Equity Valuation and Climate Change

By

Su Li

A thesis submitted to
Victoria University of Wellington
in fulfillment of the requirements for the degree of
Doctor of Philosophy in Accounting

Victoria University of Wellington

2023

RESEARCH SUPERVISORS

Professor Tony van Zijl

Professor of Accounting and Financial Management

The School of Accounting and Commercial Law

Victoria University of Wellington

New Zealand

Professor Roger Willett

Professor of Accounting

The School of Accounting and Commercial Law

Victoria University of Wellington

New Zealand

ACKNOWLEDGEMENT

First and foremost, I wish to express my sincerely gratitude and appreciation to my supervisors, Professor Tony van Zijl and Professor Roger Willett, for their professional and invaluable guidance throughout my doctoral study. Their insightful comments helped me to overcome the obstacles in the research and to make continuous progress.

I gained a lot of help from the faculty in the School of Accounting and Commercial Law during the entire period of my study. I wish to express my thanks to all of them. I would like to thank Victoria University of Wellington for granting me the Wellington Doctoral Hardship Scholarship and the Wellington Doctoral Submission Scholarship, which have provided important support for me during the final stages of my study.

I am forever indebted to my wife, Ling Li, and my family for their love, support, and encouragement during my doctoral studies.

DECLARATION

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or substantial proportions of materials which have been accepted for the award of any other degree or diploma at Victoria University of Wellington or any other educational institutions, except where due acknowledgement is made in this thesis. Any contribution made to the research by others, with whom I have worked at Victoria University of Wellington or elsewhere, is explicitly acknowledged in this thesis.

I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and conception or in style, presentation and linguistic expression is acknowledged.

Signature: Su Li

Date: 18 May 2023

ABSTRACT

The thesis investigates whether climate risk influences equity value through the channel of the accounting system and, therefore, if investors adjust their relative valuation weights on different accounting variables with the exposure to climate risk. The thesis is motived by increasing global temperatures, which are thought to cause an increase in natural disasters, have a negative impact on economic growth, and produce instability in the financial system. The negative consequences of climate change make the issue an important one for legislators, regulators, standard setters, financial intermediaries, investors, and the general public. The literature suggests that climate risk has become material in its effect on capital markets through its impact on the economy via such channels as agriculture, labor productivity, investors moods, etc. However, few studies relating the long-run effect of climate risk on capital markets through the channel of the accounting system have been undertaken to date. This thesis therefore aims to contribute to an improved understanding of the way climate risk impacts on equity valuation though its effect on the reporting on the accounting aggregates of book value, earnings, and dividends.

The thesis adopts the accounting-based valuation theoretical framework of Gordon (1962) and Ohlson (1995). The elasticity of equity market value with respect to accounting variables is the main measure used to assess the impact of accounting on market values. The elasticities on the individual accounting variables reflect the relative importance capital market participants place on the corresponding accounting variable. In the value relevance literature, the book value of equity captures accumulative past information and is viewed as a backward looking, conservative, or pessimistic measure. Earnings is considered to reflect information about the future and is viewed as a forward looking, aggressive, or optimistic measure. If the elasticities of earnings are falling over time relative to the elasticities of book value of equity, it may indicate the market is paying greater attention to the latter compared to the former and being more pessimistic about equity values, due to the impact of increasing climate risk. The central hypothesis in the thesis is therefore that there is a positive association between the long-run elasticities of book value of equity and climate risk and a negative association between the long-run elasticities of earnings and climate risk.

The method used to test this hypothesis adopts a two-stage research design. The first

stage estimates elasticities from annual cross-section regressions of U.S. data for the economy as whole and individual industries. In the second stage, a time series analysis regresses the elasticities obtained in the first stage on climate risk variables. The market value and accounting data is from a sample of 180,042 annual observations on listed U.S. firms over the period 1971 to 2017. The key climate risk measure is the annual global anomaly temperature over the same period.

The first stage results show that the models explain about 80% of the variation in stock price. The explanatory power holds for both the full sample of U.S. firms and for the subsample based on individual industries. The results demonstrate that book value of equity has a relative higher valuation importance than earnings during the period from 1971 to 2017 at both the U.S. and individual industry levels. Over the entire sample period, for the U.S. economy as a whole, market value increases by about 0.519% when the absolute value of book value of equity increases by 1%, and by 0.271% when the absolute value of earnings increases by 1%.

In the second stage, the results demonstrate that the signs of climate variables on the book value of equity and earnings are different. The results for the U.S. economy as a whole show that a 1^{o}C increases in the global anomaly temperature is associated with an increase in the elasticity for book value of equity of 0.117 whereas a 1^{o}C increase in the global anomaly temperature is associated with a decrease in the elasticity for earnings of 0.1698. Although the signs of these impacts are the same across different industries, the magnitudes vary across the industries.

The results thus provide evidence which is consistent with the hypotheses of the thesis. This thesis not only contributes to the studies in climate finance, environmental accounting, and accounting valuation, but also has important policy implications for accounting standard setters.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

GLOSSARY AND ABBREVIATIONS

CAA	Clean Air Act of 1970
CART	Classification and Regression Trees
CCDs	cumulative cooling degree days
CDP	Carbon Disclosure Project
CH_4	methane
CME	Chicago Mercantile Exchange
CO_2	carbon dioxide
EPA	Environmental Protection Agency
ERC	earnings response coefficient
ESG	Environment, Social, and Governance
ETFs	Exchange Traded Funds
ETS	Carbon Emissions Trading Scheme
FIML	Full Information Maximum Likelihood
GHG	greenhouse gases
HDDs	cumulative heating degree days
LRR-T	temperature-augmented long-run risk
NOAA	National Oceanic and Atmospheric Administration
N_2O	nitrous oxide
PDSI	Palmer Drought Severity Index
PEAD	post earnings announcement drift
ROA	return on assets
SIC	Standard Industrial Classification
SFAS	Statement of Financial Accounting Standards

TRI	Toxic Release Inventory
UNFCCC	United Nations Framework Convention on Climate Change

CHAPTER ONE

INTRODUTION

The purpose of the thesis is to investigate the impact of climate risk arising from climate change on equity valuation. With the increased concerns about climate change, many studies have begun to explore how capital markets, including stock markets, bond markets, and real estate markets, react to climate risk and attempt to reveal the underlying linking mechanisms. These mechanisms are argued to include financial stability (Batten, Sowerbutts, & Tanaka, 2020; Climate-Related Market Risk Subcommittee, 2020), political stability (Bansal & Ochoa, 2012), labor productivity (Bansal & Ochoa, 2012; Graff Zivin & Neidell, 2014), and investor mood (Goetzmann, Kim, Kumar, & Wang, 2015), and expose firms' cash flow to climate risk (Hong, Karolyi, & Scheinkman, 2020). In focusing on the way the effect of climate risk may be channeled through the accounting system into capital markets, the thesis follows in the tradition of Ball & Brown (1968) seeking to investigate the association between accounting information and stock price.

An important goal of capital market studies in accounting is to test whether the underlying economic factors that affect stock prices can be incorporated into the data generate process of accounting variables (Kothari, 2001). Research in accounting suggest that accounting numbers play a role in transferring risk information into stock prices in order to fulfill the purpose of providing useful information for investors (Penman, 2021). However, few studies have explored whether accounting variables transmit information about climate risk into the capital market. The study of this issue has important implications for "capital market investment decisions, accounting standard setting, and corporate financial disclosure decisions (p. 105)" (Kothari, 2001).

1.1 Motivation

Climate change and its impact on the environment has become a serious concern worldwide (Henderson, Reinert, Dekhtyar, & Migdal, 2018). The scientific community claims that the average global temperature has risen by 0.9^{o}C since 1880, the start of the Industrial Revolution, and predicts that the global temperature will rise 3.7^{o}C to 4.8^{o}C by 2100 unless action is taken to counter this trend (IPCC, 2014). If the temperature increases by 1.5^{o}C in 2021-2040, it will cause severe climate damage to ecosystems and society (IPCC, 2022) and the effects from climate change are likely to be irreversible within a human time scale.

The major causes blamed are the accumulated emissions of greenhouse gases (GHG), including carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), due to the burning of fossil fuels and other human activities. The Paris Agreement sets a long-term temperature goal with the intention of avoiding the worst effects of climate change well below 1.5^oC and 2^oC compared to pre-industrial levels. It is estimated that in order to reach the goal of a change in average global temperature of between 1.5^oC and 2^oC, GHG emissions will need to be reduced by between 25% and 55% compared to their levels in 2017 (IPCC, 2018).

Climate risk has become material. In the view of climatologists the continuous increase in global temperature due to greenhouse emissions has increased the frequency and intensity of extreme climate events and, consequently, has caused substantial damage to ecosystems, human health and the economy. Climate change on a global scale has been argued to reduce economic growth (Dell, Jones, & Olken, 2012), increase the financial instability (Carney, 2015; Henningsson, 2019), and cause more stringent regulations (Dechezleprêtre & Sato, 2017). Henderson, Peinert, & Oseguera (2020) find that firms adjust their business strategies, operational activities, and financial behaviours in order to adapt to climate change. Consequently, climate change significantly influences firms' performance in areas such as revenue, operational cost, and earnings (Hugon & Law, 2019). Therefore, climate change is believed to have imposed significant uncertainty on firms' financial prospects and potentially to be a source of systematic risk.

Climate risk can be catergorised into physical climate risk and transition climate risk. The former risk refers to the direct damage due to climate change and the latter to the regulatory risk when firms adopt mitigating activities such as transiting to a lower-carbon economy. The two types of climate risks are closely interrelated and likely to influence firms' future cash flows (Balvers, Du, & Zhao, 2017; Hong, Li, & Xu, 2019). Moreover, the two types of climate risk may have positive or negative pricing effects on different types of assets or firms (Giglio, Kelly, & Stroebel, 2021).

In addition to uncertainty, climate risk is also complex, which results in some special statistical characteristics, such as fat tail risk (Battiston, Dafermos, & Monasterolo,

2021) and downside tail risk (Ilhan, Sautner, & Vilkov, 2021). Another significant characteristic of climate risk is that the exposure to climate risk is heterogenous across firms, industries, regions and time periods, with firms having different ability to adapt to and tolerate risk (Giglio et al., 2021). These special characteristics present challenges to identifying whether climate risk is priced in capital markets.

A growing awareness of the risks of climate change by investors may influence their equity valuations. Beliefs about future events are considered in the accounting literature to be important factors influencing asset pricing, and are held by some to be sensitive to climate change (Hong et al., 2020). Climate events, which affect investors' expectations, can be viewed as risk information (Smith & So, 2022). In a worldwide survey of major institutional investors, Krueger, Sautner, & Starks (2020) find that investors treat climate risk as a material factor in their investment decisions. However, investors also realize that valuing climate risk is a difficult task due to the nature of the risk and the available information about the risk. Despite an increased awareness of climate risk, its valuation is challenging because the impact of climate change is long-run term and it is difficult for investors to "know with any degree of certainty the precise nature or severity of climate risks that are facing them (p. 22)" (Giglio et al., 2021).

During the valuation process, investors integrate information on both expected future cash flows and risk information to value firms' equity. Many studies in capital market accounting research find that risk factors influence investors' valuation process and drive investors to adjust the relative weights placed on individual accounting variables. Barth, Beaver, and Landsman (1998) find that when firms become financially stressed, investors place higher price multipliers on the book value of equity and lower price multipliers on earnings. The valuation process has potentially important implications for dealing with climate change because it can work as an incentive to transition economies toward lower-carbon forms and to mitigate and hedge climate risk (Giglio et al., 2021). However, whether climate risk affects equity valuation is as yet an unanswered question.

The specific research questions in this thesis address this last point and can be summarised as follows:

1) Does climate risk have a statistically significant impact on equity valuation through changes in investor perceptions of the book value of net assets and the expected value

of future earnings?

2) Does the relation between climate change and equity valuation vary among industry groups?

1.2 Theoretical Framework

This thesis adopts the Gordon (1962) and Ohlson (1995) valuation models to describe the relation between accounting variables and stock values and investigates the valuation effect of climate risk by observing the association between climate risk variables and the parameters in the valuation models. Gordon (1962) expresses stock price as the discounted value of future expected dividends. Based on the Gordon model, the Ohlson (1995) valuation model utilises the clean surplus relation and the assumption of linear information dynamics to deduce that stock price can be expressed as a function of book value of equity, abnormal earnings, as well as other information. The Ohlson (1995) model is now widely accepted and used in the accounting literature.

A comprehensive approach to investigate the usefulness of accounting information should combine both risk and benefit aspects of the valuation models, but the former is generally ignored by researchers (Penman, 2016). Accounting variables are believed by some to play a role in conveying the information about risk (Penman, 2021). By this view, the ability to convey information about risk is embodied in accounting conservatism because of differences in recognition between revenues and expenses (Barker & Penman, 2020). However, while some claim that the distortions undermine the usefulness of accounting information, others argue that accounting measurement procedures do not introduce distortions but enable accounting variables to capture information about risk.

The Ohlson (1995) provides a theoretical framework for value relevance studies. Operational models based on this theory, however, are generally expressed in additive linear forms, and suffer from econometrics problems that undermine the reliability and consistency of estimates of the parameters on the accounting variables in the models. To accurately capture the impact of climate change on equity valuation, a theoretical problem is how to correctly specify the relation between market value and accounting variables. In this regard, the thesis employs the theory proposed in Falta & Willett (2013) and Lubberink & Willett (2020), which highlights that the relation between market and accounting values should be expressed as multiplicative power law and estimated by a log-linear model. This model allows the long-run association between individual accounting variables and market value to be validly expressed in the form of elasticities.

In this context, the magnitudes of the elasticities reflect the value relevance of individual accounting variables. A larger magnitude of the elasticity implies that investors place more valuation importance on the corresponding accounting variable, and vice versa. According to the valuation theories discussed above, the time series patterns of the elasticities of accounting variables are determined by the investors' changing expectation of future firm earnings. When market participants feel pessimistic about future earnings, they pay more attention to the reported book value of equity than reported earnings.

The research questions suggested by accounting equity valuation theories, lead to expression of the questions noted in the previous sub-section as follows:

R1: Abnormal changes in climate measures such as global temperatures increase investor pessimism in estimates of future earnings resulting in increases in the equity value elasticity of book value compared to that of earnings.

R2: The impact of changes in climate measures is more noticeable in industries that are sensitive to climate change.

The thesis views climate risk as a source of the exogenous shock and examines its effects on the dynamics of the elasticities of individual accounting variable, which indicates the valuation effect of climate risk.

1.3 Research Method

The data used to test the hypotheses above is a sample of 180,042 firm year observations on listed U.S. firms over the period 1971 to 2017. The principal measure of climate risk is the annual global anomaly temperature over the period. Other measures of climate risk are considered to provide robust evidence for the baseline results, including U.S. temperature, Global CO_2 emissions, U.S. CO_2 emissions, U.S. precipitation, and the U.S. Palmer Z Index. On the one hand, the climate variables, especially the global temperature, are generally believed to be exogenous and random, which makes the research similar to a "natural experiment". On the other hand, weather is a complex and multidimensional system, which makes for difficulty in using individual variables as good summary statistics. Nevertheless, the global temperature is assumed to be a sufficient statistical measure representing the climate system.

The impacts of climate change on equity valuation are investigated in a two-stage approach. In the first stage, annual cross-sectional regressions are conducted, using the log-linear model at both the U.S. and industry levels. The estimated coefficients are the elasticity measures of stock price with respect to individual accounting variables, capturing the relationship between the market and accounting values. The estimated elasticities are then used in the second stage to test the valuation effect of climate risk.

In the second stage, time series regression models are estimated for each of the estimated coefficients obtained in the first stage using the measure of climate risk as the regressor. The signs and the magnitudes of the estimated coefficients in the second stage indicate how changes in climate influences equity valuation through the channel of accounting information. Unit root tests are conducted to check for the existence of cointegration relationships between the estimated coefficients and temperatures. These tests are to address concerns that the time series regressions may be compromised by the problem of spurious regression. Based on Bansal, Kiku, & Ochoa (2016), the temperature variables are decomposed into short-run and long-run components of climate shocks to observes the valuation effect of each component.

1.4 Summary of Key Findings

In the first stage, the results show that the multiplicative model explains about 80% of the variation in equity value. This explanatory power holds for both the U.S. sample and the subsamples for individual industries. The baseline results for the elasticities demonstrate that the book value of equity has a relative higher valuation importance than earnings during the period from 1971 to 2017 at both U.S. level and individual industries level. Specifically, for the U.S. economy as a whole, equity value increases by about 0.519% when the absolute value of book value of equity increases by 1%, and the equity value increases by 0.271% when the absolute value of earnings increases by 1%.

The results in the second stage demonstrate that the signs of climate variables associated with book value of equity and earnings are different, with a positive effect on the elasticities of book value of equity and a negative effect on the elasticities of earnings.

Specifically, the results for the U.S. economy as s whole show that a 1^oC increase in the global anomaly temperature increases the elasticity for book value of equity by 0.117 but a 1^oC increases in the global anomaly temperature decreases the elasticity for earnings by 0.1698. Although the signs of these impacts are the same across different industries, the magnitudes vary across the industries. These results provide evidence supporting the hypotheses in the thesis.

1.5 Contribution

The thesis makes contributions to the literature on value relevance of accounting, accounting-based valuation, environmental accounting, and climate finance.

First, the thesis adds to the literature on the value relevance of accounting. It uses the elasticities of equity value with respect to individual accounting variables to measure the value relevance of accounting variables. The use of log-linear model results in more valid and reliable estimation of the value relevance of the different accounting variables compared to prior studies in the literature. The linear form of market-accounting models adopted in prior studies suffer some econometric issues and results in bias and inconsistency in the estimated coefficients. These issues cannot be remedied through conventional methods because these models misspecify the market-accounting relation. According to Lubberink & Willett (2020), the correct market-accounting relation should be expressed as a multiplicative power law, which can be estimated as a log-linear model.

Second, the thesis adds to the accounting-based valuation literature. Many studies in the field reveal the specific roles of book value of equity and earnings in the valuation process (Burgstahler & Dichev, 1997; Collins, Maydew, & Weiss, 1997; Penman, 1998). The thesis provides new evidence for accounting-based valuation research. The first stage regressions show that book value of equity and earnings are complementary in the valuation process and book value of equity generally plays a more important role in valuation than earnings during the study period. Moreover, the second stage tests reveal that accounting variables transmit information about climate risk into equity value.

Third, the thesis contributes to the environmental accounting literature. The study interprets a part of the “other information” variable in the Ohlson (1995) model as climate change. The branch of studies ignores the effect of climate risk on the value relevance of individual accounting variables. The measurement of the value relevance of “other information”, as used in past studies, frequently suffers from an endogenous relationship between equity value and the “other information” variable. The use of the global anomaly temperature to measure climate risk (the “other information”) should eliminate that risk as the global anomaly temperature can be viewed as an exogenous variable.

Fourth, the thesis contributes to climate finance literature. One strand of this literature constructs and tests different measures of climate risk and their impact on market reactions. The different measures of temperature include global temperature, local temperature, daily temperature, and annual temperature (Addoum, Ng, & Ortiz-Bobea, 2020; Balvers et al., 2017; Bansal et al., 2016). The global anomaly temperature is used in the thesis as the primary measure of climate risk and also consider other climate variables.

1.6 Organisation of the Thesis

The rest of the thesis is organised as follows. Chapter two reviews the relevant literature relating to the basic research question of whether and how climate change affects equity markets. Chapter three develops the theoretical framework and propose hypotheses. Chapter four describes the research design and the regression models estimated to test the hypotheses. Chapter five conducts the tests and reports the results. Chapter six discusses the findings and Chapter seven presents the conclusion of the thesis.

CHAPTER TWO

LITERATURE REVIEW

Climate change has become an important source of economic risk (Bansal et al., 2016), which influences firms' strategy decisions, operational activities, and financial performance. Moreover, the awareness of climate risk among investors is increasing, which has a significant effect on investors' equity valuation processes (Bolton & Kacperczyk, 2021; Hong et al., 2020). The risk imposed by climate change has triggered research interest in economics, financial, accounting, and management. This chapter reviews the studies relevant to climate risk, especially, the effects of climate risk on capital markets, on firms' performance, firms' operational and financial behavior, and on investors' beliefs.

Generally, in the literature, the effects of climate change are classified into two categories: psychological explanations, which are based on weather-induced pessimism, and rational investor explanations, which are based on the different of climate risk and the impact of climate risk on firm fundamentals. The latter set of factors potentially influences the accounting-based valuation process of investors and provides a basis for the hypotheses developed in next chapter.

The chapter is organised as follows. Section 2.1 reviews studies about whether climate risk is priced in capital markets, including share, bond, and derivative markets, and theoretical explanations of the climate risk premium. Section 2.2 reviews studies on the impact of climate risk on firms' financial performance. Section 2.3 summarises studies relating to the influences of climate risk on firms' operational and financial behaviors. Section 2.4 covers studies concerned with the value relevance of environmental performance. Section 2.5 reviews studies regarding the perception of climate risk and its effects on the usefulness of financial information to investors.

2.1 The Climate Risk Premium

Studies on the relation between physical climate change and the real economy can be traced back to Nordhaus (1977). Investigation of the relationship between climate risk and returns is a fast growing literature focusing on two categories of climate risk: physical climate risk and transition risk (Giglio et al., 2021). This branch of studies is called climate finance literature. Its key issues are to investigate whether the risk arising from climate can be viewed as a source of systematic risk and, if it can, whether climate risk can be incorporated into studies on capital markets. These studies are conducted under the framework of asset pricing research and methods are conventional asset pricing methods, often using event studies, the approach of Fama & MacBeth (1973) and factor-mimicking portfolio approaches. The different characteristics of climate risk are interpreted through the lens of asset pricing models, producing mixed empirical results.

Physical climate risk refers to the potential direct damage resulting from climate change, including drought, floods, extreme precipitation, and the rise in sea level. Transition risk refers to the regulations which force or encourage firms to adopt mitigating and adapting strategies in order to transit to a lower-carbon economy. The two types of climate risks are closely interrelated in influencing firms' future cash flows (Balvers et al., 2017; Hong et al., 2019), but they have differing effects. Generally, transition risk become more important in the long-run period (Li, Shan, Tang, & Yao, 2020). Some authors classify climate risk into more detailed categories according to the requirements of their studies. Krueger et al. (2020), for instance, classify climate risk into three categories: physical, regulatory, and technological climate risk. Painter (2020) lists four types of climate risk when studying its effect on bond market: production risk, reputation risk, regulatory/litigation risk, and physical risk. Li et al. (2020) decompose transition risk into proactive and non-proactive components.

A characteristic of climate risk is its high level of uncertainty. Sautner, van Lent, Vilkov, & Zhang (2021) list various sources of uncertainty relating to climate change: carbon emissions, temperature trends due to carbon emissions, regulatory intervention, the success of developments toward lower-carbon technologies. Görgen et al. (2020) note that the process of transition to a green economy involves uncertainty about changes in environmental regulation and investors' trading behavior. An economic consequence of the high uncertainty is that it is difficult to insure against climate risk (Engle, Giglio, Kelly, Lee, & Stroebel, 2020).

In addition to uncertainty about the climate-economy relationship, there is also uncertainty in the projections of climate change, which are based on the global climate models. Although climate scientists have developed sophisticated computer models seeking to reduce uncertainty, some fundamental factors limit this endeavour. Burke, Dykema, Lobell, Miguel, & Satyanath (2015) argue that projections of the future impacts of climate change need to account for uncertainty, which results in wide range of projected impacts and higher probabilities of worst-case outcomes.

Another characteristic of climate risk is that it is highly complex and multi-faceted. Sautner, van Lent, Vilkov, & Zhang (2020) decompose the total exposure into different components, including opportunity exposure (both upside and downside aspects), physical exposure, regulatory shocks and sentiment measures. These measures reflect climate change exposure from multiple perspectives. Climate change exposures are multifaceted and different firms suffer from different aspects of exposure over time. One consequence of the complexity of climate risk is that it is difficult to create a single measure that captures all aspects of a firms' climate risk exposure (Li et al., 2020).

Because of these characteristics, researchers find that climate risk is "orthogonal" to other common risk factors and cannot be subsumed by other risk factors (Hsu, Li, & Tsou, 2022). It is very hard to price, hedge, or insure against, and the exposure to climate risk varies significantly across firms, industries, regions and time periods (Giglio et al., 2021).

Diverse measures of climate risk are used in the literature, including those relating to carbon emissions, temperature, Environment, Social, and Governance (ESG) index, severe climate events, and firm specific measures based on text analysis. The choice of the measure of climate risk depends on the requirements of the relevant research, and specifically the purpose of identifying underlying economic factors capturing differing aspects of climate risk. Identifying underlying mechanisms is an important task for this branch of research. This thesis mainly focuses on the measurement of global temperature and the pros and cons of using this measure are discussed in detail in Chapter 4, Research Design.

The challenge in constructing a climate risk measure is how to capture the multi-faceted nature of climate risk Li et al. (2020). Bolton & Kacperczyk (2021) adopt carbon emissions, including the level of emissions, changes in the level of emissions, and emission intensity to reflect climate risk. The advantage of the carbon emissions measure is that it is closely related to global climate change and captures firm-level exposures to regulatory shocks, rather than physical shocks. Hsu et al. (2022) use the data from the Toxic Release Inventory (TRI) on the amount of emitted chemicals to construct the measure of “emission intensity” scaled by total assets.

The ESG index is a widely used measure of climate risk. There are a number of different providers of ESG datasets include Bloomberg, CDP, Ceres, Thomson Reuters’ ASSET4, and Sustainalytics. These types of measure capture diverse aspects of climate risk, including current emission intensity, adaptability, which is used to indicate the ability to deal with uncertainty in transition process, and public perception. This is important because Görgen et al. (2020) argue that carbon risk should not be measured directly using carbon emission, and should take into account firms’ strategic and operational exposures. Some authors note that the ESG databases suffer from self-reporting bias, green-washing bias, limited coverage, being opaque, being self-serving, and idiosyncrasies (Görgen et al., 2020; Li et al., 2020; Nagar & Schoenfeld, 2022).

Some studies adopt a textual approach to identify firm-level climate risk. Different types of climate risk measures distinguish between the physical and transition climate risk exposures of firms. The FASB, SEC, and IFRS have called for firm specific measures (Nagar & Schoenfeld, 2022). Li et al. (2020) propose a firm specific measure of climate risk using textual analysis for earnings conference call transcript data. These contain detailed discussions about climate risk by analysts and investors. Sautner et al. (2020) adopts a machine learning approach to construct measures of climate change exposure by extracting information from earnings conference calls. Compared to other measures of climate change, such as carbon emissions, these measures are viewed as “soft” information because they are qualitative and come from the conversation between managers and analysts. Gostlow (2020) studies the identification of material firm-level physical climate risk from 8-K filings by using a textual approach. The author finds that form 8-K, which aims to provide investors with information about firms’ significant material events, contains physical climate risk information which is not mentioned in earnings calls.

2.1.1 The Reaction in Share Markets

Three hypotheses are used to test the share market’s reaction to climate risk. First is the carbon risk premium hypothesis, which holds that capital markets are efficient and climate risk is priced. If climate risk is a systematic risk, it is expected that climate risk influences the cross-section share returns and requires a premium to compensate for the risk borne by investors. Second is the carbon alpha hypothesis, which asserts that capital markets are inefficient and climate risk is mispriced. Third is the “sin stocks” or divestment hypothesis, which assumes that investors prefer shares that they believe are environment friendly (Bolton & Kacperczyk, 2021).

Bolton & Kacperczyk (2021) examine the relation between carbon emissions and share returns. They identify several channels that price the risk in carbon emissions: 1) emission intensive firms may attract a fossil fuel energy price risk, 2) regulatory intervention for emissions may occur, and 3) technological risks may eventuate when transforming to a low carbon economy. Based on a regression of monthly returns on emission and control variables, the authors find that the level of carbon emissions and change in emissions from the three channels have a significantly positive impact on share returns. Choice of measure of carbon emission intensity does not have an effect on these results.

The authors explain that the channels of regulatory intervention and technology development are only related to the total emissions and that emission intensity is a noisy measure of carbon risk exposure. This supports the belief that investors price a carbon risk premium at the firm level in all industries as all companies are exposed to various degrees of carbon risk and carbon intensity firms are distributed among a wide range of industries. Moreover, the risk premium implies a low demand for carbon intense stocks, reducing the price of high carbon intensity stocks.

Hsu et al. (2022) argue that pollution emissions are the by-product of consumption and production, and it is expected that there is a relation between pollution and share returns. The authors discuss several potential explanations addressing the emission-return relation, including behavioral, corporate governance, and regulation explanations.

Görgen et al. (2020) investigate the relationship between carbon risk and share returns by using a factor-based asset pricing model. The reasons for adopting a factor approach are that the factor-mimicking portfolios capture the systematic variation in returns which is related to underlying economic risk. These factors can help to explain the risk premium, as a compensation for bearing underlying risk. Factor-mimicking portfolios are formed by grouping firms into terciles to distinguish the sample into green firms and brown firms. The results show that the constructed factors reflect the systematic variation in returns and are orthogonal to other common risk factors. The factors increase the explanatory power of common factor models. It is concluded that the constructed factors are of relevance for asset pricing and that market participants assess the carbon risk in the valuation process.

However, some studies find that the climate risk cannot be fully incorporated into share prices, and that there is inefficiency in the share market. Hong et al. (2019) use worldwide samples to study the effect of droughts, which are more severe due to higher global temperatures, on the food industry. Severe droughts can have a devasting effect on the food industry and reduce its profitability. The measure of drought used here is Palmer Drought Severity Index (PDSI), which denotes drought intensity by compositing the information on temperature and moisture in the soil. The authors find that information about climate risk is incorporated into share prices with a significant delay.

Gostlow (2019) identifies some potential reasons why information about climate risk may not be priced in a timely fashion. First, the information from climate science is difficult to be understood by non-experts. The public is therefore unable to rationally assess the hazards from physical climate risk. Second, the asset pricing models used to examine climate risk suffer from omitted risk factors and measurement error, so that the estimated risk premium is biased if the omitted risk factors are correlated with climate risk.

2.1.2 The Reaction in Bond Markets

Another source of finance for many firms is the bond market. In some ways the effects of climate risk are more evident by bond markets than equity market (Seltzer, Starks, & Zhu, 2022). Bond markets have debt securities with different term structures and different maturities corresponding to different types of climate risk. Specifically, bondholders are more sensitive to the downside climate risk. Painter (2020) provides empirical evidence of the effects of climate change on bond markets, where maturity is more than 25 years and on short-term bonds (Correa, He, Herpfer, & Lel, 2020). Many studies focus on municipal bonds, corporate bonds, and green bonds. Generally, municipal bonds have longer term structures than corporate bonds. Compared to corporate bonds and shares, municipal bonds are more likely to be affected by climate risk because municipalities have fewer tools to hedge against climate risk (Painter, 2020). The green bond is a corporate bond defined as one where its proceeds are committed to environmental and climate-friendly projects. Green bonds are popular in industries where environmental issues are financially material, such as energy, utilities, and transportation. Corporate green bonds have increasingly appeared each year since. In 2018, 396 corporate green bonds with proceeds of US$95.7bn were issued (Flammer, 2021).

The main hypothesis in Painter (2020) is that municipal bonds have higher issuance costs if they are exposed to climate risk. Some of the findings in the paper include: 1) climate risk is priced in bond market; and 2) it is the awareness of climate change rather than the realization of climate risk that determines the required risk premium. The author notes that investors can perceive climate risk through credit ratings provided by bond rating agencies.

Correa et al. (2020) investigate the impact of natural disasters on corporate borrowing costs by distinguishing the direct effect of climate change from the effect due to updating beliefs about the severity and frequency of future disasters. The authors find that the attention to climate change amplifies its direct effect. The approach in the paper is to observe borrowers who are exposed to the risk of natural disasters but are not directly affected by the specific events. These borrowers can be viewed as indirectly affected or at-risk borrowers.

Three rationales behind the issuance of corporate green bonds include 1) it is a credible signal of environmental commitment, 2) it is “greenwashing” behavior, and 3) it is the consequence of a trade-off between financial rewards and social welfare (Flammer, 2021). By observing the effects of the issuance of green bonds on share markets, Flammer (2021) finds evidence supporting the argument of its being a credible signal for environmental commitment. The author also finds that after issuance of green bonds, firms’ carbon emissions decrease and their environmental profile increases. On the demand side, Zerbib (2019) argues that both financial motivation and a preference for pro-environmental attitudes encourages investment in green bonds. To identify the motivation of pro-environmental preferences, the author uses the green bond premium for analysis. This is defined as the yield difference between the green bond and the counterpart conventional bond. He concludes that the pro-environmental preferences have weak impact on bond prices.

Seltzer et al. (2022) investigate the relation between regulatory climate risk and corporate bonds. Among the three components of climate risk, physical, technological, and regulatory, the latter is held to be most immediately relevant to investors, being related to firms' operating costs, cash flows, and investments. The authors find that high carbon footprints lead to lower credit ratings and higher yield spreads. The effects become pronounced if the locations of the firms are under stricter environmental enforcement regimes. The authors conclude that firms' environmental performance influences their credit risk due to regulatory risk.

2.1.3 The Reaction in Derivative Markets

The derivative market can reveal forward-looking expectations about climate risk and help to capture the higher moments of climate risk. The extent of climate risk determines whether the asset pricing effects of climate can be observed in capital markets and what types of capital markets are most affected. In addition to the second moment, the higher moments of climate risk, especially the downside tail risk, have important implications for investors' valuation process. Option markets capture information about climate risk that cannot be captured in share markets.

Ilhan et al. (2021) investigate whether uncertainty involved in climate regulation is priced in option markets based on the carbon intensity of Scope 1 emissions[1]. The paper adopts three option-related measures to capture different quantities of climate risk. In addition to evidence that climate risk is priced in option market, a further insight from this analysis of the option market is that at the firm level, the regulation risk of climate change increases both the left and right tail risk, implying that such change not only involves greater risk but also more opportunities. At the industry level, the risk concentrates on the left tail, implying that this risk is systematic and undiversified, but that the right tail risk is diversified away in the pricing process. The authors also find that public attention to climate change plays an important role in pricing. Higher public attention increases the cost of hedging against downside risk for carbon-intensive firms

---

[1] United States Environmental Protection Agency (EPA) defines Scope 1, Scope 2, and Scope 3 emissions as "Scope 1 emissions are direct greenhouse (GHG) emissions that occur from sources that are controlled or owned by an organization (e.g., emissions associated with fuel combustion in boilers, furnaces, vehicles). Scope 2 emissions are indirect GHG emissions associated with the purchase of electricity, steam, heat, or cooling." "Scope 3 emissions are the result of activities from assets not owned or controlled by the reporting organization, but the organization indirectly impacts in its value chain. Scope 3 emissions include all sources not within an organization's scope 1 and 2 boundary. The scope 3 emissions for one organization are the scope 1 and 2 emissions of another organization." (EPA website, https://www.epa.gov/climateleadership/ghg-inventory-development-process-and-guidance)

because it increases the probability of firms adopting pro-climate policies.

Using measures of firm specific climate risk Sautner et al. (2020), Sautner et al. (2021) investigate the relation between climate risk and forward-looking option-implied expected returns. Based on expected returns, they observe the climate risk premium over time, demonstrating the magnitude of climate risk, and its association with economic conditions.

The authors adopt two measures of expected returns. The first is based on Martin & Wagner (2019), and mainly captures the second moment (variance) of risk quantity. The second measure considers higher moments based on Chabi-Yo & Loudis (2020), which can account for extreme left-tail risk and opportunities suggested by the right tail risk. Using the Fama & MacBeth (1973) approach, they find risk premiums from option-implied expected returns are positive. The magnitude is large for the opportunity and regulatory components of climate risk but small for the physical shock component. With respect to the dynamic pattern of the risk premium, they find that the unconditional risk premium can mask the magnitude of some subsample periods. Before 2011, the risk premium is about zero. Between 2012 and 2015, risk premium for both expected returns increases. After 2015, both premiums revert toward zero. The dynamic patterns of the risk premium are due to the changes in investors' risk preferences and in the risk magnitudes.

Schlenker & Taylor (2021) use the derivative prices associated with cumulative cooling degree days (CCDs) and cumulative heating degree days (HDDs), to reflect investors' expectation about climate change over time. The derivatives are futures contracts traded on the Chicago Mercantile Exchange (CME). The authors argue that because the derivative contracts are traded based on unrealized future weather data, they capture how markets think about the expected future climate risks. The authors find that weather shocks may be incorporated in the futures market more than two weeks ahead. The study also finds that future derivative prices capture both short-term weather changes and long-term warming trends.

2.1.4 Theoretical Explanations for a Climate Risk Premium

In addition to the large number of empirical studies, some theoretical studies provide explanations for the observed the positive climate risk premium based on the argument that climate change is an important source of economic risk (Bansal et al., 2016).

Karydas & Xepapadeas (2019) study the pricing of climate-related risk within dynamic CAPM framework. Both physical risk and transition risk are considered. The two types of climate risks are closely related. An increase in the frequency and magnitude of physical risks may lead to an increase in the introduction of more stringent environmental policies to force firms to move to a low-carbon economy. Investors' allocation decisions can be efficient if climate risk is priced appropriately. In the dynamic CAPM framework used by the authors, physical risk and transition risk are described by a Poisson process. The equity premium is determined by the probability of the severe nature disasters, which decrease equity valuations.

Bansal et al. (2016) develop a temperature-augmented long-run risk (LRR-T) model based on Bansal & Yaron (2004) to explain why persistent temperature shifts generate a positive risk premium in the stock market. They argue that when temperature reaches a "threshold level", the frequency and magnitude of disasters increase and generate a higher tail risk. The source of economic risk affects expected growth rates and discount rates. The increase in temperature increases the marginal utility of consumers and reduces the current wealth to consumption ratio, which results in a positive premium. The impact of natural disasters when temperature reaches a tipping point is assumed to be driven by a compensated compound Poisson process. Both the frequency and the damage caused by natural disasters are assumed to increase with an increase in temperature. With the adoption of Epstein & Zin (1989) utility function, the authors argue that investors prefer early resolution of uncertainty, which reveals that long-run temperature fluctuations play a role in the asset pricing process. The authors conclude that forward-looking equity prices capture the cost of long-horizon temperature fluctuations.

2.2 Climate Risk and Performance

The literature discussed in the last section demonstrates that climate risk affects capital markets. A natural extension is to investigate whether climate risk influence firms' financial performance. Studies on firm performance may help to reveal the underlying economic mechanisms by which climate risk is priced. In this branch of the literature, research adopts various econometric methods, including difference-in-difference and events studies.

Pankratz, Bauer, & Derwall (2019) investigate the relation between climate risk and firms' financial performance based on variables including: sales turn over, revenue, operating income, and profit. Here, the authors choose a measure of climate risk that is viewed as exogenous and randomly distributed by counting the number of days in the local region when the highest daily temperature exceeds certain thresholds during a financial quarter. They find that exposure to climate risk reduces firms' performance significantly. The results are industrially and geographically heterogeneous.

Brown, Gustafson, & Ivanov (2021) examine the impact of extremely cold temperatures on firms' cash flow. Climate risk variables are measured by abnormal winter snowfall, which is the difference between the average daily snow cover in each first quarter and the average over a ten-year period. The authors argue that the snow cover influences the short-term cash flow but not the firms' long-term profitability.

Based on labor supply explanation, Addoum et al. (2020) examine the impact of location-specific temperature shocks on performance in a sample of U.S. firms from 1990 to 2015. Three extreme temperature measures are defined for each location's fiscal period: average temperature, days of absolute extreme high (cool) temperature above (below) certain thresholds, and days of relative extreme temperature. The constructed temperature measures as assumed to be random and exogeneous. The results fail to support evidence of an effect on firm performance.

Hsu et al. (2022) argue that pollution emissions affect firms' cash flows in both the short and long term. In the short term, firms can avoid costs relating to environmental related investments and the costs of pollution abatement and environmental recovery. In the long term, severe pollution may occur in the presence of more stringent environmental regulation, leading to higher costs for firms with high emissions. The authors find that while emission intensity increases firm's profitability due to the cost saving from pollution abatement, but the profitability declines in the future with stricter environmental regulations.

Hsu, Lee, Peng, & Yi (2018) investigate the impact of extreme climate events on firms' operating performance (ROA) and mitigating role of technology diversification on the negative effects of extreme climate events. Natural disasters have unpredictable and unavoidable impact. They not only cause economic losses, but also disrupt firms' operations and supply chains. Their results indicate that firms with production facilities located in areas suffering natural disasters have a lower ROA. Technology can help firms reduce the disruption to operations and enable firms to be more adaptive to extreme events. Synergistic effects from diversified technologies can reduce the costs of R&D.

2.3 Climate Change and the Adaptive Activities of Firms

Human activities may cause climate change and firms can take adaptive action to mitigate and hedge against these and the associated climate related risk. Some research focuses on adaptive behavior that has long-run effects on firms' future profitability. It demonstrates some of the underlying mechanisms relating to the impact of climate change on firm fundamental performance.

Dai, Duan, Liang, & Ng (2021) study how corporations address climate change through outsourcing carbon emissions by using a sample covering 76,356 firm-country-year observations over the period from 2006 to 2018. The authors find that the motivation to outsource carbon emission is stronger for firms located in states with stringent legislation and high public environmental consciousness. There are several potential explanations for the outsourcing behaviors. First, the agency view suggests that outsourcing behaviors help to maintain firms' reputations. Second, the environment-oriented stakeholder view suggests that stakeholders have an incentive to force firms to transfer toward low-carbon economy. The third view suggests that carbon outsourcing is a cost-effective and less risky approach compared to the large amount of capital investment needed for pollution abatement. The authors find that corporations with high ESG tend to outsource carbon emissions.

Dai, Duan, & Ng (2021) argue that competition plays a role in shaping corporate environmental policies when firms face stringent regulations. The competition drives firms to develop green innovation, such as new pollution-reducing technologies, in response to stringent environmental regulation. In less competitive markets, firms have the market power to transfer costs to consumers and there is a "replacement effect" in the innovation. In competitive markets, however, firms have the motivation to gain competitive advantages through differentiation strategies by developing innovations. Adopting a triple-difference design, the authors find that high competition results in a 6% reduction in product similarity and a 5% increase in the number of corporate customers due to advantages produced by engaging in environment-friendly activities.

Heo (2021) argues that the physical climate risk has both positive and negative effects on firms. The negative effects are disruption on operations and impairment in firm value. The positive effects are new growth opportunities. An important characteristic of climate change is that it is a new source of uncertainties, which delays investment until the uncertainty resolves. Various factors, including capital intensity, operating flexibility, investment irreversibility and re-deployable capital, influence the relation between climate uncertainty and investment. Using a sample of U.S. firms from 1984 to 2017 and the Climate Change News Index as the measure of climate uncertainty, Heo (2021) finds that climate uncertainty negatively affects corporate investment, with a one standard deviation increase in climate uncertainty leading to a 6% decrease in corporate investment.

Lin, Schmid, & Weisbach (2019) argue that fluctuations in demand and product price induced by climate change causes firms to adjust their investment and asset structure polices. Based on a theory of irreversible investment, the authors predict that firms tend to adopt a flexible investment to deal with climate risk. The authors focus on electricity-generating firms. Flexible investment refers to the use of gas, oil, or pump storage as production technologies and inflexible investment refers to the use of coal and nuclear production technologies. Using the daily extreme temperature to measure climate risk, the authors find that extreme temperature increases the amount and the volatility of electricity demand and the volatility of electricity price, which motivates firms to increase the investment in flexible operations. Specifically, a one percent increase in extreme days results in a 0.8 percentage point increase in investment in flexible operations.

Based on the theoretical framework of Bolton, Chen, & Wang (2011, 2013), Javadi, Masum, Mollagholamali, & Rao (2020) investigate the impact of climate change on firms' cash holdings and predict that climate change forces firms to hold more cash for precautionary purposes. The climate risk measure used is the Palmer Drought Severity Index (PDSI) with an AR(1) model to capture the long-term trend of climate change. The main results show that cash holdings were positively related to climate risk measure. Compared to the sample mean, there is a 3% to 9.2% increase in cash holdings when these are exposed to climate risk. The authors conclude that managers tend to choose more conservative financial policies to mitigate the adverse shocks of climate risk.

Correa et al. (2020) find that climate risk forces firms to adjust their financial behaviors. In their sample, bank-dependent firms reduced their capital expenditure by 0.8%, or about 10% of the unconditional sample mean. Firms increased their cash holding relative to liabilities by about 15% relative to the unconditional sample mean. The cost of funding can therefore be a channel through which climate risk influences firms. The effects of climate-related natural disasters are transitory and moderated by perceptions of climate risks.

Brown et al. (2021) investigate if firms facing a short-term climate shock will use bank credit lines to deal with the additional demand for cash flow. The authors apply 2SLS and reduced form regression analysis to identify firms' response to the cash flows shocks arising from climate risk. These responses include credit line use, credit line size, and other liquidity management tools. Managers appear to use these tools to deal with the exogenous cash flow shocks due to climate risk. These behaviors cause renegotiation between borrowers and lenders, resulting in adjustments to interest rates and other contract terms. The authors conclude that interest rates increase, and contract terms become more onerous as climate risk increase.

By using a forward-looking physical climate risk measure, Ginglinger & Moreau (2022) investigate the impact of climate risk on capital structure. The authors argue that there are two underlying channels that determine the relation between physical climate risk and financial leverage: expected distress costs and operating costs. The former channel implies that credit rating agencies, which become more conservative when perceiving the climate risk, incorporate climate risk into their credit rating. Therefore, lenders tend to limit amount of debt and increase the spread for firms which are exposed to high climate risk. This is a supply side effect. It implies that physical climate risk devalues firm assets and increases the operating costs, which negatively influence the profitability. Also with the growing awareness of climate risk, a demand for debt is substituted for with a demand for shareholder equity. This is a demand side effect. According to the authors, the results of this study support the contention that higher physical climate risk leads to a lower leverage in the period after 2015.

2.4 Value Relevance and Climate Risk

By comparison with studies in climate finance, which focus on returns and risk premium within the framework of asset pricing, the environmental accounting literature focuses on the valuation effects of climate change based on a variant of the Ohlson (1995) model. This maintains that coefficients on the book value of equity and earnings are positive, but the coefficient on climate variables is negative. In this section of the literature, both the level of emissions and the disclosure of such information are considered to be value relevant.

The literature relating to environmental accounting provides empirical evidence on the market impact of environment-related activities and environmental performance by investigating three interrelated empirical questions: 1) the association between environmental performance and economic performance; 2) the association between environmental disclosures and environmental performance; and 3) the association between environmental disclosure and economic performance (Al-Tuwaijri, Christensen, & Hughes, 2004; Hassan & Romilly, 2017). Matsumura, Prakash, & Vera-Munoz (2014) classify the research into three categories: 1) environmental disclosures under mandatory requirements; 2) voluntary disclosure of carbon emissions; and 3) valuation effects of capital expenditures. Findings suggest that a source of valuation relevance is in the intangible assets and intangible liabilities created by firms' environment-related activities, which are not recognised by current accounting practices. Theories relevant to this area of the literature are: the resource-based view of the firm, stakeholder theory, and the Porter hypothesis (Clarkson, Li, Richardson, & Vasvari, 2011; Griffin, Lont, & Sun, 2017, etc.).

Pollution makes likely the incurrence of future compliance, abatement, regulatory, and operating costs. These costs reduce firms cash flows but are not recognized, or only partially recognized, in accounting statements. Therefore, the reporting of emissions data can provide additional information about firm value other than book value of equity and earnings. The direct emissions are more likely to be associated with regulation costs. The indirect emissions are more likely to be associated with production costs. The evidence for the value relevance of environmental performance is "strong and unambiguous" (Clarkson, 2012, p.15).

Al-Tuwaijri, et al. (2004) argue that the frequently unobservable nature of management's overall strategy makes environmental disclosure, environmental performance, and economic performance difficult to disentangle. Therefore, management strategy is often an omitted variable in explanatory models, which results in inconsistent results when testing and makes OLS estimation biased and inconsistent. Prior studies typically suffer from model misspecification. After considering the problem of model endogeneity, the authors, using a sample of 198 U.S. Standard & Poor's firms, find that environmental performance is positively associated with economic performance and with more extensive environmental disclosures.

Clarkson, Li, & Richardson (2004) investigate the value relevance of environmental capital expenditure for pollution abatement in the pulp and paper industry over the period from 1989 to 2000. These industries were subject to more stringent environmental regulation after the 1970s. Based on the environmental accounting literature, the authors argue that low-polluting firms gain benefits from environmental capital expenditure, through the creation of "green goodwill", via environmental innovation, and various competitive advantages. However, high-polluting firms incur un-booked environmental liabilities due to high-polluting firms facing obligations relating to future abatement outlays, which fail to provide incremental reward to shareholders. The authors find that the value relevance of environmental capital expenditure is related more to low-polluting firms than to high-polluting firms. In high-polluting firms, un-booked liabilities are estimated to be about $560 million.

Clarkson, Li, Pinnuck, & Richardson (2015) examines the value relevance of Green House Gases (GHG) emissions under the European Union Carbon Emissions Trading Scheme (ETS), which provides a unique background for study of the value relevance of environmental performance. The authors point out two factors that influence the value relevance of carbon emissions. The first is that emissions often exceed the related carbon allowance. The second is that compliance costs cannot be transferred to consumers, as these are measured with respect to a firms' market power and its carbon performance relative to its industry peers. Greater market power and more carbon efficiency increases the ability to pass the compliance cost to consumers who have low-demand elasticities.

The authors adopt a modified version of the Ohlson (1995) model and use a sample of 843 firm-year observations from the EU ETS over the period 2006-2009. They find that excessive emissions penalize firm value by 75 Euro dollars per tonne but that an ability to pass future compliance costs to consumers mitigates the effect. The effects are heterogenous among firms in and outside the EU ETS systems.

Based on the value relevance research framework and the data on carbon emissions reported to the Carbon Disclosure Project (CDP) from 2006 to 2008, Matsumura et al. (2014) investigate whether carbon emissions provide useful information for firm valuation. Their estimation is based on balance sheet valuations by adding a carbon emission variable into the calculation. In their regression models, the coefficient on carbon emissions is expected to be negative, on the basis that the market penalises firm value for emissions. To control for self-selection bias, a disclosure choice model is jointly estimated by using a Full Information Maximum Likelihood (FIML) approach. The authors find that the coefficient on carbon emissions is significantly negative. The marginal effect on firm value is $212,000 for each additional thousand metric tons of carbon emissions.

Griffin et al. (2017) investigate whether the greenhouse gas (GHG) emissions are value relevant by adopting a variant of Ohlson's (1995) model. Emissions are estimated for non-disclosing firms by using information from disclosing firms and comparing the valuation effect of GHG emissions between the two groups. One claimed advantage of the research design is that it resolves self-selection issues without the need to adopt Heckman's two-stage approach.

The authors find that GHG emissions have a negative impact on equity value and the valuation effect is greater for high level of GHG emission firms. Another finding is that the penalty on firm value is almost the same between the disclosing and non-disclosing firms. The former results can be attributed to the future regulator and compliance costs which reduce future cash flows but do not show up in accounting statements. The latter results are due to the fact that investors have multiple channels to obtain information about emissions. While these results in Griffin et al. (2017) are consistent with Matsumura et al. (2014)'s results that there is valuation effect of GHG emissions, the penalty on the firm value is smaller. They attribute the results to the higher cross-sectional and temporal variability of previous studies.

Berkman, Jona, & Soderstrom (2021) investigate the valuation effect of firm-specific measure of climate risk, which are constructed through 10-K disclosures of climate risk and opportunities. The valuation model adopted in the study is the modified Ohlson (1995) model. Firm-specific measures of climate risk have several advantages over the carbon emission measures referred to above: 1) they are a forward-looking measure, 2) they address multiple dimensions of climate risk; 3) they cover a large range of firms. In addition to showing supportive evidence for the value relevance of measures of climate risk, the authors also find that firm-specific measures of climate risk provide additional explanatory power and cannot be subsumed by environmental performance measures used in other studies.

2.5 Perception of Climate Risk

2.5.1 Levels of Public Concern

An awareness of climate risk encourages investors to favor the low carbon emission shares relative to high carbon emission shares, which can cause asset pricing effects. Some extreme climate events, such as local high temperatures, affect perceptions and attract attention to climate change. This effect can be amplified through communication and media channels. Beliefs about climate change play a significant role in valuation according to Hong et al. (2020). These perceptions are a channel for the pricing of climate risk. Climate events update the beliefs about the severity and frequency of climate change disasters (Correa et al., 2020).

Systemic climate changes are embedded in random fluctuations. Personal interpretation may result in faulty perceptions. Weber (2010) argues that climate change is difficult to detect and track accurately based on personal experience because it is a slow and gradual process. Moreover, the transfer of climate information from the scientific community to the general public is complicated, beyond the simple transmission of scientific facts. Social and political factors also play an important role in attracting public attention, forming expectations and interpreting climate change. Perceptions of climate change involve psychological, sociological, and cultural factors, often presented in debates among the general public, politicians, members of the media, and scientists.

Surveys can provide insights about investors' perceptions of climate risk when some aspects of climate change are unobservable from archival researchers. A survey by Krueger et al. (2020) reports the perception of climate risk among institutional investors and how they manage climate risk. Institutional investors play an important catalytic role in moving firms toward a lower-carbon economy. The respondents in the case are fund/portfolio managers, executive managing directors, investment analyst/strategists, CIOs, CEOs, CFO/CCO/Chairman/Other executives, ESG/RI specialists working for asset managers, banks, pension funds, insurance companies, and mutual funds around world.

The survey mainly addresses the issue of climate risk in four areas: investment decisions, risk management, shareholder engagement, and asset pricing. The experience of climate change, such as with global warming, increases investors' perception of climate risk. Most of the respondents believed that climate related damages are more likely to happen and become of more concern in the future. Such perceptions were distributed evenly among respondents located in different geographic regions.

Although respondents in this study ranked climate risk behind financial risks, they believed that climate risk has significant implications for firms and should be taken into their investment decisions. They also acknowledged that the nature of climate risk makes it a challenging task. Other non-financial factors that appeared to motivate investors to incorporate climate risk into their investment decisions, included reputation effects, and moral and legal considerations.

Deryugina (2013) use Gallup survey data for U.S. adults on global warming to investigate the formation and updating of beliefs about climate change in the presence of local temperature fluctuations. Public consensus has important implications for environmental related policies. However, it appears that while public concern about climate change increased in 1988, after a record hottest year in 1987 public attention disappeared soon afterwards. A lack of on-going public concern is regarded as one of the reasons for the lack of a strong international treaty relating to the control of carbon emissions.

Using a survey from 400,000 respondents, Bergquist & Warshaw (2019) construct a comprehensive index to capture public concern about climate change across individual states in U.S. from 1999 to 2017, exploring both geographic and temporal variation in public perceptions. The authors conclude that a higher temperature is a factor increasing concerns about the climate but there is no consensus of opinion about the consequences of climate change. They also find that change in state-level temperatures have only modest effects on public concerns about climate change.

2.5.2 Engagement Behaviour of Investors

Some studies investigate how investors react to the climate risk during their allocation decisions, which implies that investors' engagement is a factor that influences the valuation process of investors.

Bolton & Kacperczyk (2021) argue that the carbon risk influences institutional investors' behavior. Investors divest assets based on carbon emission intensity but not on the level of emissions.

To address climate risks, active investors prefer risk management and shareholder engagement, rather than divestment. Krueger et al. (2020) list a number of possible approaches in risk management to deal with climate risk. The rating of responses for the risk management of carbon emissions mention the following approaches: "analyzing carbon footprint of portfolio firms (38.0%), analyzing stranded asset risk (34.6%), general portfolio diversification (33.9%), ESG integration (31.7%), reducing carbon footprint of portfolio firms (29.3%), firm valuation models that incorporate climate risk (25.9%), use of third-party ESG ratings (25.6%), shareholder proposals (25.1%), hedging against climate risk (24.6%), negative/exclusionary screening (23.7%), reducing stranded asset risk (22.9%), divestment (20.2%), none (7.1%), other (3.7%)."[2]

The responses for shareholder engagement showed the following approaches were considered important: "holding discussions with management regarding the financial implications of climate risks (43%), proposing specific actions to management on climate risk issues (32%), voting against management on proposals over climate risk issues at the annual meeting (30%), submitting shareholder proposals on climate risk issues (30%), questioning management on a conference call about climate risk issues (30%), publicly criticizing management on climate risk issues (20%), voting against reelection of an y board directors due to climate risk issues (19%), legal action against management on climate risk (18%), other (1%), none(16%)."[3]

Lantushenko, Schellhorn, & Gulnara (2020) argue that investments in clean energy

[2] The data are obtained from Krueger et al. (2020, p. 1087) Table 4.
[3] The data are obtained from Krueger et al. (2020, p. 1092) Table 6

assets play an important role in low-carbon transition and mitigating global warming. They investigate the issue by using energy Exchange Traded Funds (ETFs) and find that both fund performance and climate risk, measured by cumulative global temperature anomaly, move the allocation of funds toward clean energy assets. The results show that investors are aware of climate risk and believe that such investment can bring them viable financial rewards by taking the advantage of growth opportunities in the energy industry. This awareness of financial opportunities in the clean energy industry may attract more investment in the decarbonization process.

2.5.3 Psychological Effect of Climate Risk

The effect of climate on the economy has long been recognised. Montesquieu noted that temperature is an important factor that influences labor-productivity because people feel "slothful and dispirited" when they are under high temperature (Dell, Jones, & Olken, 2014) and that climate plays an important role in the prosperity of society (Carleton & Hsiang, 2016). Recent literature analyses how climate change influences the productivity of analysts by focusing on their ability to forecast and deal with financial information. These analysts are trained professionally to assess the effects of risk on firms' fundamentals and to recommend stocks based on their assessment. Their behaviors are presumably representative of a broad range of market participants (Dehaan, Madsen, & Piotroski, 2017) and their opinions are often taken to represent capital market expectation (Bourveau & Law, 2021). This branch of the literature is generally based on the psychology and physiology literature, to explain such matters as the effects of fatigue, anxiety, depression, and limited attention to work due to unpleasant weather (Jiang, Norris, & Sun, 2021). Weather-induced moods may generate cognitive biases for sophisticate institutional investors (Goetzmann et al., 2015). Analysts tend to release less optimistic forecasts when perceiving increases in climate risk (Bourveau & Law, 2021; Cuculiza, Kumar, Xin, & Zhang, 2021; Jiang et al., 2021). It has also been argued that the speed of response to earnings announcements becomes slower in the presence of increased climate risk, which results in lower earnings response coefficients (ERC) and a larger post earnings announcement drift (PEAD) (Dehaan et al., 2017; Jiang et al., 2021).

Han, Mao, Tan, & Zhang (2020) provide two explanations for the impact of natural disasters on information disseminated by analysts. First, disasters distract analysts' attention from fulfilling their jobs due to the physiological effect of the disasters. This reduces the quality and quantity of information production and is called “distraction hypothesis”. The authors find that the distraction effect lasts about three months. Second, disasters may disrupt analysts from performing their jobs due to reduced access to the internet, loss of electrical power, and other similar problems. This type of reduction in quantity and quality of analyst information is called the “resource constraint hypothesis”. Experiencing disasters can have the following effects on analysts: 1) they allocate attention to more salient firms; 2) disasters increase the perceived uncertainty in accounting performance because of the disruption in these firms’ business operation; and 3) the complexity of information production increases.

Bourveau & Law (2021) based on the psychology literature about the effects on risk perception of extreme climate events, such as hurricanes, it is argued that analysts form more pessimistic expectations. Analysts use an “availability heuristic” to assess risk, implying that a small probability of unusual events tends to be overestimated. The use of the availability heuristic to assess risk depends on the salience of the events.

Jiang et al. (2021) investigate the influence of weather conditions on share market reactions to firms’ earning announcements. It is found that when institutional investors experience unpleasant weather, the market delays the responses to subsequent earnings news, which results in higher earnings announcement premia, indicating that the ability of investors to process information become inefficient and subject to delays. Consequently, a higher price discount is required to compensate for the additional uncertainty.

Dehaan et al. (2017) investigate how market participants’ response to new information is affected by poor environmental conditions. They argue that, with respect to earnings announcements, negative mood slows down analysts’ response to earnings news, called “decreased activity levels.” However, compensation mechanisms and competition among analysts can induce more work even if poor conditions are experienced. It is concluded that both the mood and physical effects of poor conditions (such as weather-induced pessimism and decreased activity) affect market participants. Weather induced effects on analysts will be transferred into capital markets, resulting in lower earnings response coefficients and a larger post earnings announcement drift.

CHAPTER THREE

THEORETICAL FRAMEWORK

The main aim of this thesis is to determine whether climate change influences the market value of equity through the channel of the accounting system. The study is based on an accounting-based valuation framework, particularly the Gordon (1962) and Ohlson (1995) models. An extension from Gordon (1962), the Ohlson (1995) model proposes a relation between accounting variables, such as book value of equity and earnings, and market value, which provides a theoretical foundation widely used in the value relevance studies in accounting field (Collins, Pincus, & Xie, 1999). The value relevance literature estimates coefficients on individual accounting variables that reflect their relative importance in the valuation process of investors and attempts to reveal the underlying economic. Climate risk is thought to significantly influence market value, as indicated in the last chapter. In theory, it is held that climate change leads investors to revise their expectations about the future dividend receipts and to adjust the valuation of firms according to the principles set out in Gordon (1962). Hence, it is expected that climate change will influence the coefficients on accounting variables in the valuation model.

The additive linear models adopted in prior studies are likely to result in biased and inconsistent estimated coefficients, a problem that can be circumvented by estimating log-linear models of the market-accounting relation (Lubberink & Willett, 2020). If this is done the measures of the response of market value to changes in accounting variables are elasticities, which are the key focus of this thesis.

A larger magnitude for an elasticity implies that investors place more valuation importance on the corresponding accounting variable; and, vice versa in the case of a smaller elasticity. For example, a higher elasticity of book value of equity for market values than that of earnings for market value indicates that investors pay more attention to book value than to earnings in valuing equity. The dynamics of the elasticities of accounting variables are associated with changes in investors' expectation of future firm values. An explanation for this association is that when market participants feel pessimistic about the future, they tend to focus more on book value of equity than on earnings when valuing firms, and when they feel optimistic about the future, a higher valuation weight will be placed on earnings. This suggests the existence of a complementary, negative, relationship between the value relevance of the book value of equity and the value relevance of earnings. In the value relevance studies reviewed in the previous chapter a basic assumption is that the book value of equity contains past information and is viewed as backward looking, conservative, or pessimistic and earnings contains future information, viewed as being forward looking, aggressive, or optimistic.

Also in chapter 2, studies of climate finance show that climate risk is sometimes intuitively interpreted, rightly or wrongly, as a kind of systematic risk. Under this interpretation, the downside risk is represented by higher levels of climate change. In the valuation theory outlined above, this has a negative effect on investors' perceptions of firms' future cash flows causing market participants to feel pessimistic about firms' future profitability. Consequently, if climate change influences equity value through the channel of accounting information, there will be an association between climate risk, as characterized above, and the elasticities of book value of equity and earnings. If climate change makes investors pessimistic about firms' future profitability, they will be expected to place a higher valuation weight on the book value of equity and a lower valuation weight on earnings or, equivalently, a higher elasticity on the book value of equity and a lower elasticity on earnings. Conversely, lower levels of climate change would be expected to result a lower elasticity on the book value of equity and a higher elasticity on earnings.

Consequently, the thesis predicts that with the increased exposure to climate change, the elasticity of book value of equity dominates that of earnings and that the elasticity of book value has a positive association with climate change, while the elasticity of earnings has a negative association with climate change. As the reactions to climate change varies across industries and across firms, it is expected that the valuation effect of climate change also varies across industries.

The underlying mechanism through which investors become pessimistic about firm value when experiencing climate shocks is that accounting variables have the ability to convey information about risk and investors have ability to learn through the signal of accounting information. This provides a premise to explain why the effect of climate risk on equity value may be captured through measures of value relevance.

The chapter is organised as follows. Section 3.1 discusses the accounting-based Ohlson (1995) model and its implications for value relevance studies. Section 3.2 discusses the alternative log-linear model that is used to model accounting-market relationship in this thesis. Section 3.3 and Section 3.4 discuss the relation between elasticities and climate risk. Section 3.5 explains why accounting variables have the ability to convey information about climate risk. Section 3.6 states the hypotheses relevant to answering the thesis research questions, the tests of which are reported in Chapter 5.

3.1 Accounting-Based Valuation Models

3.1.1 Ohlson (1995) Model

Accounting-based valuation models theoretically establish a link between equity values and accounting numbers. The coefficients on the accounting variables reveal the accounting and economic mechanisms through which accounting numbers determine firm value. The statistical significance and magnitude of these coefficients indicates the relative importance of accounting variables for investors in the valuation process.

The Gordon (1962) discounted dividend model, which has been widely accepted in finance and accounting literature, is the starting point for the Ohlson (1995) model. By assuming a clean surplus relation and a regularity condition, in the form of the growth rate of book value of equity being less than the discount factor, Ohlson (1995) shows that stock price can be expressed as the sum of opening book value of equity and the discounted future expected abnormal earnings. In theory, the coefficient on book value of equity is 1 and the coefficients on the expected abnormal earnings are the inverse of the discount factors, which follow a geometric series. Lo & Lys (2000) mention that the discounted dividend model and the Ohlson (1995) model are mathematically one-to-one equivalent if the clean surplus relation holds. A distinction between the two models that is important as the Ohlson's (1995) model can be interpreted as focusing on the creation and recognition of wealth, whereas the Gordon (1962) model may be interpreted as focusing on the distribution of wealth. The Ohlson (1995) model is a transformation of the discounted dividend model by expressing value with "current and future accounting numbers, book values and earnings" (Kothari, 2001). With the transformation, investors' concerns about future dividend payments are captured by the parameters on individual accounting variables in the accounting-based valuation models. On this interpretation, factors that influence investors' expectation about the future dividend payments can be captured through the fluctuations among the individual parameters.

The Ohlson (1995) model provides a way of explaining the roles of book value of equity and earnings in valuing firms and shows that "earnings and book value act as complementary value indicators (Ohlson, 1995, p. 662)." One interpretation for the model is that future profitability of firms is indicated by the difference between market and book values. Book value equals market value if expected goodwill and growth options are zero.

The important concept in the model is abnormal earnings, which is defined as "earnings minus a charge for the use of capital as measured by beginning-of-period book value multiplied by the cost of capital (Ohlson, 1995, p. 662)." The coefficient on the so-called "persistence" of abnormal earnings supposedly captures economic rents (Barth, Beaver, & Landsman, 2001), which reveals the nature of the information contained in earnings and establishes links between accounting variables and firm value (Kormendi & Lipe, 1987). Many properties of the valuation function are influenced by the assumptions made about the time series pattern of abnormal earnings. Equity value becomes more sensitive to the realization of abnormal earnings when the persistence is higher according to Ohlson (1995) who argues that the combination of discounted future dividends, clean surplus relation, and the autoregressive nature of abnormal earnings generate a "cohesive, and perhaps appealing, model of value and returns (p. 670)."

When abnormal earnings follow a mean-reverting process it is thought to capture the competitiveness in product-market which attenuates firms' ability to earn "supernormal earnings" (Kothari, 2001). Holthausen & Watts (2001) point out that abnormal earning can be regarded as an attribute investor value. They argue that appropriate attributes of firm value support correct predictions about the signs and magnitudes of the parameters on accounting numbers, determines how to establish the link between accounting variables and firm value, and avoids the issue of omitted variables.

The persistence of abnormal earnings is also believed to determine the relative importance of book value of equity and earnings in the valuation process. Based on assumptions about the persistence of abnormal earnings, firm value can be expressed as the average of current earnings and book values with different weights. Both the balance-sheet valuation model and the income-statement valuation model, either of which could be considered sufficient for equity valuation purposes, are viewed as two benchmark valuation models[4].

The balance-sheet valuation model is viewed in an economic context as a "pure stock model" and the earnings model is viewed as a "pure flow model". The general valuation model is spanned by book value and earnings with different weights applied to the two components (Gode & Ohlson, 2004). In many empirical studies, the valuation model is construed through current earnings, dividends and the book value of equity, rather than abnormal earnings.

Expected earnings is a function of current book value, current earnings and dividends. Assuming that all earnings are paid as dividends, the expected earnings equal current book value multiplied by the cost of capital (Ohlson, 1995).

> "… current book value alone determines the earnings that can be expected in the long-run if one eliminates any growth in earnings and book value due to changes in retained earnings (or capital stock) …… In the long run assets generate earnings, and conversely, earnings cannot be expected without assets (p. 677)."

In this sense, book value of equity "dominates" earnings in the context of valuation.

One contribution of Ohlson (1995) is to establish the link between the discounted dividend model and observable accounting variables (Lo & Lys, 2000) that provides a more precise form of the valuation relationship between accounting variables and stock price (Falta & Willett, 2013). Another contribution is to revive the Gordon (1962) and Preinreich (1938) models, mostly overlooked in capital market studies in recent years (Bernard, 1995; Lo & Lys, 2000; Lundholm, 1995). Third, Ohlson (1995) relates his model to dividend policy irrelevance by assuming abnormal earnings are guided by an autoregressive process (Lundholm, 1995), to capture the behaviour of abnormal earnings (Bernard, 1995). While it cannot be viewed as a complete structure, the Ohlson (1995) model provides a popular starting point to study the relation between accounting numbers and equity value, without explicitly referring to dividends (Bernard, 1995).

[4] Easton and Harris (1991) use the valuation model based only on book value to deduce a relation between earnings and returns. By combining book value and earning models, they obtain a valuation model that expresses returns as a function of earnings and earnings changes. They also argue that from a practical perspective, firms' value is a function of book value of equity and earnings.

3.1.2 Value Relevance Studies

The Ohlson (1995) model provides a theoretical framework for the market-accounting relation and a testable equation for empirical research to identify the roles of accounting variables (Lo & Lys, 2000). Many studies in the environmental accounting literature reviewed in the previous chapter adopt the modified Ohlson (1995) models by adding an environmental related variables to the original model.

Valuation theories seek to provide direct support for value relevance by establishing a link between accounting numbers and share prices. Based on these theories, value relevance studies reveal statistical associations between accounting numbers and equity value and suggest economic explanations for the relation (Holthausen & Watts, 2001). Relevance and reliability are two important criteria for accounting standards (Barth et al., 2001). Valuation models provide the primary tools in value relevance studies because the relevance and reliability of accounting numbers are tested jointly based on a well-accepted valuation model. Valuation models are used by value relevance studies to guide empirical tests and provide expectations about the magnitudes of estimated coefficients on individual accounting variables, which demonstrate that "how well particular accounting amounts reflect information used by investors (Barth et al., 2001, p. 81)." In the value relevance literature, the estimated coefficients characterize the capitalization factor of the accounting variable and are viewed as a function of risk and the time series patterns of expected future dividends (Collins & Kothari, 1989; Easton & Zmijewski, 1989).

3.2 Log-Linear Valuation Model

The choice of valuation model is a primary consideration in value relevance studies (Barth et al., 2001). However, the widely accepted Ohlson (1995) model suffers from econometric problems in both the returns and levels versions of the regression models[5]. Ohlson & Kim (2015) call for the alternative approaches to estimate the linear valuation models. A key issue involved in value relevance studies is how to obtain valid and

[5] Falta and Willett (2013) classify the conventional linear models as the level form, which is expressed as $M_{i,t} = \mathrm{k}_{i,t} + \mathbf{b}_{i,t}\mathbf{A}_{i,t}$, and the return form, which is expressed as $\frac{M_{i,t}}{M_{i,t-1}} = \mathrm{k}'_{i,t} + \mathbf{b}'_{i,t}\frac{\mathbf{A}_{i,t}}{M_{i,t-1}}$, where M denotes to market value; $\boldsymbol{A}$ denotes the vector of accounting variables, and k and $\mathbf{b}$ are constant term and coefficients on corresponding accounting variables. Both expressions are referred as additive linear models by the authors.

reliable estimated coefficients on the accounting variables. Lubberink & Willett (2020) criticise that the additive-linear model typically adopted in prior studies as leading to estimated coefficients that are "hard to interpret, exhibit great volatility, and change from study to study". These issues cannot be solved through common statistical approaches, such as deflation and choosing more "sophisticated" methods of estimation. When a model is misspecified, even large, random samples still generate biased estimates (Falta & Willett, 2013). Instead, improved specification of the accounting-market relation is required before estimation takes place (Ericsson & MacKinnon, 2002). Consideration of the basic mathematical and distributional properties of models are needed, rather than the piecemeal treatment of correlated omitted variable, heteroskedasticity, outliers and scale effects as in prior studies (Falta & Willett, 2013).

Lubberink & Willett (2020) develop a theoretical framework describing an approach that focuses on specification issues. In contrast to prior studies, which generally describe the accounting-value relation in a linear form, the study asserts that the most basic market-accounting relation should be expressed in a multiplicative power law form, which is transformed to a log-linear model for the purpose of empirical analysis. In its "level" form the log-linear model reveals the long-run relation between accounting variables and equity value. In the log-linear form of the model, the estimated coefficients on the individual accounting numbers are elasticities.

The multiplicative model is based on two assumptions. The first assumption states that "market values and accounting variables are measured on ratio scales and the market-accounting relationship is continuous and invariant to changes in these scales." The second assumption states that "The growth ratios of fundamentals accounting variables $g_i = \frac{|A_i|_t}{|A_i|_{t-1}}$ are stationary random variables, randomly sampled from the same joint distribution over time." The first assumption is self-evident since, if it was untrue no financial statement analysis of the form undertaken in virtually every textbook on the subject would be possible. Using the theory of functional equations it can be shown that from this assumption it follows that the market-accounting relation takes the form of a multiplicative power law. The second assumption implies that the variables used in the power law specification, transformed into logarithmic form to give a log-linear model, are approximately normally distributed and that the model consequently satisfies to a close degree the Gauss-Markov assumptions for the estimation of linear statistical models. The consequence of this is estimates derived from the log-linear market-accounting model by basic OLS techniques provide valid and reliable values and inferential statistics for the parameters, the elasticities, of the model and thus of the relation between equity values and the individual accounting variables.

The multiplicative valuation model expresses the equity value as the following function of accounting variables:

$$\mathrm{M} = \kappa\left(\prod_{\mathrm{i}} |A_i|^{\beta_i}\right)\omega \tag{3.1}$$

where M is the market price of a firm at specific time point; κ is a constant scale factor, which captures the investors' perception of risks in the model (Lubberink & Willett, 2020); A_i represents individual accounting variables; β_i represents the market value elasticities with respect to A_i, which in the thesis serves as the measure of value relevance of the accounting variables; ω represents an exogenous error term, assumed to be lognormal.

Eq. (3.1) can be expressed in logs to be estimated by ordinary least squares as follows:

$$log\left(M_{i,t}\right) = \alpha + \beta_1 log\left(|B|_{i,t-1}\right) + \beta_2 log\left(|E|_{i,t}\right) + \beta_3 log\left(|D|_{i,t}\right) + \beta_4 log\left(|O|_{i,t}\right) + \varepsilon_{i,t} \tag{3.2}$$

where $\alpha = log\left(\kappa_{i,t}\right)$; $\varepsilon_t = log\left(\omega_{i,\mathrm{t}}\right)$; B_{t-1} denotes opening book value of equity; E_t denotes the net income; D_t denotes the common dividends; M is defined as in (3.1); O_t denotes the remaining value, that is used to complete the balance sheet identity over time, i.e.,

$$B_t = B_{t-1} + E_t + D_t + O_t \tag{3.3}$$

The log-linear model describes the accounting-market relationship but it does not explain "why the coefficients on the book value of equity may be greater or less than those on earnings or dividends", which is key theme of the thesis. This question is explored in later chapters in the context of the research question of how climate change may affect equity value through its impact on the coefficients (elasticities) on the accounting variables.

3.3 Implications of the Use of Elasticities to Measure the Effect of Accounting Variables

The elasticities of individual accounting variables estimated from the log-linear model reflect the relative importance capital market equity investors place on the corresponding accounting variables. A higher elasticity of book value than for earnings indicates that investors pay more attention to book value rather than earnings, and vice versa. If the elasticities of earnings are falling over time relative to the elasticities of book value of equity, it indicates the market is paying greater attention to the latter over time compared to the former. Elasticities are thus interpreted as a measure of value relevance of accounting variables. Prior value-relevance studies hold that the strength of the association between accounting numbers and equity values is an indicator of the usefulness of the accounting variable for valuing the firm (Holthausen & Watts, 2001) and, in this sense, elasticities are also an indicator of usefulness.

In early literature, Kormendi & Lipe (1987) investigate the magnitude of the earnings response coefficients and argue that their magnitude maps the information about the time-series properties of earnings and the discount rates relevant to the valuation of shares. Earnings are assumed to capture investors' revision of future cash flows (Collins & Kothari, 1989; Easton & Zmijewski, 1989), though with less force than in the case of share returns (Kothari & Sloan, 1992). Ohlson (1995) uses the linear dynamic information model referred to above to describe the relation between current earnings and future predicted earnings. Extensive studies describe the generating process of earnings using an AR(1) time series model. The time series properties of earnings are determined by many economic factors, such as "competition, technology, innovation, effectiveness of corporate governances, incentive compensation policies. etc." (Kothari, 2001).

The underlying belief with respect to the book value of equity is that it captures the accumulation of information on the past. Earnings are, in contrast, viewed as a variable that contains future information about the firm. The articulated relation between book value of equity and earnings therefore is that information about past cumulative earnings is captured by the book value of equity. Hence it is considered that equity investors regard the book value of equity as an indicator of equity markets taking a "backward looking, conservative, or pessimistic" view while earnings are considered to represent a "forward looking, aggressive or optimistic" view. Huang & Zhang (2012) argue that the book value of equity conveys information about how firms use economic resources during their operations and is therefore useful to investors' decision making. Accounting conservatism in valuing net assets is thought to have possible influences on abnormal earnings. To the extent that the book value of equity is understated, it causes an offsetting effect in the calculation of future abnormal earnings in the Ohlson model (Lundholm, 1995).

3.4 When Investors Become Pessimistic

Studies in value relevance suggest that when investors become pessimistic about firm value they tend to place higher valuation weight on book value of equity and less weight on earnings and when they become optimistic about firms values they tend to place higher valuation weight on earnings and less weight on book value equity. Holthausen & Watts (2001) point out that "[i]n bad news years the earnings will be more transitory because the losses are more fully recognized in the current period than gains. In good news years, earnings will be more permanent" (p. 58).

Based on the Ohlson (1995) model, Collins et al. (1997) find that the value relevance of earnings declines during the period from 1953 to 1993, but the value relevance of book value of equity compensates for the decline in the value relevance of earnings, maintaining the aggregate value relevance of both accounting variables at an approximately constant level. They attribute the results to both the transitory components in earnings and the value of abandonment options contained in the book value of equity. Burgstahler & Dichev (1997) propose a model in which the weights of book value of equity and earnings are complementary with each other, although they state that the relation should be non-additive, rather than additive as suggested by Ohlson (1995).

Barth et al. (1998) construct accounting-based valuation model similar to Ohlson (1995). They claim and find that concerns about firms' financial condition increase the valuation importance of book value of equity and decrease the valuation importance of earnings. Moreover, they highlight that the phenomenon varies across industries due to the differing extent of unrecognised intangible assets held in each industry. Kothari and Shanken (2003) argue that "recognizing how different factors influence the estimated slope coefficient is crucially important in economic interpretations of the results from value-relevance research" (p. 71). They argue that growth and the discount rate are the economic factors driving the relative valuation importance of individual accounting variables. This results in significant time series variation in the relative importance of book value of equity and earnings for the valuation of equity. They also find that the valuation importance of earnings is negatively impacted by growth and the discount rate.

3.5 Accounting-Based Valuation and Climate Risk

An important premise for the value relevance studies is that accounting numbers provide information for the equity valuation process through associations between accounting variables and share prices (Holthausen & Watts, 2001). Prior studies generally focused on information about the future cash flow. More recent studies hold that accounting numbers have a role in conveying information about risk (Penman & Zhang, 2020). Moreover, a learning ability enables investors to update their belief about firms' values based upon new signals provided by accounting information.

Following this view, this thesis argues that information relating to climate risk can be traced to equity values through its effect on accounting numbers by investors adjusting the valuation weights they place on individual accounting variables. The valuation process can be captured by elasticities derived from the log-linear model. This thesis places this analysis in the context of risk and the ability of market participants to learn about economic factors underlying equity values through the channel of accounting numbers. The way the theoretical framework for the thesis is developed in this regard is discussed further in this section.

3.5.1 The Factor of Risk in the Valuation Model

Accounting researchers have long been interested in the relation between risk and accounting. In Ryan (1997)'s review, the author argues that accounting systems need to account for the issue of risk exposure, including the response of balance sheet items to various risks such as changes in interest rates, currencies, and commodity prices. Both the expected future cash flows and the systematic risk inherent in these cash flows need to be accounted for when valuing a firm (Beyer & Smith, 2021).

While Ohlson (1995) is a widely accepted valuation theory, it ignores the role of risk in the valuation process. Risk is an important factor in accounting-based valuation models and is a main pathway to develop and investigate the valuation model. One criticism of Ohlson's (1995) theory concerns the assumptions of risk neutral investors and non-stochastic and flat interest rates. Risk neutrality means the valuation model fails to consider pricing risk. The assumption of constant interest rates is unrealistic and a key question is how to deal with future cash flows under conditions of uncertainty. The factors of growth and risk need to be accounted for in a practically useful theory of the valuation process (Christensen & Feltham, 2009).

Incorporating the factors of dynamic risk and dynamic risk adjustment extends the basic accounting-based valuation model. Lyle, Callen, & Elliott (2013) incorporate dynamic expectations about the level of systematic risk into accounting-based valuation model to explain the negative relation between apparent changes in economy-wide risk and expected share returns. They use Vuolteenaho's (2002) return decomposition approach to find a positive relation between equity and book values and a negative relation between equity value and economy-wide risk. They also argue that the effect of risk on value is magnified through the persistence of earnings. However, Penman & Zhang (2020) point out that Lyle et al.'s (2013) analysis is based on unbiased accounting and fail to consider the effects of accounting conservatism and the resulting growth.

Recent studies argue that accounting numbers contain information about risk and the risk is priced by the stock market. Moreover, the risk in accounting numbers may be linked to the risk in consumption when valuation studies in accounting are integrated into the conventional consumption asset pricing framework (Penman & Zhu, 2022).

The ability of accounting numbers to convey information about risk is argued by some to be derived from accounting conservatism (Penman & Zhang, 2020). The role of conservatism in accounting-based valuation is explored in Zhang (2000), in which the concept of growth plays an important role in establishing the accounting-value relation through the weight on capitalized earnings being assumed to be an increasing and convex function of growth. Such arguments are consistent with accounting having the ability to convey risk information in Penman & Zhang (2020) and Penman & Zhu (2022) based upon the idea that growth of future expected earnings is risky.

The key question then becomes the conditions under which conservative accounting has the ability to convey information about risk and how the risk is priced. To answer the question, Penman & Zhang (2020) develop a single-transaction-cycle model, which is then extended into a model including multiple overlapping transaction cycles. Both the accounting recognition and measurement inform the relation between accounting variable and risk. The basic logic is that accounting conservatism influences earnings, earnings growth, and the dynamics of the book rate of return.

Penman & Zhang (2020) argue that any variable that can be used to predict future earnings, which are not realized and are thus uncertain, can potentially be an indicator of risk. In their study, accounting conservatism[6] is viewed as a mechanism of conveying risk information by accounting numbers, rather than the cause of noise in accounting numbers.

Penman & Zhu (2022) relate earnings risk to consumption risk using the accounting principle of conservatism and argue that the accounting numbers connect the relation between consumption and risk to the relation between consumption and accounting principles. This, they suggest, means that the consumption asset pricing model can be expressed in term of accounting numbers. The authors attempt to construct a pricing factor based upon accounting variables and use it to explain cross-sectional returns. The negative correlation between the factor returns and the market portfolio indicates, on this construction, the constructed factor based upon accounting variables has the ability to hedge risk in states where consumption is low. Based on consumption-based asset pricing theory and accounting principles, the study argues that this establishes a connection between accounting numbers and consumption risk.

3.5.2 The Sources of Growth in Earnings

Accounting-based valuation studies suggest the concepts of growth and risk are closely related and it is argued in some parts of the literature that both factors are generated from accounting conservatism. Many studies attempt to reveal additional sources of growth and the economic source of risk captured by accounting numbers. Zhang (2000) attributes the sources of growth to the retention of capital and investments with positive net present value. Rajan, Reichelstein, & Soliman (2007) argue that interaction of accounting conservatism and past growth in new investments result in the growth in

[6] But prior studies have a different view about the role of accounting conservatism in valuation. Collins, Kothari, Shanken, & Sloan (1994) and Kothari & Sloan (1992) argue that GAAP conventions, such as conservatism, limit the ability of earnings to capture the revision in future cash flows and growth opportunities, reducing the information content and the timeless of earnings.

firm's accounting profitability. Ohlson & Gao (2006) assert that the source of earnings growth originates from "expectations that the firm undertakes positive net present value projects." However, investments with positive net present value do not necessarily results in earnings growth. Christensen & Feltham (2009) argue that growth comes from "the sustainability and the creation of competitive advantage in the firm's product markets." Under the market competition, higher (or lower) abnormal operating income implies a decrease (increase) in performance. Competition also works to convergence of the industry-specific growth rates.

3.5.3 The Construction of the Risk Factor Using Accounting Variables

Studies on the construction of a risk factor using accounting variables provide empirical evidence that the accounting variables play a role in conveying information about risk. They convey the advantages of measuring risk based on fundamentals over measures of risk based on market returns. Specifically, accounting-based risk measures enable capture of the downside risk.

Based on earnings being a summary measure of firms' fundamental performance, Ellahie (2021) constructs earnings betas, using them to capture the systematic risk exposure of the firms. The time-varying earnings betas are estimated through a backward-rolling regression of earnings measures on an analogous earnings series with a five-year window. The authors test eleven different types of earnings including (1) the realized earnings or analysts' earnings forecasts; (2) levels earnings or change in earnings; (3) earnings scaled by lagged earnings, book value of equity, and market value individually; and (4) long-term earnings growth estimated by analysts. The validity of the constructed earning-betas is examined through different asset pricing methods, including a portfolio level analysis and a factor-mimicking portfolio analysis.

Konchitchki, Luo, Ma, & Wu (2016) distinguish the downside aspect and upside aspect of risk and use the information in earnings to construct measures of earnings downside risk. The downside and upside aspects of risk have different valuation implications and risk mainly manifests itself through downside aspect. Earnings downside risk is measured through a below-expectation variability in earnings using the "root lower partial moment" of Stone (1973) and Fishburn (1977). The authors find that compared to firms with low earnings downside risk, firms with high earnings downside risk are more likely to experience a more negative operating performance in the subsequent periods. Moreover, the effect becomes pronounced in downward macroeconomic states. The paper reflects growing interdisciplinary research on the link between accounting and the macroeconomy and its implications for equity valuation. In particular it suggests that sensitivity to downside macroeconomic states is a source of firm-level risk.

In Zhang (2013) accounting-based measures are claimed to have the ability to predict skewness of equity prices through the effect of conservatism and realization principles and option values embedded in firms' operations. "Unconditional conservatism" makes for intangible assets off balance sheet. "Conditional conservatism" writes down book value in adverse situations, but revaluations upwards do not take place under favorable conditions. On this basis, the book value of equity may be interpreted as capturing the downside risk of the firm.

3.5.4 Learning of Investors in the Valuation Process

Many valuation models ignore how accounting information helps investors to update their belief about firms' fundamentals (Chen & Schipper, 2016) as "this research is not suitable to answer questions related to how investors use accounting data to update their assessments of estimates of future cash flows. (p. 338)"

According to some viewpoints, the ability to learn plays an important role in valuation, which results in idiosyncratic return volatility across firms facing the same fundamental shocks (Armstrong, Banerjee, & Corona, 2013). The ability of accounting numbers to convey risk information and investors' learning work together to determine the level and volatility of returns in the presence of uncertainty (Heinle, Smith, & Verrecchia, 2018).

In the learnings process, investors do not observe risk factor loadings themselves but signals from a variety of sources, such as earnings announcements. Investors update their beliefs about risk based on the realization of risk factors contained in the signals. Armstrong et al. (2013) develop a dynamic partial equilibrium model with time-varying factor loadings. Learnings by investors shows the effects of investor uncertainty about factor loadings on prices and returns based on the signaling role of earnings in conveying information about risk. Firm-specific information can affect investors' uncertainty about risk-factor loadings and expected returns. If firm-specific information, such as earnings announcements, captures firm's systematic risk-factor loadings, it also influences expected returns. The persistence of factor loadings amplifies this effect. Even when the aggregate risk premium holds constant, learning from investors has an effect on valuation, for example generating time-series variation in the price-dividend ratio.

Beyer & Smith (2021) investigate how investors use earnings to learn about current and future systematic risk exposure given that these exposures are not observable directly by investors. Investors' uncertainty about firms' beta is believed to influence how prices response to firms' earnings, with the effects depending on economy conditions. This approach provides a theoretical framework to explore how accounting response coefficient depend on the macroeconomic conditions.

3.6 Hypotheses Statements

Valuation theory shows that balance sheet and income-statement models are prose two extreme on a continuum of possibilities. The general valuation model combines both extreme with different weights. Studies in value relevance indicate that the book value of equity and earnings are complementary to each other. Since the elasticities of book value of equity and earnings are the measures of value relevance adopted in this study, the first hypothesis about the relation between the elasticities of book value of equity and earnings is:

H1a: The elasticities of book value of equity and the elasticities of earnings are complementary with each other.

H1b: The elasticities of book value of equity and the elasticities of earnings do not have a complementary relationship.

Book value information has a concurrent effect on earnings. The informativeness of earnings announcements increases with the concurrent disclosure of balance sheet information. The market response of earnings increases with the disclosure of balance sheet items (Beaver, McNichols, & Wang, 2020; Collins, Li, & Xie, 2009; Francis, Schipper, & Vincent, 2002). Consequently, it is of interest to detect the total information contained in both the book value of equity and earnings. The second hypothesis about the sum of the elasticities of book value of equity and earnings is thus:

H2: The sum of the estimated elasticities of individual accounting variables amount to 1.

The valuation weights on different accounting variables can be influenced by the exogenous shocks and vary over time. The different weights are determined by the roles of the accounting variables in the valuation process. The discussion in section 3.5 suggests that accounting variables have the ability to convey risk information to equity market through conservative accounting. Climate related risk could possibly negatively influence firms' future stream of cash flows and increase the fluctuation among these cash flows. Investors' risk aversion may change due to climate risk. Specifically, with an increased awareness of climate risk, investors may become more pessimistic and feel more uncertain about firms' ability to generate future positive abnormal earnings. In this situation, investors may prefer to anchor on the book value of equity and place more valuation weight on book value and less valuation weight on earnings. Investors' adjustment to the valuation weights can be viewed as a way adaption for investors to respond climate change. Therefore, hypotheses about the relation between climate change and the elasticities of individual accounting variables are stated as follows:

H3a: The impact of climate change on the elasticities of book value of equity is positive.

H3b: The impact of climate change on the elasticities of book value of equity is not positive.

H4a: The impact of climate change on the elasticities of earnings is negative.

H4b: The impact of climate change on the elasticities of earnings is not negative.

The literature on climate risk indicates that the responses to climate risk are heterogenous among industries. Ilhan et al. (2021) point out that there is strong uncertainty in climate regulation, which includes the time, the approach, and the effectiveness of climate policy. Moreover, the uncertainty in climate regulation is heterogenous across firms even within an industry. Heterogeneity means that the same policy may have different effects on firms' equity value with respect to both its direction and magnitude. Sautner et al. (2020) find several characteristics concerning exposure to climate change. First, exposures have industry patterns. For example, utilities mainly face opportunity and regulatory risk. Second, the measures reveal the variations across industries. The heterogeneity among firms within industry shows that climate change has differing effects on firms within the industry. It also shows that different firms within an industry have different abilities to adjust towards a green economy. Third, the measures fluctuate but there is a general increasing trend. The authors find that about 70 – 97 % of the variation is explained at the firm level. Therefore, investors need to diversify their invest across industries to hedge climate change risk. Pankratz et al. (2019) find that the relation between climate risk and firms' financial performance is affected by industrial and geographic heterogeneity. Accounting studies demonstrate that different industries contain different levels of unrecognized intangible assets, which causes the pricing multiples on individual accounting variables to vary across industries (Barth et al., 1998). Climate change may cause firms in different industries to generate different levels of unrecognized intangible assets such as "research and development, brand names, technological core competencies, customer loyalty, and growth options" (Barth et al., 1998).

Hence, the fifth hypothesis is as follows:

H5a: The impact of climate change on the elasticities of individual accounting variables varies across industries.

H5b: The impact of climate change on the elasticities of individual accounting variables is homogenous across industries.

Bolton & Kacperczyk (2021) argue that the level of carbon emission is persistent and reflects a long-run carbon risk, and that changes in emissions reflect a short-run climate risk. Engle et al. (2020) note that the nature of long run climate risk is difficult to hedge against. Hong et al. (2019) argue that while panel regression with location fixed effects can be useful in identifying short-run temperature shocks, adaption is uncertainty in the long run. The severity of damages from climate change cannot be captured through consideration of short-run effects only. However, there is evidence that long-term climate risk can be priced in bond market through long-term bond issuances (Painter, 2020). Based on Bansal et al.'s (2016) temperature-augmented long-run risk (LRR-T) model, the sixth hypothesis is stated as follows:

H6: The long-run component of climate risk has significant effects on the elasticities of book value of equity and earnings; the short-run component of climate risk does not have significant effects on the elasticities of book value of equity and earnings.

CHAPTER FOUR

RESEARCH METHODOLOGY

This chapter describes the method used to test the hypotheses proposed in the last chapter, concerning the association between climate risk and the estimated elasticities of individual accounting variables with respect to market values. Section 4.1 describes the two-stage research design, which uses annual cross-sectional regressions in the first stage and time series regressions in the second stage. In this section I also discuss the econometric issues regarding climate variables to highlight the economic implications of the second-stage regressions. Section 4.2 discusses the procedure to examine the cointegration relationship between the dependent and explanatory variables in the time series analysis in the second stage. The purpose of the cointegration test is to rule out potential spurious relation in the time series regressions. Section 4.3 illustrates the sources of data used in the thesis, first the accounting and market data, second the climate risk.

4.1 Research Design

In the first part of the two-stage design, the coefficients in log-linear model are estimated year by year for the U.S. economy as a whole and for each industry. In the second part, the time sequence of these estimated coefficients on the accounting variables are investigated to see to what extent they can be explained by climate risk variables.

4.1.1 Stage 1

As explained in Chapter 3, I use the following empirical model:

$$M_{i,t} = \kappa_{i,t}|B|_{t-1}^{\beta_1}|E|_t^{\beta_2}|D|_t^{\beta_3}|O|_t^{\beta_4}\omega_{i,t} \tag{4.1}$$

where $M_{i,t}$ is the market price of firm i at time t;

κ is a constant scale factor;

β_j represents the market elasticity with respect to the relevant accounting number A_j;

ω_i represents an exogenous error term, assumed to be lognormal;

B_{t-1} represents the opening book value of equity;

E_t represents net income;

D_t represents common or ordinary dividends;

O_t represents remaining value to complete the balance sheet identity over time, i.e. $B_t = B_{t-1} + E_t + D_t + O_t$.

In order to conduct OLS regressions, magnitudes of the accounting variables in expression (4.1) are transformed to logs. Lubberink & Willett (2020) explain why no information is lost by using magnitudes of these variables in computing the elasticities in (4.1)[7]. The elasticities that result are identical to a matrix weighted average of the elasticities that would be obtained from running separate regressions on the data when it is portioned into positive and negative earnings observations.

By taking logs for variables in expression (4.1), I obtain:

$$log(M_{i,t}) = \alpha + \beta_1 log(|B|_{i,t-1}) + \beta_2 log(|E|_{i,t}) + \beta_3 log(|D|_{i,t}) + \beta_4 log(|O|_{i,t}) + \varepsilon_{i,t} \tag{4.2}$$

where $\alpha = log(\kappa_{i,t})$ and, $\varepsilon_{i,t} = log(\omega_{i,t})$.

As the magnitudes of the accounting variables exhibit close to a lognormal distribution, the coefficients in Eq. (4.2) can be validly and reliably estimated by using OLS. The conventional inferential statistics are without bias and inconsistency and there is no need to winsorise outliers (Clout & Willett, 2016; Falta & Willett, 2013). Madsen (2005) argues that the estimated coefficients from such cross-section regressions are consistent and capture information about the long-run relationship between variables. Regressions are conducted at both the U.S. national and industry levels, so that the results can be compared across industries. Following the estimation of the elasticities in the first stage annual cross-sectional regressions over the period from 1971 to 2017, I obtain a time series vector of $\hat{\alpha}$, $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\widehat{\beta_3}$, and $\widehat{\beta_4}$ for each of the U.S. economy and each SIC industry, including Mining, Construction, Manufacturing, Transportation, Wholesale, Retail, Finance, and Services; $\hat{\alpha}$, captures investor perceptions of risk; $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\widehat{\beta_3}$, $\widehat{\beta_4}$

[7] The direction of the association between the dependent and independent variables is reflected in the sign of the elasticity, similar to the way it is reflected in the sign of the coefficient in the typical "conditional mean" regression model.

measure the elasticities of the corresponding variables.

There are several pros and cons in estimating cross-sectional regressions in the first stage. First, both the market variable and the accounting variables used in stage 1 are "levels" variables. Kothari & Zimmerman (1995) argue that an advantage of levels regressions is that they avoid errors-in-variables issues with the right-hand-side variable because current market value contains information beyond the information in current accounting variables. The literature notes that levels regressions, as adopted by accounting researchers, suffer a number of econometric problems, such as omitted variable and heteroskedasticity (Kothari, 2001). Second, annual cross-sectional regressions are more powerful than the time series estimates. Fama & French (2000) argue that time series regressions suffer from low power either because the time series is too short to sustain reliable inference or the relatively small number of annual accounting variables in longer time series suffer survivor bias. The shortcoming of cross-sectional regressions is that the firm-specific information captured by time series regressions is sacrificed. Cross-section usually regression imposes a constraint that coefficients are identical across firms. Ignoring cross-sectional variation in coefficients has been held to result in bias (Easton & Zmijewski, 1989; Kormendi & Lipe, 1987). Third, while the theoretical Ohlson (1995) model includes the book value of equity, the model has the econometric advantage that by including the book value of equity can help to mitigate the issue of correlated omitted variables, which may cause anomalous negative associations between stock prices and losses (Collins et al., 1999; Francis & Schipper, 1999; Kothari & Zimmerman, 1995). Holthausen & Watts (2001) state that "those studies include a book value term that could cross-sectionally proxy for net assets value and potentially reduce the correlated omitted variables problem (for the omission of net assets.) (p. 62)."

4.1.2 Stage 2

In stage 2, the vectors of estimates of the coefficients, $\hat{\alpha}$, $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\widehat{\beta_3}$, and $\widehat{\beta_4}$, from stage 1 are used to conduct time series regressions on the climate change variables, as follow:

$$y_{jt} = \upsilon_{jt} + \gamma_j x_{jt} + \omega_{jt} \tag{4.3}$$

where y_{jt} represents in turn the estimated coefficients, $\widehat{\alpha_{J,t}}$, $\widehat{\beta_{1,J,t}}$, $\widehat{\beta_{2,J,t}}$, $\widehat{\beta_{3,J,t}}$, or $\widehat{\beta_{4,J,t}}$; x_{jt} represents the variables used to measure climate risk; j represents the U.S. economy and each SIC industry, including Mining, Construction, Manufacturing, Transportation, Wholesale, Retail, Finance, and Services. The coefficient of interest in this stage is γ_j, which captures the impact of climate risk. I am interested in both the sign and magnitude of the coefficient γ_j.

The estimated coefficients in the log model measure the market value elasticities of the accounting variables. In this respect the thesis follows in the tradition of value relevance studies. Kothari & Shanken (2003) argue that "recognizing how different factors influence the estimated slope coefficient is crucially important in economic interpretations of the results from value-relevance research" (p. 71), the estimated slope coefficient being an elasticity in this context. They argue that growth and the discount rate are the economic factors that drive the relative valuation importance of individual accounting variables. This results in significant time series variation in the comparative valuation relevance of book value of equity and earnings. The authors find that the valuation importance of earnings is negatively impacted by growth and the discount rate.

In the environmental accounting literature, environmental variables are usually directly incorporated into the Ohlson style model along with the accounting variables to capture value relevance of non-accounting information. In contrast, this thesis views climate risk as a variable that affects the value relevance of accounting variables, in particular, their elasticities. This view is nevertheless consistent with the Ohlson (1995) model, as it seeks to make the nature of the other information more precise.

The key climate variable in the study is global temperature, which is viewed as exogenous or weakly exogenous so that the thesis avoids the issue of endogenous relationships between economic performance, environmental disclosure, and environmental performance variables. Additional econometric issues involved in regressions of climate variables are discussed in the next subsection.

4.1.3 The Econometric Issues in Stage 2

In the thesis the effect of climate risk on equity value is detected through the time-series behaviour of the value-relevance elasticities in the second stage of the modelling process. There is a long debate in climate economics literature about the choice of regression approaches (cross-sectional, time-series, and panel data) to use to model the climate and economic variables of interest. These issues are extensively discussed in the climate economics literature, but are largely ignored by the literature discussed in Chapter 2.

In addition to their econometric implications, the three regression approaches noted above also involve different economic explanations of the economic consequences of climate change. Kolstad & Moore (2020) argue that identification of the economic consequences of climate change is important for developing mitigation and adaption polices.

An important issue involved in the choice of regression methods is whether the method adopted captures the long-run or short-run effects. This issue is important for the thesis because the elasticities obtained in the first stage and used as dependent variables in the second stage reflect the long accounting-market relation. Long-run effects relate to equilibrium rather than disequilibrium relationships. Thus, investigation of the economic consequences of climate change in the thesis focuses on their long-term relationship. Most studies recounted here and in Chapter 2 are not clear on whether they have a long-term or short-term focus but the construction of the regression models used make it likely that short-run effects are being confounded with long-run effects or that the differences between the two effects are not recognized.

Among studies that have recognized the difference between short-run and long-run effects, it has been noted that long-run effects may capture long-term processes that mitigate the short-run effects (Dell, Jones, & Olken, 2008; Dell et al., 2012). For example, Burke & Emerick (2016) use variation in temperature and precipitation trends to study the adaptative effects of climate change on U.S. agriculture and find that the long-run adaptation mitigates the short-run impacts of higher temperature on agricultural productivity. The absence of adaptive investment implies the likelihood future losses. There is mounting evidence that change in the global climate is changing how agents adapt their economic behaviour. Carter, Cui, Ghanem, & Mérel (2018) argue that the implications of adaptation to econometric modelling is that "whether certain econometric approaches such as cross-sectional and panel approaches were well or ill-suited to identifying impacts that implicitly allow for such climate adaptation, without actually attempting to explicitly measure the extent of it" (p. 7). Moore & Lobell (2014) argue that adaption processes should be taken into account when assessing the impacts of climate changes through econometric modelling.

From this perspective, all the three approaches mentioned above have advantages and disadvantages. The major advantage of the cross-sectional regression is that the approach enables estimation of the long-run effect of the climate variable. The effect of adaptation is incorporated into the estimated coefficients. However, a major disadvantage is that errors in specification may cause problems similar to bias due to correlated omitted variables (Mendelsohn & Massetti, 2017; Mendelsohn & Nordhaus, 1996). A major advantage of the panel data approach compared to cross-section analysis alone is in its ability to deal with heterogeneity between cross-section units and dynamic adjustments in the units. If there are lags in the variables the most reliable way to estimate long-run effects is by estimating separating cross-sections for each unit and explicitly averaging the resulting coefficients (Pesaran & Smith, 1995).

The time series variation in climate variable in a regression model can be interpreted as describing the climate-economy relationship (Hsiang, 2016) if the variation can be assumed to be random (Auffhammer, Hsiang, Schlenker, & Sobel, 2011). The annual global temperature is used here as the key explanatory variable, which is low-frequency and assumed to be exogenous. It is decomposed into long-run and short-run components to facilitate interpretation. A detailed discussion of the choice of climate variable is given in subsection 4.3.2.

4.2 Cointegration Tests

Based the argument that accounting variables convey not only information about future expected cash flow, but also information about risk exposure to climate change, the results of the time series regressions in stage 2 of the research design test whether climate risk, measured as global abnormal temperature, affects book value and earnings elasticities differently over the period from 1971 to 2017. However, in a time series context, when the dependent and independent variables are non-stationary, the possibility of nonsense or spurious regressions needs to be addressed. It can be observed from Figure 4-1, the time series pattern of the global anomaly temperature contains an obvious trend, increasing the suspicion of non-stationarity. Therefore, after the main regressions, tests are conducted to see whether the variables used in time series analysis of stage 2 contain a unit root if the dependent variables and independent variables are cointegrated. The aim of the cointegration tests is to provide evidence that there is a valid statistical association between the elasticities on the accounting variables and the global anomaly temperature, rather than a spurious association.

Doornik & Hendry (2013) refer to three types of non-stationarity including 1) integrated behavior; 2) regime switches; and 3) "inherent non-stationarity owing to innovative human behavior or natural process" (p. 230). This thesis mainly addresses the first type of non-stationarity, that is, the integrated behaviour.

Differencing and detrending, which are widely used in the literature, can transform non-stationary processes into stationary processes but such approaches come at a cost. Wooldridge (2015) notes situations, in which, when the dependent and independent variables have different kinds of trend, detrending may make the explanatory variables more amenable to sound statistical analysis. Becketti (2013) criticises differencing and detrending approaches, arguing that for trend-stationary process, first-differencing can result in a unit root in the moving average component of the process.

Harvey (1990) maintains that although the detrending approach can result in apparently reasonable results, this should be interpreted cautiously due to the downward bias in the estimated coefficients. For the differencing approach, he argues that differencing can lead to introducing a noninvertible MA(1) process into the disturbance, so that "the issue of differencing is thus subject to a good deal of confusion" (p. 250). Moreover, the model that contains only difference terms captures only short-run effects. Hendry (1995) explains that detrending will not remove the possibility of nonsense regressions if error terms are not stationary. If detrending leads to misspecification, the time trend is likely to be statistically significant and it is difficult then to decide whether the trend term should be included in the model (Banerjee, Dolado, Galbraith, & Hendry, 2003). Due to the criticisms of differencing and detrending approaches, the approach adopted in this thesis is to examine the cointegration relationships between the dependent and independent variables.

In sum, a cointegration approach is more meaningful than a differencing approach when investigating the properties of data of the type used in this thesis (Wooldridge, 2015). Hendry (1995) argues that finding cointegration, which reflects the long run relation between variables, is the key approach to solve the issue of nonsense regression rather than differencing. Banerjee et al. (2003) states that "it allows us to describe the existence of an equilibrium, or stationary, relationship among two or more time-series, each of which is individually non-stationary" (p. 136). This is important for the approach adopted in this thesis. The estimated elasticities of individual accounting variables capture the long-run relationship between accounting and market values. The long-run relationship is established through updating investors beliefs about firm future values. Equilibrium relations are established through slow and long-term processes. In the context of climate risk, investors adjust their valuation weights on individual accounting variables as an adaptive response toward their exposure to climate risk. From this perspective, if a cointegration relationship between variables in a data set exists, it overcomes some of the shortcomings in the reliance on time series analysis.

The approach taken here adopts both the augmented Dickey-Fuller and Phillips-Perron tests to detect unit roots contained in the time series variables. This serves to check the robustness of the results. The augmented Dickey-Fuller test is a parametric test while the Phillips-Perron test is a non-parametric test.

The unit root test is conducted in the Dickey-Fuller approach through conducting the following regression: $\Delta y_t = \alpha + \beta y_{t-1} + \mu_t$. Under the null hypothesis of a unit root existing, it is expected that $\hat{\beta} = 0$. The augmented Dickey-Fuller test incorporates lagged differences to deal with potential serial correlation in the error terms. The validity of the Dickey-Fuller method lies in the fact that the errors are assumed to be white noise. However, caution is required in interpreting the power of Dickey-Fuller test. If variables are close to processing a unit root, the null hypothesis of a unit root is unlikely to be rejected (Woodridge, 2015). The failure to reject the hypothesis of a unit root however is only weak evidence for the hypothesis. Another problem is that the critical values of test statistics are very sensitive to the structure of the data generation process (Banerjee et al., 2003).

The Phillips-Perron method works through corrections to the standard Dickey-Fuller statistics and deals with the issues of serial correlation in residuals by using Newey West standard errors. While it is generally believed that Phillips-Perron method has higher test power than the Dickey-Fuller method, the size of the correction does not always work well even when the sample size is fairly large (Banerjee et al., 2003).

If the dependent and independent variables are likely to contain unit roots of the same order, a cointegration relationship may exist between them. In the case of an I(1) process, cointegration means that there is a linear combination these that results in an

I(0) process. In this thesis, if the estimated market elasticities of the accounting variables have a cointegration relationship with the climate change variables, I conclude that the relation between the two variables is not caused by the other factors or a common trend. Moreover, I can conclude that levels model adopted is correctly specified. The cointegration tests adopt the Engle & Granger (1987) two stage approach by examining whether the residuals obtained stage two contain unit root. If the null hypothesis of existing unit root is rejected, the cointegration relationship between the elasticities of the accounting variable and the global anomaly temperature is proved.

All tests are conducted on both the U.S. and specific industry levels. Due to the time series pattern of the estimated coefficients appearing to have a structure break in 1982, tests for two periods are conducted separately because structure breaks may influence the outcome of the unit root tests. One period tested is from 1971 to 2017. The other is from 1982 to 2017.

4.3 Data Sources and Variables

4.3.1 Accounting and Stock Price Data

I extract the accounting data from Compustat. The stock price and the number of shares outstanding are obtained from CRSP. The data from the two datasets are merged through CCM Link table, which results in more accurate and greater numbers of matched results than other methods. The market value chosen to match with accounting data is 3 months behind the fiscal year end, to ensure the accounting information is publicly known and does not contain a data-snooping bias. As noted earlier, the sample covers the period over 1971-2017. I choose common stocks (CRSP share codes (shrcd): 10 or 11) listed on NYSE, Amex, or NASDAQ (CRSP exchange codes (exchcd) 1, 2, or 3) with no outliers eliminated. However, observations with zero value for net income, book value of equity, and market value are eliminated. Following the general approach explained in the previous chapter, the market and accounting variables are transformed by taking logs of the absolute value of the original variables. The unit of the original variables is one million dollars. Since dividends with zero value are retained, I set them to 1 to avoid not being able to take logs of zero value. A consequence of this approach is that the effect of zero dividends is not ignored.

The total number of firm-year observations is 180,042. The number of firms are roughly equally distributed across different years. The sample is classified into 10 subsamples according to the two-digit SIC to observe any different responses to climate change. In the sample, 519 observations are classified as being agriculture. Because of this limited number, the agricultural industry is ignored in the following industry level analysis. The manufacturing industry category includes the largest number of observations: 79,374. 1% of the sample is attributed into non-classifiable, and is also not included in the industry level analysis.

Table 4.1 Variable Definitions

Variable	Description
Panel A	
M	Market value. Stock price at the end of the third month of the fiscal year multiplied by the number of shares outstanding
B	Opening book value of equity – the value of common equity of last fiscal year
E	Net income
D	Common dividends
O	Balancing value; calculated by the accounting identity: $B_t = B_{t-1} + E_t + D_t + O_t$
Panel B	
Temperature	Global anomaly temperature; calculated as the annual average temperature across land and ocean minus the mean temperature over the period 1901 to 2000. The data are extracted from NOAA website.

Table 4.2 The Number of Observations among Different Industries

Industry	SIC code	Firm-year Obs.	%	Cumulative %
Agriculture	0100-0999	519	0.29	0.29
Mining	1000-1499	7,560	4.2	4.49
Construction	1500-1799	2,165	1.2	5.69
Manufacturing	2000-3999	79,374	44.09	49.78
Transport	4000-4999	15,452	8.58	58.36
Wholesale	5000-5199	6,900	3.83	62.19
Retail	5200-5999	11,605	6.45	68.64
Finance	6000-6799	29,213	16.23	84.86
Services	7000-8999	25,477	14.15	99.01
Non-classification	9900-9999	1,777	0.99	100
Total		180,042	100	

This Table summarises the firm-years observations among different industries. The classification of industry is based on the 2-digit Standard Industry Classification (SIC). Due to the limited number of observations, agriculture and non-classification are excluded from the industry level regressions.

4.3.2 Global Temperature Data

I mainly use annual temperature variables to reflect the climate change. Hsiang & Kopp (2018) describe the climate system as a complex and high-dimensional system. They suggest that global surface temperature and distributions of temperature are good summary statistics. Hsiang (2016) argues that researchers should understand that these measures are a “rough characterization of a more highly structured multidimensional distribution” (p. 45) but need to be collapsed into the dimensionality that is understandable from an economic or social perspective. Auffhammer et al. (2011) depict climate variables, such as temperature, rainfall, wind, etc., as being insufficient statistics for climate analysis because climate is regarded as the “the conditional distribution of a large random vector of environmental parameters” (p. 2). For pragmatic reasons, researchers only choose one variable that is most relevant to the research topic.

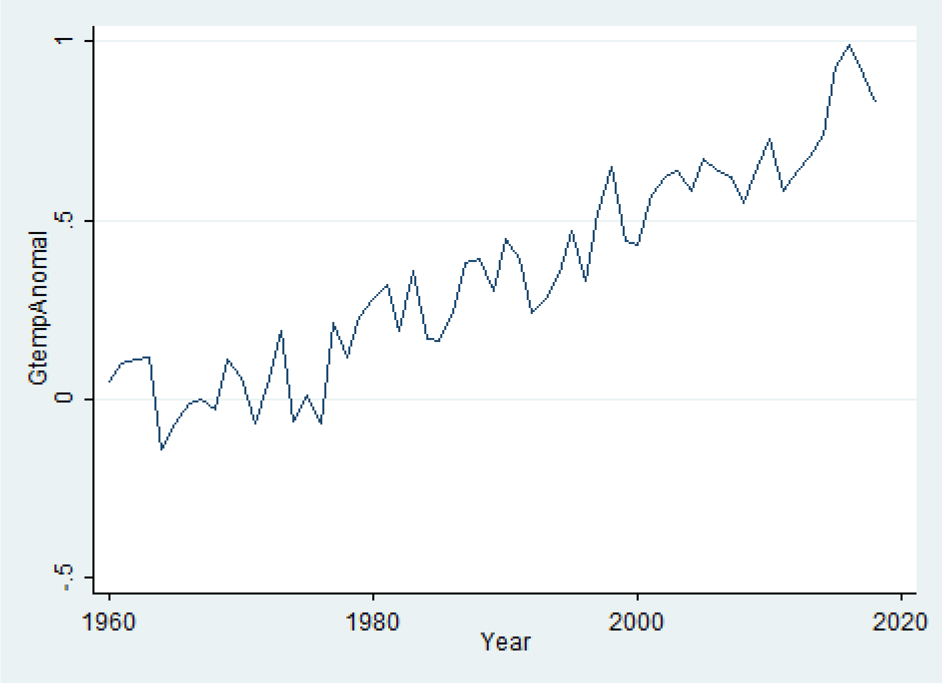
Climate change is a global phenomenon (Auffhammer, 2018). Dell et al. (2014) argue that the global shocks relate to medium and long-run effects so that it is possible to analyse the resulting adaptive actions. While identification of global rather than local shocks may omit time-varying patterns, those can be ignored if global weather shocks are random and occur over long time periods. However, spatial and seasonal heterogeneity cannot be captured by average global temperature or changes in average global temperature (Auffhammer & Schlenker, 2014).

The identification of effects depends on the length of period covered by climate distribution summaries. Short periods may identify the direct effects, but not “belief” effects, which requires longer period of time. The analysis of belief effects needs low-frequency time-series variation because of the persistence of population’ beliefs about climate change.

The primary measure of climate change in the thesis is the global annual temperature. The data on temperature are extracted from the NOAA website, which provides both global temperature and the national (U.S.) temperature. The global temperature is calculated based on an area-weighted of a 5^o x 5^o grid across land and ocean. NOAA reports an anomaly temperature, which is the temperature deviation from the mean global temperature over the period 1901 to 2000, that is 13.9^{o}C. The anomaly temperature may capture the long-run temperature risks associated with global warming

(Bansal et al., 2016). Consistent with the time period of the market and accounting data, the time series period of the climate change used in this thesis is from 1971 to 2017. Fig 4-1 depicts the time series graph of the annual global anomaly temperature over the period from 1971 to 2017, showing a continuous increase in global temperature.

Figure 4.1 The Annual Global Anomaly Temperature



The figure depicts the time series pattern of global anomaly temperature over the period 1971 to 2017. The global temperature is the average temperature across land and ocean. The abnormal temperature is calculated as the level temperature minus 13.9 ºC, which is the mean temperature over the period 1901 to 2000. The data are extracted from NOAA website https://www.ncdc.noaa.gov/monitoring-references/faq/anomalies.php#anomalies.

4.3.3 Long-run and Short-run Components of Global Temperature

Based on the Epstein-Zin style utility function, Bansal et al. (2016) develop a temperature augmented long-run risk (LRR-T) model, showing that warming temperature lowers the current wealth to consumption ratio, which, in turn influences assets valuation. The Epstein-Zin style utility function implies that agent prefer early resolution of uncertainty. If agents have a preference for early resolution of uncertainty, they become concerned about uncertainty that is persistent over a long period of time (Bansal, Kiku, & Ochoa, 2019). Therefore, Bansal et al. (2016) argue that low-frequency temperature shifts (the long-run component) have a significant impact on equity valuation, but the high-frequency temperature fluctuations (the short-run component) are a transient variation and the impact on valuation is small and insignificant, because it is the trend of global warming that increases the likelihood of breaching the threshold point of inducing damage. Bolton & Kacperczyk (2021) investigate the different effects of long-run and short-run carbon risk on stock returns by using emission levels to capture the long-run risk and change in emissions to capture the short-run risk. But they find that both the long-run and short-run risk are positively and significantly related to stock return.

Therefore, I decompose the global anomaly temperature into two components, following Bansal, Kiku, &Ochoa. (2016). One reflects the long-run component of climate risk, the shift of global temperature reflecting low-frequency temperature risk. The other is the short-run component of climate risk, the fluctuation in global. The important role of the long-run aspect of climate risk in asset pricing has been well documented in the climate finance literature, e.g., Bolton & Kacperczyk (2021) and Hong et al. (2019).

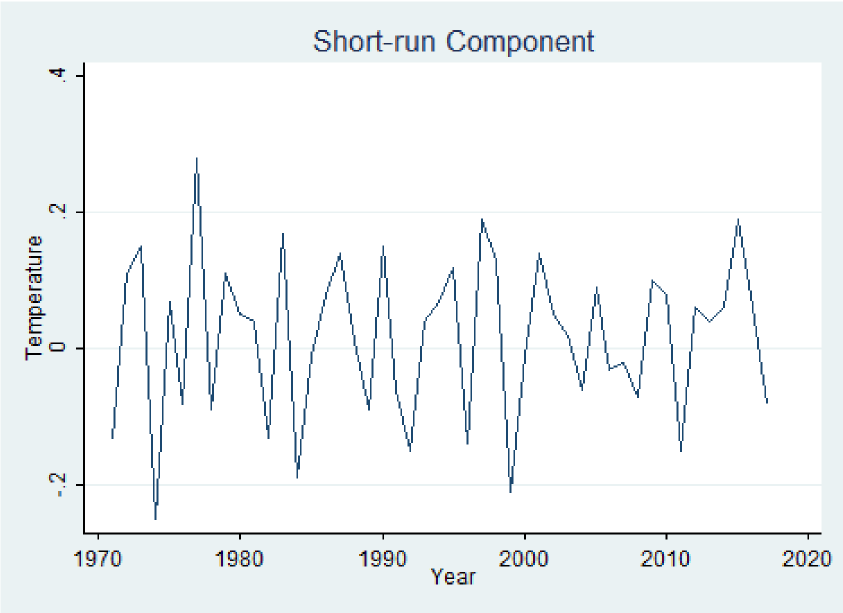
I use a 3-year moving average of the global anomaly temperature as the measure of the long-run component of climate risk and the first-order difference as the measure of the short-run component of climate risk.

I also adopt the Hodrick & Prescott (1997) filter to decompose annual global temperature into trend component, which corresponds to Bansal et al. (2016) low-frequency component, and a cycle component, which corresponds to Bansal et al. (2016) short-run fluctuations. I then use the two components decomposed from the original annual temperature variable in the subsequent analysis. In contrast to the trailing, moving average method, the Hodrick & Prescott (1997) filter includes future estimates of temperature data. Therefore, it is subject to data snooping biases (Bansal et al., 2016). The results from using Hodrick & Prescott (1997) filter are similar to the results from using moving average and difference methods.

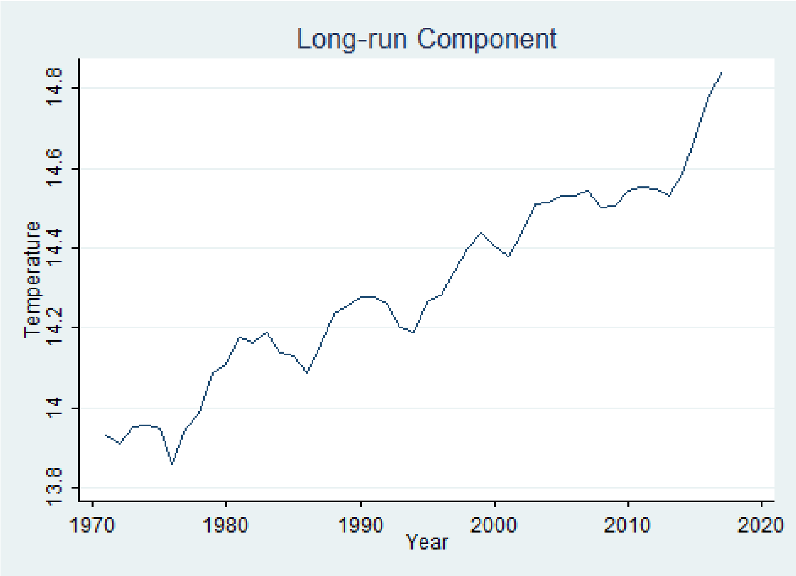
Fig. 4.2 and Fig. 4.3 depict the time series patterns of the different components of global anomaly temperature. The decomposing method in Fig. 4.2 follows Bansal, Kiku, & Ochoa (2016), with Panel A in Fig. 4.2 demonstrating the short-run component of global temperature and Panel B in Fig. 4.2 demonstrating the long-run component of global temperature. The decomposing method in Fig. 4.3 follows Hodrick and Prescott (1997), with Panel A in Fig. 4.3 demonstrating the cycle component of global temperature and Panel B in Fig. 4.3 demonstrating the trending component of global temperature. These figures show that short-run (or cycle) component of global temperature exhibits high frequency but the long-run (or trend) component of global temperature exhibits low frequency.

Figure 4.2 Decomposing the Annual Global Anomaly Temperature into Short-run and Long-run Components

A. Short-Run Component



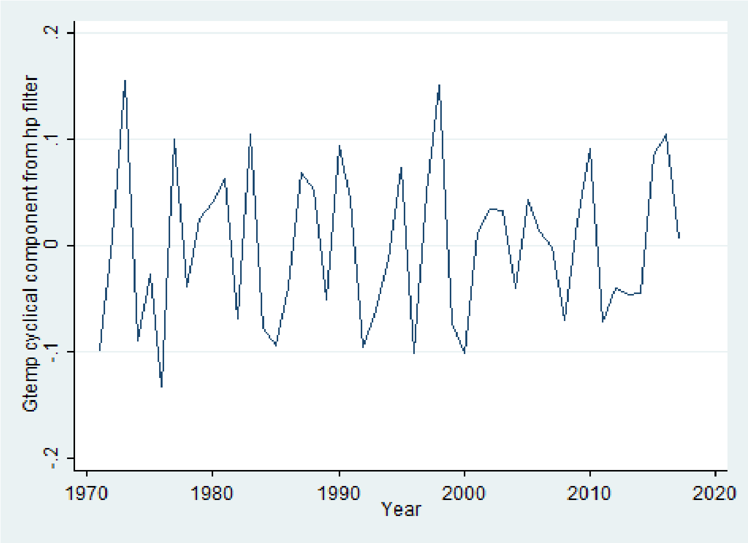
B. Long-Run Component



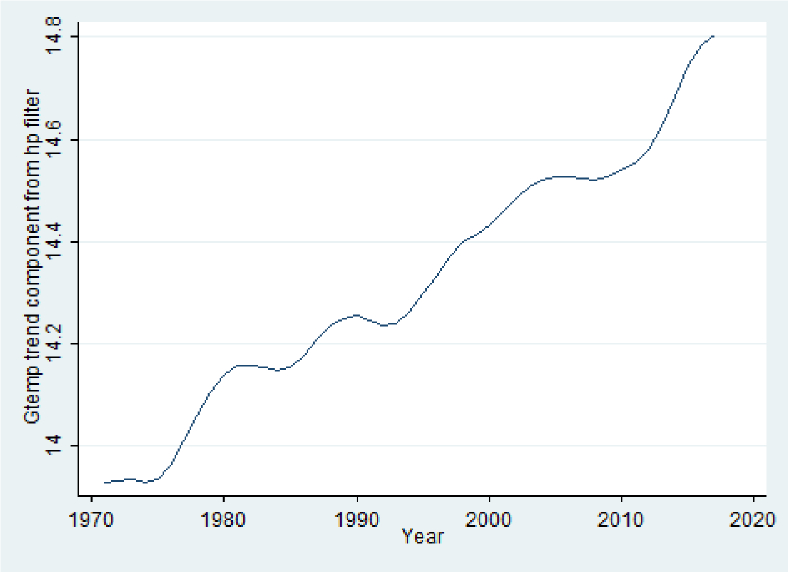
The figures depict the temperature components of global temperature following Bansal, Kiku, & Ochoa (2016). Figure 4.2A depicts the short-run components of global temperature by taking the first-order difference of the temperature variable. Figure 4.2B depicts the long-run component of global anomaly temperature by taking 3-year moving average of the temperature variable. The data are extracted from NOAA website https://www.ncdc.noaa.gov/monitoring-references/faq/anomalies.php#anomalies.

Figure 4.3 Decomposing the Annual Global Anomaly Temperature into Cycle and Trend Components

A. Cycle Component



B. Trend Component



The figures depict the temperature components of global temperature by adopting Hodrick & Prescott's (1997) approach. Figure 4.3A reflects the short-run components of climate risk contained in global temperature. It is called cycle component. Figure 4.3B reflects the long-run components of climate risk. It is called trend component. In the time series regressions, I will observe which component(s) of climate risk influence the evolution of the value relevance of book value and net income. The data are extracted from NOAA website https://www.ncdc.noaa.gov/monitoring-references/faq/anomalies.php#anomalies.

CHAPTER FIVE

RESULTS

The results reported in this Chapter are based upon the two-stage research design described in Chapter 4. In the first stage, annual market elasticities of individual accounting variables are estimated by cross-sections over time with a log-linear model. In the second stage, time series models test the impact of climate change variables on the elasticities of these accounting variables to see if they are associated with investor perceptions of the relative value relevance of book values, earnings, dividends and other accounting information.

Section 5.1 presents descriptive statistics relating to the accounting and market data. Section 5.2 reports estimated elasticities of the individual accounting variables at both U.S. economy and individual industry levels. Section 5.3 reports the impact of annual global anomaly and U.S. anomaly temperatures on each estimated elasticity. Section 5.4 distinguishes the association of long-run and short-run components of global temperature with each estimated elasticity. Section 5.5 reports the association of other climate measures, including U.S. precipitation, U.S. Palmer Z Index, World CO_2 emissions, U.S. CO_2 emissions, with each estimated elasticity. Section 5.6 reports the results of unit root and cointegration tests relating to the main variables in the second stage of modelling.

5.1 Descriptive Statistics for Accounting and Market Data

In this section, the descriptive statistics for the accounting and market data are reported at both U.S. economy and individual industry level. The sample period covers the period from 1971 to 2017. This period covers a variety of economic events, such as the transition to the "new economy", the technology bubble, and financial crises (Barth, Li, & McClure, 2022).

Table 5.1-1 reports the statistical measures of mean, standard deviation, 5th quantile, 25th quantile, 50th quantile, 75th quantile, 95th quantile, skewness, kurtosis, and the number of firm-year observations in different categories of the data. The total number of firm-year observation is 180,042.

The first row presents descriptive statistics for market value, all denominated in $USm.

The mean of market value is 1,878.18, standard deviation 12,537.13, and median 99.56. The skewness for market value is 20.52, indicating that the data are strongly right skewed. The kurtosis is 650.38, indicating that data are heavy-tailed. Market value does not follow the Gaussian distribution.

Row 2 shows descriptive statistics for the book value of equity. The mean of book value is 667.52, standard deviation 4,600.57, and median 54.67. The distribution of book value of equity is also strongly right skewed with a value of 24.57 and has heavy-tail with kurtosis equal to 837.60. The distribution of the book value of equity is also not Gaussian.

Row 3 presents descriptive statistics for earnings. The mean of earnings is 84.83, standard deviation is 909.49, and median is 3.43. In contrast to market value and book value of equity, the distribution of earnings is left skewed with skewness equal to -5.91. This implies that the earnings are negative in high proportion of firms. The kurtosis is 2,548.40, implying a heavy tail.

Rows 4 – 5 report descriptive statistics for dividends and the remaining balancing value representing other accounting information. Both variables demonstrate distributions different from Gaussian. The skewness metric for dividends is 28.27 and 43.73 for the remaining value. The kurtosis for dividend is 1,598.88 and 7,501.71 for the remaining value.

The lower part of the Table reports the results for logs of the magnitudes of all the variables. Descriptive statistics for the transformed variables are reported in row 6 – 10. The transformed data, log of the market value of equity (LM), log of the magnitude of the book value of equity (LB), and log of the magnitude of earnings (LE), becomes noticeably closer to the statistical characteristics of a Gaussian distribution.

Row 6 presents the descriptive statistics for LM. Its mean is 4.75, standard deviation 2.26, and median 4.60. After taking logs skewness reduces to 0.31from 20.52 and kurtosis reduces to 2.84 from 650.38.

Row 7 presents the descriptive statistics for LB. The mean is 4.122, standard deviation 2.10, and median 4.04. After transformation skewness is reduced to 0.18 from 24.57 and kurtosis is reduced to 3.07 from 837.60.

Row 8 presents the descriptive statistics for LE. The mean is 2.23, standard deviation

2.18, and median 2.16. After the transformation to logs skewness becomes 0.11 compared to -5.91 and kurtosis reduces to 3.21 from 2,548.40.

Rows 9 – 10 show also that the distribution of the transformed dividend and "remaining variables" become closer to the Gaussian distribution than prior to transformation.

The changes in the distributions of market value and accounting variables after transformation means that the OLS estimation based on the transformed data[8] generate more reliable estimated coefficients capturing the long-run relation between market and accounting variables. This follows from the fact that the assumptions for inferences from OLS are closer to being satisfied (Clout & Willett, 2016). In addition to the statistical advantage of reliability, the resulting log-linear model has the advantage of mathematical validity, since its form is consistent with the measurement scale properties of the model variables.

Tables 5.1-2 – 5.1-9 report the descriptive statistics for each industry, including Mining, Construction, Manufacturing, Transportation, Wholesale, Retail, Finance, and Services. These Tables have the same structure as Table 5.1-1. While the distributions vary across these industries, the log transformation results in the variables having distributions that are closer to the Gaussian distribution, with more central observations and less heavy tails.

Taking the mining industry as an example. The skewness of market value of equity after transformation is 0.23 compared to 9.41 before transformation. Similarly, the skewness of book value of equity falls to 0.2 from 13.37, the skewness of earnings to 0.07 from -2.92. The kurtosis of market value after transforming to logs is 2.39 compared to 122.02 before transformation. Similarly, for book value of equity the comparative kurtosis statistics are 2.46 compared to 245 and for earnings 2.74 compared to 357.95. The comparisons in the case of dividends and the remaining value are similar. The statistical advantages of the transformation remain in the industry level

[8] To avoid the influence of skewness on the estimations, Barth et al. (2022) adopt the machine learning technique (Classification and Regression Trees (CART) estimation) to capture the reliable market accounting relation. The shortcoming of the approach is overstating value relevance of accounting variables. But Barth et al. (2022) point out that imposing functional form will understate the explanatory power of accounting variables. In the thesis, it is shown that taking logs not only centralises the data but also remove the heavy tail. Therefore, assumptions for making inferences from OLS are better satisfied. The regressions of the log-linear model explain about 80% of variation.

analysis.

5.1-1 Descriptive Statistics for U.S. Economy as a Whole

		Mean	Standard Deviation	5th	25th	Median	75th	95th	Skewness	Kurtosis	N
1	M	1,878.179	12,537.13	3.626	22.238	99.559	535.161	5,750.235	20.517	650.383	180,042
2	B	667.518	4,600.565	1.631	13.462	54.674	236.964	2,128.982	24.565	837.601	180,042
3	E	84.831	909.491	-37.203	-0.503	3.431	24.542	305.563	-5.913	2548.4	180,042
4	D	36.509	312.544	0.43	1	1	3.84	95.2	28.267	1,598.879	180,042
5	O	-3.72	841.713	-66.8	-0.369	0.162	4.895	85.947	43.733	7,501.713	180,042
6	LM	4.75	2.261	1.288	3.102	4.601	6.283	8.657	0.307	2.838	180,042
7	LB	4.122	2.098	0.833	2.674	4.041	5.491	7.667	0.175	3.07	180,042
8	LE	2.23	2.181	-1.201	0.748	2.169	3.651	5.908	0.106	3.211	180,042
9	LD	0.797	1.749	-0.844	0	0	1.345	4.556	1.375	5.71	180,042
10	LO	-0.113	4.786	-13.498	-1.501	0.739	2.714	5.325	-1.909	7.828	180,042

The Table presents descriptive statistics for the U.S. economy. M denotes market value; B denote book value of equity; E denotes earnings; D denotes dividends; O denotes the remaining balancing value; LM denotes log of market value; LB denotes log of book value of equity; LE denotes log of earnings; LD denotes log of dividends; and LO denotes the log of remaining balancing value.

Table 5.1-2 Descriptive Statistics for Mining

		Mean	Standard Deviation	5th	25th	Median	75th	95th	Skewness	Kurtosis	N
1	M	1,508.207	6,003.37	2.445	15.306	83.475	633.686	6,359.837	9.406	122.023	7,560
2	B	700.177	3,306.354	0.878	6.967	40.473	297.863	2,914.836	13.369	245	7,560
3	E	40.169	691.166	-100.136	-1.957	0.83	18.9	325.275	-2.919	357.946	7,560
4	D	24.817	161.828	1	1	1	1.371	92.676	14.92	267.746	7,560
5	O	25.981	536.21	-30.196	-0.033	0.301	7.962	168.22	-5.138	755.34	7,560
6	LM	4.61	2.448	0.894	2.728	4.425	6.452	8.758	0.234	2.385	7,560
7	LB	3.936	2.387	0.39	2.069	3.772	5.725	7.981	0.2	2.459	7,560
8	LE	2.076	2.48	-1.752	0.249	2.028	3.865	6.236	0.07	2.742	7,560
9	LD	0.702	1.608	0	0	0	0.315	4.529	1.776	6.465	7,560
10	LO	-0.411	5.395	-15.257	-1.772	0.732	2.882	5.541	-1.778	6.389	7,560

The Table presents descriptive statistics for Mining. M denotes market value; B denote book value of equity; E denotes earnings; D denotes dividends; O denotes the remaining balancing value; LM denotes log of market value; LB denotes log of book value of equity; LE denotes log of earnings; LD denotes log of dividends; and LO denotes the log of remaining balancing value.

Table 5.1-3 Descriptive Statistics for Construction

		Mean	Standard Deviation	5th	25th	Median	75th	95th	Skewness	Kurtosis	N
1	M	529.63	1,428.939	2.881	16.052	71.825	330.659	2,735.237	5.225	39.488	2,165
2	B	310.281	794.368	2.501	13.671	54.674	216.597	1,592.851	4.527	26.278	2,165
3	E	21.025	199.602	-45.676	-0.714	3.3	19.607	209.96	-1.817	70.208	2,165
4	D	4.208	13.418	0.369	1	1	1.155	17.02	7.216	66.933	2,165
5	O	6.133	86.593	-16.6	-0.095	0.103	3.642	55.8	1.271	171.849	2,165
6	LM	4.322	2.071	1.058	2.776	4.274	5.801	7.914	0.129	2.516	2,165
7	LB	4.067	1.898	1.053	2.647	4.026	5.401	7.373	0.074	2.72	2,165
8	LE	2.124	2.014	-1.044	0.764	2.045	3.443	5.714	0.063	3.135	2,165
9	LD	0.343	1.141	-0.997	0	0	0.144	2.834	1.151	7.063	2,165
10	LO	-1.253	5.552	-15.108	-2.273	0.197	2.106	4.479	-1.744	6.055	2,165

The Table presents descriptive statistics for Construction. M denotes market value; B denote book value of equity; E denotes earnings; D denotes dividends; O denotes the remaining balancing value; LM denotes log of market value; LB denotes log of book value of equity; LE denotes log of earnings; LD denotes log of dividends; and LO denotes the log of remaining balancing value.

Table 5.1-4 Descriptive Statistics for Manufacturing

		Mean	Standard Deviation	5th	25th	Median	75th	95th	Skewness	Kurtosis	N
1	M	1,858.206	1,2984.28	3.437	18.96	82.85	448.877	5,372.135	21.796	758.419	79,374
2	B	537.16	3626.532	1.561	11.324	43.723	189.919	1714.294	24.371	829.174	79,374
3	E	85.5	877.369	-39.674	-1.095	2.276	18.54	277.308	23.279	1325.148	79,374
4	D	36.437	315.368	0.363	1	1	2.492	78.718	19.899	516.767	79,374
5	O	-16.351	659.298	-66.876	-0.242	0.117	3.844	66.366	-5.278	1832.382	79,374
6	LM	4.611	2.263	1.234	2.942	4.417	6.107	8.589	0.397	2.923	79,374
7	LB	3.93	2.059	0.766	2.491	3.813	5.265	7.454	0.236	3.12	79,374
8	LE	2.098	2.17	-1.284	0.618	2.035	3.491	5.781	0.147	3.262	79,374
9	LD	0.673	1.701	-1.013	0	0	0.913	4.366	1.498	6.661	79,374
10	LO	-0.41	4.88	-14.066	-1.858	0.472	2.547	5.14	-1.828	7.361	79,374

The Table presents descriptive statistics for Manufacturing. M denotes market value; B denote book value of equity; E denotes earnings; D denotes dividends; O denotes the remaining balancing value; LM denotes log of market value; LB denotes log of book value of equity; LE denotes log of earnings; LD denotes log of dividends; and LO denotes the log of remaining balancing value.

Table 5.1-5 Descriptive Statistics for Transportation

		Mean	**Standard Deviation**	**5^{th}**	**25^{th}**	**Median**	**75^{th}**	**95^{th}**	**Skewness**	**Kurtosis**	**N**
1	M	2,605.321	1,0911.59	6.996	53.985	289.492	1,245.242	10,996.85	11.741	187.666	15,452
2	B	1,189.308	4,766.329	1.803	29.91	151.993	713.91	5,213.045	14.078	289.909	15,452
3	E	122.812	1,111.486	-54.699	1.105	14.127	82.567	636.687	-41.11	4,144.241	15,452
4	D	85.686	428.653	0.996	1	3.558	39.585	366.087	16.162	344.315	15,452
5	O	33.248	1,671.684	-82.923	-0.704	0.608	13.611	202.545	48.51	4615.25	15,452
6	LM	5.607	2.224	1.945	3.989	5.668	7.127	9.305	0.007	2.69	15,452
7	LB	5.049	2.164	1.475	3.539	5.084	6.589	8.56	-0.112	2.826	15,452
8	LE	3.16	2.149	-0.352	1.675	3.199	4.66	6.626	-0.146	3.07	15,452
9	LD	1.891	2.195	-0.004	0	1.269	3.678	5.903	0.613	2.415	15,452
10	LO	0.952	4.312	-6.908	-0.442	1.649	3.5	5.935	-2.052	9.097	15,452

The Table presents descriptive statistics for Transportation. M denotes market value; B denote book value of equity; E denotes earnings; D denotes dividends; O denotes the remaining balancing value; LM denotes log of market value; LB denotes log of book value of equity; LE denotes log of earnings; LD denotes log of dividends; and LO denotes the log of remaining balancing value.

Table 5.1-6 Descriptive Statistics for Wholesale

		Mean	Standard Deviation	5^{th}	25^{th}	Median	75^{th}	95^{th}	Skewness	Kurtosis	N
1	M	621.43	2,352.584	2.244	9.468	40.474	234.716	2,835.447	8.471	104.842	6,900
2	B	235.041	686.012	1.604	8.175	30.031	133.124	1,272.51	5.859	48.547	6,900
3	E	26.435	130.51	-12.736	0.019	2.095	13.502	163.707	1.589	89.262	6,900
4	D	8.802	41.669	0.231	1	1	1.143	31.585	9.457	113.892	6,900
5	O	-1.521	118.911	-30.087	-0.162	0.024	1.671	38.273	-5.365	309.549	6,900
6	LM	3.959	2.203	0.808	2.248	3.701	5.458	7.95	0.427	2.583	6,900
7	LB	3.576	1.974	0.669	2.133	3.423	4.908	7.165	0.215	2.796	6,900
8	LE	1.557	2.09	-1.704	0.119	1.464	2.944	5.22	0.086	3.01	6,900
9	LD	0.358	1.402	-1.468	0	0	0.134	3.453	1.197	7.339	6,900
10	LO	-1.439	5.27	-15.315	-2.781	-0.335	1.791	4.585	-1.631	5.776	6,900

The Table presents descriptive statistics for Wholesale. M denotes market value; B denote book value of equity; E denotes earnings; D denotes dividends; O denotes the remaining balancing value; LM denotes log of market value; LB denotes log of book value of equity; LE denotes log of earnings; LD denotes log of dividends; and LO denotes the log of remaining balancing value.

Table 5.1-7 Descriptive Statistics for Retail

		Mean	Standard Deviation	5^{th}	25^{th}	Median	75^{th}	95^{th}	Skewness	Kurtosis	N
1	M	2,216.15	1,4491.75	3.189	17.784	92.31	550.098	7,172.709	20.191	649.99	11,605
2	B	553.237	3037.602	2.557	15.211	55.597	228.842	1,914	15.582	318.905	11,605
3	E	96.142	628.469	-19.171	0.287	4.548	28.04	371.749	15.846	335.569	11,605
4	D	27.632	214.525	0.271	1	1	1.926	67.6	17.72	398.363	11,605
5	O	-37.426	518.454	-144.5	-0.356	0.027	2.187	43.456	0.478	502.247	11,605
6	LM	4.693	2.378	1.16	2.878	4.525	6.31	8.878	0.346	2.749	11,605
7	LB	4.179	1.971	1.178	2.79	4.078	5.48	7.581	0.266	3.049	11,605
8	LE	2.198	2.184	-1.197	0.697	2.131	3.608	5.992	0.141	3.202	11,605
9	LD	0.575	1.672	-1.306	0	0	0.655	4.214	1.418	6.667	11,605
10	LO	-0.906	5.396	-14.841	-2.386	0.2	2.387	5.405	-1.559	5.665	11,605

The Table presents descriptive statistics for Retail. M denotes market value; B denote book value of equity; E denotes earnings; D denotes dividends; O denotes the remaining balancing value; LM denotes log of market value; LB denotes log of book value of equity; LE denotes log of earnings; LD denotes log of dividends; and LO denotes the log of remaining balancing value.

Table 5.1-8 Descriptive Statistics for Finance

		Mean	Standard Deviation	5^{th}	25^{th}	Median	75^{th}	95^{th}	Skewness	Kurtosis	N
1	M	1,973.621	11,390.69	7.06	44.422	145.818	631.514	6,068.157	14.689	281.834	29,213
2	B	1,126.298	7,888.642	4.643	33.931	102.62	363.731	3,188.02	18.873	436.94	29,213
3	E	113.529	1,225.429	-14.136	1.74	9.352	41.884	411.296	-26.429	2,267.088	29,213
4	D	38.994	273.571	0.46	1	1.954	11.003	120.877	22.238	640.599	29,213
5	O	15.759	1,100.454	-84.1	-1.991	0.125	5.83	129	34.752	2,097.829	29,213
6	LM	5.146	2.055	1.954	3.794	4.982	6.448	8.711	0.298	3.23	29,213
7	LB	4.75	1.93	1.692	3.541	4.642	5.903	8.069	0.203	3.718	29,213
8	LE	2.614	2.074	-0.637	1.256	2.531	3.93	6.153	0.138	3.425	29,213
9	LD	1.279	1.851	-0.777	0	0.67	2.398	4.795	0.741	4.004	29,213
10	LO	0.829	3.98	-4.71	-0.494	1.231	3.047	5.708	-2.194	11.164	29,213

The Table presents descriptive statistics for Finance. M denotes market value; B denote book value of equity; E denotes earnings; D denotes dividends; O denotes the remaining balancing value; LM denotes log of market value; LB denotes log of book value of equity; LE denotes log of earnings; LD denotes log of dividends; and LO denotes the log of remaining balancing value.

Table 5.1-9 Descriptive Statistics for Services

		Mean	Standard Deviation	5th	25th	Median	75th	95th	Skewness	Kurtosis	N
1	M	1,603.727	13,103.02	3.52	20.186	85.666	467.765	4,257.425	20.806	549.405	25,477
2	B	370.771	2,746.641	0.963	8.735	37.048	150.643	1,165.228	24.11	787.308	25,477
3	E	48.644	683.509	-46.298	-2.835	1.282	12.756	154.406	16.996	464.477	25,477
4	D	16.12	309.617	0.669	1	1	1	19.4	76.596	8,250.737	25,477
5	O	-1.125	516.996	-52.247	-0.032	0.553	6.861	81.348	-8.717	819.685	25,477
6	LM	4.613	2.201	1.258	3.005	4.45	6.148	8.356	0.304	2.848	25,477
7	LB	3.693	2.021	0.515	2.269	3.659	5.039	7.077	0.106	3.094	25,477
8	LE	1.956	2.051	-1.313	0.572	1.927	3.298	5.326	0.077	3.408	25,477
9	LD	0.288	1.186	-0.402	0	0	0	2.965	2.36	14.297	25,477
10	LO	0.129	4.488	-6.908	-1.191	0.917	2.726	5.129	-2.14	9.423	25,477

The Table presents descriptive statistics for Services. M denotes market value; B denote book value of equity; E denotes earnings; D denotes dividends; O denotes the remaining balancing value; LM denotes log of market value; LB denotes log of book value of equity; LE denotes log of earnings; LD denotes log of dividends; and LO denotes the log of remaining balancing value.

5.2 Estimated Elasticities

Table 5.2-1 to 5.2-9 report the results from annual cross-section regressions based on the log-linear model for the U.S. economy and individual U.S. industries. In the Tables, columns 1 – 5 present estimated intercepts and slope coefficients for the book value of equity, earnings, dividend, and the remaining value. The estimated coefficients measure the elasticities of market value with respect to individual accounting variables. Column 6 denotes the sum of elasticities for all the accounting variables, reflecting the total value relevance of all of the accounting information. Column 7 reports the R^2 for the relevant regression model and Column 8 denotes the number of firms in each regression. In the Tables, each row denotes the annual results for the years 1971 to 2017.

In Table 5.2-1, the number of firms (column 8) in each regression ranges from 1,752 (in 1971) to 5,818 (in 1997). Column 2 shows that the elasticities for book value of equity range from 0.31 (in1980) to 0.72 (in 2001). Column 3 shows that the elasticities for earnings range from 0.05 (2001) to 0.48 (in 1973). The results indicate that the elasticities for book value of equity are higher than the elasticities for earnings over the sample period. The Table also shows that in 2008, at the time of the worldwide financial crisis, the elasticity for earnings is 0.06 and the elasticity for the book value of equity is 0.68. Specific events are also associated with some years of low earnings elasticities. Ball, Sadka, & Sadka (2009) argue that changes in Statement of Financial Accounting Standards (SFAS) 142 caused many firms to write off a large amount of goodwill which generated transitory negative shocks to earnings in 2001.

Column 4 shows that the elasticities for dividends range from 0.03 (in 2005) to 0.24 (in 1991). Column 5 shows that the elasticities for remaining value range from 0.01 (in 1974) to 0.22 (in 2009). It is clear that investors place greatest valuation weight on book value of equity and earnings, the two main headline numbers in accounting reports. Column 6 shows that the total value relevance of all the accounting variables together is around 1, ranging from 0.87 (in 1983) to 1.10 (in 2001). The R^2s (column 7) range from 0.73 (in 2008) to 0.89 (in 1976), indicating that the log-linear model explains about 80% of the variation in log market value.

Figure 5.2-1 displays the relation between the elasticities of book value of equity and those of earnings by plots of the time series of the elasticities over the sample period. The Figure demonstrates that the elasticities of book value of equity (the solid line) dominate the elasticities of earnings (the dashed line) for most of the time period, indicating that the value relevance of book value of equity is greater than the value relevance of earnings. Moreover, the elasticities of the two variables are complementary. When the elasticity of book value of equity rises, the elasticity of earnings drops down, or *vice versa*. A possible structural break point between the time series pattern of the two variables is observed in 1982.

Tables 5.2-2 to 5.2-9 report the estimated results from Mining, Construction, Manufacturing, Transportation, Wholesale, Retail, Finance, and Services. The industry level results are similar to those for the U.S. economy level. However, magnitudes of the estimated coefficients vary across the industries. The characteristic behaviour of the elasticities for book value and earnings are highlighted in Figure 5.2-2, which combines the graphs for the U.S. economy and individual U.S. industry together.

Table 5.2-10 reports the mean values of the elasticities for the U.S. economy and each industry over the period from 1971 to 2017. Rows 1-5 report the mean results for $\hat{\alpha}$, $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\widehat{\beta_3}$, and $\widehat{\beta_4}$. Row 6 reports $\sum \hat{\beta}$ which is the sum of $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\widehat{\beta_3}$, and $\widehat{\beta_4}$, and reflects the total value relevance of all the accounting variables. Row 7 reports the R^2 and Row 8 lists the number of observations. Column 1 shows that for the U.S. economy as a whole, a 1% increase in the absolute value of book value of equity results in an increase in stock price by about 0.519% and a 1% increase in the absolute value of earnings results in an increase in stock price by about 0.271%. The mean values reveal that the magnitudes of the estimated elasticities vary across industries but with the same sign, ranging from 0.505 to 0.689 for $\widehat{\beta_1}$ and ranging from 0.136 to 0.316 for $\widehat{\beta_2}$. Changes in the book value of equity and earnings account for most of the proportionate change in market value in the different industries over the sample period.

In summary, the results in stage 1 of the modelling strategy supports hypotheses H1a and H2, that the elasticities of the book value of equity and earnings are complementary and the sum of the elasticities of the individual accounting variables in model (4.2) approximates to 1.

Table 5.2-1 Estimated Elasticities for U.S. Economy as a Whole

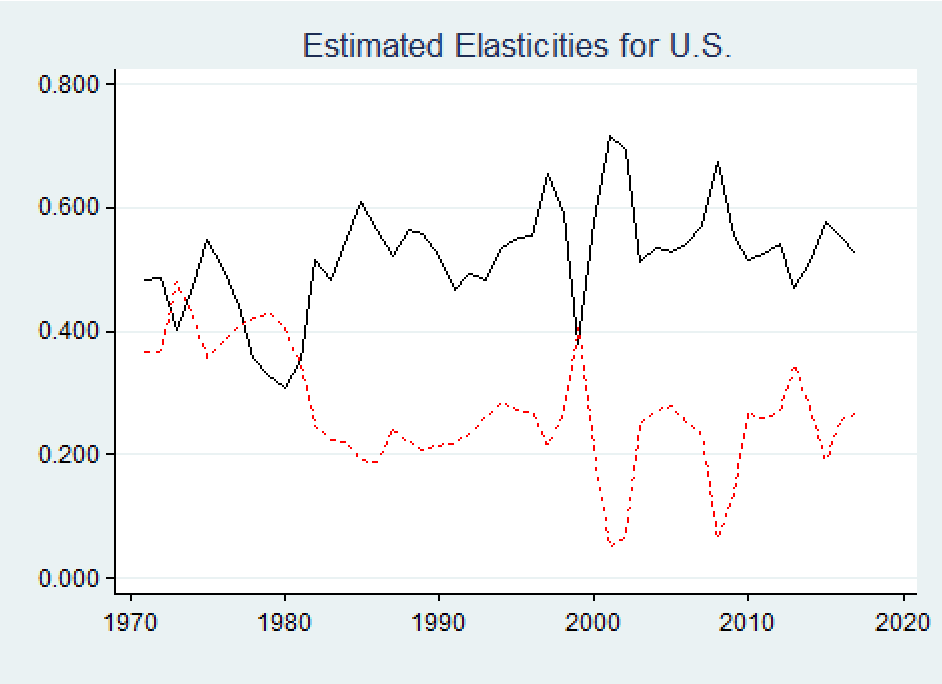
Year	Intercept	B	E	D	O	$\sum \beta$	R^2	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1971	1.873	0.484	0.367	0.125	0.027	1.003	0.859	1752
p_value	0.000	0.000	0.000	0.000	0.000			
1972	1.671	0.487	0.368	0.134	0.031	1.020	0.855	1872
p_value	0.000	0.000	0.000	0.000	0.000			
1973	1.417	0.401	0.479	0.155	0.014	1.048	0.867	2563
p_value	0.000	0.000	0.000	0.000	0.000			
1974	0.944	0.473	0.428	0.151	0.011	1.062	0.864	3152
p_value	0.000	0.000	0.000	0.000	0.000			
1975	1.042	0.547	0.358	0.141	0.016	1.062	0.877	3419
p_value	0.000	0.000	0.000	0.000	0.000			
1976	1.190	0.503	0.382	0.141	0.021	1.047	0.893	3436
p_value	0.000	0.000	0.000	0.000	0.000			
1977	1.385	0.440	0.409	0.127	0.022	0.999	0.891	3401
p_value	0.000	0.000	0.000	0.000	0.000			
1978	1.771	0.356	0.421	0.148	0.031	0.956	0.884	3309
p_value	0.000	0.000	0.000	0.000	0.000			
1979	1.776	0.329	0.429	0.131	0.037	0.926	0.859	3298
p_value	0.000	0.000	0.000	0.000	0.000			
1980	2.187	0.307	0.408	0.143	0.050	0.907	0.825	3400
p_value	0.000	0.000	0.000	0.000	0.000			
1981	1.971	0.353	0.350	0.137	0.051	0.891	0.835	3437
p_value	0.000	0.000	0.000	0.000	0.000			
1982	1.707	0.515	0.247	0.128	0.034	0.925	0.831	3647
p_value	0.000	0.000	0.000	0.000	0.000			
1983	2.100	0.482	0.224	0.114	0.051	0.873	0.824	3741
p_value	0.000	0.000	0.000	0.000	0.000			
1984	1.727	0.550	0.220	0.120	0.043	0.933	0.858	3894
p_value	0.000	0.000	0.000	0.000	0.000			
1985	1.660	0.610	0.192	0.126	0.045	0.973	0.834	4008
p_value	0.000	0.000	0.000	0.000	0.000			
1986	1.909	0.565	0.188	0.169	0.056	0.978	0.831	3940
p_value	0.000	0.000	0.000	0.000	0.000			
1987	1.851	0.522	0.240	0.156	0.052	0.971	0.839	4084
p_value	0.000	0.000	0.000	0.000	0.000			
1988	1.666	0.564	0.221	0.151	0.054	0.990	0.845	4234
p_value	0.000	0.000	0.000	0.000	0.000			
1989	1.702	0.559	0.209	0.163	0.063	0.993	0.830	4219
p_value	0.000	0.000	0.000	0.000	0.000			
1990	1.637	0.523	0.216	0.233	0.060	1.032	0.811	4154
p_value	0.000	0.000	0.000	0.000	0.000			
1991	2.113	0.467	0.219	0.241	0.082	1.008	0.804	4135

p_value	0.000	0.000	0.000	0.000	0.000			
1992	2.088	0.493	0.233	0.210	0.078	1.015	0.830	4140
p_value	0.000	0.000	0.000	0.000	0.000			
1993	2.184	0.484	0.263	0.160	0.074	0.981	0.831	4395
p_value	0.000	0.000	0.000	0.000	0.000			
1994	1.869	0.535	0.286	0.118	0.065	1.004	0.837	5163
p_value	0.000	0.000	0.000	0.000	0.000			
1995	1.994	0.551	0.272	0.097	0.077	0.996	0.817	5399
p_value	0.000	0.000	0.000	0.000	0.000			
1996	1.968	0.556	0.268	0.095	0.091	1.009	0.829	5585
p_value	0.000	0.000	0.000	0.000	0.000			
1997	1.815	0.653	0.215	0.079	0.099	1.046	0.827	5818
p_value	0.000	0.000	0.000	0.000	0.000			
1998	1.669	0.591	0.267	0.119	0.096	1.073	0.801	5571
p_value	0.000	0.000	0.000	0.000	0.000			
1999	2.353	0.379	0.405	0.056	0.137	0.976	0.748	5224
p_value	0.000	0.000	0.000	0.000	0.000			
2000	1.567	0.577	0.203	0.158	0.146	1.085	0.738	5083
p_value	0.000	0.000	0.000	0.000	0.000			
2001	1.384	0.716	0.052	0.179	0.154	1.100	0.772	4797
p_value	0.000	0.000	0.000	0.000	0.000			
2002	1.302	0.693	0.066	0.180	0.134	1.073	0.777	4457
p_value	0.000	0.000	0.000	0.000	0.000			
2003	2.264	0.512	0.250	0.092	0.138	0.991	0.830	4174
p_value	0.000	0.000	0.000	0.000	0.000			
2004	2.169	0.536	0.270	0.072	0.112	0.990	0.857	3970
p_value	0.000	0.000	0.000	0.000	0.000			
2005	2.237	0.529	0.278	0.032	0.132	0.971	0.861	3914
p_value	0.000	0.000	0.000	0.000	0.000			
2006	2.185	0.540	0.254	0.043	0.143	0.980	0.864	3820
p_value	0.000	0.000	0.000	0.000	0.000			
2007	1.788	0.571	0.231	0.052	0.157	1.011	0.838	3704
p_value	0.000	0.000	0.000	0.000	0.000			
2008	1.047	0.675	0.062	0.098	0.164	0.998	0.731	3629
p_value	0.000	0.000	0.000	0.000	0.000			
2009	1.826	0.556	0.136	0.131	0.222	1.045	0.802	3450
p_value	0.000	0.000	0.000	0.000	0.000			
2010	2.014	0.515	0.269	0.085	0.170	1.039	0.833	3282
p_value	0.000	0.000	0.000	0.000	0.000			
2011	1.867	0.526	0.259	0.078	0.170	1.033	0.841	3162
p_value	0.000	0.000	0.000	0.000	0.000			
2012	1.846	0.543	0.270	0.077	0.150	1.039	0.839	3077
p_value	0.000	0.000	0.000	0.000	0.000			
2013	2.253	0.471	0.345	0.045	0.143	1.005	0.841	3015
p_value	0.000	0.000	0.000	0.000	0.000			

2014 p_value	2.130 0.000	0.512 0.000	0.277 0.000	0.053 0.000	0.169 0.000	1.010	0.834	3030
2015 p_value	1.859 0.000	0.577 0.000	0.190 0.000	0.108 0.000	0.152 0.000	1.027	0.807	3093
2016 p_value	1.986 0.000	0.552 0.000	0.257 0.000	0.109 0.000	0.131 0.000	1.048	0.822	3034
2017 p_value	2.120 0.000	0.527 0.000	0.268 0.000	0.099 0.000	0.153 0.000	1.047	0.816	2961

The Table reports the results from annual cross-sectional regressions of the log-linear value relevance model from 1971 to 2017. The empirical model is $log(M_{i,t}) = \alpha + \beta_1 log(|B|_{i,t-1}) + \beta_2 log(|E|_{i,t}) + \beta_3 log(|D|_{i,t}) + \beta_4 log(|O|_{i,t}) + \varepsilon_{i,t}$. Column 1 contains the estimated results for the intercept term α; column 2 contains the estimated elasticities for book value, β_1; column 3 contains the estimated elasticities for net income, β_2; column 4 contains the estimated elasticities for common dividends, β_3; column 5 contains the estimated elasticities for the remaining item, β_4, which column 6 is the sum of the four estimated elasticities; column 7 is R^2; and the last column is the number of observations. The regressions are estimated by OLS. p values are listed below the corresponding estimates.

Figure 5.2-1 Time Series Patterns of Elasticities for Book Value of Equity and Net Income for U.S. Economy



The Figure depicts the time series pattern of the estimated coefficients on book value and earnings over the period shown. The x-axis shows years. The y-axis shows the estimated elasticities each year. The solid line displays the elasticities on book value in each year. The dashed line displays the estimated elasticities on net income. The graph suggests the existence of a structural break in 1982. The data are reported in Table 5.2-1, and are based on the annual cross-sectional regression model: $log(M_{i,t}) = \alpha + \beta_1 log(|B|_{i,t-1}) + \beta_2 log(|E|_{i,t}) + \beta_3 log(|D|_{i,t}) + \beta_4 log(|O|_{i,t}) + \varepsilon_{i,t}$.

Table 5.2-2 Estimated Elasticities for Mining

Year	Intercept	B	E	D	O	$\sum \beta$	R^2	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1971	1.877	0.548	0.244	0.113	-0.013	0.892	0.840	62
p_value	0.000	0.000	0.026	0.325	0.485			
1972	1.894	0.534	0.327	0.066	0.012	0.940	0.874	68
p_value	0.000	0.000	0.003	0.491	0.466			
1973	2.519	0.316	0.358	0.246	0.017	0.936	0.856	101
p_value	0.000	0.001	0.000	0.001	0.184			
1974	1.943	0.312	0.415	0.210	0.018	0.954	0.864	130
p_value	0.000	0.000	0.000	0.001	0.099			
1975	1.965	0.346	0.402	0.229	0.023	1.001	0.852	139
p_value	0.000	0.000	0.000	0.001	0.066			
1976	2.273	0.311	0.443	0.160	0.026	0.940	0.855	139
p_value	0.000	0.000	0.000	0.016	0.032			
1977	2.177	0.411	0.259	0.206	0.022	0.898	0.824	150
p_value	0.000	0.000	0.000	0.001	0.047			
1978	2.229	0.512	0.146	0.151	0.034	0.844	0.856	150
p_value	0.000	0.000	0.003	0.002	0.002			
1979	2.849	0.382	0.190	0.214	0.041	0.826	0.816	151
p_value	0.000	0.000	0.003	0.001	0.005			
1980	3.474	0.305	0.248	0.155	0.051	0.759	0.803	184
p_value	0.000	0.000	0.000	0.002	0.000			
1981	2.641	0.363	0.230	0.171	0.029	0.793	0.796	234
p_value	0.000	0.000	0.000	0.002	0.005			
1982	1.422	0.592	0.139	0.210	0.032	0.973	0.822	304
p_value	0.000	0.000	0.000	0.000	0.000			
1983	1.164	0.767	-0.039	0.233	0.029	0.989	0.806	316
p_value	0.000	0.000	0.313	0.000	0.001			
1984	1.191	0.654	-0.014	0.341	0.048	1.028	0.820	284
p_value	0.000	0.000	0.719	0.000	0.000			
1985	0.781	0.690	-0.017	0.292	0.026	0.991	0.789	243
p_value	0.000	0.000	0.679	0.000	0.013			
1986	0.890	0.806	-0.092	0.269	0.052	1.034	0.773	216
p_value	0.000	0.000	0.109	0.000	0.000			
1987	1.437	0.650	0.094	0.220	0.059	1.023	0.813	196
p_value	0.000	0.000	0.053	0.001	0.000			
1988	1.308	0.646	0.190	0.250	0.042	1.128	0.821	192
p_value	0.000	0.000	0.000	0.001	0.001			
1989	1.414	0.640	0.280	0.133	0.042	1.095	0.822	186
p_value	0.000	0.000	0.000	0.076	0.007			
1990	1.351	0.653	0.170	0.191	0.035	1.050	0.824	186
p_value	0.000	0.000	0.001	0.007	0.021			
1991	1.438	0.566	0.237	0.265	0.041	1.109	0.803	188

p_value	0.000	0.000	0.000	0.000	0.004			
1992 p_value	1.274 0.000	0.730 0.000	0.110 0.039	0.203 0.014	0.043 0.006	1.086	0.802	172
1993 p_value	2.023 0.000	0.476 0.000	0.306 0.000	0.221 0.001	0.070 0.000	1.073	0.838	179
1994 p_value	1.356 0.000	0.747 0.000	0.141 0.001	0.124 0.031	0.063 0.000	1.075	0.874	186
1995 p_value	1.542 0.000	0.723 0.000	0.203 0.000	0.133 0.044	0.014 0.375	1.073	0.822	192
1996 p_value	1.878 0.000	0.644 0.000	0.242 0.000	0.042 0.494	0.102 0.000	1.030	0.841	194
1997 p_value	1.478 0.000	0.780 0.000	0.120 0.009	0.055 0.302	0.095 0.000	1.051	0.867	188
1998 p_value	0.949 0.000	0.761 0.000	-0.003 0.954	0.212 0.001	0.150 0.000	1.120	0.837	172
1999 p_value	1.578 0.000	0.701 0.000	0.138 0.007	0.145 0.021	0.085 0.000	1.070	0.841	146
2000 p_value	1.803 0.000	0.701 0.000	0.094 0.151	0.124 0.079	0.104 0.000	1.023	0.805	138
2001 p_value	1.780 0.000	0.573 0.000	0.191 0.003	0.127 0.049	0.167 0.000	1.058	0.846	134
2002 p_value	1.248 0.000	0.733 0.000	0.001 0.982	0.138 0.043	0.193 0.000	1.066	0.845	123
2003 p_value	2.284 0.000	0.553 0.000	0.212 0.001	0.049 0.325	0.147 0.000	0.962	0.881	116
2004 p_value	2.732 0.000	0.562 0.000	0.121 0.059	0.117 0.030	0.140 0.000	0.940	0.867	112
2005 p_value	3.034 0.000	0.570 0.000	0.080 0.153	0.133 0.006	0.132 0.003	0.915	0.872	115
2006 p_value	2.475 0.000	0.596 0.000	0.118 0.039	0.128 0.003	0.125 0.001	0.966	0.888	130
2007 p_value	2.533 0.000	0.497 0.000	0.264 0.000	0.131 0.006	0.106 0.001	0.998	0.850	140
2008 p_value	1.652 0.000	0.497 0.000	0.047 0.428	0.307 0.000	0.222 0.000	1.072	0.763	146
2009 p_value	1.899 0.000	0.629 0.000	0.074 0.250	0.193 0.000	0.154 0.000	1.050	0.823	147
2010 p_value	2.728 0.000	0.509 0.000	0.202 0.002	0.118 0.012	0.158 0.000	0.986	0.844	139
2011 p_value	1.946 0.000	0.685 0.000	0.044 0.516	0.151 0.002	0.132 0.000	1.012	0.835	134
2012 p_value	1.343 0.000	0.792 0.000	-0.005 0.945	0.120 0.016	0.131 0.000	1.038	0.827	133
2013 p_value	1.987 0.000	0.665 0.000	0.138 0.021	0.110 0.014	0.049 0.093	0.962	0.845	128
2014	1.421	0.638	0.076	0.179	0.137	1.030	0.774	127

p_value	0.000	0.000	0.425	0.005	0.005			
2015	0.968	0.896	-0.230	0.215	0.106	0.988	0.762	122
p_value	0.019	0.000	0.007	0.001	0.004			
2016	1.793	0.601	0.157	0.235	0.071	1.065	0.761	115
p_value	0.000	0.000	0.104	0.001	0.100			
2017	1.760	0.627	0.189	0.187	0.044	1.047	0.771	113
p_value	0.000	0.000	0.018	0.004	0.360			

The Table reports the results from annual cross-sectional regressions of the log-linear value relevance model from 1971 to 2017. The empirical model is $log\left(M_{i,t}\right) = \alpha + \beta_1 log\left(|B|_{i,t-1}\right) + \beta_2 log\left(|E|_{i,t}\right) + \beta_3 log\left(|D|_{i,t}\right) + \beta_4 log\left(|O|_{i,t}\right) + \varepsilon_{i,t}$. Column 1 contains the estimated results for the intercept term α; column 2 contains the estimated elasticities for book value, β_1; column 3 contains the estimated elasticities for net income, β_2; column 4 contains the estimated elasticities for common dividends, β_3; column 5 contains the estimated elasticities for the remaining item, β_4, which column 6 is the sum of the four estimated elasticities; column 7 is R^2; and the last column is the number of observations. The regressions are estimated by OLS. p values are listed below the corresponding estimates.

Table 5.2-3 Estimated Elasticities for Construction

Year	Intercept	B	E	D	O	$\sum\beta$	R^2	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1971	4.034	-0.037	0.342	0.227	0.149	0.682	0.707	13
p_value	0.003	0.889	0.181	0.262	0.279			
1972	2.852	0.056	0.615	0.232	0.015	0.917	0.723	19
p_value	0.003	0.860	0.017	0.131	0.652			
1973	1.013	0.411	0.665	0.144	-0.014	1.206	0.880	33
p_value	0.014	0.006	0.000	0.149	0.361			
1974	-0.007	0.824	0.233	0.052	0.021	1.130	0.711	44
p_value	0.989	0.000	0.101	0.726	0.413			
1975	0.260	0.911	0.060	0.029	0.048	1.048	0.772	48
p_value	0.520	0.000	0.573	0.804	0.011			
1976	0.420	0.789	0.211	0.077	0.029	1.107	0.854	52
p_value	0.170	0.000	0.010	0.401	0.051			
1977	0.544	0.670	0.375	0.015	0.016	1.076	0.875	51
p_value	0.032	0.000	0.000	0.858	0.230			
1978	1.305	0.486	0.319	0.226	0.027	1.057	0.859	47
p_value	0.000	0.000	0.003	0.012	0.108			
1979	1.639	0.262	0.508	0.225	0.049	1.043	0.833	49
p_value	0.000	0.019	0.000	0.037	0.008			
1980	1.390	0.581	0.271	0.235	0.059	1.145	0.788	50
p_value	0.001	0.001	0.028	0.074	0.008			
1981	1.348	0.490	0.295	0.093	0.051	0.930	0.751	53
p_value	0.000	0.000	0.007	0.454	0.038			
1982	1.370	0.685	0.046	0.204	0.053	0.989	0.718	53
p_value	0.000	0.000	0.687	0.218	0.032			
1983	1.986	0.497	0.162	0.163	0.062	0.884	0.774	57
p_value	0.000	0.000	0.075	0.088	0.003			
1984	1.193	0.614	0.322	0.042	0.049	1.027	0.887	56
p_value	0.000	0.000	0.001	0.645	0.001			
1985	1.142	0.751	0.153	-0.002	0.019	0.921	0.755	56
p_value	0.001	0.000	0.240	0.990	0.401			
1986	1.946	0.624	-0.071	0.251	0.053	0.857	0.688	52
p_value	0.000	0.000	0.517	0.031	0.003			
1987	1.786	0.504	-0.020	0.508	0.032	1.024	0.660	55
p_value	0.000	0.000	0.865	0.005	0.073			
1988	1.065	0.747	0.072	-0.112	0.087	0.794	0.687	57
p_value	0.010	0.000	0.484	0.576	0.005			
1989	1.111	0.696	0.064	0.072	0.093	0.925	0.717	59
p_value	0.001	0.000	0.523	0.651	0.000			
1990	1.800	0.405	0.103	0.636	0.077	1.220	0.579	51
p_value	0.003	0.034	0.524	0.032	0.016			
1991	1.556	0.676	0.063	0.195	0.105	1.040	0.688	47

p_value	0.000	0.000	0.587	0.427	0.001			
1992	1.939	0.547	0.065	0.333	0.088	1.033	0.659	49
p_value	0.000	0.001	0.616	0.172	0.002			
1993	1.842	0.490	0.238	0.360	0.098	1.185	0.764	54
p_value	0.000	0.000	0.010	0.064	0.007			
1994	1.890	0.494	0.245	-0.075	0.075	0.738	0.717	64
p_value	0.000	0.000	0.017	0.705	0.002			
1995	1.825	0.585	0.080	0.151	0.052	0.867	0.596	64
p_value	0.000	0.000	0.388	0.491	0.078			
1996	1.561	0.627	0.071	0.379	0.029	1.105	0.689	63
p_value	0.000	0.000	0.558	0.045	0.248			
1997	1.530	0.760	-0.074	0.291	0.107	1.084	0.632	70
p_value	0.000	0.000	0.623	0.225	0.001			
1998	0.459	0.927	0.016	0.352	0.065	1.360	0.799	68
p_value	0.177	0.000	0.884	0.031	0.035			
1999	1.531	0.626	0.095	0.298	0.085	1.104	0.705	61
p_value	0.002	0.000	0.455	0.144	0.014			
2000	0.711	0.618	0.399	0.102	0.039	1.158	0.835	53
p_value	0.070	0.000	0.003	0.487	0.198			
2001	0.910	0.562	0.440	0.160	0.047	1.209	0.891	45
p_value	0.020	0.000	0.000	0.166	0.026			
2002	-0.558	1.022	0.036	0.227	0.070	1.354	0.875	41
p_value	0.312	0.000	0.800	0.190	0.066			
2003	0.718	0.825	0.242	0.073	-0.013	1.127	0.917	37
p_value	0.196	0.000	0.008	0.505	0.795			
2004	0.447	0.997	0.004	0.114	0.057	1.173	0.869	35
p_value	0.498	0.000	0.970	0.356	0.468			
2005	1.355	0.886	0.036	0.034	0.028	0.983	0.930	34
p_value	0.004	0.000	0.737	0.644	0.690			
2006	1.291	0.941	-0.241	0.102	0.155	0.956	0.778	36
p_value	0.080	0.000	0.161	0.391	0.094			
2007	0.924	0.991	-0.233	-0.064	0.134	0.828	0.743	35
p_value	0.230	0.000	0.156	0.641	0.022			
2008	-0.412	1.217	-0.346	0.033	0.095	1.000	0.704	35
p_value	0.693	0.000	0.034	0.822	0.161			
2009	0.626	1.024	-0.174	0.053	0.080	0.982	0.890	36
p_value	0.228	0.000	0.108	0.533	0.004			
2010	1.204	0.778	0.091	0.018	0.076	0.964	0.910	33
p_value	0.007	0.000	0.321	0.800	0.045			
2011	0.591	1.057	-0.269	0.168	0.072	1.027	0.872	34
p_value	0.294	0.000	0.025	0.066	0.103			
2012	0.491	0.934	0.133	0.092	-0.046	1.114	0.900	34
p_value	0.334	0.000	0.086	0.200	0.214			
2013	0.930	0.887	0.123	0.035	-0.010	1.036	0.924	34
p_value	0.031	0.000	0.113	0.609	0.849			
2014	0.802	0.905	0.039	0.060	0.013	1.017	0.934	37

p_value	0.024	0.000	0.636	0.352	0.711			
2015	1.848	0.609	0.203	0.142	0.017	0.971	0.869	37
p_value	0.000	0.000	0.082	0.087	0.669			
2016	1.999	0.582	0.279	0.022	0.028	0.912	0.850	38
p_value	0.000	0.000	0.011	0.780	0.459			
2017	0.929	0.860	0.123	0.032	0.025	1.041	0.861	36
p_value	0.195	0.000	0.145	0.701	0.529			

The Table reports the results from annual cross-sectional regressions of the log-linear value relevance model from 1971 to 2017. The empirical model is $log(M_{i,t}) = \alpha + \beta_1 log(|B|_{i,t-1}) + \beta_2 log(|E|_{i,t}) + \beta_3 log(|D|_{i,t}) + \beta_4 log(|O|_{i,t}) + \varepsilon_{i,t}$. Column 1 contains the estimated results for the intercept term α; column 2 contains the estimated elasticities for book value, β_1; column 3 contains the estimated elasticities for net income, β_2; column 4 contains the estimated elasticities for common dividends, β_3; column 5 contains the estimated elasticities for the remaining item, β_4, which column 6 is the sum of the four estimated elasticities; column 7 is R^2; and the last column is the number of observations. The regressions are estimated by OLS. p values are listed below the corresponding estimates.

Table 5.2-4 Estimated Elasticities for Manufacturing

Year	Intercept	B	E	D	O	$\sum \beta$	R^2	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1971	1.814	0.506	0.325	0.188	0.027	1.045	0.864	1050
p_value	0.000	0.000	0.000	0.000	0.000			
1972	1.641	0.494	0.347	0.189	0.029	1.059	0.859	1096
p_value	0.000	0.000	0.000	0.000	0.000			
1973	1.392	0.406	0.470	0.179	0.014	1.068	0.872	1407
p_value	0.000	0.000	0.000	0.000	0.000			
1974	0.921	0.487	0.404	0.169	0.010	1.072	0.860	1715
p_value	0.000	0.000	0.000	0.000	0.001			
1975	1.129	0.532	0.366	0.166	0.018	1.081	0.884	1826
p_value	0.000	0.000	0.000	0.000	0.000			
1976	1.207	0.506	0.370	0.161	0.021	1.058	0.893	1832
p_value	0.000	0.000	0.000	0.000	0.000			
1977	1.424	0.424	0.412	0.153	0.020	1.008	0.898	1784
p_value	0.000	0.000	0.000	0.000	0.000			
1978	1.875	0.314	0.455	0.164	0.034	0.968	0.894	1715
p_value	0.000	0.000	0.000	0.000	0.000			
1979	1.765	0.316	0.474	0.116	0.036	0.943	0.873	1670
p_value	0.000	0.000	0.000	0.000	0.000			
1980	2.060	0.353	0.399	0.133	0.052	0.937	0.843	1699
p_value	0.000	0.000	0.000	0.000	0.000			
1981	1.917	0.357	0.384	0.116	0.051	0.909	0.850	1678
p_value	0.000	0.000	0.000	0.000	0.000			
1982	1.890	0.480	0.256	0.155	0.037	0.927	0.820	1751
p_value	0.000	0.000	0.000	0.000	0.000			
1983	2.300	0.436	0.260	0.130	0.064	0.889	0.841	1768
p_value	0.000	0.000	0.000	0.000	0.000			
1984	1.904	0.501	0.234	0.158	0.049	0.942	0.865	1826
p_value	0.000	0.000	0.000	0.000	0.000			
1985	1.830	0.573	0.193	0.159	0.054	0.979	0.847	1877
p_value	0.000	0.000	0.000	0.000	0.000			
1986	2.060	0.519	0.225	0.200	0.061	1.005	0.841	1855
p_value	0.000	0.000	0.000	0.000	0.000			
1987	1.863	0.516	0.268	0.173	0.054	1.011	0.850	1893
p_value	0.000	0.000	0.000	0.000	0.000			
1988	1.727	0.546	0.247	0.173	0.058	1.023	0.856	1911
p_value	0.000	0.000	0.000	0.000	0.000			
1989	1.728	0.558	0.202	0.195	0.070	1.024	0.838	1895
p_value	0.000	0.000	0.000	0.000	0.000			
1990	1.752	0.476	0.251	0.277	0.064	1.068	0.812	1858
p_value	0.000	0.000	0.000	0.000	0.000			
1991	2.303	0.415	0.257	0.266	0.093	1.031	0.802	1839

p_value	0.000	0.000	0.000	0.000	0.000			
1992	2.214	0.449	0.248	0.246	0.084	1.028	0.835	1840
p_value	0.000	0.000	0.000	0.000	0.000			
1993	2.228	0.473	0.256	0.221	0.072	1.022	0.832	1940
p_value	0.000	0.000	0.000	0.000	0.000			
1994	1.976	0.530	0.267	0.166	0.082	1.045	0.851	2081
p_value	0.000	0.000	0.000	0.000	0.000			
1995	2.244	0.504	0.283	0.131	0.089	1.007	0.822	2181
p_value	0.000	0.000	0.000	0.000	0.000			
1996	2.109	0.522	0.287	0.133	0.090	1.033	0.838	2276
p_value	0.000	0.000	0.000	0.000	0.000			
1997	1.856	0.634	0.232	0.108	0.093	1.068	0.835	2386
p_value	0.000	0.000	0.000	0.000	0.000			
1998	1.550	0.612	0.267	0.141	0.091	1.111	0.818	2295
p_value	0.000	0.000	0.000	0.000	0.000			
1999	2.424	0.382	0.406	0.047	0.150	0.986	0.747	2113
p_value	0.000	0.000	0.000	0.024	0.000			
2000	1.911	0.464	0.315	0.108	0.177	1.063	0.761	1933
p_value	0.000	0.000	0.000	0.000	0.000			
2001	1.669	0.634	0.116	0.196	0.170	1.116	0.775	1887
p_value	0.000	0.000	0.000	0.000	0.000			
2002	1.425	0.641	0.103	0.237	0.128	1.108	0.765	1776
p_value	0.000	0.000	0.000	0.000	0.000			
2003	2.327	0.518	0.233	0.122	0.144	1.017	0.821	1653
p_value	0.000	0.000	0.000	0.000	0.000			
2004	2.104	0.557	0.265	0.092	0.110	1.025	0.855	1589
p_value	0.000	0.000	0.000	0.000	0.000			
2005	2.232	0.547	0.251	0.052	0.143	0.994	0.854	1569
p_value	0.000	0.000	0.000	0.000	0.000			
2006	2.156	0.558	0.237	0.060	0.152	1.007	0.859	1528
p_value	0.000	0.000	0.000	0.000	0.000			
2007	1.673	0.613	0.186	0.076	0.185	1.059	0.837	1489
p_value	0.000	0.000	0.000	0.000	0.000			
2008	1.077	0.643	0.090	0.079	0.214	1.026	0.761	1454
p_value	0.000	0.000	0.000	0.000	0.000			
2009	1.833	0.551	0.192	0.100	0.221	1.064	0.842	1367
p_value	0.000	0.000	0.000	0.000	0.000			
2010	2.120	0.503	0.300	0.084	0.161	1.049	0.854	1305
p_value	0.000	0.000	0.000	0.000	0.000			
2011	1.883	0.528	0.274	0.071	0.166	1.040	0.842	1270
p_value	0.000	0.000	0.000	0.000	0.000			
2012	1.883	0.524	0.302	0.087	0.149	1.062	0.837	1239
p_value	0.000	0.000	0.000	0.000	0.000			
2013	2.340	0.470	0.334	0.072	0.149	1.024	0.836	1214
p_value	0.000	0.000	0.000	0.000	0.000			

2014 p_value	2.125 0.000	0.518 0.000	0.324 0.000	0.018 0.269	0.155 0.000	1.016	0.839	1223
2015 p_value	1.677 0.000	0.590 0.000	0.227 0.000	0.084 0.000	0.173 0.000	1.074	0.830	1269
2016 p_value	1.687 0.000	0.608 0.000	0.239 0.000	0.104 0.000	0.162 0.000	1.114	0.827	1279
2017 p_value	1.941 0.000	0.559 0.000	0.212 0.000	0.119 0.000	0.228 0.000	1.117	0.828	1273

The Table reports the results from annual cross-sectional regressions of the log-linear value relevance model from 1971 to 2017. The empirical model is $log(M_{i,t}) = \alpha + \beta_1 log(|B|_{i,t-1}) + \beta_2 log(|E|_{i,t}) + \beta_3 log(|D|_{i,t}) + \beta_4 log(|O|_{i,t}) + \varepsilon_{i,t}$. Column 1 contains the estimated results for the intercept term α; column 2 contains the estimated elasticities for book value, β_1; column 3 contains the estimated elasticities for net income, β_2; column 4 contains the estimated elasticities for common dividends, β_3; column 5 contains the estimated elasticities for the remaining item, β_4, which column 6 is the sum of the four estimated elasticities; column 7 is R^2; and the last column is the number of observations. The regressions are estimated by OLS. p values are listed below the corresponding estimates.

Table 5.2-5 Estimated Elasticities for Transportation

Year	Intercept	B	E	D	O	$\sum \beta$	R^2	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1971	1.958	0.420	0.557	-0.100	0.025	0.902	0.880	207
p_value	0.000	0.000	0.000	0.037	0.009			
1972	1.600	0.427	0.592	-0.083	0.027	0.963	0.905	217
p_value	0.000	0.000	0.000	0.031	0.012			
1973	1.411	0.396	0.461	0.129	0.004	0.990	0.912	283
p_value	0.000	0.000	0.000	0.000	0.553			
1974	1.035	0.426	0.471	0.127	0.005	1.029	0.933	313
p_value	0.000	0.000	0.000	0.000	0.406			
1975	0.770	0.629	0.317	0.074	0.007	1.027	0.931	343
p_value	0.000	0.000	0.000	0.030	0.226			
1976	1.043	0.522	0.381	0.123	0.008	1.033	0.941	341
p_value	0.000	0.000	0.000	0.000	0.213			
1977	1.278	0.525	0.308	0.102	0.028	0.963	0.936	342
p_value	0.000	0.000	0.000	0.001	0.000			
1978	1.860	0.247	0.489	0.205	0.005	0.946	0.918	343
p_value	0.000	0.000	0.000	0.000	0.491			
1979	1.383	0.319	0.623	-0.005	0.022	0.959	0.910	338
p_value	0.000	0.000	0.000	0.893	0.006			
1980	1.891	0.284	0.544	0.044	0.031	0.905	0.842	327
p_value	0.000	0.000	0.000	0.349	0.001			
1981	1.317	0.522	0.354	-0.023	0.072	0.926	0.896	331
p_value	0.000	0.000	0.000	0.532	0.000			
1982	1.473	0.573	0.264	0.029	0.038	0.903	0.892	341
p_value	0.000	0.000	0.000	0.413	0.000			
1983	2.267	0.358	0.319	0.104	0.031	0.812	0.859	348
p_value	0.000	0.000	0.000	0.006	0.003			
1984	1.691	0.506	0.281	0.107	0.002	0.896	0.889	367
p_value	0.000	0.000	0.000	0.002	0.864			
1985	1.912	0.522	0.283	0.069	0.035	0.909	0.882	381
p_value	0.000	0.000	0.000	0.050	0.000			
1986	2.023	0.542	0.220	0.098	0.045	0.905	0.892	371
p_value	0.000	0.000	0.000	0.002	0.000			
1987	1.954	0.530	0.235	0.071	0.061	0.898	0.886	394
p_value	0.000	0.000	0.000	0.023	0.000			
1988	1.672	0.607	0.226	0.044	0.039	0.917	0.895	402
p_value	0.000	0.000	0.000	0.123	0.000			
1989	1.677	0.590	0.304	-0.009	0.068	0.953	0.869	402
p_value	0.000	0.000	0.000	0.802	0.000			
1990	1.485	0.644	0.196	0.077	0.057	0.975	0.894	405
p_value	0.000	0.000	0.000	0.010	0.000			
1991	1.993	0.550	0.208	0.099	0.075	0.932	0.887	410

p_value	0.000	0.000	0.000	0.001	0.000			
1992	2.088	0.477	0.324	0.116	0.051	0.968	0.879	413
p_value	0.000	0.000	0.000	0.000	0.000			
1993	2.372	0.459	0.321	0.035	0.087	0.902	0.859	433
p_value	0.000	0.000	0.000	0.234	0.000			
1994	2.057	0.478	0.411	-0.013	0.047	0.923	0.877	452
p_value	0.000	0.000	0.000	0.633	0.000			
1995	1.951	0.603	0.230	0.021	0.088	0.942	0.849	462
p_value	0.000	0.000	0.000	0.456	0.000			
1996	1.892	0.529	0.291	0.069	0.101	0.990	0.873	468
p_value	0.000	0.000	0.000	0.008	0.000			
1997	1.853	0.650	0.214	0.023	0.103	0.991	0.838	480
p_value	0.000	0.000	0.000	0.411	0.000			
1998	1.832	0.554	0.289	0.076	0.100	1.017	0.845	432
p_value	0.000	0.000	0.000	0.010	0.000			
1999	2.169	0.423	0.428	-0.039	0.169	0.981	0.866	390
p_value	0.000	0.000	0.000	0.140	0.000			
2000	1.544	0.626	0.152	0.138	0.126	1.042	0.772	364
p_value	0.000	0.000	0.000	0.000	0.000			
2001	1.002	0.834	-0.030	0.149	0.100	1.053	0.829	334
p_value	0.000	0.000	0.458	0.000	0.000			
2002	1.185	0.748	-0.067	0.156	0.165	1.002	0.811	298
p_value	0.000	0.000	0.152	0.000	0.000			
2003	2.212	0.428	0.381	0.091	0.077	0.977	0.852	289
p_value	0.000	0.000	0.000	0.001	0.000			
2004	2.395	0.445	0.290	0.121	0.097	0.953	0.831	299
p_value	0.000	0.000	0.000	0.000	0.000			
2005	2.360	0.439	0.322	0.089	0.117	0.967	0.870	293
p_value	0.000	0.000	0.000	0.001	0.000			
2006	2.409	0.471	0.300	0.078	0.103	0.952	0.863	282
p_value	0.000	0.000	0.000	0.004	0.000			
2007	1.933	0.515	0.329	0.058	0.075	0.977	0.853	269
p_value	0.000	0.000	0.000	0.036	0.002			
2008	1.169	0.749	-0.069	0.204	0.083	0.967	0.750	264
p_value	0.000	0.000	0.279	0.000	0.012			
2009	1.881	0.587	0.169	0.102	0.116	0.975	0.866	253
p_value	0.000	0.000	0.000	0.000	0.000			
2010	2.050	0.540	0.287	0.033	0.108	0.968	0.884	246
p_value	0.000	0.000	0.000	0.230	0.000			
2011	2.266	0.503	0.207	0.109	0.154	0.973	0.877	232
p_value	0.000	0.000	0.000	0.000	0.000			
2012	2.155	0.452	0.356	0.108	0.109	1.025	0.889	230
p_value	0.000	0.000	0.000	0.000	0.000			
2013	2.419	0.413	0.458	0.048	0.059	0.978	0.882	221
p_value	0.000	0.000	0.000	0.084	0.013			

2014 p_value	2.088 0.000	0.550 0.000	0.281 0.000	0.062 0.032	0.113 0.000	1.006	0.882	222
2015 p_value	2.267 0.000	0.452 0.000	0.379 0.000	0.162 0.000	0.001 0.968	0.995	0.852	217
2016 p_value	2.728 0.000	0.396 0.000	0.359 0.000	0.180 0.000	0.015 0.628	0.950	0.831	206
2017 p_value	2.900 0.000	0.286 0.000	0.430 0.000	0.218 0.000	0.006 0.835	0.941	0.817	197

The Table reports the results from annual cross-sectional regressions of the log-linear value relevance model from 1971 to 2017. The empirical model is $log\left(M_{i,t}\right) = \alpha + \beta_1 log\left(|B|_{i,t-1}\right) + \beta_2 log\left(|E|_{i,t}\right) + \beta_3 log\left(|D|_{i,t}\right) + \beta_4 log\left(|O|_{i,t}\right) + \varepsilon_{i,t}$. Column 1 contains the estimated results for the intercept term α; column 2 contains the estimated elasticities for book value, β_1; column 3 contains the estimated elasticities for net income, β_2; column 4 contains the estimated elasticities for common dividends, β_3; column 5 contains the estimated elasticities for the remaining item, β_4, which column 6 is the sum of the four estimated elasticities; column 7 is R^2; and the last column is the number of observations. The regressions are estimated by OLS. p values are listed below the corresponding estimates.

.

Table 5.2-6 Estimated Elasticities for Wholesale

Year	Intercept	B	E	D	O	$\sum \beta$	R^2	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1971	1.176	0.609	0.384	-0.013	0.013	0.992	0.787	72
p_value	0.000	0.000	0.000	0.886	0.378			
1972	1.411	0.518	0.449	-0.037	0.035	0.964	0.816	81
p_value	0.000	0.000	0.000	0.652	0.013			
1973	0.897	0.512	0.469	0.065	0.005	1.051	0.785	116
p_value	0.000	0.000	0.000	0.385	0.657			
1974	0.348	0.601	0.390	0.008	-0.005	0.995	0.736	153
p_value	0.108	0.000	0.000	0.888	0.665			
1975	0.646	0.671	0.263	0.115	0.031	1.079	0.735	171
p_value	0.002	0.000	0.000	0.033	0.012			
1976	0.438	0.762	0.197	0.114	0.026	1.099	0.811	171
p_value	0.031	0.000	0.000	0.025	0.007			
1977	0.913	0.538	0.429	0.098	0.015	1.081	0.864	164
p_value	0.000	0.000	0.000	0.027	0.079			
1978	1.186	0.486	0.403	0.112	0.022	1.023	0.834	160
p_value	0.000	0.000	0.000	0.033	0.035			
1979	1.183	0.536	0.258	0.141	0.043	0.978	0.822	163
p_value	0.000	0.000	0.000	0.006	0.000			
1980	1.842	0.338	0.435	0.183	0.035	0.992	0.813	160
p_value	0.000	0.000	0.000	0.003	0.004			
1981	1.611	0.346	0.432	0.215	0.032	1.025	0.798	162
p_value	0.000	0.000	0.000	0.001	0.010			
1982	0.978	0.670	0.151	0.178	0.025	1.024	0.761	165
p_value	0.000	0.000	0.008	0.006	0.060			
1983	1.701	0.519	0.240	0.233	0.023	1.015	0.776	177
p_value	0.000	0.000	0.000	0.000	0.046			
1984	1.374	0.614	0.247	0.106	0.034	1.002	0.854	175
p_value	0.000	0.000	0.000	0.032	0.005			
1985	1.148	0.722	0.107	0.164	0.032	1.024	0.798	182
p_value	0.000	0.000	0.039	0.005	0.010			
1986	1.045	0.787	0.138	0.073	0.032	1.029	0.804	176
p_value	0.000	0.000	0.021	0.245	0.020			
1987	1.400	0.621	0.270	0.108	0.043	1.041	0.826	178
p_value	0.000	0.000	0.000	0.032	0.000			
1988	1.795	0.438	0.309	0.275	0.043	1.066	0.780	201
p_value	0.000	0.000	0.000	0.000	0.000			
1989	1.389	0.614	0.176	0.236	0.036	1.063	0.810	194
p_value	0.000	0.000	0.000	0.001	0.003			
1990	1.524	0.508	0.218	0.340	0.037	1.104	0.771	189
p_value	0.000	0.000	0.000	0.000	0.003			
1991	1.822	0.483	0.288	0.247	0.068	1.086	0.774	174

p_value	0.000	0.000	0.000	0.007	0.000			
1992	1.933	0.512	0.182	0.292	0.065	1.051	0.774	176
p_value	0.000	0.000	0.002	0.000	0.000			
1993	1.987	0.570	0.203	0.169	0.073	1.014	0.821	179
p_value	0.000	0.000	0.000	0.016	0.000			
1994	1.670	0.580	0.248	0.170	0.047	1.044	0.797	198
p_value	0.000	0.000	0.000	0.013	0.001			
1995	1.552	0.676	0.196	0.032	0.063	0.968	0.775	204
p_value	0.000	0.000	0.001	0.599	0.000			
1996	1.843	0.650	0.113	0.142	0.083	0.987	0.730	220
p_value	0.000	0.000	0.075	0.070	0.000			
1997	1.730	0.681	0.135	0.110	0.103	1.030	0.808	219
p_value	0.000	0.000	0.011	0.100	0.000			
1998	1.716	0.580	0.224	0.108	0.088	1.000	0.786	205
p_value	0.000	0.000	0.000	0.093	0.000			
1999	1.921	0.435	0.353	0.205	0.061	1.053	0.776	193
p_value	0.000	0.000	0.000	0.003	0.005			
2000	1.080	0.618	0.212	0.183	0.130	1.144	0.680	174
p_value	0.000	0.000	0.009	0.065	0.000			
2001	0.526	0.807	0.247	0.045	0.104	1.203	0.784	149
p_value	0.074	0.000	0.001	0.555	0.000			
2002	0.231	0.880	0.095	0.098	0.113	1.185	0.794	136
p_value	0.465	0.000	0.210	0.259	0.002			
2003	1.219	0.674	0.288	0.087	0.069	1.118	0.815	125
p_value	0.000	0.000	0.000	0.273	0.012			
2004	2.063	0.497	0.339	0.120	0.103	1.058	0.882	117
p_value	0.000	0.000	0.000	0.039	0.000			
2005	1.922	0.492	0.424	0.070	0.086	1.072	0.866	110
p_value	0.000	0.000	0.000	0.217	0.002			
2006	1.843	0.552	0.389	0.077	0.031	1.049	0.918	108
p_value	0.000	0.000	0.000	0.080	0.181			
2007	1.421	0.645	0.244	0.084	0.115	1.088	0.908	110
p_value	0.000	0.000	0.001	0.068	0.000			
2008	-0.300	1.044	-0.062	0.161	0.068	1.211	0.872	101
p_value	0.373	0.000	0.543	0.007	0.102			
2009	0.990	0.806	0.084	0.109	0.085	1.084	0.880	92
p_value	0.002	0.000	0.238	0.032	0.012			
2010	1.132	0.704	0.284	0.103	0.013	1.103	0.924	92
p_value	0.000	0.000	0.000	0.008	0.668			
2011	1.301	0.684	0.184	0.179	0.056	1.103	0.832	93
p_value	0.000	0.000	0.014	0.003	0.165			
2012	0.963	0.681	0.309	0.122	0.015	1.127	0.841	92
p_value	0.015	0.000	0.001	0.025	0.655			
2013	1.512	0.487	0.534	0.086	0.037	1.144	0.886	84
p_value	0.000	0.000	0.000	0.069	0.279			

2014 p_value	1.362 0.001	0.711 0.000	0.126 0.102	0.172 0.003	0.109 0.016	1.118	0.837	83
2015 p_value	0.294 0.516	0.999 0.000	-0.023 0.832	0.158 0.010	0.018 0.756	1.152	0.805	88
2016 p_value	1.463 0.000	0.632 0.000	0.250 0.003	0.128 0.013	0.121 0.002	1.131	0.842	85
2017 p_value	1.410 0.000	0.658 0.000	0.326 0.000	0.043 0.322	0.039 0.344	1.066	0.860	83

The Table reports the results from annual cross-sectional regressions of the log-linear value relevance model from 1971 to 2017. The empirical model is $log(M_{i,t}) = \alpha + \beta_1 log(|B|_{i,t-1}) + \beta_2 log(|E|_{i,t}) + \beta_3 log(|D|_{i,t}) + \beta_4 log(|O|_{i,t}) + \varepsilon_{i,t}$. Column 1 contains the estimated results for the intercept term α; column 2 contains the estimated elasticities for book value, β_1; column 3 contains the estimated elasticities for net income, β_2; column 4 contains the estimated elasticities for common dividends, β_3; column 5 contains the estimated elasticities for the remaining item, β_4, which column 6 is the sum of the four estimated elasticities; column 7 is R^2; and the last column is the number of observations. The regressions are estimated by OLS. p values are listed below the corresponding estimates.

Table 5.2-7 Estimated Elasticities for Retail

Year	Intercept	B	E	D	O	$\sum \beta$	R^2	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1971	2.527	0.276	0.569	0.138	0.042	1.025	0.833	131
p_value	0.000	0.004	0.000	0.099	0.002			
1972	2.089	0.372	0.503	0.102	0.054	1.030	0.777	143
p_value	0.000	0.000	0.000	0.222	0.000			
1973	1.343	0.404	0.561	0.068	0.023	1.056	0.814	179
p_value	0.000	0.000	0.000	0.275	0.027			
1974	1.001	0.372	0.644	0.098	0.014	1.128	0.815	271
p_value	0.000	0.000	0.000	0.015	0.069			
1975	1.007	0.473	0.543	0.065	0.006	1.086	0.817	286
p_value	0.000	0.000	0.000	0.081	0.448			
1976	1.055	0.499	0.505	0.082	0.026	1.113	0.864	287
p_value	0.000	0.000	0.000	0.015	0.000			
1977	0.758	0.547	0.533	0.021	0.017	1.119	0.870	293
p_value	0.000	0.000	0.000	0.504	0.016			
1978	1.234	0.438	0.539	0.079	0.014	1.070	0.881	278
p_value	0.000	0.000	0.000	0.019	0.058			
1979	0.894	0.552	0.404	0.096	0.019	1.070	0.888	260
p_value	0.000	0.000	0.000	0.003	0.010			
1980	1.472	0.346	0.553	0.112	0.018	1.029	0.866	260
p_value	0.000	0.000	0.000	0.002	0.023			
1981	1.328	0.476	0.434	0.100	0.039	1.050	0.859	243
p_value	0.000	0.000	0.000	0.009	0.000			
1982	1.303	0.582	0.306	0.123	0.037	1.048	0.830	247
p_value	0.000	0.000	0.000	0.005	0.000			
1983	2.105	0.500	0.305	0.121	0.048	0.974	0.802	242
p_value	0.000	0.000	0.000	0.009	0.000			
1984	1.789	0.470	0.406	0.105	0.035	1.016	0.871	256
p_value	0.000	0.000	0.000	0.014	0.000			
1985	0.980	0.834	0.129	0.098	0.029	1.089	0.818	273
p_value	0.000	0.000	0.009	0.049	0.004			
1986	1.561	0.701	0.209	0.114	0.054	1.078	0.819	252
p_value	0.000	0.000	0.000	0.046	0.000			
1987	1.422	0.666	0.278	0.094	0.041	1.080	0.811	268
p_value	0.000	0.000	0.000	0.056	0.000			
1988	1.464	0.638	0.250	0.082	0.053	1.023	0.835	277
p_value	0.000	0.000	0.000	0.054	0.000			
1989	1.476	0.649	0.258	0.099	0.052	1.057	0.852	268
p_value	0.000	0.000	0.000	0.040	0.000			
1990	0.626	0.856	0.144	0.111	0.054	1.164	0.823	250
p_value	0.002	0.000	0.007	0.067	0.000			
1991	1.618	0.649	0.151	0.206	0.080	1.085	0.773	255

p_value	0.000	0.000	0.017	0.003	0.000			
1992	1.849	0.623	0.170	0.187	0.084	1.063	0.795	263
p_value	0.000	0.000	0.001	0.003	0.000			
1993	2.079	0.560	0.233	0.126	0.098	1.017	0.814	300
p_value	0.000	0.000	0.000	0.013	0.000			
1994	1.702	0.609	0.278	0.064	0.083	1.035	0.820	338
p_value	0.000	0.000	0.000	0.168	0.000			
1995	1.459	0.678	0.201	0.069	0.086	1.035	0.802	349
p_value	0.000	0.000	0.000	0.126	0.000			
1996	1.047	0.830	0.095	0.080	0.110	1.115	0.821	347
p_value	0.000	0.000	0.029	0.089	0.000			
1997	1.629	0.662	0.169	0.166	0.115	1.113	0.802	355
p_value	0.000	0.000	0.000	0.001	0.000			
1998	1.455	0.651	0.292	0.152	0.063	1.160	0.801	342
p_value	0.000	0.000	0.000	0.002	0.000			
1999	1.724	0.507	0.405	0.160	0.068	1.140	0.824	329
p_value	0.000	0.000	0.000	0.001	0.000			
2000	0.923	0.722	0.187	0.154	0.077	1.141	0.758	317
p_value	0.000	0.000	0.001	0.006	0.000			
2001	1.056	0.698	0.285	0.032	0.100	1.116	0.798	269
p_value	0.000	0.000	0.000	0.567	0.000			
2002	1.082	0.707	0.267	0.054	0.131	1.159	0.835	257
p_value	0.000	0.000	0.000	0.319	0.000			
2003	1.504	0.622	0.312	0.035	0.087	1.056	0.803	249
p_value	0.000	0.000	0.000	0.514	0.001			
2004	1.932	0.553	0.374	0.020	0.071	1.019	0.890	226
p_value	0.000	0.000	0.000	0.568	0.000			
2005	2.390	0.441	0.372	-0.011	0.171	0.973	0.890	226
p_value	0.000	0.000	0.000	0.723	0.000			
2006	1.988	0.588	0.292	-0.012	0.135	1.003	0.903	213
p_value	0.000	0.000	0.000	0.687	0.000			
2007	1.547	0.620	0.218	0.041	0.205	1.085	0.875	207
p_value	0.000	0.000	0.000	0.237	0.000			
2008	0.695	0.707	0.142	0.090	0.187	1.126	0.773	197
p_value	0.043	0.000	0.037	0.093	0.000			
2009	2.060	0.504	0.174	0.090	0.258	1.026	0.786	189
p_value	0.000	0.000	0.009	0.048	0.000			
2010	2.117	0.544	0.205	0.090	0.215	1.052	0.877	184
p_value	0.000	0.000	0.000	0.005	0.000			
2011	2.129	0.427	0.400	0.025	0.177	1.029	0.886	177
p_value	0.000	0.000	0.000	0.433	0.000			
2012	1.961	0.551	0.204	0.051	0.230	1.036	0.849	175
p_value	0.000	0.000	0.001	0.171	0.000			
2013	2.301	0.499	0.215	0.078	0.256	1.049	0.818	179
p_value	0.000	0.000	0.002	0.040	0.000			

2014 p_value	2.285 0.000	0.497 0.000	0.252 0.000	0.067 0.042	0.231 0.000	1.046	0.862	177
2015 p_value	1.984 0.000	0.636 0.000	0.172 0.001	0.121 0.001	0.133 0.000	1.062	0.826	179
2016 p_value	2.470 0.000	0.360 0.000	0.432 0.000	0.091 0.012	0.139 0.000	1.021	0.831	174
2017 p_value	2.309 0.000	0.469 0.000	0.259 0.000	0.143 0.000	0.168 0.000	1.039	0.821	168

The Table reports the results from annual cross-sectional regressions of the log-linear value relevance model from 1971 to 2017. The empirical model is $log(M_{i,t}) = \alpha + \beta_1 log(|B|_{i,t-1}) + \beta_2 log(|E|_{i,t}) + \beta_3 log(|D|_{i,t}) + \beta_4 log(|O|_{i,t}) + \varepsilon_{i,t}$. Column 1 contains the estimated results for the intercept term α; column 2 contains the estimated elasticities for book value, β_1; column 3 contains the estimated elasticities for net income, β_2; column 4 contains the estimated elasticities for common dividends, β_3; column 5 contains the estimated elasticities for the remaining item, β_4, which column 6 is the sum of the four estimated elasticities; column 7 is R^2; and the last column is the number of observations. The regressions are estimated by OLS. p values are listed below the corresponding estimates.

Table 5.2-8 Estimated Elasticities for Finance

Year	Intercept	B	E	D	O	$\sum\beta$	R^2	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1971	1.776	0.474	0.422	0.077	0.033	1.006	0.898	92
p_value	0.000	0.000	0.000	0.208	0.028			
1972	1.198	0.628	0.223	0.168	0.019	1.037	0.878	109
p_value	0.000	0.000	0.006	0.023	0.254			
1973	1.510	0.337	0.592	0.096	0.017	1.041	0.887	254
p_value	0.000	0.000	0.000	0.050	0.093			
1974	0.577	0.635	0.264	0.153	0.026	1.078	0.878	283
p_value	0.001	0.000	0.000	0.001	0.001			
1975	0.567	0.670	0.242	0.155	0.015	1.083	0.891	318
p_value	0.000	0.000	0.000	0.000	0.047			
1976	1.024	0.531	0.342	0.148	0.018	1.039	0.915	322
p_value	0.000	0.000	0.000	0.000	0.001			
1977	1.310	0.431	0.396	0.142	0.015	0.983	0.906	325
p_value	0.000	0.000	0.000	0.000	0.017			
1978	1.537	0.438	0.301	0.179	0.028	0.947	0.899	327
p_value	0.000	0.000	0.000	0.000	0.000			
1979	1.799	0.270	0.390	0.205	0.023	0.888	0.902	353
p_value	0.000	0.000	0.000	0.000	0.000			
1980	1.857	0.357	0.360	0.154	0.022	0.892	0.869	378
p_value	0.000	0.000	0.000	0.000	0.001			
1981	1.790	0.352	0.283	0.245	0.038	0.918	0.873	389
p_value	0.000	0.000	0.000	0.000	0.000			
1982	1.489	0.522	0.218	0.192	0.018	0.950	0.886	400
p_value	0.000	0.000	0.000	0.000	0.011			
1983	1.754	0.517	0.195	0.138	0.039	0.889	0.880	415
p_value	0.000	0.000	0.000	0.000	0.000			
1984	1.626	0.567	0.202	0.120	0.030	0.920	0.879	439
p_value	0.000	0.000	0.000	0.000	0.000			
1985	1.975	0.445	0.358	0.149	0.027	0.980	0.861	435
p_value	0.000	0.000	0.000	0.000	0.003			
1986	2.138	0.448	0.244	0.214	0.039	0.945	0.867	435
p_value	0.000	0.000	0.000	0.000	0.000			
1987	1.766	0.507	0.153	0.271	0.027	0.957	0.863	475
p_value	0.000	0.000	0.000	0.000	0.001			
1988	1.473	0.568	0.117	0.287	0.037	1.009	0.849	518
p_value	0.000	0.000	0.001	0.000	0.000			
1989	1.529	0.556	0.118	0.258	0.043	0.974	0.825	556
p_value	0.000	0.000	0.000	0.000	0.000			
1990	1.395	0.533	0.097	0.354	0.045	1.029	0.807	553
p_value	0.000	0.000	0.011	0.000	0.000			
1991	1.854	0.472	0.178	0.327	0.053	1.030	0.837	558

p_value	0.000	0.000	0.000	0.000	0.000			
1992	1.937	0.511	0.220	0.228	0.067	1.025	0.865	562
p_value	0.000	0.000	0.000	0.000	0.000			
1993	2.206	0.403	0.308	0.200	0.049	0.960	0.874	584
p_value	0.000	0.000	0.000	0.000	0.000			
1994	1.674	0.480	0.353	0.149	0.021	1.004	0.896	1057
p_value	0.000	0.000	0.000	0.000	0.001			
1995	1.699	0.534	0.320	0.130	0.040	1.024	0.910	1077
p_value	0.000	0.000	0.000	0.000	0.000			
1996	1.600	0.580	0.314	0.096	0.041	1.030	0.917	1069
p_value	0.000	0.000	0.000	0.000	0.000			
1997	1.850	0.586	0.302	0.108	0.055	1.051	0.911	1021
p_value	0.000	0.000	0.000	0.000	0.000			
1998	1.900	0.467	0.374	0.170	0.039	1.050	0.877	960
p_value	0.000	0.000	0.000	0.000	0.000			
1999	1.849	0.399	0.435	0.135	0.047	1.016	0.863	960
p_value	0.000	0.000	0.000	0.000	0.000			
2000	1.149	0.621	0.295	0.116	0.085	1.118	0.884	1028
p_value	0.000	0.000	0.000	0.000	0.000			
2001	1.074	0.741	0.153	0.143	0.076	1.114	0.891	952
p_value	0.000	0.000	0.000	0.000	0.000			
2002	1.336	0.652	0.214	0.120	0.054	1.040	0.896	921
p_value	0.000	0.000	0.000	0.000	0.000			
2003	1.971	0.522	0.334	0.088	0.062	1.006	0.935	901
p_value	0.000	0.000	0.000	0.000	0.000			
2004	1.882	0.557	0.311	0.055	0.066	0.990	0.939	842
p_value	0.000	0.000	0.000	0.000	0.000			
2005	2.017	0.493	0.425	0.000	0.052	0.969	0.942	837
p_value	0.000	0.000	0.000	0.982	0.000			
2006	2.050	0.507	0.335	0.031	0.100	0.972	0.927	833
p_value	0.000	0.000	0.000	0.042	0.000			
2007	2.016	0.449	0.304	0.085	0.110	0.948	0.895	816
p_value	0.000	0.000	0.000	0.000	0.000			
2008	0.563	0.757	-0.056	0.136	0.119	0.956	0.729	790
p_value	0.002	0.000	0.054	0.000	0.000			
2009	1.105	0.673	-0.059	0.268	0.219	1.100	0.820	763
p_value	0.000	0.000	0.019	0.000	0.000			
2010	1.096	0.669	0.107	0.177	0.152	1.105	0.850	721
p_value	0.000	0.000	0.000	0.000	0.000			
2011	1.286	0.603	0.202	0.124	0.130	1.059	0.879	699
p_value	0.000	0.000	0.000	0.000	0.000			
2012	1.571	0.575	0.236	0.107	0.095	1.014	0.888	675
p_value	0.000	0.000	0.000	0.000	0.000			
2013	1.814	0.502	0.351	0.054	0.094	1.001	0.904	660
p_value	0.000	0.000	0.000	0.003	0.000			

2014 p_value	1.903 0.000	0.491 0.000	0.317 0.000	0.089 0.000	0.108 0.000	1.005	0.911	655
2015 p_value	1.771 0.000	0.525 0.000	0.291 0.000	0.098 0.000	0.072 0.000	0.986	0.899	653
2016 p_value	2.073 0.000	0.512 0.000	0.269 0.000	0.119 0.000	0.088 0.000	0.989	0.916	637
2017 p_value	2.226 0.000	0.485 0.000	0.293 0.000	0.101 0.000	0.094 0.000	0.973	0.910	606

The Table reports the results from annual cross-sectional regressions of the log-linear value relevance model from 1971 to 2017. The empirical model is $log(M_{i,t}) = \alpha + \beta_1 log(|B|_{i,t-1}) + \beta_2 log(|E|_{i,t}) + \beta_3 log(|D|_{i,t}) + \beta_4 log(|O|_{i,t}) + \varepsilon_{i,t}$. Column 1 contains the estimated results for the intercept term α; column 2 contains the estimated elasticities for book value, β_1; column 3 contains the estimated elasticities for net income, β_2; column 4 contains the estimated elasticities for common dividends, β_3; column 5 contains the estimated elasticities for the remaining item, β_4, which column 6 is the sum of the four estimated elasticities; column 7 is R^2; and the last column is the number of observations. The regressions are estimated by OLS. p values are listed below the corresponding estimates.

Table 5.2-9 Estimated Elasticities for Services

Year	Intercept	B	E	D	O	$\sum\beta$	R^2	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1971	2.030	0.536	0.321	0.170	0.053	1.080	0.822	109
p_value	0.000	0.000	0.000	0.015	0.002			
1972	1.922	0.499	0.261	0.230	0.085	1.075	0.771	123
p_value	0.000	0.000	0.002	0.002	0.000			
1973	1.416	0.457	0.397	0.166	0.030	1.051	0.750	164
p_value	0.000	0.000	0.000	0.014	0.018			
1974	1.109	0.426	0.435	0.221	0.007	1.087	0.797	209
p_value	0.000	0.000	0.000	0.000	0.457			
1975	1.163	0.520	0.424	0.148	0.019	1.110	0.844	248
p_value	0.000	0.000	0.000	0.001	0.010			
1976	1.333	0.416	0.528	0.111	0.020	1.074	0.867	251
p_value	0.000	0.000	0.000	0.003	0.007			
1977	1.541	0.448	0.416	0.099	0.038	1.001	0.838	250
p_value	0.000	0.000	0.000	0.014	0.000			
1978	1.930	0.346	0.469	0.087	0.041	0.943	0.841	249
p_value	0.000	0.000	0.000	0.024	0.000			
1979	1.935	0.309	0.471	0.116	0.038	0.935	0.790	271
p_value	0.000	0.000	0.000	0.004	0.000			
1980	2.320	0.269	0.507	0.114	0.048	0.939	0.805	295
p_value	0.000	0.000	0.000	0.006	0.000			
1981	1.982	0.434	0.329	0.092	0.058	0.913	0.789	299
p_value	0.000	0.000	0.000	0.014	0.000			
1982	1.967	0.482	0.354	0.037	0.040	0.913	0.788	329
p_value	0.000	0.000	0.000	0.356	0.000			
1983	2.357	0.455	0.246	0.135	0.052	0.888	0.730	359
p_value	0.000	0.000	0.000	0.005	0.000			
1984	1.917	0.554	0.250	0.085	0.045	0.934	0.764	428
p_value	0.000	0.000	0.000	0.061	0.000			
1985	1.888	0.592	0.226	0.083	0.048	0.950	0.739	499
p_value	0.000	0.000	0.000	0.060	0.000			
1986	2.112	0.544	0.215	0.202	0.052	1.013	0.746	514
p_value	0.000	0.000	0.000	0.000	0.000			
1987	2.191	0.449	0.289	0.187	0.072	0.996	0.753	565
p_value	0.000	0.000	0.000	0.000	0.000			
1988	1.800	0.588	0.179	0.172	0.067	1.006	0.768	606
p_value	0.000	0.000	0.000	0.000	0.000			
1989	1.924	0.527	0.222	0.198	0.070	1.018	0.749	588
p_value	0.000	0.000	0.000	0.000	0.000			
1990	1.720	0.562	0.225	0.175	0.072	1.034	0.735	590
p_value	0.000	0.000	0.000	0.000	0.000			
1991	2.219	0.494	0.179	0.307	0.092	1.073	0.723	588

p_value	0.000	0.000	0.000	0.000	0.000			
1992 p_value	2.199 0.000	0.484 0.000	0.242 0.000	0.219 0.000	0.102 0.000	1.047	0.740	602
1993 p_value	2.215 0.000	0.496 0.000	0.284 0.000	0.187 0.000	0.077 0.000	1.043	0.755	656
1994 p_value	1.882 0.000	0.611 0.000	0.235 0.000	0.160 0.001	0.084 0.000	1.090	0.743	713
1995 p_value	1.899 0.000	0.677 0.000	0.197 0.000	0.089 0.050	0.095 0.000	1.057	0.739	787
1996 p_value	1.988 0.000	0.637 0.000	0.202 0.000	0.077 0.054	0.106 0.000	1.022	0.739	865
1997 p_value	1.836 0.000	0.714 0.000	0.193 0.000	0.087 0.045	0.116 0.000	1.109	0.743	1014
1998 p_value	1.954 0.000	0.559 0.000	0.284 0.000	0.130 0.006	0.156 0.000	1.129	0.701	1013
1999 p_value	2.806 0.000	0.371 0.000	0.299 0.000	0.066 0.215	0.217 0.000	0.952	0.639	961
2000 p_value	1.266 0.000	0.753 0.000	-0.037 0.241	0.291 0.000	0.186 0.000	1.193	0.590	1007
2001 p_value	1.348 0.000	0.835 0.000	-0.185 0.000	0.288 0.000	0.226 0.000	1.163	0.667	964
2002 p_value	1.370 0.000	0.719 0.000	-0.038 0.217	0.277 0.000	0.182 0.000	1.141	0.661	850
2003 p_value	2.584 0.000	0.507 0.000	0.140 0.000	0.174 0.000	0.206 0.000	1.028	0.752	754
2004 p_value	2.397 0.000	0.527 0.000	0.226 0.000	0.132 0.000	0.139 0.000	1.023	0.790	703
2005 p_value	2.356 0.000	0.558 0.000	0.191 0.000	0.109 0.000	0.171 0.000	1.028	0.800	683
2006 p_value	2.402 0.000	0.545 0.000	0.174 0.000	0.087 0.002	0.186 0.000	0.992	0.798	650
2007 p_value	2.051 0.000	0.582 0.000	0.145 0.000	0.138 0.000	0.190 0.000	1.054	0.783	597
2008 p_value	1.530 0.000	0.607 0.000	0.028 0.448	0.150 0.000	0.253 0.000	1.038	0.708	593
2009 p_value	2.259 0.000	0.458 0.000	0.167 0.000	0.136 0.000	0.338 0.000	1.099	0.793	572
2010 p_value	2.376 0.000	0.478 0.000	0.250 0.000	0.084 0.003	0.220 0.000	1.032	0.808	538
2011 p_value	2.152 0.000	0.507 0.000	0.201 0.000	0.066 0.025	0.262 0.000	1.036	0.807	503
2012 p_value	2.009 0.000	0.568 0.000	0.136 0.000	0.027 0.312	0.309 0.000	1.040	0.808	482
2013 p_value	2.539 0.000	0.496 0.000	0.185 0.000	0.022 0.353	0.302 0.000	1.004	0.845	479

2014 p_value	2.225 0.000	0.568 0.000	0.139 0.000	0.070 0.005	0.276 0.000	1.053	0.814	490
2015 p_value	1.883 0.000	0.600 0.000	0.146 0.000	0.091 0.001	0.254 0.000	1.090	0.791	511
2016 p_value	2.108 0.000	0.561 0.000	0.204 0.000	0.065 0.012	0.247 0.000	1.076	0.796	483
2017 p_value	2.235 0.000	0.553 0.000	0.197 0.000	0.084 0.003	0.275 0.000	1.108	0.783	473

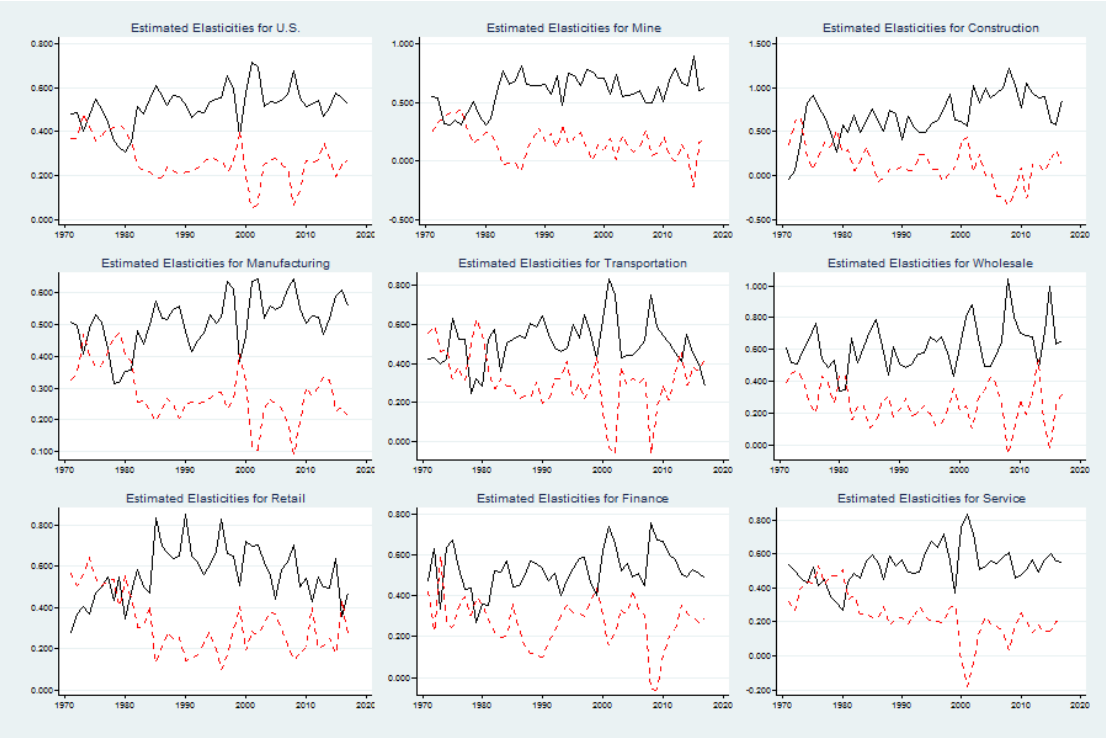
The Table reports the results from annual cross-sectional regressions of the log-linear value relevance model from 1971 to 2017. The empirical model is $log(M_{i,t}) = \alpha + \beta_1 log(|B|_{i,t-1}) + \beta_2 log(|E|_{i,t}) + \beta_3 log(|D|_{i,t}) + \beta_4 log(|O|_{i,t}) + \varepsilon_{i,t}$. Column 1 contains the estimated results for the intercept term α; column 2 contains the estimated elasticities for book value, β_1; column 3 contains the estimated elasticities for net income, β_2; column 4 contains the estimated elasticities for common dividends, β_3; column 5 contains the estimated elasticities for the remaining item, β_4, which column 6 is the sum of the four estimated elasticities; column 7 is R^2; and the last column is the number of observations. The regressions are estimated by OLS. p values are listed below the corresponding estimates.

Table 5.2-10 Mean Value of the Estimated Elasticities for U.S. and Each Industry

		U.S.	Mining	Construction	Manufacturing	Transportation	Wholesale	Retail	Finance	Services
1	$\hat{\alpha}$	1.810	1.824	1.216	1.855	1.848	1.290	1.590	1.608	1.971
	t	36.386	20.719	10.551	36.602	27.009	16.721	21.305	26.464	35.272
	t Newy West	29.810	16.249	8.763	29.979	21.381	13.878	17.413	21.209	29.835
2	$\widehat{\beta_1}$	0.519	0.593	0.689	0.507	0.505	0.620	0.565	0.522	0.529
	t	41.651	27.815	18.909	42.610	29.146	29.599	29.557	35.302	33.735
	t Newy West	33.040	21.921	14.972	33.481	24.355	24.938	24.316	29.985	26.944
3	$\widehat{\beta_2}$	0.271	0.154	0.136	0.282	0.312	0.259	0.316	0.269	0.237
	t	19.334	7.867	4.390	21.863	14.672	13.881	15.120	15.412	11.698
	t Newy West	14.806	6.399	3.471	16.678	11.977	11.935	11.658	12.682	8.776
4	$\widehat{\beta_3}$	0.123	0.175	0.149	0.140	0.078	0.132	0.091	0.152	0.137
	t	17.874	17.840	6.908	16.374	7.748	11.797	13.217	14.097	13.430
	t Newy West	13.532	14.768	6.425	12.313	6.819	9.564	10.394	10.682	10.525
5	$\widehat{\beta_4}$	0.092	0.077	0.054	0.099	0.065	0.054	0.094	0.058	0.132
	t	11.372	9.435	8.957	11.016	9.706	10.592	9.109	9.649	9.660
	t Newy West	8.208	7.154	7.644	8.050	7.506	9.093	6.658	7.162	7.010
6	$\sum \hat{\beta}$	1.004	0.999	1.029	1.028	0.961	1.065	1.066	1.002	1.036
7	R^2	0.831	0.828	0.788	0.838	0.871	0.814	0.831	0.883	0.766
8	N	3831	161	46	1689	329	147	247	622	542

The Table reports the mean results from annual cross-sectional OLS regressions of the log-linear valuation model over the period 1971 to 2017. The empirical model is $log\left(M_{i,t}\right) = \alpha + \beta_1 log\left(|B|_{i,t-1}\right) + \beta_2 log\left(|E|_{i,t}\right) + \beta_3 log\left(|D|_{i,t}\right) + \beta_4 log\left(|O|_{i,t}\right) + \varepsilon_{i,t}$. Rows 1- 5 show the mean results of relevant coefficients in each model respectively. Row 6 denotes the sum of the elasticities for the relevant model. Row 7 denotes the R^2 for each model. Row 8 denotes the number of observations in each model. Both the t statistics and Newy West t statistics are calculated based on the time series standard errors of the estimated elasticities and are reported below each mean value of the estimated elasticities. The columns contain data for the U.S economy (column 1) or individual industries (columns 2 – 9).

Figure 5.2-2. Time Series Pattern of Elasticities for Book Value of Equity and Net Income for U.S. Economy and the U.S. Industries



The Figure depicts the time series pattern of the estimated elasticities of book value and earnings over the period shown. The x-axis shows years. The y-axis shows the estimated elasticities each year. The solid line displays the elasticities on book value in each year. The dashed line displays the estimated elasticities on net income. Each panel is based on data either for the U.S. economy or the named individual U.S. industries. The data are reported in Table 5.2 – 1 to 5.2 – 9, and are based on the annual cross-sectional regression model: $log\left(M_{i,t}\right) = \alpha + \beta_1 log\left(|B|_{i,t-1}\right) + \beta_2 log\left(|E|_{i,t}\right) + \beta_3 log\left(|D|_{i,t}\right) + \beta_4 log\left(|O|_{i,t}\right) + \varepsilon_{i,t}$.

5.3 The Association of Climate Change with Elasticities of the Accounting Variables

This section reports the results from time series regressions of each estimated elasticity obtained in section 5.2 on the variables of global anomaly temperatures and U.S. temperatures. The coefficient on the "Weather" variable reflects the impact of climate change on the equity valuation process.

5.3.1 Annual Global Temperature

Table 5.3.1-1 reports the results from regressing $\hat{\alpha}$ on global temperature. Rows 1 – 9 present the results for the U.S. economy and the industries of Mining, Construction, Manufacturing, Transportation, Wholesale, Retail, Finance, and Services. Row 1 shows that global anomaly temperature has positive effect on $\hat{\alpha}$ with the coefficient equal to 0.554 (p-value = 0.002) for U.S. economy as a whole. Rows 2 – 3 show that the anomaly global temperature has negative impact on $\hat{\alpha}$ in Mining, and Construction, and the impact is insignificant. However, the anomaly global temperature has positive impact on Manufacturing, Transportation, Wholesale, Retail, Finance, and Services. Except Wholesale, all the positive impacts are significant.

Table 5.3.1-2 reports the results from regression of $\widehat{\beta_1}$, the elasticity of book value of equity, on global temperature, showing that the coefficients on the temperature variables are all positive for the U.S. economy and its individual industries. Row 1 shows that coefficient on global temperature for the U.S. economy is 0.117 with p-value equal to 0.013. Among individual industries, the coefficients on global temperature range from 0.037 (Transportation) to 0.463 (Construction), indicating heterogeneity at the industry level. The coefficients are insignificant for Transportation, Retail, and Finance. The results indicate that the value relevance of book value of equity increases with increase in temperature, is consistent with investors tending to put more weight on book value of equity during the valuation process with the perception of climate risk.

Table 5.3.1-3 reports the results from regression of $\widehat{\beta_2}$, the elasticity of earnings, on global temperature. The Table shows that the coefficients on the temperature variable are all negative for the U.S. economy and its individual industries. Row 1 shows that coefficient on global temperature for U.S. is -0.70 with a p-value equal to 0.001. Rows 2 – 9 show that the magnitude of coefficients varies across the individual industries, ranging from -0.32 (Services) to -0.07 (Finance). Except for Finance and Transportation, all the negative impacts are statistically significant. The results indicate that the value relevance of earnings decreases with the increase in temperature, consistent with investors putting less weight on earnings during the valuation process with an increase in the perception of climate risk.

Table 5.3.1-4 reports the results from regression of $\widehat{\beta_3}$, the elasticity of dividends, on global temperature. The results in the Table are mixed. Row 1 shows that coefficient on global temperature for U.S. is -0.078 with a p-value of 0.002. Among rows 2 – 9, the coefficients on global temperature are positive for Transportation and Wholesale, but are negative for other industries. Moreover, the coefficients are not statistically significant for Mining, Construction, Wholesale, and Retail.

Table 5.3.1-5 reports the results from regression of $\widehat{\beta_4}$, the elasticities of the remaining accounting variables in the model on global temperature. Row 1 shows that coefficient on global temperature for U.S. is 0.179 with a highly significant p-value. Among rows 2 – 9, coefficients on global temperature are significantly positive, ranging from 0.065 with a p-value of 0.000 (Wholesale) to 0.302 with a p-value of 0.000 (Services). An exception is Construction (-0.008 with p-value = 0.721).

The main findings on the association of the elasticities of the accounting variables with global temperature can be summarised as follows: with the perception of climate risk, investors will view book value of equity as an anchor in the valuation process, putting higher valuation weight on book value of equity and less valuation weight on earnings. The results provide evidence supporting hypotheses H3a and H4a, that is the impact of climate risk on the elasticity of book value of equity is positive and the impact of climate risk on the elasticity of earnings is negative. Climate risk is the underlying mechanism that drives investors to give greater weighting to the book value of equity than earnings during the valuation process.

Table 5.3.1-1 Regression of $\hat{\alpha}$ on Global Temperature

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	1.578	18.2755	0	0.5544	3.1633	0.0028	0.1637	47
2	Mining	1.8592	11.016	0	-0.0853	-0.2489	0.8046	-0.0208	47
3	Construction	1.4821	6.8586	0	-0.6363	-1.4505	0.1538	0.0234	47
4	Manufacturing	1.6848	18.2027	0	0.4055	2.158	0.0363	0.0736	47
5	Transportation	1.4124	13.2287	0	1.0409	4.803	0	0.3242	47
6	Wholesale	1.2076	8.1989	0	0.1957	0.6547	0.516	-0.0126	47
7	Retail	1.2464	9.5944	0	0.8205	3.1116	0.0032	0.1588	47
8	Finance	1.3877	12.6148	0	0.5253	2.3524	0.0231	0.0897	47
9	Services	1.7217	17.5848	0	0.5956	2.9971	0.0044	0.1479	47

The Table reports the results from the time series regressions of the estimated coefficient $\hat{\alpha}$ on the global temperature variable. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\hat{\alpha}$, x_t denotes global anomaly temperature, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or its individual industries.

Table 5.3.1-2 Regression of $\widehat{\beta_1}$ on Global Temperature

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.4704	21.0615	0	0.1168	2.5773	0.0133	0.1093	47
2	Mining	0.4849	13.3781	0	0.2591	3.5218	0.001	0.1986	47
3	Construction	0.4951	8.1036	0	0.4635	3.7374	0.0005	0.2199	47
4	Manufacturing	0.4464	22.1123	0	0.1459	3.5598	0.0009	0.2024	47
5	Transportation	0.4897	14.7708	0	0.0371	0.5518	0.5838	-0.0154	47
6	Wholesale	0.5556	14.4022	0	0.1542	1.9693	0.0551	0.0589	47
7	Retail	0.5299	14.6513	0	0.0843	1.1476	0.2572	0.0068	47
8	Finance	0.4953	17.6926	0	0.0646	1.1376	0.2613	0.0064	47
9	Services	0.4673	16.6443	0	0.1479	2.5952	0.0127	0.1109	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_1}$ on the global temperature variable. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_1}$, x_t denotes global anomaly temperature, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or its individual industries.

Table 5.3.1-3 Regression of $\widehat{\beta_2}$ on Global Temperature

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.3418	14.365	0	-0.1698	-3.5166	0.001	0.1981	47
2	Mining	0.2598	7.9477	0	-0.2525	-3.8056	0.0004	0.2267	47
3	Construction	0.2671	4.8578	0	-0.3124	-2.799	0.0075	0.1294	47
4	Manufacturing	0.3488	16.0323	0	-0.1601	-3.6255	0.0007	0.2089	47
5	Transportation	0.3865	9.9836	0	-0.1772	-2.2555	0.029	0.0816	47
6	Wholesale	0.3034	8.6982	0	-0.1069	-1.5103	0.138	0.0271	47
7	Retail	0.4311	12.4809	0	-0.276	-3.9361	0.0003	0.2396	47
8	Finance	0.3	9.0768	0	-0.074	-1.1029	0.2759	0.0047	47
9	Services	0.3701	11.8822	0	-0.3174	-5.0208	0	0.3448	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_2}$ on the global temperature variable. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_2}$, x_t denotes global anomaly temperature, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or its individual industries.

Table 5.3.1-4 Regression $\widehat{\beta_3}$ on Global Temperature

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.1553	13.127	0	-0.0783	-3.2601	0.0021	0.1731	47
2	Mining	0.1924	10.3633	0	-0.0417	-1.1066	0.2744	0.0049	47
3	Construction	0.1851	4.5227	0	-0.0861	-1.0357	0.3059	0.0016	47
4	Manufacturing	0.1883	13.4294	0	-0.1156	-4.0631	0.0002	0.2521	47
5	Transportation	0.0386	2.1326	0.0384	0.0948	2.581	0.0132	0.1096	47
6	Wholesale	0.126	5.8674	0	0.0148	0.3388	0.7364	-0.0196	47
7	Retail	0.1049	8.0762	0	-0.0331	-1.2572	0.2152	0.0125	47
8	Finance	0.1847	9.2578	0	-0.0772	-1.9068	0.0629	0.0542	47
9	Services	0.1649	8.7029	0	-0.0667	-1.7343	0.0897	0.0418	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_3}$ on the global temperature variable. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_3}$, x_t denotes global anomaly temperature, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or its individual industries.

Table 5.3.1-5 Regression $\widehat{\beta_4}$ on Global Temperature

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.0166	2.0478	0.0464	0.179	10.8503	0	0.7173	47
2	Mining	0.0179	1.5288	0.1333	0.1405	5.9115	0	0.4246	47
3	Construction	0.0576	4.9794	0	-0.0084	-0.3589	0.7214	-0.0193	47
4	Manufacturing	0.015	1.6755	0.1008	0.2006	11.0118	0	0.7233	47
5	Transportation	0.0324	2.8155	0.0072	0.0778	3.3323	0.0017	0.1801	47
6	Wholesale	0.0263	3.1115	0.0032	0.0653	3.8057	0.0004	0.2267	47
7	Retail	0.0092	0.7006	0.4872	0.2033	7.6417	0	0.5551	47
8	Finance	0.0142	1.6452	0.1069	0.1055	6.0044	0	0.4325	47
9	Services	0.0059	0.4152	0.68	0.3021	10.5494	0	0.7057	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_4}$ on the global temperature variable. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_4}$, x_t denotes global anomaly temperature, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or its individual industries.

5.3.2 Annual U.S. Temperature

Table 5.3.2-1 – 5.3.2-5 report the association of annual U.S. temperature on the individual estimated coefficients obtained in stage 1 of the estimation process. Table 5.3.2-1 reports the results from regressing $\hat{\alpha}$ on U.S. temperature. Compared with Table 5.3.1-1, the magnitudes of the association with U.S. temperatures are generally less than those with global temperatures. For example, the coefficient on global temperature in the sample of U.S. economy as a whole is 0.554 with a p-value of 0.003. However, the coefficient on the U.S. temperature variable in the same sample is 0.09 with a p-value of 0.067. The coefficient on global temperature for Construction is -0.636 with a p-value of 0.154 compared to a coefficient on the U.S. temperature variable for Construction of -0.107 with a p-value of 0.338.

Table 5.3.2-2 reports the results from regressing $\widehat{\beta_1}$, the elasticity of the book value of equity, on U.S. temperatures. The U.S temperature has a positive association with the elasticity of book value. However, the results for Transportation, Wholesale, Retail, and Finance are not statistically significant. Compared with the results from global temperatures, the magnitudes of the coefficients on U.S. temperatures are reduced. Row 1 of Table 5.3.2 -2 shows that the coefficient on U.S. temperatures for the U.S. economy as a whole is 0.02 with a p-value of 0.07, less than the corresponding coefficient on global temperature, which is 0.12 with a p-value of 0.01.

Table 5.3.2-3 reports the results from regressing $\widehat{\beta_2}$, the elasticity of earnings, on U.S. temperatures. U.S. temperature has a negative association with the elasticity of earnings. Compared with the results for the global temperature variable, the magnitudes of the coefficients on U.S. temperatures are reduced. For example, the coefficient on U.S. temperature for U.S. economy as a whole is -0.03 with a p-value of 0.05, whereas the corresponding coefficient on global temperature is -0.17 with a p-value of 0.00.

Table 5.3.1-4 reports the results from regressing $\widehat{\beta_3}$, the elasticity of dividends, on U.S. temperatures. Table 5.3.1-5 reports the results from regressing $\widehat{\beta_4}$, the elasticities of remaining factor, on U.S. temperatures. The results for the U.S. temperature variable are similar with those for the global temperature variable but the magnitudes of the coefficients for U.S. temperatures are less than those for global temperature.

In sum, when using U.S. temperature as an explanatory variable, the results are similar with those when using global temperature. The magnitude of the coefficients is less but the results using the U.S. temperature variable provides weakly supportive evidence for the baseline results.

Table 5.3.2-1 Regression of $\hat{\alpha}$ on U.S. Temperature

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	1.7463	29.5171	0	0.0871	1.8802	0.0666	0.0522	47
2	Mining	1.8686	17.2916	0	-0.0615	-0.7269	0.471	-0.0104	47
3	Construction	1.2939	9.1877	0	-0.1067	-0.9677	0.3384	-0.0014	47
4	Manufacturing	1.8179	29.3927	0	0.0501	1.0344	0.3065	0.0015	47
5	Transportation	1.7081	22.3919	0	0.1911	3.1995	0.0025	0.1672	47
6	Wholesale	1.2605	13.2759	0	0.0396	0.5328	0.5968	-0.0158	47
7	Retail	1.4895	16.8495	0	0.137	1.9789	0.054	0.0596	47
8	Finance	1.526	21.2028	0	0.1113	1.9756	0.0544	0.0594	47
9	Services	1.9104	28.4305	0	0.0827	1.5721	0.1229	0.031	47

The Table reports the results from the time series regressions of the estimated coefficient $\hat{\alpha}$ on the global temperature variable. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\hat{\alpha}$, x_t denotes U.S. temperature, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or its individual industries.

Table 5.3.2-2 Regression of $\widehat{\beta_1}$ on U.S. Temperature

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.5033	33.9374	0	0.0217	1.8714	0.0678	0.0516	47
2	Mining	0.5519	22.9552	0	0.0566	3.0083	0.0043	0.1489	47
3	Construction	0.6312	14.8797	0	0.0792	2.3845	0.0214	0.0924	47
4	Manufacturing	0.4864	35.6151	0	0.0287	2.6813	0.0102	0.1186	47
5	Transportation	0.5002	23.4074	0	0.0069	0.4111	0.6829	-0.0184	47
6	Wholesale	0.6096	23.6905	0	0.0145	0.7216	0.4743	-0.0105	47
7	Retail	0.5553	23.6527	0	0.0136	0.7385	0.464	-0.01	47
8	Finance	0.5166	28.3645	0	0.0078	0.5485	0.5861	-0.0154	47
9	Services	0.5056	27.5119	0	0.0322	2.2404	0.03	0.0804	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_1}$ on the global temperature variable. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_1}$, x_t denotes U.S. temperature, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or its individual industries.

Table 5.3.2-3 Regression of $\widehat{\beta_2}$ on U.S. Temperature

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.2901	17.5373	0	-0.0265	-2.0422	0.047	0.0645	47
2	Mining	0.1898	8.502	0	-0.0488	-2.7913	0.0077	0.1286	47
3	Construction	0.1747	4.719	0	-0.0524	-1.8072	0.0774	0.0469	47
4	Manufacturing	0.3014	19.988	0	-0.0268	-2.267	0.0282	0.0826	47
5	Transportation	0.3355	13.1128	0	-0.0317	-1.5805	0.121	0.0315	47
6	Wholesale	0.2569	11.1667	0	0.0023	0.1297	0.8974	-0.0218	47
7	Retail	0.3416	13.7338	0	-0.0355	-1.8234	0.0749	0.0481	47
8	Finance	0.2701	12.5331	0	-0.0016	-0.092	0.9271	-0.022	47
9	Services	0.2831	12.8514	0	-0.0626	-3.6273	0.0007	0.209	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_2}$ on the global temperature variable. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_2}$, x_t denotes U.S. temperature, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or its individual industries.

Table 5.3.2-4 Regression of $\widehat{\beta_3}$ on U.S. Temperature

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.1298	15.7344	0	-0.01	-1.5413	0.1303	0.029	47
2	Mining	0.1797	14.9231	0	-0.0066	-0.6966	0.4897	-0.0113	47
3	Construction	0.1537	5.7737	0	-0.0064	-0.3046	0.7621	-0.0201	47
4	Manufacturing	0.1516	15.0124	0	-0.016	-2.0254	0.0488	0.0632	47
5	Transportation	0.0625	5.3025	0	0.0215	2.3324	0.0242	0.088	47
6	Wholesale	0.1322	9.5526	0	0	-0.0017	0.9987	-0.0222	47
7	Retail	0.0954	11.3206	0	-0.006	-0.9076	0.3689	-0.0038	47
8	Finance	0.1619	12.3433	0	-0.013	-1.2669	0.2117	0.013	47
9	Services	0.1399	11.1226	0	-0.0039	-0.399	0.6918	-0.0186	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_3}$ on the global temperature variable. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_3}$, x_t denotes U.S. temperature, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or its individual industries.

Table 5.3.2-5 Regression of $\widehat{\beta_4}$ on U.S. Temperature

		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	0.069	8.5909	0	0.0309	4.908	0	0.3342	47
2	Mining	0.0595	6.6161	0	0.0235	3.3302	0.0017	0.1799	47
3	Construction	0.0561	7.5395	0	-0.0027	-0.4691	0.6413	-0.0172	47
4	Manufacturing	0.0725	8.3239	0	0.0361	5.2988	0	0.3705	47
5	Transportation	0.0539	6.9543	0	0.0151	2.4817	0.0169	0.1008	47
6	Wholesale	0.047	7.8146	0	0.0091	1.9352	0.0593	0.0563	47
7	Retail	0.0723	6.3202	0	0.03	3.3509	0.0016	0.1819	47
8	Finance	0.0473	6.8563	0	0.0152	2.8153	0.0072	0.1309	47
9	Services	0.0921	6.92	0	0.0549	5.2696	0	0.3679	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_4}$ on the global temperature variable. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_4}$, x_t denotes U.S. temperature, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or its individual industries.

5.4 Long-run and Short-run Components of Global Temperature

5.4.1 Decomposition of the Global Temperature Following Bansal, Kiku, & Ochoa (2016)

Table 5.4.1-1 to 5.4.1-5 report the effects of long- and short-run components of global temperature, formed by taking the moving average and the first order difference following Bansal et al. (2016). Panel A and Panel B of each Table have the same structure as the Tables reported in previous subsections. Panel C of each Table includes both the long- and short-run components of global temperature with each row representing the results for the U.S. economy or its individual industries.

Table 5.4.1-1 reports in Panel A the regressions of $\hat{\alpha}$ on the long-run component of global temperature, in Panel B the short-run component of global temperature, and in Panel C both the long-run and short-run components of global temperature. Comparison of Panel A with Table 5.3.1-1 shows that the magnitude of coefficients on temperature increases to some extent and becomes more significant. For example, for the U.S. economy as a whole, the coefficient on the long-run component of global temperature is 0.617 with a p-value of 0.002. In contrast, the counterpart coefficient on total global temperature in Table 5.3.1-1 is 0.554 with a p-value of 0.003.

Panel B shows that the coefficient on the short run temperature variable is in all cases not significant.

Panel C shows that when considering both the long-run and short-run component together, the long-run component maintains significance, whereas the short-run component, as in Panel C, is not statistically significant.

Tables 5.4.1-2, 3, 4, and 5 Panel A report the results from the regression of $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\widehat{\beta_3}$, and $\widehat{\beta_4}$ on the long-run component of global temperature, in Panel B the short-run component of global temperature, and in Panel C both the long-run and short-run components of global temperature together.

In summary, the above results show that in most cases the long-run component is statistically significant at the 0.01 or 0.05 level, but in all cases the short-run component is not significant. Take the results for U.S. as an example. In the regression of $\widehat{\beta_1}$, the coefficient on the long-run component of global temperature is 0.134, with a p value of

0.008 but the coefficient on the short-run component of global temperature is not significant. The results therefore show a strong association on value relevance with long-run changes in the climate, but not for short-run changes in the climate. The collective evidence is consistent in this respect with the long-run risk explanation of climate risk, showing that the impacts of climate risk can persist over long time period. The results provide supportive evidence for the hypothesis H6, that is the long-run component of climate risk has significant effects on the elasticities of book value of equity and earnings but the short-run component of climate risk does not have such effects.

Table 5.4.1-1 Regression of $\hat{\alpha}$ on the Long-run and Short-run Components of Global Temperature

A: Long-run									
		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	-7.0246	-2.6334	0.0115	0.6178	3.3125	0.0018	0.1782	47
2	Mining	3.6281	0.6903	0.4936	-0.1262	-0.3434	0.7329	-0.0196	47
3	Construction	12.1108	1.8088	0.0772	-0.7619	-1.6275	0.1106	0.0346	47
4	Manufacturing	-4.9467	-1.7325	0.09	0.4756	2.3824	0.0215	0.0923	47
5	Transportation	-15.0643	-4.6742	0	1.1827	5.2484	0	0.3659	47
6	Wholesale	-2.0648	-0.4504	0.6546	0.2346	0.7318	0.4681	-0.0102	47
7	Retail	-11.966	-3.0075	0.0043	0.9479	3.4076	0.0014	0.1874	47
8	Finance	-5.9657	-1.7277	0.0909	0.5296	2.1937	0.0335	0.0765	47
9	Services	-7.9016	-2.6338	0.0115	0.6904	3.2913	0.0019	0.1761	47
B: Short-run									
		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	1.8111	35.5916	0	-0.0481	-0.1124	0.911	-0.0219	47
2	Mining	1.823	20.2489	0	0.0264	0.0349	0.9723	-0.0222	47
3	Construction	1.206	10.2659	0	0.5347	0.5413	0.591	-0.0156	47
4	Manufacturing	1.8566	35.8459	0	-0.1118	-0.2568	0.7985	-0.0207	47
5	Transportation	1.8516	26.479	0	-0.1831	-0.3114	0.7569	-0.02	47
6	Wholesale	1.293	16.4059	0	-0.1933	-0.2916	0.7719	-0.0203	47
7	Retail	1.5936	20.8972	0	-0.1994	-0.311	0.7572	-0.02	47
8	Finance	1.6026	25.8706	0	0.2788	0.5352	0.5951	-0.0158	47
9	Services	1.9765	34.722	0	-0.297	-0.6204	0.5381	-0.0136	47

The Table reports the results from the time series regressions of the estimated coefficient $\hat{\alpha}$ on the long-run or short-run components of global temperature variable separately. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\hat{\alpha}$, x_t denotes the long-run or short-run components of global anomaly temperature, and ω_t denotes the error term. Panel A reports results by using the long-run component of global temperature variable as an explanatory variable. Panel B reports results by using the short-run component of global temperature variable as an explanatory variable. In both Panels, each row presents the result for the U.S. economy as a whole or the individual industries.

C: Long-run & Short-run

		Intercept	t	p_value	Weather_Long	t	p_value	Weather_Short	t	p_value	AdjR^2	N
1	U.S.	-7.0338	-2.6081	0.0124	0.6185	3.2801	0.002	-0.0742	-0.1912	0.8492	0.1602	47
2	Mining	3.632	0.6832	0.4981	-0.1265	-0.3403	0.7352	0.0318	0.0416	0.967	-0.0427	47
3	Construction	12.1813	1.8057	0.0778	-0.7675	-1.6272	0.1108	0.5671	0.5844	0.562	0.0203	47
4	Manufacturing	-4.9631	-1.7205	0.0924	0.4769	2.3645	0.0225	-0.1319	-0.318	0.752	0.0738	47
5	Transportation	-15.0933	-4.6432	0	1.185	5.2135	0	-0.233	-0.4984	0.6207	0.3551	47
6	Wholesale	-2.0901	-0.4512	0.654	0.2366	0.7305	0.469	-0.2032	-0.305	0.7618	-0.031	47
7	Retail	-11.9957	-2.9866	0.0046	0.9503	3.3839	0.0015	-0.2395	-0.4145	0.6805	0.1722	47
8	Finance	-5.9338	-1.7041	0.0954	0.527	2.1647	0.0359	0.2566	0.5122	0.6111	0.0611	47
9	Services	-7.9422	-2.6341	0.0116	0.6936	3.2901	0.002	-0.3262	-0.7521	0.456	0.1681	47

The Table reports the results from the time series regressions of the estimated coefficient $\hat{\alpha}$ on the long-run and short-run components of global temperature variable separately. The econometric model is $y_t = \upsilon_t + \gamma_L x\_L_t + \gamma_S x\_S_t + \omega_t$, , where y_t denotes $\hat{\alpha}$, $x_L_t$denotes the long-run component of global anomaly temperature; x_S_t denotes short-run component of global anomaly temperature, and ω_t denotes the error term. Each row presents the result for the U.S. economy as a whole or the individual industries.

Table 5.4.1-2 Regression of $\widehat{\beta_1}$ on the Long-run and Short-run Components of Global Temperature

A: Long-run									
		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	-1.3914	-2.0195	0.0494	0.1336	2.7736	0.008	0.127	47
2	Mining	-3.4388	-3.0562	0.0038	0.282	3.5841	0.0008	0.2048	47
3	Construction	-7.3839	-4.0634	0.0002	0.5645	4.4433	0.0001	0.2895	47
4	Manufacturing	-1.8212	-2.9289	0.0053	0.1628	3.7456	0.0005	0.2207	47
5	Transportation	0.0087	0.0084	0.9933	0.0347	0.4803	0.6334	-0.017	47
6	Wholesale	-1.8658	-1.5589	0.126	0.1738	2.0774	0.0435	0.0672	47
7	Retail	-0.6402	-0.5669	0.5736	0.0843	1.0676	0.2914	0.003	47
8	Finance	-0.8432	-0.9793	0.3327	0.0955	1.5861	0.1197	0.0319	47
9	Services	-1.7794	-2.0389	0.0474	0.1614	2.6457	0.0112	0.1154	47
B: Short-run									
		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.5179	40.8241	0	0.0732	0.6859	0.4963	-0.0116	47
2	Mining	0.591	27.2421	0	0.1341	0.735	0.4661	-0.0101	47
3	Construction	0.6946	18.8149	0	-0.2956	-0.9522	0.3461	-0.002	47
4	Manufacturing	0.5063	41.7426	0	0.0645	0.6329	0.53	-0.0132	47
5	Transportation	0.5025	28.6775	0	0.1543	1.047	0.3007	0.0021	47
6	Wholesale	0.6185	28.9461	0	0.0963	0.5359	0.5947	-0.0157	47
7	Retail	0.5619	29.1245	0	0.182	1.1218	0.2679	0.0056	47
8	Finance	0.5238	34.7495	0	-0.0782	-0.6168	0.5405	-0.0137	47
9	Services	0.5265	33.2728	0	0.1507	1.1324	0.2635	0.0061	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_1}$ on the long-run or short-run components of global temperature variable separately. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_1}$, x_t denotes the long-run or short-run component of global anomaly temperature, and ω_t denotes the error term. Panel A reports the results by using long-run components of global temperature variable as explanatory variable. Panel B reports the results by using short-run component of global temperature variable as explanatory variable. In both Panels, each row presents the result for the U.S. economy as a whole or the individual industries.

C: Long-run & Short-run

		Intercept	t	p_value	Weather_Long	t	p_value	Weather_Short	t	p_value	AdjR^2	N
1	U.S.	-1.383	-1.9949	0.0523	0.1329	2.7424	0.0088	0.0676	0.6775	0.5016	0.1164	47
2	Mining	-3.4236	-3.0274	0.0041	0.2807	3.5506	0.0009	0.1222	0.7515	0.4564	0.197	47
3	Construction	-7.4236	-4.1077	0.0002	0.5677	4.4927	0.0001	-0.3195	-1.229	0.2256	0.2975	47
4	Manufacturing	-1.814	-2.8978	0.0058	0.1623	3.7071	0.0006	0.0577	0.6408	0.525	0.2104	47
5	Transportation	0.0277	0.0268	0.9787	0.0332	0.4594	0.6482	0.1529	1.0281	0.3095	-0.0157	47
6	Wholesale	-1.8548	-1.5366	0.1315	0.173	2.0493	0.0464	0.089	0.5125	0.6109	0.0517	47
7	Retail	-0.618	-0.5485	0.5861	0.0825	1.0473	0.3007	0.1785	1.1013	0.2767	0.0077	47
8	Finance	-0.8535	-0.9848	0.3301	0.0963	1.5893	0.1191	-0.0822	-0.6596	0.513	0.0196	47
9	Services	-1.7615	-2.0253	0.0489	0.16	2.6311	0.0117	0.1439	1.1505	0.2562	0.1217	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_1}$ on the long-run and short-run components of global temperature variable separately. The econometric model is $y_t = v_t + \gamma_L x\_L_t + \gamma_S x\_S_t + \omega_t$, , where y_t denotes $\widehat{\beta_1}$, $x_L_t$denotes the long-run component of global anomaly temperature; x_S_t denotes short-run component of global anomaly temperature, and ω_t denotes the error term. Each row presents the result for the U.S. economy as a whole or the individual industries.

Table 5.4.1-3 Regression of $\widehat{\beta_2}$ on the Long-run and Short-run Components of Global Temperature

A: Long-run									
		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	3.038	4.1708	0.0001	-0.1935	-3.7997	0.0004	0.2261	47
2	Mining	3.8731	3.7551	0.0005	-0.2601	-3.6063	0.0008	0.207	47
3	Construction	6.0025	3.6652	0.0006	-0.4102	-3.5825	0.0008	0.2046	47
4	Manufacturing	2.985	4.5446	0	-0.189	-4.1162	0.0002	0.2574	47
5	Transportation	3.044	2.5245	0.0152	-0.191	-2.2658	0.0283	0.0825	47
6	Wholesale	2.222	2.0671	0.0445	-0.1373	-1.8267	0.0744	0.0483	47
7	Retail	4.7781	4.5253	0	-0.3121	-4.227	0.0001	0.2683	47
8	Finance	1.6812	1.6447	0.107	-0.0988	-1.3818	0.1739	0.0194	47
9	Services	5.3592	5.6915	0	-0.3582	-5.4404	0	0.3834	47
B: Short-run									
		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.272	19.0631	0	-0.0707	-0.5894	0.5586	-0.0144	47
2	Mining	0.1575	7.9818	0	-0.1931	-1.1634	0.2508	0.0076	47
3	Construction	0.1299	4.172	0.0001	0.353	1.3482	0.1844	0.0175	47
4	Manufacturing	0.2819	21.3835	0	-0.0072	-0.0653	0.9482	-0.0221	47
5	Transportation	0.3145	14.5156	0	-0.1219	-0.6689	0.507	-0.0122	47
6	Wholesale	0.2586	13.5671	0	0.0022	0.0136	0.9892	-0.0222	47
7	Retail	0.3184	15.0419	0	-0.157	-0.882	0.3825	-0.0049	47
8	Finance	0.2681	15.0348	0	0.0479	0.3195	0.7508	-0.0199	47
9	Services	0.2395	11.6139	0	-0.1263	-0.7283	0.4702	-0.0103	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_2}$ on the long-run or short-run components of global temperature variable separately. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_2}$, x_t denotes the long-run or short-run component of global anomaly temperature, and ω_t denotes the error term. Panel A reports the results by using long-run components of global temperature variable as explanatory variable. Panel B reports the results by using short-run component of global temperature variable as explanatory variable. In both Panels, each row presents the result for the U.S. economy as a whole or the individual industries.

C: Long-run & Short-run

		Intercept	t	p_value	Weather_Long	t	p_value	Weather_Short	t	p_value	AdjR^2	N
1	U.S.	3.0303	4.1293	0.0002	-0.1929	-3.7593	0.0005	-0.0626	-0.5927	0.5564	0.2148	47
2	Mining	3.8504	3.7543	0.0005	-0.2583	-3.6012	0.0008	-0.1822	-1.2349	0.2234	0.2161	47
3	Construction	6.0485	3.7561	0.0005	-0.4139	-3.6759	0.0006	0.3704	1.5991	0.117	0.2312	47
4	Manufacturing	2.9851	4.4932	0.0001	-0.189	-4.0695	0.0002	0.0007	0.0076	0.9939	0.2405	47
5	Transportation	3.0299	2.4963	0.0164	-0.1899	-2.2375	0.0304	-0.1139	-0.6521	0.5178	0.0706	47
6	Wholesale	2.223	2.0446	0.0469	-0.1374	-1.8071	0.0776	0.008	0.051	0.9595	0.0268	47
7	Retail	4.7603	4.5024	0	-0.3106	-4.2018	0.0001	-0.1439	-0.9461	0.3493	0.2666	47
8	Finance	1.6877	1.6346	0.1093	-0.0993	-1.3752	0.176	0.0521	0.3507	0.7275	-0.0001	47
9	Services	5.3454	5.655	0	-0.3571	-5.4025	0	-0.1112	-0.8179	0.4178	0.3788	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_2}$ on the long-run and short-run components of global temperature variable separately. The econometric model is $y_t = v_t + \gamma_L x\_L_t + \gamma_S x\_S_t + \omega_t$, , where y_t denotes $\widehat{\beta_2}$, $x_L_t$denotes the long-run component of global anomaly temperature; x_S_t denotes short-run component of global anomaly temperature, and ω_t denotes the error term. Each row presents the result for the U.S. economy as a whole or the individual industries.

Table 5.4.1-4 Regression of $\widehat{\beta_3}$ on the Long-run and Short-run Components of Global Temperature

A: Long-run									
		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	1.4335	3.9801	0.0002	-0.0917	-3.6405	0.0007	0.2103	47
2	Mining	0.859	1.4877	0.1438	-0.0478	-1.1849	0.2423	0.0087	47
3	Construction	1.7836	1.4072	0.1662	-0.1143	-1.2898	0.2037	0.0142	47
4	Manufacturing	2.0297	4.7632	0	-0.1322	-4.4355	0.0001	0.2887	47
5	Transportation	-1.366	-2.4209	0.0196	0.101	2.5599	0.0139	0.1077	47
6	Wholesale	-0.2568	-0.3848	0.7022	0.0272	0.5829	0.5629	-0.0146	47
7	Retail	0.4655	1.1412	0.2598	-0.0262	-0.9182	0.3634	-0.0034	47
8	Finance	1.5178	2.4738	0.0172	-0.0955	-2.2258	0.0311	0.0792	47
9	Services	1.1894	2.0182	0.0496	-0.0736	-1.786	0.0808	0.0454	47
B: Short-run									
		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.1222	17.4459	0	0.0156	0.2649	0.7923	-0.0206	47
2	Mining	0.1753	17.4809	0	-0.0178	-0.2108	0.834	-0.0212	47
3	Construction	0.1473	6.6923	0	0.1001	0.5408	0.5913	-0.0156	47
4	Manufacturing	0.1398	16.0021	0	0.0023	0.0315	0.975	-0.0222	47
5	Transportation	0.0785	7.5976	0	-0.0123	-0.1421	0.8876	-0.0218	47
6	Wholesale	0.133	11.6392	0	-0.0478	-0.4973	0.6214	-0.0166	47
7	Retail	0.0923	13.3152	0	-0.0708	-1.2143	0.231	0.0102	47
8	Finance	0.1517	13.7433	0	0.04	0.4307	0.6687	-0.018	47
9	Services	0.1366	13.1019	0	0.0197	0.2251	0.8229	-0.0211	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_3}$ on the long-run or short-run components of global temperature variable separately. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_3}$, x_t denotes the long-run or short-run component of global anomaly temperature, and ω_t denotes the error term. Panel A reports the results by using long-run components of global temperature variable as explanatory variable. Panel B reports the results by using short-run component of global temperature variable as explanatory variable. In both Panels, each row presents the result for the U.S. economy as a whole or the individual industries.

C: Long-run & Short-run

		Intercept	t	p_value	Weather_Long	t	p_value	Weather_Short	t	p_value	AdjR^2	N
1	U.S.	1.4359	3.9478	0.0003	-0.0919	-3.6124	0.0008	0.0195	0.3722	0.7115	0.1949	47
2	Mining	0.857	1.4681	0.1492	-0.0477	-1.1681	0.2491	-0.0158	-0.1876	0.852	-0.013	47
3	Construction	1.7966	1.4067	0.1666	-0.1153	-1.2915	0.2033	0.1049	0.5712	0.5708	-0.0008	47
4	Manufacturing	2.0307	4.7123	0	-0.1322	-4.3885	0.0001	0.0079	0.1273	0.8993	0.2728	47
5	Transportation	-1.3681	-2.3982	0.0208	0.1012	2.5361	0.0148	-0.0166	-0.2024	0.8406	0.0883	47
6	Wholesale	-0.2629	-0.3905	0.698	0.0277	0.5883	0.5594	-0.049	-0.5056	0.6157	-0.0316	47
7	Retail	0.4568	1.125	0.2667	-0.0255	-0.8979	0.3741	-0.0697	-1.193	0.2392	0.0059	47
8	Finance	1.5232	2.4614	0.0178	-0.0959	-2.2167	0.0319	0.044	0.4944	0.6235	0.0634	47
9	Services	1.1922	2.0017	0.0515	-0.0738	-1.7726	0.0832	0.0229	0.2667	0.7909	0.0253	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_3}$ on the long-run and short-run components of global temperature variable separately. The econometric model is $y_t = \upsilon_t + \gamma_L x\_L_t + \gamma_S x\_S_t + \omega_t$, , where y_t denotes $\widehat{\beta_3}$, $x_L_t$denotes the long-run component of global anomaly temperature; x_S_t denotes short-run component of global anomaly temperature, and ω_t denotes the error term. Each row presents the result for the U.S. economy as a whole or the individual industries.

Table 5.4.1-5 Regression of $\widehat{\beta_4}$ on the Long-run and Short-run Components of Global Temperature

A: Long-run									
		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	-2.8125	-13.3251	0	0.2031	13.7611	0	0.8037	47
2	Mining	-2.1218	-5.9052	0	0.1537	6.1196	0	0.4421	47
3	Construction	0.015	0.0415	0.9671	0.0027	0.1084	0.9142	-0.022	47
4	Manufacturing	-3.2031	-14.8556	0	0.2309	15.317	0	0.8355	47
5	Transportation	-1.2646	-3.6389	0.0007	0.093	3.8263	0.0004	0.2287	47
6	Wholesale	-0.9985	-3.8544	0.0004	0.0736	4.0621	0.0002	0.252	47
7	Retail	-3.1829	-8.3681	0	0.2292	8.6173	0	0.6143	47
8	Finance	-1.704	-6.8404	0	0.1232	7.076	0	0.5161	47
9	Services	-4.7147	-12.211	0	0.3389	12.5556	0	0.773	47
B: Short-run									
		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	0.0913	11.0905	0	0.0147	0.212	0.8331	-0.0212	47
2	Mining	0.0761	9.173	0	0.034	0.4875	0.6283	-0.0169	47
3	Construction	0.0555	9.206	0	-0.0767	-1.5129	0.1373	0.0273	47
4	Manufacturing	0.0991	10.7769	0	-0.0038	-0.0487	0.9614	-0.0222	47
5	Transportation	0.0652	9.5314	0	-0.014	-0.2426	0.8094	-0.0209	47
6	Wholesale	0.0533	10.311	0	0.018	0.4137	0.6811	-0.0183	47
7	Retail	0.0936	8.8562	0	0.0402	0.4518	0.6536	-0.0176	47
8	Finance	0.0585	9.4493	0	-0.0053	-0.1017	0.9195	-0.022	47
9	Services	0.1316	9.4021	0	0.0422	0.3585	0.7216	-0.0193	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_4}$ on the long-run or short-run components of global temperature variable separately. The econometric models are $y_t = v_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_4}$, x_t denotes the long-run or short-run component of global anomaly temperature, and ω_t denotes the error term. Panel A reports the results by using long-run components of global temperature variable as explanatory variable. Panel B reports the results by using short-run component of global temperature variable as explanatory variable. In both Panels, each row presents the result for the U.S. economy as a whole or the individual industries.

C: Long-run & Short-run

		Intercept	t	p_value	Weather_Long	t	p_value	Weather_Short	t	p_value	AdjR^2	N
1	U.S.	-2.8118	-13.1765	0	0.203	13.6065	0	0.0061	0.1995	0.8428	0.7994	47
2	Mining	-2.1184	-5.8473	0	0.1535	6.0583	0	0.0275	0.5285	0.5998	0.433	47
3	Construction	0.0054	0.0152	0.9879	0.0035	0.1405	0.8889	-0.0768	-1.4989	0.141	0.0056	47
4	Manufacturing	-3.2047	-14.726	0	0.231	15.1835	0	-0.0135	-0.4314	0.6683	0.8325	47
5	Transportation	-1.2668	-3.6091	0.0008	0.0932	3.7954	0.0004	-0.0179	-0.3541	0.725	0.2134	47
6	Wholesale	-0.9966	-3.8104	0.0004	0.0734	4.0149	0.0002	0.0149	0.3958	0.6942	0.2378	47
7	Retail	-3.1791	-8.2921	0	0.2289	8.5374	0	0.0305	0.5531	0.583	0.6082	47
8	Finance	-1.7053	-6.7745	0	0.1233	7.0081	0	-0.0105	-0.2898	0.7733	0.5061	47
9	Services	-4.7112	-12.0977	0	0.3387	12.4375	0	0.0279	0.4983	0.6207	0.7691	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_4}$ on the long-run and short-run components of global temperature variable separately. The econometric model is $y_t = \upsilon_t + \gamma_L x\_L_t + \gamma_S x\_S_t + \omega_t$, , where y_t denotes $\widehat{\beta_4}$, $x_L_t$denotes the long-run component of global anomaly temperature; x_S_t denotes short-run component of global anomaly temperature, and ω_t denotes the error term. Each row presents the result for the U.S. economy as a whole or the individual industries.

5.4.2 Decomposition the Global Temperature Variable Following Hodrick & Prescott (1997)

The structure of all the Tables in this section is the same as those in subsection 5.4.1. The difference is that the total global temperature is decomposed by following Hodrick & Prescott (1997), rather than Bansal, Kiku, & Ochoa (2016). The results derived from using the Hodrick & Prescott (1997) approach also show that it is the long-run component of global temperature, rather than the short-run component, that has a significantly influences the estimated elasticity estimated in stage one. The long-run component of global temperature has a positive association with the elasticity of book value of equity, and a negative association with the elasticities of earnings. Both approaches result in the same conclusion about the association with the long-run and short-run components of global temperature.

Table 5.4.2-1 Panel reports the results from the regression of $\hat{\alpha}$ on the long-run component of global temperature, Panel B the short-run component of global temperature, and in Panel C both long-run and short-run components of global temperature. Tables 5.4.2-2 to 5.4.2-5 report the results from similar regressions of $\widehat{\beta_1}$ through $\widehat{\beta_4}$ on the different components of global temperature.

Table 5.4.2-1 Regression of $\hat{\alpha}$ on the Cycle and Trend Components of Global Temperature

A: Long-run									
		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	-6.822	-2.5232	0.0152	0.6029	3.1932	0.0026	0.1666	47
2	Mining	4.2574	0.8056	0.4247	-0.17	-0.4606	0.6473	-0.0174	47
3	Construction	12.76	1.8995	0.0639	-0.8063	-1.7188	0.0925	0.0408	47
4	Manufacturing	-4.9119	-1.7067	0.0948	0.4726	2.3514	0.0231	0.0896	47
5	Transportation	-14.8059	-4.5055	0	1.1631	5.0687	0	0.3493	47
6	Wholesale	-0.8087	-0.1746	0.8622	0.1465	0.4531	0.6526	-0.0176	47
7	Retail	-11.6674	-2.8926	0.0059	0.9259	3.2873	0.002	0.1757	47
8	Finance	-5.8747	-1.6871	0.0985	0.5226	2.1491	0.037	0.0729	47
9	Services	-7.475	-2.4472	0.0184	0.6597	3.093	0.0034	0.157	47
B: Short-run									
		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	1.81	36.1671	0	0.4656	0.6776	0.5015	-0.0119	47
2	Mining	1.8232	20.5799	0	0.7715	0.6343	0.5291	-0.0132	47
3	Construction	1.2154	10.4567	0	0.714	0.4474	0.6567	-0.0177	47
4	Manufacturing	1.8546	36.2013	0	-0.0054	-0.0077	0.9939	-0.0222	47
5	Transportation	1.8481	26.8044	0	0.533	0.563	0.5762	-0.0151	47
6	Wholesale	1.2892	16.6615	0	0.8874	0.8353	0.4079	-0.0066	47
7	Retail	1.5899	21.0931	0	0.3213	0.3105	0.7576	-0.02	47
8	Finance	1.6073	26.5621	0	0.9714	1.1693	0.2485	0.0079	47
9	Services	1.971	34.9711	0	0.3687	0.4765	0.636	-0.0171	47

The Table reports the results from the time series regressions of the estimated coefficient $\hat{\alpha}$ on the long-run or short-run components of global temperature variable separately. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\hat{\alpha}$, x_t denotes the long-run or short-run components of global anomaly temperature, and ω_t denotes the error term. Panel A reports results by using the long-run component of global temperature variable as an explanatory variable. Panel B reports results by using the short-run component of global temperature variable as an explanatory variable. In both Panels, each row presents the result for the U.S. economy as a whole or the individual industries.

C: Long-run & Short-run

		Intercept	t	p_value	Weather_Long	t	p_value	Weather_Short	t	p_value	$AdjR^2$	N
1	U.S.	-6.7025	-2.4372	0.0189	0.5945	3.0959	0.0034	0.2299	0.3625	0.7187	0.1502	47
2	Mining	4.6999	0.8778	0.3848	-0.2009	-0.5373	0.5937	0.8511	0.6892	0.4943	-0.0294	47
3	Construction	13.3053	1.9542	0.057	-0.8444	-1.776	0.0827	1.0487	0.6678	0.5077	0.0288	47
4	Manufacturing	-5.0136	-1.7118	0.094	0.4797	2.3453	0.0236	-0.1956	-0.2895	0.7736	0.0707	47
5	Transportation	-14.7681	-4.4122	0.0001	1.1605	4.965	0	0.0729	0.0944	0.9252	0.3346	47
6	Wholesale	-0.3712	-0.0792	0.9372	0.116	0.3544	0.7247	0.8415	0.7787	0.4403	-0.0266	47
7	Retail	-11.6916	-2.8456	0.0067	0.9276	3.233	0.0023	-0.0464	-0.049	0.9611	0.157	47
8	Finance	-5.4715	-1.5585	0.1263	0.4944	2.0166	0.0499	0.7754	0.9576	0.3435	0.0712	47
9	Services	-7.4185	-2.3849	0.0215	0.6558	3.0189	0.0042	0.1087	0.1516	0.8802	0.1383	47

The Table reports the results from the time series regressions of the estimated coefficient $\hat{\alpha}$ on the long-run and short-run components of global temperature variable separately. The econometric model is $y_t = v_t + \gamma_L x\_L_t + \gamma_S x\_S_t + \omega_t$, , where y_t denotes $\hat{\alpha}$, $x_L_t$denotes the long-run component of global anomaly temperature; x_S_t denotes short-run component of global anomaly temperature, and ω_t denotes the error term. Each row presents the result for the U.S. economy as a whole or the individual industries.

Table 5.4.2-2 Regression of $\widehat{\beta_1}$ on the Cycle and Trend Components of Global Temperature

A: Long-run									
		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	-1.5391	-2.2477	0.0295	0.1438	3.0064	0.0043	0.1488	47
2	Mining	-3.6692	-3.2886	0.002	0.2977	3.821	0.0004	0.2282	47
3	Construction	-7.4963	-4.1118	0.0002	0.5717	4.4905	0	0.2941	47
4	Manufacturing	-1.9181	-3.0992	0.0033	0.1694	3.9197	0.0003	0.238	47
5	Transportation	-0.1703	-0.164	0.8705	0.0472	0.6506	0.5186	-0.0127	47
6	Wholesale	-2.3522	-1.9921	0.0524	0.2076	2.5178	0.0154	0.104	47
7	Retail	-0.8516	-0.7527	0.4556	0.0989	1.2524	0.2169	0.0122	47
8	Finance	-0.9124	-1.0553	0.2969	0.1002	1.6598	0.1039	0.0367	47
9	Services	-1.9805	-2.2844	0.0271	0.1753	2.8953	0.0058	0.1383	47
B: Short-run									
		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.5193	41.3063	0	-0.0843	-0.4883	0.6277	-0.0168	47
2	Mining	0.5934	27.5165	0	0.0435	0.147	0.8838	-0.0217	47
3	Construction	0.6894	18.8053	0	-0.3487	-0.6928	0.492	-0.0114	47
4	Manufacturing	0.5074	42.1436	0	0.0048	0.0288	0.9771	-0.0222	47
5	Transportation	0.5053	28.8379	0	-0.043	-0.1786	0.8591	-0.0215	47
6	Wholesale	0.6203	29.6474	0	-0.3057	-1.0643	0.2929	0.0029	47
7	Retail	0.5652	29.2341	0	-0.0092	-0.0348	0.9724	-0.0222	47
8	Finance	0.5225	35.6241	0	-0.272	-1.3509	0.1835	0.0176	47
9	Services	0.5293	33.3756	0	-0.0335	-0.1538	0.8785	-0.0217	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_1}$ on the long-run or short-run components of global temperature variable separately. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_1}$, x_t denotes the long-run or short-run component of global anomaly temperature, and ω_t denotes the error term. Panel A reports the results by using long-run components of global temperature variable as explanatory variable. Panel B reports the results by using short-run component of global temperature variable as explanatory variable. In both Panels, each row presents the result for the U.S. economy as a whole or the individual industries.

C: Long-run & Short-run

		Intercept	t	p_value	Weather_Long	t	p_value	Weather_Short	t	p_value	AdjR^2	N
1	U.S.	-1.6136	-2.3345	0.0242	0.149	3.0862	0.0035	-0.1433	-0.8991	0.3735	0.1451	47
2	Mining	-3.7085	-3.2661	0.0021	0.3005	3.7892	0.0005	-0.0756	-0.2886	0.7742	0.2121	47
3	Construction	-7.7998	-4.2915	0.0001	0.5929	4.6715	0	-0.5838	-1.3926	0.1707	0.3085	47
4	Manufacturing	-1.951	-3.1014	0.0034	0.1717	3.9086	0.0003	-0.0633	-0.4363	0.6647	0.224	47
5	Transportation	-0.2028	-0.1918	0.8487	0.0495	0.6699	0.5064	-0.0626	-0.2566	0.7987	-0.0342	47
6	Wholesale	-2.5569	-2.1763	0.0349	0.2219	2.7046	0.0097	-0.3937	-1.4529	0.1533	0.1256	47
7	Retail	-0.8771	-0.7614	0.4505	0.1007	1.2521	0.2171	-0.0492	-0.1851	0.854	-0.0095	47
8	Finance	-1.0768	-1.2579	0.2151	0.1117	1.8685	0.0684	-0.3163	-1.602	0.1163	0.0692	47
9	Services	-2.0348	-2.311	0.0256	0.1791	2.9125	0.0056	-0.1045	-0.5145	0.6095	0.124	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_1}$ on the long-run and short-run components of global temperature variable separately. The econometric model is $y_t = \upsilon_t + \gamma_L x\_L_t + \gamma_S x\_S_t + \omega_t$, , where y_t denotes $\widehat{\beta_1}$, $x_L_t$denotes the long-run component of global anomaly temperature; x_S_t denotes short-run component of global anomaly temperature, and ω_t denotes the error term. Each row presents the result for the U.S. economy as a whole or the individual industries.

Table 5.4.2-3 Regression of $\widehat{\beta_2}$ on the Cycle and Trend Components of Global Temperature

A: Long-run									
		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	3.1326	4.3114	0.0001	-0.1999	-3.9394	0.0003	0.2399	47
2	Mining	4.1261	4.0488	0.0002	-0.2774	-3.8982	0.0003	0.2358	47
3	Construction	5.8841	3.5433	0.0009	-0.4014	-3.4617	0.0012	0.1927	47
4	Manufacturing	3.002	4.5405	0	-0.19	-4.1149	0.0002	0.2573	47
5	Transportation	3.2166	2.668	0.0106	-0.2028	-2.4093	0.0201	0.0946	47
6	Wholesale	2.4605	2.2948	0.0265	-0.1538	-2.0539	0.0458	0.0654	47
7	Retail	4.9489	4.717	0	-0.3236	-4.4169	0.0001	0.2869	47
8	Finance	1.6117	1.5629	0.1251	-0.0938	-1.3023	0.1994	0.0149	47
9	Services	5.5317	5.9446	0	-0.3698	-5.6905	0	0.4055	47
B: Short-run									
		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	0.2707	19.1252	0	0.0232	0.1196	0.9053	-0.0219	47
2	Mining	0.1541	7.8226	0	-0.1807	-0.6681	0.5075	-0.0122	47
3	Construction	0.1361	4.3811	0.0001	0.4112	0.9639	0.3402	-0.0015	47
4	Manufacturing	0.2817	21.634	0	0.039	0.2181	0.8283	-0.0211	47
5	Transportation	0.3123	14.5148	0	-0.0385	-0.1302	0.897	-0.0218	47
6	Wholesale	0.2585	13.9607	0	0.3195	1.2568	0.2153	0.0124	47
7	Retail	0.3155	14.955	0	0.0247	0.0854	0.9324	-0.0221	47
8	Finance	0.2689	15.2616	0	0.0833	0.3443	0.7322	-0.0195	47
9	Services	0.2372	11.5703	0	0.0019	0.0069	0.9945	-0.0222	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_2}$ on the long-run or short-run components of global temperature variable separately. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_2}$, x_t denotes the long-run or short-run component of global anomaly temperature, and ω_t denotes the error term. Panel A reports the results by using long-run components of global temperature variable as explanatory variable. Panel B reports the results by using short-run component of global temperature variable as explanatory variable. In both Panels, each row presents the result for the U.S. economy as a whole or the individual industries.

C: Long-run & Short-run

		Intercept	t	p_value	Weather_Long	t	p_value	Weather_Short	t	p_value	AdjR^2	N
1	U.S.	3.1867	4.3238	0.0001	-0.2037	-3.9571	0.0003	0.104	0.6117	0.5439	0.2292	47
2	Mining	4.0888	3.9428	0.0003	-0.2748	-3.7947	0.0004	-0.0718	-0.3001	0.7655	0.2201	47
3	Construction	6.185	3.7513	0.0005	-0.4225	-3.6692	0.0007	0.5787	1.5218	0.1352	0.2157	47
4	Manufacturing	3.0624	4.576	0	-0.1942	-4.1556	0.0001	0.116	0.7515	0.4564	0.25	47
5	Transportation	3.2387	2.6378	0.0115	-0.2044	-2.3838	0.0215	0.0426	0.1503	0.8812	0.0745	47
6	Wholesale	2.6613	2.5043	0.0161	-0.1678	-2.2614	0.0287	0.386	1.575	0.1224	0.0952	47
7	Retail	5.0297	4.7276	0	-0.3292	-4.4316	0.0001	0.1553	0.6327	0.5302	0.2773	47
8	Finance	1.6752	1.5995	0.1169	-0.0982	-1.3429	0.1862	0.1222	0.5061	0.6153	-0.0017	47
9	Services	5.6101	5.9506	0	-0.3753	-5.6998	0	0.1507	0.693	0.4919	0.3986	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_2}$ on the long-run and short-run components of global temperature variable separately. The econometric model is $y_t = \upsilon_t + \gamma_L x\_L_t + \gamma_S x\_S_t + \omega_t$, , where y_t denotes $\widehat{\beta_2}$, $x_L_t$denotes the long-run component of global anomaly temperature; x_S_t denotes short-run component of global anomaly temperature, and ω_t denotes the error term. Each row presents the result for the U.S. economy as a whole or the individual industries.

Table 5.4.2-4 Regression of $\widehat{\beta_3}$ on the Cycle and Trend Components of Global Temperature

A: Long-run									
		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	1.4811	4.1223	0.0002	-0.0949	-3.7819	0.0005	0.2243	47
2	Mining	0.9622	1.6637	0.1031	-0.055	-1.3614	0.1802	0.0182	47
3	Construction	1.8208	1.4282	0.1601	-0.1168	-1.3114	0.1964	0.0154	47
4	Manufacturing	2.0937	4.9412	0	-0.1365	-4.6117	0	0.3058	47
5	Transportation	-1.4351	-2.5423	0.0145	0.1057	2.6813	0.0102	0.1186	47
6	Wholesale	-0.1116	-0.1658	0.8691	0.017	0.3621	0.719	-0.0193	47
7	Retail	0.5746	1.4081	0.166	-0.0338	-1.1852	0.2421	0.0087	47
8	Finance	1.6385	2.6784	0.0103	-0.1038	-2.4296	0.0192	0.0963	47
9	Services	1.2585	2.1307	0.0386	-0.0783	-1.8991	0.064	0.0536	47
B: Short-run									
		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	0.1225	17.7121	0	0.041	0.4318	0.668	-0.018	47
2	Mining	0.1749	17.6947	0	0.0702	0.517	0.6077	-0.0162	47
3	Construction	0.149	6.8565	0	0.1807	0.6054	0.5479	-0.014	47
4	Manufacturing	0.1399	16.1989	0	0.0197	0.166	0.8689	-0.0216	47
5	Transportation	0.0782	7.6725	0	0.0507	0.3622	0.7189	-0.0193	47
6	Wholesale	0.1321	11.6674	0	0.0018	0.0116	0.9908	-0.0222	47
7	Retail	0.091	13.1194	0	-0.0525	-0.5507	0.5845	-0.0154	47
8	Finance	0.1523	14.097	0	0.1513	1.0198	0.3133	0.0009	47
9	Services	0.137	13.2831	0	0.0072	0.0509	0.9597	-0.0222	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_3}$ on the long-run or short-run components of global temperature variable separately. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_3}$, x_t denotes the long-run or short-run component of global anomaly temperature, and ω_t denotes the error term. Panel A reports the results by using long-run components of global temperature variable as explanatory variable. Panel B reports the results by using short-run component of global temperature variable as explanatory variable. In both Panels, each row presents the result for the U.S. economy as a whole or the individual industries.

C: Long-run & Short-run

		Intercept	t	p_value	Weather_Long	t	p_value	Weather_Short	t	p_value	$AdjR^2$	N
1	U.S.	1.5225	4.203	0.0001	-0.0978	-3.8654	0.0004	0.0798	0.9545	0.345	0.2228	47
2	Mining	1.0107	1.7248	0.0916	-0.0584	-1.4266	0.1608	0.0933	0.6904	0.4936	0.0067	47
3	Construction	1.9406	1.5044	0.1396	-0.1251	-1.389	0.1718	0.2303	0.774	0.4431	0.0066	47
4	Manufacturing	2.1326	4.9729	0	-0.1392	-4.6474	0	0.0749	0.7569	0.4532	0.2992	47
5	Transportation	-1.4304	-2.4878	0.0167	0.1054	2.6242	0.0119	0.0089	0.0674	0.9466	0.0987	47
6	Wholesale	-0.1142	-0.1665	0.8685	0.0172	0.3593	0.7211	-0.005	-0.0317	0.9748	-0.0424	47
7	Retail	0.554	1.3353	0.1886	-0.0323	-1.1161	0.2705	-0.0396	-0.4143	0.6807	-0.0099	47
8	Finance	1.74	2.8527	0.0066	-0.1109	-2.6033	0.0125	0.1953	1.3879	0.1721	0.1145	47
9	Services	1.2787	2.1271	0.0391	-0.0797	-1.8995	0.0641	0.0388	0.28	0.7808	0.0338	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_3}$ on the long-run and short-run components of global temperature variable separately. The econometric model is $y_t = \upsilon_t + \gamma_L x\_L_t + \gamma_S x\_S_t + \omega_t$, , where y_t denotes $\widehat{\beta_3}$, x_L_t denotes the long-run component of global anomaly temperature; x_S_t denotes short-run component of global anomaly temperature, and ω_t denotes the error term. Each row presents the result for the U.S. economy as a whole or the individual industries.

Table 5.4.2-5 Regression of $\widehat{\beta_4}$ on the Cycle and Trend Components of Global Temperature

A: Long-run									
		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	-2.8699	-14.3294	0	0.2068	14.7888	0	0.8256	47
2	Mining	-2.2186	-6.3376	0	0.1603	6.5577	0	0.4773	47
3	Construction	0.1394	0.3837	0.703	-0.006	-0.2348	0.8154	-0.021	47
4	Manufacturing	-3.2321	-15.0717	0	0.2326	15.5356	0	0.8394	47
5	Transportation	-1.2853	-3.6852	0.0006	0.0943	3.8719	0.0003	0.2332	47
6	Wholesale	-1.0398	-4.0372	0.0002	0.0764	4.2461	0.0001	0.2702	47
7	Retail	-3.3051	-9.112	0	0.2374	9.3733	0	0.6538	47
8	Finance	-1.7093	-6.7907	0	0.1235	7.0238	0	0.5124	47
9	Services	-4.8517	-13.5655	0	0.3481	13.9375	0	0.8077	47
B: Short-run									
		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	0.0916	11.2501	0	0.0176	0.1577	0.8754	-0.0217	47
2	Mining	0.0767	9.34	0	0.036	0.3188	0.7513	-0.0199	47
3	Construction	0.0541	8.8865	0	-0.0421	-0.5034	0.6171	-0.0165	47
4	Manufacturing	0.099	10.8961	0	0.0095	0.0765	0.9393	-0.0221	47
5	Transportation	0.065	9.6229	0	-0.0408	-0.4407	0.6615	-0.0178	47
6	Wholesale	0.0536	10.4766	0	-0.0037	-0.0528	0.9581	-0.0222	47
7	Retail	0.0943	9.0099	0	-0.0072	-0.0504	0.96	-0.0222	47
8	Finance	0.0584	9.5447	0	-0.0065	-0.0778	0.9384	-0.0221	47
9	Services	0.1323	9.5577	0	0.04	0.2103	0.8344	-0.0212	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_4}$ on the long-run or short-run components of global temperature variable separately. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_4}$, x_t denotes the long-run or short-run component of global anomaly temperature, and ω_t denotes the error term. Panel A reports the results by using long-run components of global temperature variable as explanatory variable. Panel B reports the results by using short-run component of global temperature variable as explanatory variable. In both Panels, each row presents the result for the U.S. economy as a whole or the individual industries.

C: Long-run & Short-run

		Intercept	t	p_value	Weather_Long	t	p_value	Weather_Short	t	p_value	AdjR^2	N
1	U.S.	-2.9039	-14.5557	0	0.2092	15.0169	0	-0.0653	-1.4194	0.1628	0.8294	47
2	Mining	-2.2331	-6.2707	0	0.1613	6.487	0	-0.028	-0.3409	0.7348	0.4668	47
3	Construction	0.1185	0.3209	0.7498	-0.0045	-0.1743	0.8624	-0.0403	-0.4734	0.6382	-0.0389	47
4	Manufacturing	-3.2757	-15.4914	0	0.2357	15.9618	0	-0.0839	-1.7201	0.0924	0.8461	47
5	Transportation	-1.3266	-3.7743	0.0005	0.0972	3.9597	0.0003	-0.0794	-0.9792	0.3329	0.2325	47
6	Wholesale	-1.0577	-4.0466	0.0002	0.0776	4.2524	0.0001	-0.0345	-0.572	0.5702	0.2591	47
7	Retail	-3.3586	-9.2441	0	0.2412	9.5051	0	-0.1029	-1.2274	0.2262	0.6576	47
8	Finance	-1.7386	-6.8514	0	0.1255	7.0827	0	-0.0563	-0.9618	0.3414	0.5116	47
9	Services	-4.9034	-13.6785	0	0.3517	14.0497	0	-0.0995	-1.2029	0.2355	0.8096	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_4}$ on the long-run and short-run components of global temperature variable separately. The econometric model is $y_t = \upsilon_t + \gamma_L x\_L_t + \gamma_S x\_S_t + \omega_t$, , where y_t denotes $\widehat{\beta_4}$, x_L_t denotes the long-run component of global anomaly temperature; x_S_t denotes short-run component of global anomaly temperature, and ω_t denotes the error term. Each row presents the result for the U.S. economy as a whole or the individual industries.

5.5 Other Measures of Climate Risk

5.5.1 U.S. Precipitation

Table 5.5.1-1 to Table 5.5.1-5 report the results from regressions using U.S. precipitation data as the explanatory weather variable. In these Tables, each row demonstrates the results for the U.S. economy as a whole or individual U.S. industries.

Table 5.5.1-1 shows that U.S. precipitation has a positive impact on $\hat{\alpha}$ for the U.S. economy as a whole and most industries except Mining, but all the coefficients are not significant.

Table 5.5.1-2 shows that U.S. precipitation has a negative impact on $\widehat{\beta_1}$ for the U.S. economy as a whole and some U.S. industries. Other industries have a negative coefficient. None of the coefficients are statistically significant.

Table 5.5.1-3 shows that U.S. precipitation has a positive $\widehat{\beta_2}$ coefficient for the U.S. economy as a whole and most industries. However, again the coefficients are not significant.

Tables 5.5.1-4 show the association of U.S. precipitation with the elasticity on dividends and Tables 5.5.1-5 show its association with the elasticity of the other accounting variable. In all cases the coefficients on U.S. precipitation are not statistically significant.

Table 5.5.1-1 Regression of $\hat{\alpha}$ on U.S. Precipitation

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	1.2943	1.7222	0.0919	0.0167	0.688	0.495	-0.0116	47
2	Mining	2.8553	2.1509	0.0369	-0.0333	-0.779	0.4401	-0.0086	47
3	Construction	-1.0223	-0.5953	0.5546	0.0723	1.3061	0.1982	0.0151	47
4	Manufacturing	1.4615	1.905	0.0632	0.0127	0.5136	0.6101	-0.0163	47
5	Transportation	0.8142	0.7923	0.4323	0.0334	1.0086	0.3186	0.0004	47
6	Wholesale	0.7901	0.6761	0.5025	0.0161	0.4283	0.6705	-0.0181	47
7	Retail	0.6839	0.6078	0.5464	0.0293	0.8072	0.4238	-0.0076	47
8	Finance	0.8755	0.9558	0.3443	0.0236	0.8011	0.4273	-0.0078	47
9	Services	1.4827	1.7537	0.0863	0.0158	0.579	0.5655	-0.0147	47

The Table reports the results from the time series regressions of the estimated coefficient $\hat{\alpha}$ from the first stage modelling on U.S. precipitation data. The econometric models are $y_t = v_t + \gamma x_t + \omega_t$, where y_t denotes $\hat{\alpha}$, x_t denotes U.S. precipitation, and ω_t denotes the error term. Each row represents the results for the U.S. economy as a whole or individual U.S. industries.

Table 5.5.1-2 Regression of $\widehat{\beta_1}$ on U.S. Precipitation

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.5666	2.9948	0.0045	-0.0015	-0.2505	0.8033	-0.0208	47
2	Mining	0.3868	1.1994	0.2367	0.0067	0.6422	0.524	-0.0129	47
3	Construction	1.2095	2.2072	0.0324	-0.0168	-0.9516	0.3464	-0.0021	47
4	Manufacturing	0.5479	3.0316	0.004	-0.0013	-0.2245	0.8234	-0.0211	47
5	Transportation	0.7582	2.9103	0.0056	-0.0082	-0.973	0.3358	-0.0012	47
6	Wholesale	0.4178	1.319	0.1939	0.0065	0.6406	0.525	-0.013	47
7	Retail	0.5391	1.8568	0.0699	0.0008	0.0901	0.9286	-0.022	47
8	Finance	0.6566	2.9341	0.0052	-0.0043	-0.6013	0.5507	-0.0141	47
9	Services	0.5765	2.4209	0.0196	-0.0015	-0.1988	0.8433	-0.0213	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_1}$ from the first stage modelling on U.S. precipitation data. The econometric models are $y_t = v_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_1}$, x_t denotes U.S. precipitation, and ω_t denotes the error term. Each row represents the results for the U.S. economy as a whole or individual U.S. industries.

Table 5.5.1-3 Regression of $\widehat{\beta_2}$ on U.S. Precipitation

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.2254	1.0608	0.2944	0.0015	0.2136	0.8318	-0.0212	47
2	Mining	0.4312	1.4643	0.1501	-0.0089	-0.9433	0.3506	-0.0024	47
3	Construction	-0.0637	-0.1354	0.8929	0.0065	0.426	0.6721	-0.0181	47
4	Manufacturing	0.2483	1.2692	0.2109	0.0011	0.1714	0.8646	-0.0216	47
5	Transportation	0.1064	0.3308	0.7423	0.0066	0.6413	0.5246	-0.013	47
6	Wholesale	0.5875	2.1089	0.0406	-0.0106	-1.1833	0.2429	0.0086	47
7	Retail	0.5323	1.6883	0.0983	-0.007	-0.6889	0.4944	-0.0116	47
8	Finance	0.1289	0.4877	0.6281	0.0045	0.5316	0.5976	-0.0158	47
9	Services	0.0096	0.0313	0.9752	0.0073	0.7455	0.4598	-0.0098	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_2}$ from the first stage modelling on U.S. precipitation data. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_2}$, x_t denotes U.S. precipitation, and ω_t denotes the error term. Each row represents the results for the U.S. economy as a whole or individual U.S. industries.

Table 5.5.1-4 Regression of $\widehat{\beta_3}$ on U.S. Precipitation

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.1104	1.0615	0.2941	0.0004	0.116	0.9082	-0.0219	47
2	Mining	-0.0094	-0.0644	0.9489	0.006	1.2627	0.2132	0.0128	47
3	Construction	-0.3902	-1.2281	0.2258	0.0174	1.7012	0.0958	0.0395	47
4	Manufacturing	0.0893	0.6894	0.4941	0.0016	0.3916	0.6972	-0.0188	47
5	Transportation	0.0063	0.0413	0.9673	0.0023	0.4713	0.6397	-0.0172	47
6	Wholesale	0.2088	1.2306	0.2249	-0.0025	-0.453	0.6527	-0.0176	47
7	Retail	-0.0546	-0.5337	0.5961	0.0047	1.4268	0.1605	0.022	47
8	Finance	0.198	1.2075	0.2335	-0.0015	-0.279	0.7815	-0.0205	47
9	Services	0.2519	1.6364	0.1087	-0.0037	-0.7481	0.4583	-0.0097	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_3}$ from the first stage modelling on U.S. precipitation data. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_3}$, x_t denotes U.S. precipitation, and ω_t denotes the error term. Each row represents the results for the U.S. economy as a whole or individual U.S. industries.

Table 5.5.1-5 Regression of $\widehat{\beta_4}$ on U.S. Precipitation

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.1558	1.2772	0.2081	-0.0021	-0.5272	0.6007	-0.0159	47
2	Mining	0.1464	1.19	0.2403	-0.0023	-0.5677	0.5731	-0.015	47
3	Construction	0.0898	0.9804	0.3321	-0.0012	-0.3904	0.6981	-0.0188	47
4	Manufacturing	0.1611	1.1834	0.2429	-0.002	-0.4572	0.6497	-0.0175	47
5	Transportation	0.2148	2.1676	0.0355	-0.0048	-1.5156	0.1366	0.0274	47
6	Wholesale	0.0852	1.1095	0.2731	-0.001	-0.4116	0.6826	-0.0184	47
7	Retail	0.1309	0.8333	0.4091	-0.0012	-0.2335	0.8164	-0.021	47
8	Finance	0.0755	0.8219	0.4154	-0.0006	-0.1867	0.8528	-0.0214	47
9	Services	0.2301	1.1085	0.2735	-0.0032	-0.4719	0.6393	-0.0172	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_4}$ from the first stage modelling on U.S. precipitation data. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_4}$, x_t denotes U.S. precipitation, and ω_t denotes the error term. Each row represents the results for the U.S. economy as a whole or individual U.S. industries.

5.5.2 U.S. Palmer Z Index

Tables 5.5.2-1 to Table 5.5.2-5 report the results from regressions using the U.S. Palmer Z Index as an explanatory variable. In these Tables, each row demonstrates the results for the U.S. economy as a whole or individual U.S. industries.

Table 5.5.2-1 shows that the U.S. Palmer Z Index has a positive association with $\hat{\alpha}$ for U.S. economy as a whole and most industries, but all the coefficients are not statistically significant except for Construction.

Table 5.5.2-2 shows that the U.S Palmer Z Index has a negative association with $\widehat{\beta_1}$ for U.S. economy as a whole and most industries except for Wholesale. All the coefficients are not significant.

Table 5.5.2-3 shows that the U.S Palmer Z Index has a positive association with $\widehat{\beta_2}$ for U.S. economy as a whole and most industries. However, the coefficients are not significant.

Table 5.5.2-4 shows the association of the U.S. Palmer Z Index with $\widehat{\beta_3}$. All the coefficients on U.S. Palmer Z Index are not significant. Table 5.5.2-5 shows the association of the U.S. Palmer Z Index with $\widehat{\beta_4}$. The results for U.S. economy as a whole, Manufacturing, Transportation, and Services are significant.

5.5.2-1 Regression of $\hat{\alpha}$ on the U.S. Palmer Z Index

		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	1.8081	34.3717	0	0.0079	0.1371	0.8916	-0.0218	47
2	Mining	1.8381	19.812	0	-0.0545	-0.5392	0.5924	-0.0157	47
3	Construction	1.1557	9.796	0	0.2226	1.7323	0.0901	0.0417	47
4	Manufacturing	1.8502	34.5571	0	0.0162	0.2779	0.7824	-0.0205	47
5	Transportation	1.85	25.5639	0	-0.0063	-0.0802	0.9364	-0.0221	47
6	Wholesale	1.2817	15.7337	0	0.029	0.3268	0.7453	-0.0198	47
7	Retail	1.5786	20.0551	0	0.0422	0.4928	0.6245	-0.0167	47
8	Finance	1.6049	24.9854	0	0.0103	0.1474	0.8835	-0.0217	47
9	Services	1.966	33.2971	0	0.0189	0.2946	0.7697	-0.0203	47

The Table reports the results from the time series regressions of the estimated coefficient $\hat{\alpha}$ from the first stage modelling on U.S. precipitation data. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\hat{\alpha}$, x_t denotes U.S. Palmer Z Index, and ω_t denotes the error term. Each row represents the results for the U.S. economy as a whole or individual U.S. industries.

5.5.2-2 Regression of $\widehat{\beta_1}$ on the U.S. Palmer Z Index

		Intercept	t	p_value	Weather	t	p_value	$AdjR^2$	N
1	U.S.	0.5216	39.7096	0	-0.0085	-0.5921	0.5568	-0.0143	47
2	Mining	0.5962	26.4785	0	-0.0104	-0.4258	0.6723	-0.0181	47
3	Construction	0.7066	18.8267	0	-0.0643	-1.5739	0.1225	0.0311	47
4	Manufacturing	0.51	40.7056	0	-0.0094	-0.6909	0.4932	-0.0115	47
5	Transportation	0.5098	28.0296	0	-0.0169	-0.8513	0.3991	-0.006	47
6	Wholesale	0.6166	27.9207	0	0.0134	0.5572	0.5801	-0.0152	47
7	Retail	0.5676	28.1165	0	-0.0089	-0.4034	0.6885	-0.0185	47
8	Finance	0.5244	33.5854	0	-0.0076	-0.4473	0.6568	-0.0177	47
9	Services	0.5342	32.5771	0	-0.0184	-1.0326	0.3073	0.0014	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_1}$ from the first stage modelling on U.S. precipitation data. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_1}$, x_t denotes U.S. Palmer Z Index, and ω_t denotes the error term. Each row represents the results for the U.S. economy as a whole or individual U.S. industries.

5.5.2-3 Regression $\widehat{\beta_2}$ on the U.S. Palmer Z Index

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.2674	18.1756	0	0.0121	0.7559	0.4536	-0.0094	47
2	Mining	0.1521	7.3516	0	0.0073	0.3249	0.7468	-0.0198	47
3	Construction	0.1297	3.9715	0.0003	0.0244	0.6845	0.4972	-0.0117	47
4	Manufacturing	0.2794	20.5796	0	0.0086	0.5801	0.5647	-0.0146	47
5	Transportation	0.3048	13.7382	0	0.0278	1.1525	0.2552	0.0071	47
6	Wholesale	0.2661	13.7635	0	-0.0278	-1.3197	0.1936	0.0159	47
7	Retail	0.3147	14.2599	0	0.0032	0.1345	0.8936	-0.0218	47
8	Finance	0.2669	14.4828	0	0.0079	0.3922	0.6968	-0.0187	47
9	Services	0.2248	10.9677	0	0.0461	2.0642	0.0448	0.0662	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_2}$ from the first stage modelling on U.S. precipitation data. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_2}$, x_t denotes U.S. Palmer Z Index, and ω_t denotes the error term. Each row represents the results for the U.S. economy as a whole or individual U.S. industries.

5.5.2-4 Regression of $\widehat{\beta_3}$ on the U.S. Palmer Z Index

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.1213	16.7947	0	0.0044	0.5622	0.5768	-0.0151	47
2	Mining	0.1711	16.799	0	0.0143	1.286	0.205	0.014	47
3	Construction	0.139	6.2492	0	0.0374	1.5456	0.1292	0.0293	47
4	Manufacturing	0.1366	15.3817	0	0.012	1.2448	0.2196	0.0118	47
5	Transportation	0.0807	7.6085	0	-0.0091	-0.7896	0.4339	-0.0083	47
6	Wholesale	0.1349	11.4606	0	-0.0101	-0.7848	0.4367	-0.0084	47
7	Retail	0.0876	12.3875	0	0.0128	1.6603	0.1038	0.0368	47
8	Finance	0.1519	13.2866	0	0.002	0.1575	0.8755	-0.0217	47
9	Services	0.1382	12.8401	0	-0.0047	-0.4034	0.6886	-0.0185	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_3}$ from the first stage modelling on U.S. precipitation data. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_3}$, x_t denotes U.S. Palmer Z Index, and ω_t denotes the error term. Each row represents the results for the U.S. economy as a whole or individual U.S. industries.

5.5.2-5 Regression of $\widehat{\beta_4}$ on the U.S. Palmer Z Index

		Intercept	t	p_value	Weather	t	p_value	AdjR^2	N
1	U.S.	0.0966	11.883	0	-0.0186	-2.099	0.0415	0.0689	47
2	Mining	0.0808	9.6722	0	-0.015	-1.6524	0.1054	0.0363	47
3	Construction	0.054	8.4475	0	0.0005	0.0761	0.9396	-0.0221	47
4	Manufacturing	0.1049	11.6167	0	-0.0217	-2.2115	0.0321	0.078	47
5	Transportation	0.0693	10.2943	0	-0.016	-2.1866	0.034	0.076	47
6	Wholesale	0.0552	10.4093	0	-0.0057	-0.9805	0.3321	-0.0008	47
7	Retail	0.0986	9.1885	0	-0.0159	-1.3622	0.1799	0.0183	47
8	Finance	0.0606	9.6087	0	-0.0081	-1.1774	0.2452	0.0083	47
9	Services	0.1413	10.2706	0	-0.0332	-2.2176	0.0317	0.0785	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_4}$ from the first stage modelling on U.S. precipitation data. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_4}$, x_t denotes U.S. Palmer Z Index, and ω_t denotes the error term. Each row represents the results for the U.S. economy as a whole or individual U.S. industries.

5.5.3 World CO_2 Emissions

Table 5.5.3-1 to 5.5.3-5 report the results using World CO_2 emissions as the explanatory weather variable in the regressions for $\hat{\alpha}$, $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\widehat{\beta_3}$, and $\widehat{\beta_4}$. Each row of the Tables represents the regression results for the U.S economy as a whole and individual U.S. industries.

The results show that the coefficients for $\widehat{\beta_3}$, and $\widehat{\beta_4}$ are significant for the U.S. economy as a whole but generally the coefficient are not significant.

5.5.3-1 Regression of $\hat{\alpha}$ on World CO_2 Emissions

		Intercept	t	p_value	W_CO2	t	p_value	AdjR2	N
1	U.S.	1.8705	2.6998	0.01	0.0173	0.1077	0.9148	-0.0235	47
2	Mining	0.3461	0.2756	0.7842	0.3565	1.224	0.2278	0.0115	47
3	Construction	5.6463	3.1275	0.0032	-1.0282	-2.4558	0.0183	0.1047	47
4	Manufacturing	2.6515	3.7913	0.0005	-0.1526	-0.9411	0.352	-0.0027	47
5	Transportation	0.8124	0.8958	0.3755	0.2489	1.1834	0.2433	0.0092	47
6	Wholesale	3.2066	2.9036	0.0059	-0.3991	-1.5586	0.1266	0.0322	47
7	Retail	1.1513	1.0733	0.2893	0.1199	0.4818	0.6324	-0.0182	47
8	Finance	2.3556	2.521	0.0156	-0.1466	-0.6767	0.5023	-0.0128	47
9	Services	1.5217	2.0299	0.0487	0.1352	0.7776	0.4412	-0.0093	47

The Table reports the results from the time series regressions of the estimated coefficient $\hat{\alpha}$ on World CO_2 emissions. The econometric models are $y_t = v_t + \gamma x_t + \omega_t$, where y_t denotes $\hat{\alpha}$, x_t denotes World CO_2 emissions, and ω_t denotes the error term. Each row shows results for the U.S. economy as a whole or individual U.S. industries.

5.5.3-2 Regression of $\widehat{\beta_1}$ on World CO_2 Emissions

		Intercept	t	p_value	W_CO2	t	p_value	AdjR2	N
1	U.S.	0.566	2.8139	0.0074	-0.0107	-0.2303	0.819	-0.0225	47
2	Mining	0.7004	2.2975	0.0266	-0.0266	-0.3766	0.7084	-0.0204	47
3	Construction	-1.0734	-1.7785	0.0826	0.4154	2.9682	0.0049	0.1537	47
4	Manufacturing	0.4211	2.2701	0.0284	0.0198	0.4613	0.6469	-0.0186	47
5	Transportation	0.7239	2.4764	0.0174	-0.0485	-0.7159	0.478	-0.0115	47
6	Wholesale	0.3863	1.1377	0.2617	0.0495	0.6281	0.5333	-0.0143	47
7	Retail	0.7171	1.9614	0.0565	-0.0324	-0.382	0.7044	-0.0203	47
8	Finance	0.4244	1.795	0.0798	0.0232	0.4228	0.6746	-0.0195	47
9	Services	0.6366	2.4213	0.0199	-0.0259	-0.4242	0.6736	-0.0194	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_1}$ on World CO_2 emissions. The econometric models are $y_t = v_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_1}$, x_t denotes World CO_2 emissions, and ω_t denotes the error term. Each row shows results for the U.S. economy as a whole or individual U.S. industries.

5.5.3-3 Regression of $\widehat{\beta_2}$ on World CO_2 Emissions

		Intercept	t	p_value	W_CO2	t	p_value	AdjR2	N
1	U.S.	0.2842	1.1659	0.2502	-0.0092	-0.1624	0.8718	-0.0232	47
2	Mining	0.2725	0.9592	0.3429	-0.0264	-0.4014	0.6902	-0.0199	47
3	Construction	1.4088	1.987	0.0535	-0.3017	-1.8347	0.0736	0.0522	47
4	Manufacturing	0.3661	1.5888	0.1196	-0.0261	-0.4878	0.6283	-0.018	47
5	Transportation	0.1997	0.5226	0.604	0.0234	0.2643	0.7929	-0.0221	47
6	Wholesale	-0.1566	-0.4802	0.6336	0.0949	1.255	0.2164	0.0132	47
7	Retail	0.8558	2.0386	0.0478	-0.1324	-1.3597	0.1812	0.0194	47
8	Finance	0.3737	1.4645	0.1505	-0.0309	-0.5221	0.6044	-0.0172	47
9	Services	0.6463	1.7959	0.0797	-0.1016	-1.2181	0.23	0.0111	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_2}$ on World CO_2 emissions. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_2}$, x_t denotes World CO_2 emissions, and ω_t denotes the error term. Each row shows results for the U.S. economy as a whole or individual U.S. industries.

5.5.3-4 Regression of $\widehat{\beta_3}$ on World CO_2 Emissions

		Intercept	t	p_value	W_CO2	t	p_value	AdjR2	N
1	U.S.	0.3111	3.6811	0.0007	-0.0481	-2.4524	0.0184	0.1044	47
2	Mining	0.461	2.2236	0.0316	-0.0667	-1.3876	0.1726	0.0211	47
3	Construction	0.56	1.5776	0.1222	-0.1	-1.2153	0.231	0.011	47
4	Manufacturing	0.3873	3.6132	0.0008	-0.0587	-2.3599	0.023	0.0961	47
5	Transportation	-0.1499	-0.9106	0.3677	0.0452	1.1834	0.2433	0.0092	47
6	Wholesale	0.2896	1.2265	0.2268	-0.0367	-0.6697	0.5067	-0.013	47
7	Retail	0.167	1.5062	0.1395	-0.0186	-0.7227	0.4739	-0.0112	47
8	Finance	0.3503	1.7961	0.0797	-0.0479	-1.0583	0.296	0.0028	47
9	Services	0.278	1.8392	0.073	-0.0311	-0.8868	0.3802	-0.005	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_3}$ on World CO_2 emissions. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_3}$, x_t denotes World CO_2 emissions, and ω_t denotes the error term. Each row shows results for the U.S. economy as a whole or individual U.S. industries.

5.5.3-5 Regression of $\widehat{\beta_4}$ on World CO_2 Emissions

		Intercept	t	p_value	W_CO$_2$	t	p_value	AdjR^2	N
1	U.S.	-0.3742	-3.2294	0.0024	0.1133	4.2152	0.0001	0.2806	47
2	Mining	-0.3841	-2.5743	0.0137	0.1124	3.2492	0.0023	0.1818	47
3	Construction	-0.1124	-0.6414	0.5248	0.0453	1.1132	0.2719	0.0055	47
4	Manufacturing	-0.5053	-3.7075	0.0006	0.1466	4.6393	0	0.3231	47
5	Transportation	-0.0824	-0.6715	0.5056	0.0394	1.3843	0.1736	0.0209	47
6	Wholesale	0.0398	0.3496	0.7284	0.008	0.3025	0.7638	-0.0216	47
7	Retail	-0.8871	-5.9557	0	0.2367	6.8535	0	0.5167	47
8	Finance	-0.212	-2.6412	0.0116	0.0659	3.5415	0.001	0.2116	47
9	Services	-0.8558	-4.8956	0	0.2355	5.809	0	0.4323	47

The Table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_4}$ on World CO_2 emissions. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_4}$, x_t denotes World CO_2 emissions, and ω_t denotes the error term. Each row shows results for the U.S. economy as a whole or individual U.S. industries.

5.5.4 U.S. CO_2 Emissions

Tables 5.5.4-1 to Table 5.5.4-5 report the results of using U.S. CO_2 emissions as the explanatory weather variable in the regressions to test the impact on the accounting elasticities. Each row of the table represents the regression results for the U.S economy as a whole or individual U.S. industries. Compared with the results based on World CO_2 emission, the results based on U.S. CO_2 emissions have significant association with most of the elasticities obtained from stage one of the estimation process.

Table 5.5.4-1 shows that U.S CO_2 emissions have a negative association with $\hat{\alpha}$ for the U.S. economy as a whole and most U.S. industries but only in the cases of Mining, Transportation, and Services are the coefficient significant.

Table 5.5.4-2 shows that U.S. CO_2 emissions have significantly negative association with $\widehat{\beta_1}$ for the U.S. economy as a whole and all industries other than Finance.

Table 5.5.4-3 shows that U.S. CO_2 emissions have a significantly positive association with $\widehat{\beta_2}$ for the U.S. economy as a whole and all U.S. industries.

The results for $\widehat{\beta_1}$ and $\widehat{\beta_2}$ are the exact opposite to the results obtained for global temperature.

The results in Table 5.5.4-4 show positive and significant coefficient only for the U.S. economy as a whole and Manufacturing. In Table 5.5.4-5, U.S. CO_2 emissions have significantly negative association for $\widehat{\beta_4}$ in all cases other than Wholesale.

5.5.4-1 Regression of $\hat{\alpha}$ on U.S. CO_2 Emissions

		Intercept	t	p_value	U.S.CO_2	t	p_value	AdjR^2	N
1	U.S.	2.9345	4.535	0	-0.0508	-1.5335	0.1326	0.0305	47
2	Mining	-1.4889	-1.341	0.1871	0.1729	3.0422	0.004	0.1611	47
3	Construction	-0.2599	-0.1414	0.8882	0.0762	0.8094	0.4229	-0.0081	47
4	Manufacturing	3.0094	4.5616	0	-0.0521	-1.542	0.1306	0.031	47
5	Transportation	3.8145	4.5812	0	-0.0992	-2.3261	0.0249	0.093	47
6	Wholesale	1.6034	1.4713	0.1487	-0.0058	-0.1046	0.9172	-0.0235	47
7	Retail	2.837	2.7918	0.0079	-0.0601	-1.1547	0.2548	0.0077	47
8	Finance	2.538	2.8431	0.0069	-0.0417	-0.9134	0.3662	-0.0039	47
9	Services	3.3938	4.8733	0	-0.0663	-1.8586	0.0701	0.054	47

The table reports the results from the time series regressions of the estimated coefficient $\hat{\alpha}$ on the U.S. CO_2 emissions. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\hat{\alpha}$, x_t denotes U.S. CO_2 emissions, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or individual industries.

5.5.4-2 Regression of $\widehat{\beta_1}$ on U.S. CO_2 Emissions

		Intercept	t	p_value	U.S.CO_2	t	p_value	AdjR^2	N
1	U.S.	1.0491	5.9981	0	-0.0272	-3.0348	0.0041	0.1603	47
2	Mining	1.5472	6.1283	0	-0.0494	-3.8181	0.0004	0.24	47
3	Construction	2.4118	4.1563	0.0002	-0.0872	-2.9349	0.0054	0.1504	47
4	Manufacturing	1.0086	6.2777	0	-0.0258	-3.1338	0.0031	0.1702	47
5	Transportation	1.0785	4.0179	0.0002	-0.0289	-2.1045	0.0414	0.0739	47
6	Wholesale	1.1606	3.6772	0.0007	-0.0288	-1.7841	0.0816	0.0483	47
7	Retail	1.4384	4.4224	0.0001	-0.0442	-2.6532	0.0112	0.1232	47
8	Finance	0.8484	3.8253	0.0004	-0.0166	-1.4658	0.1501	0.026	47
9	Services	1.0418	4.3429	0.0001	-0.0265	-2.1587	0.0366	0.0784	47

The table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_1}$ on the U.S. CO_2 emissions. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_1}$, x_t denotes U.S. CO_2 emissions, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or individual industries.

5.5.4-3 Regression of $\widehat{\beta_2}$ on U.S. CO_2 Emissions

		Intercept	t	p_value	U.S.CO_2	t	p_value	AdjR^2	N
1	U.S.	-0.5926	-3.0414	0.004	0.043	4.3093	0.0001	0.2901	47
2	Mining	-0.729	-3.0885	0.0036	0.0456	3.7713	0.0005	0.2352	47
3	Construction	-2.0754	-3.3422	0.0018	0.1123	3.5312	0.001	0.2106	47
4	Manufacturing	-0.5793	-3.2112	0.0025	0.0428	4.6318	0	0.3223	47
5	Transportation	-0.7353	-2.2277	0.0313	0.0532	3.1464	0.003	0.1715	47
6	Wholesale	-0.2965	-0.9651	0.34	0.0281	1.789	0.0808	0.0487	47
7	Retail	-1.5511	-5.2117	0	0.0943	6.1912	0	0.4647	47
8	Finance	-0.2709	-1.1646	0.2507	0.0263	2.2062	0.0329	0.0825	47
9	Services	-0.8944	-2.9127	0.0057	0.0567	3.6033	0.0008	0.218	47

The table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_2}$ on the U.S. CO_2 emissions. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_2}$, x_t denotes U.S. CO_2 emissions, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or individual industries.

5.5.4-4 Regression of $\widehat{\beta_3}$ on U.S. CO_2 Emissions

		Intercept	t	p_value	U.S.CO_2	t	p_value	AdjR^2	N
1	U.S.	-0.0796	-0.9719	0.3367	0.0094	2.2524	0.0296	0.0865	47
2	Mining	0.2764	1.3624	0.1803	-0.0053	-0.5057	0.6157	-0.0176	47
3	Construction	0.1214	0.3503	0.7278	0.0004	0.024	0.9809	-0.0238	47
4	Manufacturing	-0.0593	-0.5634	0.5761	0.01	1.8509	0.0712	0.0534	47
5	Transportation	0.2341	1.4834	0.1454	-0.0097	-1.2053	0.2348	0.0104	47
6	Wholesale	0.2728	1.2032	0.2356	-0.0072	-0.6233	0.5365	-0.0144	47
7	Retail	0.2076	1.9689	0.0556	-0.0062	-1.1461	0.2582	0.0072	47
8	Finance	0.0455	0.2405	0.8111	0.0051	0.525	0.6024	-0.0171	47
9	Services	-0.0023	-0.0162	0.9871	0.0075	1.0168	0.3151	0.0008	47

The table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_3}$ on the U.S. CO_2 emissions. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_3}$, x_t denotes U.S. CO_2 emissions, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or individual industries.

5.5.4-5 Regression of $\widehat{\beta_4}$ on U.S. CO_2 Emissions

		Intercept	t	p_value	U.S.CO_2	t	p_value	AdjR^2	N
1	U.S.	0.6797	6.8296	0	-0.0291	-5.71	0	0.4236	47
2	Mining	0.5864	4.1487	0.0002	-0.025	-3.4544	0.0013	0.2027	47
3	Construction	0.3035	1.8151	0.0767	-0.0114	-1.327	0.1917	0.0174	47
4	Manufacturing	0.8203	6.8564	0	-0.0357	-5.8242	0	0.4336	47
5	Transportation	0.4974	4.8631	0	-0.0211	-4.0233	0.0002	0.261	47
6	Wholesale	0.2105	1.9593	0.0567	-0.007	-1.2719	0.2104	0.0142	47
7	Retail	1.16	8.6631	0	-0.0528	-7.705	0	0.5758	47
8	Finance	0.4086	5.7858	0	-0.0173	-4.7857	0	0.3375	47
9	Services	1.1683	7.2096	0	-0.0519	-6.2575	0	0.4702	47

The table reports the results from the time series regressions of the estimated coefficient $\widehat{\beta_4}$ on the U.S. CO_2 emissions. The econometric models are $y_t = \upsilon_t + \gamma x_t + \omega_t$, where y_t denotes $\widehat{\beta_4}$, x_t denotes U.S. CO_2 emissions, and ω_t denotes the error term. Each row represents the result for the U.S. economy as a whole or individual industries.

5.6 Cointegration Tests

5.6.1 Unit Root Tests for Estimated Elasticities and Temperatures

Tables 5.6.1-1 to 5.6.1-5 report the results for the unit root tests of the vector of estimated coefficients in stage 1, $\hat{\alpha}$, $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\widehat{\beta_3}$, and $\widehat{\beta_4}$ for the U.S. economy as a whole and individual U.S. industries, which are shown in each row. The test results for the period from 1971 to 2017 are reported in Columns (2) – (5) and results over the period from 1982 to 2017 are reported in Columns (6) – (9). For each period, results from Augmented Dickey Fuller tests and Phillips Perron tests, both with four lags, are reported. Column (2), (4), (6), (8) report the test statistics $Z(t)$, and Column (3), (5), (7), (9) report the corresponding p values.

In Table 5.6.1-1, $Z(t)$ for the U.S. economy as a whole over the entire sample period is -4.945. with a p-value of 0.000 under the Augmented Dickey-Fuller test. This indicates that the null hypothesis that there exists unit root in the time series of $\hat{\alpha}$ is rejected. However, the results in individual industries are mixed. Over the entire sample period with the Augmented Dickey-Fuller method, the $Z(t)$ for Mining is -1.180 with a p-value of 0.682, the $Z(t)$ for Construction is -1.714 with a p-value of 0.424, and the $Z(t)$ for Wholesale is -2.455, with a p-value of 0.127. For these industries, the null hypothesis that there exists a unit root in the time series of $\hat{\alpha}$ is not rejected based on the Augmented Dickey-Fuller test. However, over the entire sample period with Augmented Dickey-Fuller test, the null hypothesis that there exists unit root in the time series of $\hat{\alpha}$ is rejected based on the statistics $Z(t)$ for Manufacturing, Retail, Finance, and Services. The results in Table 5.6.1-1 and in most of the Tables in this subsection and the next demonstrate that the Phillips Perron test has more power to reject the null hypothesis than does the Augmented Dickey-Fuller test.

Table 5.6.1-2 reports the results of unit root tests for the elasticity of book value of equity, $\widehat{\beta_1}$. Over the entire sample period with Augmented Dickey-Fuller method, the $Z(t)$ for the U.S. economy as a whole is -2.006 with a p-value of 0.284, indicating that the null hypothesis that there exists unit root in the time series of $\widehat{\beta_1}$ is not rejected. Except for Wholesale, for which the $Z(t)$ is -2.600 with a p-value of 0.093 over the entire sample period with Augmented Dickey-Fuller method, the results for other industries indicate that the null hypothesis that there exists a unit root in the time series of $\widehat{\beta_1}$ is not rejected.

Table 5.6.1-3 reports the unit root tests for the elasticity of earnings, $\widehat{\beta_2}$. Over the entire sample period with Augmented Dickey-Fuller method, the $Z(t)$ for the U.S. economy as a whole is -2.120 with a p-value of 0.236, indicating that the null hypothesis that there exits unit root in the time series of $\widehat{\beta_2}$ is not rejected. However, the results in individual industries are mixed. Over the entire sample period with Augmented Dickey-Fuller method, the $Z(t)$ for Mining is -2.762 with a p-value of 0.064, the $Z(t)$ for Wholesale is -3.347 with a p-value of 0.013, and the $Z(t)$ for Finance is -3.250 with a p-value of 0.017. For these industries the null hypothesis that there exists unit root in the time series of $\widehat{\beta_2}$ is rejected. For the other industries, the null hypothesis that there exists a unit root in the time series of $\widehat{\beta_2}$ is not rejected.

Table 5.6.1-4 reports the unit root tests for the elasticity of dividends, $\widehat{\beta_3}$. Over the entire sample period with Augmented Dickey-Fuller method, the $Z(t)$ for the U.S. economy as a whole is -2.901 with a p-value of 0.045, indicating that the null hypothesis that there exists unit root in the time series of $\widehat{\beta_3}$ is rejected. The results for individual industries are mixed. For industries including Mining, Wholesale, Finance, and Services, the null hypothesis is not rejected. For industries including Construction, Manufacturing, Transport, and Retail, the null hypothesis is rejected.

Table 5.6.1-5 reports the unit root tests for the elasticities of the other accounting variable, $\widehat{\beta_4}$. Over the entire sample period with Augmented Dickey-Fuller method, the $Z(t)$ for U.S. economy as a whole and individual industries the null hypothesis is not rejected.

Table 5.6.1-6 reports the unit root tests for the annual anomaly temperature variable, including the global temperature and the U.S. temperature. In addition to the different time periods, the tests include situation with the trend terms in the model and the situation without the trend terms in the model. Four lags are included in both the Augmented Dickey Fuller and Phillips Perron tests. Column (1) indicates the time periods. Column (2) indicates the specific temperature variable which is tested. Columns (3) – (6) report the results which are obtained from the models including the trend term. Columns (7) – (10) report the results from the models that do not include the trend term. Over the entire sample period with Augmented Dickey-Fuller method, the $Z(t)$ for global temperature is -3.912 with a p-value of 0.012 and the $Z(t)$ for U.S. Temperature is -3.242 with a p-value of 0.076. This leads to rejecting the null hypothesis that there exists a unit root in the time series of the global temperature and the U.S. temperature data. If the models do not include trend terms, the $Z(t)$ for global temperature is 0.261 with a p-value of 0.931 and the $Z(t)$ for U.S. Temperature is -0.859 with a p-value of 0.8011. This leads to not rejecting the null hypothesis that there exists a unit root in the time series of the global temperature and the U.S. temperature.

For both the estimated elasticities and the temperature variables, there exists weak evidence that there are unit roots among these variables. On this basis, the cointegration relationships between the elasticities and the temperature variable are tested and the results are reported in the next subsection.

5.6.1-1 Unit Root Tests for $\hat{\alpha}$

		1971-2017				1982-2017			
		Augmented Dickey-Fuller		Phillips Perron		Augmented Dickey-Fuller		Phillips Perron	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Z(t)	p-value	Z(t)	p-value	Z(t)	p-value	Z(t)	p-value
1	U.S.	-4.9452	0	-4.8065	0.0001	-5.0662	0	-5.7736	0
2	Mining	-1.1803	0.682	-2.0597	0.261	-0.8099	0.8162	-2.2759	0.1799
3	Construction	-1.7141	0.4239	-4.2019	0.0007	-0.9675	0.7649	-4.109	0.0009
4	Manufacturing	-3.8224	0.0027	-4.6816	0.0001	-2.6795	0.0776	-5.1625	0
5	Transport	-2.9548	0.0393	-4.4252	0.0003	-3.1812	0.0211	-5.2518	0
6	Wholesale	-2.4551	0.1268	-4.8797	0	-1.2511	0.6512	-3.8619	0.0023
7	Retail	-2.9068	0.0446	-5.529	0	-2.4681	0.1234	-4.4254	0.0003
8	Finance	-4.2888	0.0005	-3.9468	0.0017	-3.9045	0.002	-3.6442	0.005
9	Services	-4.2561	0.0005	-5.122	0	-5.1915	0	-5.8195	0

The Table reports the unit root test for the time series variable $\hat{\alpha}$ with Augmented Dickey-Fuller and Phillips Perron methods. The statistic of the tests is $Z(t)$ and the p-value for it is reported in the next column. Columns (2) – (5) are tests based on data over the period from 1971 to 2017. Columns (6) – (9) are tests over the period 1982 to 2017. Each row shows results for the U.S. economy as a whole or for individual U.S. industries.

5.6.1-2 Unit Root Tests for $\widehat{\beta_1}$

		1971-2017				1982-2017			
		Augmented Dickey-Fuller		Phillips Perron		Augmented Dickey-Fuller		Phillips Perron	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Z(t)	p-value	Z(t)	p-value	Z(t)	p-value	Z(t)	p-value
1	U.S.	-2.0057	0.2841	-3.0341	0.0318	-2.5908	0.0949	-4.4472	0.0002
2	Mining	-1.1767	0.6835	-2.0182	0.2786	-0.8959	0.7893	-4.3846	0.0003
3	Construction	-1.6299	0.4676	-4.5453	0.0002	-1.3204	0.6198	-3.8425	0.0025
4	Manufacturing	-1.9516	0.3082	-2.9988	0.035	-2.0123	0.2812	-3.6964	0.0042
5	Transport	-2.3557	0.1546	-4.2284	0.0006	-3.1076	0.026	-5.2871	0
6	Wholesale	-2.5997	0.093	-5.1689	0	-1.3636	0.5996	-4.2741	0.0005
7	Retail	-1.4926	0.5372	-4.165	0.0008	-2.0176	0.2789	-4.542	0.0002
8	Finance	-2.3915	0.1442	-4.6568	0.0001	-2.4326	0.1328	-3.8694	0.0023
9	Services	-1.6077	0.4797	-3.3563	0.0125	-2.1135	0.2391	-4.1042	0.001

The Table reports the unit root test for the time series variable $\widehat{\beta_1}$ with Augmented Dickey-Fuller and Phillips Perron methods. The statistic of the tests is $Z(t)$ and the p-value for it is reported in the next column. Columns (2) – (5) are tests based on data over the period from 1971 to 2017. Columns (6) – (9) are tests over the period 1982 to 2017. Each row shows results for the U.S. economy as a whole or for individual U.S. industries.

5.6.1-3 Unit Root Tests for $\widehat{\beta_2}$

		1971-2017				1982-2017			
		Augmented Dickey-Fuller		Phillips Perron		Augmented Dickey-Fuller		Phillips Perron	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Z(t)	p-value	Z(t)	p-value	Z(t)	p-value	Z(t)	p-value
1	U.S.	-2.1204	0.2364	-2.5103	0.113	-2.7912	0.0595	-3.3443	0.013
2	Mining	-2.7623	0.0639	-3.3846	0.0115	-3.0492	0.0306	-4.4605	0.0002
3	Construction	-2.2662	0.1831	-5.7711	0	-3.2317	0.0182	-4.0614	0.0011
4	Manufacturing	-1.9838	0.2937	-2.3523	0.1556	-2.231	0.1952	-3.1489	0.0231
5	Transport	-2.4062	0.14	-3.5985	0.0058	-2.8671	0.0493	-4.4849	0.0002
6	Wholesale	-3.3468	0.0129	-5.2159	0	-4.175	0.0007	-4.9765	0
7	Retail	-1.7547	0.4032	-2.8842	0.0472	-2.6654	0.0802	-5.4954	0
8	Finance	-3.2501	0.0173	-4.8151	0.0001	-3.1048	0.0262	-3.6357	0.0051
9	Services	-1.7896	0.3856	-2.4707	0.1228	-1.92	0.3227	-3.0961	0.0268

The Table reports the unit root test for the time series variable $\widehat{\beta_2}$ with Augmented Dickey-Fuller and Phillips Perron methods. The statistic of the tests is $Z(t)$ and the p-value for it is reported in the next column. Columns (2) – (5) are tests based on data over the period from 1971 to 2017. Columns (6) – (9) are tests over the period 1982 to 2017. Each row shows results for the U.S. economy as a whole or for individual U.S. industries.

5.6.1-4 Unit Root Tests for $\widehat{\beta_3}$

		1971-2017				1982-2017			
		Augmented Dickey-Fuller		Phillips Perron		Augmented Dickey-Fuller		Phillips Perron	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Z(t)	p-value	Z(t)	p-value	Z(t)	p-value	Z(t)	p-value
1	U.S.	-2.9011	0.0452	-3.5347	0.0071	-2.4291	0.1337	-3.0691	0.0289
2	Mining	-1.6341	0.4653	-3.4388	0.0097	-2.5836	0.0964	-1.6685	0.4474
3	Construction	-3.1602	0.0224	-6.8006	0	-3.072	0.0287	-5.8613	0
4	Manufacturing	-2.7743	0.062	-3.6651	0.0046	-2.2131	0.2015	-3.23	0.0183
5	Transport	-2.7169	0.0712	-4.2238	0.0006	-1.2831	0.6369	-4.4914	0.0002
6	Wholesale	-2.2315	0.195	-4.8824	0	-1.9393	0.3138	-4.4601	0.0002
7	Retail	-2.9849	0.0363	-4.3296	0.0004	-2.4223	0.1355	-3.6208	0.0054
8	Finance	-1.7388	0.4112	-3.1296	0.0244	-1.3154	0.6221	-2.1574	0.2221
9	Services	-2.3469	0.1573	-3.6389	0.0051	-2.1806	0.2133	-3.7226	0.0038

The Table reports the unit root test for the time series variable $\widehat{\beta_3}$ with Augmented Dickey-Fuller and Phillips Perron methods. The statistic of the tests is $Z(t)$ and the p-value for it is reported in the next column. Columns (2) – (5) are tests based on data over the period from 1971 to 2017. Columns (6) – (9) are tests over the period 1982 to 2017. Each row shows results for the U.S. economy as a whole or for individual U.S. industries.

5.6.1-5 Unit Root Tests for $\widehat{\beta_4}$

		1971-2017				1982-2017			
		Augmented Dickey-Fuller		Phillips Perron		Augmented Dickey-Fuller		Phillips Perron	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Z(t)	p-value	Z(t)	p-value	Z(t)	p-value	Z(t)	p-value
1	U.S.	-0.9853	0.7586	-1	0.7532	-1.2548	0.6496	-1.3684	0.5973
2	Mining	-1.1664	0.6879	-3.8215	0.0027	-1.3539	0.6042	-3.9284	0.0018
3	Construction	-2.2844	0.177	-2.0453	0.2671	-2.6089	0.0912	-1.6861	0.4383
4	Manufacturing	-0.5526	0.8813	-1.4446	0.5607	-0.7995	0.8193	-1.8231	0.369
5	Transport	-2.3482	0.1569	-2.8573	0.0505	-2.6854	0.0766	-2.8401	0.0528
6	Wholesale	-2.2119	0.202	-4.1781	0.0007	-2.8121	0.0566	-3.8444	0.0025
7	Retail	-1.0109	0.7493	-1.94	0.3135	-1.223	0.6636	-2.2572	0.1861
8	Finance	-1.5086	0.5293	-2.2253	0.1972	-1.7201	0.4208	-2.4707	0.1228
9	Services	-1.7153	0.4233	-1.6545	0.4547	-1.8378	0.3619	-1.6806	0.4412

The Table reports the unit root test for the time series variable $\widehat{\beta_4}$ with Augmented Dickey-Fuller and Phillips Perron methods. The statistic of the tests is $Z(t)$ and the p-value for it is reported in the next column. Columns (2) – (5) are tests based on data over the period from 1971 to 2017. Columns (6) – (9) are tests over the period 1982 to 2017. Each row shows results for the U.S. economy as a whole or for individual U.S. industries.

5.6.1-6 Unit Root Tests for Temperature

		Include the trend terms in test				No trend terms in test			
		Augmented Dickey Fuller		Phillips Perron		Augmented Dickey Fuller		Phillips Perron	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Z(t)	p-value	Z(t)	p-value	Z(t)	p-value	Z(t)	p-value
1971-2017	Global Temperature	-3.9116	0.0117	-5.241	0.0001	-0.2613	0.9308	-1.2125	0.6682
	U.S. Temperature	-3.2422	0.0763	-5.7955	0	-0.8591	0.8011	-3.6593	0.0047
1982-2017	Global Temperature	-2.8071	0.1943	-4.0861	0.0066	-0.074	0.952	-0.9865	0.7582
	U.S. Temperature	-2.5717	0.2931	-4.7824	0.0005	-1.2897	0.6339	-3.6517	0.0048

The table reports the unit root test for the time series variables of the global temperature and the U.S. temperature with Augmented Dickey-Fuller and Phillips Perron methods. The statistic of the tests is Z(t) and the p-value for it is reported in the next column. Column (3) – (6) are the tests including the trend term in the model. Column (7) – (10) are the tests not including the trend term in the model. For the two temperature variables, two time periods are considered. One period is from 1971 to 2017 and another period is from 1982 to 2017.

5.6.2 Cointegration Tests

Tables 5.6.2-1 to 5.6.2-5 report the results for testing the cointegration relationship between the vector of estimated coefficients, $\hat{\alpha}$, $\widehat{\beta_1}$, $\widehat{\beta_2}$, $\widehat{\beta_3}$, and $\widehat{\beta_4}$, and temperature variables based on the Engle-Granger's two-step approach. Columns (3) – (6) report the results over the entire sample from 1971 to 2017. Columns (7) – (10) report the results over the period from 1982 to 2017. In each time period, both the Augmented Dickey-Fuller and the Philips Perron tests are used, applying the Engle-Granger approach. The rows of these tables are divided into two parts. The upper part reports the results for global temperature and the lower part reports the results for U.S. temperature. Each part includes testing results for the U.S. economy as a whole and individual U.S. industries.

Table 5.6.2-1 reports the results of cointegration tests for $\hat{\alpha}$. With respect to the global temperature, over the entire sample period with Augmented Dickey-Fuller method, the $Z(t)$ for the U.S. economy as a whole is -4.447 with a p-value of 0.000, indicating that the null hypothesis that there exists unit root in the time series of the residuals obtained in the first stage of Engle-Granger approach is rejected. This is evidence consistent with the existence of a cointegration relationship between $\hat{\alpha}$ and global temperature. Except for the Mining industry, other industries, including Construction, Manufacturing, Transport, Wholesale, Retail, Finance, and Services, also show evidence of a cointegration relationship between $\hat{\alpha}$ and global temperature. Using U.S. temperature data leads to the same conclusion.

Table 5.6.2-2 reports the results of cointegration tests for $\widehat{\beta_1}$. With respect to the global temperature, over the entire sample period with Augmented Dickey-Fuller method, the $Z(t)$ for the U.S. economy as a whole is -3.157 with a p-value of 0.023, indicating that the null hypothesis that there exists a unit root in the time series of the residuals obtained in the first stage of Engle-Granger approach is rejected. Therefore, again there exists evidence of a cointegration relationship between $\widehat{\beta_1}$ and global temperature. Except for the Retail and Services industries, the evidence for other industries indicates a cointegration relationship between $\widehat{\beta_1}$ and global temperature. With respect to the U.S. temperature variable, the results are different. the $Z(t)$ for U.S. economy as a whole is -2.538 with a p-value of 0.106. Therefore, at the U.S. level, there not exists evidence of a cointegration relationship between $\widehat{\beta_1}$ and U.S. temperature. At the industry level, also, except for the Manufacturing and Finance industries, the other industries, do not show evidence of a cointegration relationship between $\widehat{\beta_1}$ and U.S. temperature.

Table 5.6.2-3 reports the results of cointegration tests for $\widehat{\beta_2}$. With respect to the global temperature, over the entire sample period with Augmented Dickey-Fuller method, $Z(t)$ for the U.S. economy as a whole is -2.622 with a p-value of 0.089. This is evidence of a cointegration relationship between $\widehat{\beta_2}$ and global temperature. At the industry level, with the exception of Transport and Retail, other industries, including Mining, Construction, Manufacturing, Wholesale, Finance, and Services, also show evidence of a cointegration relationship between $\widehat{\beta_2}$ and global temperature. With respect to the U.S. temperature data, the evidence on the U.S economy as a whole does not indicate a cointegration between $\widehat{\beta_2}$ and U.S. temperature, for which $Z(t)$ is -2.468 with a p-value of 0.123. At the industry level, Mining, Construction, Wholesale, and Finance show evidence of a co-integration between $\widehat{\beta_2}$ and U.S. temperature.

Table 5.6.2-4 reports the results of cointegration tests for $\widehat{\beta_3}$. With respect to the global temperature, over the entire sample period with Augmented Dickey-Fuller method, the $Z(t)$ for the U.S. economy as a whole is -3.488 with a p-value of 0.008. This is evidence of a cointegration relationship between $\widehat{\beta_3}$ and global temperature. At the industry level, Construction, Manufacturing, Transport, Wholesale, Retail, Finance, and Services show similar evidence for cointegration relationship between $\widehat{\beta_3}$ and the global temperature. With respect to the U.S. temperature data, the U.S. economy as a whole shows a cointegration relationship between $\widehat{\beta_3}$ and the U.S. temperature. At the industry level, also, Construction, Manufacturing, Transport, Wholesale, Retail, and Services show a cointegration relationship between $\widehat{\beta_3}$ and U.S. temperature data.

Table 5.6.2-5 reports cointegration tests for $\widehat{\beta_4}$. With respect to the global temperature and the U.S. temperature, over the entire sample period with Augmented Dickey-Fuller method, the U.S economy as a whole does not show evidence of cointegration between $\widehat{\beta_4}$ and the temperature variables. The results for the industry level are mixed.

I conclude that the overall evidence shows that the vector of estimated coefficients has a robust cointegration relationship with global temperature. However, the evidence of a cointegration relationship with U.S. temperature data is weak. Therefore, the results in this subsection support the claim the global temperature is an appropriate measure of climate risk with which to test its impact on equity valuation.

5.6.2-1 Cointegration Tests for $\hat{\alpha}$

		1971-2017				1982-2017			
		Augmented Dickey-Fuller		Phillips Perron		Augmented Dickey-Fuller		Phillips Perron	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Z(t)	p-value	Z(t)	p-value	Z(t)	p-value	Z(t)	p-value
Global Temperature	U.S.	-4.4661	0.0002	-4.967	0	-4.9795	0	-5.6887	0
	Mining	-2.5038	0.1146	-3.4553	0.0092	-1.8898	0.3369	-3.6492	0.0049
	Construction	-3.0675	0.0291	-4.9215	0	-2.0036	0.285	-5.1082	0
	Manufacturing	-3.5329	0.0072	-4.6333	0.0001	-4.1132	0.0009	-6.2756	0
	Transportation	-3.898	0.002	-5.0769	0	-3.6662	0.0046	-4.6528	0.0001
	Wholesale	-2.6884	0.0761	-5.0832	0	-2.5247	0.1096	-4.7619	0.0001
	Retail	-2.9105	0.0441	-5.487	0	-2.5721	0.0989	-4.3471	0.0004
	Finance	-3.6042	0.0057	-4.2137	0.0006	-4.1833	0.0007	-4.1624	0.0008
	Services	-4.2109	0.0006	-5.557	0	-5.4612	0	-6.6499	0
U.S. Temperature	U.S.	-4.9145	0	-4.8554	0	-4.9346	0	-5.6787	0
	Mining	-2.2975	0.1728	-3.3743	0.0119	-2.0585	0.2615	-3.5838	0.0061
	Construction	-2.7887	0.0599	-4.9932	0	-1.8218	0.3697	-4.8257	0
	Manufacturing	-3.7561	0.0034	-4.6054	0.0001	-3.2173	0.019	-5.4394	0
	Transportation	-3.5992	0.0058	-4.6227	0.0001	-3.437	0.0098	-4.7903	0.0001
	Wholesale	-2.7216	0.0704	-5.0839	0	-1.8836	0.3398	-4.3349	0.0004
	Retail	-2.8849	0.0471	-5.441	0	-2.4557	0.1266	-4.3434	0.0004
	Finance	-4.1424	0.0008	-4.2873	0.0005	-3.6685	0.0046	-4.089	0.001
	Services	-4.2717	0.0005	-5.3706	0	-5.2836	0	-6.6348	0

The Table reports the cointegration test between the estimated coefficient $\hat{\alpha}$ and the temperature variable based on the Engle and Granger two-stage approach. The statistic $Z(t)$ is based on the time series residuals of a regression of $\hat{\alpha}$ on the temperature variable using the Augmented Dicky-Fuller or Phillips Perron methods. The p-value for $Z(t)$ is reported in the next column. The temperature variables include the global anomaly temperature and the U.S. anomaly temperature. The former is reported in the upper part of the table and the latter is reported in the lower part of the table. Each row represents the test results for the U.S economy as a whole or individual U.S. industries. Columns (3) – (6) are the results of tests over the period from 1971 to 2017. Columns (7) – (10) are the results of tests over the period 1982 to 2017.

5.6.2-2 Cointegration Tests for $\widehat{\beta_1}$

		1971-2017				1982-2017			
		Augmented Dickey-Fuller		Phillips Perron		Augmented Dickey-Fuller		Phillips Perron	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Z(t)	p-value	Z(t)	p-value	Z(t)	p-value	Z(t)	p-value
Global Temperature	U.S.	-3.1572	0.0226	-3.7801	0.0031	-2.8524	0.0512	-4.5607	0.0002
	Mining	-2.6764	0.0782	-4.355	0.0004	-2.976	0.0372	-6.1962	0
	Construction	-2.8791	0.0478	-5.2605	0	-1.7251	0.4182	-4.7068	0.0001
	Manufacturing	-3.9059	0.002	-4.1714	0.0007	-3.1806	0.0211	-4.7396	0.0001
	Transportation	-2.2403	0.192	-3.8873	0.0021	-2.9707	0.0377	-4.6099	0.0001
	Wholesale	-4.8119	0.0001	-5.9928	0	-4.1939	0.0007	-5.9056	0
	Retail	-1.4376	0.5641	-4.3195	0.0004	-2.1321	0.2318	-4.563	0.0002
	Finance	-3.5667	0.0064	-5.4386	0	-3.3514	0.0127	-5.0666	0
	Services	-2.4942	0.1169	-4.1249	0.0009	-2.3577	0.154	-4.4377	0.0003
U.S. Temperature	U.S.	-2.5383	0.1064	-3.8537	0.0024	-2.7534	0.0652	-4.4418	0.0003
	Mining	-2.5424	0.1055	-4.0281	0.0013	-3.0358	0.0317	-6.0501	0
	Construction	-2.1433	0.2274	-5.4236	0	-1.6401	0.4622	-4.3438	0.0004
	Manufacturing	-2.8237	0.055	-4.0852	0.001	-2.3706	0.1502	-4.0471	0.0012
	Transportation	-2.2291	0.1958	-3.9475	0.0017	-2.7447	0.0666	-4.6121	0.0001
	Wholesale	-3.8587	0.0024	-5.8345	0	-2.4077	0.1396	-4.8628	0
	Retail	-1.6309	0.467	-4.7005	0.0001	-1.9604	0.3042	-4.5087	0.0002
	Finance	-2.9734	0.0375	-5.239	0	-2.6834	0.0769	-4.5489	0.0002
	Services	-2.2976	0.1727	-4.1805	0.0007	-2.3842	0.1462	-4.4278	0.0003

The Table reports the cointegration test between the estimated elasticity $\widehat{\beta_1}$ and the temperature variable based on the Engle and Granger two-stage approach. The statistic $Z(t)$ is based on the time series residuals of a regression of $\widehat{\beta_1}$ on the temperature variable using the

Augmented Dicky-Fuller or Phillips Perron methods. The p-value for $Z(t)$ is reported in the next column. The temperature variables include the global anomaly temperature and the U.S. anomaly temperature. The former is reported in the upper part of the table and the latter is reported in the lower part of the table. Each row represents the test results for the U.S economy as a whole or individual U.S. industries. Columns (3) – (6) are the results of tests over the period from 1971 to 2017. Columns (7) – (10) are the results of tests over the period 1982 to 2017.

5.6.2-3 Cointegration Tests for $\widehat{\beta_2}$

		1971-2017				1982-2017			
		Augmented Dickey-Fuller		Phillips Perron		Augmented Dickey-Fuller		Phillips Perron	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Z(t)	p-value	Z(t)	p-value	Z(t)	p-value	Z(t)	p-value
Global Temperature	U.S.	-2.622	0.0885	-3.1498	0.0231	-3.1429	0.0235	-3.3712	0.012
	Mining	-3.2827	0.0157	-4.4127	0.0003	-4.2712	0.0005	-4.5988	0.0001
	Construction	-2.8019	0.058	-6.3667	0	-3.1094	0.0259	-4.2297	0.0006
	Manufacturing	-2.7657	0.0633	-3.4421	0.0096	-2.9383	0.0411	-3.3073	0.0146
	Transportation	-2.2683	0.1824	-3.6946	0.0042	-2.08	0.2526	-4.0346	0.0012
	Wholesale	-4.1012	0.001	-5.6682	0	-4.2749	0.0005	-5.1051	0
	Retail	-1.6325	0.4662	-3.9588	0.0016	-2.8031	0.0578	-5.7516	0
	Finance	-3.3601	0.0124	-4.8725	0	-3.1776	0.0213	-3.5973	0.0058
	Services	-2.5717	0.099	-3.4852	0.0084	-2.3265	0.1636	-3.3639	0.0123
U.S. Temperature	U.S.	-2.4681	0.1234	-3.189	0.0206	-2.8536	0.051	-3.3654	0.0122
	Mining	-3.0319	0.032	-4.0309	0.0013	-3.7037	0.0041	-4.4742	0.0002
	Construction	-2.6483	0.0834	-6.5214	0	-3.0189	0.0332	-4.1429	0.0008
	Manufacturing	-2.4053	0.1402	-3.1319	0.0243	-2.3384	0.1599	-3.1263	0.0247
	Transportation	-2.2341	0.1941	-3.671	0.0045	-2.0352	0.2714	-4.0076	0.0014
	Wholesale	-3.8516	0.0024	-5.568	0	-4.4648	0.0002	-5.1019	0
	Retail	-1.8841	0.3396	-3.9792	0.0015	-2.565	0.1005	-5.538	0
	Finance	-3.2524	0.0171	-4.76	0.0001	-3.5055	0.0078	-3.725	0.0038
	Services	-2.1424	0.2278	-3.6524	0.0048	-2.0948	0.2466	-3.3841	0.0115

The Table reports the cointegration test between the estimated elasticity $\widehat{\beta_2}$ and the temperature variable based on the Engle and Granger two-stage approach. The statistic $Z(t)$ is based on the time series residuals of a regression of $\widehat{\beta_2}$ on the temperature variable using the Augmented

Dicky-Fuller or Phillips Perron methods. The p-value for $Z(t)$ is reported in the next column. The temperature variables include the global anomaly temperature and the U.S. anomaly temperature. The former is reported in the upper part of the table and the latter is reported in the lower part of the table. Each row represents the test results for the U.S economy as a whole or individual U.S. industries. Columns (3) – (6) are the results of tests over the period from 1971 to 2017. Columns (7) – (10) are the results of tests over the period 1982 to 2017.

5.6.2-4 Cointegration Tests for $\widehat{\beta_3}$

		1971-2017				1982-2017			
		Augmented Dickey-Fuller		Phillips Perron		Augmented Dickey-Fuller		Phillips Perron	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Z(t)	p-value	Z(t)	p-value	Z(t)	p-value	Z(t)	p-value
Global Temperature	U.S.	-3.4881	0.0083	-3.8916	0.0021	-2.8853	0.0471	-3.3196	0.014
	Mining	-2.5031	0.1147	-4.7593	0.0001	-3.0589	0.0297	-3.2131	0.0192
	Construction	-3.1896	0.0206	-6.8028	0	-3.7993	0.0029	-6.1092	0
	Manufacturing	-3.0171	0.0333	-4.0701	0.0011	-2.8689	0.0491	-3.6791	0.0044
	Transportation	-4.7433	0.0001	-4.9649	0	-4.4823	0.0002	-5.1205	0
	Wholesale	-2.7156	0.0714	-5.3656	0	-3.2458	0.0175	-5.5396	0
	Retail	-2.845	0.0521	-4.283	0.0005	-2.1554	0.2228	-3.3926	0.0112
	Finance	-2.7635	0.0637	-3.9322	0.0018	-2.4161	0.1372	-3.0973	0.0268
	Services	-2.7073	0.0728	-3.968	0.0016	-2.7968	0.0587	-4.2171	0.0006
U.S. Temperature	U.S.	-3.0617	0.0295	-3.6381	0.0051	-2.2833	0.1774	-2.9978	0.0351
	Mining	-2.5383	0.1064	-4.6219	0.0001	-3.6652	0.0046	-3.0817	0.0279
	Construction	-3.1896	0.0206	-6.8019	0	-3.2303	0.0183	-5.9058	0
	Manufacturing	-2.8152	0.0561	-3.9072	0.002	-2.1579	0.2219	-3.3689	0.0121
	Transportation	-4.3404	0.0004	-4.7675	0.0001	-2.9772	0.0371	-4.7944	0.0001
	Wholesale	-2.7266	0.0695	-5.3856	0	-2.7505	0.0657	-5.5086	0
	Retail	-2.8291	0.0542	-4.2746	0.0005	-2.1817	0.213	-3.4354	0.0098
	Finance	-2.5068	0.1138	-3.7992	0.0029	-2.1564	0.2224	-2.8285	0.0543
	Services	-2.6879	0.0762	-4.0069	0.0014	-2.8207	0.0554	-4.2219	0.0006

The Table reports the cointegration test between the estimated elasticity $\widehat{\beta_3}$ and the temperature variable based on the Engle and Granger two-stage approach. The statistic $Z(t)$ is based on the time series residuals of a regression of $\widehat{\beta_3}$ on the temperature variable using the

Augmented Dicky-Fuller or Phillips Perron methods. The p-value for $Z(t)$ is reported in the next column. The temperature variables include the global anomaly temperature and the U.S. anomaly temperature. The former is reported in the upper part of the table and the latter is reported in the lower part of the table. Each row represents the test results for the U.S economy as a whole or individual U.S. industries. Columns (3) – (6) are the results of tests over the period from 1971 to 2017. Columns (7) – (10) are the results of tests over the period 1982 to 2017.

5.6.2-5 Cointegration Tests for $\widehat{\beta_4}$

		1971-2017				1982-2017			
		Augmented Dickey-Fuller		Phillips Perron		Augmented Dickey-Fuller		Phillips Perron	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Z(t)	p-value	Z(t)	p-value	Z(t)	p-value	Z(t)	p-value
Global Temperature	U.S.	-2.3118	0.1682	-3.5237	0.0074	-1.8913	0.3362	-2.7999	0.0583
	Mining	-1.6313	0.4668	-6.3543	0	-1.3217	0.6192	-5.5691	0
	Construction	-2.9428	0.0406	-5.3373	0	-2.6591	0.0814	-4.4632	0.0002
	Manufacturing	-2.7121	0.072	-4.6586	0.0001	-2.2399	0.1921	-3.8971	0.0021
	Transportation	-2.057	0.2622	-2.4069	0.1398	-1.9904	0.2908	-2.3177	0.1663
	Wholesale	-2.7716	0.0625	-4.4382	0.0003	-2.7003	0.074	-3.7239	0.0038
	Retail	-2.7076	0.0727	-4.1621	0.0008	-2.3051	0.1703	-3.5378	0.0071
	Finance	-2.8438	0.0523	-3.8495	0.0024	-2.5123	0.1125	-3.1406	0.0237
	Services	-2.6875	0.0762	-3.8319	0.0026	-2.4675	0.1236	-3.1866	0.0208
U.S. Temperature	U.S.	-1.7283	0.4166	-2.9784	0.037	-1.6459	0.4592	-2.1894	0.2101
	Mining	-1.4649	0.5508	-4.723	0.0001	-1.2626	0.6461	-4.1045	0.001
	Construction	-2.9933	0.0355	-5.6737	0	-2.6231	0.0883	-4.6914	0.0001
	Manufacturing	-1.4442	0.5609	-3.3098	0.0144	-1.1856	0.6798	-2.5432	0.1053
	Transportation	-2.3508	0.1561	-2.4736	0.122	-2.0093	0.2825	-2.2724	0.181
	Wholesale	-2.4417	0.1303	-4.2874	0.0005	-2.7679	0.063	-3.5766	0.0062
	Retail	-2.1526	0.2239	-3.5861	0.006	-1.7993	0.3808	-2.9544	0.0394
	Finance	-2.0655	0.2586	-3.2748	0.016	-1.885	0.3391	-2.7004	0.074
	Services	-1.4939	0.5365	-3.0987	0.0266	-1.5364	0.5154	-2.1916	0.2093

The Table reports the co-integration test between the estimated elasticity $\widehat{\beta_4}$ and the temperature variable based on the Engle and Granger two-stage approach. The statistic $Z(t)$ is based on the time series residuals of a regression of $\widehat{\beta_4}$ on the temperature variable using the

Augmented Dicky-Fuller or Phillips Perron methods. The p-value for $Z(t)$ is reported in the next column. The temperature variables include the global anomaly temperature and the U.S. anomaly temperature. The former is reported in the upper part of the table and the latter is reported in the lower part of the table. Each row represents the test results for the U.S economy as a whole or individual U.S. industries. Columns (3) – (6) are the results of tests over the period from 1971 to 2017. Columns (7) – (10) are the results of tests over the period 1982 to 2017.

CHAPTER SIX

DISCUSSION

The thesis aims to investigate the impacts of climate risk on equity valuation through the channel of the accounting system. For this purpose, the thesis adopts a two-stage research design. In the first stage, I conduct annual cross-sectional regressions of the log market value on the logs of book value of equity, earnings, dividends, and the remaining value based on a multiplicative valuation model. In the second stage, the estimated vector of coefficients (elasticities) from the first stage are regressed on climate risk measures. The main hypothesis is that climate risk increases the relative importance of the book value of equity in valuation and reduces the relative importance of earnings in valuation. The findings in Chapter 5 provide supportive evidence for the proposed hypothesis in the thesis.

This chapter discusses the findings in Chapter 5 and compares them with related prior studies. Section 6.1 discusses the findings in the first stage and Section 6.2 discusses the findings in the second stage.

6.1 Discussion of Findings in Stage 1

6.1.1 The Specification of the Valuation Model

An important aspect of the thesis is the adoption of a multiplicative valuation model of the accounting-market relation. As a results, the measure of the value relevance of individual accounting variables is the elasticity of market price for each accounting variable. The multiplicative valuation model improves the statistical specification and generates a consistent and reliable estimation compared to the traditional additive models (Falta & Willett, 2013). Moreover, the results of the thesis demonstrate that the multiplicative valuation model explains at least 80% variation in stock price.

Prior studies commonly use an additive linear model, either in a “levels” form or “return” form, to estimate the value relevance of induvial accounting variable. This approach typically results in biased and inconsistent estimation. The methods used to solve these problems in the literature are unsatisfactory from an econometric viewpoint.

6.1.2 The Information Content of Accounting Variables

In the thesis, the elasticities of individual accounting variables are estimated annually at the U.S. level and the industry level. The magnitude of the elasticities reflects the information content of the corresponding accounting variables. An important research topic in the value relevance literature is to observe whether the information content of accounting variables increases or decreases over time and the relative importance of the accounting variables with respect to the information content. In prior studies, some focus on the sign and magnitude of the estimated coefficients, some studies focus on the explanatory power R^2, and some consider both measures. The findings in the thesis show that the elasticity of book value of equity increases and the elasticity of earnings declines over the sample period. The findings are consistent with the prior studies (e.g., Barth et al. (1998) and Collins et al. (1997)).

The thesis finds that the sum of the elasticities of all the accounting variables approximates to 1 over the period from 1971 to 2017. The decline in the relevance of earnings is compensated by the increase in the value relevance of book value of equity. The results hold at both U.S. and industry levels. The findings are consistent with prior studies focusing on how value relevance of accounting variables change over time, including Collins et al. (1997) and Francis & Schipper (1999), which attribute to the results to the abandonment option involved in book value of equity, and Barth et al. (2022), which attributes the results to the new economy. Huang & Zhang (2012) emphasise the incremental role of balance sheet items in explaining stock returns compared to earnings when investors become more uncertain about the future earnings.

6.1.3 Exogenous Shocks

Another important finding in Chapter 5 is that over the sample period, the elasticities of book value of equity almost dominate the elasticities of earnings. The domination happens not only at the U.S. level but also the industry level (see Figure 5.2-2). Revealing the underlying economic reasons is an important task in the value relevance studies. Prior studies, such as Barth et al. (1998), also find that investors, when facing pressure from risk, tend to put higher valuation weight on book value of equity and less valuation weight on earning, therefore, exhibiting the complementary relationship between book value of equity and earnings in the valuation process. The thesis attributes the phenomenon to the book value of equity capturing accumulated past information and reflecting conservatism and investor pessimism. In contrast earnings contains expectations and estimates about future events and reflects investor optimistic. The thesis argues that climate risk causes increases in the elasticities of book value of equity and reduces the elasticities of earnings. Although the explanations are different, prior studies also obtain similar results.

Kothari & Shanken (2003) argue that investigation of the economic factors that determine the time-series variation in the estimated coefficients is largely ignored by prior studies. This is an important question about how to interpret the estimated coefficients obtained from value-relevance regressions. They point out that "recognizing how different factors influence the estimated slope coefficient is of crucial importance in economic interpretations of the results from value-relevance research" (p. 71). This thesis attributes part of the underlying reasons for these findings to investor pessimism due to climate risk, which has become material and significantly influences the economic system. From this perspective, a closely related paper is Barth et al. (1998), which regards financial health as the driver. An important difference between the two sources of risk is that the global temperature, the measure of climate risk in the thesis, is generally believed to be exogenous. The characteristic of exogeneity is important for the second stage test because as Kothari & Shanken (2003) argue, correct inferences from the value relevance tests requires the absence of confounding factors.

6.1.4 The Implication for Accounting Policy

Holthausen & Watts (2001) argue that value relevance studies do not have implications for accounting policy and, therefore, are useless for standard setters. This is because the value relevance studies lack descriptive theories which explain and predict accounting standard setting. But the findings in the thesis do provide useful information for standard setters.

The key objective of accounting is to provide information that is useful to investors. Because information on climate risk has become increasingly important to investors today, the study also has a significant implication for the means to achieving the objective of accounting. Lev (2018) has criticised the shift from focus on the income statement to the balance sheet in the development of the Conceptual Frameworks adopted by both the FASB and the IASB as it has led to decreasing usefulness of accounting information. However, the estimated elasticities of book value of equity and earnings provide solid evidence that the information from balance sheet plays a more important role in valuation than the information from earnings.

6.2 Discussion of Findings in Stage 2

6.2.1 Market Reaction to Climate Risk

The key objective of the thesis is to test whether climate risk is incorporated into stock price through the channel of accounting information. The argument is tested through regression of the vector of estimated coefficients (elasticities) obtained in the first stage on the climate risk variable. In the thesis the global temperature is the primary variable. But other climate related measures, such as U.S. temperature, precipitation, CO_2 emissions, are also considered in the robustness analysis. If accounting information is the channel conveying climate risk information to the stock market, it is expected that the coefficient on climate risk is statistically significant. The signs of the coefficients capture investors' valuation process based on accounting information. The results reported in Chapter 5 provide solid evidence to support the claim of association. The findings in section 5.3 show that the global temperature positively influence the elasticity of book value of equity and negatively influence the elasticity of earnings. The effects occur at both the U.S. level and the industry level. The thesis provides an explanation for these observations. The book value of equity reflects the aggregate of past information and earnings capture investors' expectation about future. When investors become pessimistic about the future due to climate risk, they tend to put relatively higher valuation importance on the book value of equity and less on earnings.

The thesis finds that over the sample period from 1970 to 2017 the book value of equity plays a dominant role in valuation compared to earnings and attributes the phenomenon to climate change. This is consistent with the fact that there is a significant change in legislation in U.S since 1970s. Since the 1970s, environmental regulations in the United States have become more stringent (Dechezlepretre & Sato, 2017). The enactment of the Clean Air Act of 1970 (CAA) enhances the enforcement powers of the federal government. As long ago as December 2, 1970, in the U.S. the Environmental Protection Agency (EPA) was established under its National Environmental Policy Act to permit the response to environmental issues to be contained within one federal agency (EPA, 2019). A number of international regulations aim to reduce global warming by limiting the emissions of greenhouse gas, such as United Nations

Framework Convention on Climate Change (UNFCCC), Kyoto Protocol, and Pairs Agreement. Therefore, climate issues have become an important concern for legislators, regulators, standard setters, businesses, institutional investors, financial intermediaries, and the public.

The findings are consistent with the literature on climate finance, which justifies climate risk as a material and systematic risk that is priced in the stock market (Balvers et al., 2017; Bolton & Kacperczyk, 2021; Görgen et al., 2020). Climate finance research attributes the pricing of climate risk to factors such as economic channels including agriculture, labor productivity, investors mood, and consumer demand (Goetzmann et al., 2015; Graff Zivin & Neidell, 2014; Hong et al., 2019; Pankratz et al., 2019). The potential channel of accounting information is largely ignored by prior studies. The thesis fills the gap.

The findings in section 5.3 also show the magnitudes of the estimated coefficients on global temperature vary across industries. The findings are consistent with the studies in climate finance (e.g., Addoum et al. (2020) and Sautner et al. (2020)), which highlight that the market reactions to climate risk are heterogenous across industries.

6.2.2 The Impact on Performance

There are many studies investigating the impacts of climate risk on firms' financial performance, such as earnings, revenues, and cash flows (Brown et al., 2021; Kirk, Stice, & Stice, 2022; Pankratz et al., 2019). These studies generally find that climate risk negatively influence firms' financial performance. While this is not the purpose of the thesis, the tests in the thesis also provide indirect evidence to corroborate the findings of these studies. In the thesis, the regression of elasticities of earnings on global temperature results in the significantly negative coefficient because investors predict that future earnings become more uncertain due to climate risk.

6.2.3 The Long-run Component of Climate Risk

The thesis also observes the impacts of the different components, the long-run and short-run components of global temperature, on the vector of estimated elasticities, that is the valuation effects of different components of global temperature. The findings show that only the long-run component of the global temperature significantly influences the dynamics of each estimated coefficient at both the U.S. level and the industry level.

Therefore, the thesis provides the supportive evidence for Bansal et al.'s (2016) theory of long-run temperature risk, which claims that investors prefer early resolution of uncertainty and concern about uncertainty remains persistent over a long period of time (Bansal et al., 2019).

The findings about different components of climate risk are consistent with other studies on climate risk. Bolton & Kacperczyk (2021) investigate the different effects of long-run and short-run carbon risk on stock returns by using emission levels to capture the long-run risk and change in emissions to capture the short-run risk. But they find that both the long-run and short-run risk are positively and significantly related to stock return. Hong et al. (2019) use Palmer Drought Severity Index (PDSI), the degree of drought, to measure the climate risk. In the study, the authors adopt an AR(1) model to capture the trend of PDSI, interpreted as the long-run component of climate change. The thesis uses the Palmer Z index which captures the short-term drought condition, rather than the long-run trend of PDSI, to proxy for the measure of climate risk and observes the valuation effect. The findings in the thesis are not significant at both U.S. and individual industry levels.

The long-run effect of the global temperature observed in the thesis is also consistent with the annual cross-sectional regressions based multiplicative valuation model used in the first stage. The annual cross-sectional regressions capture the long-run relationship between accounting variables and stock prices in equilibrium. However, before reaching equilibrium, the accounting-market relation fluctuates around the equilibrium point. Therefore, exploring the short-run effect is an interesting topic. There are studies focusing on the short-run effect through special research design. Brown et al. (2021) use the average daily snow cover as the measure of climate risk. Such measure only influences the short-term flow and, therefore, rule out the long-term effect of climate risk. The study finds the negative impact of short-term climate risk on cash flow. The findings of thesis only justify the long-run effect of climate risk. The lack of short-run effect can be attributed to the limitation of the research design used in the thesis.

6.2.4 The Quantity of Climate Risk

The climate finance literature argues that climate risk is a complex, multifaceted risk. Studies focusing on derivative markets, such as Ilhan et al. (2021) and Sautner et al. (2021), reveal that in addition to the second moment, the higher moments of climate risk, especially the downside tail risk, are important in the valuation process, which makes climate risk more difficult to price. The findings in the thesis that investors place a higher valuation weight on book value of equity provide an explanation for how investors deal with the higher moments of climate risk when valuing the firms. The accounting literature has recognised that book value of equity contains information about options (Barth et al., 1998; Burgstahler & Dichev, 1997; Collins et al., 1999).

6.2.5 The Psychological Effect

The thesis claims that when investors are pessimistic about firms' future value, they tend to place higher valuation weight on book value of equity. Although the argument is developed under the valuation framework, it is consistent with other studies based on psychological framework. Dehaan et al. (2017) and Jiang et al. (2021) find that the psychological and physiological effects of climate risk influence the ability of investors to deal with public information and their trading behavior, resulting in smaller earnings response coefficient (ERC) and larger post earnings announcement drift (PEAD) (Dehaan et al., 2017).

CHAPTER SEVEN

CONCLUSION

7.1 Summary and Main Findings

Climate risk has been extensively explored in the economics, finance, and accounting literatures. Studies have revealed that climate risk is incorporated into share prices through a variety of channels, including industry type, labor productivity, and investor mood. However, whether accounting information has the ability to convey information about climate risk into share prices is moot. A purpose of accounting information is to transfer useful information to investors. With the increasing importance of climate risk, the research question, does climate risk influence equity value through the channel of the accounting system, becomes more important. The thesis seeks to answer this question. The findings in the thesis provide evidence that the answer to the research question is in the affirmative.

The literature relating to climate risk is reviewed in Chapter 2. The review includes the market reactions to climate risk, how climate risk influence firms' performance, the relation between climate risk and firms' adaptive behaviour, whether climate risk is value relevant information, and the importance of perceptions of climate risk.

The hypotheses in the thesis are developed under the Ohlson valuation framework. The book value of equity reflects accumulated past information and is viewed as conservative and pessimistic. Earnings reflect future information and are viewed as less conservative and more optimistic. Therefore, investors adjust their valuation weights on individual accounting variables, placing a higher valuation weight on the book value of equity as climate risk increases.

The thesis adopts a two-stage research design. In the first stage, the log-linear model is used to estimate the accounting-market relation, by measuring the elasticities of individual accounting variables. Using 180,042 listed U.S. firms over the period 1971 to 2017, the tests in the first stage involve annual regressions of equity value on the book value of equity, earnings, dividends and remaining value to obtain time series of estimated elasticities of the accounting variables. The advantage of the log-linear model is that the elasticities of individual accounting variables are reliable and consistent estimates of the long-run accounting-market relation. In the second stage of the research design, the estimated elasticities obtained in the first stage are used in a time series analysis, regressing these on climate change variables. The results provide evidence that climate risk is transferred into equity values through accounting information. The key climate risk variable used in the second stage is the global anomaly temperature, which is viewed as an exogenous variable. Other climate variables are also used to provide robust evidence for the baseline results. In addition, the temperature variable is decomposed into long-run and short-run components to observe each component's valuation effect based on the approach adopted in Bansal, Kiku, & Ochoa (2016) and Hodrick & Prescott (1997).

The evidence reported in Chapter 5 supports the argument that climate risk can be transferred into equity values through the channel of accounting information systems. Descriptive statistics show that, after taking logs of the accounting and market data, these data are closer to the Gaussian distribution, making the OLS estimates amenable to standard statistical inference analysis. The results from the first stage show that the log-linear models explain about 80% variation in equity value. The sum of the estimated elasticities of individual accounting variables is approximately equal 1, indicating a close long-run relation between equity and book values. Comparison of the time series patterns of the elasticities of the book value of equity and earnings shows that they are complementary.

The tests in the second stage of the research design are intended to see whether climate risk is associated with the elasticities of the accounting variables. The findings show that global temperature has a positive association with the elasticity of book value of equity and a negative association with the elasticity of earnings. For the different components of the global temperature, the results relating to the long-run component of the global temperature are significant but those relating to the short-run component are not. To verify that the association between the global temperature and the elasticities of accounting variables is not spurious, cointegration between the elasticities and global temperature is tested based on the Engle & Granger (1987) two-stage approach. Cointegration between the variables is shown to exist.

7.2 Limitations

The thesis involves some limitations. First, effects of climate risk are only observed at the U.S. and industry levels. Due to the two-stage research design, the estimated coefficients reflect the means of U.S. or individual industries, the heterogenous effects at firm level are ignored. The climate finance literature demonstrates that actions relating to climate risk vary not only across industries but also firms. Another limitation relating to the research design is that the geographical heterogeneity cannot be captured.

Second, the reliability of the results in stage 1 of the research design is the premise for tests in stage 2. The regressions in stage 1 do not consider the cross-sectional variation in the estimated coefficients by implicitly imposing the constraint in the annual regressions that the average elasticities are identical across firms. Prior studies in value relevance suggest that both cross-sectional variation and intertemporal variation of the underlying parameters may differ.

Third, the thesis investigates the reactions of individual industries to climate risk based on the assumption that different industries have different sensitivity to climate risk. However, the classification of climate sensitivity based on industry is subject to measurement error that confounds the findings in stage 2 to some extent.

Fourth, while the thesis refers to different types of climate risk, physical climate risk and transition climate risk, which may have different implications for valuation, the variable used in models that proxy for climate risk does not discriminate between types of climate risk.

7.3 Directions for Future Research

There are several directions for future research. First, consideration could be given to adopting different approaches to estimation of the elasticities of accounting variables by incorporating both cross-sectional and intertemporal variation. A natural extension would be to use a dynamic version of the log-linear model to estimate elasticities by firm.

Second, the size of the sample could be expanded by incorporating publicly listed firms worldwide. The advantage of an enlarged sample would be the ability to capture the effect of different regulatory environments to better distinguish physical climate risk from transition climate risk and to observe the valuation effects of each type of climate risk.

Third, future research could observe the effects of significant events, including the signing of the Kyoto Protocol, which might change public awareness of climate risk.

REFERENCES

Addoum, J. M., Ng, D. T., & Ortiz-Bobea, A. (2020). Temperature shocks and establishment sales. *The Review of Financial Studies, 33*(3), 1331-1366.

Al-Tuwaijri, S. A., Christensen, T. E., & Hughes Ii, K. E. (2004). The relations among environmental disclosure, environmental performance, and economic performance: a simultaneous equations approach. *Accounting, organizations and society*, *29*(5-6), 447-471.

Armstrong, C. S., Banerjee, S., & Corona, C. (2013). Factor-loading uncertainty and expected returns. *The Review of Financial Studies, 26*(1), 158-207.

Auffhammer, M. (2018). Quantifying economic damages from climate change. *Journal of Economic Perspectives, 32*(4), 33-52.

Auffhammer, M., Hsiang, S. M., Schlenker, W., & Sobel, A. (2011). Global climate models and climate data: a user guide for economists. Retrieved from https://www.climateandforests-undp.org/sites/default/files/downloads/reep_auffhammer_hsiang_schlenker_sobel_v6.pdf

Auffhammer, M., & Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics, 100*(46), 555-561.

Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of accounting research*, 159-178.

Ball, R., Sadka, G., & Sadka, R. (2009). Aggregate earnings and asset prices. *Journal of accounting research, 47*(5), 1097-1133.

Balvers, R., Du, D., & Zhao, X. (2017). Temperature shocks and the cost of equity capital: Implications for climate change perceptions. *Journal of Banking & Finance, 77*, 18-34.

Banerjee, A., Dolado, J. J., Galbraith, J. W., & Hendry, D. (2003). *Co-integration, Error Correction, and the Econometric Analysis of Non-Stationary Data*: Oxford University Press.

Bansal, R., Kiku, D., & Ochoa, M. (2016). Price of long-run temperature shifts in capital markets. Retrieved from https://www.nber.org/system/files/working_papers/w22529/w22529.pdf

Bansal, R., Kiku, D., & Ochoa, M. (2019). Climate change risk. *preprint*. Retrieved from https://www.frbsf.org/wp-content/uploads/sites/4/Paper-5-2019-11-8-Kiku-1PM-1st-paper.pdf

Bansal, R., & Ochoa, M. (2012). Temperature, aggregate risk, and expected returns. *NBER Working Paper, 17575*, 10-11. Retrieved from https://web.archive.org/web/20150912041240id_/https://faculty.fuqua.duke.edu/~rb7/bio/Temp_risk.pdf

Bansal, R., & Yaron, A. (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *The Journal of Finance, 59*(4), 1481-1509.

Barker, R., & Penman, S. (2020). Moving the conceptual framework forward: Accounting for uncertainty. *Contemporary Accounting Research, 37*(1), 322-357.

Barth, M. E., Beaver, W. H., & Landsman, W. R. (1998). Relative valuation roles of equity book value and net income as a function of financial health. *Journal of Accounting and Economics, 25*(1), 1-34.

Barth, M. E., Beaver, W. H., & Landsman, W. R. (2001). The relevance of the value relevance literature for financial accounting standard setting: another view.

Journal of Accounting and Economics, 31(1-3), 77-104.
Barth, M. E., Li, K., & McClure, C. (2022). Evolution in value relevance of accounting information. *The Accounting Review, Forthcoming*
Batten, S., Sowerbutts, R., & Tanaka, M. (2020). Climate change: Macroeconomic impact and implications for monetary policy. In: Walker, T., Gramlich, D., Bitar, M., Fardnia, P. (eds) *Ecological, Societal, and Technological Risks and the Financial Sector*, 13-38. Palgrave Macmillan, Cham.
Battiston, S., Dafermos, Y., & Monasterolo, I. (2021). Climate risks and financial stability. *Journal of Financial Stability*, *54*, 100867.
Beaver, W. H, McNichols, M. F., & Wang, Z. Z. (2020). Increased market response to earnings announcements in the 21st century: An empirical investigation. *Journal of Accounting and Economics*, *69*(1), 101244.
Becketti, S. (2013). *Introduction to time series using Stata* (Vol. 4905): Stata Press College Station, TX.
Bergquist, Parrish, & Warshaw, Christopher. (2019). Does global warming increase public concern about climate change? *The Journal of Politics, 81*(2), 686-691.
Berkman, H., Jona, J., & Soderstrom, N. S. (2021). Firm-specific climate risk and market valuation. *Available at SSRN:* https://ssrn.com/abstract=2775552 or http://dx.doi.org/10.2139/ssrn.2775552.
Bernard, V. L. (1995). The Feltham-Ohlson framework: implications for empiricists. *Contemporary Accounting Research*, *11*(2), 7333-747
Beyer, A., & Smith, K. C. (2021). Learning about risk-factor exposures from earnings: Implications for asset pricing and manipulation. *Journal of Accounting and Economics*, *72*(1), 101404.
Bolton, P., Chen, H., & Wang, N. (2011). A unified theory of Tobin's q, corporate investment, financing, and risk management. *The Journal of Finance, 66*(5), 1545-1578.
Bolton, P., Chen, H., & Wang, N. (2013). Market timing, investment, and risk management. *Journal of Financial Economics, 109*(1), 40-62.
Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517-549.
Bourveau, T., & Law, K. F. (2021). Do disruptive life events affect how analysts assess risk? Evidence from deadly hurricanes. *The Accounting Review*, *96*(3), 121-140.
Brown, J. R., Gustafson, M. T., & Ivanov, I. T. (2021). Weathering cash flow shocks. *The journal of Finance*, *76*(4), 1731-1772.
Burgstahler, D. C., & Dichev, I. D. (1997). Earnings, adaptation and equity value. *The Accounting review*, *72*(2), 187-215.
Burke, M., Dykema, J., Lobell, D. B., Miguel, E., & Satyanath, S.. (2015). Incorporating climate uncertainty into estimates of climate change impacts. *Review of Economics and Statistics, 97*(2), 461-471.
Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy, 8*(3), 106-140.
Carleton, T. A, & Hsiang, S. M. (2016). Social and economic impacts of climate. *Science, 353*(6304).
Carney, M. (2015). Breaking the tragedy of the horizon – climate change and financial stability. Retrieved from https://www.bis.org/review/r151009a.pdf
Carter, C., Cui, X., Ghanem, D., & Mérel, P. (2018). Identifying the economic impacts of climate change on agriculture. *Annual Review of Resource Economics, 10*(1), 361-380.
Chabi-Yo, F., & Loudis, J. (2020). The conditional expected market return. *Journal of*

Financial Economics, 137(3), 752-786.
Chen, Q., & Schipper, K. (2016). Comments and observations regarding the relation between theory and empirical research in contemporary accounting research. *Foundations and Trends® in Accounting, 10*(2-4), 314-360.
Christensen, P. O., & Feltham, G. A. (2009). Equity Valuation. *Foundations and Trends (R) in Accounting, 4*(1), 1-112.
Clarkson, P. M. (2012). The valuation relevance of environmental performance: Evidence from the academic literature. In: S. Jones & J. Ratnatunga (Eds.), *Contemporary issues in sustainability accounting, assurance and reporting*, 11-42, Emerald Group Publishing.
Clarkson, P. M., Li, Y., Pinnuck, M., & Richardson, G. D. (2015). The valuation relevance of greenhouse gas emissions under the European Union carbon emissions trading scheme. *European Accounting Review, 24*(3), 551-580.
Clarkson, P. M., Li, Y., & Richardson, G. D. (2004). The market valuation of environmental capital expenditures by pulp and paper companies. *The Accounting Review, 79*(2), 329-353.
Clarkson, P. M., Li, Y., Richardson, G. D., & Vasvari, F. P. (2011). Does it really pay to be green? Determinants and consequences of proactive environmental strategies. *Journal of Accounting and Public Policy, 30*(2), 122-144.
Climate-Related Market Risk Subcommittee (2020). Managing climate risk in the U.S. financial system. *Report of the Climate-Related Subcommittee Market Risk Advisory Committee of the US Commodity Futures Trading Commission*. Retrieved from https://www.cftc.gov/sites/default/files/2020-09/9-9-20%20Report%20of%20the%20Subcommittee%20on%20Climate-Related%20Market%20Risk%20-%20Managing%20Climate%20Risk%20in%20the%20U.S.%20Financial%20System%20for%20posting.pdf
Clout, V. J., & Willett, R. (2016). Analysing the market–book value relation in large Australian and US firms: implications for fundamental analysis and the market–book ratio. *Accounting & Finance, 56*(4), 1017-1040.
Collins, D. W., Kothari, S. P., Shanken, J., & Sloan, R. G. (1994). Lack of timeliness and noise as explanations for the low contemporaneuos return-earnings association. *Journal of Accounting and Economics, 18*(3), 289-324.
Collins, D. W., & Kothari, S. P. (1989). An analysis of intertemporal and cross-sectional determinants of earnings response coefficients. *Journal of Accounting and Economics, 11*(2-3), 143-181.
Collins, D. W., Li, O. Z., & Xie, H. (2009). What drives the increased informativeness of earnings announcements over time? *Review of Accounting Studies, 14*(1), 1-30.
Collins, D. W., Maydew, E. L., & Weiss, I. S. (1997). Changes in the value-relevance of earnings and book values over the past forty years. *Journal of Accounting and Economics, 24*(1), 39-67.
Collins, D. W., Pincus, M., & Xie, H. (1999). Equity valuation and negative earnings: The role of book value of equity. *The Accounting Review, 74*(1), 29-61.
Correa, R., He, A., Herpfer, C., & Lel, U. (2020). The rising tide lifts some interest rates: Climate change, natural disasters and loan pricing. *Available at SSRN:* https://ssrn.com/abstract=3710451 or http://dx.doi.org/10.2139/ssrn.3710451.
Cuculiza, C., Kumar, A., Xin, W., & Zhang, C. (2021). Climate Change, Analyst Forecasts, and Market Behavior. *Available at SSRN:* https://ssrn.com/abstract=3781157 or http://dx.doi.org/10.2139/ssrn.3781157.
Dai, R., Duan, R., Liang, H., & Ng, L. (2021). Outsourcing Climate Change.

Available at SSRN: https://ssrn.com/abstract=3765485 or http://dx.doi.org/10.2139/ssrn.3765485.

Dai, R., Duan, R., & Ng, L. (2021). Do environmental regulations do more harm than good? Evidence from competition and innovation. *Available at SSRN:* https://ssrn.com/abstract=3746138 or http://dx.doi.org/10.2139/ssrn.3746138.

Dechezleprêtre, A., & Sato, M. (2017). The Impacts of Environmental Regulations on Competitiveness. *Review of Environmental Economics and Policy, 11*(2), 183-206.

Dehaan, E., Madsen, J., & Piotroski, J. D. (2017). Do weather-induced moods affect the processing of earnings news? *Journal of Accounting Research, 55*(3), 509-550.

Dell, M., Jones, B. F., & Olken, B. N. A. (2008). Climate change and economic growth: Evidence from the last half century. Retrieved from https://www.nber.org/system/files/working_papers/w14132/w14132.pdf

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics, 4*(3), 66-95.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature, 52*(3), 740-798.

Deryugina, T. (2013). How do people update? The effects of local weather fluctuations on beliefs about global warming. *Climatic change, 118*(2), 397-416.

Doornik, J. A., & Hendry, D. F. (2013). *PcGive 14 Volume I: Empirical Econometric Modelling*. Timberlake Consultants Ltd.

Easton, P. D., & Harris, T. S. (1991). Earnings as an explanatory variable for returns. *Journal of Accounting Research, 29*(1), 19-36.

Easton, P. D., & Zmijewski, M. E. (1989). Cross-sectional variation in the stock market response to accounting earnings announcements. *Journal of Accounting and Economics, 11*(2-3), 117-141.

Ellahie, A. (2021). Earnings beta. *Review of Accounting Studies, 26*(1), 81-122.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies, 33*(3), 1184-1216.

Engle, R. F, & Granger, C. J. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: Journal of the Econometric Society, 55*(2), 251-276.

EPA. (2019). The origins of EPA. Retrieved from https://www.epa.gov/history/origins-epa

Epstein, L. G, & Zin, S. E. (1989). Substitution, Risk Aversion, and the Temporal Behavior of Consumption. *Econometrica, 57*(4), 937-969.

Ericsson, N. R., & MacKinnon, J. G. (2002). Distributions of error correction tests for cointegration. *The Econometrics Journal, 5*(2), 285-318.

Falta, M.l, & Willett, R. J. (2013). The impact of exponential growth variables on regression models of the market–accounting relation. *Journal of Accounting, Auditing & Finance, 28*(3), 243-272.

Fama, E. F., & French, K. R. (2000). Forecasting profitability and earnings. *The Journal of Business, 73*(2), 161-175.

Fama, E. F, & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy, 81*(3), 607-636.

Fishburn, P. C. (1977). Mean-risk analysis with risk associated with below target return. *The American Economic Review, 67*(2), 116-126

Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics, 142*(2), 499-516.
Francis, J., & Schipper, K.. (1999). Have financial statements lost their relevance? *Journal of Accounting Research, 37*(2), 319-352.
Francis, J., Schipper, K., & Vincent, L. (2002). Expanded disclosures and the increased usefulness of earnings announcements. *The Accounting Review, 77*(3), 515-546.
Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate finance. *Annual Review of Financial Economics, 13*(1), 15-36.
Ginglinger, E., & Moreau, Q. (2022). Climate Risk and Capital Structure. *Available at SSRN:* https://ssrn.com/abstract=3327185 or http://dx.doi.org/10.2139/ssrn.3327185.
Gode, D., & Ohlson, J. (2004). Accounting-based valuation with changing interest rates. *Review of Accounting Studies, 9*(4), 419-441.
Goetzmann, W. N., Kim, D., Kumar, A., & Wang, Q. (2015). Weather-induced mood, institutional investors, and stock returns. *The Review of Financial Studies, 28*(1), 73-111.
Gordon, M. J. (1962). *The investment, financing, and valuation of the corporation*: RD Irwin.
Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., & Wilkens, M. (2020). Carbon risk. *Available at SSRN:* https://ssrn.com/abstract=2930897 or http://dx.doi.org/10.2139/ssrn.2930897.
Gostlow, G. (2019). Pricing climate risk. *Available at SSRN:* https://ssrn.com/abstract=3501013 or http://dx.doi.org/10.2139/ssrn.3501013.
Gostlow, G. (2020). The materiality and measurement of physical climate risk: evidence from Form 8-K. *Available at SSRN:* https://ssrn.com/abstract=3736100 or http://dx.doi.org/10.2139/ssrn.3736100.
Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics, 32*(1), 1-26.
Griffin, P. A., Lont, D. H., & Sun, E. Y. (2017). The relevance to investors of greenhouse gas emission disclosures. *Contemporary Accounting Research, 34*(2), 1265-1297.
Han, Y., Mao, C. X, Tan, H., & Zhang, C. (2020). Distracted Analysts: Evidence from Climatic Disasters. *Available at SSRN:* https://ssrn.com/abstract=3625803 or http://dx.doi.org/10.2139/ssrn.3625803.
Harvey, A. C. (1990). *The econometric analysis of time series*: Mit Press.
Hassan, O. A., & Romilly, P. (2017). Relations between corporate economic performance, environmental disclosure and greenhouse gas emissions: new insights. *Business Strategy and The Environment, 27*(7), 893-909.
Heinle, M. S., Smith, K. C., & Verrecchia, R. E. (2018). Risk-factor disclosure and asset prices. *The Accounting Review, 93*(2), 191-208.
Henderson, R. M, Reinert, S. A, & Migdal, A. (2018). Climate change in 2018: Implications for business. Retrieved from https://courseware.cutm.ac.in/wp-content/uploads/2020/06/climate-change-2018-Harvard-Business-School-1.pdf
Henderson, R. M, Reinert, S. A., Dekhtyar, P., & Migdal, A. (2020). Climate Change in 2020: Implications for Business. Retrieved from https://www.alumni.hbs.edu/Documents/events/Climate_Change_in_2020_Implications_in_Business.pdf
Hendry, D. F. (1995). *Dynamic econometrics*: Oxford University Press on Demand.
Henningsson, J. (2019). Will the Banker Become a Climate Activist? In *Challenges in*

Managing Sustainable Business (pp. 231-249): Springer.
Heo, Y. (2021). Climate Uncertainty and Corporate Investment: Evidence from State-Led Climate Change Adaptation Plans. *Available at SSRN:* https://ssrn.com/abstract=3816477 or http://dx.doi.org/10.2139/ssrn.3816477.
Hodrick, R. J, & Prescott, E. C. (1997). Postwar US business cycles: an empirical investigation. *Journal of Money, credit, and Banking*, *29*(1), 1-16.
Holthausen, R. W, & Watts, R. L. (2001). The relevance of the value-relevance literature for financial accounting standard setting. *Journal of Accounting and Economics*, *31*(1-3), 3-75.
Hong, H., Karolyi, G. A., & Scheinkman, J. A. (2020). Climate finance. *The Review of Financial Studies, 33*(3), 1011-1023.
Hong, H., Li, F. W., & Xu, J. (2019). Climate risks and market efficiency. *Journal of Econometrics*, *208*(1), 265-281.
Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics, 8*(1), 43-75.
Hsiang, S., & Kopp, R. E. (2018). An economist's guide to climate change science. *Journal of Economic Perspectives, 32*(4), 3-32.
Hsu, P., Lee, H., Peng, S., & Yi, L. (2018). Natural disasters, technology diversity, and operating performance. *Review of Economics and Statistics*, *100*(4), 619-630.
Hsu, P., Li, K., & Tsou, C.. (2022). The pollution premium. *Journal of Finance, Forthcoming*.
Huang, Y., & Zhang, G. (2012). An examination of the incremental usefulness of balance-sheet information beyond earnings in explaining stock returns. *Journal of Accounting, Auditing & Finance*, *27*(2), 267-293.
Hugon, A., & Law, K. (2019). Impact of climate change on firm earnings: evidence from temperature anomalies. *Available at SSRN:* https://ssrn.com/abstract=3271386 or http://dx.doi.org/10.2139/ssrn.3271386.
Ilhan, E., Sautner, Z., & Vilkov, G. (2021). Carbon Tail Risk. *The Review of Financial Studies*, *34*(3), 1540-1571.
IPCC. (2014). Summary for policymakers. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Retrieved from https://www.ipcc.ch/site/assets/uploads/2018/02/ipcc_wg3_ar5_summary-for-policymakers.pdf
IPCC. (2018). Summary for policymakers. In: Global Warming of 1.5^{o}C. An IPCC Special Report on the impacts of global warmings of 1.5^{o}C above pre-industry levels and related global greenhouse gas emission pathway, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. Retrieved from https://www.ipcc.ch/site/assets/uploads/sites/2/2022/06/SPM_version_report_LR.pdf
IPCC. (2022). Summary for policymakers. In: Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group III to the sixth Assessment Report of the Intergovernmental Panel on Climate Change. Retrieved from https://www.ipcc.ch/report/ar6/wg2/downloads/report/IPCC_AR6_WGII_SummaryForPolicymakers.pdf
Javadi, S., Masum, A. A., Mollagholamali, M., & Rao, R. P. (2020). Climate Change and Corporate Cash Holdings: Global Evidence. *Available at SSRN:* https://ssrn.com/abstract=3717092 or http://dx.doi.org/10.2139/ssrn.3717092.

Jiang, D., Norris, D., & Sun, L. (2021). Weather, institutional investors and earnings news. *Journal of Corporate Finance*, *69*, 101990.
Karydas, C., & Xepapadeas, A. (2019). Climate change financial risks: pricing and portfolio allocation. Retrieved from https://www.econstor.eu/bitstream/10419/222582/1/168650943X.pdf
Kirk, M., Stice, D., & Stice, H. (2022). The Real Effects of Weather on Firm Performance, Analyst Forecasts, and Stock Prices. *Available at SSRN:* https://ssrn.com/abstract=4007090 or http://dx.doi.org/10.2139/ssrn.4007090.
Kolstad, C. D., & Moore, F. C. (2020). Estimating the economic impacts of climate change using weather observations. *Review of Environmental Economics and Policy*, *14*(1), 1-24
Konchitchki, Y., Luo, Y., Ma, M. , & Wu, F. (2016). Accounting-based downside risk, cost of capital, and the macroeconomy. *Review of Accounting Studies, 21*(1), 1-36.
Kormendi, R., & Lipe, R. (1987). Earnings innovations, earnings persistence, and stock returns. *Journal of Business, 60*(3)323-345.
Kothari, S. P. (2001). Capital markets research in accounting. *Journal of Accounting and Economics*, *31*(1-3), 105-231.
Kothari, S. P., & Shanken, J. (2003). Time-series coefficient variation in value-relevance regressions: A discussion of Core, Guay, and Van Buskirk and new evidence. *Journal of Accounting and Economics, 34*(1-3), 69-87.
Kothari, S. P., & Zimmerman, J. L. (1995). Price and return models. *Journal of Accounting and Economics, 20*(2), 155-192.
Kothari, S. P, & Sloan, R. G. (1992). Information in prices about future earnings: Implications for earnings response coefficients. *Journal of Accounting and Economics, 15*(2-3), 143-171.
Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, *33*(3), 1067-1111.
Lantushenko, V., Schellhorn, C. D., & Gulnara, R. (2020). Climate Change Concerns Meet Return-Chasing: Evidence from Energy ETFs. *Financial Review*, *57*(2), 247-272
Lev, B. (2018). The deteriorating usefulness of financial report information and how to reverse it. *Accounting and Business Research*, *48*(5), 465-493.
Li, Q., Shan, H., Tang, Y., & Yao, V. (2020). Corporate climate risk: Measurements and responses. *Available at SSRN:* https://ssrn.com/abstract=3508497 or http://dx.doi.org/10.2139/ssrn.3508497.
Lin, C., Schmid, T., & Weisbach, M. S. (2019). *Climate change, operating flexibility and corporate investment decisions*. Retrieved from https://www.nber.org/system/files/working_papers/w26441/w26441.pdf
Lo, K., & Lys, T. (2000). The Ohlson model: contribution to valuation theory, limitations, and empirical applications. *Journal of Accounting, Auditing & Finance*, *15*(3), 337-367.
Lubberink, M., & Willett, R. J. (2020). The Fundamental Relation Between Firm Market and Accounting Values Is a Multiplicative Power Law. *Available at SSRN:* https://ssrn.com/abstract=3531319 or http://dx.doi.org/10.2139/ssrn.3531319.
Lundholm, R. J. (1995). A tutorial on the Ohlson and Feltham/Ohlson models: answers to some frequently asked questions. *Contemporary Accounting Research*, *11*(2), 749-761.
Lyle, M. R., Callen, J. L., & Elliott, R. J. (2013). Dynamic risk, accounting-based

valuation and firm fundamentals. *Review of Accounting Studies, 18*(4), 899-929.

Madsen, E. (2005). Estimating cointegrating relations from a cross section. *The Econometrics Journal*, *8*(3), 380-405.

Martin, I. W. R., & Wagner, C. (2019). What is the Expected Return on a Stock? *The Journal of Finance, 74*(4), 1887-1929.

Matsumura, E. M., Prakash, R., & Vera-Munoz, S. C. (2014). Firm-value effects of carbon emissions and carbon disclosures. *The Accounting Review, 89*(2), 695-724.

Mendelsohn, R., & Massetti, E. (2017). The Use of Cross-Sectional Analysis to Measure Climate Impacts on Agriculture: Theory and Evidence. *Review of Environmental Economics and Policy, 11*(2), 280-298.

Mendelsohn, R., & Nordhaus, W. (1996). The impact of global warming on agriculture: Reply. *The American Economic Review, 86*(5), 1312-1315.

Moore, F. C., & Lobell, D. B. (2014). Adaptation potential of European agriculture in response to climate change. *Nature climate change, 4*(7), 610-614.

Nagar, V., & Schoenfeld, J. (2022). Measuring weather exposure with annual reports. *Review Accounting Studies, Forthcoming*.

Nordhaus, W. D. (1977). Economic growth and climate: the carbon dioxide problem. *The American Economic Review, 67*(1), 341-346.

Ohlson, J. A. (1995). Earnings, book values, and dividends in equity valuation. *Contemporary Accounting Research*, *11*(2), 661-687.

Ohlson, J. A, & Kim, S. (2015). Linear valuation without OLS: the Theil-Sen estimation approach. *Review of Accounting Studies, 20*(1), 395-435.

Ohlson, J., & Gao, Z. (2006). Earnings, earnings growth and value. *Foundations and Trends® in Accounting, 1*(1), 1-70.

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics, 135*(2), 468-482.

Pankratz, N., Bauer, R., & Derwall, J. (2019). Climate change, firm performance, and investor surprises. *Available at SSRN:* https://ssrn.com/abstract=3443146 or http://dx.doi.org/10.2139/ssrn.3443146.

Penman, S. (2016). Valuation: accounting for risk and the expected return. *Abacus, 52*(1), 106-130.

Penman, S. (2021). Accounting for Risk. *Foundations and Trends® in Accounting, 15*(4), 373-507.

Penman, S. H. (1998). Combining earnings and book value in equity valuation. *Contemporary Accounting Research, 15*(3), 291-324.

Penman, S., & Zhang, X. (2020). A theoretical analysis connecting conservative accounting to the cost of capital. *Journal of Accounting and Economics, 69*(1), 101236.

Penman, S., & Zhu, J. (2022). An accounting-based asset pricing model and a fundamental factor. *Journal of Accounting and Economics*, *73*(2-3), 101476.

Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics, 68*(1), 79-113.

Preinreich, G. A. D. (1938) Annual survey of economic theory: the theory of depreciation. *Econometrica, 6*(3), 219-241

Rajan, M. V., Reichelstein, S., & Soliman, M. T. (2007). Conservatism, growth, and return on investment. *Review of Accounting Studies*, *12*(2), 325-370.

Ryan, S. G. (1997). A survey of research relating accounting numbers to systematic equity risk, with implications for risk disclosure policy and future research. *Accounting Horizons, 11*(2), 82.

Sautner, Z., van Lent, L., Vilkov, G., & Zhang, R. (2020). Firm-level climate change exposure. *Available at SSRN:* https://ssrn.com/abstract=3642508 or http://dx.doi.org/10.2139/ssrn.3642508.

Sautner, Z., van Lent, L., Vilkov, G., & Zhang, R. (2021). Pricing Climate Change Exposure. *Available at SSRN:* https://ssrn.com/abstract=3792366 or http://dx.doi.org/10.2139/ssrn.3792366.

Schlenker, W., & Taylor, C. A. (2021). Market expectations of a warming climate. *Journal of Financial Economics*, *142*(2), 627-640.

Seltzer, L. H., Starks, L., & Zhu, Q. (2022). Climate regulatory risk and corporate bonds. Retrieved from https://www.nber.org/system/files/working_papers/w29994/w29994.pdf

Smith, K. C, & So, E. C. (2022). Measuring risk information. *Journal of Accounting Research*, *60*(2), 375-426.

Stone, B. K. (1973). A general class of three-parameter risk measures. *The Journal of Finance*, *28*(3), 675-685

Vuolteenaho, T. (2002). What drives firm-level stock returns? *The Journal of Finance*, *57*(1), 233-264.

Weber, E. U. (2010). What shapes perceptions of climate change? *Wiley Interdisciplinary Reviews: Climate Change*, *1*(3), 332-342.

Wooldridge, J. M. (2015). Introductory econometrics: A modern approach. Cengage Learning.

Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of Banking & Finance*, *98*, 39-60.

Zhang, X. (2000). Conservative accounting and equity valuation. *Journal of Accounting and Economics*, *29*(1), 125-149.

Zhang, X. (2013). Book-to-market ratio and skewness of stock returns. *The Accounting Review*, *88*(6), 2213-2240.