The Effects Of Natural Disasters On Long-Run Economic Growth
Chul-Kyu Kim, University of Michigan

Reassessment of the Weather Effect: Stock Prices and Wall Street Weather
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The Michigan Journal of Business intends to provide undergraduate students worldwide with a platform for exceptional work in the field of business. The Journal seeks to publish distinguished theses, empirical research, case studies, and theories in issues relating to areas of Accounting, Economics, Finance, Marketing, Management, Operations Management, Information Systems, Business Law, Corporate Ethics, and Public Policy. The Journal is distributed and cataloged in prestigious university libraries around the world, and is enlisted in the Directories of Open Access Journals (DOAJ), a scholarly journal database that enlists more than 3000 of the world’s leading publications. The contemporary business environment is exceedingly complex. Analyzing this real world phenomenon through traditional applications of theories often yield a suboptimal understanding of the world. The Journal, accordingly, encourages work that takes an interdisciplinary approach to understanding a topic and emphasizes the importance of incorporating the knowledge of liberal arts into an area of interest. By providing a venue to recognize high quality work, the Journal gives an incentive for students to explore their area of interest, rewarding them with the experience to share the power of knowledge with others. The Journal’s mission and philosophy parallel the mission of the University of Michigan, the premier research university in the United States.
CONTRIBUTOR INFORMATION

The Journal only accepts works from undergraduate students or works completed during undergraduate study. Each manuscript submitted should include a short abstract, author information, and any acknowledgements. Papers will be evaluated based upon sound analysis, originality of argument, and novelty of research. For more information on submitting article for publication, please visit www.michiganjb.org.

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The organization is entirely student-run, with an editorial staff of about 20 of the top students at the Department of Economics and the Stephen M. Ross School of Business at the University of Michigan. Each semester, the Michigan Journal of Business calls for papers from undergraduate students around the world. Throughout the semester, the editorial board carefully reviews, selects, and edits exceptional work for publication. Faculty willing to advise the Journal is formed from each department to give minor oversight for the project. Throughout the process, a blind review process is implemented to ensure an impartial review of all submissions.

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EDITOR’S NOTE

The Michigan Journal of Business is proud to present its seventh edition of exemplary undergraduate theses. Thanks to the continued support from students and faculty at the Stephen M. Ross School of Business as well as the valuable contributions from undergraduates worldwide, the Journal has been able to provide a viable platform for sharing undergraduate findings with a larger academic community. Our publication is accessible from over 200 libraries including the United States Library of Congress, Harvard Business School’s Baker Library and Princeton’s Main Library as well as the Directory of Open Access Journals.

Following a far-reaching ‘call for papers’ process, our board was able to consider 31 articles covering a vast array of topics, which is not so surprising considering the breadth of disciplines we cater to. The four that were settled on retained this variety to an extent, so we decided to continue our ‘free-standing’ articles structure for this issue. That is not to say that they don’t share any common theme. In fact, one might notice that all but one of them consider society’s relationship with the environment in one sense or another.

Starting this edition of the Journal off is one such article, aptly titled, “The Effects of Natural Disasters on Long Run Economic Growth.” In this study, Chul-Kyu Kim extends the analysis of a well-known work to a more recent data set as well as offers a theoretical approach to the topic. The previous study had found surprising evidence that natural disaster frequency may be positively correlated with economic growth in the long run. In the face conflicting reports from other studies, this work not only presents a more recent empirical sampling but also inspects the factors of production that are likely to serve as channels for these effects.

We follow this study with another one that considers correlations between the weather and the economy, though in a much subtler context. In “Reassessment of the Weather Effect: Stock Prices and Wall Street Weather” Mitra Akhtari adds to an ongoing discussion about the existence of a correlation between daily stock returns and the weather conditions in New York City (presumably, home to many investors). After multiple regressions, generally finding evidence for such a correlation, the author proposes an explanation that coincides with those offered in previous literature.

The third article shifts the Journal’s focus to the pricing of a peculiar financial instrument: life settlements. In “On Life Settlement Pricing” Bilkan Erkman methodically develops a more comprehensive pricing structure for these unique securities, which incorporates a mortality forecasting model as well as the insurer’s credit risk. This is followed by an attempt to test the notion that these instruments are uncorrelated to the broader market, and thus a
safer investment, which proves to shed a bit more light on their use as financial instruments.

This issue of the Journal is brought to a close with an article that examines investors’ perceptions of environmentally friendly ventures. In particular, how does a firm’s being ‘green’ affect its stock evaluation? Gregory Videen examines this in “Effects of Green Business on Firm Value”. Despite mixed sentiment from prior literature as well as somewhat inconclusive empirical results, the author presents a thoughtful discussion of what explanations may underlie this problem.

As always, we would like to extend our gratitude to the many contributors and faculty supervisors that makes this publication possible. In particular, we would like to thank Professor Tammy Feldman for always being available to offer advice in the methods and direction of the Journal along with our many other advisors at the Stephen M. Ross School of Business for their help reaching out to other schools for submissions. Ms. Erika Busch was instrumental in our logistical operations as well. Mr. Thomas C. Jones and the Alumni Association of the Ross School of Business have consistently shown their support through their financial contributions. Thank you to the editorial board for another semester’s worth of diligent work. And finally, thank you to the authors who not only provide the content through their insightful work but also endure several rounds of revisions.

Dominic Spadacene
Editor-In-Chief
The Effects Of Natural Disasters On
Long-Run Economic Growth

Chul-Kyu Kim
University of Michigan

Abstract

Major catastrophes such as the Southeast Asian tsunami, hurricane Katrina, and the Haiti earthquake have recently spurred research regarding the relationship between natural disasters and long-run economic growth. This study examines the conjecture that disaster risks can promote economic growth through the process of Schumpeterian creative destruction, utilizing the method developed in Skidmore and Toya (2002), for the 1990-2004 period. The channels whereby disaster risks affect economic growth are also identified using the Solow model framework developed in Dacy and Kunreuther (1969) and Okuyama (2003). My study finds continuing evidence to support that climatic disasters contribute to human capital accumulation while geologic disasters lead to human capital destruction.

1 I graduated from the University of Michigan in May 2010 with a B.A. in Economics and Mathematics. This paper was originally written as an honors thesis under the guidance of Professor Kathryn M. Dominguez and Stephen W. Salant whom I would like to thank for their insight and assistance. I also want to thank my family and Eunji Lee for their love and support.
I. Introduction

On January 12, 2010, a catastrophic earthquake struck Haiti, greatly damaging the undeveloped country. One estimate reports that this disaster killed more than 230,000 people and rendered 1.2 million homeless. There is no doubt that a natural disaster such as the one that occurred in Haiti has a negative impact on the economy in the short run. However, there are mixed and inconclusive understandings regarding the effects of natural disasters on the long-run economy. One of the first influential studies regarding the relationship between natural disasters and long-run economic growth was conducted by Skidmore and Toya in 2002. In their cross-country study of 89 countries, Skidmore and Toya found a surprising result: countries that were subjected to disasters showed faster economic growth. At first glance, this finding hardly seems conceivable. Given the damage inflicted on affected areas, how can natural disasters ever be positive economic events? To further explore the relationship between disasters and economic growth, this paper tests Skidmore and Toya’s finding for the period 1990-2004. This study also identifies the channels whereby disaster risks affect economic growth.

II. Definitions

People have dealt with disasters throughout history and in every part of the globe. A disaster can be defined as a situation or event, which overwhelms local capacity, necessitating a request to national or international level for external assistance. Disasters that are caused by nature are called natural disasters, examples of which include avalanches, earthquakes, floods, forest fires, hurricanes, lightning, tornados, tsunamis, and volcanic eruptions. Of course, not all disasters are caused by nature; some disasters have human origins. Such disasters include wars, terrorist attacks, nuclear incidents, epidemic diseases, industrial accidents, and transportation accidents.

III. Literature Review

The economics of natural disasters is a nascent field. Cavallo and Noy state that “compared to the vast amount of research done in natural sciences and other social sciences, economic research on natural disasters and their consequences is fairly limited”. The book The Economics of Natural Disasters: Implications for Federal Policy by Dacy and Kunreuther (1969) is often regarded as the field’s pioneering work, but there have been few subsequent

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3 This is the official definition of a disaster by EM-DAT: http://www.emdat.be/glossary/9.
4 Due to lack of reliable data, human related disasters are excluded from the discussion of this paper.
5 The literature review draws heavily on Cavallo and Noy (2009).
6 Cavallo and Noy 2009, 6.
studies. However, recent major catastrophes including the Southeast Asian tsunami and Hurricane Katrina heightened interest in this field.

The body of research in the literature of economics of natural disasters can be categorized into two groups. One group considers the short-run effects of disasters on GDP while the second examines the long-run effects of disasters on economic growth. The short-run studies include: Albala-Bertrand (1993), Kahn (2005), Anbarci et al. (2005), Bluedorn (2005), Raddatz (2007), Strobl (2008), Loayza et al. (2009), Noy (2009), Rodriguez-Oreggia et al. (2009), Leiter et al. (2009), Mechler (2009) and Hochrainer (2009); while long-run studies include: Skidmore and Toya (2002), Noy and Nualsri (2007), Cuaresma et al. (2008), Jaramillo (2009), Raddatz (2009) and Hallegatte and Dumas (2009). Compared to the many short-run studies there have been fewer long-run studies conducted in the literature.

Among the few long-run studies is an article by Skidmore and Toya (2002), which is regarded as the first piece of empirical research on the subject. In their cross-sectional study, Skidmore and Toya use the number of natural disasters normalized by land area in each of the 89 countries included in the sample during the period 1960-1990. They reach a somewhat counterintuitive conclusion that disaster risks may promote long-run economic growth. Specifically, they find that the frequency of climatic disasters is positively correlated with human capital accumulation, growth in total factor productivity (TFP) and per capita GDP growth.

Interestingly, Noy and Nualsri’s (2007) results supported the opposite conclusion. Using a panel of five-year country level data, they find a negative correlation between disaster effects and the long-run economic growth rate. The work of Jaramillo (2009) and Raddatz (2009) also supports the conclusion reached by Noy and Nualsri (2007). For example, Raddatz, using panel time series techniques, finds that “in the long run, a climate related disaster is linked to reductions in real GDP per capita by at least 0.6 percent”.

The Schumpeterian “creative destruction” process is one of the key ex-

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7 Abbreviations for this paper include:
- GDP: Gross Domestic Product
- CRED: Center For Research on Epidemiology of Disasters
- TFP: Total Factor Productivity
- GNI: Gross National Income
8 This paper focuses on the long-run effects. For a comprehensive survey of the literature, see Cavallo and Noy (2009).
9 For example, Cuaresma et al. (2008) state that “To our knowledge, the article by Skidmore and Toya (2002) is the only piece of empirical research that assesses directly the long-run economic impact of natural disasters” (p.1).
10 See figures 1 and 2 for some initial evidence regarding the relationship between the number of disasters and economic growth.
planations for the conclusions reached by Skidmore and Toya (2002). They explain that “disasters may provide an opportunity to update the capital stock, thus encouraging the adoption of new technologies”.\textsuperscript{12} Cuaresma et al. (2008) and Hallegatte and Dumas (2009) test this creative destruction hypothesis. The former study utilizes an empirical approach and reaches the conclusion that “creative destruction only occurs in developed countries”.\textsuperscript{13} The latter study makes use of a calibrated endogenous growth theoretical model and concludes that “disasters do not have positive effects on the economy and large disasters can lead to poverty traps”.\textsuperscript{14}

The study by Skidmore and Toya (2002) has inspired several pieces of subsequent research, the majority of which find contrary results. This paper serves as a robustness test for their study. Specifically, I extend their work to a more recent period, from 1990 to 2004, to see if the same relationship between growth and disaster frequencies can be found. Note that compared to 1960-1990, the recent period is marked by considerable improvements in the recording of minor disasters. In the Emergency Events Database (EM-DAT), despite the shorter time span, the total number of counted natural disasters is twice as large over the period 1990-2007 than 1960-1990.\textsuperscript{15} Given the absence of agreement regarding the long-run effects of disasters in literature, it would be valuable to explore if Skidmore and Toya’s findings hold in the recent period characterized by improved data recording.

\textbf{IV. Disaster Data}

Disaster data for this paper come from the Emergency Events Database (EM-DAT), the best available and most widely used database for research on disasters.\textsuperscript{16} This database is maintained by the Center for Research on the Epidemiology of Disasters (CRED) at the Catholic University of Louvain, Belgium. Since its establishment in 1973, CRED has compiled data on global disasters from 1900 to the present.

CRED uses a standardized method in data compilation and it has not changed its criteria for recording a disaster since its establishment. For a disaster to be entered into the CRED database, at least one of the following criteria must be fulfilled: (1) 10 or more people are reported killed; (2) 100 or more people are reported affected/injured/homeless; (3) a state of emergency is de-

\textsuperscript{12} Skidmore and Toya 2002, 665.
\textsuperscript{13} Cuaresma, Hlouskova and Obersteiner 2008, 9.
\textsuperscript{14} Hallegatte and Dumas 2009, 783.
\textsuperscript{15} In the database, the total number of natural disasters from 1960 to 1990 is 3,065, whereas the total number of natural disasters from 1990 to 2007 is 6,665. Regina Below, a database manager at CRED, explains that this increase was mainly due to a better recording of minor disaster events (email to the author).
\textsuperscript{16} A less extensive source is the Munich Re dataset at: http://mrnathan.munichre.com/.
EM-DAT reports information on the frequency of disaster events, the number of people killed, the number of people affected, and the estimated damage costs in U.S. dollars. However, Skidmore and Toya (2002) use only the frequency data in their study. They give three reasons for not using the damage and casualties data. First, damage and casualties data are not always available and sometimes predictions for missing values are not very accurate (2002, p.670). Second, they are more likely to be endogenously determined by the level of income whereas disaster frequency is exogenously determined regardless of income level. For example, wealthy countries intrinsically face higher economic damage since they have more physical capital at risk when faced with a natural disaster. On the other hand, wealthier countries are less likely to entail human life loss since they have better medical care and rigorous regulations on building codes, engineering, and other safety precautions (2002, p.670). Finally, Skidmore and Toya (2002) argue that disaster damage is sometimes exaggerated in developing countries in order to secure international assistance (p.670).

The number of disaster events is indeed the most exogenous information that can be found in the CRED database. Whenever a natural event satisfying one of the four criteria occurs in a country, it gets recorded in the database regardless of the income level of the country. However, it is questionable whether frequencies alone can reflect actual disaster risks. By the CRED criteria, a local storm that killed 10 people is assigned the same frequency value as Hurricane Katrina. Table 1 lists the top 5 deadliest natural disasters that occurred in the U.S. from 1990 to 2009. It shows that there is a great deal of variation in terms of intensity even among the top 5 deadliest disasters. In fact, Hurricane Katrina alone left more casualties than the other four combined. Skidmore and Toya acknowledge that frequency alone does not reveal the actual disaster risk that countries face and comment that “more accurate data on disaster risk would be a valuable contribution”.

V. Theory of Disaster Effects on Long Run Growth

In the long run, disaster risks can affect the aggregate economy through its factors of production. Altered decisions on the factors of production eventu-

18 By CRED definition, the affected people are those who require immediate assistance during the period of emergency. See CRED glossary for more definitions: http://www.emdat.be/glossary/9
19 This phenomenon is widely recognized in the literature. See for example, Albala-Bertrand (1993) and Yang (2008).
There have been some efforts to come up with reliable data for disaster risks. For example, Yang (2008) uses data on storm intensity measured by wind speed to develop the “Mean Storm Index”.
ally shape the output level and thus the standard of living for the economy. In this section, I propose two hypotheses and a model that explain how disaster risks can change the level of investment on the factors of production.

First, the effect of disaster risks on the long-run physical capital investment is obscure. One might conclude that higher risk of physical capital destruction due to disasters reduces the investment on physical capital. This can be true if a country faces a constant risk of a certain disaster. However, disasters can also provide an opportunity to update and upgrade the capital stock, “allowing the adoption of new technology that is apt for the skilled labor”.22

Second, disaster risks, especially the climatic ones, can lead to increased human capital investment. Climatic disasters can be regarded as a proxy for risk to physical capital rather than human capital; severe weather conditions are more likely to pose major threats to physical capital while forecasting abilities make human capital less vulnerable to climatic disasters. In an endogenous growth framework where individuals choose their level of investment between physical and human capital, higher climatic disaster risks reduce the expected return to physical capital, which in turn increase the relative return to human capital. Skidmore and Toya claim that “The higher relative return to human capital may lead to an increased emphasis on human capital investment.”23

To offer insights on the effects of a climatic disaster on long-run growth, I utilize the Solow model (Solow, 1956) framework employed by Dacy and Kunreuther (1969) and Okuyama (2003). Also, I conceptualize Skidmore and Toya’s conjecture that higher climatic disaster risks can lead to more investment in human capital using the Solow model.

Consider the constant returns to scale production function of an economy with no technological progress:24

\[ Y = F(K, L) \]  

(1)

where \( Y \) denotes the total output, \( K \), the level of capital accumulation, and \( L \), the amount of labor input. With the property of constant returns to scale, the production function can be converted into the per-capita form:

\[ y = f(k) \]  

(2)

where \( y \) is per-capita output and \( k \) is per-capita capital stock. Let \( s \) denote the

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21 Jack Hirshleifer shows how continuing recurrences of plague lead to a period of depression in the century following the Black Death (1966, p.28). Although plague is substantially different from a climatic disaster in that it is a major threat to human capital rather than physical capital, his study shows that continuing recurrences can shatter a factor of production.


24 This assumption of no technological progress will be relaxed later in this section.
The Effects Of Natural Disasters On Long-Run Economic Growth

saving rate, $\delta$, the depreciation rate, and $n$, the population growth rate. Then the steady state level of capital stock $k^*$ satisfies the following condition:

$$\Delta k = s \cdot f(k) - (n + \delta) \cdot k = 0.$$  \hspace{1cm} (3)

Arranging terms,

$$s \cdot f(k^*) = (n + \delta) \cdot k^*.$$  \hspace{1cm} (4)

This steady state situation is described at point A of Figure 3. Now suppose that a climatic disaster occurs and damages physical capital but leaves the human population unharmed. The amount of per-capita capital stock decreases from $k^*$ to $k_d$, and the economy’s output per-capita decreases from the steady state level $y^*$ to $y_{d^*}$.

In the aftermath of the disaster, the economy is assumed to go through a recovery period. In the recovery period, resources are allocated toward the reconstruction of the damaged capital stock. Moreover, there might also be international aid that can further stimulate physical capital accumulation. Hence the economy experiences a short period of higher saving $s_r$, which in turn accelerates the speed of recovery. As the economy recovers from the damage, the saving rate goes back to the original saving rate, $s$. The economy returns back to the steady state per-capita capital stock, $k^*$, (movement from D to A) and the steady state per-capita output level, $y^*$.

The same point can be made using the growth rate of per capita capital stock. Dividing both sides of the equation (3), the growth rate of $k$, $\gamma_k$, can be written as:

$$\gamma_k = \frac{\Delta k}{k} = \frac{s \cdot f(k)}{k} - (n + \delta).$$  \hspace{1cm} (5)

In the steady state, there is no change in $\gamma_k$, so the economy is initially at point A of Figure 4 where

$$\frac{s \cdot f(k)}{k} = (n + \delta).$$  \hspace{1cm} (6)

With the climatic disaster, the level of capital stock decreases to $k_d$ and output falls because of the shock caused by the disaster. Now, as the economy goes through the recovery period, the saving rate increases due to the massive reconstruction effort and foreign aid, accelerating the speed of recovery. As the reconstruction progresses, the saving rate eventually returns to the previous level and the capital growth rate returns back to the steady state level of zero. (movement from D to A)
Now I relax the assumption of no technological progress. Suppose an economy with initial technology level $A(t)$ has a constant technology growth rate of $x$. This economy now experiences the same climatic disaster described above. As Skidmore and Toya (2002) point out, there might be a “creative destruction” effect on the reconstruction process - old capital stock that needed replacement before the disaster is updated with newer technologies. Therefore, during the recovery period, the technology growth rate increases temporarily from $x$ to $xr$, as shown in Figure 5. The technology growth rate eventually returns to its original level once the recovery is complete since the replacement itself cannot induce technological progress. Using a labor augmenting technological progress model (Barro and Sala-I-Martin, 1995) Equation (1) becomes:

$$Y = F[ K, L \cdot A(t) ]$$

where $L \cdot A(t)$ denotes the amount of effective labor (defined to be $\hat{L}$), a measure that reflects productivity of each worker. The capital per effective worker, $\hat{k}$, can be written as:

$$\hat{k} = \frac{K}{L \cdot A(t)} = \frac{k}{A(t)}$$

and the output per effective worker can be written as:

$$\hat{y} = \frac{Y}{L} = f(\hat{k})$$

The change in per-capita capital stock becomes:

$$\Delta k = s \cdot f[ \hat{k}, A(t) ] - ( n + \delta ) \cdot \hat{k}$$

which can be further reduced to:

$$\Delta \hat{k} = s \cdot f(\hat{k}) - ( x + n + \delta ) \cdot \hat{k}$$

Dividing both sides of (11) by $\hat{k}$, growth rate of capital per effective worker is:

$$\gamma_i = \frac{s \cdot f(\hat{k})}{\hat{k}} - ( x + n + \delta )$$

Since there is no change in capital per effective worker at the steady state, the following condition should apply (point A of Figure 6):
The Effects Of Natural Disasters On Long-Run Economic Growth

When a disaster occurs, the capital stock per effective worker decreases from the steady state level to \( k_d \). At this point, the growth rate of capital per effective worker is B-C. As was the case with the economy which featured no technological progress, the reconstruction effort coupled with foreign aid raises the saving rate from \( s \) to \( s_r \), contributing to the increase in the growth rate of capital per effective worker. However, as shown in Figure 5, the economy whose capital stock is upgraded during the recovery period also experiences a higher rate of technological growth, \( x_r \). With the “creative destruction” process in effect, the growth rate of capital per effective worker is now D-E, which is lower than the capital growth rate with no technological replacement, D-C (Figure 6). To further justify this effect, Okuyama (2003) explains that “a higher rate of technological progress leads to a faster growth of the effective labor”.25 Compared to the period of the regular technological growth rate, \( x \), more resources are spent on making each worker more productive in the period of the higher technological growth rate, \( x_r \). That is, during the reconstruction process, the technology-replacing economy directs more resources towards human capital rather than physical capital than the economy with no technology replacement. This model suggests that climatic disasters can induce human capital investment for an economy that experiences creative destruction during the recovery period.

VI. Methodology

To test the proposed theory and examine the relationship between natural disasters and growth rate, I use the frequency data from EM-DAT and apply the method employed by Skidmore and Toya in 2002 for the period 1990 to 2004. One important strategy they use is the categorization of natural disasters into two groups; the climatic disaster group and the geologic disaster group. I adopt their categorization but I employ slightly different definitions of the two categories in order to be more consistent with the definitions used by CRED. Specifically, I define climatic events to be the events caused by atmospheric processes (meteorological) plus the events caused by deviations in the normal water cycle (hydrological). By the CRED classification, the climatic disaster group consists of storms, including thunderstorms, blizzards, sandstorms, generic storms, tornados, and orographic storms among others, and also includes flood and wet mass movement. Also, I define the geologic disaster events to be

\[
\frac{s \cdot f (\hat{k}^*)}{\hat{k}^*} = (x + n + \delta)
\]

the events originating from solid earth. Earthquakes, volcanic eruptions, rock falls, avalanches, landslides, subsidences and other dry mass movements fall into this category.\textsuperscript{26}

The rationale behind this separation is that climatic and geologic risks may influence factors of production differently and may thus have different effects on the long-run economy. Compared to geologic disasters, climatic disasters are more frequent, often occurring in a particular period of time during a year. Climatic disasters are also more predictable, hence it is possible for people to evacuate the affected region beforehand. On the other hand, geologic disasters are less frequent and more irregular in their occurrence. They are also less predictable, which impedes the population’s ability to evacuate. Therefore, as Skidmore and Toya claim, “climatic disasters are a reasonable proxy for risk to physical capital while geologic disasters may be perceived as a threat to both human and physical capital”.\textsuperscript{27}

VII. Results and Analysis

\textit{Disasters and economic growth}

Table 2 reports the results from a simple semi-logarithmic regression. The dependent variable is per capita GDP growth rate and the explanatory variables include the number of per land disasters. The relevant time period for columns (1) and (2) is 1960-1990 and the time period for columns (3) and (4) is 1990-2004.\textsuperscript{28} Consistent with Skidmore and Toya (2002), I find a positive and statistically significant relationship between the growth rate and the number of total (climatic + geologic) disasters normalized by land area for the period 1960-1990. I also find a similar relationship between the growth rate and disaster frequencies in the recent period, 1990-2004, though the relationship is not as significant as was the case in the previous period.\textsuperscript{29}

In the first period (1960-1990), there is a stronger correlation between per capita GDP growth and the number of per land climatic disasters (heteroskedasticity-robust t statistic=2.97) but there is no statistically significant relationship between the growth rate and the number of per land geologic disasters.

\textsuperscript{26} In my data for example, if Haiti had exactly 4 storms and 1 earthquake in 1980, I add 4 to its climatic disasters variable and 1 to its geologic disasters variable for that year. For specific classification of each disaster type, see http://www.emdat.be/classification.

\textsuperscript{27} Skidmore and Toya 2002, 671-672.

\textsuperscript{28} For more information about the variables, see Appendix tables A and B.

\textsuperscript{29} Columns (1) and (2) is a replication of Skidmore and Toya (2002, p.671). The slight differences in t statistics come from a different disaggregation of climatic and geologic disasters. See p.671 for their definition of the two disaster groups.

\textsuperscript{29} This positive relationship between the growth rate and disaster frequencies can be also found in figures 1 and 2. Note the slope of the fitted values is flatter in the recent period.
The Effects Of Natural Disasters On Long-Run Economic Growth

However, in the second period (1990-2004), the relationship between climatic disasters and the growth rate gets weaker (t=1.65) compared to the relationship between total disasters and the growth rate (t=2.17). Clearly, there seems to be less of a distinction between the climatic disasters and geologic disasters in terms of their relevance to the growth rate in the recent period. One possible explanation for this is the potential difference in disaster recording over time; as discussed previously, the CRED database has only recently started to record minor disasters. The minor disasters, which were not counted in the earlier period, may make each disaster group less distinct from each other and serve to mitigate the relationship between disaster risk and economic growth for the later period. Another reason presented by Skidmore in a personal communication to the author on April 2, 2010 is the difference in forecasting ability and communication level in the two periods. He suggests that there was an important interaction between disaster propensity and improvements in communication in the earlier period, 1960-1990. During this period, improving accuracy in weather forecasting became increasingly beneficial for people in the disaster-prone area. In the short run, they could evacuate from the afflicted region, and in the long run, they could make better long-term investments. After the 90’s; however, the communication revolution had already run its course, so the benefit from improving communication also decreased and one no longer observes any relationship between climatic disasters and investment decisions.

Table 3 reports the results from a growth regression that includes some of the control variables that are typically considered to be key determinants of economic growth for the period 1960-1990. Skidmore and Toya (2002) use the following multiple linear regression (MLR) model:

\[ G_t = \alpha + \beta I_t + \gamma O_t + \delta K_t + \delta Y_{i,t} + \varepsilon_t \]  

where \( G_t \) represents the average growth rate of real GDP per capita during the period \( t \), \( I_t \), the average ratio of investment to GDP in period \( t \), \( O_t \), the level of openness during the period \( t \), \( K_t \), the average annual growth rate of physical capital stock per capita in \( t \), and \( Y_{i,t} \), the log of initial income in the initial year \( i \) for the period \( t \).  

As explained by many growth theoretical models, an economy that al-

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30 This is a replication of the regression done by Skidmore and Toya (2002, p.673) included here for comparison.

31 Log in this paper means the natural logarithmic function (log of base e). I take a natural log of a variable in order to stabilize the variance of a sample, linearize the relationship between the independent variables and the dependent variables, and to normalize positively skewed distributions of the variables (Bland, 2000). Also, for the disaster variables, I add one to the frequency before I take a natural log in order to avoid arithmetic error.
locates a greater proportion of its output to investment grows faster, so $I$ is expected to be positively correlated with the growth rate. A country with greater degree of openness is more likely to adopt new technology and improve institutions that are critical for economic development, hence the coefficient for $O$ is expected to be positive. Also, since capital stock is essentially one of the factors of production, countries with faster growing capital stock are assumed to experience a faster growing output level. However, the coefficient for the initial income level depends greatly on the period of consideration and the number of observations. For the particular period 1960-1990, the world by and large observed a rapid increase in GDP compared to other periods. The countries that initially started with low income levels are more likely to show higher growth rates, making it plausible to expect a negative coefficient for the initial income variable.

Table 3 reports the estimated coefficients and heteroskedasticity-robust t statistics (in brackets) from an ordinary least squares (OLS) regression. Column (1) of the table shows that all the estimates for the explanatory variables are statistically significant at the one percent level. Consistent with Skidmore and Toya (2002), after accounting for the investment ratio to GDP, openness, growth in capital stock and initial income, I find a positive and statistically significant relationship between the number of total disasters normalized by land area and per capita GDP growth (Column 2). As Column (3) shows, the positive relationship is even stronger for the number of climatic disasters ($t=2.43$). However, I find no statistical significance with which to reject the null hypothesis that there is no relationship between the number of geologic disasters and per capita GDP growth for this period ($t=-0.34$). In all cases the semi-logarithmic regression equations fit the data moderately well, explaining more than 70% of the variation in per capita GDP growth rate.

Table 4 lists the results of a similar regression for the recent period, 1990-2004. I use major components of GDP, such as consumption, investment and government spending as the explanatory variables. While one would expect to find positive coefficients for other components of GDP, the robust positive relationship between government spending and growth is noteworthy. I also

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32 For example, in my sample of 88 countries, the mean GDP growth rate is 0.02 (2%) for the period 1960-1990, while the mean GDP growth rate is 0.0167 (1.67%) for the period 1990-2004. See Appendix table B for the summary statistics.

33 Similar relationships can be found even without the normalization by land area. (Skidmore and Toya, 2002) But it is more reasonable to normalize the frequency by the land area because large countries are more likely to have more disasters.

34 The gross domestic savings variable is also added to increase the explanatory power. The correlation between this variable and the investment ratio variable is 0.5490.

add the disaster variables that are not normalized by land area to explore the
effects of normalization.

Controlling for investment, government spending, consumption and gross
domestic savings, I find a positive and statistically significant relationship be-
tween the number of per land total disasters and per capita GDP growth in the
period 1990 to 2004. The relationship is not very significant unless I normalize
the number of total disasters by land area (t=1.34). For the geologic disasters,
I find no significant relationship whether I use the total number or the number
normalized by land area. For the climatic disasters, I find a positive and signifi-
cant relationship between the number of climatic disasters and per capita GDP
growth rate regardless of the normalization.

In summary, Skidmore and Toya’s findings (2002) continue to hold for
the recent period of enhanced disaster recording. The regression analysis sug-
gests a robust positive correlation between the frequency of disasters and long-
run economic growth in both periods of consideration. The major difference
between the two periods is that the number of per land climatic disasters re-
veals a weaker correlation than the number of per land total disasters in the
later period.

Disasters and physical capital investment

In an attempt to identify the channels through which disasters affect eco-
nomic growth, I first investigate the relationship between measures of physical
capital and the number of disasters. The measures of physical capital include
investment ratio to GDP, growth in capital stock, and the ratio of gross capital
formation to GDP. Columns (1) and (2) of Table 5 show the relationship be-
tween investment ratio to GDP and the disaster variables from a simple semi-
logarithmic regression. Consistent with Skidmore and Toya (2002, p.679), for
the period 1960-1990, no significant relationship is found between investment
and disasters. This is also the case after controlling for initial income and the
level of secondary schooling (Columns 3 and 4).

Table 6 lists similar regression results for the earlier period using growth
in capital stock as the dependent variable. With a simple regression, I find
a significant relationship at the ten percent level (t=1.72) between climatic
disasters and growth in capital stock (Column 2). However, after including
additional explanatory variables and regional dummies, this relationship dis-
appears (Column 4).

The same results are found for the recent period, 1990-2004. In Table
7, I find no significant relationship between the investment to GDP ratio and
disasters of any kind. In Table 8, I use the ratio of gross capital formation to
GDP as my dependent variable but still find no relationship, regardless of the
inclusion of control variables. The physical capital regressions show that disaster coefficients are generally negative. However, statistically insignificant coefficients suggest that physical capital is not a good candidate for the route whereby disasters affect economic growth.

**Disasters and human capital investment**

The conjecture proposed by Skidmore and Toya (2002) together with the theoretical model presented in this paper suggest that climatic disaster risk can promote human capital investment. Provided that a society can choose its level of investment in the factors of production, more climatic risk to physical capital makes human capital relatively attractive, which in turn induces the society to invest more in human capital than physical capital (Skidmore and Toya, 2002). Human capital accumulation, which by nature enjoys the benefit of knowledge spillover, fosters economic growth as emphasized by many endogenous theoretical models (Lucas, 1988). This section explores the relationship between human capital investment and disaster risks empirically.

As in other studies, since human capital can be ambiguous in definition, I employ some proxies for human capital investment such as educational expenditure, secondary and tertiary school enrollment ratio, and the annual growth rate of secondary schooling year. I start with a replication of Skidmore and Toya’s study (2002, p.680). Table 9 reports the regression results of the first independent variable, the average annual growth rate of secondary schooling year for the period 1960-1990. After accounting for initial income, initial years of secondary schooling, fertility rate and the investment rate, I find a robust positive relationship between growth in secondary schooling years and per land climatic disasters (Column 4). This result is consistent with that of Skidmore and Toya’s (2002, p.680), except that the negative relationship between geologic disasters and the dependent variable disappears after incorporating additional explanatory variables such as fertility rate (1960-1985, average) and investment ratio.

Table 10 shows the results of the same regression except that this time, the dependent variable is the average gross secondary school enrollment ratio for the period 1960-1985. Again, the positive relationship between climatic disasters and the dependent variable is weaker (10% significance level) than that of Skidmore and Toya’s (2002 p.680) after the inclusion of the other explanatory variables. The secondary school enrollment ratio also shows a similar positive correlation with the climatic disasters for the recent period, 1990-2004 (Column 4, Table 11).

In Columns (1) and (2) of Table 12, I present regression estimates of the tertiary school enrollment ratio that include the explanatory variables dis-
cussed previously. After accounting for initial income, investment ratio and regional dummies, I find no significant relationship between the tertiary school enrollment ratio and the frequency of climatic disasters. However, I find a negative and statistically significant relationship between tertiary school enrollment and the geologic disasters (Column 2). One possible explanation may be that the geologic disasters induced emigration of educated people to countries that were not included in this sample.

In Columns (3) and (4) of Table 12, I list the results of a similar regression with average educational expenditure (% of GNI, 1990-2007) as the dependent variable. Similar to my results from the previous regression, I only find a negative relationship between geologic disasters and educational expenditure ($t=-2.59$). Compared to the enrollment ratio variables, educational expenditure reflects the direct interest of a society in its human capital investment. One explanation for the negative relationship may be that the geologic disasters in this period posed a threat that was serious enough to lower the expected return to human capital investment.

VIII. Conclusion

The empirical evidence found in this paper suggests that there is a positive correlation between long-run economic growth and the frequency of the disasters. The positive correlation is consistent in both periods of consideration: the period studied by Skidmore and Toya, 1960-1990 and the recent period, 1990-2004. This study also explored the channels whereby disasters affect economic growth, both theoretically and empirically. For the period 1960-1990, Skidmore and Toya (2002) find that “human capital accumulation and technological development spurred by climatic disasters are the main routes through which disasters affect economic growth. The empirical study for the recent period shows weaker evidence for climatic disasters inducing human capital accumulation, but stronger evidence for geologic disasters leading to human capital destruction.

One should keep in mind that the empirical analysis in this paper was conducted by using disaster frequency data in isolation. As discussed previously, the frequency data are indeed the most exogenous information that can be found in the EM-DAT database. However, there surely is a price for excluding casualties and damage costs data in the analysis; disaster frequency alone

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36 Since data are not readily available, I use tertiary school enrollment ratio of 1999 to maximize the number of observations for the sample. This can be viewed as a crude measure of the average ratio from 1990 to 2004.
may fail to fully represent the level of actual disaster risk. Further study on this subject should explore measures that are not predetermined by the income level but are at the same time reasonably representative of the actual disaster risk. The absence of such a measure may be one important source of the disagreement in the current long-run studies. Nevertheless, the evidence found in this study suggests that risks associated with natural disasters provide substantial implications regarding a society’s investment decisions on its factors of production.

37 Using a more endogenous measure that takes into account the casualties and damage data can lead to a very different conclusion than using the frequency data alone. One such measure is the Climate Risk Index (CRI). For more information about CRI, see figures 7 (a), (b) (Appendix) and Harmeling (2008).
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References


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Figures and Tables

Figure 1. Relationship between the number of disasters and GDP growth rate: 1960-1990.

Figure 2. Relationship between the number of disasters and GDP growth rate: 1990-2004.
Source: EM-DAT
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Figure 3. Solow Model with a Disaster.
Source: Okuyama (2003, p.15)

Figure 4: Dynamics of Recovery.
Source: Okuyama (2003, p.16)
Figure 5. Technological Progress and a Disaster.

Figure 6. Transitional Dynamics with Technological Progress.
Note: Some changes in notation were made by the author for Figure 6.
Table 1. Top 5 Deadliest Natural Disasters: USA 1990-2009

<table>
<thead>
<tr>
<th>Rank</th>
<th>Dates</th>
<th>Type</th>
<th>Sub type</th>
<th>Name</th>
<th>Killed</th>
<th>Total affected</th>
<th>Damage ($ Mil.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Aug 2005</td>
<td>Storm</td>
<td>Tropical cyclone</td>
<td>Katrina</td>
<td>1833</td>
<td>11,000,148</td>
<td>10000</td>
</tr>
<tr>
<td>2</td>
<td>Jul 1995</td>
<td>Extreme temperature</td>
<td>Heat wave</td>
<td></td>
<td>670</td>
<td>5,000,000</td>
<td>11000</td>
</tr>
<tr>
<td>3</td>
<td>Mar 1993</td>
<td>Storm</td>
<td></td>
<td></td>
<td>270</td>
<td>3,000,010</td>
<td>7000</td>
</tr>
<tr>
<td>4</td>
<td>Jul 1999</td>
<td>Extreme temperature</td>
<td>Heat wave</td>
<td></td>
<td>257</td>
<td>2,100,000</td>
<td>7000</td>
</tr>
<tr>
<td>5</td>
<td>Jul 2002</td>
<td>Epidemic</td>
<td>Infectious Diseases</td>
<td>West Nile Fever</td>
<td>214</td>
<td>640,064</td>
<td>2500</td>
</tr>
</tbody>
</table>

Source: EM-DAT: The OFDA/CRED International Disaster Database.
www.emdat.be - Université Catholique de Louvain - Brussels – Belgium.
### Table 2. Regression table with dependent variables GDP Growth Rates

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>(1) Per Capita GDP Growth Rate (1960-1990)</th>
<th>(2) Per Capita GDP Growth Rate (1990-2004)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per Land Total</td>
<td>0.00230***</td>
<td></td>
</tr>
<tr>
<td>Disasters (1960-1990)</td>
<td>[2.61]</td>
<td></td>
</tr>
<tr>
<td>Per Land Climatic</td>
<td>0.00242***</td>
<td></td>
</tr>
<tr>
<td>Disasters (1960-1990)</td>
<td>[2.97]</td>
<td></td>
</tr>
<tr>
<td>Per Land Geologic</td>
<td>~0.000521</td>
<td></td>
</tr>
<tr>
<td>Disasters (1960-1990)</td>
<td>[-0.63]</td>
<td></td>
</tr>
<tr>
<td>Per Land Total</td>
<td></td>
<td>0.00235**</td>
</tr>
<tr>
<td>Disasters (1990-2004)</td>
<td>[2.17]</td>
<td></td>
</tr>
<tr>
<td>Per Land Climatic</td>
<td></td>
<td>0.00186*</td>
</tr>
<tr>
<td>Disasters (1990-2004)</td>
<td>[1.65]</td>
<td></td>
</tr>
<tr>
<td>Per Land Geologic</td>
<td></td>
<td>0.00118</td>
</tr>
<tr>
<td>Disasters (1990-2004)</td>
<td>[1.27]</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.00885*</td>
<td>0.00451</td>
</tr>
<tr>
<td></td>
<td>[1.91]</td>
<td>[0.76]</td>
</tr>
<tr>
<td>Observations</td>
<td>88</td>
<td>88</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.08</td>
<td>0.04</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1

Notes: The estimates are obtained from a semi logarithmic regression model. The regressions are done with SUR (Seemingly Unrelated Regression) method. Columns (1) and (3) show the results of one set of SUR, columns (2) and (4) present the results of the other set.

The robust z statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.

** indicates that the estimate is statistically significant at the five percent level.

* indicates that the estimate is statistically significant at the ten percent level.

See Skidmore and Toya (2002, p.671) for their results for column (1) and (2).
### Table 3. Regression table with the dependent variable GDP Growth Rate: 1960-1990

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable: Per Capita GDP Growth Rate (1960-1990)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Investment / GDP (1960-1990)</td>
<td>0.0650***</td>
<td>0.0810***</td>
<td>0.0816***</td>
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<tr>
<td></td>
<td>[3.18]</td>
<td>[4.15]</td>
<td>[4.06]</td>
</tr>
<tr>
<td>Openness (1965-1990)</td>
<td>0.0169***</td>
<td>0.0147***</td>
<td>0.0143***</td>
</tr>
<tr>
<td></td>
<td>[5.05]</td>
<td>[5.00]</td>
<td>[4.56]</td>
</tr>
<tr>
<td>Growth in Capital Stock (1960-1985)</td>
<td>0.0142***</td>
<td>0.0134***</td>
<td>0.0134***</td>
</tr>
<tr>
<td></td>
<td>[5.34]</td>
<td>[5.01]</td>
<td>[4.95]</td>
</tr>
<tr>
<td>Log of Initial Income (1960)</td>
<td>-0.00512***</td>
<td>-0.00601***</td>
<td>-0.00610***</td>
</tr>
<tr>
<td>Per Land Total Disasters (1960-1990)</td>
<td></td>
<td>0.00147**</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>[2.36]</td>
<td></td>
</tr>
<tr>
<td>Per Land Climatic Disasters (1960-1990)</td>
<td></td>
<td></td>
<td>0.00153**</td>
</tr>
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<td>[2.43]</td>
</tr>
<tr>
<td>Per Land Geologic Disasters (1960-1990)</td>
<td></td>
<td></td>
<td>-0.000162</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[-0.34]</td>
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<tr>
<td>Constant</td>
<td>0.0293***</td>
<td>0.0273***</td>
<td>0.0284***</td>
</tr>
<tr>
<td></td>
<td>[2.93]</td>
<td>[2.96]</td>
<td>[3.08]</td>
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<tr>
<td>Observations</td>
<td>82</td>
<td>82</td>
<td>82</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.73</td>
<td>0.76</td>
<td>0.76</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1

Notes: The estimates are obtained from a semi-logarithmic regression model. Robust statistics are reported in brackets. *** indicates that the estimate is statistically significant at the one percent level. ** indicates that the estimate is statistically significant at the five percent level. * indicates that the estimate is statistically significant at the ten percent level. This regression is a replication of Sidiaone and Toya (2002, p.673).
| Table 4. Regression table with dependent variable Average Per Capita GDP Growth Rate: 1990-2004 |
|--------------------------------------------------|--------------------------------------------------|--------------------------------------------------|--------------------------------------------------|--------------------------------------------------|--------------------------------------------------|
| (1)                                              | (2)                                              | (3)                                              | (4)                                              | (5)                                              |
| Dependent Variable: Per Capita GDP Growth Rate (1990-2004) |
| Investment / GDP (1990-2004)                     | 0.00110***                                      | 0.00102***                                      | 0.00105***                                      | 0.00108***                                      | 0.00108***                                      |
|                                                 | [4.44]                                           | [4.13]                                           | [4.22]                                           | [4.38]                                           | [4.38]                                           |
| Government Spending / GDP (1990-2004)            | 0.00111***                                      | 0.00118***                                      | 0.00119***                                      | 0.00113***                                      | 0.00115***                                      |
|                                                 | [3.64]                                           | [3.79]                                           | [3.80]                                           | [3.68]                                           | [3.73]                                           |
| Consumption / GDP (1990-2004)                    | 0.00913***                                      | 0.00814***                                      | 0.00827***                                      | 0.00903***                                      | 0.00930***                                      |
|                                                 | [3.84]                                           | [3.43]                                           | [3.50]                                           | [3.84]                                           | [3.83]                                           |
| Gross Domestic Savings / GDP (1990-2007)         | 0.00133***                                      | 0.00132***                                      | 0.00132***                                      | 0.00133***                                      | 0.00137***                                      |
|                                                 | [4.70]                                           | [4.96]                                           | [4.92]                                           | [4.67]                                           | [4.59]                                           |
| Per Land Total Disasters (1990-2004)             | 0.00231***                                      |                                                  |                                                  |                                                  |                                                  |
|                                                 | [2.49]                                           |                                                  |                                                  |                                                  |                                                  |
| Per Land Climatic Disasters (1990-2004)          |                                                  | 0.00206**                                       |                                                  |                                                  |                                                  |
|                                                 |                                                  | [2.66]                                           |                                                  |                                                  |                                                  |
| Per Land Geologic Disasters (1990-2004)          |                                                  |                                                  | 0.000516                                        |                                                  |                                                  |
|                                                 |                                                  |                                                  | [0.67]                                           |                                                  |                                                  |
| Total Disasters (1990-2004)                      |                                                  |                                                  |                                                  | 0.0000192                                       |                                                  |
|                                                 |                                                  |                                                  |                                                  | [1.34]                                           |                                                  |
| Climatic Disasters (1990-2004)                   |                                                  |                                                  |                                                  |                                                  | 0.0000354**                                     |
|                                                 |                                                  |                                                  |                                                  |                                                  | [2.58]                                           |
| Geologic Disasters (1990-2004)                   |                                                  |                                                  |                                                  |                                                  | -0.00013                                         |
|                                                 |                                                  |                                                  |                                                  |                                                  | [-1.52]                                          |
| Constant                                         | -0.109***                                       | -0.115***                                       | -0.116***                                       | -0.109***                                       | -0.112***                                       |
| Observations                                     | 88                                               | 88                                               | 88                                               | 88                                               | 88                                               |
| R-squared                                        | 0.4                                              | 0.4                                              | 0.45                                             | 0.4                                              | 0.41                                             |

*** p<0.01, ** p<0.05, * p<0.1

Notes: The estimates are obtained from a semi-logarithmic regression model.
The gross domestic savings ratio to GDP variable is relevant for the period 1990 to 2007.
All the other variables including the CRED disaster variables are relevant for the period 1990 to 2004.
Robust t-statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.
** indicates that the estimate is statistically significant at the five percent level.
* indicates that the estimate is statistically significant at the ten percent level.
### Table 5. Regression table with dependent variable Investment/GDP: 1960-1990

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable: Investment/GDP (1960-1990)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log of Initial Income (1960)</td>
<td>0.0400***</td>
<td></td>
<td>0.0406***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[2.87]</td>
<td></td>
<td>[2.91]</td>
<td></td>
</tr>
<tr>
<td>Log of Secondary schooling (1960)</td>
<td>0.0174</td>
<td></td>
<td>0.0169</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[1.51]</td>
<td></td>
<td>[1.47]</td>
<td></td>
</tr>
<tr>
<td>Per Land Total Disasters (1960-1990)</td>
<td>0.000255</td>
<td></td>
<td>-0.00522</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.054]</td>
<td></td>
<td>[-1.44]</td>
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<td>Per Land Climatic Disasters (1960-1990)</td>
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<td>Per Land Geologic Disasters (1960-1990)</td>
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<td>-0.00192</td>
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<td>R-squared</td>
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<td>0.44</td>
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</table>

**Notes:**
The estimates are obtained from a semi logarithmic regression model.
Robust t statistics are reported in brackets.
** *** indicates that the estimate is statistically significant at the one percent level.
** ** indicates that the estimate is statistically significant at the five percent level.
* * * indicates that the estimate is statistically significant at the ten percent level.
This regression is a replication of Skidmore and Toya (2002, p. 679).
Table 6. Regression table with dependent variable Growth in Capital Stock :1960-1985

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<td>Log of Secondary schooling (1960)</td>
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<td>0.607*</td>
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<td>Per Land Geologic Disasters</td>
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<td>0.440**</td>
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<td>1.714*</td>
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<td>[1.74]</td>
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<td>0.42</td>
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</table>

*** p<0.01, ** p<0.05, * p<0.1

Notes: The estimates are obtained from a semi-logarithmic regression model.
Robust t statistics are reported in brackets.
*** indicates that the estimate is statistically significant at the one percent level.
** indicates that the estimate is statistically significant at the five percent level.
* indicates that the estimate is statistically significant at the ten percent level.
This regression is a replication of Skidmore and Toya (2002, p.679).
Table 7. Regression table with dependent variable Investment/ GDP: 1990-2004

<table>
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<td></td>
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<tr>
<td>Log of Initial Income (1990)</td>
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<td>4.627***</td>
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<td>[4.92]</td>
<td>[4.70]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log of Secondary school enrollment (1990)</td>
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<td>1.405</td>
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</tr>
<tr>
<td></td>
<td>[1.05]</td>
<td>[1.00]</td>
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<td>Per Land Total Disasters (1990-2004)</td>
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<td>Per Land Climatic Disasters (1990-2004)</td>
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<td>-0.251</td>
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<tr>
<td></td>
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<td></td>
<td></td>
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<td>Per Land Geologic Disasters (1990-2004)</td>
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<td>-0.0574</td>
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<td></td>
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<td>[-2.19]</td>
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<td>R-squared</td>
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</table>

Notes: The estimates are obtained from a semi logarithmic regression model. Robust t statistics are reported in brackets. 
*** indicates that the estimate is statistically significant at the one percent level. 
** indicates that the estimate is statistically significant at the five percent level. 
* indicates that the estimate is statistically significant at the ten percent level.
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
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<th>(4)</th>
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</thead>
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<td>Log of Initial Income (1990)</td>
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<td>-0.658</td>
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<td>1.184</td>
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<td>[0.93]</td>
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<td>enrollment (1990)</td>
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<td>Openness (1990-2004)</td>
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<td>[2.40]</td>
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<td>[-1.39]</td>
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<td>[-0.97]</td>
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<td>4.898**</td>
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<td>[2.22]</td>
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<td>(1990-2004)</td>
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<td>Per Land GeoLogic Disasters</td>
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<td>-0.0731</td>
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<td>[-0.27]</td>
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<td>(1990-2004)</td>
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<td>Constant</td>
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<td>18.62***</td>
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<td>[1.34]</td>
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<td>R-squared</td>
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<td>0.03</td>
<td>0.28</td>
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</table>

Notes: The estimates are obtained from a semi-logarithmic regression model. Robust t statistics are reported in brackets. *** indicates that the estimate is statistically significant at the one percent level. ** indicates that the estimate is statistically significant at the five percent level. * indicates that the estimate is statistically significant at the ten percent level.
### Table 9. Regression table with dependent variable Growth in Secondary Schooling Year:1960-1990

<table>
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<th>(4)</th>
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<td>0.00661**</td>
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<td>Fertility (1960-1985)</td>
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<td>[-0.45]</td>
<td>[-0.15]</td>
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<tr>
<td>Investment/GDP (1960-1990)</td>
<td>0.144***</td>
<td>0.144***</td>
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<td>Per Land Total Disasters</td>
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<td>0.00247***</td>
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<td>(1960-1990)</td>
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<td></td>
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<td>0.00261***</td>
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<td>[-2.79]</td>
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<td>R-squared</td>
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<td>0.01</td>
<td>0.78</td>
<td>0.79</td>
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*** p<0.01, ** p<0.05, * p<0.1

Notes: The estimates are obtained from a semi logarithmic regression model. Robust t statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.
** indicates that the estimate is statistically significant at the five percent level.
* indicates that the estimate is statistically significant at the ten percent level.

This regression is a replication of Skidmore and Toya (2002, p. 680).
Table 10. Regression table with dependent variable Secondary School Enrollment Ratio: 1960-1985

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<td>Enrollment Ratio</td>
<td>Enrollment Ratio</td>
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<td>0.102***</td>
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<td>[4.40]</td>
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<td>Log of Secondary Schooling (1960)</td>
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<td>[0.65]</td>
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</tr>
<tr>
<td>Fertility (1960-1985)</td>
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<td>Investment/GDP (1960-1990)</td>
<td>0.950***</td>
<td>0.956***</td>
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<td>Per Land Total Disasters (1960-1990)</td>
<td>0.0289***</td>
<td>0.0108*</td>
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<td>Per Land Climatic Disasters (1960-1990)</td>
<td>0.0339***</td>
<td>0.0122*</td>
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<td>Per Land Geologic Disasters (1960-1990)</td>
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<td>[-1.74]</td>
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<td>R-squared</td>
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*** p<0.01, ** p<0.05, * p<0.1

Notes: The estimates are obtained from a semi-logarithmic regression model. Robust statistics are reported in brackets.

*** indicates that the estimate is statistically significant at the one percent level.
** indicates that the estimate is statistically significant at the five percent level.
* indicates that the estimate is statistically significant at the ten percent level.

This regression is a replication of Shidmoe and Toya (2002, p.680).
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<td>Investment / GDP (1990-2004)</td>
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<td></td>
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<td>Sub-Saharan Africa</td>
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<td>Latin America</td>
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<td></td>
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<td>OECD</td>
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<td></td>
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<tr>
<td>Per Land Total Disasters (1990-2004)</td>
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<tr>
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</tr>
<tr>
<td>Per Land Climatic Disasters (1990-2004)</td>
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<tr>
<td>Per Land Geologic Disasters (1990-2004)</td>
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<td>Observations</td>
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<tr>
<td>R-squared</td>
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<tr>
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</tr>
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*** p<0.01, ** p<0.05, * p<0.1

Notes: The estimates are obtained from a semi-logarithmic regression model. Robust statistics are reported in brackets. *** indicates that the estimate is statistically significant at the one percent level. ** indicates that the estimate is statistically significant at the five percent level. * indicates that the estimate is statistically significant at the ten percent level.
Table 12. Regression table with dependent variables Tertiary School Enrollment Ratio (1999) and Educational Expenditure (1990-2007)

<table>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<td>Log of Initial Income (1990)</td>
<td>0.0820***</td>
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<td>0.956***</td>
<td>0.793***</td>
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<td></td>
<td>[4.13]</td>
<td>[3.49]</td>
<td>[3.30]</td>
<td>[2.60]</td>
</tr>
<tr>
<td>Investment / GDP (1990-2004)</td>
<td>0.00222</td>
<td>0.0018</td>
<td>0.0239</td>
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*** p<0.01, ** p<0.05, * p<0.1

Notes: The estimates are obtained from a semi-logarithmic regression model.
Robust statistics are reported in brackets.
For countries for which no tertiary school enrollment data are found for 1999, data for the next available year is used (mostly 2002). Countries that are excluded for the first two regressions (columns 1 and 2) are Ecuador, Germany, Haiti, Kenya, Singapore, Sri Lanka and Syrian Arab Republic. The country with no educational expenditure data is Papua New Guinea.
### Appendix Table A. Definitions and Sources of Variables

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<th>Variables</th>
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<th>Source</th>
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<td>Per Capita GDP Growth Rate</td>
<td>Average annual growth rate of real GDP per capita (Constant Prices) for the period 1990-2004.</td>
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</tr>
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<td>Logarithm of real GDP per capita in 1960.</td>
<td>SH1</td>
</tr>
<tr>
<td>Log of Initial Income (1990)</td>
<td>Logarithm of real GDP per capita in 1990.</td>
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<td>Government Spending GDP</td>
<td>Average Government Share of CGDP (% of GDP) for the period 1990-2004.</td>
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<tr>
<td>Gross Domestic Savings / GDP</td>
<td>Average Growth Domestic Savings (% of GDP) (1990-2007)</td>
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<td>Average net fertility rate for the period 1960-1985.</td>
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<td>The fraction of years during the period 1965-90 in which the country is rated as an open economy according to the criteria in Sachs and Warner (1995).</td>
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<td>Openness (1990-2004)</td>
<td>Logarithm of average openness in current prices for the period 1990-2004 where openness is defined to be exports plus imports divided by real GDP.</td>
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<td>Logarithm of 1+ number of total disaster events per million square miles for the period 1960-1990.</td>
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<tr>
<td>Investment / GDP (1960-1990)</td>
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*Continued*
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<thead>
<tr>
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<td>Log of Secondary schooling (1960)</td>
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<td>Log of Secondary school enrollment (1990)</td>
<td>Logarithm of gross secondary school enrollment ratio in 1990.</td>
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<td>Latin America</td>
<td>Dummy for Latin-American countries.</td>
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<td>NIEs and ASEAN</td>
<td>Dummy for NIEs and ASEAN member countries.</td>
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<td>OECD</td>
<td>Dummy for OECD member countries.</td>
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</tr>
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Sources:
BL1: Barro and Lee (1994).
KL: King and Levine (1994).
SH1: Summers and Heston (1994).
WDI2: World Development Indicators (2009).
WMP: World Mapper.38

38 Available at http://www.worldmapper.org/display.php?selected=163.t
### Appendix Table B. Summary Statistics

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## Appendix Table C. List of Countries

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The Effects Of Natural Disasters On Long-Run Economic Growth

<Figure 7 (a): World map of hazard hotspots and countries most affected from 1998-2007 according to CRI>
The underlying map is taken from CARE 2008
Note: on the map, blue areas with striped overlay represent risk hotspots with predicted significant increase in population density. The darker the underlying color, the higher is the expected increase in population density.
Source: Harmeling (2008, p.8)

<Figure 7 (b): World map of Climatic Risk Index Ranking 1990-2008>
Source: Harmeling (2009, p.8)
Reassessment of the Weather Effect: Stock Prices and Wall Street Weather

Mitra Akhtari

University of California, Berkeley

Abstract

Psychology literature has long established the effect of sunshine on mood. Recent research in behavioral finance has investigated whether investors’ mood fluctuations induced by hours of sunshine affect investment decisions in a significant manner such that equity mispricing follows. Some research in this area has concluded that there is a systematic relationship between security markets and local weather, while other research has found no relationship between investment decisions and hours of sunshine. This paper aims to study the weather effect and its possible evolution over time in an effort to consolidate the different findings in the field. Sunshine and daily market return are positively correlated for New York City from 1948 to 2010. However, this relationship exhibits a distinct cyclical pattern over the last 50 years. One possible explanation for the existence of such a pattern is the entry of ‘non-rational’ investors into the market during certain periods which results in the identification of a significant weather effect. This finding supports the view that security markets are to some extent irrational.

1 University of California, Berkeley 2010, Economics
I. Introduction

Sunshine affects mood and mood can shape behavior. Thus it is plausible to test if weather is related to economic outcomes, such as market return. The ‘weather effect’ is documented by some, Saunders (1993) and Hirshleifer and Shumway (2003), and claimed an exercise in data mining by others, Kramer and Runde (1997). In the following paper, I study the relationship between weather and equity prices over time using various measures of the change in weather and market return.

To test the hypothesis that sunshine affects stock returns, I use simple regressions to examine the relationship between the daily cloudiness, the inverse of sunshine, of New York City and the return on the Dow Jones Industrial Average index. For the time period of 1948 to 2010, there is a negative relationship between average cloudiness and DJI gross simple return. After controlling for market anomalies, such as the January and weekend effects, a change in weather from sunny to overcast skies is associated with an additional .79 percentage point decline in gross return (t-statistic = -2.81). Thus the weather effect seems to exist for this time period in New York City. Based on prevailing psychological research, my findings support the fact that investors feel more optimistic on sunny days and are more willing to invest in risky assets; this change in behavior leads to higher stock prices. If the same simple regression is used to study 30-year subsamples at a time, although the estimated coefficient on average cloudiness is negative for all periods, the relationship between cloudiness and market return is statistically insignificant for some sub-samples. To analyze whether the sunshine effect is robust over time, I measure the return difference between good and bad weather days for each year and study its evolution over time. Once the volatility of this difference in returns variable is reduced by computing its moving average, it is positive for almost all years and slightly increasing over the past 50 years. The market return is higher on good weather days, defined as exceptionally sunny days, than on bad weather days, defined as exceptionally cloudy days. This difference in returns is strongly persistent and increasing for periods such as 1975 to 1980 or the late 1990s; for other sub-samples, namely 2000 to 2008, the difference in returns of sunny vs. cloudy days is sharply decreasing. It must be mentioned that stocks in the DJI represent claims on geographically diversified firms. Hence a local weather effect must work through local trading agents. The relationship between local weather and stock returns that is established in this paper implies that, although investors are located across the country, the trading patterns of agents in New York City have a significant effect on overall DJI performance.
One possible explanation for the rise and fall of the sunshine effect over time is the entry of small investors into the market during periods in which equity investment attracts popular attention. These non-professionals’ misattribution of good mood on sunny days extends to their investment decision-making process more so than professional investors allow for such a psychological bias. Hence the weather effect is more pronounced for certain years, specifically those periods for which the market is not dominated by perfectly rational investors. This finding supports the theoretical argument of Mehra and Sah (2002) that investors’ feelings have a significant effect on equity prices. Furthermore, the increase of the weather effect for certain time periods provides empirical evidence for the ‘limits to arbitrage’ argument made by Barberis and Thaler (2002): equities can remain mispriced, due to the actions of a small subset of investors, even if arbitrageurs suspect mispricing.

The overall implication of these results is that there is a significant relationship between weather and stock prices; this relationship exhibits a cyclical pattern over the past half-century. Thus, depending on the years under study, a researcher may find a significant relationship between weather and stock prices or may find insignificant results and label the weather effect “an exercise in data mining.” However, I conclude that extreme and intermediate weather changes in New York City are strongly correlated with within day DJI return.

II. Related Literature

Recent research in behavioral economics, for instance Loewenstein (2000, p. 426), argues that emotions ‘propel behavior in directions that are different from that dictated by a weighing of the long-term costs and benefits of disparate actions.’ One area of decision-making where emotions and feelings are relevant is equity pricing. Behavioral finance researchers have recently begun to investigate whether investors’ emotions influence their decision-making and if such an impact on behavior has significant economic outcomes. One area of research pertinent to the topic of this paper is mood misattribution. This area considers the effect of environmental factors such as weather and social settings on equity pricing. This literature suggests that supposedly rational investors are affected by feelings, which are at times induced by unrelated events in their surroundings, and the effect of feelings on behavior influences investment decisions and market outcomes.

There is extensive literature on three decision-making models: the traditional consequentialist model, the anticipated emotions model, and the risk-as-feelings model. In traditional models of decision-making that involve risk and uncertainty, the decision-maker is assumed to quantitatively weigh the costs and benefits of possible outcomes and choose the one with the best risk-benefit
trade-off. This ‘consequentialist perspective’ ignores the fact that the decision-maker is affected by feelings. Lucey and Dowling (2005) cite extensive literature that documents the influence of feelings on decisions, especially risky ones. In light of such studies, improvements have been made to the traditional model to account for the impact of anticipated emotions, or emotions experienced by the decision-maker conditional on the perceived outcome. However, even this advancement to the model ignores the impact of the current emotional state of the decision-maker. Therefore, Loewenstein et al. (2001) developed the ‘risk-as-feelings’ model to incorporate people’s current emotions and feelings into the decision-making process. They establish the relevance of feelings to the decision-making process by making three basic assumptions. They argue that cognitive evaluations induce emotional reactions: emotions are ‘considered by most contemporary theories to be postcognitive, that is, to occur only after considerable cognitive operations have been accomplished’ (Zajonc, 1980, p. 151). Conversely, emotions inform cognitive evaluations: people in positive moods make more optimistic choices and people in negative moods make more pessimistic choices (Johnson and Tversky, 1983). Finally, Loewenstein et al. (2001) argue that feelings can affect behavior. Through these assumptions, they arrive at their model.

If decision-making processes that involve risk and uncertainty are affected by feelings, then it is certainly true that investors, who are constantly engaged in assessing risky opportunities, are influenced by feelings. One may ask, however, whether the effect of feelings equates to changes in equity pricing. It could be possible that individual investors make suboptimal decisions due to mood misattribution, but rational market forces, such as arbitrage, ensure that fundamentals are accurately priced. Mehra and Sah (2002) provide support for significant economic outcomes as a result of decisions that are affected by feelings. According to Mehra and Sah (2002), investors’ feelings affect equity prices if:

1. Investors’ ‘subjective parameters’ (level of risk aversion, judgment of appropriate discount factors, etc) fluctuate over time due to changes in mood;

2. The effects of these changes in mood are widely and uniformly experienced by market players;

3. Investors do not realize that their decisions are being influenced by such mood fluctuations.

This gives rise to the question: if the above conditions hold only for a subset of investors, are equity prices still affected by mood fluctuations? The traditional
view has been that even if some investors misprice equity, informed and rational market participants will arbitrage the mispricing away. However, Barberis and Thaler (2002) point to the ‘limits of arbitrage.’ In particular, they point to implementation costs, the inherent risk associated with the unpredictability of irrational investors, and the fundamental risk in equity markets as some limits to arbitrage. Consequently, equities can remain mispriced even if arbitrageurs suspect mispricing and this mispricing can occur as a result of the actions of only a small subset of investors.

Based on the above discussion, fluctuations in mood influence the decision-making of investors which can affect the equilibrium stock prices. Furthermore, Schwarz and Clore (1983) document how mood can inform decisions even when the cause of the mood change is unrelated to the decision being made. This ‘mood misattribution’ has encouraged behavioral finance researchers to investigate whether factors that determine mood, but are irrelevant to the pricing of fundamentals, affect equity investment decisions.

One such determinant of feelings is sunlight. Psychology literature has long established sunshine to affect mood and feelings. From the traditional efficient market perspective, since sunlight affects the weather, it may also affect agricultural and construction industries. The market will then adjust to this ‘exogenous variation’ accordingly. However, in modern capitalistic economies, agriculture plays a small role and should not affect the price of a stock index, especially if such an index is not composed primarily of weather-related industries. Also, sunshine that occurs in one particular location is not representative of the weather in the entire economy. On the contrary, the risk-as-feelings model predicts that when the sun shines, people are more optimistic and, hence, more inclined to buy stocks. They incorrectly attribute their good mood to positive economic prospects rather than good weather. The effect of hours of sunlight on investors’ feelings meets the three requirements proposed by Mehra and Sah (2002): unknown uniform mood fluctuations over time experienced by a large group of people. Hence investors’ mood fluctuations induced by sunshine can in turn affect equity pricing; this suggests that sunshine is positively correlated with stock returns.

Saunders (1993) examines whether there is a relationship between local New York City weather and daily changes in New York-based equities. Specifically, Saunders’ hypothesis is that negative mood effects of bad weather, which he defines as cloudy days, result in lower stock prices and the positive mood effects of good weather, or clear days, result in higher stock prices. Based on the matching of a cloud-cover variable to daily data for the Dow Jones Industrial Average from 1927 to 1989 and value-weighted and equal-weighted NYSE/AMEX indices for 1962 to 1989, Saunders (1993) finds a
significant relationship between the level of cloud-cover in New York City and stock prices. This estimated effect of local weather on stock prices is robust with respect to market anomalies such as the January, weekend, and small-firm effects.

Hirshleifer and Shumway (2003) study whether psychological biases affect stock returns on a more global scale. They study 26 international financial centers from 1982 to 1997. Using panel data rather than a long time series, they test for the sunshine effect throughout the entire world. The research de-seasonalizes cloud-cover to avoid identifying a relationship between the market return and cloud-cover that may be due to other seasonal affects. Using more sophisticated methodology than simple regressions, their results show that 18 of the 26 cities have a negative coefficient measuring the relationship between cloud-cover and the equity index return, and four of the cities have a significant negative relationship. Thus Hirshleifer and Shumway (2003) conclude that days with high cloud-cover are associated with lower return, even once adverse weather conditions, such as rain and snow, are controlled for.

Other studies have been done to further understand the weather effect. Goetzmann and Zhu (2002) investigate the weather effect for a particular group of agents in the market. These researchers use a database of trading accounts of approximately 80,000 investors from 1991 to 1996 to understand whether investors trade differently based on the weather. Their analysis of trading activity in five major U.S. cities finds no difference in individuals’ propensity to buy or sell equities on cloudy days as opposed to sunny days. This suggests that the weather effect is caused by market participants other than individual traders, such as market-makers, news providers, or other agents physically located in the city of the exchange. Specifically, they find NYSE spreads widen on cloudy days, suggesting that the behavior of market makers is related to the weather with greater bid-ask spreads (greater risk aversion) for cloudy days.

The most recent work on this topic is a paper by Symeonidis et al. (2008) which investigates the impact of weather on stock market volatility. This research uses the same data set as Hirshleifer and Shumway (2003), for which the weather effect is empirically evident, and finds historical volatility estimates to have a negative relationship with sunshine. The researchers argue that weather may affect volatility by increasing the diversity of opinions amongst traders regarding the true value of assets. They conjecture that investors belong to one of two groups: ‘rational’ investors, as assumed in the Efficient Market Hypothesis, or ‘behavioral’ investors, as assumed in the risk-as-feelings model. To the extent that weather affects the mood of behavioral investors, excess volatility will result from a divergence of opinions among the two groups of investors.

In contrast to the studies mentioned above which all, in one way or an-
other, confirm the weather effect, the relationship between market return and the weather is not confirmed in two studies by Kramer and Runde (1997) and Trombley (1997). Kramer and Runde (1997) analyze the return on a German stock index which was traded exclusively on the Frankfurt stock exchange from 1960 to 1990. They find any weather effects to be nonrobust with respect to the way that data is classified; both a positive and a negative weather effect can be established depending on the test procedure used. Trombley (1997) uses the same data as Saunders (1993) to illustrate that the conclusions drawn by Saunders (1993) are not robust to alternative definitions of the cloud-cover variable and the choice of which return to compare.

This paper reassesses the weather effect in an attempt to consolidate the current findings on whether environmental factors, such as hours of sunshine, which influence investor mood, can systematically affect stock prices. In particular, I use residual analysis of historical data to investigate possible patterns in the weather effect. If such a pattern includes periods of rise and fall, then the detection of such an effect is dependent upon the chosen period of analysis. Furthermore, I study the weather effect using alternative definitions of cloudiness. If the relationship between weather and stock returns is dependent on the measure of cloudiness used, then a thorough analysis of the topic should choose the most appropriate definition of cloud cover.

III. Data

To examine whether stock returns and the weather are correlated, I use two data sets: one contains weather information for New York City and the other pertains to the market return. I gather weather data from the National Climatic Data Center of the National Oceanic and Atmospheric Administration (www.ncdc.noaa.gov). Specifically, I use the Integrated Surface Data recorded from LaGuardia, New York City, since this station is the one physically closest to Wall Street. This data set contains information on various meteorological variables, such as temperature, precipitation, wind, and cloud-cover, from 1948 to 2010. Previous research done on influential weather variables has established ‘hours of sunshine’ as the most significant predictor of mood. Since hours of sunshine are inversely related to the presence of clouds, and also to be consistent with previous research, I use cloud-cover measures in constructing a variable that approximates daily sunshine levels. Cloud-cover ranges from 0 for clear skies to 8 for overcast. Prior to 1972, all observations were recorded on the hour or every 3 hours; the recent data includes many more observations.

2 Persinger (1975) and Cunningham (1979) find that number of hours of sunshine is inversely correlated to negative mood. Howarth and Hoffman (1984) find “cynical, doubting outlook,” or skepticism, is inversely related to hours of sunshine: across eight weather variables, hours of sunshine was the one significant variable for predicting optimism scores.
for overcast days. Thus, to avoid oversampling of days with worse weather, only observations that are recorded 9 minutes before the hour or on the hour are used. This greatly improves the quality of the data by eliminating clustered and redundant observations. I measure cloudiness in two ways: I calculate the simple average of cloud-cover for each day and I define an extreme weather variable to distinguish completely clear days from days with severe weather. This variable is equal to -1 for clear days, 1 for overcast days, and 0 for days with intermediate weather. This extreme weather variable is meant to capture the possibility that differences in returns for intermediate weather changes are rather small. Saunders (1993) contributes almost all of the lower return on cloudy days to the two extreme cloud-cover groups by pointing out that partially cloudy days are not particularly depressing.

To measure market performance, I collect the daily index return of the Dow Jones Industrial Average (DJI) using Yahoo! Finance (www.finance.yahoo.com). From July 1, 1948 to March 31, 2010, I compute the daily gross simple return to keep consistent with earlier studies. I also calculate the 24-hour return, in natural logarithm, as the difference between today’s closing price and the previous day’s closing price. Additionally, I compute within day and overnight return: within day return is the difference, in natural logarithm, between today’s closing price and today’s opening price and overnight return is the difference between today’s opening price and the previous day’s closing price, again in natural logarithm. The sum of these two measures gives the 24-hour return, defined earlier as the difference in closing prices, or the close-to-close return.

Furthermore, I measure the return difference between good and bad weather days as follows. To des seasonalize the weather data, I calculate the average weather for each month throughout all years and measure the residual weather for each day relative to this average. Then for each year, I calculate two measures of return using the close-to-close return: one for days with unusually cloudy weather, or days in the 90th percentile of extremely cloudy days, and one for days with unusually sunny weather, or days in the 90th percentile of extremely sunny days. Finally, for each year, I compute the difference of these two returns, or the residual-difference, to measure how much higher the return is on exceptionally sunny days as opposed to the return on exceptionally cloudy days.

IV. Evidence and Discussion

To proceed with testing the hypothesis that local weather and stock returns are correlated, I first replicate the results of earlier studies that find such a relationship. I then consider the evolution of this effect over time. Addition-
Reassessment of the Weather Effect

ally, I study the robustness of the weather effect using various measures of return. Finally, I examine whether the driving force behind this relationship is extreme weather or daily weather changes.

A. Replication of Earlier Results

I estimate a simple regression, similar to Saunders (1993), of the following form:

$R_t = \beta_0 + \beta_1 C_t + \beta_2 R_{t-1} + \sum_{t=1}^{11} \tau_i M_{it} + \sum_{t=2}^{5} \delta_i D_{it} + \varepsilon_t$

in which $R_t$ is defined as the gross return of the DJI on day $t$, $M$ is a month dummy, with December omitted, $D$ is a day-of-the-week dummy, with Friday omitted, $C$ is the average cloud cover variable, and $\varepsilon$ is the error term. The lagged return variable $R_{t-1}$ is included to control price movement persistence. Day and month dummies are included in the regression to control for seasonal and day-of-the-week anomalies. The results in Table 1 report the ordinary least squares estimates of some of the coefficients in the above regression. The second column of Table 1 reports estimates for the entire time period; the third column reports the estimates for a smaller window of time, specifically for the years 1962 to 1989. I find that New York City cloud cover is significantly correlated with the DJI return even after seasonal effects are controlled for. These results mirror the findings of Saunders (1993), especially for the sub-sample of 1962 to 1989, which Saunders also analyzes. The coefficient estimates, standard errors, and $t$-statistics are almost identical to the ones found by Saunders (1993).

Additionally, results from Hirshleifer and Shumway (2001) can be replicated by considering data from 1982 to 1997. In simple regressions of their city-by-city tests, although statistically insignificant, they find a negative estimated coefficient on cloud-cover for New York City. For this sub-sample, I estimate the parameter on cloud-cover to be -.00010 with $t$-statistic (-1.60). A discussion of why the weather effect is statistically insignificant for this period follows below.
B. Weather Effect Over Time

Although the weather effect seems to influence the market return, it is worthwhile to study its persistence over time. Local New York City weather is an insignificant predictor of DJI close-to-close return in the more recent years, 2000-2010. One prediction might be that the weather effect has been declining over time due to the proliferation of high-frequency trading that makes trading decisions based on quantitative measures. To test for the linear decrease of the weather effect, I estimate the following simple regression:

\[ R_t = \beta_0 + \beta_1 C_t + \beta_2 (C_t \times T) + \sum_{i=1}^{t=11} \tau_i M_{it} + \sum_{i=2}^{t=5} \delta_i D_{it} + e_t \]

in which \( R_t \) refers to close-to-close return and a positive coefficient on the interaction of time and cloud-cover, \( C_t \times T \), allows for \( \beta_1 \) to approach 0 as time passes. The estimated coefficient on the interaction term is, however, very close to zero with t-statistic of (-.14) and, thus, insignificant. So it is not the case that the weather effect has disappeared in a linear way over time. If the main regression from Section 4A is studied separately for 30 year windows,

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3 A discussion for why close-to-close return is an appropriate measure of return will follow in Section 4C.
Reassessment of the Weather Effect

it seems that the coefficient on the average cloud-cover variable is sometimes significant and sometimes not significant. This suggests that the weather effect is present only during particular periods.

To analyze the evolution of the weather effect over time, I use the residual-difference return variable to detect the possible patterns in the data. As described in Section 3, I deseasonalize the cloud-cover variable so that the computed weather effect excludes any contributions that cloud-cover makes to seasonal return patterns. Unusually sunny days, those in the 90th percentile of sunny days when compared to the monthly average, are separated from unusually overcast days, those days in the 90th percentile of cloudy days as compared to the monthly average. Then the respective return for each of these weather types is computed on a yearly basis. I compute the residual-difference return as the close-to-close return on good weather days minus the close-to-close return on bad weather days. To reduce the volatility of the residual-difference return, I calculate, for each year, the average of the past ten years’ residual-difference return. Figure 1 shows the plot of this moving average over all years for which such an average could be computed. The linear line which best fits the data has a slope of .000014 and \( t \)-statistic of (2.39), and is, thus, significant at the 5% level. It is clear from Figure 1 that the DJI return is higher on very sunny days: almost all residual-difference return averages are above zero. This result confirms the existence of a correlation between sunshine and stock returns. It is also clear from Figure 1 that there are periods of time in which the weather effect is strong and increasing and periods in which the weather effect is declining. It is interesting to point out that that the rise and fall in the weather effect over even a short span of time can have a large impact on parameter estimates. Using the close-to-close return in a simple regression, the analysis of the time periods 1975 to 1985 and 1975 to 1987 result in very different estimates of the coefficient on cloud-cover. Table 2 summarizes these results. As Figure 1 shows, the weather effect is sharply declining in 1986 and 1987. As these years are added to the analysis, the estimated parameter on cloud-cover, reported in the Period 2 panel of Table 2, becomes statistically insignificant. So in establishing a correlation between local New York City weather and the DJI return, the time period of the analysis must be given careful consideration.
The weather effect has been slightly increasing over the past half-century and there are definite patterns present in the weather effect. Saunders (1993)
acknowledges that the relationship between stock price changes and weather decreases significantly for the last sub-period of his sample, from January 1, 1983 through December, 31, 1989, and this is clear from Figure 1 as well. He claims that these results may reflect the evolution of more global influences on security prices, particularly the increased importance of index futures trading in Chicago since 1982. However, this claim may be incorrect because global influences have been on the rise for the past two decades and yet there is still an upward trend seen in the weather effect throughout the 1990s. The presence of the sunshine effect in New York City in the 1990s is also confirmed by Hirshleifer and Shumway (2003) when they estimate a significant logit coefficient on cloud-cover for the eight-year period from 1990 to 1997. Thus they reject Saunders’ conclusion that the weather effect may be of purely historical interest. Figure 1 clearly illustrates that the weather effect is present even after the publication of Saunders’ paper in 1993 and confirms the finding by Hirshleifer and Shumway (2003).

One possible explanation for the rise and fall in the weather effect may simply be that market trends and cyclical weather patterns match up in certain periods. Alternatively, by observing that the weather effect peaks during the ‘dot-com bubble’ and falls significantly during the recent financial crisis, it can be argued that the weather effect is stronger when the stock market is popular with non-professional investors who are presumably less rational than investment professionals.

C. Various Measures of Return

The dependent variable in Section 4A, which is used to ensure consistency with previous studies, measures the gross return within a day. I further investigate the weather effect using the overnight as well as the 24-hour return.

I estimate a similar regression to the specification in 4A:

$$R_t = \beta_0 + \beta_1 C_t + \sum_{i=1}^{11} \tau_i M_{it} + \sum_{i=2}^{5} \delta_i D_{it} + \varepsilon_t$$

in which $R_t$ is defined as either the within day return, the overnight return, or the close-to-close return defined in Section 3. Monthly and day-of-the week indicators are defined similar to the model represented by Table 1. The estimates of the coefficients on the average cloud-cover variable are reported in Table 3 for all three definitions of the dependent variable. As expected, by natural log properties, the parameter estimate of the overnight return and the within day return add to give the parameter estimate of the close-to-close return. Also,
since for small changes, the logarithmic function approximately calculates percentage change, it is expected that the estimates of the regression which uses the within day return, Table 3, is close to the estimates of the regression which uses percentage change of DJI, Table 1. The results of the second column indicate that New York City weather does not predict the overnight return of the DJI; on the other hand, local cloud cover is significantly correlated with within day return. Thus the correlation between local weather and close-to-close return of the DJI can be completely attributed to how weather is related to within day return as opposed to overnight return.

This finding confirms the prediction made by Hirshleifer and Shumway (2003) that it is not the news (as in weather forecasts) that the day will be sunny which causes an immediate and complete positive stock price reaction. Rather it is the occurrence of sunshine that correlates to a change in prices. The fact that the weather effect is completely driven by the within day return, and not overnight return, suggests that it is the current weather that affects peoples’ psychological state. If overnight return and stock returns were significantly correlated, a possible explanation could be that the prediction of tomorrow’s weather, which is most accurate the night before, affects investor mood.

<table>
<thead>
<tr>
<th>Table 3 - Parameter Estimates for Regressions on Alternative Measures of Return of DJI: NYC, 1948-2010</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Explanatory variable</strong></td>
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<tr>
<td><strong>Model 1 - overnight return:</strong></td>
</tr>
<tr>
<td>Cloud cover</td>
</tr>
<tr>
<td>Adjusted R-squared:</td>
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<tr>
<td><strong>Model 2 - within day return:</strong></td>
</tr>
<tr>
<td>Cloud cover</td>
</tr>
<tr>
<td>Adjusted R-squared:</td>
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<tr>
<td><strong>Model 3 - close-to-close return:</strong></td>
</tr>
<tr>
<td>Cloud cover</td>
</tr>
<tr>
<td>Adjusted R-squared:</td>
</tr>
<tr>
<td>Number of observations:</td>
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</tbody>
</table>

Notes: Cloud-cover data are from National Climatic Data Center, DJI data are from Yahoo! Finance. The dependent variable varies for each model, t statistics are given in parentheses. *** Significant at the 1% level.
and therefore their risk-taking behavior. However, it is unlikely that weather forecasts, or *predictions*, are a determinant of people’s mood. Since weather and overnight return are unrelated to one another, one can conclude that it is today’s occurrence of sunshine that drives the weather effect, not people’s predictions about hours of sunshine.

Since within day return and close-to-close return parameter estimates are very close to one another in magnitude and overnight return is irrelevant to the study of the weather effect, I will proceed to use close-to-close return in my analysis.

**D. Extreme Weather Effect**

Saunders (1993) claims that although the relationship between the weather and the market return is monotonic across all cloud-cover groups, extreme weather days affect returns considerably more. He proceeds to use only a cloud-cover variable that distinguishes 0-20 percent cloudy days from 100 percent cloudy days in his analysis; he argues that there would be little expected variation in mood on days with cloud cover between 20 and 90 percent. To test the hypothesis that it is extreme weather changes that drive the result, I define the extreme-weather variable as described in Section 3. This variable uses an ordinal scale and is designed to permit a linear estimate of the non-linear relationship between cloud cover and stock prices as driven by the two extreme cloud cover groups. First, I estimate the model:

\[
R_t = \beta_0 + \beta_1 EW_t + \sum_{t=1}^{t=11} \tau_i M_{it} + \sum_{t=2}^{t=5} \delta_i D_{it} + \varepsilon_t
\]

in which \( R_t \) refers to close-to-close return, \( EW \) is the extreme-weather variable, and monthly and day-of-the-week indicators are included to control for seasonal anomalies. I also restrict my analysis to the period from 1962 to 1985: according to the patterns found in Section 4B, the weather effect is strongly present in this period. Thus estimates of the extreme-weather effect will not be tainted by the patterns in the weather effect over time. Table 4 reports the result of this regression in the panel for Model 1. Extreme weather changes are significantly related to the DJI close-to-close return. The Model 2 panel in this table uses the exact same regression as above with the average cloud-cover variable as the explanatory variable. The estimate on cloud-cover is higher than those estimated in previous sections. This is to be expected since the time period considered in this regression is a period with strong, and increasing, weather effects, as seen in Figure 1. The last model in Table 4, Model 3, reports estimates for the following specification:
in which extreme-weather and cloud-cover are both used as explanatory variables. The parameter estimate on extreme-weather is not significant once daily cloudiness is controlled for: inclusion of variables that proxy extreme weather changes and intermediate weather changes in the regression results in significant estimates of intermediate weather changes and statistically insignificant estimates for extreme weather changes.

Consistent with the findings of Trombley (1997) and Kramer and Runde (1997), the estimates of the above specifications imply that careful consideration must be given to how cloudiness measures are defined in studying the weather effect. Hirshleifer and Shumway (2003) confirm that regressions of return on changes in cloudiness and regressions that replace the cloudiness variable with a variable which measures extreme weather produce similar re-
Reassessment of the Weather Effect

Table 4 verifies that the two predictions are in fact similar: Model 1 estimates that a change from clear to overcast results in an additional .12 percentage point fall in DJI close-to-close return (.059 percent fall for a change from sunny to intermediate and .059 percent fall for a change from intermediate to overcast) and Model 2 estimates that a change from clear to overcast will result in an additional .14 percentage point decrease in the DJI return. However, it is not evident that the weather effect is predominantly and exclusively driven by the two extreme groups of cloudiness, as Saunders (1993) has previously attributed. Inherent in using an ordinal scale of \{-1, 0, 1\} to categorize and distinguish the two extreme cloud-cover groups is the assumption that a change from any level of partial cloudiness to overcast induces the same mood change in investors as a change from sunny to any level of partial cloudiness. This assumption may be incorrect if one kind of change in weather, for example the change from very little clouds to overcast, has a deeper impact on investor mood than a change from very cloudy to overcast skies. So extreme weather does explain changes in stock returns; however, intermediate weather changes are also important.

V. Conclusion

The evidence discussed above supports previous literatures’ finding that hours of sunshine in New York City has a significant correlation with stock prices. This supports the view that investor psychology does influence asset prices. If it is the case that people tend to evaluate future prospects more optimistically when they are in a good mood than when they are in a bad mood and sunshine results in better a mood, then sunnier days are associated with investors being more willing to take on risky investments, such as stocks, as opposed to less risky investments, or bonds.

The relationship between weather and market return has been slightly increasing over the past half-century. However, in long time-series analysis, since both periods of distinct growth as well as periods of decline are present, the estimates can either be significant or insignificant depending on the period which dominates. Hirshleifer and Shumway (2003) confirm the sunshine effect using panel data. However, the analysis of panel data can be misleading since their period of study is from 1982 to 1997, a period which includes strong growth of the weather effect for New York City. The other 25 cities in their study may very well have variation over time in their respective sunshine effects; the period under study may be one characterized by a strong and increasing weather effect for those cities which they estimated to have a negative cloud-cover coefficient.

The 1990s were certainly a period of strong economic growth for Amer-
ica, partly due to the success of the stock market. During this period, many ‘average Joes’ entered the stock market to take advantage of hefty returns. Although these investors were located across the country, it is safe to assume that many of them were located in New York City, the largest financial center of the United States. These non-professional investors may be considered less rational players in the market and more likely the subject of psychological biases. This may help explain the sharp increase in the weather effect throughout the 1990s: the average investor misattributes his good mood due to sunny weather to generally favorable economic prospects and is more inclined to buy stocks on sunny days. As previously mentioned, due to limits of arbitrage, even the actions of a small subset of investors can result in mispricing. This explanation is inline with the argument made by Symeonidis et al. (2008) which categorizes investors as either rational or behavioral and attributes the relationship between weather and excess volatility to the differing opinions of these two groups of investors with respect to equity pricing. The ‘average Joes’ explanation can also help explain the conclusion made by Goetzmann and Zhu (2002) that there is no difference in individuals’ propensity to trade equities on cloudy days as opposed to sunny days. Goetzmann and Zhu (2002) study investors’ profiles from 1991 to 1996. During this period, many non-professionals entered the market and caused the significant increase of the weather effect. Overall Goetzmann and Zhu (2002) find no significant difference in trading patterns for sunny days as opposed to trading patterns for cloudy days. There are still many rational investors who do not misattribute their good mood to improved economic prospects and the trading volume of these investors is far greater than that of ‘irrational’ investors. However, the misattribution of behavioral investors, who were previously mostly absent from the market, has caused the weather effect to increase sharply in the 1990s from its previous level.

With careful consideration given to extreme, as well as intermediate, measures of daily cloudiness, it is confirmed that there is a relationship between local New York City weather and the within day return of the DJI index; for some periods this relationship is stronger than others. If exogenous measures, such as weather, that affect investor mood can predict returns in the market, an argument can be made for the inclusion of behavioral variables in asset pricing models. One direction for future research regarding the weather effect is to consider the channel, or agent, through which the weather effect operates. There should be further investigation of how the weather affects the attitudes of market makers, news providers, or other market agents that are physically located in the city of the exchange. Cloudy days are more depressing for everyone, not just investors!
References


On Life Settlement Pricing

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Abstract

Although life settlements as financial products have been in existence and active use in financial markets for quite some time, their pricing has never reached the level of transparency and standardization envisioned by Wall Street. This lack of standardization has been and still is the major roadblock against widespread use of life settlements as investment, diversification and portfolio risk management tools. However, the recent crisis of 2007 has revealed high levels of correlation among existing financial instruments that are in widespread use. This revelation raised an avid interest in new financial instruments that show low correlation to strong market swings. In this respect, life settlements and related products such as death bonds have gained popularity among practitioners and academics alike. This paper proposes a standard pricing framework for life settlements that is consistent with existing methods of risk management and sensitivity analysis widely used in fixed income products.

1 Bilkan Erkmen is a senior in the Economics Department at Princeton University and he is pursuing minors in finance and applied & computational mathematics. His research interests lie in the application of financial mathematics and computational methods to asset pricing problems. The author wishes to extend his warmest thanks to Yuliy Sannikov for his insightful comments and terrific guidance throughout the research process.
I. Introduction

The revelation of high levels of correlation among existing financial instruments and their underlying assets during the mortgage-backed securities crisis in 2007 has sparked tremendous interest among investors for new instruments and assets, which have low, and potentially zero, correlation to the broader market. In this respect, Wall Street investment banks have turned their eyes towards one of the biggest asset classes in the United States: Life Insurance with $5.1 trillion in assets in 2007 (American Council of Life Insurers, 2008). When compared with the $5.08 trillion of Treasury securities in the outstanding US bond market debt in 2007 (Securities Industry and Financial Markets Association, 2009), the sheer size of the life insurance industry makes it a substantial untapped market. Moreover, Weber & Hause (2008) argue that a life insurance policy is uncorrelated against almost any other asset class as the payment of the death benefit is based on the event of death, not a market event that may cause a change in its value. These attributes seem to make life insurance an attractive investment vehicle and contribute significantly to the case for a secondary market in life insurance.

Therefore, the current idea of financial institutions involves the purchasing of large pools of life settlements - life insurance policies no longer needed or wanted by their owners - at prices higher than their cash surrender values, which are dened as the buy back prices of the policies by the insurer. These pools are then securitized into bonds, or the so-called death bonds, that will be sold to investors following the promise of an attractive return, a greater yield to maturity than that offered by a same-maturity government bond without risk adjustment, and low correlation to the broader market (BusinessWeek, 2007). So far, most of the life settlement transactions have been done by life settlement providers, which have typically sold these policies to hedge funds. However, Wall Street rms now recognize the profit prospects in life settlement transactions and banks, including Goldman Sachs and Credit Suisse, have already acted well ahead of their rivals in preparing for a future secondary market in life insurance (New York Times, 2009). The Economist (2009) reports an estimated market size of $18 billion for life settlements as of June 2009 and Kamath & Sledge (2005) expect it to grow to a $160 billion industry by 2010. Despite increasing interest in the industry and the gradual expansion of the market, further growth, according to A.M. Best (2008), depends on increased clarity, standardization as well as transparency of the valuation of life settlements.

According to a research study by Insurance Studies Institute (2008), there are currently two main pricing methodologies: Deterministic Pricing and Prob-
abilistic Pricing. Since the value of the life settlement is a function of the life expectancy for the deterministic model and of the probability density function of death conditional on survival until the transaction time for the probabilistic model, a mortality forecasting model needs to be developed to analytically describe these actuarial concepts. Moreover, the value of the life settlement is dependent on the credit risk of the insurer as the secondary market purchaser of the policy needs to be compensated for its credit risk exposure. Consequently, the credit risk of the insurer needs to be priced into the appropriate valuation methodology.

This paper, hence, constructs an analytical valuation expression for life settlements that incorporates the probability density function of death conditional on survival until transaction time, the credit risk of the insurer and the term structure of interest rates. In reaching this result, it first conducts a literature review and states in the light of existing research its contribution to the field of life settlement pricing. It then lays out the theoretical framework, describes the data used, implements the theory to data, presents its results and concludes with a discussion of its shortcomings and potential improvements.

II. Literature Review

Pricing Methodologies

Although my research into the economic literature has failed to find an analytical pricing expression for life settlements, it is possible to construct these expressions from the descriptions of the deterministic and probabilistic pricing methodologies for life settlement valuation as detailed in an Insurance Studies Institute research brief (2008). The basic assumption of the deterministic pricing model is that in addition to the purchase price, the secondary market purchaser of the life insurance policy continues to pay the policy premiums, conventionally monthly, until the insured’s estimated time of death, which corresponds to the policy owner’s life expectancy. The value of the life settlement is then determined by computing the present value of the policy face value, also named the death benefit, less the total present value of all future premium payments until the estimated time of death. The appropriate discount rate applied to the cash stream, assuming zero credit risk for the insurance company, is the discount rate from the Treasury yield curve, since the risk-free return the investor would have otherwise realized is the corresponding yield from the yield curve.

Consider continuous time $t$ such that $t \in [t_0, \infty)$, whereby $t_0, t_1, t_2, \ldots, t_1, \ldots$ denote monthly separated discrete points along the continuous time line, when the premium payments are made. Then,
Let \( t_0 < t_1 < t_2 < \ldots < t_1 < \ldots \)

Let \( D^E \) denote the estimated time of death, or the life expectancy, and \( D^F \) the last year in which a premium payment is made, \( V_{t_0} \) denote the \( t_0 \) value of the life insurance policy, \( V_{\text{terminal}} \) $ the policy face value, or alternatively the death benefit that will be paid out upon the policy owner’s death, \( A_t \) the monthly premium payment at time \( t \), and \( r_t \) the interest rate at time \( t \).

**Definition** Assuming continuous compounding, the Deterministic Pricing Model is defined as,

\[
V_{t_0} = V_{\text{terminal}} \cdot e^{-\int_{t_0}^{D^E} r(\tau) d\tau} - \sum_{i=0}^{D^F} A_{t_i} \cdot e^{-\int_{t_0}^{t_i} r(\tau) d\tau}
\]  

(1)

The deterministic pricing approach is built on the assumption of equivalence between the expected time of death, \( D^E \), and the actual time of death, \( D \). However, this assumption is a strong and unrealistic one as data on individual hazard curves indicate substantial probability of death occurrence before as well as after the estimated time of death.

Consequently, a probabilistic pricing methodology that takes into account individual hazard curves is more suitable for the valuation of life settlements. The probabilistic approach computes the probability density function of death conditional on survival until the transaction time to assign probabilistic weights to cash flows. In addition to the notation introduced above, let \( \text{pdf}_D(t; C | D \geq t_0) \) be the probability density function of time until death for a person born into a given cohort \( C \) conditional on survival until \( t_0 \).

**Definition** Assuming continuous compounding, the Probabilistic Pricing Model is defined,

\[
V_{t_0} = \int_{t_0}^{\infty} V_{\text{terminal}} \cdot \text{pdf}_D(\tau; C | D \geq t_0) \cdot e^{-\int_{t_0}^{\tau} r_s ds} d\tau - \sum_{i=0}^{D^F} e^{-\int_{t_i}^{t_0} r_s ds} \cdot A_{t_i} \cdot \int_{t_i}^{\infty} \text{pdf}_D(\tau; C | D \geq t_0) d\tau
\]  

(2)

In the Probabilistic Pricing Model, both the cash inflow and outflow are weighted at each time step by the conditional probability density function of time until death and are discounted back to the present using the appropriate discount factor.
**Mortality Forecasting Methods**

With the selection of the appropriate pricing methodology, a mortality forecasting model is needed to describe the conditional probability density function of time until death. In this respect, Lee & Carter (1992) developed a commonly used extrapolative method using statistical time series techniques, in which the mortality level was represented by a single index. The logarithm of the central mortality rate, denoted $m_{x,t}$, is modeled as a linear function of unobserved period-specific intensity index, $k_t$, with parameters dependent on age, $a_x$ and $b_x$.

$$\ln(m_{x,t}) = a_x + b_x k_t + \epsilon_{x,t}$$  \hspace{1cm} (3)

$$m_{x,t} = e^{a_x + b_x k_t + \epsilon_{x,t}}$$  \hspace{1cm} (4)

where $m_{x,t}$ is defined as the percentage of deaths of people aged $x$ last birthday in an average population during calendar year $t$ (Plat, 2007). In the model, $a_x$ is the general shape of the hazard rate across different ages and $b_x$ indicates how different ages react to changes in $k$ such that,

$$\frac{d}{dt} \ln(m_{x,t}) = b_x \cdot \frac{d}{dt} k_t$$  \hspace{1cm} (5)

where $k_t$ is described by a random walk with constant drift.

Lee (2000) identifies that extrapolation may not always be a sensible approach to employ. He argues that the behavior of the mortality index, $k_t$, between 1900 and 1996, the time horizon used in the Lee & Carter model, is not representative of the historical trend and therefore cannot possibly reflect a fundamental property of the mortality change over time. He also points out the Lee-Carter model’s failure to incorporate positive future effects, such as breakthroughs in medical technology, that may accelerate mortality decline.

Renshaw & Haberman (2006) expand on the Lee-Carter model to incorporate cohort effects - effects dependent on year of birth,

$$\ln(m_{x,t}) = a_x + b_1 x \cdot k_t + b_2 x \cdot \gamma_{t-x}$$  \hspace{1cm} (6)

where $\gamma_{t-x}$ is the cohort effect. For countries with observed cohort effects in the past, Renshaw-Haberman model provides a much better fit than the Lee-Carter model.

Cairns et al (2006a) introduce a model of $q_{x,t}$, the initial mortality rate - defined as the probability that a person aged $x$ dies in the next calendar year (Plat, 2007) - with a bivariate ($k_1, k_2$) random walk with drift,

$$\text{logit}(q_{x,t}) = \ln\left(\frac{q_{x,t}}{1 - q_{x,t}}\right) = k_1 t + k_2 (x - x)$$  \hspace{1cm} (7)
where \( \bar{x} \) is the mean age. However, this model is designed for higher ages only, so it yields a poor fit for lower ages and Plat (2007) argues that it results in biologically unreasonable projections.

Further contributions to the field of stochastic mortality forecasting including Renshaw & Haberman 2005, Currie 2006 and Cairns \textit{et al} 2008 allow for phenomena such as cohort effects and introduce further sources of randomness by describing stochastic processes for more parameters in the model for \( \ln(m_x) \). Plat (2007), however, highlights that cohort effects are observed mostly until 1945 since these effects only materialize later in life. Therefore, application of mortality forecasting models with cohort effects results in the projection of the cohort effects for young ages, which can be volatile, into the future. Given the possibly temporary nature of these effects, such as drug and alcohol abuse, it is uncertain whether they are actually persistent into the future.

**Credit Risk and Credit Spread of a Risky Bond**

Quantification of credit risk is essential to accurate defaultable contingent claims analysis. In the case of life settlements, the secondary market purchaser of the life insurance policy is exposed to the default risk of the insurer. Hence, the purchaser of the life settlement needs to be compensated for the credit risk of the insurer with an additional spread over the risk-free yield. There are essentially two approaches to credit risk modeling: (1) Structural Models and (2) Reduced-Form Models. While structural models provide a link between the credit spread and the capital structure of a firm and thus provide an economic intuition for the credit risk, reduced-form models do not provide any such economic intuition and characterize default as a sudden change.

**Structural Model**

One popular structural method for the assessment of credit risk is the Merton model (Merton, 1974). This model is the first structural model that gives firm default an economic intuition and links the default event to underlying firm asset, debt and equity dynamics. Its simplicity, mathematical elegance and fundamental connection to the Black-Scholes equity option pricing framework have fueled Merton model’s widespread use. Current structural methods, those including endogenous default (Leland and Toft, 1996) or proposing jump-diffusion processes to describe the asset value process (Zhou, 1997), are all based on the original paper by Merton.

The model assumes that a firm has a certain amount of zero-coupon debt that will become due at a future time \( T \). Thus, the company defaults if it fails to meet its payment obligation, that is, the value of its assets is less than the
promised debt payment at $T$. In this case, the equity, $E$, of the company becomes a European call option on the assets of the firm with maturity $T$ and strike price equal to the face value of the debt $D$. In the model, the assets, $A$, follow a log-normal diffusion process,

$$dA_t = \mu_A A_t dt + \sigma_A A_t dW$$  \hspace{1cm} (8)

where $\mu_A$ and $\sigma_A$, assumed constant, are the instantaneous rate of return and volatility of the assets respectively and $W$ is a standard Wiener process such that $dW \sim N(0, dt)$.

**Definition** The residual value after the debt repayment is,

$$E_T = \max(A_T - D, 0)$$  \hspace{1cm} (9)

Using the Black-Scholes option pricing formula and assuming constant interest rate $r$, the time $t$ value of the equity, $E_t$, is,

$$E_t = A_t \Phi(d_1) - D e^{-r(T-t)} \Phi(d_2)$$  \hspace{1cm} (10)

$$d_1 = \frac{\ln(A_t e^{r(T-t)}/D)}{\sigma_A \sqrt{T-t}} + \frac{1}{2} \sigma_A \sqrt{T-t} \quad d_2 = d_1 - \sigma_A \sqrt{T-t}$$  \hspace{1cm} (11)

Since, the market value of the firm’s assets, $A_t$, and the instantaneous volatility of assets, $\sigma_A$, are not directly observable, the model estimates $A_t$ and $\sigma_A$ from the market value of the firm’s equity and the equity’s instantaneous volatility using an approach suggested by Jones et al (1984). Since, the equity value is a function of the asset value, Ito’s Lemma can be used to show,

$$E_t \sigma_E = \frac{\partial E}{\partial A} A_t \sigma_A$$  \hspace{1cm} (12)

Since $\frac{\partial E}{\partial A} = \Phi(d_1)$ from Equation (10),

$$[A_t \Phi(d_1) - D e^{-r(T-t)} \Phi(d_2)] \sigma_E = \Phi(d_1) A_t \sigma_A$$  \hspace{1cm} (13)

Then define $L_t$ to be a measure of the leverage of a firm at time $t$ such that,

$$L_t = \frac{D e^{-r(T-t)}}{A_t}$$  \hspace{1cm} (14)

It follows from Equation (13) that,

$$\sigma_E = \frac{\Phi(d_1) \sigma_A}{\Phi(d_1) - L(t) \Phi(d_2)}$$  \hspace{1cm} (15)

Equations (10) and (15) are solved for the two unknowns $A_t$ and $\sigma_A$. 

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To compute the credit spread on the defaultable bond, denoted $s$, we use an accounting identity.

**Definition** The value of a company’s assets at any point equals the sum of its equity value and debt. Let $B_t$ denote the market value of debt at time $t$ and $y$ the bond yield,

$$A_t = E_t + B_t$$

(16)

It follows from Equation (10) that,

$$B_t = A_t - A_t \Phi(d_1) - D e^{-r(T-t)} \Phi(d_2) = A_t \Phi[-d_1] + L_t \Phi(d_2)$$

(17)

Since the time $t$ market value of the debt is defined by its yield such that $B_t = De^{-y(T-t)},$

$$De^{-y(T-t)} e^{-(r-y)(T-t)} = e^{-(r-y)(T-t)} A_t \Phi(-d_1) + L_t \Phi(d_2)$$

(18)

$$De^{-r(T-t)} = e^{-(r-y)(T-t)} A_t \Phi(-d_1) + L_t \Phi(d_2)$$

(19)

$$(r - y)(T - t) = \ln \left\{ \frac{1}{L_t} \Phi(-d_1) + L_t \Phi(d_2) \right\} = \ln \left\{ \frac{\Phi(-d_1)}{L_t} + \Phi(d_2) \right\}$$

(20)

Thus,

$$s = y - r = -\ln \left\{ \frac{\Phi(-d_1)}{L_t} + \Phi(d_2) \right\} \frac{1}{T - t}$$

(21)

**Reduced-Form Model**

**Definition** The default time, $\mathbb{D}$, is the first jump of a Poisson process, so it is exponentially distributed with intensity $\theta$,

$$\mathbb{P} (\mathbb{D} > T) = e^{-\theta(T-t_0)}$$

(22)

A defaultable claim of $1 at time $T$ either pays $1 at time $T$ with a probability $e^{-\theta(T-t_0)}$ or pays nothing due to default with probability $1 - e^{-\theta(T-t_0)}$. If we denote the time zero price of this defaultable claim by $P^c_{(t_0,T)}$, the interest rate by $r$ which is assumed constant and the risk-neutral probability measure by $\mathbb{Q}$, we have

$$P^c_{(t_0,T)} = e^{-r(T-t_0)} \mathbb{E}^Q (1_{[\mathbb{D} > T]})$$

(23)

$$= e^{-r(T-t_0)} [1 \cdot \mathbb{P}^Q (\mathbb{D} > T) + 0 \cdot \mathbb{P}^Q (\mathbb{D} \leq T)] = e^{-r(T-t_0)} [1 \cdot e^{-\theta(T-t_0)}]$$

(24)

$$= e^{-y(T-t_0)} = e^{-(r+\theta)(T-t_0)}$$

(25)
Therefore, the effect of risk of default on the yield of a defaultable contingent claim is to add a spread of $\theta$.

III. Contribution of Financial Literature

My paper aims to construct a simplified mortality forecasting model, similar to the original Lee-Carter model, based on the analysis of $q_{x,t}$ with respect to $x$ for a given year $t = \bar{t}$. Then, $q_{x,\bar{t}}$ is a series of observations of the hazard rate across different age groups $x$ in a given year, $\bar{t}$. Thus, $q_{x,\bar{t}}$ is modeled as an exponential function with two parameters. Using nonlinear least squares regression technique, each parameter is estimated for all the given years to result in two separate time series, which are assumed independent of each other. Each time series is then modeled as a stochastic differential equation, where the drift is parametrized with a deterministic function and the diffusion is described by a mean-reverting Ornstein-Uhlenbeck process, which is the continuous time analog of the discrete time AR(1) process. Then, using the definition of the hazard rate as the ratio of the conditional probability density function of time until death to the survival distribution function, we derive from the hazard rate process, the conditional probability density function of time until death and the cumulative mortality distribution, which are used in the pricing model.

Additionally, my paper intends to investigate the standard assumption of zero correlation between life insurance instruments, specifically the life settlement, and the broader market. In contrast to the claim that “the death benefit is based on the event of death - not a market event” (Weber & Hause, 2008, pp. 66), the death benefit can only be collected if the insurer does not default. Therefore, the policyholder as well as the secondary market purchaser of the life insurance policy are exposed to considerable credit risk through the insurer (Cowley & Cummins, 2005), although almost all life insurance companies have above A rating. Consequently, in a life settlement transaction, the secondary market purchaser of the policy not only prices the conditional probability of death of the policyholder in the future but also the credit risk of the insurer. The inclusion of credit risk has two main consequences. First, an additional credit spread is priced into the discount factor. Second, assuming the stock market performance is an appropriate proxy for the market participants’ reactions to news, the value of the life settlement is positively correlated with the stock market performance through the credit risk of the insurer. Since almost all insurance companies invest in assets and instruments that are readily available in the market, the returns on these assets are linked to the performance of the market. Therefore, while it is not reasonable to expect a strong correlation between the credit spreads and the stock market performance on a daily basis,
in times of unexpectedly strong performances, either in the negative or the positive direction, by the stock market, credit spreads should in theory reflect a movement in the opposite direction as changes in the asset values might affect the companies’ ability to meet their debt repayment obligations.

I aim to quantify the credit risk exposure of the life settlement purchaser via the spot credit spread. The spot credit spread, also termed the Z-spread, is computed by discounting the cash flows of a corporate bond by the spot yield curve and pricing in an additional spread to match the observed bond price.

IV. Theoretical Framework

Mortality Forecasting Model

Modeling $q_{x,t}$ for a given $t = \bar{t}$ as an exponential function, let $\beta^1_t$ and $\beta^2_t$ be two parameters of the exponential hazard rate function $q_{x,t}$

$$q_{x,t} = \beta^1_t e^{\beta^2_t x}$$

where $\beta^1_t$ and $\beta^2_t$ are modeled as two stochastic differential equations whose long term trends are parameterized by deterministic functions of time and non-anticipative error terms described by two independent mean-reverting Ornstein-Uhlenbeck processes.

Definition Let $W^\epsilon_t$ and $W^\xi_t$ be two independent Brownian motions such that $dW^\epsilon_t, dW^\xi_t \sim N(0, dt)$, $\epsilon$ and $\xi$ the errors of the diffusion processes, $g_{\beta_1}(t)$ and $g_{\beta_2}(t)$ the deterministic functions of $t$, $\vartheta$ and $\varphi$ the mean-revision rates $\sigma_{\epsilon}$, $\sigma_{\xi}$ and $\mu_{\epsilon}$, $\mu_{\xi}$ the standard deviations and the means of errors for $\beta^1_t$ and $\beta^2_t$ respectively,

$$d\beta^1_t = d g_{\beta_1}(t) + \vartheta(\mu_{\epsilon} - \epsilon_t)dt + \sigma_{\epsilon} dW^\epsilon_t$$

$$d\beta^2_t = d g_{\beta_2}(t) + \varphi(\mu_{\xi} - \xi_t)dt + \sigma_{\xi} dW^\xi_t$$

For some arbitrary initial point in time, $o$, for which the initial values, $\beta^1_o, g_{\beta_1}(o)$ and $\epsilon_o$, are known,

$$\int_0^t d\beta^1_\tau = \int_0^t d g_{\beta_1}(\tau) + \int_0^t \vartheta(\mu_{\epsilon} - \epsilon_\tau)d\tau + \int_0^t \sigma_{\epsilon} dW^\epsilon_\tau$$

$$\beta^1_t = \beta^1_o + g_{\beta_1}(t) - g_{\beta_1}(o) + \epsilon_o e^{-\vartheta(t-o)} + \mu_{\epsilon}(1 - e^{-\vartheta(t-o)}) + \int_0^t \sigma_{\epsilon} e^{-\vartheta(t-\tau)} dW^\epsilon_\tau$$

and similarly,

$$\int_0^t d\beta^2_\tau = \int_0^t d g_{\beta_2}(\tau) + \int_0^t \varphi(\mu_{\xi} - \xi_\tau)d\tau + \int_0^t \sigma_{\xi} dW^\xi_\tau$$

$$\beta^2_t = \beta^2_o + g_{\beta_2}(t) - g_{\beta_2}(o) + \xi_o e^{-\varphi(t-o)} + \mu_{\xi}(1 - e^{-\varphi(t-o)}) + \int_0^t \sigma_{\xi} e^{-\varphi(t-\tau)} dW^\xi_\tau$$
Since both $dW_t^x$ and $dW_t^y$ are normally distributed, the $\beta_t^1$ and $\beta_t^2$ processes are also normally distributed. Therefore, the exact distributions of the $\beta_t^1$ and $\beta_t^2$ processes are completely described by their expectation and variance,

$$
\mathbb{E}(\beta_t^1) = \beta_0^1 + g_{\beta_t}(t) - g_{\beta_t}(\alpha) + \epsilon_0 e^{-\theta(t-\alpha)} + \mu_e(1 - e^{-\theta(t-\alpha)})
$$

(32)

$$
\text{Var}(\beta_t^1) = \text{Var}(\int_0^t \sigma_e e^{-\theta(t-\tau)} dW_t^e)
$$

(33)

**Lemma 4.1** Variance is defined as,

$$
\text{Var}(X) = \mathbb{E}(X^2) - (\mathbb{E}(X))^2
$$

(34)

**Lemma 4.2** The mean and the variance of the stochastic integral $\int \theta_s dW_s$ are

$$
\mathbb{E}(\int_0^t \theta_s dW_s) = 0
$$

(35)

$$
\mathbb{E}(\int_0^t \theta_s dW_s)^2 = \mathbb{E}(\int_0^t \theta_s^2 ds)
$$

(36)

It follows from Lemma 4.1 and Lemma 4.2 that,

$$
\mathbb{E}(\int_0^t \sigma_e e^{-\theta(t-\tau)} dW_t^e) = 0
$$

(37)

$$
\text{Var}(\int_0^t \sigma_e e^{-\theta(t-\tau)} dW_t^e) = \mathbb{E}\{(\int_0^t \sigma_e e^{-\theta(t-\tau)} dW_t^e)^2\}
$$

$$
= \mathbb{E}\int_0^t \sigma_e^2 e^{-2\theta(t-\tau)} d\tau = \sigma_e^2 e^{-2\theta t} (\frac{e^{2\theta t}}{2\theta} - \frac{e^{2\theta \alpha}}{2\theta})
$$

(38)

$$
= \sigma_e^2 (1 - e^{-2\theta(t-\alpha)}/2\theta)
$$

(39)

(40)

Thus, $\beta_t^1$ is distributed normally,

$$
\beta_t^1 \sim N(\beta_0^1 + g_{\beta_t}(t) - g_{\beta_t}(\alpha) + \epsilon_0 e^{-\theta(t-\alpha)} + \mu_e(1 - e^{-\theta(t-\alpha)}), \sigma_e^2 (1 - e^{-2\theta(t-\alpha)}/2\theta))
$$

**Definition** Let $X$ be a random variable such that $X \sim N(0, 1),

$$
\beta_t^1 = \beta_0^1 + g_{\beta_t}(t) - g_{\beta_t}(\alpha) + \epsilon_0 e^{-\theta(t-\alpha)} + \mu_e(1 - e^{-\theta(t-\alpha)}) + \sigma \sqrt{\frac{1 - e^{-2\theta(t-\alpha)}}{2\theta}} X
$$

(41)

with
Similarly, let $Y$ be a random variable such that $Y \sim N(0,1)$, then

\[ \mathbb{E}(\beta^1_t) = \beta^1_o + g_{\beta_1}(t) - g_{\beta_1}(0) + \varepsilon_o e^{-\theta(t-o)} + \mu_e(1 - e^{-\theta(t-o)}) \]  
\[ \text{Var}(\beta^1_t) = \sigma^2 + \frac{1 - e^{-2\theta(t-o)}}{2\theta} \]  

Lemma 4.3 Let $C$ denote the birth time of the individual. Since age is the difference between the current time and the time of birth,

\[ x = t - C \]

where $C$ is fixed for any given individual.

Lemma 4.4 The hazard rate is defined as,

\[ q_{t;C} = \frac{pdf_{D}(t;C)}{1 - cdf_{D}(t;C)} \]

Proposition 4.5 Let $H(t;C) = 1 - cdf_{D}(t;C)$ and $\frac{\partial}{\partial t}H(t;C) = h(t;C) = -pdf_{D}(t;C)$. It follows from Lemma 4.3 and Lemma 4.4 that,

\[ q_{t;C} = \frac{-h(t;C)}{H(t;C)} \]

Integrating both sides from $C$ to $t$,

\[ - \int_C^t q_{t;C} d\tau = \ln(H(t;C)) \]

Definition The probability density function of death and cumulative probability distribution of death are defined as,

\[ cdf_{D}(t;C) = 1 - e^{-\int_C^t q_{t;C} d\tau} \]
\[ pdf_{D}(t;C) = \frac{\partial}{\partial t}[1 - e^{-\int_C^t q_{t;C} d\tau}] \]

where,
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where $X,Y \sim N(0, 1)$ and $X,Y$ are independent.

**Spot Z-spread**

Using the probabilistic pricing framework introduced previously, we now introduce credit risk into the model. From the perspective of the bank, the credit risk of the insurance company can be quantified with a static spread above the risk-free zero yield curve. The Z-spread is that static spread above the risk-free zero yield curve, which makes the sum of the present value of all the cash flows of the bond equal to its observed market price. In this sense, it is a measure of the company’s default and liquidity risk.

**Definition** Let $r(t)$ be the interest rate at time $t$, $R_{(t_0, t)}$ be the discount factor for a risk-free zero coupon bond maturing at time $t$ as seen from $t_0$ and $S_{t_0}$ be the Z-spread at time $t_0$. The price of a continuously compounded risk-free zero coupon bond paying 1$ at maturity is,

\[ P^g_{(t_0, t)} = e^{-\int_{t_0}^{t} r_s \, ds} \]  

or equivalently,

\[ P^g_{(t_0, t)} = \{ \beta^1_0 + g_{\beta_1}(t) - g_{\beta_1}(0) + \varepsilon_0 e^{-\theta(t-t_0)} + \mu_0 (1-e^{-\theta(t-t_0)}) + \int_{t_0}^{t} \sigma_0 e^{-\theta(t-t_0)} dW^z_t \} \]  

where $X,Y \sim N(0, 1)$ and $X,Y$ are independent.

\[ \text{Lemma 4.6 Each coupon payment, } C_{t_i} \text{ of the coupon bond can be treated as a zero coupon bond with maturity equal to the coupon payment date, } t_i \text{ and face value equal to the coupon it itself.} \]
It follows from Lemma 4.6 that,

\[ P_{(t_0, t_n)} = \sum_{i=1}^{n} C_i e^{-[R(t_0, t_i) + S_0](t_i - t_0)} + F e^{-[R(t_0, t_{max}) + S_0](t_n - t_0)} \]  \tag{57}

The spot Z-spread is the value of \( S_0 \) that makes the right hand side of Equation (57) equal to the observed bond price \( P_{(t_0, t_n)} \).

**The Life Settlement Pricing Model**

**Assumption 4.7** Assume that the only available life insurance contract available in the market is the continuous whole life insurance policy, although in real life there is a wide array of life insurance contracts with different cash flow dynamics.

**Definition** Combining the models and the assumption given above, the life settlement price is defined as the sum of the present values of all cash flows weighted by the conditional probability density function of time until death for an individual born into a cohort \( C \).

\[
V_{t_0} = \int_{t_0}^{\infty} V_{\text{terminal}} \cdot e^{-[R(t_0, \tau) + S_0](\tau - t_0)} \cdot pdf_D(\tau; C|D \geq t_0) \, d\tau \\
- \sum_{i=0}^{\infty} A_{i+1} \cdot e^{-[R(t_0, t_i) + S_0](t_i - t_0)} \cdot \int_{t_i}^{\infty} pdf_D(\tau; C|D \geq t_0) \, d\tau 
\tag{58}
\]

**Lemma 4.8** From the definition of probability density function, for any \( t_0 > C \) and \( t \geq 0 \),

\[
pdf_D(t_0 + t; C|D \geq t_0) = P(t + t_0 \leq D \leq t + t_0 + dt; C|D \geq t_0) 
\]

for some infinitesimally small change \( dt \). Then, from the definition of conditional probability,

\[
P(t + t_0 \leq D \leq t + t_0 + dt; C|D \geq t_0) = \frac{P(t + t_0 \leq D \leq t + t_0 + dt \cap D \geq t_0; C)}{P(D \geq t_0; C)} 
\]

Let \( \omega_1 \) be the event that \( \{ t + t_0 \leq D \leq t + t_0 + dt \} \) and \( \omega_2 \) be the event that \( \{ D \geq t_0 \} \). Since \( \omega_1 \subseteq \omega_2 \), \( \omega_1 \cap \omega_2 = \omega_1 \). Therefore,

\[
\frac{P(t + t_0 \leq D \leq t + t_0 + dt \cap D \geq t_0; C)}{P(D \geq t_0; C)} = \frac{P(t + t_0 \leq D \leq t + t_0 + dt; C)}{P(D \geq t_0; C)} 
\]

which then results in,

\[
pdf_D(t_0 + t; C|D \geq t_0) = \frac{pdf_D(t_0 + t; C)}{1 - cdf_D(t_0; C)} 
\]
It follows from Lemma 4.7 that for any $C \geq t_0 \geq t$, $pdf_D(t; C|D \geq t_0)$ is defined as,

$$pdf_D(t; C|D \geq t_0) = \frac{pdf_D(t; C)}{1 - cdf_D(t_0; C)} \tag{59}$$

$$= q_{t; C} \cdot e^{-\int_0^t q_{t; C} d\tau} \tag{60}$$

$$= q_{t; C} \cdot e^{-\int_q^t q_{t; C} d\tau} \tag{61}$$

Similarly, for any $C \leq t_0 \leq t$, $cdf_D(t; C|D \geq t_0)$ is defined as following,

$$cdf_D(t; C|D \geq t_0) = P(D \leq t; C|D \geq t_0) \tag{62}$$

$$= \frac{P(D \leq t \cap D \geq t_0; C)}{P(D \geq t_0; C)} = \frac{P(t_0 \leq D \leq t; C)}{P(D \geq t_0; C)} \tag{63}$$

$$= \frac{\int_{t_0}^t q_{t; C} \cdot e^{-\int_0^\tau q_{t; C} d\tau} d\tau}{e^{-\int_0^\tau q_{t; C} d\tau}} \tag{64}$$

Thus, we rewrite the pricing model as,

$$V_{t_0} = \int_{t_0}^{\infty} V_{terminal} \cdot e^{-\int_{R(t_0, \tau) + S_0}(\tau-t_0)} \cdot pdf_D(\tau; C|D \geq t_0) d\tau \tag{65}$$

$$- \sum_{i=0}^{\infty} A_t \cdot e^{-\int_{R(t_0, t_i) + S_0}(t_i-t_0)} \cdot \int_{t_i}^{\infty} pdf_D(\tau; C|D \geq t_0) d\tau$$

$$= \int_{t_0}^{\infty} V_{terminal} \cdot e^{-\int_{R(t_0, \tau) + S_0}(\tau-t_0)} \cdot q_{t; C} \cdot e^{-\int_0^\tau q_{t; C} d\tau} \tag{66}$$

$$- \sum_{i=0}^{\infty} A_t \cdot e^{-\int_{R(t_0, t_i) + S_0}(t_i-t_0)} \cdot e^{-\int_0^\tau q_{t; C} d\tau}$$

The hazard rate, $q_{t; C}$, is defined as,

$$q_{t; C} = \left\{ \beta_0 + g_{\beta_1}(t) - g_{\beta_1}(0) + e_0 e^{-\gamma(t-t_0)} + \mu_c(1 - e^{-\gamma(t-t_0)}) + \sigma_c \sqrt{1 - e^{-2\gamma(t-t_0)}} X \right\} \tag{67}$$

$$\cdot e^{-\int_{R(t_0; t-i; C) - g_{\beta_2}(0) + e_0 e^{-\gamma(t-t_0)} + \mu_c(1 - e^{-\gamma(t-t_0)}) + \sigma_c \sqrt{1 - e^{-2\gamma(t-t_0)}} Y}$$

$X, Y \sim N(0, 1)$ and $X, Y$ are independent.

**V. Data**

This paper uses three main sources for data. The mortality data comes from The Human Mortality Database, which contains calculations of death rates and life tables for national populations of more than thirty countries, including the United States, Canada, Australia and the countries of western Europe. We use yearly life tables for the United States covering the years from 1933 until 2006 to model the mortality distributions. Each life table in the da-
The database contains mortality information for every age until 110. Between every two successive ages, the life table includes the central death rate, the probability of death, the number of deaths, the average length of survival for people dying in the interval and the number of survivors at the beginning of the interval.

The yield curve data comes from the U.S. Treasury’s website, which contains the yields on 1-month, 3-month, 6-month, 1-year, 2-year, 3-year, 5-year, 7-year, 10-year, 20-year and 30-year Treasury bonds from 1990 until today on a daily basis. We then fit a Nelson-Siegel function to the observed yields to construct the yield curve.

Finally, the data on the observed bond prices of the insurance company comes from the TRACE (Trade Reporting and Compliance Engine) database. The database contains information on corporate bond transactions of all brokers and dealers who are FINRA (Financial Industry Regulatory Authority) members. The database provides the transaction date, the transaction time, the effective yield to maturity and the price for the selected bond within the chosen time horizon.

VI. Implementation to Data

Mortality Forecasting Model

If we assume that people under the age of thirty are not eligible to enter into a life settlement transaction, it suffices to model hazard rates only for individuals of thirty years or more of age. For a given year \( t = \hat{t} \), we model the hazard rate \( q_{t,c} \) as an exponential function,

\[
q_{t,c} = \beta_1^t e^{\beta_2^t (\hat{t} - c)}
\]

where \( \beta_1^t \) and \( \beta_2^t \) are two time dependent parameters and can be estimated for a given year by non-linear least squares regression. For \( t = 2006 \), the plot of \( q_{2006,c} \) yields,
Estimating the two parameters $\beta^1_t$ and $\beta^2_t$ for all the years in which hazard rate observations are available results in a collection of random variables over time $\{\beta^1_t, \beta^2_t : t \in [o, \infty)\}$, which can be described by two stochastic differential equations. The plot of $\{\beta^1_t\}$ against $t$ yields,
The plot shows random mean-reverting fluctuations around a long term deterministic trend.

**Assumption 6.1** We model the change in $\beta_1^t$ as a change in a deterministic function of time with errors following a mean-reverting Ornstein-Uhlenbeck process,

$$d\beta_1^t = dg_\beta(t) + \vartheta(\mu_c - \epsilon_1)dt + \sigma_\epsilon dW^\tau_t$$  \hspace{1cm} (69)

The solution to this stochastic differential equation is,

$$\beta_1^t = \beta_0^1 + g_\beta(t) - g_\beta(0) + \epsilon_1 e^{-\vartheta(t_0)} + \mu_\epsilon(1 - e^{-\vartheta(t_0)}) + \int_0^t \sigma_\epsilon e^{-\vartheta(t-\tau)} dW^\tau_\tau$$  \hspace{1cm} (70)

**Assumption 6.2** The deterministic part of the function is modeled as an exponential function,

$$g_\beta(t) = \gamma_1 e^{\gamma_2 t}$$  \hspace{1cm} (71)

where $\gamma_1 = 0.0021$ and $\gamma_2 = -0.0271$ by non-linear least squares regression.

**Assumption 6.3** The residuals are modeled as an Ornstein-Uhlenbeck process,
\[ \epsilon_{t+dt} = \epsilon_t e^{-\vartheta t} + \mu_e (1 - e^{-\vartheta dt}) + \sigma_e \sqrt{\frac{1 - e^{-2\vartheta dt}}{2\vartheta}} X \]  

(72)

where \( X \sim N (0, 1) \).

The three parameters, \( \vartheta \) the mean-reversion rate, \( \mu_e \) the mean error value and \( \sigma_e \) the standard deviation of error terms are estimated using the maximum likelihood estimation methodology. After much algebraic manipulation, details of which are given in the appendix, the following solutions are achieved for \( \mu_e, \sigma_e \) and \( \vartheta \):

\[
\mu_e = \frac{\sum_{i=1}^{n} \epsilon_{t_i} \sum_{i=1}^{n} \epsilon_{t_{i-1}} - \sum_{i=1}^{n} \epsilon_{t_{i-1}} \sum_{i=1}^{n} \epsilon_{t_i}}{n(\sum_{i=1}^{n} \epsilon_{t_{i-1}}^2 - \sum_{i=1}^{n} \epsilon_{t_{i-1}} \epsilon_{t_i}) - [\sum_{i=1}^{n} \epsilon_{t_{i-1}}^2]^2 - \sum_{i=1}^{n} \epsilon_{t_{i-1}} \sum_{i=1}^{n} \epsilon_{t_i}]}
\]

(73)

\[
\sigma_e = \frac{2\vartheta}{n(1 - e^{-2\vartheta dt})} \left[ \sum_{i=1}^{n} \epsilon_{t_i}^2 - 2e^{-\vartheta dt} \sum_{i=1}^{n} \epsilon_{t_i} \epsilon_{t_{i-1}} + e^{-2\vartheta dt} \sum_{i=1}^{n} \epsilon_{t_{i-1}}^2 \right]
\]

(74)

\[
\vartheta = -\frac{1}{dt} \ln \left\{ \frac{\sum_{i=1}^{n} \epsilon_{t_{i-1}} \epsilon_{t_i} - \mu_e \sum_{i=1}^{n} \epsilon_{t_{i-1}} - \mu_e \sum_{i=1}^{n} \epsilon_{t_i} + n \mu_e^2}{\sum_{i=1}^{n} \epsilon_{t_{i-1}}^2 - 2\mu_e \sum_{i=1}^{n} \epsilon_{t_{i-1}} + n \mu_e^2} \right\}
\]

(75)

This maximum likelihood estimators for \( \mu_e, \sigma_e \) and \( \vartheta \) are \(-8.0322 \cdot 10^{-5}\), \(5.1223 \cdot 10^{-4}\) and \(0.0244\) respectively. Thus,

\[
\beta_1^t = \gamma_1 e^{\gamma_2 (t - \vartheta)} + e_{t-\vartheta} (t - \vartheta) + \mu_e (1 - e^{-\vartheta t}) + \sigma_e \sqrt{\frac{1 - e^{-2\vartheta (t-\vartheta)}}{2\vartheta}} X
\]

(76)

where \( X \sim N (0, 1) \). Similarly, the plot of \( \{\beta_2(t)\} \) against \( t \) yields,
Assumption 6.4 We model the change in $\beta_2 t$ as a change in a deterministic function of time with errors following a mean-reverting Ornstein-Uhlenbeck process,

$$d\beta_2^2 = dg_{\beta_2}(t) + \phi(\mu_\varepsilon - \varepsilon_t)dt + \sigma_\varepsilon dW^\varepsilon_t$$  \hspace{2cm} (77)

The solution of this stochastic differential equation is,

$$\beta_2^2 = \beta_2^2(o) + g_{\beta_2}(o) + \varepsilon_0 e^{-\phi(t-o)} + \mu_\varepsilon(1 - e^{-\phi(t-o)}) + \int_o^t \sigma_\varepsilon e^{-\phi(t-\tau)}dW^\varepsilon_\tau$$  \hspace{2cm} (78)

Assumption 6.5 The deterministic part of the function has the form,

$$g_{\beta_2}(t) = \alpha_1 + \alpha_2 t$$ \hspace{2cm} (79)

where $\alpha_1 = 0.0505$ and $\alpha_2 = 0.0003$ by ordinary least squares regression.

Assumption 6.6 The residuals are then modeled as a mean-reverting Ornstein-Uhlenbeck process.
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where \( Y \sim N(0, 1) \).

Using maximum likelihood estimation, the three parameters \( \mu, \sigma \), and \( \varphi \) are 1.2120, 2.6502 \( \cdot 10^{-4} \) and 2.3015 \( \cdot 10^{-4} \). Thus,

\[
\beta_1^2 = \alpha_2(t - \alpha) + \epsilon_0 e^{-\varphi(t-\alpha)} + \mu_\epsilon (1 - e^{-\varphi(t-\alpha)}) + \sigma_\epsilon \sqrt{\frac{1 - e^{-2\varphi(t-\alpha)}}{2\varphi}} Y
\]

where \( Y \sim N(0, 1) \).

**Definition** The hazard rate model is,

\[
q_{t:C} = \beta_1^1 e^{\beta_1^2(t-C)}
\]

Substituting in the expressions for \( \beta_1^1 \) and \( \beta_1^2 \),

\[
q_{t:C} = (\gamma_1 e^{\gamma_2(\epsilon^t - \epsilon^\alpha)} + \epsilon_0 e^{-\varphi(t-\alpha)} + \mu_\epsilon (1 - e^{-\varphi(t-\alpha)}) + \sigma_\epsilon \sqrt{\frac{1 - e^{-2\varphi(t-\alpha)}}{2\varphi}} Y
\]

where \( \gamma_1 = 0.0021, \gamma_2 = -0.0271, \mu_\epsilon = -8.0322 \cdot 10^{-5}, \sigma_\epsilon = 5.1223 \cdot 10^{-5}, \varphi = 0.0244, \alpha_1 = 0.0505, \alpha_2 = 0.0003, \mu = 1.2120, \sigma = 2.6502 \cdot 10^{-4} \) and \( \varphi = 2.3015 \cdot 10^{-4} \).

The unconditional probability density function of time until death, \( pdf_D(t; C) \) and the cumulative probability distribution of death, \( cdf_D(t; C) \), are defined as,

\[
pdf_D(t; C) = q_{t:C} \cdot e^{-\int_C t q_{\tau:C} d\tau}
\]

\[
cdf_D(t; C) = 1 - e^{-\int_C t q_{\tau:C} d\tau}
\]

The simulation of the \( pdf_D(t; C) \) against \( t \) for the 1970 cohort, \( C = 1970 \) yields,
Since \( q_{t:C} \) is a function of time \( t \) with two normally distributed random variables \( X, Y \), we can compute both its expected value and its variance. We therefore know the entire distribution of \( q_{t:C} \) at any \( t \) for any given cohort \( C \). Although there is an entire distribution of the \( q_{t:C} \), the best estimate of the actual distribution of \( q_{t:C} \) is its expected value at any \( t \).

**Definition** Let,

\[
\begin{align*}
  u(t) &= \gamma_1 e^{\alpha t} (e^t - e^o) + \epsilon_0 e^{-\beta(t-o)} + \mu_c (1 - e^{-\beta(t-o)}) + \sigma_e \sqrt{\frac{1 - e^{-2\beta(t-o)}}{2\beta}} X \\
  v(t, C) &= e^{(t-C)(\alpha_2(t-o) + \epsilon_2 e^{-\beta(t-o)} + \mu_c (1 - e^{-\beta(t-o)}) + \sigma_e \sqrt{\frac{1 - e^{-2\beta(t-o)}}{2\beta}} Y}
\end{align*}
\]  

**Lemma 6.7** For two independent random variables \( A \) and \( B \),

\[
E(f(A)g(B)) = E(f(A))E(g(B))
\]  

Since \( X, Y \) are independent, it follows from Lemma 6.7 that,

\[
E(q_{t:C}) = E(u(t)v(t, C)) = E(u(t))E(v(t, C))
\]  

where,
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\[ \mathbb{E}(u(t)) = \gamma_1 e^{\gamma_2 (e^t - e^0)} + \epsilon_o e^{-\theta (t-o)} + \mu_e (1 - e^{-\theta (t-o)}) \] (90)

\[ \mathbb{E}(v(t, C)) = e^{(t-C)(\alpha_2(t-o) + \epsilon_o e^{-\psi(t-o)} + \mu_e (1 - e^{-\psi(t-o)}) + \frac{1}{2} (t-C)^2 \sigma_2^2 \frac{1-e^{-2\psi(t-o)}}{2 \varphi}} \] (91)

Therefore,

\[ \mathbb{E}(q_{t, C}) = \left[ \gamma_1 e^{\gamma_2 (e^t - e^0)} + \epsilon_o e^{-\theta (t-o)} + \mu_e (1 - e^{-\theta (t-o)}) \right] e^{(t-C)(\alpha_2(t-o) + \epsilon_o e^{-\psi(t-o)} + \mu_e (1 - e^{-\psi(t-o)}) + \frac{1}{2} (t-C)^2 \sigma_2^2 \frac{1-e^{-2\psi(t-o)}}{2 \varphi}} \] (92)

The plot of pdf\(_D(t; C)\) based on \( \mathbb{E}(q_{t, C}) \) against \( t \) for the 1970 cohort, \( C = 1970 \) yields,

![Plot of pdf\(_D(t; C)\) based on \( \mathbb{E}(q_{t, C}) \) against \( t \) for the 1970 cohort, \( C = 1970 \).](image)

Thus, we can now compute the mortality density function of any individual belonging to a certain cohort \( C \) to be used in the pricing model.

**VII. Results**

In this section, we first explore the distribution of life settlement prices with respect to the underlying stochastic distributions of the hazard function, the probability density function and the cumulative distribution function of death. Secondly, we analyze the sensitivity of life settlements to changes in the independent variables. In this respect, we price whole life insurance policies.
covering individuals of different cohort groups to investigate the relationship of life settlement values to cohort groups. We, then, investigate the premium, interest rate and credit spread sensitivities of life settlements for different cohort groups. We finally discuss the relationship between credit spreads and the stock market performance to understand how life settlement prices may be correlated to stock market.

To price life settlements, we have gathered the following whole life insurance policy quotes from Prudential Financial Inc.:

<table>
<thead>
<tr>
<th>Coverage</th>
<th>Purchase Age</th>
<th>Monthly Premium</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1,000,000</td>
<td>40</td>
<td>$706</td>
</tr>
<tr>
<td>$1,000,000</td>
<td>45</td>
<td>$893</td>
</tr>
<tr>
<td>$1,000,000</td>
<td>50</td>
<td>$1156</td>
</tr>
<tr>
<td>$1,000,000</td>
<td>55</td>
<td>$1469</td>
</tr>
<tr>
<td>$1,000,000</td>
<td>60</td>
<td>$1942</td>
</tr>
<tr>
<td>$1,000,000</td>
<td>65</td>
<td>$2605</td>
</tr>
</tbody>
</table>

For the following analyses, we select the transaction date to be April 09, 2010, the policy purchase age to be 40 and the premium size to be $\$706$ for all cohorts considered.

**Life Settlement Sensitivity to Underlying Distributions**

In pricing life settlements, assumptions are made regarding the distributions of the underlying hazard function, the probability density function and the cumulative distribution function of death to compute the probability of death occurrence at each instant of time and value the cash flows generated by the life settlement. Since these underlying probability distributions are themselves stochastic, they assume different values with corresponding probabilities. Therefore, it is important to analyze how the life settlement prices are distributed with respect to different underlying probability distributions. To analyze this, we run a Monte-Carlo simulation of the different values the underlying distributions can assume and look at the distribution of the life settlement prices with the above assumptions.
The QQ-plot and the normal probability plot suggest that the life settlement prices are normally distributed. To measure the variance of the distribution, we fit a normal distribution to the distribution of life settlement prices using maximum likelihood estimation.

**Definition** Let \( \mu_{V_0} \) and \( \sigma_{V_0} \) be the mean and the standard deviation of the distribution of life settlement prices. Then, \( V_0 \) is distributed such that,

\[
V_0 \sim N(249, 970, 4066)
\]  

(93)

where the 95% confidence intervals for \( \mu_{V_0} \) and \( \sigma_{V_0} \) are,

\[
\mu_{V_0} \in [249, 610, 250, 330] \quad \text{and} \quad \sigma_{V_0} \in [3829, 4335]
\]  

(94)

In general, while one can use the expected distributions of the underlying probability distributions to price the life settlement, it is also desirable to determine the distribution of life settlement prices, using a Monte-Carlo simulation methodology, to measure the sensitivity of the life settlement prices to the underlying distributions.
**Cohort Sensitivity of Life Settlements**

Since the probability of death occurrence at any future age is higher conditional upon survival until a higher age, \( \mathbb{P}(D = t' + t | D \geq t') > \mathbb{P}(D = t_0 + t | D \geq t_0) \) for any \( t' > t_0 \), it is natural to expect that the secondary market price of the life insurance policy will be higher for individuals who are older at the time of the sale. With higher probability of death occurrence, there is also a higher probability of the secondary market purchaser receiving the terminal payoff, \( V_{\text{terminal}} \), and a lower probability of making the monthly premium payments, \( A_t \).

Consequently, the expected present value of the cash inflow - the terminal payoff \( V_{\text{terminal}} \) - increases while the expected present value of the cash outflow - the premium payments \( A_t \) - decreases, leading to an overall increase in the expected net present value of the cash flows, \( V_{t_0} \).

The plot of the life settlement price, \( V_{t_0} \), against the cohort of the policy owner, \( C \), for policy purchase age of 40 and monthly premium payment of $706 yields,

![Plot of life settlement price against cohort](image)

As expected, the model predicts that the life settlement price, \( V_{t_0} \), quickly goes towards zero as the policy owner’s age at the time of the sale converges to...
wards the policy purchase age.

**Premium Sensitivity of The Life Settlements**

Since the cash outflow is completely determined by the monthly premium payments, the secondary market price of the life insurance policy is expected to be inversely related to the size of the monthly premium payments. The plot of the life insurance settlement price, $V_{t_0}$, against monthly premium payments, $A_t$, for different cohort groups, $C$, yields,

It appears that the sensitivity of the life settlement price, $V_{t_0}$, to the premium size increases in reverse proportion to the age of the policy owner at the time of the sale. From the model, the sensitivity of the life settlement price to the premium size is simply the partial derivative of the life settlement price with respect to the premium,

\[
\frac{\partial V_{t_0}}{\partial A_t} = \frac{\partial}{\partial A_t} \left\{ -\sum_{i=0}^{\infty} A_t e^{-[R_{t_0,i}+S_0 ](t_i-t_0)} \int_{t_i}^{\infty} p(D;C|D \geq t_0) d\tau \right\} \tag{95}
\]

\[
= -\sum_{i=0}^{\infty} e^{-[R_{t_0,i}+S_0 ](t_i-t_0)} \int_{t_i}^{\infty} p(D;C|D \geq t_0) d\tau \tag{96}
\]
Since the $e^{-[R(t_i,t_0)+S_0](t_i-t_0)}$ term is constant, let $c_i$ denote it,

\[
\frac{\partial V_{t_i}}{\partial A_{t_i}} = -\sum_{i=0}^{\infty} c_i \int_{t_i}^{\infty} pdf_D(\tau;C|D \geq t_0) d\tau
\]  

(97)

By Lemma 4.7 in Section 4.4,

\[
\frac{\partial V_{t_i}}{\partial A_{t_i}} = -\sum_{i=0}^{\infty} c_i \int_{t_i}^{\infty} \frac{pdf_D(\tau;C)}{1 - cd(D(t_0;C))} d\tau
\]  

(98)

\[
= -\sum_{i=0}^{\infty} \frac{c_i}{1 - cd(D(t_0;C))} \int_{t_i}^{\infty} pdf_D(\tau;C) d\tau
\]  

(99)

\[
= -\sum_{i=0}^{\infty} \frac{c_i}{1 - cd(D(t_0;C))} \int_{t_i}^{\infty} pdf_D(\tau;C) d\tau
\]  

(100)

\[
= -\sum_{i=0}^{\infty} e^{-[R(t_i,t_0)+S_0](t_i-t_0)} \frac{1 - cd(D(t_0;C))}{1 - cd(D(t_0;C))}
\]  

(101)

Since $cd(D(t_i;C))$ is lower for lower ages, $\frac{\partial V_{t_i}}{\partial A_{t_i}}$ is greater in the absolute sense and therefore a given change in the premium size, $\Delta A_{t_i}$, leads to a bigger change in the life settlement price $\Delta V_{t_i}$, which creates the observed convexity of the premium sensitivity plot of life settlements.

**Interest Rate Sensitivity of Life Settlements**

We define the interest rate sensitivity of the life settlement as the change in the life settlement value for a given parallel shift of the entire spot yield curve. For an insurance policy owner born into the 1950 cohort with policy purchase age of 40 and monthly premium payment of $706, the plot of the interest rate sensitivity of the life settlement yields,
The life settlement is highly sensitive to interest rates as the life settlement’s value declines by as much as 7.2% in response to a parallel shift of the yield curve by 50 basis points.

\[ V_{t_0} \text{ is given by,} \]

\[ V_{t_0} = \int_{t_0}^{\infty} \text{V}_{\text{terminal}} \cdot e^{-\left[R_{(t_0, \tau)} + S_0 \right](\tau - t_0)} \cdot \text{pdf}_D(\tau; C|D \geq t_0) d\tau - \sum_{i=0}^{\infty} A_{t_i} \cdot e^{-\left[R_{(t_0, t_i)} + S_0 \right](t_i - t_0)} \int_{t_i}^{\infty} \text{pdf}_D(\tau; C|D \geq t_0) d\tau \]  

(102)

Then for \( t > t_0 \)

\[ \frac{\partial V_{t_0}}{\partial R(t_0, \tau)} = - \int_{t_0}^{\infty} \text{V}_{\text{terminal}} \cdot e^{-\left[R_{(t_0, \tau)} + S_0 \right](\tau - t_0)} \cdot (\tau - t_0) \cdot \text{pdf}_D(\tau; C|D \geq t_0) d\tau + \sum_{i=0}^{\infty} A_{t_i} \cdot e^{-\left[R_{(t_0, t_i)} + S_0 \right](t_i - t_0)} \cdot (t_i - t_0) \int_{t_i}^{\infty} \text{pdf}_D(\tau; C|D \geq t_0) d\tau \]  

(103)

which is the sum of the time weighted present values of the cash flows in the life settlement transaction.
Lemma 7.1 For bonds, Macaulay duration, $D$, is defined as the relative present value weighted time to receive each cash flow,

$$D = \frac{1}{V} \sum_{i=1}^{n} P(i) t(i)$$  \hspace{1cm} (104)

Duration is also a measure of how the value $V$ of a bond changes in relation to parallel shifts of the yield curve,

$$\frac{\partial V}{\partial R} = -D \cdot V$$ \hspace{1cm} (105)

ignore convexity.

Thus, it is possible to define a duration for the life settlement in much the same way. If we let $D_{LS}$ denote the duration of the life settlement,

$$D_{LS} = -\frac{1}{V_{t_0}} \cdot \frac{\partial V_{t_0}}{\partial R_{(t_0,t)}}$$ \hspace{1cm} (106)

where $V_{t_0}$ and $\frac{\partial V_{t_0}}{\partial R_{(t_0,t)}}$ are defined as shown above. Then,

$$\frac{\Delta V_{t_0}}{V_{t_0}} = -D_{LS} \cdot \Delta R$$ \hspace{1cm} (107)

Corollary to the interest rate sensitivity of the life settlement, the same formula can be used to measure the Z-spread sensitivity of the life settlement. Since the discount factor is composed of both the yield curve and the Z-spread, a change in either one of the terms results in a change of the discount factor.

Lemma 7.2 Let $\psi$ denote the discount factor such that $\psi_{(t_0,t)} = R_{(t_0,t)} + S_{t_0}$. Then the total differential of $\psi_{(t_0,t)}$ is,

$$d\psi_{(t_0,t)} = dR_{(t_0,t)} + dS_{t_0}$$ \hspace{1cm} (108)

Definition Using the duration concept introduced above, let $D_{GLS}$ denote generalized duration,

$$D_{GLS} = -\frac{1}{V_{t_0}} \cdot \frac{\partial V_{t_0}}{\partial \psi_{(t_0,t)}}$$ \hspace{1cm} (109)

with,

$$\frac{\partial V_{t_0}}{\partial R_{(t_0,t)}} = \frac{\partial V_{t_0}}{\partial \psi_{(t_0,t)}} \cdot \frac{\partial \psi_{(t_0,t)}}{\partial R_{(t_0,t)}}$$
$$\frac{\partial V_{t_0}}{\partial S_{t_0}} = \frac{\partial V_{t_0}}{\partial \psi_{(t_0,t)}} \cdot \frac{\partial \psi_{(t_0,t)}}{\partial S_{t_0}}$$ \hspace{1cm} (110)
If we apply this new definition to measure the sensitivity of the life settlement to the discount factor,

$$\frac{\partial V_t}{V_t} = -D^{GLS} \cdot \Delta \psi$$  \hspace{1cm} (111)

VIII. Conclusion

As seen from the results section, the life settlement price is highly sensitive to the cohort of the policy owner and to changes in the yield curve. The cohort of the policy owner affects the distribution of the conditional probability density function of time until death and thus determines the weighting of the cash flows. It is therefore important that the modeling of the conditional probability density function of time until death be as robust as possible. Similarly, a model of the yield curve dynamics may be useful in predicting particularly opportune moments to purchase a life settlement. The credit spread model, though not directly applicable to the spot pricing of the life settlement, is helpful in conveying qualitative information about the investors’ credit risk exposure through the life settlement transaction. Also, the implementation of the credit spread model to MetLife Inc. reveals a correlation of 0.5 between the credit spread volatility of MetLife and that of S&P 500, thus challenging the claim by Weber & Hause that a life insurance policy is uncorrelated against almost any other asset class.

The main shortcoming of this paper is its neglect of potential adverse selection. Adverse selection in life settlements may occur due to asymmetric information access between the investor and the policy owner. The policy owner might have information about his health, lifestyle or other factors that may affect his individual conditional probability density function of time until death that the investor might not have access to. It is therefore reasonable to expect that majority of the life insurance policy owners, who create the supply side of the life settlement market, have a certain motivation to sell their policies, other than their financial inability to meet their obligation to make premium payments. In this sense, the life settlement market may resemble the classic lemons market. Taking this information asymmetry into consideration, investors wishing to purchase life settlements should in fact price an additional “information asymmetry premium” into their valuation. Another shortcoming is the limitation on the type of life insurance policy analyzed in this paper. The assumption of continuous whole life insurance policy with fixed premia payments calls for modifications of the model to account for different life insurance contracts and payment patterns.

A technical shortcoming of the model is its assumption of independence
between the Brownian Motions driving the two parameters that describe the exponential distribution of the hazard function. The immediate remedy to this problem seems to be the introduction of correlation into the model to make it more realistic. This expansion of the model, however, is sure to bring additional mathematical complications. Finally, the credit spread model is defined as a mean reverting AR(1) process with a pure stochastic volatility model. While mean-reversion is a reasonable choice, as evidenced by its heavy use in the literature, the pure stochastic volatility model does not provide any economic intuition about the source of the volatility. One may therefore try to regress historical credit spread data on other economic variables such as inflation, growth, stock market performance, etc. to find an economic reasoning for the volatility. Alternatively, one may use a Markov chain to create a regime-switching volatility model (Hamilton, 1989) to account for high and low volatility periods.

Besides technical precision, one should not ignore the role of psychological factors in the development of the life settlement industry. The description of life settlements as “macabre investments” by BusinessWeek (2007) indicates the shocking novelty of the proposed investment vehicle and the unpreparedness of investors for such an instrument. Introduction of death bonds will definitely raise ethical issues and the market may grow at a slower pace than anticipated. However, this shock will eventually wane with the instrument’s continued presence in the capital markets and institutions will incorporate life settlements into their array of investment tools.
On Life Settlement Pricing

References


Human Mortality Database provides detailed mortality and population data to researchers, students, journalists, policy analysts, and others interest in the history of human longevity (www.mortality.org)


As mentioned in subsection 6.1 under Assumption 6.3, the residuals are modeled as an Ornstein-Uhlenbeck process with,

$$
\epsilon_{t+dt} = \epsilon_t e^{-\theta dt} + \mu_\epsilon \left(1 - e^{-\theta dt}\right) + \sigma_\epsilon \sqrt{\frac{1 - e^{-2\theta dt}}{2\theta}} X, \quad X \sim N(0, 1)
$$

(112)

Since $X$ is normally distributed,

$$
\mathbb{E}(\epsilon_t | \epsilon_{t-dt}; \mu_\epsilon, \sigma_\epsilon, \vartheta) = \epsilon_{t-dt} e^{-\theta dt} + \mu_\epsilon (1 - e^{-\theta dt})
$$

(113)

$$
\text{Var}(\epsilon_t | \epsilon_{t-dt}; \mu_\epsilon, \sigma_\epsilon, \vartheta) = \sigma_\epsilon^2 \frac{1 - e^{-2\theta dt}}{2\theta}
$$

(114)

Therefore, the conditional probability distribution of $\epsilon_t$ given $\epsilon_{t-dt}$ is,

$$
f(\epsilon_t | \epsilon_{t-dt}; \mu_\epsilon, \sigma_\epsilon, \vartheta) = \frac{1}{\sqrt{2\pi \sigma_\epsilon^2 1 - e^{-2\theta dt}}} e^{-\frac{(\epsilon_t - \epsilon_{t-dt} e^{-\theta dt} - \mu_\epsilon (1 - e^{-\theta dt}))^2}{2\sigma_\epsilon^2 1 - e^{-2\theta dt}}}
$$

(115)

**Definition** Then, the log-likelihood function of a sequence of observations $(\epsilon_t, \epsilon_{t+1}, \ldots, \epsilon_{t_n})$, where $\epsilon_t - \epsilon_{t-1} = dt$ is,

$$
\mathcal{L}(\mu_\epsilon, \sigma_\epsilon, \vartheta) = \sum_{i=1}^{n} \ln(f(\epsilon_t | \epsilon_{t-1}; \mu_\epsilon, \sigma_\epsilon, \vartheta))
$$

(116)

$$
= -\frac{n}{2} \ln(2\pi) - n \cdot \ln(\sigma_\epsilon \sqrt{\frac{1 - e^{-2\theta dt}}{2\theta}}) - \frac{\vartheta}{\sigma_\epsilon^2 (1 - e^{-2\theta dt})} \sum_{i=1}^{n} (\epsilon_t - \epsilon_{t-1} e^{-\theta dt} - \mu_\epsilon (1 - e^{-\theta dt}))^2
$$

(117)

Taking the partial derivatives with respect to each parameter and setting them equal to zero,

$$
\frac{\partial \mathcal{L}(\mu_\epsilon, \sigma_\epsilon, \vartheta)}{\partial \mu_\epsilon} = \frac{2\vartheta}{\sigma_\epsilon^2 (1 - e^{-2\theta dt})} \sum_{i=1}^{n} (\epsilon_t - \epsilon_{t-1} e^{-\theta dt} - \mu_\epsilon (1 - e^{-\theta dt})) = 0
$$

(118)

Since $\vartheta \neq 0$, the above expression equals zero only if the sum term equals zero,

$$
\sum_{i=1}^{n} (\epsilon_t - \epsilon_{t-1} e^{-\theta dt} - \mu_\epsilon (1 - e^{-\theta dt})) = 0
$$

(119)

Solving the above expression for $\mu_\epsilon$,
\[
\mu_\varepsilon = \frac{\sum_{i=1}^{n} [\epsilon_{t_i} - \epsilon_{t_{i-1}} e^{-\vartheta dt}]}{n (1 - e^{-\vartheta dt})}
\]  

(120)

To compute for \(\sigma_\varepsilon\),

\[
\frac{\partial \mathcal{L}(\mu_\varepsilon, \sigma_\varepsilon, \vartheta)}{\partial (\sigma_\varepsilon \sqrt{\frac{1-e^{-2\vartheta dt}}{2\sigma_\varepsilon}})} = \frac{n}{\sigma_\varepsilon \sqrt{\frac{1-e^{-2\vartheta dt}}{2\sigma_\varepsilon}}} \frac{\sum_{i=1}^{n} \left(\epsilon_{t_i} - \mu_\varepsilon - e^{-\vartheta dt} (\epsilon_{t_{i-1}} - \mu_\varepsilon)\right)^2}{\sigma_\varepsilon^3 (\frac{1-e^{-2\vartheta dt}}{2\sigma_\varepsilon})^{3/2}} = 0
\]  

(121)

Solving for \(\sigma_\varepsilon\) yields,

\[
\sigma_\varepsilon^2 = \frac{2\vartheta \sum_{i=1}^{n} [\epsilon_{t_i} - \mu_\varepsilon - e^{-\vartheta dt} (\epsilon_{t_{i-1}} - \mu_\varepsilon)]^2}{n (1 - e^{-2\vartheta dt})}
\]  

(122)

Finally, to compute for \(\vartheta\),

\[
\frac{\partial \mathcal{L}(\mu_\varepsilon, \sigma_\varepsilon, \vartheta)}{\partial \vartheta} = -\frac{e^{-\vartheta dt}}{\sigma_\varepsilon^2 (1-e^{-2\vartheta dt})} \sum_{i=1}^{n} (\epsilon_{t_i} - \mu_\varepsilon) (\epsilon_{t_{i-1}} - \mu_\varepsilon) - e^{-\vartheta dt} (\epsilon_{t_{i-1}} - \mu_\varepsilon)^2 = 0
\]  

(123)

Solving the above expression for \(\vartheta\),

\[
\vartheta = -\frac{1}{\Delta t} \ln \left\{ \frac{\sum_{i=1}^{n} (\epsilon_{t_i} - \mu_\varepsilon) (\epsilon_{t_{i-1}} - \mu_\varepsilon)}{\sum_{i=1}^{n} (\epsilon_{t_{i-1}} - \mu_\varepsilon)^2} \right\}
\]  

(124)

Using algebraic manipulations, the solutions for \(\mu_\varepsilon\), \(\sigma_\varepsilon\) and \(\vartheta\) are,

\[
\mu_\varepsilon = \frac{\sum_{i=1}^{n} \epsilon_{t_i} - \sum_{i=1}^{n} \epsilon_{t_{i-1}} \epsilon_{t_i}}{n (\sum_{i=1}^{n} \epsilon_{t_{i-1}} e^{-\vartheta dt} + \sum_{i=1}^{n} \epsilon_{t_i} e^{-\vartheta dt} - \sum_{i=1}^{n} \epsilon_{t_{i-1}} \epsilon_{t_i})}
\]  

(125)

\[
\sigma_\varepsilon = \frac{2\vartheta}{n(1-e^{-2\vartheta dt})} \left[ \sum_{i=1}^{n} \epsilon_{t_i}^2 - 2\vartheta (\sum_{i=1}^{n} \epsilon_{t_i} \epsilon_{t_{i-1}} + e^{-\vartheta dt} \sum_{i=1}^{n} \epsilon_{t_i}^2) - 2(\sum_{i=1}^{n} \epsilon_{t_{i-1}} e^{-\vartheta dt})^2 - 2n \mu_\varepsilon^2 (1-e^{-2\vartheta dt}) \right]
\]  

(126)

\[
\vartheta = -\frac{1}{\Delta t} \ln \left\{ \frac{\sum_{i=1}^{n} \epsilon_{t_{i-1}} \epsilon_{t_i} - \mu_\varepsilon \sum_{i=1}^{n} \epsilon_{t_{i-1}} - \mu_\varepsilon \sum_{i=1}^{n} \epsilon_{t_i} + n \mu_\varepsilon^2}{\sum_{i=1}^{n} \epsilon_{t_{i-1}}^2 - 2\mu_\varepsilon \sum_{i=1}^{n} \epsilon_{t_{i-1}} + n \mu_\varepsilon^2} \right\}
\]  

(127)
Effects of Green Business on Firm Value

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Abstract

This event study tests the impact corporate environmental announcements have on the financial valuation of a firm. The research looks at the set of companies listed in the Dow Jones Industrial Average from 1998 through 2008. Public environmental announcements made by each of the companies were tracked over time using two major news sources, The Wall Street Journal and The New York Times. An event study performed on both positive and negative announcements allows a better understanding of how investors react to different types of environmental news. While the study found that the abnormal returns of positive announcements had no statistical significance, the study analysis attempts to develop a better understanding of why firms would choose to undertake positive environmental policies.

¹ Submitted under the faculty supervision of Professor Alfred Marcus, in partial fulfillment of the requirements for the Bachelor of Science in Business degree, summa cum laude, Department of Finance, Carlson School of Management, University of Minnesota, Spring 2010. Greg Videen, an undergraduate student at the University of Minnesota Carlson School of Management, completed this analysis during his senior year as part of his graduation requirements. His thesis was co-awarded the Dean’s Honors Thesis Award for Best Undergraduate Thesis. Greg graduated summa cum laude in May 2010 with majors in Finance and International Business and a minor in Spanish studies. As an undergraduate, Greg was interested in corporate social responsibility and demonstrated this as an officer and founding member of the student group Green Biz. Greg is originally from Plymouth, MN and now works at Deloitte Consulting post-graduation where he continues to pursue environmental initiatives.
I. Introduction

Environmental issues have become a concern on a global level. These issues range from conservation and energy use, to deforestation and water shortage. Because large corporations are an integral part of global society, many are beginning to feel pressure from their constituents to operate in a more environmentally-friendly manner to help solve the problem. Every stakeholder, from shareholders and consumers to community members and competitors, is affected by the actions a company takes regarding the environment. No longer do firms simply act in accordance with environmental legislation, and in avoidance of regulatory fines (Hoffman, 2000). In today’s rapidly growing economy, firms are expected to fully understand the impact they have on the resources that will be available for future generations (Marcus & Fremeth, 2009). All of this increased attention to environmental responsibility has brought up questions as to what the financial implications are for firms that chose to operate in an environmentally-friendly manner.

The purpose of this investigation will be to analyze whether, and to what extent, there have been financial performance benefits realized by major corporations in various industries that have implemented positive changes to their environmental strategies. I hope to build on existing research that has already attempted to identify financial reasons that firms would chose to undertake these types of initiatives. The focus of my study will be on large, publicly traded firms that have had sustained success as members of the Dow Jones industrial average since the creation of the Kyoto Protocol in 1997. The Kyoto protocol is an agreement linked to the United Nations Framework Convention on Climate Change, and is part of a worldwide effort to reducing greenhouse gas emissions. While the United States has not formally committed to the protocol, this ten year period from 1998 through 2008 has brought about many changes in firm’s strategies in regards to the environment, specifically relating to emissions controls, and the worldwide media attention brought about by the green phenomenon. It will be easiest to track firms from the Dow Jones Industrial Average due to the amount of attention they are given by widely read sources of financial news such as the Wall Street Journal and the New York Times. Stock valuation will be the measure of firm financial performance as it is publicly available and market participants are quick to react to any changes. This comparison will then allow me to analyze if, and the extent to which, investors respond to positive green announcements when they occur without knowledge of the full extent of the future benefits or costs. This fluctuation will be compared to what would be expected under the capital asset pricing model (CAPM) with the assumption of efficient markets. According to this
model, investors are rational, calculating, and self-interested. Their investment decisions are based on their best assessments of the future costs and benefits of these announcements on the firm’s bottom line.

My hypothesis is that there will be a positive change in stock price greater than would be expected without the announcement of the event. I hypothesize that shareholders will anticipate long-term benefits of business acting in an environmentally responsible manner. Of course, it is possible that investors may view these events in a different light and according to a different scheme of reasoning than the one presented here. They may actually believe that acting in an environmentally responsible manner will hurt a firm’s future financial prospects and may punish the firm by withdrawing their support and selling the stock. My hypothesis that investors will react positively to environmental responsibility rests on the assumption that shareholder interests and environmental responsibility are in alignment and that investors will perceive positive benefits in responsible actions. However, the opposite may be the case and investors may see environmental responsibility as being potentially costly and hurting the firm’s bottom line. Regardless of how investors behave in response to announcements of environmental responsibility, they can be mistaken if efficient market assumptions are relaxed and the inherent uncertainty of the future costs and benefits of any corporate action is considered.

The driving question behind the research is if firms are truly undertaking these green policies to improve financial performance or if they feel it is simply moral responsibility. If there is a positive association between investor reaction and environmental responsibility, then one can infer that corporate financial performance and responsibility are in harmony. That is to say that responsible action is a win for both companies and the environment. On the other hand, if the association is negative, then corporations that act in an environmentally responsible way are doing so without the benefit of market reward. From the Kantian or deontological perspective of pure duty regardless of consequences as developed by philosopher Immanuel Kant in the 17th century, they are displaying a higher level of moral responsibility, one that they are pursuing regardless of the benefits to shareholders or immediate financial gain. In the past, some of a firm’s morally responsible behavior has – it has been argued – routinely resulted in increased profits. As stated by Mark White (1992) in *The Greening of American Business*, “It has been argued that investments in better working conditions, equal opportunity programs, and community affairs benefit companies and shareholders in the long run” (p. 52). This study will see if shareholders support this view with regard to the environmentally responsible actions of Dow Jones companies in the time period of 1998 through 2008.
The next section, Section 2, will include a literature review of past articles that are relevant to my work. Section 3 will then lay out the methodology of the study in more detail. Following this will be Section 4 with the results and Section 5 with an analysis of the findings. The final section, Section 6, will interpret the meaning and significance of the results.

II. Literature Review

**Corporate Social Responsibility and Environmental Awareness**

Ethics in business is a topic of recent discussion by scholars from all disciplines. Firms are realizing the backlash of poor ethics on their brand equity as well. Large scandals such as that at Enron or Arthur Anderson are the extreme cases. More subtle ethical violations have emerged and are becoming a recurring topic in popular documentaries such as *The Big One* (Michael Moore, 1998) and *The Corporation* (Mark Achbar & Jennifer Abbott, 2003). This has led stakeholders of a firm to emerge as a broader group that corporations need to worry about as opposed to solely shareholders and profits.

There is no obvious answer as to what role the corporation should play in society. Corporate Social Responsibility (CSR) is a term that has been coined to describe the relationship between business and society (Snider et al., 2003). Terms such as “socially responsible” and “corporate citizen” are sought after by the most admired firms in the United States and worldwide. For example, *Corporate Responsibility Magazine* releases an annual report on the 100 Best Corporate Citizens, a designation which does not come easily to its winners. The three pillars of CSR are widely recognized as economic, social and environmental. Economic responsibility refers to the firm being profitable and a sustainable business entity. Social and environmental responsibility can have different meanings to different businesses, but generally refer to how the firm deals with these types of issues through its business operations. Social issues are generally more related to people, such as treatment of workers and impact on people in the community, which firms usually take on by implementing internal controls or through ethical sourcing such as volunteer work and donations. Environmental issues relate to everything in the physical environment of the world. This covers a wide range of issues, such as controlling packaging waste and energy consumption to ceasing to use toxic chemicals in the production process. In the end, the term generally relates to natural resource use and preservation. The environmental pillar of the CSR framework will be the focus of this paper.

Over the course of just a few decades we have witnessed a change in how corporations view their environmental responsibilities. Hoffman (2000), in his
book *Competitive Environmental Strategy* breaks down the past views into four periods: industrial environmentalism (1960-1970), regulatory environmentalism (1971-1981), environmentalism as social responsibility (1982-1988), and strategic environmentalism (1989-1999). During the 1960s, corporations were first introduced to the idea of corporate environmental responsibility as environmental groups began to form as a reaction to environmental crises caused by corporate activities. The year 1970 brought about the government-formed Environmental Protection Agency (EPA) which was charged with protecting human health and the environment. This era brought about changes to legislation and the development of a “checks and balances” system to monitor how different companies treat the environment. Corporations soon began to fear being subject to costly fines and violations so much so that some began to go beyond mere compliance with the law. Operating in accordance with the environment began to be seen as a risk mitigation strategy to avoid the possibility of future fines. As President Ronald Regan took office and began to reduce regulation on business, social activism increased, taking the people’s voices straight to the company through public displays. Fearing harm to their image, corporations took an even stronger role in establishing acceptable environmental practices to promote social responsibility. These changes have brought about new discussions regarding what view the firm should take toward its natural environment.

**Development of Environmental Strategy**

As environmental awareness continues to increase, corporations are beginning to view the benefits that can be achieved through strong environmental performance. Many large corporations are forming an environment function in their corporate structure that no longer simply monitors regulations, but has a strategic role in the company. These companies are realizing that there are many opportunities to apply the concepts of sustainability and the three R’s (reduce, reuse, and recycle) in the business world. In many cases, these types of actions lead to increased efficiency and cost reductions, and entrepreneurial opportunities for new product introductions to solve environmental problems.

Operating in an environmentally-sustainable manner may not always be the most effective way to operate, especially if there are increased costs involved; however, many firms are still undertaking these initiatives. Many researchers (Klassen & McLaughlin, 1996; Filbeck & Gorman, 2004; Gilley, et al., 2000; Molina-Azonrin, et al., 2009) have asked what benefits firms receive from being green, and whether or not this is something that shareholders value. Past research has been driving to answer these questions through a variety of different methods, yet no concrete agreements have been reached.
The bulk of evidence either suggests it pays to be green or does not negatively affect a firm’s bottom line, but the context and conditions under which it pays to be green are still controversial. For instance, it may pay only for startups in environmentally-friendly businesses, for firms that can demonstrate lower costs through waste reduction or for mid-size firms with prior poor environmental reputations that make improvements in environmental performance. The conditions under which it pays or fails to pay to be green have to be better specified. This section will look at how past research has advanced the discussion around why firms undertake environmental management strategies and how to evaluate the effect on firm profitability.

One idea is what is known today as the “win-lose” perspective. This is the traditional way firms began to look at environmental strategy. As shown below in Figure 1, the “win-lose” proposition states that environmental benefits can only be achieved through increased costs (Hoffman, 2000).

Opposing the “win-lose” perspective; the “win-win” perspective says that environmental and economic benefits can come together. Figure 2 shows how “costs of addressing environmental regulations can be minimized, if not eliminated, through innovation that delivers other competitive benefits to the firm” (Hoffman 2000, p. 6). For example, the argument is not that a reduction of pollution is always accompanied by better economic performance, but rather to say that the expenses incurred to reduce pollution can be partly or completely offset by gains made elsewhere, such as fewer regulatory fines or reduced cleanup costs (Ambec & Lanoie, 2008). Both of these perspectives hold valid points, so it is nearly impossible to defend one as holding true under every situation.
Indeed, there has been a recognized shift in how companies approach environmentalism. Over time, more and more companies view “going green” as an environmental strategy with possible benefits to the firm as opposed to simply environmental management or something they have to do because of regulatory compliance (Hoffman, 2000). No longer are many firms simply acting to comply with regulations, but they have in many cases identified competitive advantages by being better environmental stewards. Examples of such benefits are less waste, new product introductions for which a “green-minded” consumer may be willing to pay a premium, less regulatory scrutiny or better reputation. It is for these reasons that a mixed-motive perspective also has gained its popularity. Essentially fusing the “win-win” and “win-lose” perspectives, the mixed-motive model acknowledges the possibility of economic gain from environmental protection, as well as the possibility for higher costs. As shown below in Figure 3, the mixed-motive perspective demonstrates that while there are higher costs that come with increases in environmental protection, it is possible to have positive impact on both fronts.

\[\text{Figure 2: Win-Win Scenario}\]

\[\text{Degree of Environmental Protection} \quad \text{High} \quad \text{Low}\
\text{Low} \quad \text{High} \quad \text{Economic Growth}\]

Source: Figure 1.2 from Hoffman (2000, p. 7)
A more intriguing way of looking at environmental efforts is the possibility that firms are not acting in an environmentally-friendly manner to increase their profit margins, but are doing what will truly make all stakeholders better off. This benefit could be in the form of less pollution, preservation of resources, lower waste containment and energy costs or a variety of other benefits. As Hoffman (2000) describes, “shareholder equity may remain the single most important criterion for corporate survival, but environmental responsibilities are infiltrating the taken-for-granted beliefs that have previously guided that pursuit” (p. 14). In a 2007 study conducted by Ernst & Young, it was found that 35% of valuation decisions are based on non-financial data and that strategy execution is the most important non-financial factor driving shareholder valuations. Raised awareness of non-financial considerations has caused more information to be publicly available, and investors are increasingly reacting to this type of knowledge.

One way that firms are trying to demonstrate their commitment to the environment is through CSR reports. A study on CSR reporting disclosures finds that it is not uncommon for U.S. firms to produce these reports; however, the authors note that due to the overall positive tone of these disclosures, they are being used primarily as a means of marketing (Holder-Webb et al., 2009). It is also commonly thought that firms do not fully understand what they should be reporting to their constituents. Ullmann (1985) found that self-disclosure of policies relating to environmental issues does not always correlate with objective, third-party measures of environmental performance. Holder-Webb (2009) notes that, while environmental matters were not discussed as often as
other CSR activities in disclosure surveys, these types of disclosures received considerable focus when they were discussed. A 2005 KPMG International survey also notes that only 21% of companies actively seek to provide the information requested by shareholders regarding CSR (KPMG, 2005). All of this research signifies that while environmental reporting is important to constituents, firms have not yet found effective ways to market their social responsibility to their stakeholders. If this is truly the case, stakeholders are likely turning to other sources, such as the media, rather than company created reports to find unbiased information on firm practices. Because of this, I have chosen to analyze articles from the *New York Times* and *Wall Street Journal* in my study as it would appear that these articles would be less biased towards benefiting the company. These articles are also more likely to include new information on firm undertakings, where as a year-end report likely contains information already known in the market.

The interesting aspect of CSR is that there are varying degrees of beliefs about whether more socially responsible firms always generate greater returns. In one report conducted by the Alliance for Environmental Innovation, 70 studies on this topic were reviewed and it was concluded that companies that outperform peers on environmental dimensions also outperform on stock returns by about 2% (Hoffman 2000). This seems to contradict the findings of Benson et al. (2006) in their study of socially responsible investment (SRI) funds, in which it was found that SRI funds do not significantly outperform conventional funds. Benson et al.’s results seem to indicate that the only benefit investors receive is the “feel-good” factor. If this is the case, the question arises as to whether firms are simply ignoring greater returns in lieu of fulfilling a certain role in society.

In a recent exchange in the *Academy of Management Perspectives*, two opposing viewpoints are discussed. Siegel (2009) argues for the more traditional view on green management in saying that managers “have an obligation to deploy the firm’s resources as effectively as possible...to maximize the wealth of the firm” (p. 10). Marcus and Fremeth (2009) take a holistic approach in saying that society expects management to act in an environmentally responsible manner when making decisions. Their piece poses the question that even if it does not pay more, does it really pay any less in comparison to other potentially risky initiatives such as mergers and acquisitions or fundamental innovation in products, services and business models. Finally the question remains as to what extent firms feel compelled to act in an environmentally ethical manner, or if all actions are taken in hopes of generating higher profits.
Testing of Environmental and Financial Performance Benefits

Testing the benefits that environmental strategy brings to corporations has proven to be a difficult task. One reason is that there are many variables that play a role in how financial performance is measured and how environmental performance is measured. Molina-Azonrín, Claver-Cortés, López-Gamero, and Tari (2009) conducted a literature review of 32 studies that tested the correlation between environmental performance and financial performance. Through their work they concluded that while the impact of environmental management on performance is not always easy to understand, a real commitment to green management may result in a positive influence on financial performance. The study also recognized that there may be a two-way interaction between financial performance and environmental performance, which makes it hard to conclude cause-and-effect relationships (Molina-Azonrín, et al., 2009). Hoffman (2000) agrees with these findings in saying that “…no case studies can claim a cause-and-effect relationship between environmental performance and financial performance, [however] a correlation between the two is a powerful indicator of future success” (p. 80).

One method of analyzing performance is looking at how a company’s stock price reacts to the announcement of environmental performance. Arguably, the most widely recognized method of testing a causal relationship in the financial world is the event study. Event studies were originally derived from Fama (1970) with his work on efficient capital markets. His theory on efficient capital markets says that the stock price of a firm should reflect all publicly available information at that point in time. From this, we should be able to tell if a certain announcement affects the stock price of a firm to a greater degree than what would be normally expected given the random variation of stock prices. This event study methodology allows the statistical testing of how any perceived events affect the price of a stock assuming efficient capital markets.

Event studies have been often used in the area of environmental research, but rarely do they test for an event having a positive effect (Ambec & Lanoie, 2008). One example where the event was hypothesized to have a positive effect on financial performance comes from a study by Klassen and McLaughlin (1996). Using an event study, the researchers attempt to assess financial benefits realized from operating greener. Specifically, they investigated benefits of long-term cost savings resulting from reduced emissions, greater resource efficiency, or fewer legal and regulatory fines. Events were defined to be environmental awards (positive events) or environmental crises (negative events). They find a positive effect on performance of such positive events and also that the degree of the effect on financial performance tends to vary across
industries. These findings apply to news articles containing specific keywords from the NEXIS database of newswire services over the time period of 1985 to 1991. The implication is that a positive award, while not directly affecting financial performance and under the assumption that investors are evaluating the event in terms of generation of future cash flows, will indicate the prospects of higher future performance and more cost reductions through a better environmental consciousness. The opposite can also be said of a crisis’s negative implications. This finding indicates that investors do place value on a firm being recognized as environmentally responsible. This idea of stock price reaction to positive announcements is the main driver of the research presented in this paper.

The idea of environmental event studies has been replicated by other notable studies as well, each with its own unique perspective. Gilley et al. (2000) used an event study to test the influence of environmental initiatives on anticipated economic performance. This study also looked at environmental announcements in the Wall Street Journal over the period of 1983 through 1996. Another similar study was conducted by Filbeck & Gorman (2004). This event study looked at how different types of environmental announcements affected Standard and Poor’s 500 indexed companies based on articles listed in the News and Bibliography Section of Investor Responsibility Research Center during the period of 1999 and 2001. My research will examine the same question addressed by these cited studies among Dow Jones companies over the recent ten year period of 1998 through 2008. The Dow Jones company selection of my study may be different than previous samples in that these companies are thought to be the most influential firms in the economy and therefore likely to be more closely followed by the popular press.

While the research has shown that there are some links between firm performance measures and environmental announcements, there is still no clear distinction of why these policies are being undertaken. Traditional financial theory assumes that firms undertake certain policies to appease the requests of their shareholders. This study will test to see if this holds true with environmental related policies. To prove this I have analyzed stock price movement around events thought to be green which should give us an indication of how shareholders value these types of announcements. My research attempts to estimate the benefits that shareholders see in the implementation of environmentally-friendly practices across firms and industries. That is if, and to what extent, shareholders actually realize these benefits, or if they perceive environmentally responsible actions as costs. I hope to advance the research about why firms adapt environmentally-friendly policies; if it is to boost financial performance or if it is to fulfill a different obligation held by non-financial
stakeholders of the firm. That is, to discover whether the firms themselves see environmental announcements as an investment for the future or as an unnecessary additional cost. It is intended to spur interest in corporate environmental policies as well as to provoke shareholders to hold firms to a greater degree of responsibility in their actions. The hope is that similar studies will be undertaken in order to truly understand the motivations of corporations when implementing these changes.

III. Methodology

My study estimates the effects of publicly announced, positive green business undertakings on the financial performance of large U.S. firms. Market value of the firm’s stock is used as the measurement of performance for the firm under the assumption that firms are acting in the interests of their shareholders. My thesis uses an event study approach to evaluate how shareholders of the firm react to a firm’s announcements of positive green business compared to what would be expected in the absence of such an announcement.

An event study is the best way to answer the research question at hand because it allows me to analyze a large number of announcements. Event studies are built off the assumption that markets act efficiently. This study assumes the semi-strong form market efficiency, meaning that all previous firm announcements are already reflected in the stock price, and any new announcement that is made will be immediately reflected by a change in stock price (Fama, 1970). A change in stock price is widely believed to indicate a change in expectations about future performance. In previous environmental literature, event studies have been used as a tool to evaluate effects on firm performance (Klassen & McLaughlin, 1996). I have built my study methodology off of that described by MacKinlay (1997) in his seminal article. This article is cited in similar environmental announcement event studies (e.g. Nagayama & Fumiko, 2006) and can be followed as a detailed template for event study methodologies. In order to be consistent with other environmental event studies, I will use much of the terminology used by Gilley et al. (2000). All of the event study methodology will be run through Eventus on the University of Pennsylvania Wharton Research Data Services website [see Appendix E]. The steps for completing the research will be as follows:

Identify events and event windows

The event in my study is the public announcement of a green development within a firm. Selection of a green announcement has been decided based upon the inclusion of at least one keyword from a list of environmentally related terms in the articles headline or abstract [see Appendix B]. Results re-
Effects of Green Business on Firm Value

turned under these key words have been sorted, and only the relevant articles containing what is deemed as “new information” have been included. Events were classified as being positive or negative in terms of how the firm acted regarding the environment. Events were divided into 12 positive event categories and 3 negative event categories based on the type of information disseminated in the announcement [see Appendix C]. The 15 categories were created to align to those used by Filbeck & Gorman (2004), but were adjusted to include a broader range of event types. Articles were individually categorized by the author using subjective judgment, and all announcements were weighted equally. All announcements were made public in two widely read sources that are considered to be reliable by investors, the New York Times and Wall Street Journal.

According to McKinlay (1997), “it is customary to define the event window larger than the specific period of interest. This permits examination of periods surrounding the event” (p. 14-15). For this reason, I have tested multiple event windows in my study. This allows a better examination of how the period surrounding the event has been affected. Also, an event could be skewed if it coincides with other announcements that could affect the pricing of the security during the event window (e.g. M&A, earnings announcements, stock splits). The impact of co-occurring announcements will be effectively negated by the size of the data.

**Determine selection criteria of firms to be included in the study**

The study will attempt to see the impact of events on large U.S.-based firms that have been successful during the period. Based on these criteria, a firm being listed in the Dow Jones Industrial Average index for the latest ten year period for which data is available was used as the basis of inclusion. I will be looking at the 21 firms that were included in the Dow Jones Industrial Average during the entire period from January 1, 1998 through December 31, 2008 [see Appendix A]. While this may create a source of selection bias, it has been done in order to look at only the largest, most successful companies for this ten year period. In addition, I have chosen to look at this period because of the increased awareness of environmental issues occurring during this time frame.

**Measure abnormal returns in order to test event’s impact**

With event study methodologies, the returns of each firm’s common stock are compared to the stock market index to identify abnormalities. The actual common stock returns over event windows are compared to the normal/expected returns, and the differences are called abnormal returns (Gilley et al. 2000). This can be represented through the use of Equation 1:
Equation 1 measures the abnormal return, $A_{it}$, for the firm $i$ at time $t$. Time $t$ will encompass the entire event window. $R_{it}$ is the actual return observed on time $t$, and $R^e_{it}$ is the return that would have been expected based on the market model (defined below). I have chosen to use the University of Chicago’s Center for Research in Security Prices (CRSP) value-weighted index to represent market returns. Using the value-weighted index is recommended by Canina, Michaely, Thaler, & Womack (1998) in their article on CRSP value-weighted versus equal weighted index use with the statement “most financial economists know that compounding the returns on any portfolio, other than the value-weighted index portfolio, induces an upward bias…” (p.403). Historical returns of each firm plus the movement of this market index will be used to predict the expected return. In order to calculate the expected return of a stock, this is illustrated by the following pricing model based on CAPM:

$$R^e_{it} = \alpha_i + \beta_{i,m} * R_{mt} \tag{2}$$

where $R^e_{it}$ is the expected return for firm $i$ at time $t$, $\alpha_i$ is the difference between the observed price of stock $i$ and the price of stock $i$ predicted by the model over the estimation window, $\beta_{i,m}$ is the measure of correlation between the firm $i$ and the market over the estimation window, and $R_{mt}$ is the observed return of the market at time $t$. In order to get the variables $\alpha_i$ and $\beta_{i,m}$, a regression is run on the historical returns of the stock price of stock $i$ and on the market value of the market index over the estimation window (defined below).

**Define the estimation window**

The estimation window is the time period used to calculate $R^e_{it}$ in the formula in step 3. The estimation window of 200 days ending 50 days before the event date will be used. Estimation windows vary greatly amongst past research (Klassen and McLaughlin (1996), McKinlay (1997) & Filbeck & Gorman (2004)). After testing the differential effects estimation windows played on the data, it was concluded that role was minimal. For this reason, I chose to use an estimation window that incorporated comparable to the different event windows used by these three main studies that I have followed. The estimation window does not include the event window $t$ in order to prevent the event from influencing the normal returns. A regression has been run over the data of $R_{mt}$ and historic $R_{it}$ during the estimation window for each event in order to calculate variables $\alpha_i$ and $\beta_{i,m}$. 

$$A_{it} = R_{it} - R^e_{it} \tag{1}$$
Design of the testing framework

The statistical tests will be done using the STATA program [see Appendix F for STATA commands used]. The first step is to find the cumulative abnormal return, $CAR_i$, for each event window $t$ over a specific interval indicated by $T1$ to $T2$ ($T1$ is the starting day of the event window and $T2$ is the ending day):

$$CAR_i = \sum_{t=T1}^{T2} A_{it}$$

(3)

The abnormal returns will be averaged across events to provide mean cumulative average abnormal returns across $N$ events.

$$\overline{CAR} = \frac{1}{N} \sum_{i=1}^{N} CAR_i$$

(4)

This formula can be used to find the cumulative average return for a specific type of announcement, for all announcements by firm, or for the overall cumulative effect by adjusting the $N$. The null hypothesis is that environmental events have no impact on the behavior of the returns, while the alternative is that returns are different from 0:

$$H_0: \mu = 0$$

(5)

$$H_A: \mu \neq 0$$

(6)

To show this, I will test the significance of the cumulative average abnormal returns to see if they are statistically different from 0. This will involve the use of a $t$ test. The first step will be to find the estimated standard deviation, which can be done with the following equation:

$$S = \sqrt{\frac{1}{N - 1} \sum_{t=T1}^{T2} (CAR_i - \overline{CAR})^2}$$

(7)

Once the estimated standard deviation has been calculated I can calculate the $t$ value using the following equation:

$$t = \frac{\mu CAR}{\sigma_e / \sqrt{N}}$$

(8)
Finally, I can compute the \( p \) value to determine if the abnormal returns caused by this event are statistically significant (p-value will be compared to a significance level of .05 and 0.10). Using this statistical test, I will be able to accept or reject the null hypothesis in an attempt to draw conclusions about how shareholders view green announcements.

I evaluated two different hypotheses in my research. The first hypothesis is that there is a correlation between positive environmental announcements and the change in stock price. To test this hypothesis, I ran a regression on the mean abnormal returns of the different events and if the event is classified as a positive or negative event. My second hypothesis is that positive environmental announcements correlate with positive change in stock price. To test this hypothesis, I have looked at the aggregate mean abnormal returns for positive events and for negative events.

**IV. Results**

From the data collected, it is difficult to make strong conclusions about how shareholders react to environmentally positive events. Table 1 displays that there is little statistical significance between an event being positive or negative and the event window return. This would mean the null hypothesis is not rejected, as the mean abnormal returns are not statistically different from 0. Based on the high P-scores, it can be said that it is nearly impossible to predict whether returns will be positive or negative after an environmentally related announcement and that there is no correlation between positive environmental announcements and changes in stock price.

Table 2 shows that while statistical correlation was not proven, there was a tendency for negative environmental events to have a greater return than positive events in this specific data set [See Appendix G for average daily returns for the different announcement types]. This evidence fails to support hypothesis 2, that positive events will on average produce higher returns than negative events. It is also important to note that there were nearly twice as many positive events as negative events included in the study, so this could be a result of sampling error. If more events were analyzed, the average returns may begin to even out between the two different categories as the average for all returns is relatively close to 0.
My results are similar to those of other event studies. Gilley et al. (2000) found that there was no overall effect of environmental announcements, but the type of environmental initiative does make a difference. Filbeck & Gorman (2004) proved similar findings. While they did identify certain categories of announcements that did have strong effects, such as environmental awards and lawsuits as originally studied by Klassen & McLaughlin (1996), the vast majority of positive and negative announcements showed no significance. My results, that a positive environmental event has no statistical relation to stock price movements, are consistent with the findings of these previous studies.

While it is hard to draw any major conclusions from the results, there is still room for discussion around how environmental announcements affect a company’s financial performance. The main driving question behind the research is why firms partake in environmental initiatives. In traditional finance...
literature, the main reason a firm would undertake any action is to benefit shareholders (Palmer et al., 1995); however, based on the results from this study, it is clear that environmental announcements do not have a consistent effect on equity valuation. The results actually showed the contrary, that the less prominent negative events caused a slightly higher jump in valuation than the more common positive environmental announcements. There are multiple ways one could explain this finding.

The first would be that firms may no longer see their shareholders as their main constituents. As mentioned before, recent literature identifies a wide array of firm stakeholders that should be included in any decision the firm makes. This would say that while shareholders do not see the value of an environmental decision, the net benefit to the stakeholders outweighs the shareholders in this specific case. This would indicate a radical shift in the way corporations view their obligations to society. While this is a possible explanation, it may not be the most plausible.

A second potential explanation would be that investors do not realize the value of environmental initiatives. Benner (2009) explains this in relation to how analysts react to firms undertaking new technological pursuits. It was found that in the two cases Benner analyzed (transition to digital film and changes in telecommunications), analysts did not react positively to incumbent firms trying to change their core technology. Analysts did not believe that firms had the capacity to deal with such large technological changes, and it was thought that these changes would upset the firm’s existing models of profitability. In the end, these firms were bypassed by competitors entering into these markets with new technologies. This shows that analysts are highly skeptical of a firm trying to completely alter its core strategy through new technology. This misunderstanding may be the same issue as seen with environmental strategy; analysts may not have a good idea of how the markets will change based on new environmental initiatives. Another point to note is that startup firms can easily incorporate new environmental practices, while mature firms like those covered in this study find it more difficult to adapt old practices to compete. This would also follow the findings of Cochran and Wood (1984) that asset age is negatively correlated with CSR rankings. Older firms have trouble reacting to new environmental programs because of the high capital investments they have in their current assets, and the negative reaction investors have to higher costs. It is thus thought that management may have to act against shareholder short-term interests in certain cases in order to ensure the firm’s long-term survival and competitiveness (Benner, 2009). The cost of investing in environmental initiatives now may produce very little monetary benefit today or in the future, which discourages analysts and shareholders. In
cases where stakeholders do not demand a change, a firm may need to forgo these investments because of investors’ traditional understanding of value. In order to get investors and analysts to support the change, management needs to convince them of the future benefits that are provided by the change.

A third possibility would be that shareholders of these companies already expected the companies to be green. According to market efficiency theory, all information in the market should be priced into current equity valuation. It is very possible that these companies were already thought to be green by shareholders and that the announcements brought no new information to the market. This could have to do with the size of the companies analyzed or the types of announcements selected. It is very possible that due to their size, information is discovered long before it is finally announced by the firm. If a firm makes a credible attempt at being known as environmentally friendly, any further actions may just be supporting this initial announcement. It is also possible that investors just expect firms to follow these types of actions and it is not surprising to them when the firm actually announces them. They may even be expecting more in certain cases so when the announcement does come, the shareholders are slightly disappointed at the firm’s attempts to be green. This could also support the findings of Klassen & McLaughlin (1996). Investors are pleasantly surprised when a firm wins an award, and investors need to adjust their valuation of the company upwards. However, when an environmental crisis occurs, investors are shocked by lack of environmental controls the company had in place.

A final possibility is that shareholders simply do not trade based on information presented in these specific news publications. While the Wall Street Journal and the New York Times are very reputable sources and many previous environmental event studies have used them (Gilley et al., 2000), it is difficult to say if they are the leading sources investors use to make investment decisions regarding environmental initiatives. It is also possible that the types of events being announced by these sources are not pieces of news that investors find useful. It is thought that firms usually announce positive pieces of news in order to develop good public relations (Holder-Web et al., 2008). News sources then may only be reiterating information that the firm has already made clear to its shareholders. On the other hand, if something is unannounced by the firm, news sources will only announce the material that they find relevant, which may be more negative in nature or be information that is not highly valued by investors.
VI. Conclusion

The purpose of this study is to add insight into the question of why firms pursue positive environmental initiatives. While past literature has done a good job of looking at how investors react to negative environmental announcements, reactions to positive announcements has been much harder to understand. This paper used methodologies developed in the past on a new sample of firms and a different source of announcements. While the results showed no strong conclusions about how investors price the announcements, there are many explanations which deserve future consideration.

While it is difficult to say for certain why the results came out the way they did, there are many aspects of the study that can be built upon by future research. Future studies would be encouraged to expand the announcement base. This would allow more companies to be analyzed as well as more events. It would also be beneficial to take a closer look at the keywords used and the criteria used for including an announcement. This list may need to be expanded in order to incorporate a larger variety of environmental announcements. I also recommend looking at news published in other sources. Third party sources are recommended due to noted examples of firms using self announced environmental news as public relations material more than as meaningful news items, but it is important to find articles that bring new information to the market. One option to study this may be to look only at disclosures that are filed with the SEC to avoid a bias effect. Finally, timing of the announcements could play a role. Management may strategically time press releases to get the most positive reaction, or cause the least harm, in financial markets.

Future studies also should more closely examine the effects event window size has on results. It would seem plausible to get desired results through data mining the event window size. It needs to be agreed upon over what size event window an environmental announcement has an impact on trading. There may be opportunity to conduct long run event studies on this topic to see how green firms compare to competitors in the long run. This may be even more intriguing to look at through industry specific cases.

Lastly, it is important to note the trend of firm environmental initiatives. As displayed in Appendix D, the number of announcements recognized by this study has increased drastically over time. This is something that should be considered going forward with environmental event studies as more announcements are clearly being made. The nature of these more numerous recent announcements should be compared to past announcements to possibly get a better understanding of why firms are continually announcing more environmental initiatives if there really is no recognized financial benefit.
The question of why firms undertake environmental initiatives will continue to be researched. It could be said that at the very least environmentally positive announcements don’t hurt shareholders, as the benefits are clearly not “win-win” in all cases. This means that the tangible and intangible benefits of environmentally-friendly actions may exactly equal the costs of pursuing these initiatives. There is also something to be said about the possible insurance effect of being green. Having strong goodwill built up in the environmental community can be very beneficial when a crisis does occur. Continued research is encouraged to build upon the findings of this and other past studies to further understand the role of environmental responsibility in the business world.
References


Ernst & Young LLP. Measures that Matter. (2007).


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Appendices

Appendix A. Full list of firms analyzed

<table>
<thead>
<tr>
<th>Company Name</th>
<th>Ticker</th>
</tr>
</thead>
<tbody>
<tr>
<td>3M Company</td>
<td>MMM</td>
</tr>
<tr>
<td>Alcoa Incorporated</td>
<td>AA</td>
</tr>
<tr>
<td>American Express Company</td>
<td>AXP</td>
</tr>
<tr>
<td>Boeing Corporation</td>
<td>BA</td>
</tr>
<tr>
<td>Caterpillar Incorporated</td>
<td>CAT</td>
</tr>
<tr>
<td>Citigroup Incorporated (formerly Traveler's Group)</td>
<td>C</td>
</tr>
<tr>
<td>Coca-Cola Company</td>
<td>KO</td>
</tr>
<tr>
<td>DuPont</td>
<td>DD</td>
</tr>
<tr>
<td>Exxon Mobil Corporation</td>
<td>XOM</td>
</tr>
<tr>
<td>General Electric Company</td>
<td>GE</td>
</tr>
<tr>
<td>General Motors Corporation</td>
<td>GM</td>
</tr>
<tr>
<td>Hewlett-Packard Company</td>
<td>HPQ</td>
</tr>
<tr>
<td>International Business Machines</td>
<td>IBM</td>
</tr>
<tr>
<td>Johnson &amp; Johnson</td>
<td>JNJ</td>
</tr>
<tr>
<td>J.P. Morgan Chase &amp; Company</td>
<td>JPM</td>
</tr>
<tr>
<td>McDonald's Corporation</td>
<td>MCD</td>
</tr>
<tr>
<td>Merck &amp; Company, Incorporated</td>
<td>MRK</td>
</tr>
<tr>
<td>Procter &amp; Gamble Company</td>
<td>PG</td>
</tr>
<tr>
<td>United Technologies Corporation</td>
<td>UTX</td>
</tr>
<tr>
<td>Wal-Mart Stores Incorporated</td>
<td>WMT</td>
</tr>
<tr>
<td>Walt Disney Company</td>
<td>DIS</td>
</tr>
</tbody>
</table>

Appendix B. Factiva search details

The searches for articles were done through the Factiva search. The parameters were as follows:

- Articles published during the time period from January 1, 1998 through December 31, 2008.
- Articles published by the Wall Street Journal or the New York Times in the print or online editions.
- Keywords were located in the articles headline or lead paragraph.
- The articles needed to contain at least one of the following words:

<table>
<thead>
<tr>
<th>alternative fuel</th>
<th>carbon trad*</th>
<th>EPA</th>
<th>ISO 140*</th>
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<tr>
<td>battery</td>
<td>clean air</td>
<td>ethanol</td>
<td>Kyoto</td>
</tr>
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<td>biodegradable</td>
<td>climate change</td>
<td>fuel cell</td>
<td>Life Cycle</td>
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<tr>
<td>biofuel</td>
<td>coal gasification</td>
<td>global warming</td>
<td>recycl*</td>
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<tr>
<td>cap and trade</td>
<td>energy efficient*</td>
<td>green</td>
<td>renewable energy</td>
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<tr>
<td>carbon emission</td>
<td>Environmental Protection Agency</td>
<td>greenhouse gas</td>
<td>solar</td>
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<tr>
<td>carbon neutral</td>
<td>environmental*</td>
<td>hybrid</td>
<td>wind</td>
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</table>

* = word is truncated and can contain any characters following
Appendix C. Categorization of Event Types

Positive Event Types
- New product/service or new orders for products
- Process innovations (cost control)
- Positive political lobbying
- Stakeholder actions for the firm’s environmental policy
- Settlement of outstanding violation
- Positive environmental announcement by rival
- Negative environmental announcement by rival
- Harmful product line dropped or modified
- Investment made into environmentally friendly
- Partnerships/coalitions for environmental benefit
- Environmental agreements reached
- Firm voluntarily acts in positive environmental manner

Negative Event Types
- Stakeholder actions opposed to the firm’s environmental policy
- New violations
- Firm acts in a negative manner towards environment

Appendix D. Number of announcements by year

![Graph showing positive environmental announcements by year]

Appendix E. Eventus setup options
- Basic daily returns
- CRSP value weighted market index
- Market-adjusted returns were used
- Autodate was used for events occurring on non-trading days (move to next day if happen on non-trade day)
- Ordinary Least Squares (OLS) estimate method
Appendix F. STATA command used for regression

```
reg: x1 ivar1 ivar2 ivar3 ivar4 ivar5, robust
```

x1 = Mean total return  
ivar1 = Asset size  
ivar2 = Employees  
ivar3 = Net Income  
ivar4 = Earnings Before Interest and Tax  
ivar5 = Revenue

All independent variables are taken from the previous year-end report.
Appendix G. Abnormal returns for each day using different announcement types

<table>
<thead>
<tr>
<th>Day</th>
<th>Positive Announcements (N=178)</th>
<th>Negative Announcements (N=65)</th>
<th>All Announcements (N=243)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.16%</td>
<td>-0.06%</td>
</tr>
<tr>
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<td>-0.07%</td>
<td>0.15%</td>
<td>-0.01%</td>
</tr>
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<td>-8</td>
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<td>-0.11%</td>
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<tr>
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<td>0.00%</td>
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<tr>
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<td>-0.02%</td>
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<td>-0.05%</td>
<td>0.02%</td>
</tr>
<tr>
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