudes and choices in everyday life, and they have also revealed that even the most important human decisions are not immune to the power of superstitious beliefs (e.g. Kaku, 1974; Campbell, 1996; Ankerberg and Weldon, 1999; Torgler, 2003). Yet, very few empirical examinations have been carried out in such an area by economists and finance researchers. Few recent examples include the articles of Dichev and Janes (2003) and Yuan et al. (2006) on the alleged link between equity returns and lunar phases.

One may conjecture that such a dearth of investigations has been caused by (1) the assumption that people tend to behave rationally, (2) the view that superstition is not worth of scientific scrutiny, and (3) the view that, even if some people's decisions were affected by superstitious beliefs, this would not be likely to produce any detectible impact on relevant aggregate economic/financial variables. In response to the first and second concerns, one should consider that superstition may produce real effects in the same way that self-fulfilling prophecies do. As an example, the reader may think about the well known fact that in many western countries the number 13 is considered an unlucky number and building owners will sometimes deliberately skip a floor so numbered[44]. Assuming for simplicity that building owners are fully rational, their choice is likely to have been determined by the worry that their business might be negatively affected by the existence of superstitious tenants or customers. If people believe that other people hold superstitious beliefs, then, just like in the case of self-fulfilling prophecies, superstition may indeed produce real consequences. In turn, as long as superstitious beliefs are able to spur real effects in the realm of human decision-making, then it is my opinion that they should become the object of scientific investigation. As for the third argument, it is certainly true that a large set of superstitious beliefs (e.g. avoiding walking under ladders, throwing salt over one's shoulder) is unlikely to have any significant impact on relevant macro variables. Yet, this fact alone, should not preclude research to be conducted in this area. Testing whether superstition can exert an influence on interesting financial variables is possible provided that one identifies a superstitious belief that can influence the attitudes of large groups of investors at the same time and in a predictable fashion. If the decisions of the marginal investor are affected by such a factor, then a detectible aggregate effect should follow.

In order to achieve such a goal, the present investigation focuses on the superstitious beliefs allegedly attached to total eclipses, which are natural phenomena that can be observed approximately at the same time by millions of individuals on earth.

[44] According to a spokesman for Otis Elevator Company, the world's largest manufacturer of elevators, around 85% of the buildings in the world do not feature a named 13th floor (Perkins, 2002).

Folklorists have provided solid evidence that, for thousands of years, solar and lunar eclipses have been frequently interpreted as bad presages in many societies around the planet. More interestingly, they have also documented that such beliefs are still somewhat rooted in many modern cultures[45]. The occurrence of eclipses has been (wrongly) commonly taken as a bad omen, that is a sign that would precede the occurrence of horrible events such as famines, calamities, and outbreaks of lethal diseases. The existence of such an alleged link has been disproved by modern science and, as such, one can safely conclude that eclipses are a purely exogenous factor in the context of the present analysis. Total eclipses could produce an actual effect on some macro socioeconomic variables only if people attached some superstitious beliefs to eclipses themselves.

Reformulating this view in the context of financial markets, one would expect that, (1) if agents were entirely rational and asset prices efficiently incorporated all relevant information (null hypothesis), then the occurrence of total eclipses would have no impact whatsoever on equity returns. Similarly, (2) if investors held superstitious beliefs yet the stock market was fully efficient, then one would not expect stock returns to follow any abnormal pattern in correspondence of an eclipse; after all, eclipses are perfectly predictable events and, therefore, asset prices should already incorporate their future occurrence. Only if superstition was at work and, concomitantly, the stock market was not entirely efficient, then one would expect to observe a (negative) relationship between the occurrence of total eclipses and stock returns. Consequently, the present study appears to be appealing on two grounds: if the null hypothesis of no relationship

[45] See Goldman (1940), Greenlee (1945), Allison (1948), Seibold (1967), Hand and Talley (1984), Castro (1995), Vojcik (1996), and Milan (2000).

between eclipses and equity returns was rejected, that would suggest that (1) some psychological factors (i.e., superstitious beliefs) play a role in determining investors' decisions and (2) financial markets conceal some inefficiencies that could be profitably exploited by an informed agent.

The investigation conducted here is interlinked with a growing body of literature that analyzes how some economically neutral yet psychologically relevant factors can affect investors' behavior. The effects of mood on asset prices have been extensively documented (e.g. Saunder, 1993; Hirshleifer and Shumway, 2003; Kamstra et al., 2003; Krivelyova and Robotti, 2003; Cao and Wei, 2005). Interestingly, some environmental variables that are believed to be capable of triggering mood changes (e.g. sunshine, cloud cover, temperature, geomagnetic field) may also exhibit a link with the occurrence of total solar eclipses, so it turns out to be necessary to control for those factors in order to demonstrate that the impact of total eclipses on equity returns, if any, is not due to some already known cause. Analogously, as total lunar eclipses only take place during full moon periods, one needs to make sure that the eclipse effect is not generated by the lunar-cycle effect identified by Dichev and Janes (2003) and Yuan et al. (2006).

The empirical examination, conducted using a large sample of daily data on three major US stock market indices, shows that the occurrence of total eclipses is indeed associated with lower-than-average returns, consistently with the view that superstitious beliefs contribute to shape investors' decisions and, concurrently, the Efficient Market Theory does not hold strictly. Not surprisingly, when the analysis focuses on the total eclipses visible in north America, the eclipse effect turns out to be even stronger. It is also shown that such an effect, which is both statistically significant and economically relevant, can be used to construct some profitable trading strategies and, consequently, it seems to qualify as a market anomaly.

What makes the analysis of superstition particularly appealing from a social scientist's perspective, and what distinguishes it from the literature on investor mood, is that the former refers to a purely self-fulfilling and self-reinforcing phenomenon. Explaining what triggers people's actions is the core of any social science, and it is in my opinion that any force that can drive human behavior and is capable of producing tangible effects in multiple spheres of human life should be granted thorough investigation.

The rest of the chapter is organized as follows. Section 3.1 describes the mechanisms through which superstitions are conjectured to emerge. Section 3.2 reviews the empirical analyses that have been conducted in such an area in the fields of economics and finance, and section 3.4 puts forward the superstition hypothesis that is tested in the present work. Section 3.5 illustrates the mechanics of the phenomenon under investigation (i.e. eclipses) and section 3.6 discusses some of the controls that need to be employed. Section 3.7 describes the data, whereas the empirical analysis is contained in section 3.8. Section 3.9 discusses the implications that the findings have in light of the Efficient Market Theory. Section 3.10 provides some concluding remarks.

3.2. Origin of Superstitious Beliefs

The term "superstition" is recurrently used in common speech and is typically employed in a pejorative sense. In most instances, its meaning is merely assumed rather than defined. Numerous definitions have been proposed in the fields of psychology and sociology. Considering the goal of the present analysis, it has been chosen to focus on one particular definition, that is the one advanced by Jarvis (1980), according to whom superstition is "an attitude individually held by people which relate their existence to the general order of the cosmos but which is not based upon empirical evidence nor incorporated within the institutionalized belief systems of a society as defined by leading representatives of these systems at any given time."

Jarvis also offers a classification of superstitions, which may be sorted into taboos, spells, and omens. Omens are signs that believers consider as prophecies and may have to do with bad luck, good luck, and death. Taboos involve prohibitions whose violation may give origin to a punishment. Lastly, spells are measures employed to promote good luck or get around bad luck.

Needless to say, sociologists have long been puzzled by the survival of superstition in modern industrialized societies. In the nineteenth century, they anticipated that superstition "would gradually fade away in the face of that rationalism and empiricism which was presumed to be characteristic of modern capitalist society" (Campbell, 1996). Yet, several investigations show that the levels of superstition have not decreased substantially during the twentieth century. Campbell (1996), based on several surveys undertaken in Britain between the 1950s and the 1980s, illustrates that a large portion of the population is consistently willing to depict themselves as superstitious, and a considerable fraction even admits to "engaging in some superstitious practices". Similarly, Ankerberg and Weldon (1999), surveying the literature on the effects of astrology on human behavior, uncover evidence that the influence of the former on the latter has clearly intensified in recent decades. Torgler (2003), analyzing a sample of data from seventeen countries, claims that citizens of most countries display a fairly high level of superstition in terms of beliefs in horoscope, good luck charms, and fortune-tellers. In 1990, Gallup polls showed that 25% of the U.S. population believed in astrology (Gallup, 1990) and, based on the results of two other surveys (Gallup, 1978; Stark and Bainbridge, 1985), it seems that this figure has remained relatively steady in recent years[46].

Up to now, most of the theories proposed to rationalize superstition have been given either an anthropological or a psychological foundation. According to Skinner (1948), superstitious beliefs develop through an incorrect learning process. More specifically, individuals may tend to draw erroneous conclusions when they are unable to precisely identify cause-and-effect relationships. Superstitions typically arise following a recurrent pattern: a person (group of people) has to deal with uncertainty about a future relevant event or outcome (factor 1); before the event takes place or the outcome is

[46] A simple search conducted using any Internet search engine reveals that there exist literally hundreds of web sites that deliver trading signals based on the tools of astrology and the horoscope. Lo et al. (2000) state that "it has been argued that the difference between fundamental analysis and technical analysis is not unlike the difference between astronomy and astrology". Here it is claimed that "financial astrology" itself appears to have been following the footsteps of technical analysis. Testing the predictions of the former does not seem to be substantially different from testing the predictions of the latter, as the mechanics of both fields are heavily based on self-fulfilling expectations. While the latter discipline has received considerable academic scrutiny, the same cannot be said for the former. In a broad sense, together with the studies of Dichev and Janes (2003) and Yuan et al. (2006) on the lunar cycle, the present work may be considered as a first effort in this direction.

uncovered, something fortuitous happens (factor 2); the accidental event is then interpreted as cause, even if, in fact, there is no relationship at all between factor 1 and factor 2. Subsequent fortuitous reiterations of this accidental association of events then act as a positive reinforcer.

Anthropologist Malinowski (1948) maintains that superstitions cannot be labeled as pointless primitive beliefs, as they are psychologically needed for existence and fulfill some essential functions within a culture. His "theory of the gap" asserts that superstition fills the void of the unknown and reduces anxiety. Scheibe and Sarbin (1965) summarize these ideas claiming that "where he lacks truth and needs it, (man) makes it up, somehow". Cohen at al. (1959) find that people are more likely to distort facts or logic rather than abandon their superstitions.

As highlighted by Henslin (1967), the social context plays a key role in the survival and diffusion of superstitions. Individuals' behavior originates in a social framework and is reacted to by significant others who serve as reinforces. Behaviors are then transmitted or taught to new members and, as a result, become part of a culture. Scheibe and Sarbin (1965) summarize this argument asserting that "it is as if each culture presents its participants with a rule book which states standard beliefs about what leads to what".

Interestingly, even the (supposedly) most important human decisions (e.g. reproduction, health) do not appear to be immune to superstition (e.g. Kaku, 1974; Stevenson, 2000; Do and Phung, 2006). It seems therefore natural to wonder whether some superstitious beliefs extend to economic decisions. The next section discusses the evidence that has been uncovered in this area.

3.3. Superstitious Beliefs and Economic Decisions: Empirical Evidence

In the last two decades, relatively few studies have been carried out in the fields of economics and finance on the relationship between superstition and decision-making. Woo and Kwok (1994), analyzing license plate auctions in Hong Kong, discover that plates featuring the number 8 (a sign of good luck in Cantonese-speaking countries) are sold for statistically higher prices than plates featuring the number 4 (a sign of bad luck).

Kolb and Rodriguez (1987), employing a sample of U.S. daily returns from the CRSP value- and equally weighted indices from 1962 through 1985, find that mean returns for Friday the Thirteenths are significantly lower than those of other Fridays, which is what one would expect according to the "Friday the Thirteenth" superstition[47].

Brown at al. (2002) investigate the effect of superstition on price clustering in some Asia-Pacific financial markets (Australia, Hong Kong, Indonesia, the Philippines, Singapore and Taiwan). In the Chinese culture some numbers are considered highly inauspicious (e.g. number 4), whereas others (e.g. number 8) are considered highly auspicious (e.g. number 8). The authors uncover some evidence in support of the view that Chinese superstitions play a role in shaping the number preferences of traders in Hong Kong, but the evidence is weak for the remaining five countries.

Since foreign investors' trading might eliminate the traces of any culture-specific superstition from the time series of equity returns, Brown and Mitchell (2004) focus on

[47] Some subsequent studies carried out by other authors, using different samples, have not lent support to such a finding, though. See Dyl and Maberly (1988), Chamberlain et al. (1991), and Coutts (1999).

trading at the Shanghai and Shenzhen stock exchanges, between 1990 and 2002. A strict segmentation characterized these two markets over much of the period under consideration, as domestic investors were only allowed to trade A-shares, whereas foreign investors were only allowed to trade B-shares. The authors claim that the prices of A-shares are statistically more likely to end in 8 than in 4, while such a pattern is much weaker for B-shares, consistently with the Chinese superstition story.

A valuable lesson taught by these investigations is that, as the degree of integration among international financial markets has considerably increased during the recent decades, in order to test the influence of superstition on investment decisions one should isolate some beliefs that are shared by many cultures around the world.

3.4. Testable Hypothesis: Solar and Lunar Eclipses as Evil Presages

The folklore literature provides extensive evidence about the widespread interpretation of total eclipses as bad omens. In Hindu mythology, it is believed that some demons "biting" the sun or the moon are responsible for the occurrence of eclipses, which are deemed as ominous events (Dickens, 1996). Such a symbolism has not disappeared, and many Indians still think that some catastrophe will occur[48]. In Thailand, devotees burn black joss sticks and hand over offerings in the days that precede an eclipse, and when it takes place they clash gongs and explode firecrackers to scare the demon that is believed to be "biting " the sun or the moon. Likewise, in Cambodia, during solar eclipses thousands of people shoot with handguns and rifles to frighten the moon and "help the sun escape". In China, solar eclipses were taken as bad omens and people used to think that the emperor might die when those phenomena occurred. In Japan, people used to think that eclipses were symptoms of a disease that hit the sun and that protection was needed if one wanted to stay away from such a disease. Milan (2000) asserts that, even in our time, some Japanese people will cover their wells to prevent their water from being infected by the disease hitting the sun. Eskimos' beliefs are analogous to the Japanese's and some Eskimos will turn over utensils to prevent them from being contaminated. One of the two key books of orthodox Judaism, the Talmud (Sukkah 29a), declares that "An eclipse of the sun is a bad omen for the world". Goldman (1940)

[48] See, for example, Asiaweek - October, 20 1995.

provides evidence that the Cubeo Indians, a group of natives that live in southeastern Colombia, rush out of their houses and scream at the beginning of an eclipse. When one of them hears an answer to her shouts, that is taken as a presage that he or she will soon pass away after suffering from the same disease that hit the sun. In many rural areas of Mexico it is still believed that, when a solar eclipse takes place, pregnant women are at risk of having a baby with a cleft lip (Castro, 1995).

Moving the focus to the United States, Vojcik (1996) claims that the dropping of atomic bombs in Japan at the end of World War II has initiated an "era of nuclear apocalypticism that has flourished in American religious culture, folklore and popular culture". Wilson (1977) and Boyer (1992) cite numerous surveys that indicate how apocalyptic speculations are pervasive at a popular level, and assert that millions of Americans at present hold beliefs about an approaching destruction of the world. According to a 1994 survey conducted for *U.S. News & World Report*, many people think the Bible should be taken literally when it narrates about a Battle of Armageddon (44%) and a final Judgment Day (60%)[49]. In this regard, the book of Revelation, which has been one of the main sources of inspiration for most contemporary Christian prophecy, contains a clear reference to what has been typically considered a total solar eclipse. More specifically, when describing the opening of the seven seals that precedes the end of the world, the book of Revelation (6:12) reads: "And I saw when he opened the sixth seal, and there was a great earthquake; and the sun became black as sackcloth of hair". Hand (1961-1964), in his massive collection on popular beliefs and superstitions, includes eclipses among the signs of an imminent doomsday. Similarly, Hand and Talley

[49] U.S. News & World Report, 19 December 1994, p. 64.

(1984), in a similar compilation, list eclipses as one of the signs that precede the end of the world.

Taken as a whole, there appears to exist a large body of evidence in support of the view that total eclipses, for centuries or even millennia, have been interpreted as bad omens in numerous societies around the world. Contemporary investigations also seem to indicate that such superstitious beliefs have not been completely abandoned, though their sphere of influence is probably restricted and only a relatively small fraction of the population is likely to be affected.

Interestingly, the stock market features at least two of the characteristics that Campbell (1996) considers as essential for the development and survival of superstitions: (1) outcomes are very relevant (losing money is extremely different from winning money) and (2), the participants are aware of their lack of control over the outcomes themselves (i.e., equity returns seem to be randomly distributed and no theory seems to work when investors are called upon to predict future returns). As a result, financial markets appear to provide an ideal setting for testing whether superstitious beliefs contribute to shape human choices.

Given the evidence discussed in this section, it appears that a very specific hypothesis can be put forward and subsequently tested empirically. More specifically, the investigations conducted in the field of folkloristics about total eclipses suggest that, if the marginal investor attached superstitious beliefs to such natural phenomena, then their occurrence should be anticipated to worsen her expectations about the future developments of the economy, in turn causing a reduced demand for stocks and, ultimately, having a negative impact on equity returns.

3.5. The Physics of Eclipses

Total solar eclipses take place when the moon passes in front of the sun and obscures it entirely. Overall, the duration of such natural phenomena is limited to a couple of hours, at most, and totality generally lasts for less than seven minutes. Empirically, eclipses have been found to have a temporary influence on numerous geophysical variables and also on plants, animals' behavior and human beings' health. Kotrappa et al. (1981) claim that solar eclipses are associated with increases in relative humidity and conspicuous falls in ground level temperature[50]. Keshavan et al. (1981), and Strestik and Jaroslav (1999) document a corresponding variation in the Earth's geomagnetic field.

Solar eclipses have also been found to alter the circadian rhythm of plants (Häberle et al., 2001), and animals (Wojtusiak et al., 1975a; 1975b; 1976), yet, to the best of my knowledge, no evidence has been produced on their ability to influence the human circadian rhythm[51].

Hundreds of investigations have documented one specific effect of solar eclipses on human, i.e. solar retinopathy. This is a medical condition that is caused by

[50] Some of the locations monitored by the authors experienced a drop in temperature up to about 10° C.

[51] A circadian rhythm is a type of "biological clock" that presides over numerous physiological processes of plants, animals and even humans. It partly determined by some external cues, such as temperature and sunlight. For a literature review on the role of circadian rhythms, see Paranjpe and Sharma (2005). Clock shifting at the beginning and end of daylight saving time has been shown to produce some effects on sleep patterns and, in turn, on human behavior (Kamstra et al., 2000). On the other hand, solar eclipses are transitory events and totality lasts no more than few minutes. As a result, it seems safe to assume, as a working hypothesis, that solar eclipses do not produce any shift in people's biological clocks that, in turn, might be responsible for changes in their behavior.

unprotected or inappropriate sun gazing or exposure, whose risks have been known since at least the time of Plato (Shuttleworth and Galloway, 2002). Staring at the sun with a naked eye or without a proper filter, even during an eclipse, may cause serious damages, and such harmful effects may have contributed, over the centuries, to develop and reinforce the superstitious beliefs attached to solar eclipses. Recent surveys have revealed that there is still a great deal of uncertainty among the general public about how to view an occultation of the sun in safety (Shuttleworth and Galloway, 2002), which may suggest that, for many people, the physics of solar eclipses, to a certain extent, remains a mystery.

3.6. Environment, Emotional State, and Equity returns

Over the last fifteen years, behavioral finance researchers have accumulated considerable evidence about the effects that alterations in the Earth and space environments can exert on investor mood and, ultimately, on investment decisions and equity returns. Taken as a whole, this body of research casts doubt on the view that economic agents are entirely rational and calls for the inclusion of behavioral variables into asset pricing models.

Saunders (1993) can be credited with making the seminal contribution in this area. In particular, he finds that the weather in New York (percentage daily cloud cover) is highly correlated with the returns of three major indices of the U.S. stock market, and suggests that sunshine influences people's mood, which in turn affect the demand for risky stocks and, ultimately, stock returns (the better investor mood, the higher equity returns). Along similar lines have moved several subsequent investigations (Krämer and Runde, 1997; Hirshleifer and Shumway, 2003; Pardo and Valor, 2003; Goetzmann and Zhu, 2003; Loughran and Schultz, 2004).

Adopting an analogous approach, Cao and Wei (2005), using a sample of data from eight industrialized countries, find that stock returns are negatively correlated with the temperature prevailing in the cities that host the corresponding stock exchanges.

Kamstra et al. (2003) assert that much of the seasonal pattern found in stock returns is attributable to the so-called seasonal affective disorder (SAD). After discussing the evidence produced in the fields of medicine and psychology that shows a positive relationship between the length of the night and seasonal depression, as well as between depression and risk aversion, the authors examine whether the seasonal variation in the length of the day (measured at different latitudes) is correlated with equity returns. Their empirical findings appear to be consistent with the existence of an SAD effect, and suggest that such a mood effect is both statistically and economically significant.

Krivelyova and Robotti (2003), drawing upon a body of psychiatric research that documents how changes in the geomagnetic field can influence people's mood, test whether stock returns exhibit an abnormal pattern during geomagnetic storms, and find some support for their hypothesis. Controlling for other well-known market anomalies, the authors show that the occurrence of geomagnetic storms produces a statistically significant negative (lagged) influence on equity returns in nine industrialized countries.

Finally, Dichev and Janes (2003) and Yuan et al. (2006) uncover some evidence in support of the view that the lunar cycle exerts an influence on people's behavior, in general, and on investment decisions, in particular. Their findings seem to suggest that stock returns are higher-than-average during new moon periods and lower-than-average during full moon periods.

3.7. Data

Here the analysis is centered upon the U.S. market and covers three broad stock market indices: S&P500, Dow Jones Industrial Average and Nasdaq Composite. Data about equity returns have been collected from Yahoo! Finance[52]. Daily log returns, adjusted for dividends, have then been computed from January 2, 1930 through January 27, 2006 for the S&P500 and Dow Jones indices. In the case of the Nasdaq index, the sample covers the period February 8, 1971 through January 27, 2006. Table 3.1 allows a graphical inspection of the data and shows that the time series of stock returns under investigation suffer from negative skewness and excess kurtosis.

Table 3.1 also include summary statistics for two sub-samples of the S&P500 and Dow Jones indices: January 2, 1946 through January 27, 2006 and January 2, 1970 through January 27, 2006. Three reasons have led to such a choice. First, as shown in some previous studies, during the Great depression equity returns were exceedingly volatile compared to the subsequent decades, and such a pattern might obscure the role played by the phenomenon under scrutiny (Schwert, 1989). Second, as pointed out in section 3.2, superstitious beliefs appear to have revived in the American culture following World War II; as a result, and also in order to leave out the events associated with the war, January 2, 1946 has been chosen as the starting date for the first sub-period. Moreover, in order to obtain results that are comparable across the three market indices in

[52] http://finance.yahoo.com/.

terms of time span, a second sub-sample has been constructed whose starting date is January 2, 1970. Naturally, such a method can also be interpreted as a form of robustness check, as a case for a superstition effect can only be made if the empirical evidence is relatively stable over time.

Data about solar and lunar eclipses have been collected from NASA[53]. Only total eclipses have been considered, and their date has been determined according to Universal Time[54]. Considering the whole sample, total solar eclipses seem to be visible somewhere on Earth every seventeen months, on average (53 observations overall).

NASA also provides information about the geographic region in which each total eclipse is visible. Initially, given the small number of observations, the analysis is conducted using all total eclipses, whereas, at a subsequent stage, attention is restricted to those eclipses visible in north America. Newspapers and other news providers around the world generally document the occurrence of a total solar eclipses visible somewhere on Earth, but given that stock markets are not fully integrated, one would expect eclipses visible in the U.S. to have a stronger impact on the domestic stock market[55]. As this process of news circulation takes some time (newspapers giving accounts of this event are normally issued on the subsequent day), one should think about the possibility that the effect of total eclipses on the equity market, if any, may be a lagged one.

Total lunar eclipses occur somewhat more often than solar ones, and can also be seen from a much larger area on Earth. Considering the whole sample, 64 such

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[53] http://sunearth.gsfc.nasa.gov/eclipse.html.

[54] The underlying idea is that total eclipses are special in that there is a powerful symbolic meaning attached to them. There exist two other kinds of solar eclipses: annular and hybrid. Lunar eclipses can also be of penumbral type. A preliminary empirical analysis of eclipses other than total, not reported here for brevity, has suggested that they do not seem to exhibit any systematic relationship with equity returns.

[55] See, for example, Shuttleworth and Galloway (2002).

occurrences have been recorded. As such, total lunar eclipses are visible somewhere on Earth every fourteen months, on average. When solar and lunar eclipses are combined, the frequency increases to one occurrence every eight months, on average.

Data about the Earth's geomagnetic field have been collected from the National Geophysical Data Center in Boulder, Colorado. Unlike Krivelyova and Robotti (2003), who measure geomagnetic activity through the *Ap* index, the present analysis employs the *aa* index[56]. The only difference between the two indices originates from the fact that data coming from different panels of observatories are used in their construction, and no significant difference in the empirical results should be expected. The time series employed here spans from January 2, 1940 through December 31, 1998.

Data about temperature and cloud cover in New York have been obtained from the National Climatic Data Center in Asheville, North Carolina[57]. The former extends over the period January 2, 1964 through January 27, 2006, whereas the latter spans from January 4, 1965 to April 30, 1996. The SAD variable (daily number of hours of night in New York city) has been calculated according to the methodology suggested by Kamstra et al. (2003).

Finally, following Yuan et al. (2006), in order to capture the alleged effects of the lunar cycle it has been chosen to construct two dummy variables: a full-moon dummy, taking the value of 1 up to three days before and after each full moon date and 0

[56] http://www.ngdc.noaa.gov/stp/GEOMAG/aastar.shtml. The choice has been motivated by data availability reasons.

[57] http://lwf.ncdc.noaa.gov/oa/ncdc.html. In particular, the data have been provided by the JFK airport station.

otherwise, and a new-moon dummy, taking the value of 1 up to three days before and after each new moon date. Data about the lunar phases have been obtained from NASA[58].

[58] http://sunearth.gsfc.nasa.gov/eclipse/phase/phasecat.html.

3.8. Econometric Analysis

A preliminary investigation, conducted using the empirical methodology that will be illustrated in this section, has produced no evidence of a contemporaneous relationship between total eclipses and stock market returns[59]. As such, the rest of the analysis will focus on the detection of a lagged effect. From a theoretical viewpoint, this may be justified by the fact that a large portion of the market participants get to know about the occurrence of an eclipse from the mass media, and typically with a time lag that is a natural outcome of the process of information diffusion (e.g. newspapers). A lagged *eclipse* dummy has been created that takes the value of 1 on the trading day that immediately follows a total eclipse and zero otherwise. As it will be shown, the outcomes of the tests employed here do seem to support the hypothesis that the occurrence of eclipses produces a negative lagged impact on investment decisions[60].

3.8.1. Total Eclipses and Magnitude of Equity Returns

The analysis starts off with a simple t-test aimed at verifying if equity returns are lower than average on the trading days that immediately follow the occurrence of total

[59] The results are not reported here for brevity.
[60] The same analysis has been carried out using alternative lags for such a dummy variable. No statistical evidence has been found in this regard. Analogously, no anomalous behavior of stock returns has been detected on the days that immediately preceded total eclipses.

eclipses[61]. Table 3.2 displays the outcomes of this test and reveals that, on average, daily equity returns are negative when they are preceded by a total eclipse. Such a result arises in correspondence to every market index and sample period examined. On the other hand, daily stock returns are estimated to be positive, on average, during "ordinary" trading days (i.e., days that do not follow total eclipses). When the whole sample is considered, for the Dow and S&P500 indices the difference between the two means is approximately 0.2%, and is statistically significant at standard confidence levels (p-value below 0.10).

The divergence is even larger when the focus is moved to the intermediate sample. For the two above-mentioned indices, stock returns are lower (roughly by 0.25%) on the trading days that follow total eclipses than on ordinary days, the difference being statistically significant at least at the 5% level.

The most recent sub-sample generates similar results. Across the three market indices, equity returns are consistently lower after a total eclipse has taken place than on regular days, the effect being both economically and statistically significant (p-value below 0.01). On average, the difference is about 0.45%.

Taken as a whole, these estimates tell a consistent story and provide some initial support to the hypothesis that equity returns negatively react to the occurrence of solar and lunar eclipses. Such an outcome is compatible with the view that (at least some) investors hold superstitious beliefs about these natural phenomena and take such beliefs into account (either consciously or subconsciously) when they are called upon to make financial decisions. Interestingly, the table also suggests that the magnitude of the alleged superstition effect seems to have grown in the last decades.

[61] More specifically, stock returns are regressed on a constant and a lagged eclipse dummy, and Newey-West heteroskedasticity and serial correlation robust standard errors are calculated (max 5 lags). The t-test determines whether the coefficient on the eclipse dummy is statistically different from zero.

Another possible explanation is that, even if the marginal investor is fully rational, she may assume that a large fraction of the population holds superstitious beliefs and, in turn, may plan her investment decisions accordingly in an attempt to take advantage of the price changes caused by superstitious investors (self-fulfilling prophecy). In this regard, the empirical regularity documented and discussed above suggests that rational investors, if existing at all, cannot completely eliminate the alleged superstition effect.

3.8.2. Total Eclipses and Direction of Equity Returns

The previous section tried to verify if stock returns tend to be lower than average when they are preceded by a total eclipse. In this section, instead, the goal is to determine if also the direction of equity returns is affected to some extent by the occurrence of total eclipses.

In order to perform such a task a sign test can be employed, which determines if the direction of a market index change after a specific event (i.e. a total eclipse) is systematically different from the direction that one would be anticipating simply based on the unconditional distribution of returns. In other words, the objective is to verify whether there is a recurrent pattern in the stock return "data generating process" according to which returns tend to be not only lower after an eclipse than on regular days but also negative.

The unconditional probability of observing a negative daily return has been estimated from the data themselves for each sub-sample and stock market index, as shown in Table 3.3. The null hypothesis assumed for testing purposes is that the number of negative returns actually observed in each sub-sample after a total eclipse is not different from the number that one would anticipate to observe when drawing a random sample. The binomial distribution is then employed to calculate the probability of observing a number of negative returns greater or equal to the one actually observed in the sample. It follows that such a probability may then be used as a one tail p-value for the purpose of determining whether to reject or not to reject the null hypothesis.

Table 3.3 displays the outcomes of such a test. Depending on the market index and sub-period analyzed, the estimated unconditional probability of observing a negative return (fourth column) ranges between 43.8% and 48.4%. When the whole sample is examined, for the Dow and S&P500 indices there is some mild evidence that equity returns are more likely to be negative on those trading days that directly follow the occurrence of total eclipses (p-value below 0.09).

The results are somewhat less clear-cut when the intermediate sub-sample is evaluated, though there is still some marginal evidence in favor of the view that total eclipses seem to alter the direction of the following trading day's equity returns in the expected way.

Lastly, when the most recent sub-sample is assessed, all three indices reveal that, after an eclipse, a negative return is much more likely to be observed than a positive one, the corresponding p-values being less than or equal to 0.01. Depending on the market index considered, the probability that equity returns turn out to be negative following a total eclipse ranges between 64% and 67%, whereas the same probability ranges between 43.8% and 48.5% on ordinary trading days.

Once again, overall, the findings appear to be consistent with the view that the occurrence of total eclipses causes an abnormal behavior of stock returns, and such a departure is consistent with what one would anticipate based on the superstition story discussed in the previous sections. Taken as a whole, the tests carried out in the previous and current section suggest that, after a total eclipse, not only stock returns tend to be lower than they would be otherwise, but they even tend to be negative. Up to this stage of the analysis no control variable has been employed. The next step will consist in verifying whether the empirical regularities documented here can be explained in light of some standard economic variables or based on some psychological factors advanced in the behavioral finance literature.

3.8.3. Multivariate Model

The initial goal is to purge the time series of equity returns from any residual autocorrelations. This is done by estimating the following equation by OLS and performing statistical inference using Newey-West adjusted standard errors (max 5 lags)

$$r_t = \alpha + \sum_{k=1}^{p} \beta_{t-k} r_{t-k} + \mu_{Eclipse} Eclipse_{t-1} + \varepsilon_t \tag{3.1}$$

where r_t is the daily stock return between time *t-1* and time *t*, and $Eclipse_{t-1}$ is a lagged dummy variable that takes the value of 1 when a total eclipse has taken place at time *t-1*. Lagged returns up to p periods are added to the model when statistically significant.

Table 3.4 displays the estimated coefficients and corresponding p-values. The index returns included in the present sample seem to exhibit the typical autocorrelation structure that has been detected in the finance literature, for the coefficients on the lagged returns are statistically significant up to the second lag. When evaluating the whole sample, the coefficient $\mu_{eclipse}$ turns out to be negative and statistically different from zero for both the S&P500 and Dow Jones indices. The point estimate of the eclipse effect is approximately –0.2%. Analogous results are obtained when the intermediate sample (1946-2006) is assessed. In this case the marginal effect turns out to be both slightly more economically relevant (-0.23%) and statistically significant. Lastly, when the focus is moved to the most recent sub-sample (1970-2006), the eclipse effect still clearly emerges across the three market indices, and its size appears to be particularly large (-0.4%). Additionally, the null hypothesis of no relationship with the dependent variable can be rejected at remarkably high confidence levels.

3.8.4. Controlling for Behavioral Factors

In principle, the empirical regularity documented in the previous sections might be caused by other factors. As a result, it is critical to control for all the variables that are influenced by the physics of eclipses and, at the same time, have been shown to have a relationship with stock returns.

Cao and Wei (2004) have documented the existence of a link between equity returns and temperature and, at the same time, Kotroppa et al. (1981) have shown that total solar eclipses can influence the Earth's ground temperature. As a result, a variable that measures the daily temperature in New York city will be added to the regression equation. Based on the same rationale, one also needs to control for the SAD effect, the percentage cloud cover in New York, and Earth's geomagnetic activity.

Dichev and Janes (2003) and Yuan et al. (2006) claim that stock returns are generally higher during new-moon periods than full-moon periods. Since solar eclipses can only occur during a new moon, whereas lunar eclipses can only take place during a full moon, one will also want to control for the lunar cycle. This is done by adding the full moon and new moon dummies, previously discussed, to the regression equation.

The intersection of the time series of all the variables involved generates a sample that covers the period from January 4, 1965 through April 30, 1996 for the S&P500 and Dow Jones indices, and from February 8, 1971 through April 30, 1996 for the Nasdaq index. The following model has been fitted by OLS and using Newey-West adjusted standard errors (max 5 lags):

$$\begin{aligned} r_t = \alpha &+ \sum_{k=1}^{p} \beta_{t-k} r_{t-k} + \mu_{Eclipse} Eclipse_{t-1} + \gamma_{Monday} Monday_t + \\ &+ \lambda_{SAD} SAD_t + \lambda_{Temperature} Temperature_t + \lambda_{Cloud} Cloud_t + \\ &+ \lambda_{Geomagnetic} Geomagnetic_{t-1} + \delta_{Newmoon} Newmoon_t + \\ &+ \delta_{Fullmoon} Fullmoon_t + \varepsilon_t \end{aligned} \tag{3.2}$$

where $Temperature_t$ measures the daily temperature (Fahrenheit degrees) in New York, $Cloud_t$ measures sky cloudiness in New York[62], and $Geomagnetic_{t-1}$ is a lagged dummy that takes the value of 1 when the *aa* geomagnetic index is greater than 60 at time $t-1$.

[62] Sky cover is measured in tenths, where 0 means less than 10% coverage and 10 means 100% coverage.

Newmoon$_t$ is a dummy that takes the value of 1 up to three days before and after each new-moon day, and *Fullmoon$_t$* is a dummy that takes the value of 1 up to three days before and after each full-moon day. *SAD$_t$* captures the number of hours of night in New York and has been adjusted so as to incorporate the occurrence of total solar eclipses[63].

It is natural to wonder whether the occurrence of total eclipses follows any particular pattern in terms of day of the week or calendar month[64]. Figure 3.1 classifies the total eclipses that occurred in the whole sample by day of the week, and reveals that no recurrent pattern seems to exist. Nevertheless, with the purpose of getting more precise estimates, a *Monday* dummy has been added to model [3.2], taking the value of 1 when the trading day *t* is a Monday and zero otherwise.

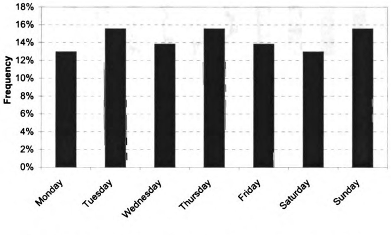

Figure 3.1 Empirical frequency of total eclipses by day of the week.

[63] One hour of night has been added to the SAD variable on each day in which a total solar eclipse occurred, except in the summer and spring when the value of the SAD variable remains equal to zero. This is a very conservative choice, as totality typically lasts for very few minutes, so that the actual amount of daylight is not significantly reduced. Estimation has also been conducted without adjusting the SAD variable. The results are practically identical.

[64] The periodicity and recurrence of eclipses is governed by the so-called Saros cycle, a period of approximately 6,585.3 days (18 years 11 days 8 hours). Any two eclipses separated by one Saros cycle share very similar geometries (Espenak, 1987).

Similarly, Figure 3.2 sorts all total eclipses by month. Based on such a categorization, total eclipses do not appear to occur evenly throughout the year. Instead, they seem relatively more likely to take place in October, November and June. For this reason, model [3.2] has been estimated both with and without a whole set of monthly dummies. The outcomes are practically the same in both cases and, as such, only the estimates associated with the more parsimonious model are reported and discussed here.

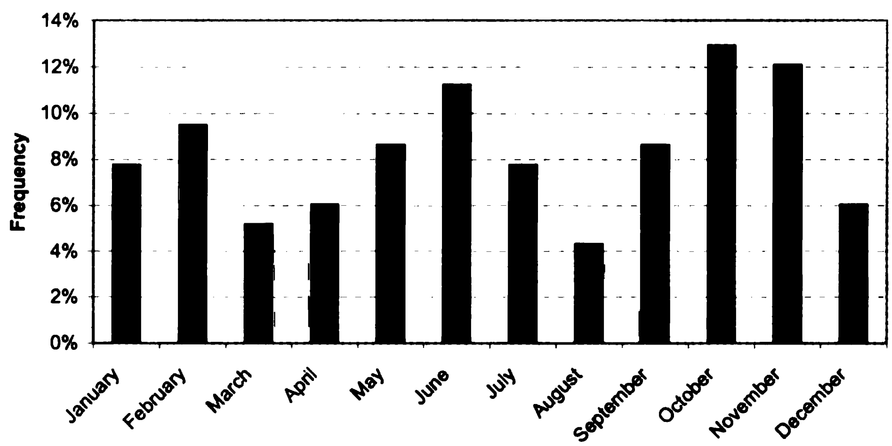

Figure 3.2 Empirical frequency of total eclipses by calendar month.

Table 3.5 displays the empirical estimates, which are very similar across the three market indices and suggest that the superstition effect previously documented does not seem attributable to other well-known market anomalies that may have a connection with total eclipses. In particular, equity returns following a total eclipse are estimated to be approximately 0.35% lower than they would be otherwise, all else equal. As a result, the coefficient on the eclipse dummy appears to be not only highly statistically significant (p-value below 0.01) but also economically relevant.

As for the other explanatory variables, only the Monday dummy and the percentage sky cover appear to be significantly correlated with equity returns, and the signs of such effects are coherent with the typical results documented in the literature. It is worth to mention that the SAD variable turns out to be individually statistically insignificant, but it is jointly significant with the temperature variable. Since these two variables follow a very similar seasonal pattern, it seems hard to isolate the contribution that each of them gives, if any, to determining the behavior of stock returns.

3.8.5. Controlling for Economic News

In principle, one would also want to check whether the empirical regularity previously discussed is merely attributable to some economic shocks that took place concurrently with (or the day after) total eclipses rather than to these natural phenomena themselves. Such a question can be answered accurately only if one is able to identify the time series of unexpected economic shocks that affected the stock market. In turn, in order to isolate the unexpected components of a sequence of economic shocks, one would need a good measure of investors' expectations[65]. Since such a strategy seems quite impractical, here it has been chosen to adopt an indirect approach and take advantage of the investors' expectations that are embedded in the term structure of interest rates.

Previous research has shown that the Yield Curve, in particular the yield spread between some long-term and short-term Treasury bonds, incorporates some information

[65] For a review of the issues associated with such a strategy, see Rigobon and Sack (2006).

useful for predicting inflation, economic activity, and future short-term interest rates[66]. The underlying idea is that the shape of the Yield Curve changes in response to changing expectations about the future dynamics of interest rates, and changes in expectations are caused by the arrival of new pieces of information on the market.

In the present context, the yield spread can be used to capture unexpected economic shocks to the extent that such shocks are incorporated into the shape of the Yield Curve itself. More specifically, the spread between the interest rates on the ten-year US Treasury bond and the three-month Treasury bill is added to the regression equation [2]. Furthermore, contemporaneous and lagged changes in such a spread are added to the model if statistically significant, so that the regression equation becomes:

$$\begin{aligned} r_t = \alpha &+ \sum_{k=1}^{p} \beta_{t-k} r_{t-k} + \mu_{Eclipse} Eclipse_{t-1} + \gamma_{Monday} Monday_t + \\ &+ \lambda_{SAD} SAD_t + \lambda_{Temperature} Temperature_t + \lambda_{Cloud} Cloud_t + \\ &+ \lambda_{Geomagnetic} Geomagnetic_{t-1} + \delta_{Newmoon} Newmoon_t + \\ &+ \delta_{Fullmoon} Fullmoon_t + \eta_{Spread} Spread_t + \eta_t^{\Delta Spread} \Delta Spread_t + \\ &+ \eta_{t-1}^{\Delta Spread} \Delta Spread_{t-1} + \varepsilon_t \end{aligned} \tag{3.3}$$

where $Spread_t$ is the yield spread discussed above, $\Delta Spread_t$ is the change in such a spread between time $t-1$ and time t, and $\Delta Spread_{t-1}$ is its change between time $t-2$ and time $t-1$.

The estimated coefficients are collected in Table 3.6 and show that the yield spread indeed seems to contain some useful information about the economic activity. In

[66] See, for example, Estrella and Hardouvelis (1991), Plosser and Rouwenhorst (1994), Estrella and Mishkin (1997), Dueker (1997), Estrella and Mishkin (1998), and Hamilton and Kim (2002).

particular, it exhibits a positive significant correlation with equity returns. Furthermore, lagged changes in the yield spread also appear to incorporate some valuable information in terms of asset pricing.

If one accepts as true the view that the arrival of new relevant economic information is reflected into the shape of the yield curve, then the findings are once again consistent with the hypothesis that superstition plays a role in investment decisions. Indeed the coefficients on the eclipse dummy are highly statistically significant and economically relevant across the three market indices. Put in another way, based on the previous tests, there appears to be no reason to conclude that the abnormal behavior of stock returns following total eclipses is caused by the market reaction to the arrival of new economic information.

3.8.6. Direct vs. Indirect Visibility of the Phenomenon

So far, the empirical analysis has been conducted including all the total eclipses that were visible somewhere on Earth during the sample period under consideration. One may argue though that, if the superstition story contains some truth, then the size of the eclipse effect should be larger when the sample is cut down so as to include only those total eclipses that were visible in north America and, therefore, could directly affect U.S. investors.

Once such an adjustment is made, the number of total eclipses recorded in the relevant sample period (1965-1996) shrinks from 49 to 29. Indeed, when models [3.2] and [3] are re-estimated considering only the eclipses visible in north America, the statistical significance of the eclipse dummy stays practically unchanged whereas the magnitude of its coefficient increases in absolute value. More precisely, the estimates, which are very similar across the three market indices and the two regression models, suggest that when a total eclipse is visible in north America, equity returns in the U.S. market are estimated to fall by approximately 0.45% on the following trading day, all else equal. Once again, these outcomes seem to be hard to reconcile with fully rational asset pricing, and are in line with the superstition hypothesis under observation.

3.8.7. Controlling for Time-Varying Volatility

The stock market index returns analyzed here appear to be characterized by volatility clustering and excess kurtosis. In order to deal directly with such issues a GARCH framework may be employed to jointly model the mean and variance of returns (Engle, 1982). More specifically, the following GARCH (1,1) model has been estimated by quasi-maximum likelihood and using the Huber-White estimator of variance:

$$\begin{aligned} r_t = \alpha &+ \sum_{k=1}^{p} \beta_{t-k} r_{t-k} + \mu_{Eclipse} Eclipse_{t-1} + \gamma_{Monday} Monday_t + \\ &+ \lambda_{SAD} SAD_t + \lambda_{Temperature} Temperature_t + \lambda_{Cloud} Cloud_t + \\ &+ \lambda_{Geomagnetic} Geomagnetic_{t-1} + \delta_{Newmoon} Newmoon_t + \\ &+ \delta_{Fullmoon} Fullmoon_t + \eta_{Spread} Spread_t + \eta_t^{\Delta Spread} \Delta Spread_t + \\ &+ \eta_{t-1}^{\Delta Spread} \Delta Spread_{t-1} + \varepsilon_t \end{aligned} \tag{3.4}$$

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

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

The results, not reported here for brevity, are comparable to the ones discussed in the previous sections. When the GARCH model is used, the superstition effect is estimated to be slightly smaller than in model [3.3][67]. Such an effect is still statistically significant and economically relevant. As for the remaining variables, their patterns are analogous to the ones previously described.

Overall, it seems safe to conclude that the evidence in support of the superstition story has proven to be robust to the use of alternative sets of controls and estimation techniques. It is natural to wonder whether such an empirical regularity can be exploited to construct some profitable trading strategy, which would make it a market anomaly. This is precisely the goal of the next section.

[67] When all eclipses are evaluated, the superstition effect ranges from –0.25% to –0.3%, depending on the particular market index. Similarly, when the sample includes only the total eclipses that were visible in north America, the superstition effect ranges from –0.32% to –0.38%.

3.9. Superstitious Beliefs, Investment Decisions, and Efficient Market Theory

It is worth to stress here that, as mentioned earlier, total eclipses are perfectly predictable events. As a result, if the stock market was entirely efficient, the occurrence of total eclipses should have no effect whatsoever on equity returns even if investors attached superstitious beliefs to such phenomena and were affected by those same beliefs when making financial decisions[68].

Yet, there seems to exist the opportunity to exploit the empirical regularities associated with total eclipses. If, at the beginning of 1970, an investor had bought a portfolio of stocks that replicated the S&P500, for example, and subsequently adopted a simple buy-and-hold strategy, holding her portfolio until the beginning of 2006, then she would have earned an average annual return of 7.59%[69]. If, instead, such an investor had implemented an active trading strategy based on the occurrence of total eclipses (i.e., sell when a total eclipse takes place and buy back at the end of the following trading day), then she would have earned an average annual "excess return" of approximately 0.6%.

Considering that total eclipses took place every eight months, on average, over the sample period, it seems safe to assume that a trading strategy based on the superstition effect would have allowed investors to gain an excess return over a passive strategy even

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[68] NASA has already calculated all the total eclipses that will be visible somewhere on Earth within the next two thousand years.

[69] In this section daily stock returns are computed as the change in a given stock market index divided by the previous trading day's closing value. No loss of generality should be anticipated as a result of this choice.

if transaction costs are taken into account[70]. The excess return could be even larger if agents were allowed to sell short and/or trade derivatives. Analogous results can also be obtained by applying the same trading strategy to the Dow Jones and Nasdaq indices.

Taken as a whole, these findings suggest that the superstition effect not only takes the form of a recurrent pattern in the time series of equity returns, but truly seems to represent a violation of the efficient market hypothesis, as its own existence and magnitude reveals the existence of some unexploited profit opportunities. In a larger perspective, it can be concluded that the empirical results seem hard to reconcile with fully rational asset pricing and lend support to the view that investment decisions can be influenced by some purely psychological factors (e.g. superstitious beliefs).

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

3.10. Concluding Remarks

This chapter has focused on the link that seems to exist between the occurrence of total eclipses and U.S. equity returns. The analysis has been motivated by the hypothesis that human decision-making can be influenced by superstitious beliefs, which finds support in several empirical investigations conducted in the fields of sociology and psychology.

More specifically, the work is aimed at verifying whether the superstitious beliefs attached to total eclipses, as documented by folklorists, can influence investors buying/selling decisions in the same way they have affected human behavior in many societies for centuries. Since the evidence produced in the field of folkloristics suggests that these natural phenomena have been commonly interpreted as evil omens, it is conjectured that their occurrence might be taken as a presage of future poor performances of the economy, in turn inducing investors to shy away from stocks and, ultimately, decreasing stock returns, all else equal.

Such a hypothesis has then been put to test using daily data from the U.S. stock market covering a relatively long period of time. The results have revealed that the occurrence of total eclipses is associated with an abnormal behavior of equity returns. In particular, after controlling for a set of behavioral and economic variables, stock returns appear to be lower than average in the aftermath of total eclipses, which is consistent with the superstition story proposed here.

Since eclipses are perfectly predictable events, the existence of such unexploited empirical regularities also questions the validity of the efficient market theory. Additionally, in a larger perspective, these findings challenge the view that investors are entirely rational and that only purely economic factors are relevant for asset pricing.

Table 3.1 Summary statistics of US stock returns

This table displays summary statistics of daily log returns on three US stock market indices: S&P500, Dow Jones Industrial Average and Nasdaq. Returns are in percentage points.

Index Period	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis
S&P500 01/02/1930-01/27/2006 (20014 obs)	.0204	1.1140	-22.899	15.366	-.347	22.679
S&P500 01/02/1946-01/27/2006 (15237 obs)	.0282	.9011	-22.899	8.708	-1.307	35.792
S&P500 01/02/1970-01/27/2006 (9108 obs)	.0289	.9972	-22.899	8.708	-1.398	37.652
Dow Jones 01/02/1930-01/27/2006 (19104 obs)	.0198	1.1134	-25.631	14.27	-.543	29.347
Dow Jones 01/02/1946-01/27/2006 (15109 obs)	.0267	.9096	-25.631	9.666	-1.633	50.116
Dow Jones 01/02/1970-01/27/2006 (9108 obs)	.0286	1.0263	-25.631	9.666	-1.752	49.990
Nasdaq 02/08/1971-01/27/2006 (8826 obs)	.0355	1.1946	-12.043	13.254	-.313	13.774

Table 3.2 Comparison of mean returns

This table displays daily mean returns on trading days following a total eclipse (second column) and on "regular" days (third column). The number of observations is in parenthesis. The last column contains the t-statistics of a difference of means test (p-values are in brackets). More precisely, returns are regressed on a constant and a one-day lagged eclipse dummy, and Newey-West heteroskedasticity and serial correlation robust standard errors are computed (max 5 lags). The test verifies whether the coefficient on the eclipse dummy is statistically different from zero. Returns are in percentage points. One, two and three asterisks denote statistical significance at the 10%, 5% and 1% level, respectively.

Index Period	Day after total eclipse Mean	Regular days Mean	Difference	t-test
S&P500 01/02/1930-01/27/2006	-.208 (117)	.022 (19896)	-0.186*	-1.82 [0.07]
S&P500 01/02/1930-12/31/1945	-.063 (23)	-.004 (4752)	-0.059	-0.25 [0.80]
S&P500 01/02/1946-12/31/1969	.130 (38)	.026 (6090)	0.103	0.55 [0.59]
S&P500 01/02/1946-01/27/2006	-.249 (94)	.029 (15143)	-0.220**	-1.93 [0.05]
S&P500 01/02/1970-01/27/2006	-.470 (56)	.031 (9052)	-0.439***	-3.29 [0.01]
Dow Jones 01/02/1930-01/27/2006	-.225 (117)	.021 (18986)	-0.204**	-2.03 [0.04]
Dow Jones 01/02/1930-12/31/1945	-.118 (23)	-.005 (3971)	-.113	-0.40 [0.68]
Dow Jones 01/02/1946-12/31/1969	.080 (38)	.023 (5963)	.0573	0.34 [0.74]
Dow Jones 01/02/1946-01/27/2006	-.255 (94)	.028 (15015)	-0.227**	-2.17 [0.03]
Dow Jones 01/02/1970-01/27/2006	-.451 (56)	.031 (9052)	-0.420***	-3.30 [0.01]
Nasdaq 02/08/1971-01/27/2006	-.433 (55)	.038 (8770)	-0.395***	-2.51 [0.01]

Table 3.3 Sign test

This table displays the results of a sign test on the direction of stock returns following a total eclipse. The second column contains the number of eclipses that occurred in each sub-sample (*trials*). The third column shows the total number of negative returns observed (*successes*). The fourth column shows the estimated unconditional probability of observing a *success* (negative return) in each particular sub-sample for a given index. The number of observations is in parenthesis. The last column contains the probability of observing a number of negative returns greater or equal to the number actually observed, based on the binomial distribution. Note: observations containing neither positive nor negative returns have been dropped. One, two and three asterisks denote statistical significance at the 10%, 5% and 1% level, respectively.

Index Period	Number of total eclipses	Number of negative returns after eclipses	Probability of negative return	One-tail p-value
S&P500 01/02/1930-01/27/2006	117	63*	0.472 (19637)	0.089
S&P500 01/02/1930-12/31/1945	23	12	0.4833 (4571)	0.435
S&P500 01/02/1946-12/31/1969	38	14	0.4580 (5985)	0.899
S&P500 01/02/1946-01/27/2006	94	51*	0.469 (15066)	0.092
S&P500 01/02/1970-01/27/2006	56	37***	0.477 (9081)	0.004
Dow Jones 01/02/1930-01/27/2006	117	64*	0.479 (19019)	0.083
Dow Jones 01/02/1930-12/31/1945	23	13	0.4838 (3979)	0.283
Dow Jones 01/02/1946-12/31/1969	38	15	0.4681 (5971)	0.857
Dow Jones 01/02/1946-01/27/2006	94	51	0.478 (15040)	0.125
Dow Jones 01/02/1970-01/27/2006	56	36**	0.484 (9069)	0.012
Nasdaq 02/08/1971-01/27/2006	55	37***	0.438 (8789)	0.001

Table 3.4 Regression analysis

This table contains the estimated coefficients of regression model [3.1]. P-values computed using Newey-West adjusted standard errors (max 5 lags) are in parenthesis. The number of observations is displayed in the sixth column. The coefficients are in percentage points. One, two and three asterisks denote statistical significance at the 10%, 5% and 1% level, respectively.

Index Period	α	β_{t-1}	β_{t-2}	$\mu_{Eclipse}$	Obs.
S&P500 01/02/1930-01/27/2006	.021*** (0.008)	.049*** (0.000)	-.024 (0.112)	-.192* (0.060)	20012
S&P500 01/02/1946-01/27/2006	.028*** (0.000)	.085*** (0.000)	-.047*** (0.004)	-.231** (0.042)	15237
S&P500 01/02/1970-01/27/2006	.031*** (0.003)	.069*** (0.000)	-.032 (0.149)	-.443*** (0.001)	9108
Dow Jones 01/02/1930-01/27/2006	.021** (0.011)	.027* (0.070)		-.207** (0.040)	19103
Dow Jones 01/02/1946-01/27/2006	.027*** (0.000)	.076*** (0.000)	-.047** (0.011)	-.235** (0.025)	15109
Dow Jones 01/02/1970-01/27/2006	.031*** (0.004)	.057*** (0.000)	-.039* (0.099)	-.422*** (0.001)	9108
Nasdaq 02/08/1971-01/27/2006	.034*** (0.007)	.102*** (0.000)		-.414*** (0.007)	8825

Table 3.5 Controlling for behavioral factors

This table contains the estimated coefficients of regression model [3.2]. P-values computed using Newey-West adjusted standard errors (max 5 lags) are in parenthesis. The coefficients are in percentage points. One, two and three asterisks denote statistical significance at the 10%, 5% and 1% level, respectively.

Index Period	S&P500 01/04/1965-04/30/1996	Dow Jones 01/04/1965-04/30/1996	Nasdaq 02/08/1971-04/30/1996
α	.088* (0.073)	.096* (0.063)	.182*** (0.000)
β_{t-1}	.124*** (0.000)	.096*** (0.000)	.288*** (0.000)
$\mu_{Eclipse}$	-.368*** (0.003)	-.392*** (0.002)	-.367*** (0.003)
γ_{Monday}	-.131*** (0.000)	-.107*** (0.001)	-.280*** (0.000)
λ_{SAD}	.013 (0.244)	.014 (0.269)	.013 (0.279)
$\lambda_{Temperature}$	-.001 (0.830)	-.001 (0.595)	-.001 (0.219)
λ_{Cloud}	-.009** (0.012)	-.009*** (0.008)	-.011*** (0.001)
$\lambda_{Geomagnetic}$	.064 (0.164)	.074 (0.117)	.064 (0.182)
$\delta_{Newmoon}$	.020 (0.384)	.032 (0.203)	.007 (0.765)
$\delta_{Fullmoon}$	.011 (0.648)	.014 (0.583)	-.004 (0.852)
Observations	7886	7886	6372
Total eclipses in the sample	49	49	40

Table 3.6 Controlling for economic news

This table contains the estimated coefficients of regression model [3.3]. P-values computed using Newey-West adjusted standard errors (max 5 lags) are in parenthesis. The coefficients are in percentage points. One, two and three asterisks denote statistical significance at the 10%, 5% and 1% level, respectively.

Index Period	S&P500 01/04/1965-04/30/1996	Dow Jones 01/04/1965-04/30/1996	Nasdaq 02/08/1971-04/30/1996
α	.081 (0.108)	.082 (0.122)	.175*** (0.001)
β_{t-1}	.123*** (0.000)	.096*** (0.000)	.284*** (0.000)
$\mu_{Eclipse}$	-.348*** (0.005)	-.376*** (0.003)	-.359*** (0.003)
γ_{Monday}	-.139*** (0.000)	-.123*** (0.000)	-.291*** (0.000)
λ_{SAD}	.009 (0.422)	.011 (0.393)	.009 (0.464)
$\lambda_{Temperature}$	-.001 (0.531)	-.001 (0.439)	-.001 (0.119)
λ_{Cloud}	-.009** (0.017)	-.009** (0.012)	-.011*** (0.001)
$\lambda_{Geomagnetic}$	.053 (0.255)	.065 (0.175)	.061 (0.215)
$\delta_{Newmoon}$	.018 (0.436)	.033 (0.200)	.006 (0.808)
$\delta_{Fullmoon}$	.012 (0.622)	.017 (0.494)	-.006 (0.798)
$\eta_{YieldSpread}$	.017** (0.034)	.018** (0.029)	.016* (0.057)
$\eta_t^{\Delta Spread}$	-.746*** (0.001)	-.698*** (0.003)	-.477*** (0.002)
$\eta_{t-1}^{\Delta Spread}$	.376*** (0.006)	.458*** (0.001)	.323* (0.057)
Observations	7536	7592	6122
Total eclipses in the sample	49	49	40

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