THREE ESSAYS ON ASSET PRICING IN REGIME AND ESG ENVIRONMENTS

by

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Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy

at

Dalhousie University
Halifax, Nova Scotia
December 2019

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Abstract

Asset pricing has been a focal point among a broad range of financial studies. Traditional asset pricing models are encountering challenges by empirical data and sustainable compliance. For example, the Black-Scholes-Merton (BSM) model exhibits the "volatility smile" puzzle and the role that sustainability plays in accounting for asset pricing remains controversial. Based on these observations, I raise three research questions. First, can an option valuation model with a pricing kernel that depends on market regimes address volatility smile and be consistent with observed market prices? Second, how do the Environment, Social and Governance (ESG) ratings affect asset prices across different economic sectors, firm sizes, and time horizons? Third, since the macroeconomic environment affects firms' strategies and financial performance, how do ESG ratings affect stock returns across market regimes? I address these questions in three essays. The first essay reveals that the proposed model can predict the market option prices more accurate than the alternative models (Black-Scholes-Merton, Heston-Nandi, Hardy) do for both the in-sample and out-of-sample data across regimes. The second essay finds that ESG ratings have a positive effect on stock returns, particularly for sensitive industries (gas, oil, chemical, mining, alcohol, and tobacco, etc.), for large capitalization firms, and for long-term investment horizons. The third essay uses a machine learning method to identify market regime using 134 macroeconomic factors and a factor model to discover a positive relationship between ESG and asset returns in the bear regime. The factor model also show that the impact of ESG rating on stock returns in a sector, given a market regime, depends significantly on the level of demand in that sector under that market regime.

List of Abbreviations and Symbols Used

BSM Black-Scholes-Merton Model

CSR Corporate Social Responsibility

ESG Environmental, Social and Governance

GARCH Generalized Auto-regressive Conditional Heteroskedasticity

GDP Gross Domestic Product

HN Heston-Nandi Model

MNZ Regime-switching Option Pricing Model Proposed in the First Essay

H High-volatility Regime

L Low-volatility Regime

HMM Hidden Markov Model

NBER National Bureau of Economic Research

SPX S&P 500 Index

LEI Lagged Economic Indicator Index

TIP Total Industrial Production

CPI Consumer Price Index

YSD Yield Spread

CSD Credit Spread

UEM Unemployment Rate

CBOE Chicago Board Options Exchange

MAE Mean Absolute Error

PSR Prediction Success Rate

NOAA National Oceanic and Atmospheric Administration

NASA National Aeronautics and Space Administration

IPCC Intergovernmental Panel on Climate Change

UNGC United Nations Global Compact

PRI Principles for Responsible Investment

SRI Socially Responsible Investing

TRBC Thomson Reuters Business Classification

KLD Kinder, Lydenberg, and Domini

SR Socially Responsible

CFP Corporate Financial Performance

MKT Market Excess Return

HML High Minus Low

SMB Small Minus Big

MOM Momentum

CRSP Center for Research in Security Prices

EWR Assset4 Equal Weighted Ratings

IH Induced Heating

LASSO Least Absolute Shrinkage and Selection Operator

FRED Federal Reserve Economic Data

PCA Principal Component Analysis

RS Regime-switching Model

VAR Vector Auto-regressive Process

EM Expectation and Maximization Algorithm

W_t macroeconomic variables at time t

A_{M_t}, B_{M_t} regime-dependent parameters

Z_t standard multivariate normal random variables

S_t price of underlying asset at time t

M_t market regime at time t

μ regime-dependent annualized mean of underlying asset return

σ regime-dependent annualized volatility for underlying asset return

S_t price of the underlying asset at time t

R asset returns

f_{R_t} density function of logarithmic return of the underlying asset from time $t-1$ to t

ϕ_n normal density function conditional on regime n

p_t prior probability of regime 1 at time t

B_t price of risk-free asset at time t

$f_{t,T}$ forward rate between time t and T

ξ extended Black-Scholes pricing kernel

L low-volatility regime

H high-volatility regime

C European call option price

C_l European call option conditional on low-volatility regime

C_h European call option conditional on high-volatility regime

q_0^n posterior probability of regime n at time 0

$P_{M_t,M_{t+1}}$ constant transition probability from regime M_t to regime M_{t+1}

P constant transition probability

P_h constant transition probability from Hardy's Model

R_{ft} risk-free rate at time t

R_{mt} return of market portfolio at time t

α_i,$\beta_{1,i}$,$\beta_{2,i}$,$\beta_{3,i}$,$\beta_{4,i}$ parameters of linear Carhart four-factor model

ϵ_{it} the residual of the linear Carhart four-factor model

α_{i,M_t},β_{1i,M_t},β_{2i,M_t},β_{3i,M_t},β_{4i,M_t} parameters of the regime-dependent Carhart four-factor model

ϵ_{i,M_t} residual of the regime-dependent Carhart four-factor model

$\mathbf{y}$ response variable in LASSO

$\mathbf{X}$ vector of covariates in LASSO

λ tunning variable in LASSO

F_t macroeconomic factors in the auto-regressive regime-switching model

a_{M_t}, b_{M_t} and γ_{M_t} parameters of the auto-regressive regime-switching model

T_{M_{t-1},M_t} time-varying transition probability from time $t-1$ to time t

p_t prior probability at time t

a regime-dependent intercepts of the vector auto-regressive model

b regime-dependent matrix of the sensitivities of the macroeconomic indicators

$\mathbb{Z}$ multivariate independently normally distributed vector of errors

Ψ set of parameters in Bayes information criterion

Acknowledgements

First and foremost, I would like to express my greatest appreciation to Drs. Kuan Xu and Yonggan Zhao, my Ph.D. thesis co-supervisors, for equipping me with insight into the financial study and shaping me as a scholar with the ability of independent thinking. Without their valuable guidance, impressive kindness, and patience, I could not see the light. I would like to thank Drs. Iraj Fooladi and Mevlude Akbulut-Yuksel, my Ph.D. thesis committee members for their great support.

I would like to thank Dr. Jason Wei for his generous support. My thanks also go to Drs. Yulia Kotlyarova, Barry Lesser, Christos Ntantamis, Jun Zhou and Norovsambuu Tumennasan, and all the professors in the Department of Economics who have helped and inspired me. I am thankful to Lily Shen, Obed Owusu, Henry Hu, Sara Zhang, and all my friends who participated in my Ph.D. study. Thanks also to all participants in the GRASFI conference at Oxford University and the Sustainable Finance conference at Queens' University for their valuable comments to my research. I would like to thank the Department of Economics and Faculty of Management at Dalhousie University, and Nova Scotia Government, for their generous financial support.

As I was working on my thesis, Dr. Feng Liu offered me an research visit at the Research Institute of China Galaxy Securities in the summer of 2018. I got tremendous encouragement from Dr. Liu about my research. The ESG research is profoundly important for our time and future generations.

My deepest gratitude goes to my parents for their selfless love, moral support and goes to Polly Chen, my lovely wife, for her encouragement and company in times of difficulty.

Chapter 1

Introduction

Since the 1980s, technological innovation and an information explosion have occurred in the global economy and the financial market has changed rapidly. The financial market is critical for growth and capital allocation. Most recently, sustainability has drawn more attention and is also incorporated into the role of financial activities. In 2002, the International Finance Corporation (managed by the World Bank) and ABN-AMRO Bank proposed a series of fundamental principles about corporate responsibility to the environment and to society. In the following year, 10 multinational banks, including Citibank and Barclays, jointly established the "Equator Principles", which require financial institutions to formally evaluate the environmental and social effects generated in the process of international project financing. The Equator Principles, therefore, serve as the inception of "Green Finance". Over the past 20 years, the sustainable philosophy in finance, which emphasizes harmonious coexistence between human and natural ecology, has drawn close attention in a global context, and the green financial market has become increasingly important.

Among a large variety of fields in financial research, asset pricing has been one of the most widely discussed topics. Considering that the financial industry, with the introduction and integration of new concepts, is in the process of a profound structural change, a number of classical theories in asset pricing, such as the Markowitz portfolio selection theory (Markowitz, 1959), the Black-Scholes-Merton (BSM) option pricing model (Black and Scholes, 1973; Merton, 1973) and the Fama-French three-factor model (Fama and French, 1993), have been challenged by new thinking on economic regimes and sustainability. Particularly, the BSM model sets the volatility of the underlying asset returns as a constant, while the actual data have shown that volatility is dynamic. This raises the famous "volatility smile" puzzle. Hence, the first objective of this thesis is to extend the option pricing model based on the BSM framework and develop an option pricing model that can capture prices in the actual market with greater accuracy. Further, integrating sustainability is a new topic. It is also of interest to investigate the role that sustainability plays in the dynamics of asset prices. The second objective of this study is to examine how sustainable finance affects stock pricing in the financial market.

The first essay (Chapter 2) focuses on option pricing in the conventional financial market. In 1973, Black, Scholes, and Merton developed an option pricing model that makes pricing for financial derivatives feasible. This path-breaking achievement has laid a solid foundation for option pricing. However, the BSM model assumes that the market is complete and that the dynamics of a stock price follows a normal distribution, both of which contradict empirical findings. In light of the BSM framework, in the first essay (Chapter 2) I develop an alternative option pricing model that captures price fluctuations in the actual financial market. To address market incompleteness and the changing macroeconomic environment, I employ the regime-switching method in the pricing process.

The second essay (Chapter 3) focuses on the effect of corporate social responsibility (CSR) practices on companies' stock returns. Climate change induced by human activities since the industrial revolution and a series of social conflicts such as poverty, income and wealth inequality, gender and racial discrimination and human rights deprivation left by the growth of the private ownership economy become new challenges. The international community now advocates a balance between the economy and the environment to achieve sustainable development. As a response, in the financial market, a universal standard of CSR, the Environmental, Social, and Governance (ESG) scoring system for firms, has been created to evaluate corporate sustainability, ethics, and management ability. Investing in ESG rating involves extra costs, but whether and how firms can benefit from a high ESG rating is not clear. In this essay, I examine the relationship between stock prices and their ESG rating using the Carhart four-factor asset pricing model.

The third essay (Chapter 4) continues to focus on the effect of ESG rating on stock returns. However, unlike the second essay, it takes market regimes into consideration. The macroeconomic environment potentially affects firms' businesses and performances. During an economic recession, when survival becomes the priority for most firms, investing in CSR may or may not be preferred. However, based on the positive reactions and substantial supports to social responsibility implementation by Canon, WPP, Alibaba, etc. during the 2008-2009 financial crisis, I argue that CSR may act as a proactive investment for a company to hedge its risk in an economic downturn. Thus, in this essay, I probe the specific impact of ESG rating on stock returns under different market conditions which are revealed by a machine learning method.

Chapter 2

Option Pricing under Different Regime Shifts

2.1 Introduction

During the turmoil in the global financial markets over the past 30 years, the traditional option pricing models encountered a series of challenges, as they could not predict actual option prices. It is well known that, in a complete market as in the Black-Scholes-Merton (Black and Scholes, 1973; Merton, 1973) and the Cox-Ross-Rubinstein (Cox et al., 1979) models, there exists only one risk-neutral probability measure and option prices are uniquely determined. However, the empirical evidence shows that asset returns exhibit higher volatilities in economic contraction than in economic expansion. This empirical finding naturally contradicts the assumption of market completeness and elicits an incomplete market setting for the dynamics of the underlying asset returns. Hence, it is of interest to explore an option pricing model that captures the actual market dynamics more precisely.

There has long been consensus that existing option pricing models do not perform satisfactorily, as surveyed by Bakshi et al. (1997). For example, in-the-money calls and out-of-the-money puts on the S&P 500 price index are usually underpriced by the BSM model, while the model overprices out-of-the-money calls and in-the-money puts. The volatility of the underlying asset returns is a key component of an option-pricing model. Standard models set this quantity as a constant (Black and Scholes, 1973; Cox et al., 1979; Merton, 1973), while the empirical evidence show that volatility changes over time. There have been attempts to fix this deficiency in the literature. Merton (1976), Hull and White (1990), Heston (1993) allow for jump-diffusion processes or stochastic volatility to capture discontinuity in the underlying asset prices and to relax the constancy of volatility. A general auto-regressive and conditional heteroskedasticity (GARCH) process has been widely used for volatility modeling (Bollerslev, 1986; Chorro et al., 2012; Christoffersen et al., 2012, 2008; Duan, 1995; Durham et al., 2015; Engle, 1982; Engle and Siriwardane, 2017; Heston and Nandi, 2000; Kanniainen et al., 2014; Ritchken and Trevor, 1999). However, the GARCH model has its main drawback in asset pricing: lacking consideration of the effects of the macroeconomic environment. The financial market, as a primary component of the aggregate economy, mirrors the macroeconomic environment. Thus, fluctuations of factors in the financial market, such as earnings, cash flows, discount rate, and asset volatility, can also be accounted for by the economic outlook. Since volatility serves as a key factor in the process of option pricing, its expectation is heavily impacted by the macro-economy. Consequently, without observing external economic circumstances, estimation of volatility and the option prices may suffer from significant biases.

To overcome the limitations of the current option pricing model, this essay proposes a mechanism to capture the actual changes in the macroeconomic environment and its effects on the financial market. Life marches in twists and turns, and so does an economy. Due to alterations of individual perception, expectation, and uncertainty level, people make different decisions about consumption, investment, and saving over time; therefore, the financial market evolves with these alterations. Simultaneously, a changing macroeconomic environment affects people's belief and confidence in the market and their economic activities. To characterize the dynamic relationship between macroeconomic conditions of the market and microeconomic behaviors of agents, distinguishing market regimes is desirable in current research. There are two typical regimes, bull and bear, accounting for two opposite states in the financial market: a bull regime represents a positive market status in which asset prices tend to increase consistently, and the economy reveals a strengthening trend. Investors' attitudes toward the financial market under a bull regime are generally optimistic, confident, and even speculative. In contrast, a bear regime indicates a financial downturn where prices slump, and the economy is sluggish. Investors are less ambitious and more cautious in a bear market, so that their investment strategies are relatively conservative (Kahneman and Tversky, 1979).

Hamilton (1989) introduces a innovative regime-switching method to capture structural changes in economic time series, accommodating market regime shifts, such as recession and currency crises. After the unveiling of a regime-switching mechanism in finance and economics, the following three decades saw an increasing number of studies incorporating regime-switching model into a broad range of analyses including equity option (Aingworth et al., 2006; Bollen, 1998; Boyle and Draviam, 2007; Boyle, 1988; Buffington and Elliott, 2002; Elliott et al., 2005; Guo, 2001; Khaliq and Liu, 2009; Liu, 2010; Yao et al., 2006; Yuen and Yang, 2010a,b), interest rate derivatives (Bansal and Zhou, 2002; Liu, 2012), portfolio selection (Zhou and Yin, 2003), trading rules (Eloe et al., 2008; Yin et al., 2002; Zhang, 2001; Zhang et al., 2005) and others.The regime-switching method has gradually attracted a wider attention in a global context.

Current research has investigated the changing patterns of options' prices by modeling underlying asset returns in a regime-switching process. Naik (1993) studies a jump-diffusion model with two regimes (high- and low-volatility regimes) and provides a method of pricing European options by employing a density function of time spent in a regime. His finding shows that investors can hedge against the possibility of volatility regime shifts. Yao et al. (2006) examine two and three regimes for European options using risk-neutral valuation. They use numerical examples to demonstrate the existence of the volatility smile. Fuh et al. (2012) develop a tree model to compute the price of European call options. Lee (2014) provides a numerical method for option prices under regime-switching jump-diffusion model. He solves a partial integro-differential equation for European options and a complementary liner problem for American options. Liu and Nguyen (2015) develop a regime–dependent tree model for option pricing, and extend Heston's stochastic volatility model with a jump component. They find that the prices for European and American options from regime-switching models fit better the real market data. Biswas et al. (2018) apply a stochastic volatility model to price a European call option where the parameters follow a semi-Markov modulated Heston process.

Hardy (2001) is the first to derive a recursive pricing formula under two market regimes for long-term options. She shows that a regime-switching model in a steady state fits data better than conventional pricing models, such as the GARCH model. She extends the BSM by allowing the volatility of the underlying asset returns to switch according to a two-regime Markov chain, but the distribution of the single-period logarithmic return of the underlying asset is still normal, conditional on the current regime of the economy. The price of an option is derived by applying the BSM formula to each of the event paths of the binomial tree generated using the volatility process for the underlying asset returns. To calculate options' prices, the Hardy model assumes a steady-state distribution of regimes at each point in time, as Bayesian updating on probabilities of the regimes at any point in time cannot be carried out with the Hardy model. An option pricing model in a steady state may perform well for long-term options; but, it is not satisfactory in a financial market with frequent fluctuations. The model proposed in this paper addresses this issue by incorporating the likelihood of regimes into option pricing. This essay shows that the proposed model incorporates the Hardy model as a special case.

Since there has been no universal metric to define a bear or bull market up to now, the identification of regimes remains controversial. From a microeconomic perspective, shifts of regimes are characterized by changes in asset prices and investors' activities, which include market confidence, expectation, and speculative mentality. In a macroeconomic sense, significant movements of macroeconomic factors such as GDP, interest rate, and unemployment rate are expected to reflect regime switches because alterations in consumption and investment decisions resulted from changes in expected cash flows and expected discount rate, which are both determined by the aggregate economic environment. There is a strand of literature that has studied the market volatility through business cycles. Schwert (1989), Engle and Rangel (2008), and Engle et al. (2013) find that the fundamental volatility process is significantly related to macroeconomic factors. Dorion (2016) extends Engle et al. (2013)'s model and presents an option valuation model, in which macroeconomic variables partly determine the option prices. Accounting for macroeconomic variables can improve volatility forecasts significantly. However, most studies in the literature identify market regimes by extracting information from the dynamics of asset prices but neglect the role that the macroeconomy plays in market regimes. To fill the knowledge gap in the current literature, this study identifies market regimes by taking macroeconomic variables into account.

This essay first develops a hidden Markov model to characterize economic strength using macroeconomic indicators. With the estimated hidden Markov model for the economic conditions, the underlying asset returns are characterized by high- and low-volatility regimes, which are associated with contraction and expansion of economic conditions, respectively. With an extension of the BSM pricing kernel for regimes, I then derive a formula for options' prices, which depend on the posterior probabilities of market regimes. The evaluation process decomposes the option's value into conditional expectations along all economic event paths, which are categorized by the numbers of high-volatility and low-volatility regimes before the option's expiration date. Although the proposed model setting is radically different from the Hardy model, I will show that these two models converge into the same option pricing formula when the posterior probabilities of the regimes coincide with the steady-state probabilities and the return parameters of the two models are equal. The option prices by the Hardy model are based on a steady-state probability. However, the actual financial market with frequent fluctuations is less likely to be a steady state. Yet, options prices derived by the proposed model depend on the posterior probabilities of the regimes at any point in time, which are carried out by the Bayesian updating process. It proves that my model prices are much closer to the actual market prices, with an additional risk premium induced for high-volatility regimes.

To evaluate the model performance, I use the S&P 500 index options with expiration less than or equal to 12 months. To cover a broad level of market conditions, I retrieve monthly data from Datastream for the period August 2005 to December

2009, which experiences both bull and bear markets. I use LIBOR/Swap zero rates as a proxy of the risk-free asset. The model-predicted option prices are compared with those predicted by the three benchmark models: BSM, Hardy, and Heston-Nandi (HN). The comparison analyses are based on the standard metric, *mean absolute error*, which is separately carried out with options prices and the implied volatilities. Empirical results from this study provide strong evidence that the S&P 500 index option prices predicted by the proposed model are much more accurate than those predicted by the BSM, Hardy, and HN models.

The remainder of this paper is organized as follows. In Section 2, I discuss the modeling approach to the underlying asset prices and volatility regimes. In Section 3, I derive a pricing formula for European options based on an extended Black-Scholes type of pricing kernel. In Section 4, I present the model implementation with the S&P 500 index options and compares the model performance with the benchmark models, BSM model, Hardy, and Heston-Nandi, under the commonly used performance metric. Section 5 concludes the paper.

2.2 Modeling Asset Returns

2.2.1 Macroeconomic indicators

I develop a hidden Markov regime-switching model using macroeconomic indicators to estimate the unobserved market regimes. Denote the observed macroeconomic variables as W_t at time t and the unobserved economic regime as M_t, which take two distinct values for ease of exposition. I assume that

$$W_t = A_{M_t} + B_{M_t} Z_t$$

where A_{M_t}, B_{M_t} are regime-dependent parameters. Z_t is a standard multivariate normal random variable and independent over time. There are two distinct regimes and they follow a first-order Markov chain with an initial regime distribution q_0 and a constant transition matrix $P = \{p_{ij}\}$, where p_{ij} is the transition probability of the market transitioning from regime i at time $t-1$ to regime j at time t.

In this setting, given that the future economy is in a specific regime, the economic activities jointly follow a multivariate normal distribution. Unconditionally, the economic activities jointly follow a multivariate mixture normal distribution in which the prior probabilities of the regime at time t act as mixing coefficients of the mixture model.

2.2.2 Underlying asset returns and risk-free rates

Let S_t be the price of the underlying asset at time t. Conditional on the regime M_t at time t, I assume that the logarithmic price, S_t, of the underlying asset follows a normal distribution with mean and standard deviation depending on the economic regime M_t.

Hardy (2001) assumes that the logarithmic price of the underlying asset obeys the following stochastic process:

$$\ln S_t = \ln S_{t-1} + \mu_{M_{t-1}}\tau + \sigma_{M_{t-1}}\sqrt{\tau}Z_t. \tag{2.1}$$

This setting implies that the single-period logarithmic asset return, $\ln(S_t/S_{t-1})$, is normally distributed with the location parameters switching according to a two-regime Markov chain, but it does not depend on the concurrent regime at time t. Under the Hardy model, the statistical distribution of the underlying asset return at time t is completely specified given the regime distribution at time $t-1$. Conditional on the current regime of the economy, the logarithmic return for the Hardy model is still normal. The problem is that the posterior probabilities of the regime, which are part of the option pricing formula, are unknown at time t with the Hardy model, as the return from $t-1$ to t does not depend on the regime at time t. Therefore, the steady-state regime distribution must be used to calculate the options prices with the Hardy model (2.1). With the hidden Markov model setting, posterior probabilities at any point in time are readily obtained under Bayesian updating. As the empirical analysis shows, posterior probabilities are a key input to the option pricing formula.

The proposed hidden Markov model in this essay is different from the Hardy (2001) model:

$$\ln S_t = \ln S_{t-1} + \mu_{M_t}\tau + \sigma_{M_t}\sqrt{\tau}Z_t. \tag{2.2}$$

In other words, the single-period logarithmic return of the underlying asset from time $t-1$ to t, $R_t = \ln(S_t/S_{t-1})$, follows a conditional normal distribution:

$$(R_t|M_t = n) \ \sim N(\mu_n\tau, \sigma_n^2\tau), \quad \forall n = 1, 2, \tag{2.3}$$

where μ_n and σ_n are the regime-dependent annualized mean and volatility of the asset return, given that the regime at time t is k. τ is the timespan between two consecutive time epoch. Unconditionally, R_t follows a mixture of normal distributions with mixing coefficients being the prior probabilities of the regimes at time t. This setting extends the Hardy model with different distributions for the underlying asset returns in different economic regimes. I assume that there are only two regimes and the single-period logarithmic return of the underlying asset follows a mixture distribution with a density function of the form:

$$f_{R_t}(x) = p_t\phi_1(x) + (1 - p_t)\phi_2(x),$$

where $\phi_n(x)$ is a normal density function with mean $\mu_n\tau$ and standard deviations $\sigma_n\sqrt{\tau}$, given the regime at time t is n, for $n = 1, 2$. p_t is the prior probability of regime 1 at time t. In this setting, I assume that, given the regime at time t, the statistical distribution of the asset return from time $t-1$ to t is completely determined and is independent of the economic regime at time $t-1$. However, the unconditional distribution of the one-period asset return depends on the concurrent regimes. Since regimes are not observable, posterior probabilities of the regimes are a key quantity for the options pricing model.

I assume that there is a risk-free asset. At any time t, I need to estimate the value of \$1 to be paid at time T. If the spot rates for time t and T are known, the no-arbitrage value of \$1 of risk-free asset should be exactly equal to $B_{t,T} = e^{-f_{t,T}(T-t)\tau}$, where $f_{t,T}$ is the forward rate between time t and T. This is to say that, for \$1 payment at any future time T, its present value at time t should be obtained by discounting at the forward rate. Thus, the price of the risk-free asset, B_t, obeys the following deterministic process over time:

$$\ln B_t = \ln B_{t-1} + f_t\tau$$

where f_t is the one-period forward interest rate between $t-1$ and t and is the instantaneous short rate for continuous-time models. Most option pricing models in the literature take this quantity as constant, which indicates a flat term structure of interest rates. To capture the time value of money, I assume a time-varying term structure of interest rates. In the empirical analysis, I use the LIBOR/Swap rates to price the S&P 500 Index options.

2.3 The Option Pricing Model

Suppose there is a call option on the underlying asset with a strike price K and time periods to expiration T. The intention is to find the fair price of the option. In addition to the setting as in (2.3) for the logarithmic asset return, I allow the underlying asset to pay dividends at a constant yield δ.

2.3.1 A pricing kernel with regimes

I extend the Black-Scholes pricing kernel by including the regime characteristics. The pricing kernel, ξ_t, can be recursively defined as

$$\xi_t = \xi_{t-1} e^{-(f_t - \frac{1}{2}\eta_t^2)\tau - \eta_t\sqrt{\tau}Z_t},$$

where $\xi_0 = 1$, Z_t is a standard normal random variable, and

$$\eta_t = \frac{\mu_{M_t} - f_t + \delta + \frac{1}{2}\sigma_{M_t}^2}{\sigma_{M_t}}.$$

Thus, $\left\{\xi_t S_t e^{\delta \cdot t \cdot \tau}\right\}$ is a martingale and the associated risk neutral-probability measure, $\mathcal{Q}$, is given by

$$E^{Q}[I_A] = E[\xi_T I_A]/E[\xi_T],$$

where A is an event by time T, I_A is the indicator function for event A, and $E^{\mathcal{Q}}[\cdot]$ is the expectation operator under $\mathcal{Q}$.

Under the risk-neutral probability measure, the price of the underlying asset at time t can be represented as

$$S_t = S_{t-1} e^{(f_t - \delta - \frac{1}{2}\sigma_{M_t}^2)\tau + \sigma_{M_t}\sqrt{\tau}\ Z_t}.$$

As in the Black-Scholes model, the specified pricing kernel also eliminates the drift and includes the volatility in the risk-neutral pricing mechanism.

Under the risk-neutral valuation, the price of the call option equals

$$C = e^{-(r_T T \tau)} E^{\mathcal{Q}}[(S_T - K)^+], \tag{2.4}$$

where r_T is the risk-free rate for time T.

Denote the one-period logarithmic return of the underlying asset from time $t-1$ to t as

$$R_t = (f_t - \delta - \tfrac{1}{2}\sigma_{M_t}^2)\tau + \sigma_{M_t}\sqrt{\tau}\ Z_t.$$

Then,

$$S_T = S_0 e^{R_1 + R_2 + \cdots + R_T}.$$

Since R_t is normally distributed conditional on M_t, $t = 1, 2, \cdots, T$, then $R_1 + R_2 + \cdots + R_T$ is also normally distributed given a regime path, $(M_1, M_2, \cdots, M_T)$. Hence, I can use the Black-Scholes formula to find the value of the option along each of the regime paths from time 1 to T, and the option price is the weighted average of the path dependent values. Let

$$BS(path) = e^{-(r_T T \tau)} E^{\mathcal{Q}}[(S_T - K)^+ | path].$$

Then, the option pricing formula (2.4) is alternatively expressed as

$$C = q_0^h \sum_{path} BS(path) \Pr(path | M_0 = H) + q_0^l \sum_{path} BS(path) \Pr(path | M_0 = L), \quad (2.5)$$

where q_0^n is the posterior probability of regime n at time 0. The probability of a path, $(M_1, M_2, \cdots, M_T)$, given M_0 equals

$$P_{M_0 M_1} * P_{M_1 M_2} * \cdots * P_{M_{T-1} M_T}$$

where $P_{M_t M_{t+1}}$ is the transition probability from regime M_t at t to regime M_{t+1} at $t+1$. As a result, evaluating a call option is equivalent to finding the probability of each regime path from the present time to the option's expiration date.

I will provide a simple iteration process to calculate the probabilities of the regime paths. For a standard binomial model, path probabilities are easily calculated following the binomial expansion formula. However, the probability of an event path for the proposed model depends on the branching process of the regimes over time, as the transition probabilities depend on the actual regime at any point in time. Let $u(k,t)$ be the probability of the event paths with k periods in high volatility regime H and $t-k$ periods in low volatility regime L if the current regime is an H regime and the option is to expire in t periods. Similarly, let $d(k,t)$ be the probability of the regime path with k periods in regime H and $t-k$ periods in regime L if the current regime is an L and the option is to expire in t periods. By the total probability formula, the following recursion can be easily derived[1],

$$\begin{cases} u(k,t) & = p_{hh}\ u(k-1,t-1) + p_{hl}\ d(k,t-1) \\ d(k,t) & = p_{lh}\ u(k-1,t-1) + p_{ll}\ d(k,t-1) \end{cases} \tag{2.6}$$

where $t = 1, 2, \cdots, T$; $\quad k = 1, 2, \cdots, t$. Initial values of $u(k,t)$ and $d(k,t)$ for the above iteration process (2.6) are $u(0,0) = d(0,0) = 1$, $u(k,0) = d(k,0) = 0$ for $k > 0$, $u(0,t) = p_{hl}p_{ll}^{t-1}$, and $d(0,t) = p_{ll}^{t}$. Denote $\bar{\sigma}_k = \sqrt{\frac{1}{T}(k\sigma_h^2 + (T-k)\sigma_l^2)}$. The logarithmic return of the underlying asset for a regime path with k periods in regime H and $T-k$ periods in regime L is normally distributed with an annualized mean $(r_T - \delta - \frac{1}{2}\bar{\sigma}_k^2)$ and an annualized variance $\bar{\sigma}_k^2$ under the risk-neutral probability measure. Hence

$$C(h) = \sum_{k=0}^{T} u(k,T) BH(T, \hat{\sigma}_k) \qquad \text{and} \qquad C(l) = \sum_{k=0}^{T} d(k,T) BL(T, \hat{\sigma}_k)$$

where BH and BL are values from Black-Scholes formula in regime H and L, respectively. Thus, the option pricing formula (2.5) becomes

$$C = q_0^h \sum_{k=0}^{T} u(k,T) \Pr(path|M_0 = H) + q_0^l \sum_{k=0}^{T} d(k,T) \Pr(path|M_0 = L). \tag{2.7}$$

and the put option prices can be easily derived from call-put parity.

2.4 Empirical Analysis

This section provides an empirical analysis of the option pricing model with market data. To see the model's prediction power with macroeconomic indicators, I first estimate the macroeconomic regime-switching model. Under the *mean absolute error* criterion, I then compare the option prices predicted by my model with those predicted by the benchmark option pricing models.

[1]Thanks go to Dr. Huawei Niu for his confirmation proof to my proof.

2.4.1 Regime specification by HMM

The National Bureau of Economic Research (NBER) business cycle dating committee retrospectively divides economic conditions into two regimes, contraction and expansion. The NBER analysis of economic peaks and troughs is an assessment of the economic conditions in a period based on the observed market activities and economic indicators over time. Different from NBER, I use a set of macroeconomic indicators to model the dynamics of the regimes, assuming that the economic activities jointly follow a hidden Markov model with economic regimes being unobservable over time. To be consistent with the NBER analysis, I set the time period in the model testing and comparison as a month.

For regime estimation, I use the following seven typical macroeconomic variables: the S&P 500 index (SPX), lagged economic indicator index (LEI), total industrial production (TIP), consumer price index (CPI), spread in 20-year yield and 3-month T-bill (YSD), spread between the U.S. Interbank 3M Interest Rate and the 3 Month T-bill (CSD), and the unemployment rate (UEM). Monthly data from 1980/01 to 2008/12 are used for model estimation, and the expectation and maximum likelihood algorithm developed by Dempster et al. (1977) is implemented. Based on the BIC, the optimal number of regimes is 2. The estimated probability transition matrix is

$$P = \begin{bmatrix} 0.9701 & 0.0299 \\ 0.1053 & 0.8947 \end{bmatrix}. \tag{2.8}$$

The diagonal dominance in the estimated transition probability matrix indicates that the retaining probability in a specific regime is substantially large once the economy is in that regime.

To see the significance of the proposed model in capturing economic conditions, I compare the model-inferred regimes over time with the business cycle dates. Furthermore, interpreting the low-volatility (L) regimes as expansion periods and high-volatility (H) regimes as contraction periods, the inferred regimes coincide with NBER business cycle dates for more than 90% of the time periods. For the period March

1980 to June 2017, 86 months are characterized as high-volatility regimes, and 362 months are characterized as low-volatility regimes. Figure 2.1 depicts monthly returns of the S&P 500 index (SPX) and the inferred market regimes over time.

Figure 2.1 shows that the volatilities of the monthly SPX returns are clustered. The dates with high posterior probabilities of H regime reflect the weak economic periods associated with negative asset returns most of the time. The changing amplitude of the index return implies that the risk level changes over time.

The conditional volatility of SPX for regime L is estimated as $\sigma_l = 0.1276$ with a positive conditional expected annualized return of $\mu_l = 0.1022$, while the conditional annualized volatility of SPX for regime H is estimated as $\sigma_h = 0.2309$ with a negative conditional expected annualized return of $\mu_h = -0.0417$. This is consistent with the financial market observations, where volatility is high for a bear market and low for a bull market. The unconditional volatility at each time t depends on the prior probabilities of the concurrent regime, which can be calculated as

$$\sqrt{p_h(t)(\sigma_h^2 + (\mu_h - \bar{\mu}(t))^2) + p_l(t)(\sigma_l^2 + (\mu_l - \bar{\mu}(t))^2}$$

where $p_h(t)$ and $p_l(t)$ are the prior probabilities of regimes H and L at time t, respectively, and $\bar{\mu}(t) = p_h(t)\mu_h + p_l(t)\mu_l$.

2.4.2 Estimation of the alternative option pricing models

As pointed out, option prices depend on the posterior probabilities of concurrent regimes. This is a very different setting from that of the Hardy model. Table 2.1 demonstrates how option prices change with the posterior probability distribution of regimes. As expected, both call and put prices increase as the posterior probability of the high-volatility regime rises. If the posterior distribution of regimes coincides with steady-state distribution, shown as (0.2212, 0.7788) in Table 2.1, option prices by the proposed model are the same as the prices by the Hardy model for the same underlying asset return parameters. Therefore, the Hardy model is a special case of the proposed model.

In Table 2.1, the accurate estimation of posterior probabilities of the regimes is important for the determination of option prices. The simple assumption that the stock market remains at a steady state does not lead to a satisfactory prediction.

For model comparison, I now present the parameter estimates for some alternative models: BSM, Hardy, and Heston and Nandi. The volatility of the BSM model is estimated as the standard deviation of the same in-sample SPX data. It is calculated as 0.1521. The transition matrix for the Hardy model is estimated as

$$P_h = \begin{bmatrix} 0.9241 & 0.0759 \\ 0.3149 & 0.6851 \end{bmatrix}$$

which is quite different from the proposed regime-switching model because of the different model setting. Furthermore, the annualized volatility with the Hardy model is 0.1149 for the low-volatility regime and 0.2588 for the high-volatility regime.

To estimate the Heston-Nandi model, I use the same notation as Heston and Nandi (2000). To be consistent with the original Heston-Nandi model, the daily data of the S&P 500 index for the same in-sample period (1980/03 - 2008/12) are used for model estimation. The estimated parameters are $\alpha = 3.6640 \times 10^{-6}$, $\beta = 0.8856$, $\gamma = 145.7474$, $\lambda = 0.4887$, and $\omega = 0.67 \times 10^{-11}$. The initial variance of the return on the underlying asset, as an input to the Heston-Nandi option pricing model, is estimated using the sample variance of the SPX index return for the past two years.

The SPX index level is adjusted according to the dividend yield paid out before the time to expiration. There are several ways of dealing with dividends in the literature; one of them is to use the present value of cash dividends during the option life as the expected dividend payment (Bakshi et al., 1997; Harvey and Whaley, 1992). Following this idea, the index level used in the model is adjusted by the dividend yield.

2.4.3 Performance of the alternative option pricing models

The monthly S&P 500 index options for the period August 2005 to December 2009 from the Chicago Board of Options Exchange (CBOE) are retrieved for model testing and comparison, and the resulting 1,164 options are selected for this study. The in-sample option data span the period from August 2005 to December 2008 with 759 options, and the out-of-sample data span the period from January 2009 to December 2009 with 405 options. Since the selected index options stop trading before the market opens on the third Friday of each month (AM settlement), I choose the closing price on the third Thursday of each month for this study. As the S&P 500 index options market is an active market, it is analyzed by researchers and analysts to test European option valuation models (Rubinstein, 1994).

I evaluate and compare the performances of the following four option pricing models, BSM, Hardy, HN, and the proposed regime-switching model (MNZ). To analyze model performances, I use the standard metric, *mean absolute error* (MAE), which is defined as the absolute value of difference between the predicted and observed prices.[2] Smaller pricing errors imply better performance of a model. However, this metric favors small option prices over large ones. Since there may be an unbalanced error measurement by directly applying the metric to options prices, I will also apply the metric to a more balanced quantity called *implied volatility*, which has become a standard measurement for evaluating an option pricing model. The implied volatility criterion essentially transforms an option's price to a balanced quantity measuring the volatility of the underlying asset return, regardless of the market price of an option. The advantage of the implied volatility criterion is that the pricing error is measured as the "distance" between the volatility implied by the model price and the volatility implied by the market-traded price of an option.

As the goal of the regime-switching modeling approach is to characterize the option premium due to macroeconomic risk, the analysis will focus on the model performances for both the low-volatility and high-volatility regimes to see what can

[2]Mean absolute error is measured by $\frac{\sum |p_{x,i}-p_i|}{N}$, where $p_{x,i}$ is the option i's price from model x, p_i is the market price for option i, and N is the number of observations.

be added by this proposed model. The essay shows the advantage of the regime-switching model over the alternative models in that market.

Applying MAE metric to option prices

To examine the dependence of option prices on economic regimes, I conduct the analysis for the sample data by regimes . Then, I look into the valuation model's effectiveness with the two option-specific parameters — moneyness and time to expiration. I study both call and put options.

Table 2.2 presents the mean absolute valuation error of option prices for alternative models by sample type — in-sample and out-of-sample.

The analyses are conducted for both call and put options, for both L and H regimes. With regards to sample types, the results for the full sample show that option valuation with the MNZ model is more accurate than those with the alternative models, as the mean absolute errors for both call and put option classes are lower than the alternative models. For the H regime, the MNZ model performs strongest for all sample types among the alternative models. For regime L, the results are mixed for the MNZ model, as the valuation error is higher for the out-of-sample data and lower for the in-sample data than the alternative models. It is noted that the HN model performs strongest in the low-volatility market for the out-of-sample data. Nevertheless, the strongest overall performance of the MNZ model for regime H for both call and put options indicates that this regime-switching model is able to delineate the impacts of financial crises on option prices.

Although the MAE for low-volatility regimes are smaller than for high-volatility regimes, the MNZ model has the smallest valuation error gap across the two regimes among the four models being compared. This indicates that the MNZ model has relatively stable performance across regimes.[3] In addition, the pricing errors of the

[3]For high-volatility regimes, the mean absolute pricing errors for the BSM, Hardy and HN models are almost twice as high as for low-volatility regimes; the gap of mean absolute pricing errors across regimes for the MNZ model is much smaller compared to that for alternative models.

alternative models are similar in low-volatility regimes. The model performance disparities are mostly raised from their pricing capacity in a high-volatility regime. From the view of risk control, a model that has good behavior during a financial crisis is more appealing. This indicates that the pricing stability across market regimes and/or the trustworthy pricing ability for the market downturn is a prominent factor in determining the pricing capacity of a model.

I now analyze the effects of moneyness on options valuation errors. Moneyness is defined as the ratio of the strike price and the current underlying asset price, K/S_0, where K is the strike price, and S_0 is the current underlying asset price. Options data are divided into five categories by the range of moneyness. For call options, the five categories, $[0-0.7)$, $[0.7-0.9)$, $[0.9-1.1)$, $[1.1-1.3)$, and $[1.3-\infty)$, represent "deeply in the money", "in the money ", "around the money", "out of the money", and "deeply out of the money", respectively. For put options, with the same ranges of moneyness, the five categories are named in reverse order (e.g.,$[0-0.7)$ denotes "deeply out of the money" for put options). Table 2.3 presents the mean absolute valuation errors by moneyness.

Overall, the MNZ model has the lowest mean absolute error for both call and put options in the moneyness ranges of "[0.9 - 1.1)", "[1.1-1.3)", and "[1.3-∞)", in comparison to alternative models. Particularly, the mean absolute pricing error for the MNZ model is 13.3740 for call option at "around the money", while corresponding values for the other three models are for 18.8822 the BSM model, 19.0928 for the Hardy model, and 17.3959 for the HN model. For moneyness ranges of "[0 - 0.7)" and "[0.7 - 0.9)", the HN and MNZ models perform similarly and slightly better than other models. From Table 2.3, the mean absolute pricing error estimated with the HN model for call options in the moneyness range of "[0 - 0.7)", and "[0.7 - 0.9)" are 4.6198, and 12.1071, respectively, while the MNZ model has 4.6663 and 12.1650, respectively, for the same type of options. The outcomes for put options are similar to that for call options.

Time to expiration is another important parameter that affects option prices. To understand the model performance better, I divide the options into three categories by the range of expiration time. Options with expiration time being less than or equal to 4 months, between 5 and 8 months, and in the range of 9 to 12 months, are categorized as short, medium, and long expiration time, respectively. Table 2.4 presents model valuation errors for call and put options by expiration time.

It is shown that, with various expiration times, the MNZ model consistently has the smallest average pricing errors for both call and put options. I find that average pricing errors increase with options' expiration time for all the four models. For all three ranges, the MNZ model has the lowest value of average pricing errors for both call and put options in high volatility-regimes. In low-volatility regimes, the performances of the Hardy, HN, and MNZ models are similar and slightly better than the BSM model. The outcomes for put options are similar to that for call options.

Tables 2.2, 2.3, and 2.4 present the mean absolute pricing errors for the alternative models, without providing further information about the distribution of pricing errors. To evaluate the stability of a pricing model, I examine the prediction success rate for a given error threshold. Let p_x be the price from model x and p the observed market price of an option in a given sample, $\mathcal{O}$. I use the following error size measure for model comparison. For any given $\alpha \geq 0$ and model x, I define the *prediction success rate* as

$$PSR_x(\alpha) = \frac{size\ of\ \{p : \frac{|p_x - p|}{p} \leq \alpha, p \in \mathcal{O}\}}{size\ of\ \mathcal{O}}.$$

That is, $PSR_x(\alpha)$ is the percentage of options for which the absolute percentage pricing errors for model x are less than the threshold α.

Figures 2.2 and 2.3 depict the prediction success rate versus pricing error threshold up to 0.15. Overall, the MNZ model has a higher prediction success rate than the other alternative models for both calls and puts. In particular, the MNZ model dominates the alternative models when the market is in a high-volatility regime, while the result is mixed for a low-volatility regime. Overall, all models have higher prediction success rates for a low-volatility regime than for a high-volatility regime.

It find that prediction success rates are similar for calls and puts. For example, the prediction success rates for error threshold 0.1 are about 60% for both calls and puts.

Applying MAE metric to implied volatilities

One of the disadvantages with the mean absolute error or mean absolute percentage error criteria is that the size of the measured error depends on the level of actual observed prices. In other words, error measurements based on these criteria are not consistent with each other. Options with small prices favor the mean absolute error criterion, while options with large prices favor the mean absolute percentage error criterion. Thus, if these criteria are used for evaluating model performance on a sample of options with a wide range of option prices, the analysis will not be accurate and may even be biased.

In the Black-Scholes formula, the only unobservable model parameter is "volatility", which gives a convenient tool to measure the performance of a model. This quantity can be viewed as a monotonic transformation of the option price, which actually brings the measured quantity close to a certain level. As an illustration, if the Black-Scholes model is actually the true model for characterizing the underlying asset price dynamics, the implied volatilities for all options should be a constant, independent of options' strike price and time to expiration. The market-implied volatility of an option is the solution of the volatility parameter to the equation, which sets the price under the Black-Scholes model equal to the market price of the option. For another option pricing model, the model-implied volatility of the same option is defined as the solution of the volatility parameter to the same equation, with the market price being replaced by the model price of the option.

To evaluate the performance of a model, I use a metric to measure the distance of the model-implied volatility and the market-implied volatility for a selected sample of options. If a model is accurate, the model-implied volatility equals the market-implied volatility for any option. If the model-implied volatility is less than (greater than) the market-implied volatility, I then see that the model price is less than (greater than) the market price. For each pair of options' strike price and expiration time, I use in-the-money call or put options to calculate the market-implied volatility and the model-implied volatility. Figure 2.4 depicts the empirical distribution of the difference between the model-implied volatility and the market-implied volatility with in-the-money options.

Without differentiating strike prices and expiration time, it is shown that all four alternative models price the options lower than the market on average. The mean of market-implied volatility is 26.80% with standard deviation of 9.37%, while the means of model-implied volatilities are 18.92% for the MNZ model, 17.21% for the Hardy model, 15.21% for the BSM model, and 17.20% for the HN model, with standard deviations of 3.12%, 2.39%, 0%, and 3.23%, respectively.

To obtain a general performance of the alternative models, I present the mean difference in volatility between the model-implied volatility and the market-implied volatility for all four models in Table 2.5.

It is shown that the MNZ model performs better than the alternative models for all ranges of expiration time. The HN model performs better than both the Hardy and BSM model, while the BSM model is the weakest model by this criterion. For each of the expiration times from 1 month to 9 months, the mean differences in the implied volatilities across the strike prices are given in Table 2.5.

To further examine look at the performance of alternative models, I divide the options into different categories by expiration time. The goal is to find a functional relationship between implied volatilities and strike prices. I find that implied volatilities versus strike prices exhibit a "smile" shape for a given expiration time. The closer this functional relationship is to the market volatility, the stronger the model performs. I examine the implied volatility curves for both the market and alternative models in Figure **??**. I find that no models have a clear dominance for all strike price levels.

2.5 Conclusion

This essay develops a discrete-time option pricing model, assuming the underlying asset return distribution switches between market regimes. The model proposed contributes to both theoretical frameworks and practical applications. I propose dynamic pricing with economic regime shifts. It has practical implications in real-world valuation and investment management.

First, this research provides a general approach for option pricing with asset return distribution regime switches, adapting to macroeconomic conditions over time. Considering that the derivative market is extremely dynamic, many researchers argue that a sophisticated and practical valuation model is needed. The model proposed provides an analytical solution for European options with high feasibility and applicability. Second, the proposed model precisely captures the market regime-dependent pricing and incorporates the posterior probabilities of regimes into the pricing mechanism.

The evidence provided shows that the proposed option pricing model outperforms the alternative models under several commonly used metrics. The option pricing valuation errors of all models are measured for different categories, such as in-sample, out-of-sample, expiration time, and moneyness. In addition, the strong performance of the proposed model is reinforced by a higher prediction success rate than the alternative models. One disadvantage of pricing errors under the metric of MAE is that the size of the pricing error depends on the level of the measured quantity; therefore, pricing error measurement may be inconsistent and biased. Therefore, the MAE is applied to market-implied volatilities and model-implied volatilities to resolve the issue. Overall, the proposed option pricing model in this essay outperforms the benchmark models.

Moreover, all models are examined under economic regimes, which are implied by the proposed model. Typically, the slope of investors' utility functions is steeper for losses than gains. Thus, investors value gains or dislike losses more in a high-volatility regime than in a low-volatility regime. The performance of the pricing model for a high-volatility regime shall be valued more. Attributed to the ability to identify the economic conditions, the proposed option pricing model performs significantly better than the alternative models developed in the literature.

Several perspectives are implied for future studies. First, due to the model's high flexibility, it is also able to price for American options. Second, the proposed model can formulate an optimized profitable investment strategy for both individual investors and fund managers, because it captures the market regime-dependent pricing approach for options in a more precise way. With a strong prediction capability, the proposed model is applicable in both broad and narrow senses.

Table 2.1: Option prices with posterior probabilities of regimes

Posterior Probability (High, Low)	3-month call option prices	3-month put option prices
(1.0000, 0.0000)	4.9882	3.4994
(0.9000, 0.1000)	4.8351	3.3463
(0.8000, 0.2000)	4.6820	3.1932
(0.7000, 0.3000)	4.5290	3.0402
(0.6000, 0.4000)	4.3759	2.8871
(0.5000, 0.5000)	4.2228	2.7340
(0.4000, 0.6000)	4.0697	2.5809
(0.3000, 0.7000)	3.9166	2.4278
(0.2212, 0.7788)	3.7960	2.3072
(0.2000, 0.8000)	3.7636	2.2748
(0.1000, 0.9000)	3.6105	2.1217
(0.0000, 1.0000)	3.4574	1.9686

This table demonstrates the dependence of option prices on the posterior probabilities. H means the high-volatility regime, while L represents the low-volatility regime. The call and put options are written on the underlying asset with initial price $S_0 = 100$, strike price $K = 100$, and time to maturity $T = 3$ months. The annualized volatilities are $\sigma_l = 0.1276$ (low volatility regime) and $\sigma_h = 0.2309$ (high volatility regime). The annualized risk-free rate is set to be $r = 6\%$. Using the same model parameters, the proposed model produces the same option price as the Hardy model when the posterior probabilities coincide with the steady-state distribution $(0.2212, 0.7788)$. It is observed that both call and put option prices increase with the posterior probability of the high-volatility regime, and option prices are substantially different for various levels of posterior probabilities.

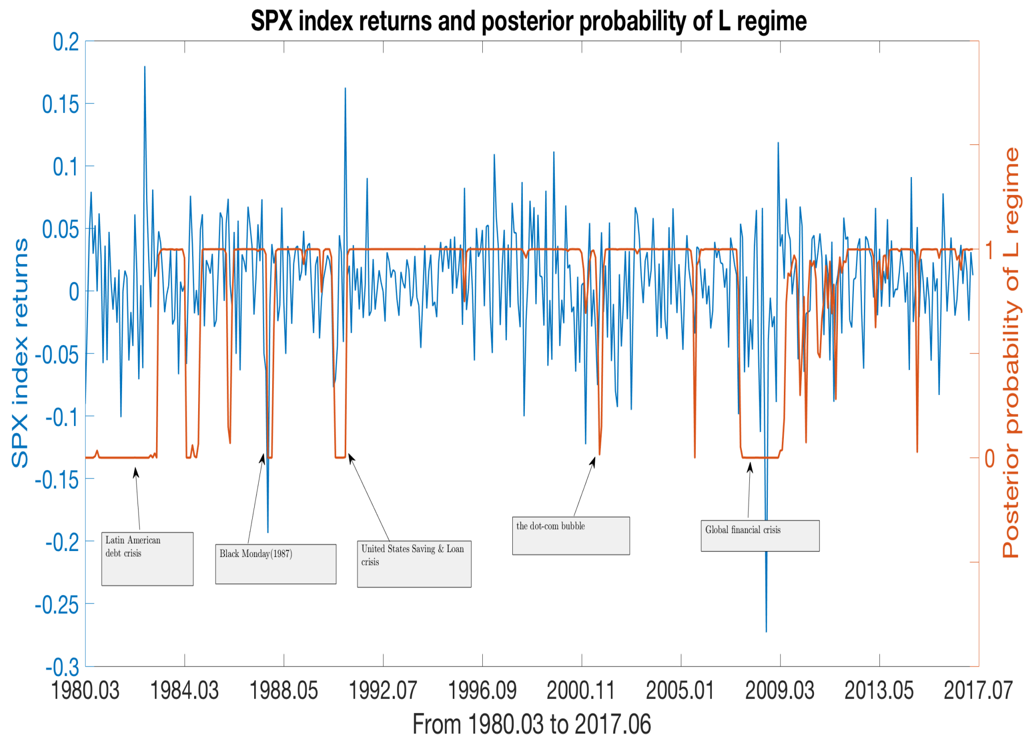

Figure 2.1: Monthly returns of the S&P 500 Index versus the posterior probabilities of low volatility regime (L)

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This figure illustrates monthly returns of the S&P 500 index and the implied market regimes over time, where the left y-axis measures the scale of monthly returns of the S&P 500 Index and the right y-axis represents model-implied posterior probabilities. It is worth noting that the estimated high- and low-volatility regimes are consistent with the empirical performance of the S&P 500 index at very high accuracy. The volatility in an economic recession is much higher than in an economic boom. From March 1980 to June 2017, a few significant financial recessions occurred, which include the Latin American debt crisis from 1980 to 1983, "Black Monday" in 1987, the U.S. savings and loan crisis, the dot-com bubble, and the 2008 global financial crisis. The model-implied posterior probabilities accurately capture those economic downturns: all of the financial recessions during the sample period are captured.

Table 2.2: Mean absolute pricing error by data sample

	Call Options			Put options			
	L	H	All	L	H	All	Observation
Full Sample							
BSM	7.9572	14.1515	11.7887	8.0688	14.5729	12.092	1164
Hardy	7.6971	14.1091	11.6633	7.7868	14.5191	11.9511	1164
HN	7.5605	12.9304	10.8821	7.5174	13.3462	11.1228	1164
MNZ	7.7011	10.3971	9.3687	7.8445	10.6563	9.5838	1164
In Sample							
BSM	7.5003	14.2263	11.8159	7.2735	14.4432	11.8738	759
Hardy	7.1291	14.2114	11.6733	6.8660	14.4113	11.7073	759
HN	7.3862	12.6903	10.7895	6.9095	12.8988	10.7524	759
MNZ	6.9424	9.9867	8.8957	6.7649	9.9734	8.8236	759
Out of Sample							
BSM	8.6797	13.9952	11.7378	9.3265	14.8442	12.5009	405
Hardy	8.5955	13.8953	11.6445	9.2428	14.7446	12.4081	405
HN	7.8361	13.4323	11.0556	8.4787	14.2813	11.8170	405
MNZ	8.9008	11.2549	10.2552	9.5516	12.0837	11.0083	405

The full-sample period spans August 2005 – December 2009. The in-sample period spans August 2005 – December 2008 while the out-of-sample period spans January 2009 – December 2009. L denotes the model-implied low-volatility regime, and H represents the model-implied high-volatility regime. The Mean absolute pricing error is measured by $\frac{\sum |p_{x,i}-p_i|}{N}$, where $p_{x,i}$ is the option i's price from model x, p_i is the market price for option i, and N is the number of observations. The mean absolute pricing error without differentiating L and H regime is also reported in the columns labeled “All”.

Table 2.3: Mean absolute valuation error by moneyness

Model	Moneyness	Call Option			Put Option			Observation
		L	H	All	L	H	All	
	$[0-0.7)$	3.3601	5.6370	4.7713	2.6857	4.7968	3.9941	192
	$[0.7-0.9)$	7.7065	18.6649	14.0128	7.6467	18.2647	13.7570	318
BSM	$[0.9-1.1)$	11.7408	24.9018	18.8822	11.8351	25.4958	19.2476	352
	$[1.1-1.3)$	6.7747	9.2644	8.5304	7.8711	10.3465	9.6167	173
	$[1.3-\infty)$	0.4806	2.0584	1.7648	1.9724	4.2599	3.8343	129
	$[0-0.7)$	3.3066	5.5975	4.7265	2.6317	4.7573	3.9491	192
	$[0.7-0.9)$	7.2420	18.2601	13.5826	7.1589	17.8515	13.3122	318
Hardy	$[0.9-1.1)$	11.5539	25.4476	19.0928	11.6047	26.0427	19.4390	352
	$[1.1-1.3)$	6.5104	8.9026	8.1974	7.6236	9.9340	9.2529	173
	$[1.3-\infty)$	0.2614	1.9453	1.6320	1.7329	4.1403	3.6924	129
	$[0-0.7)$	3.2225	5.4769	4.6198	2.4678	4.6333	3.8100	192
	$[0.7-0.9)$	6.1337	16.5136	12.1071	5.6499	16.0919	11.6590	318
HN	$[0.9-1.1)$	11.9609	21.9772	17.3959	12.0270	22.5587	17.7417	352
	$[1.1-1.3)$	6.9272	9.9638	9.0686	8.0021	11.0677	10.1640	173
	$[1.3-\infty)$	0.6071	2.1229	1.8409	2.0990	4.3246	3.9106	129
	$[0-0.7)$	3.3302	5.4859	4.6663	2.6558	4.6431	3.8875	192
	$[0.7-0.9)$	7.8799	15.3260	12.1650	7.8201	14.8890	11.8881	318
MNZ	$[0.9-1.1)$	11.2920	15.1290	13.3740	11.4538	15.5004	13.6495	352
	$[1.1-1.3)$	5.6129	7.8547	7.1938	6.7725	8.4716	7.9707	173
	$[1.3-\infty)$	0.3377	1.7190	1.4620	1.8288	3.8212	3.4505	129

This table displays the mean absolute pricing errors by moneyness. Moneyness is defined as K/S_0, and is divided into 5 categories: $[0-0.7)$, $[0.7-0.9)$, $[0.9-1.1)$, $[1.1-1.3)$, and $[1.3-\infty)$, corresponding to "deeply in the money", "in the money", "around the money", "out of the money", and "deeply out of the money" for call options (for put option, the order is reversed). L denotes the model-implied low-volatility regime while H represents the model-implied high-volatility regime. The Mean absolute pricing error is measured by $\frac{\sum |p_{x,i}-p_i|}{N}$, where $p_{x,i}$ is the option i's price from model x, p_i is the market price for option i, and N is the number of observations. The mean absolute pricing error without differentiating L and H regime is also reported in the "All" columns.

Table 2.4: Mean absolute valuation error by expiration time

		Call Option			Put Option			
Model	Expiration	L	H	All	L	H	All	Observation
BSM	1-4 month	5.3976	9.7076	8.2889	4.5473	9.6484	7.9693	559
	5-8 month	8.1852	16.7683	13.3973	8.9522	18.5348	14.7712	331
	9-12 month	11.3519	22.0716	16.9856	12.1699	21.8671	17.2662	274
Hardy	1-4 month	5.2831	9.7163	8.2571	4.3999	9.6412	7.9160	559
	5-8 month	7.8229	16.6866	13.2054	8.5436	18.4511	14.5599	331
	9-12 month	10.9882	21.9508	16.7495	11.8236	21.7339	17.0319	274
HN	1-4 month	5.1165	8.9062	7.6588	4.2890	8.8355	7.3390	559
	5-8 month	7.9141	15.2881	12.392	8.4059	17.0631	13.6630	331
	9-12 month	10.666	20.1192	15.6341	11.1983	19.9044	15.7738	274
MNZ	1-4 month	5.3250	7.5901	6.8446	4.4707	7.2573	6.3400	559
	5-8 month	7.7322	11.8962	10.2608	8.5925	13.5611	11.6096	331
	9-12 month	11.033	15.6144	13.4407	11.8717	15.4536	13.7541	274

This table shows the call and put option valuation errors for different models by 3 expiration time lengths. The sample is from 2005 August to 2009 December, including 1,164 option contracts with various expiration times. Options are divided into three categories by expiration time: "1-4 month" represents the category of options with expiration time less than or equal to 4 months; "5-8 month" stands for the category of options with expiration greater than 4 months and less than or equal to 8 months; and "9-12 month" denotes the category of options with expiration time greater than 8 months and less than or equal to 12 months. It is shown that, in the high-volatility regime (H) and all regime (All), the MNZ model outperforms the alternative models in all three categories. The Mean absolute pricing error is measured by $\frac{\sum |p_{x,i}-p_i|}{N}$, where $p_{x,i}$ is the option i's price from model x , p_i is the market price for option i, and N is the number of observations.

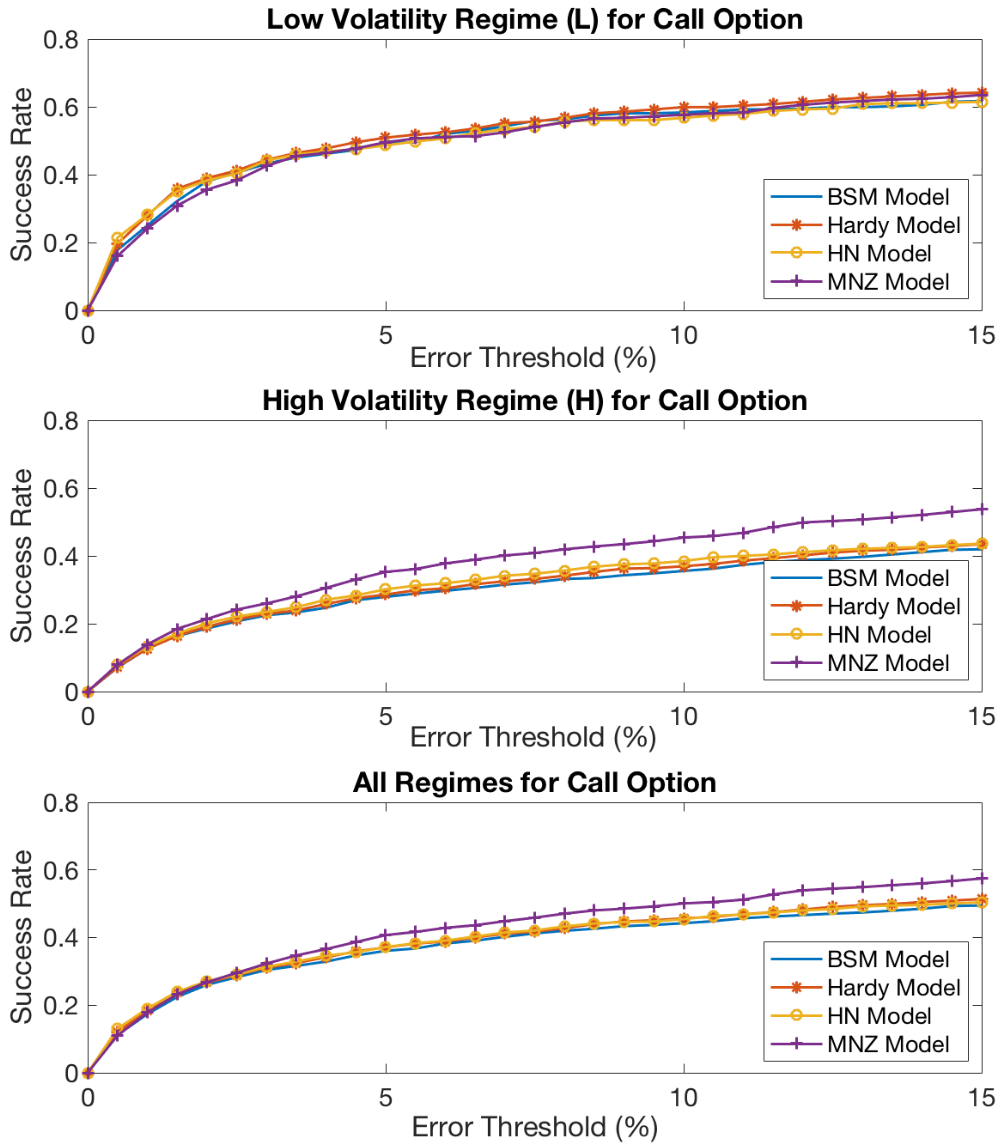

Figure 2.2: Prediction success rate versus pricing error threshold for call options

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This figure illustrates the prediction success rate versus error threshold up to 15% of actual option prices for call options in different regimes. The prediction success rate is defined in Section 2.4.3. The results of the four alternative models for "low-volatility regime" are mixed. Yet, the MNZ model has the best performance for "high-volatility regime" and "both low and high volatility regimes" among alternative models.

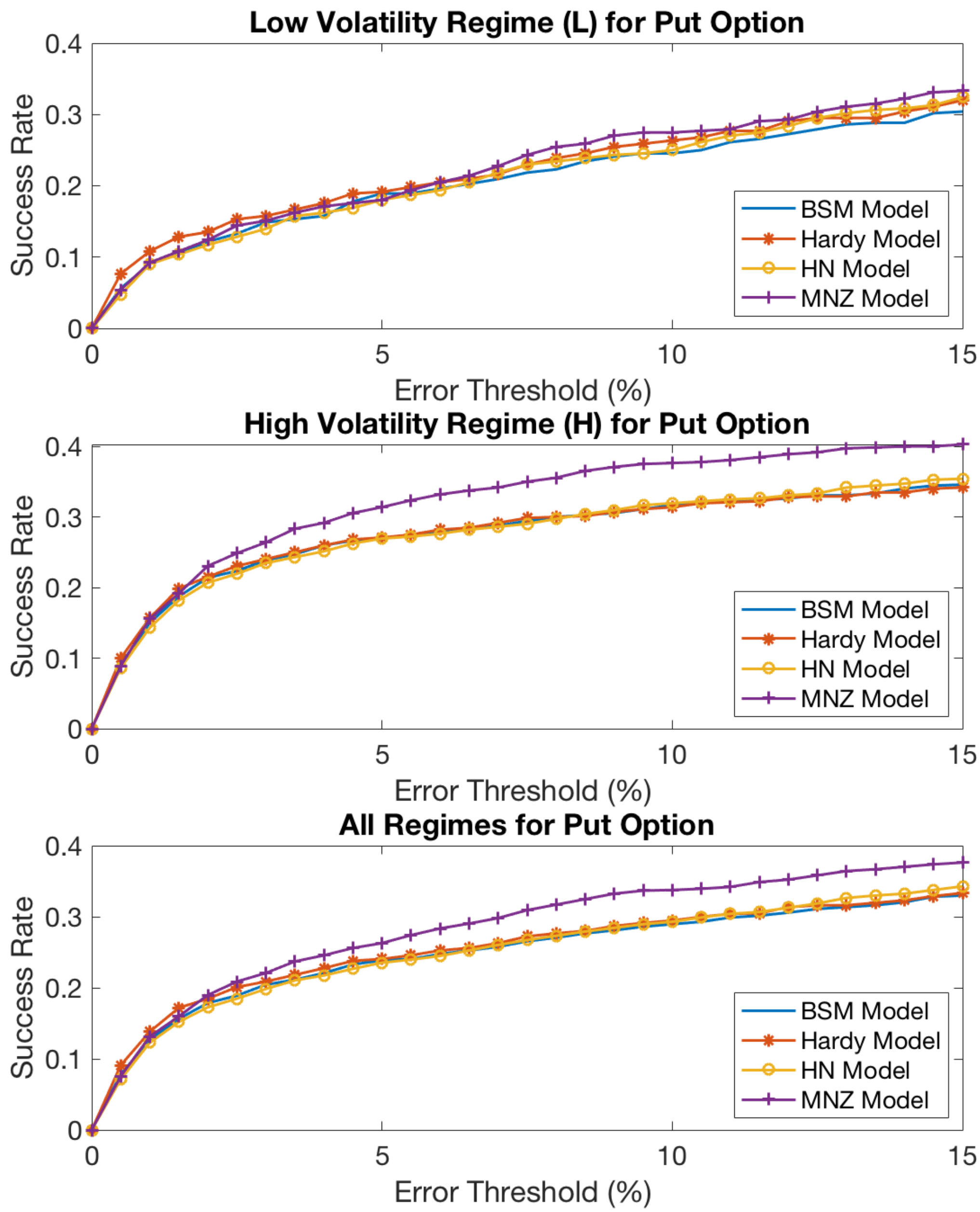

Figure 2.3: Prediction success rate versus pricing error threshold for put options

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This figure depicts the prediction success rate versus error threshold up to 15% of the actual option prices for put options in different regimes. The prediction success rate is defined in Section 2.4.3. In “low-volatility regime”, the HN model performs better around and before the 10% threshold while other models’ performances are mixed. In “high-volatility regime” and “both low and high volatility regimes”, the MNZ model performs the best among alternative models.

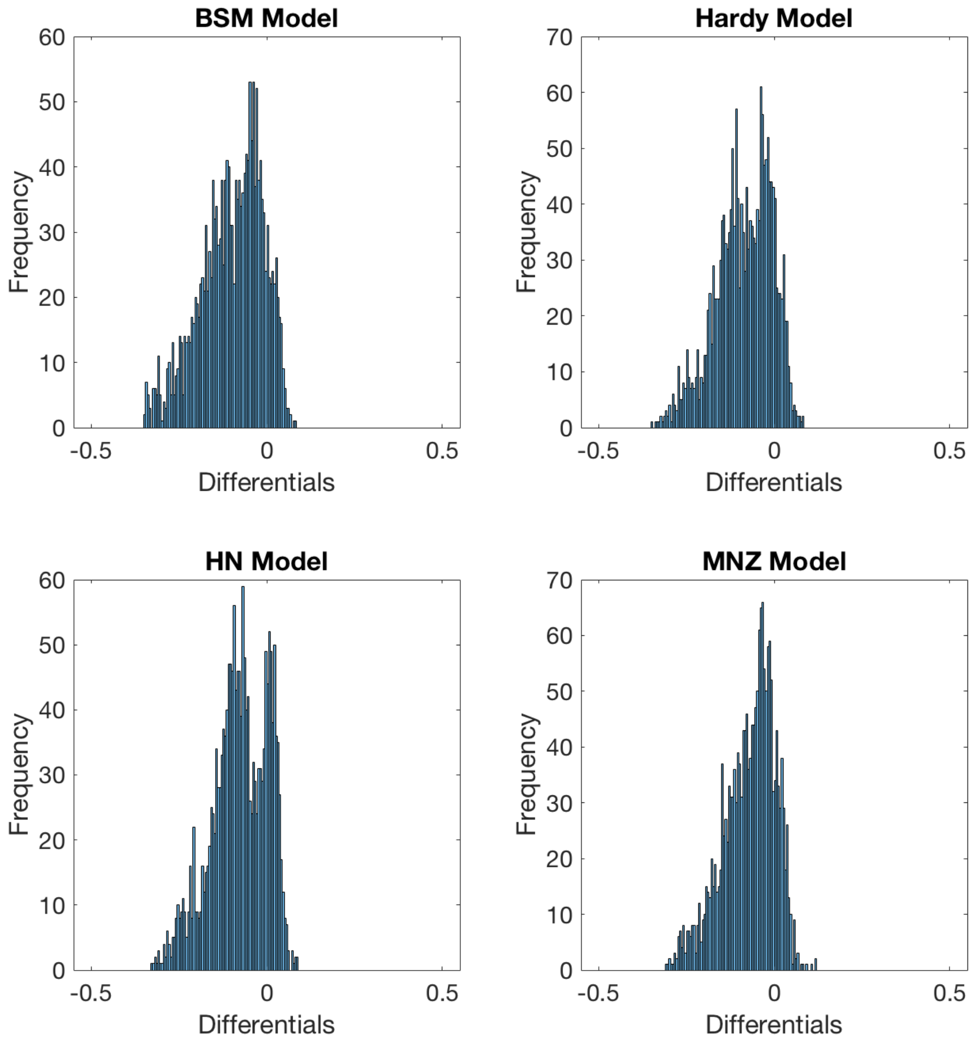

Figure 2.4: Distribution of differentials between model-implied volatilities and market-implied volatilities for in-the-money options

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This figure presents the histograms of the differences between model-implied volatilities and market-implied volatilities for four alternative models, without differentiating strike prices and expiration time. On average, all models produce lower option prices than market prices, as the sample distribution is left-skewed. The means differentials of the implied volatilities are -11.59% for the BSM model, -9.60% for Hardy model, -9.60% for HN model, -7.88% for the MNZ model, with standard deviations of 9.37%, 8.10%, 8.85%, and 7.89%, respectively.

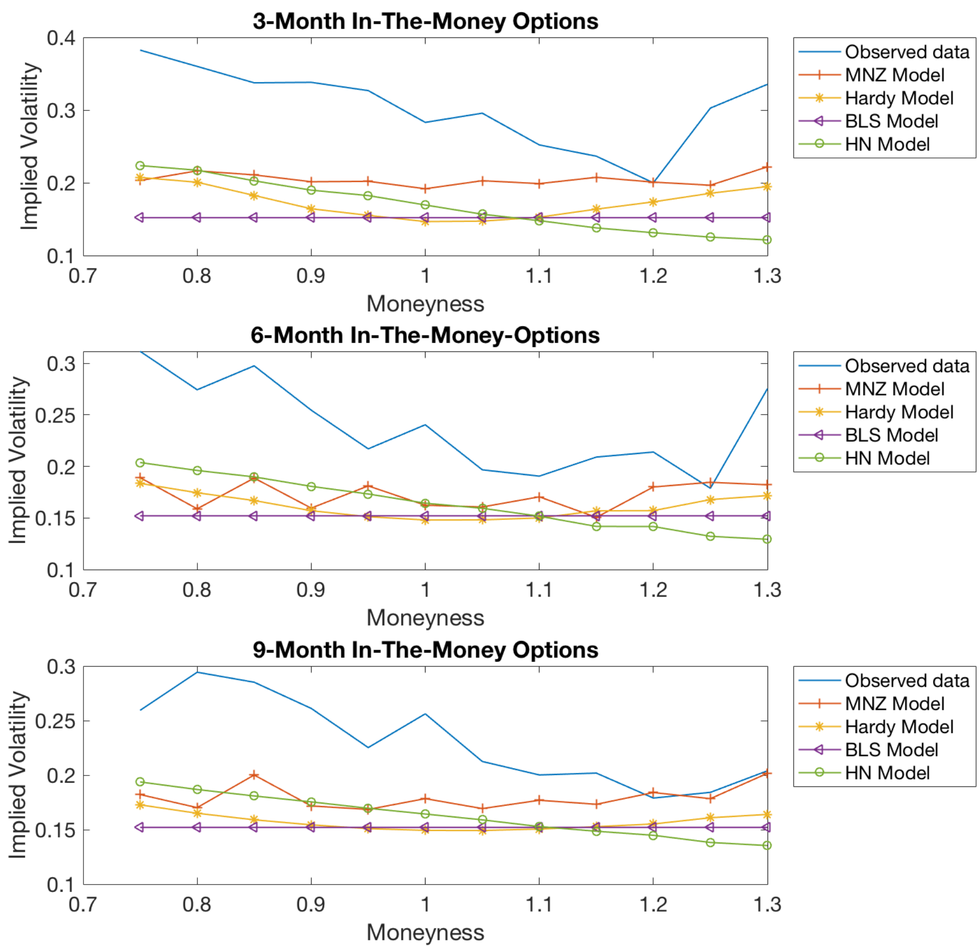

Figure 2.5: Implied volatilities with in-the-money options

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This figure exhibits the implied volatility curves across strike prices with three, six, and nine months to expiration for in-the-money options. As shown in the figure, all models have smaller implied volatilities than the market-implied volatility. The line with triangle marks (the MNZ model) moves most closely with market-implied volatilities, in comparison to other implied volatility curves. The mean of market implied volatilities is 26.80% with a standard deviation of 9.37%, while the means of model-implied volatilities are 18.92% for the MNZ model, 17.21% for the Hardy model, 15.21% for the BSM model, and 17.20% for the HN model, with standard deviations of 3.12%, 2.39%, 0%, and 3.23%, respectively.

Table 2.5: Mean absolute differential implied volatilities

Model	1M	2M	3M	4M	5M	6M	7M	8M	9M
BSM	0.1427	0.1395	0.1656	0.1387	0.1245	0.1058	0.1004	0.1080	0.1039
Hardy	0.1131	0.1119	0.1409	0.1125	0.1042	0.0879	0.0851	0.0932	0.0898
HN	0.1211	0.1183	0.1459	0.1109	0.1134	0.0883	0.0844	0.0954	0.0908
MNZ	0.1044	0.1015	0.1173	0.1013	0.0869	0.0831	0.0690	0.0753	0.0747

This table presents the mean absolute errors of the model-implied volatility and market-implied volatility with various expiration times up to 9 months. The columns represent the expiration months. For example, "1M" represents the options with 1 month to expiration. It shows that the MNZ model has the smallest mean absolute error with implied volatilities across expiration months.

Chapter 3

Financial Impact of ESG Rating across Sectors and Firm Sizes over Time: New Evidence

3.1 Introduction

3.1.1 Background

The Industrial Revolution began in the 18th century and successfully transformed human lives from agrarian to industrial societies. Accompanying the invention and massive employment of machinery in manufacturing, metallurgy, chemicals, petroleum refining, electrics, and the subsequent automotive industry, the participating countries experienced a significant enrichment of material resources and a tremendous increase in GDP.

Meanwhile, this epochal event led to negative consequences for both natural and social environments. On the one hand, industry-induced greenhouse gas emissions act as a crucial factor accounting for climate change, which threatened the viability of lives on Earth.[1] According to NOAA's Mauna Loa CO_2 record (see Figures 3.1a and 3.1b), the level of carbon dioxide emissions has consistently increased since the Industrial Revolution; it broke the historical record (300 parts per million) in the 1950s and has kept rapidly growing. Consequently, global temperature data also show a fast warming trend over the past century (see Figure 3.2, NASA's Earth Observatory). A series of aftermaths including shrinking ice sheets, glacial retreat, rising sea level, extreme weather events, ocean acidification, and species extinction are underway on a global scale (IPCC,[2] 2014). On the other hand, the Industrial Revolution has indirectly intensified social conflicts: emerging industries have widened the wealth gap between bourgeois and workers and global warming induced by human activities

[1]As Cook et al. (2016) conclude, more than 97% of the 2412 published studies in peer-reviewed scientific journals support that global-warming trends over the past century are attributable to human activities.

[2]IPCC stands for Intergovernmental Panel on Climate Change.

has worsen global economic inequality (Diffenbaugh and Burke, 2019). Urban overcrowding, poor diets and sanitation accompanied by tough and dangerous working conditions in polluting industries such as metallurgy and chemicals has caused permanent health problems for the working class (Haley, 1978). Unregulated working hours and mass use of child labor constitute a deprivation of basic human rights (Ashton, 1948; Del Col, 1911). Male-preferred working environments enabled men to be the main income earner in their families and led to a long-term decline in the economic role of females (Frader, 2005). The growth of the economy is given priority over the natural and social environments, causing non-sustainable development. As a result, humans face an ethical dilemma: balancing the economy and the environment to move from non-sustainable to sustainable development.

As a product of the Industrial Revolution, firms gain profits from mass production using advanced machinery technology; they are also responsible for the moral conundrums presented by climate change. In 2000, the United Nations launched the world's largest corporate sustainability initiative—UN Global Compact (UNGC)—to advocate that enterprises worldwide adopt socially responsible policies and disclose their strategies to the public. Apart from focusing on environmental improvement, the UNGC appeals to firms for social environment reconstruction, which includes human rights, labor, and anti-corruption, in order to achieve the global development goals.[3] Since 2000, an increasing number of firms have paid great attention to CSR. Nowadays, the measurement of a firm's performance is not confined to financial results; it also takes non-financial characteristics into consideration. Social responsibility implementation eventually plays an important role in accounting for monetary outcomes.

[3] The global development objectives include the 8 Millennium Development Goals launched in 2000 for 2015 and the 17 Sustainable Development Goals assembled in 2015 for 2030. The current-stage SDGs are: 1) No Poverty, 2) Zero Hunger, 3) Good Health and Well-being, 4) Quality Education, 5) Gender Equality, 6) Clean Water and Sanitation, 7) Affordable and Clean Energy, 8) Decent Work and Economic Growth, 9) Industry, Innovation, and Infrastructure, 10) Reduced Inequality, 11) Sustainable Cities and Communities, 12) Sustainable Consumption and Production, 13) Climate Action, 14) Life Below Water, 15) Life On Land, 16) Peace, Justice, and Strong Institutions, 17) Partnerships for the Goals (UN, 2014)

3.1.2 Introduction of ESG

To quantify the non-financial characteristics of a firm following the UN principles, Environmental, Social and Governance (ESG) is emerging. Constituted by three major components, ESG aims to investigate corporate performance from the perspectives of sustainability (environmental maintenance), ethics (well-being of employees, suppliers, and customers) and management (leadership, executive pay, audits, internal controls, and shareholders' rights), respectively. ESG criteria, therefore, are a set of standards that measure how a firm performs on those socially conscious aspects.

Before the acknowledgment of CSR and ESG, most of the financial market was dominated by the concept of 'self-interest' or shareholder value in economics. As a representative opponent of philanthropy in business, Friedman (1970) argues that social responsibility negatively affects firms' financial performance because the cost of ethical behavior would outweigh its benefits. However, by the end of the 20th century, Friedman's assumption had been to be challenged by Coleman (1988) who introduces "social capital" into value measurement.[4] Levering and Moskowitz (1998) first release the ranking of the best-to-work-for firms in the United States based on their CSR implementations (meeting ESG criteria) and corresponding financial performance. This was published in magazine Fortune, and gained an international attention from both media and the public. This publication enforced an increasing number of companies to take their social responsibility seriously.

In January 2004, former UN Secretary General Kofi Annan invited more than 50 CEOs of major financial companies to participate in a joint initiative under the auspices of the UN Global Compact in which International Finance Corporation (IFC) and the Swiss Government also provided supports. This initiative aimed to "develop guidelines and recommendations on how to better integrate environmental, social and corporate governance issues in asset management, securities brokerage services and

[4] Coleman (1988) states that social capital is effective in aiding the formation of human capital based on the finding that both social capital in family and in the adult community surrounding the school reduce the probability of students dropping out of high school. His conclusion implies that socially responsible behaviors by a firm, as an accumulation of social capital, may help to improve its value.

associated research functions" (Compact, 2004). In the following year, 2005, the term ESG was first and officially coined in a landmark report entitled "Who Cares Wins" and produced by the initiative. Meanwhile, the "Freshfield Report" published by United Nations Environment Programme (UNEP) emphasized that ESG issues are closely related to financial valuation. These two reports formally introduced ESG into the global financial market. In 2006, the UN enacted six Principles for Responsible Investment (PRI), providing universal standards for responsible investment which were based on the ESG criteria. This action further demonstrates the crucial role that the ESG criteria play in accounting for corporate financial outcomes.

Currently, the ESG rating system is one of the most prevalent and credible grading mechanisms worldwide. It is used by investors to evaluate a firm on multiple dimensions before making an investment decision. From the demand side, accompanying the wide adoption of ESG criteria, investment strategies that incorporate ethical considerations are emerging. The processes of investing in firms that are identified to be highly responsible to the society following ESG criteria compose socially responsible investments (SRI). The main difference between SRI and conventional investments is that SRI applies a series of investment screens to select firms that meet certain ESG criteria (no tobacco or alcohol producers, gambling products suppliers, weapons makers, or firms that violate employees' human rights) (Renneboog et al., 2008b). According to the U.S. Forum for Sustainable and Responsible Investments, by 2018, SRI assets accounted for 25% ($12 trillion) of total assets under professional management in the United States, and that share was 38% higher than in 2016. Particularly, impact investing, which is defined as an investment in firms, organizations, and funds with the commercial purpose of solving social or environmental problems, was the fastest-growing area of SRI. According to the World Economic Forum, approximately $1 trillion of assets will be committed to impact investing by 2020, at a growth of $250 billion annually (O'Donohoe et al., 2010).

In response to the surge in demand for ESG information from the supply side, more ESG data providers have emerged. One of the main ESG data vendors, Bloomberg, witnessed an almost fourfold increase in registration for ESG data on their platform between 2012 and 2018. The other leading ESG data provider, Thomson Reuters, has been expanding its ESG universe since 2008. According to the Global Initiative for Sustainability Ratings in 2018, over 100 organizations are now collecting and analyzing firm-level ESG data. A rising number of them are in the process of internationalizing the universe of firms they cover (Eccles and Stroehle, 2018).

3.1.3 Objectives

In the existing literature, the impact of ESG rating on the financial performance of firms still remains to be found. In this essay, I aim to probe whether an investor or a firm can financially benefit from referring to ESG criteria when making an investment decision. If ESG does affect financial outcomes of firms, to what extent does it explain their performance? In light of those questions, the main objective of this paper is to explore the relationship between asset returns and ESG ratings in the U.S. financial market and how this relationship changes across sectors and firm sizes and over time. To answer the main questions, I construct dynamic portfolios based on the ESG rating over time.

Depending on the type of industry, costs and effectiveness of ESG implementation differ across sectors. For example, high-polluting industries, such as chemicals, face higher costs to maintain environmental scores compared to low-polluting counterparts. In addition, feasibilities of ESG reinforcement varies among firms of different sizes: relative to small firms, large firms are likely to have more resources, making it easier to engage in ESG reinforcement. Moreover, payoffs from ESG strategies generally take time to realize. Hence, financial returns from ESG strategies predictably change with time. In this essay, I look into the impact of ESG rating across sectors,[5] and firm sizes, and over time horizons (short run, medium run, and long run). In

[5]The sectors are based on Thomson Reuters Business Classification (TRBC). TRBC is the classification for global companies. It covers 10 economic sectors, 28 business sectors, 54 industry groups, 143 industries, and 837 activities. The 10 economic sectors are Energy, Basic Materials, Industrials, Cyclical Consumer Goods & Services, Non-Cyclical Consumer Goods & Services, Financials, Healthcare, Technology, Telecommunications Services, and Utilities.

this study, I pose three main hypotheses. First, stocks from distinct sectors react differently to a change of ESG rating. The second hypothesis is that the capitalization level of firms plays a prominent role in accounting for the relationship between stock returns and ESG performance. Third, the impact of ESG rating on portfolios' performance changes with time horizons.

The remainder of this essay is organized as follows: Section 2 conducts a literature review of the effect of ESG scores on the financial performance of firms in the global market and explains the hypotheses for this study. Section 3 explains the theoretical framework and methodology. Section 4 describes ESG data sources. Section 5 elaborates empirical results. Section 6 concludes the essay and proposes a direction for future research.

3.2 Literature Review and Hypotheses

The studies on direct impact of ESG ratings on financial outcomes did not emerge until the 2000s. Before a systematic integration and universal application of ESG criteria, studies on the financial implications of worldwide social responsible investment (SRI) are based on a variety of CSR information providers, such as the Kinder, Lydenberg, and Domini (KLD) database, Dow Jones Sustainability Indices, and Avanzi SRI dataset. The majority of studies examine the relationship between financial performance and social responsibility (SR) using either mutual funds or stocks (individuals or portfolios). The results are ambiguous: some papers reveal a positive effect of SR implementation while others do not. In this section, I summarize current studies that analyze the impacts of CSR and the subsequent consequent ESG ratings on corporate financial performance (CFP). Since the literature also sheds light on the roles of industrial characteristics, firm capitalization, and time lag in accounting for the correlation between CFP and ESG, I discuss the financial implications of ESG from multiple perspectives and propose hypotheses for this study.

3.2.1 Assets selection

For mutual funds, researchers analyze the financial benefits of social responsibility by comparing socially responsible mutual funds with conventional mutual funds. Empirical findings from the UK, US, Australia, Europe, and Asia-Pacific countries suggest that the average Jensen's alpha, which represents abnormal return, of SRI funds is not significantly different from that of non-SRI funds (Bauer et al., 2007, 2005; Goldreyer and Diltz, 1999; Gregory et al., 1997; Hamilton et al., 1993; Kreander et al., 2005; Mallin et al., 1995; Statman, 2000) and that SRI funds strongly underperform benchmark portfolios and conventional funds (Bauer et al., 2006; Renneboog et al., 2008a). Only a small fraction of studies support the contention that ESG yields a positive effect on funds' return (Barnett and Salomon, 2006).

However, those findings based on mutual funds' performance suffer from some obvious drawbacks. First, fund-managing ability varies across fund managers so that the performance of SRI funds is affected by fund managers and cannot be independently attributed to the existence of social responsibility itself (Kempf and Osthoff, 2007; Sauer, 1997). Second, the SR status of SRI funds may be inconsistent over time with changing SR behaviors of firms and consistent improvement of criteria. This leads to the misspecification of mutual funds' SR status (Wimmer, 2013).

For stock portfolios, scholars explores the SRI and corporate financial performance (CFP) relationship mainly through comparing the financial performance of stock portfolios with higher SR ratings and lower-rated portfolios. The literature reveals two contradictory findings about the relationship (Preston and O'bannon, 1997; Sauer, 1997). The first finding states that the use of the SR rating system positively affects the financial performance of stock portfolios. Kempf and Osthoff (2007) use a trading strategy of longing the stocks with high social responsibility ratings and shorting the stocks with low social responsible ratings.[6] They implement the strategy on the stocks in S&P 500 and DS 400 indices from 1992 to 2004 and find that the high-low portfolio strategy result in significantly high abnormal returns (up to 8.7% per

[6] The socially responsible rating is provided by Domini Research & Analytics (KLD).

year), which imply social responsible stocks perform better financially than their counterparts. Statman and Glushkov (2009) and Eccles et al. (2014) also find a significant positive link between CFP and SRI. The second finding suggests that investors should no longer expect abnormal returns with higher SR rating. Halbritter and Dorfleitner (2015) investigate the impact of sustainability issues on corporate stock returns.[7] Using the same methodology as Kempf and Osthoff (2007), they show that both magnitude and direction of the impact substantially vary by ESG rating providers, firm sample universe, and time horizon. This indicates that ESG does not have a deterministic and unconditional impact on stock returns of firms. Auer and Schuhmacher (2016) provide empirical evidence for a negative ESG-CFP relationship based on ESG investing performance in the U.S., Asia-Pacific countries, and Europe. They find that use of ESG ratings when selecting stocks does not help investors get superior risk-adjusted performance compared to passive stock market investments. Hamilton et al. (1993) state that SRI neither adds nor destroys portfolio value since CSR cannot be priced in the actual financial market. Analyzing ESG's impact on the performance of stock portfolios may avoid biases induced by the mutual funds mentioned in above paragraph.

The research on ESG criteria is relatively new. Despite the availability and quantity of ESG rating data, most of the existing literature relies on KLD database or some sample selection procedures[8] to access the ESG criteria. However, the KLD database has some limitations. It does not adequately capture significant corporate governance factors, such as board structure, accountability, reporting, and disclosure (Galbreath, 2013). Some studies focus only on environmental dimension (Hussain, 1999; Uecker-Mercado and Walker, 2012) or on governance dimension of ESG (Jo and Harjoto, 2011). This is troublesome because these studies ignore the trade-off effects among all ESG dimensions (Delmas and Blass, 2010).

[7] The ESG ratings are based on Asset 4 from Thomson Reuters, Bloomberg, and KLD Research & Analytics.

[8] For example, shunning stock screening procedure to select the non-social responsible stocks (Statman and Glushkov, 2009) and identifying firms with certain sustainable policies (Eccles et al., 2014).

3.2.2 Factors influencing ESG-CFP relationship

The ESG rating system uses the same criteria to assess all stocks. However, stocks originate from different sectors; ESG ratings could vary across the sectors due to the nature of sectoral particularities. The sensitivity of stock returns to ESG scores, therefore, is significantly different amongst sectors. The firms in different sectors are exposed to different levels of ESG risk, especially the environmental (E) risk in such a carbon-constrained economy.

For instance, ESG scores of stocks in the chemicals industry are consistently low, as air or water pollution from chemical emissions is still inevitable given the current state of technology, which may significantly affect their environmental scores. In contrast, stocks in the financial industry are generally highly ranked because there is less pollution of the environment. However, the financial performance of the chemicals industry may be more sensitive to environmental rating than the financial industry, because pollution from refinery is more severe than real estate development (Chatterji and Levine, 2006). A survey of ESG fund managers determines the top 10 sectors that are most sensitive to ESG, [9] among which energy and utility companies are most affected by ESG issues (Maier, 2007). I hypothesize that ESG scores have a lower marginal impact on stock returns for economic sectors that have a higher probability of inducing negative social externalities:

Hypothesis 1: Stocks from distinct sectors react differently to ESG rating.

The Fama-French three-factor model demonstrates that small-cap stocks outperform large-cap stocks on average in a global context (Switzer (2010); Eun et al. (2008); Arnott and Hsu (2008); Bauman et al. (1998)). Controlling the firm-size effect therefore becomes necessary in analyzing asset returns. In addition, large-cap firms gain more attention from the public due to their fame; both positive and negative socially relevant news from those firms diffuse and ferment quickly in this information

[9] Oil & gas producers; Gas, water & multi-utilities; Electricity; Automobiles & parts; Forestry & paper; Chemicals; Mining; Food producers; Construction & materials; and Travel & leisure.

era. Aouadi and Marsat (2018) study more than 4000 firms worldwide and find that the ESG scores only increase on the values of the high-attention firms.[10] As a consequence, compared to small-cap businesses, large-cap firms are more responsive to socially responsible rating.

However, noncompliance or misbehaviors by large-cap firms are also more likely to be disclosed under public invigilation. Therefore, I hypothesize that ESG scores impose a higher effect on stock returns of large-cap firms than that on small ones:

Hypothesis 2: The capitalization level of a firm plays a prominent role in accounting for the relationship between financial returns and ESG performance.

Because of the increased attention paid to ESG investing, more firms are integrating ESG into their investment strategies. Investors care about the implications of firms' ESG. Although ESG implementation can be costly for firms, and the shareholders may not benefit from such a investing immediately. For example, the investment in renewable energy technology, such as solar panels, sacrifices the profit of a firm in the short run for long-run outcomes. Bénabou and Tirole (2010) claim that the firms' non-socially responsible activities (e.g., those economize the pollution) may enhance the short-term profit. Nevertheless, it will damage firms' goodwill and creates future risk of consumer boycott (Sen and Bhattacharya, 2001), difficulty in employing talented workers (Greening and Turban, 2000), or environmental clean-up costs.[11] Extensive literature finds that long-term rewards for firms' socially responsible activities are attributed to employee job satisfaction (Edmans, 2012), higher consumer satisfaction and loyalty (Xie, 2014), higher probability of survival (Fatemi et al., 2015), and positive consumer attitude (Kim and Moon, 2015). Thus, ESG investing is a strategy of maximizing profit from a long-run perspective (Bénabou and Tirole,

[10]High-attention firms are the firms which are larger, with high visibility, more followed by analysts, etc.

[11] For example, BP's strategy of cost-cutting and economizing safety caused the most severe oil spill in history. BP is responsible for the clean-up cost and received the largest corporate fine ($18.7 billion) in U.S. history.

2010) and the high ESG scored firms attract long-term investors (Starks et al., 2017). Therefore, I hypothesize that the effect of ESG varies over time:

Hypothesis 3: The long-term performance of stocks meeting ESG criteria is more significant compared to the short-term one.

3.3 Methodology

In order to investigate whether ESG plays a prominent role in effecting asset returns, I employ the conventional Carhart four-factor model (Carhart, 1997) following existing literature (Derwall et al., 2005; Halbritter and Dorfleitner, 2015; Kempf and Osthoff, 2007; Lins et al., 2017). Nofsinger and Varma (2014) investigate the performance of SRI using CAPM, Fama-French three factor, and Carhart four-factor models. They find that the results remain unchanged. Renneboog et al. (2008a) find that the difference between Carhart four-factor model and Fama-French five-factor model abnormal returns of SRI funds is economically small. The functional form of the conventional Carhart four-factor model is expressed as:

$$R_{it} - R_{ft} = \alpha_i + \beta_{1i}(R_{mt} - R_{ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}MOM_t + \epsilon_{it} \quad (3.1)$$

Here, SMB is the size factor, which represents the difference of the average returns between three small portfolios and three big portfolios. HML is the value factor, which denotes the average returns on two value portfolios minus that of the two growth portfolios. The MOM is the return of the high-return portfolio minus the return of the low-return portfolio over the past 12 months.[12] $R_{mt} - R_{ft}$ is the market excess return, in which R_m is the value weighted return of all CRSP firms, and $R_{it} - R_{ft}$ is the excess return of portfolio i at time t over the risk-free rate (Fama and French, 1993, 1996) . α_i, β_{1i}, β_{2i}, β_{3i}, β_{4i} and ϵ_{it} are the linear model parameters of Equation

[12]The market excess return, size factor, value factor, and momentum factor are taken from the Kenneth R. French data library, available at `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

(3.1).

The primary objective of the essay is to examine how abnormal returns vary from high to low in ESG rating portfolios[13] across sectors and firm sizes, and over time horizons. At time t, I sort the stock portfolios into high/low rating-ESG portfolios based on the ESG ranking at time $t-1$. The high ESG-rating portfolios consist of the top 10%, 20% 30% 40% 50% of all stocks, while the low ESG-rating portfolios consist of the bottom 10%, 20%, 30%, 40%, 50% of all the stocks. I hold the portfolios until time $t+1$ and reconstruct the high/low portfolios based on the ESG ranking at time t. A dynamic portfolio can be created by repeating the above procedure over time. To investigate the impact of ESG on stock portfolio across different time horizons, I introduce three different time lags to the above portfolio construction procedure. The high/low portfolios, which are constructed at time t based on the ESG ranking at $t-1Y$, $t-3Y$ and $t-5Y$,[14] are employed for short-run, medium-run, and long-run ESG impact analysis. To further examine the effectiveness of ESG, I implement a high-low strategy, shorting in low ESG-rating portfolios and longing in high ESG-rating portfolios. An alpha under the high-low strategy is equivalent to the alpha from a high ESG-rating portfolio (e.g., top 10%) minus the alpha from its low ESG-rating counterpart (bottom 10%). High-low strategy enables me to estimate the difference between abnormal returns of high ESG-rating portfolios and those of low ESG-rating portfolios. As firm sizes and sectors are less likely changes overtime, the endogeneity is not an issue in this study.

The ESG rating system assesses all stocks according to the same criteria. However, stocks originate from different sectors; ESG grades may vary across sectors due to differentiation of sectoral characteristics. If the bottom 10% stocks all come from the same sector while the top 10% stocks entirely originate from another sector; comparisons, in this case, have sectoral bias.

To evaluate the ESG scores distribution across different sectors, I divide stocks into two categories, restricted and unrestricted samples, by sectors. In the restricted

[13]A stock portfolio in this sense indicates a group of individual stocks with similar ESG scores.
[14]The time lag unit (Y) is year.

sample, I respectively rank stocks by ESG criteria in each of 10 sectors,[15] rearranging the stocks in every group of high/low ESG-rating portfolios to ensure that each division of ESG score distribution (top/bottom 10% to 50%) consists of stocks from all 10 economic sectors. In unrestricted sample, I rank stocks by ESG criteria by ignoring their sectors. The identification of sectors is based on Thomson Reuters Business Classification (TRBC),[16] which includes Energy, Basic Materials, Industrials, Cyclical Consumer Goods & Services, Non-Cyclical Consumer Goods & Services, Financials, Healthcare, Technology, Telecommunications Services, and Utilities.

I construct stock portfolios using both equally-weighted and capitalization-weighted methods. Equally weighted stocks explain alphas derived from the equally-weighted portfolios. In contrast, the cap-weighted portfolios generate alphas by putting different weights on each stock based on their market capitalization (higher capitalization implies higher weight). The capitalization-weighted portfolios allow me to observe, with similar ESG ranking, how abnormal returns of large capitalized firms differ from small capitalized ones. To further investigate the impact of ESG in terms of firm size, I divide the sample into large-cap stocks (top 30% of firm sizes) and small-cap stocks (bottom 30% of firm sizes). I repeat the above ESG portfolio construction process for large-cap and small-cap stock samples.

3.4 ESG Rating Data

Most studies in the existing ESG literature refer to the so called ASSET4 Equal Weighted Ratings (EWR), which is the old ESG scoring methodology by Thomson Reuters, as the standard of assessing the ESG performance of firms. I use a recent upgrade of databases in 2017, [17] an enhanced and replaced version of EWR, Thomson Reuters ESG scores, for my ESG analysis.

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[15] One may explore deeper into TRBC code by dividing the sample into 28 business sectors or 54 industry groups if the sample is large enough.

[16] TRBC covers 10 sectors, 28 business sectors, 54 industry groups, 143 industries, and 837 activities.

[17] `https://infobase.thomsonreuters.com/infobase/media/upload/infostream/Infostream_Q2_17.pdf`

Thomson Reuters is a corporation providing integrated and intelligent information to firms and professionals. It offers comprehensive ESG data that cover over 7,000 public firms globally across 10 main sectors[18] each year[19] since 2002. More than 400 different ESG metrics dispersed across 10 categories under three dimensions (Environmental, Social, and Governance) are applied to account for relative ESG performances of businesses. Specifically, over the 10 themes, the Environmental pillar covers resource use, emission, and innovation; the Social pillar covers workforce, human rights, community wellbeing, and product responsibility; the Governance pillar covers management, shareholders and social responsibility strategy.[20] A combination of those 10 themes (with proportionate weight to the count of measures in each category) generates the three-pillar scores and the final ESG score, reflecting firms' ESG performance, commitment, and effectiveness.

Thomson Reuters ESG scores derive from a multi-channel data collecting mechanism. Research analysts obtain ESG data primarily, but not merely from the firm's annual reports, firm websites, nonprofit organizations, stock exchange filings, corporate social responsibility reports, and news sources all contribute to composing ESG information of firms. With over 400 ESG measures, data analysts survey manually at each firm so that each measure is standardized and comparable across firms. One hundred and seventy eight most comparable and relevant fields are finally selected to power the overall ESG assessment and scoring process.

One major enhancement of Thomson Reuters ESG scores compared to EWR is that it introduces a percentile rank scoring methodology, allowing for the calculation of category specified ESG scores and eliminating hidden layers of calculations. Percentile rank scoring is adopted to calculate the 10 category scores by examining the proportion of firms that are worse than or the same as the current one (in terms of one ESG value) in all firms that have such value.

[18] The 10 sectors include energy, basic materials, industrials, cyclical consumption, non-cyclical consumption, financials healthcare, technology, telecommunication, and utilities.

[19] In general, ESG reported data are updated annually in line with firms' ESG disclosure. Thomson Reuters does refresh data more frequently when a significant change in the reporting or corporate structure occurs during the year.

[20] See Table B.1 in Appendix for detailed explanation.

In order to assess the ESG performance of firms in each category, Thomson Reuters introduces category benchmarks, which represents another improvement in relation to EWR. TRBC Industry Group serves as the benchmark for the Environmental and Social categories because these topics are more relevant and similar to the firms within the same industries. To compute the Governance category scores, Country of Headquarters is selected as the benchmark, as best governance practices are more consistent within countries.

Thomson Reuters also put different weights on each category when calculating the overall ESG score for each firm. Category weights are accounted for by the number of indicators (measures) in each category compared to all 178 indicators in the Thomson Reuters ESG score framework. A higher weight implies a higher maturity in disclosure. For example, management that contains 34 indicators of rating (composition, diversity, independence, committees, compensation) are weighted heavier than human rights, which includes only 8 indicators. Table B.2 in Appendix specifically lists the counts and weights of each category.[21]

I use monthly U.S. ESG rating data for more than 2400 firms from 2002 to 2018. The earliest ESG rating data is 2002. Since the establishing dates of some firms are later than 2002 and some firms do not report ESG related information until later years, not all the firms have ESG rating data from 2002. As one aim of this study is to examine the impact of the ESG rating on stock portfolios' financial performance in terms of different time horizons, the firms with only few years' ESG rating data are excluded. Meanwhile, I include as many firms as possible. Therefore, I exclude the firms without ESG ratings until 2015[22] and the data contain 1508 firms.

Table 3.1 provides the descriptive statistics of ESG scores for the samples across sectors. The average and median of the ESG scores for the full sample are 49.86 and 48.04, respectively. The ESG scores vary across sectors. For example, the sector of Non-cyclical consumer goods and services has the highest mean ESG score at 55.27,

[21]This table is retrieved from Refinitiv. See `https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology` for reference.

[22]There are more than 600 firms added to the ESG rating database in the year 2015.

while the sector of healthcare has the lowest mean ESG score at 46.92. Large-cap stocks (56.72) tend to have higher ESG scores with larger volatility (16.92) than the small-cap stocks (41.62) with small volatility (13.20) on average. The ESG scores across small-cap and large-cap stocks are dissimilar by sectors.

3.5 Empirical Results

3.5.1 Aggregate impact of ESG rating

I find that, in general, the higher ESG-rating portfolios do not outperform the lower ESG-rating ones from the perspective of abnormal returns. Based on my definition of time horizon in this study, "short term" represents the effect of a ESG score in year T on its corresponding stock return in year T+1; "medium term" indicates year T's ESG implication on year T+3's stock returns; and "long term" extends the examination on stock performance to year T+5. As Figure 3.3 shows, the alphas for all stock portfolios are negative, and the differences between the high- and low ESG-rating stock abnormal returns (high-low strategy) are non-positive over all cut-off rates and across all types of the sample in the short- and medium-term. In the long run, such differences become positive in equally-weighted samples while still remain negative in cap-weighted portfolios.

However, the high ESG-rating portfolios hold lower systematic risk compared to the low-rating counterparts. In the Carhart four-factor model with both restricted (Table 3.2) and unrestricted samples (Table 3.3), the coefficients of excess return to the market (MKT) for the low ESG-rating stocks are significantly higher than those for the high ESG-rating stocks. This implies that the low ESG-rating stocks have higher market risk than the stocks with high ESG-rating stocks. Fama and French have argued that the size of the underlying firm (SMB) and the ratio of the book value of equity to market value (LMH) are two 'risk-based' explanatory variables. The former serves as a proxy for the required returns for bearing exposure to small stocks, and the latter is a proxy for investors' required returns for bearing "financial distress" (Fama and French, 1995). The results reveals that the coefficients of SMB and LMH for the low ESG-rating portfolios are consistently higher than those in the high ESG-rating ones (see Tables 3.2 and 3.3). This indicates that low ESG-rating stocks are exposed to higher systematic risk than high ESG-rating stocks are. Although the coefficients of MOM do not display a regular pattern in the model, the momentum effects are significant in most cases.

3.5.2 Upshots of the sector, market capitalization, and time horizon

Tables 3.2, 3.3, and Figure 3.3 show that the results do not differ between restricted and unrestricted models. This is because the ESG scores tend to be uniformly distributed across sectors. This finding supports unbiased comparison of ESG financial implications across sectors. The impact of ESG on stock returns does vary across sectors and firm sizes, and over time. Figure 3.4 illustrates the 'high-low strategy' abnormal returns across 10 economic sectors over time using the equally-weighted approach. For most sectors, ESG acts as a positive indicator to account for abnormal returns over time. Considering that the number of firms available within each sector in the dataset is limited, I only compare the stocks ranked top-and-bottom 30% and 50% in this subsection. Without incorporating the time horizon and focusing on the short-run outcomes, I find that a half of the 10 sectors containing Energy, Industrials, Technology, Telecommunication, and Utilities yield a positive gap between high and low ESG-rating alphas. However, when I take the time horizon into account, in seven sectors, namely Energy, Basic material, Industrials, Non-cyclical Consumer Goods and Services, Financials, Healthcare, and Technology, the 'high-low strategy' alphas tend to be increase over time periods. Among the seven sectors, Energy, Industrials, and Technology sectors show a clearly growing trend of the magnitude of the 'high-low strategy' alphas at the 30% cut off rate, implying that the highest 30% of ESG-rating stocks increasingly outperform the lowest 30% stocks over time. The other four sector (Basic Material, Non-cyclical Consumer Goods and Services, Financials, and Healthcare) initially have negative 'high-low strategy' alphas, whereas the negative gaps shrink as time lags increase. In particular, at the 50% cut-off rate, Non-cyclical Consumer Goods and Services, Basic Materials, and Financial sectors experience a sign-altering in the 'high-low strategy' abnormal returns. One explanation is that the costs of ESG contribution reduce the firms' financial return at the early stage of ESG construction, and the consequent benefits surpass the costs when the constructing process matures. On the other hand, ESG does not play a positive role in Cyclical Consumer Goods and Services, Telecommunication Services, and Utilities sectors overtime.

Correspondingly, Figure 3.5 depicts the industry-level 'high-low strategy' abnormal returns based on market capitalization-weighted portfolios; the results are significantly different from those under equally-weighted sample stocks. In the short run, only Healthcare, Telecommunication Services, and Utilities generate positive 'high-low strategy' alphas, whereas the other seven sectors show a negative gap in the abnormal returns between high ESG-rating and low ESG-rating stock portfolios. Adding time lag into my analysis, ESG is effective in improving the abnormal returns of stocks in the long run for only four economic sectors: Energy, Basic material, Industrials, and Non-cyclical Consumer Goods and Services.

By comparing Figures 3.4 and 3.5, I generalize three key findings. First, equally-weighted stocks generate dramatically different outcomes from cap-weighted portfolios in Financials, Healthcare, and Technology industries. Since large-size firms make up a higher proportion in stock portfolios by applying capitalization weight, the stock returns under this method are partial to the financial performance of large-cap firms. In the proposed models, the 'high-low strategy' abnormal return for the financial sector, in the long run, is positive with equally-weighted portfolios, while it becomes negative under cap weight. This implies that, in the long term, the abnormal returns for large firms in the financial sector react more negatively to ESG rating compared to small-cap businesses, which is similar to the Technology industry. Oppositely, large-cap firms benefit more from ESG than small ones.

To reinforce my findings in terms of firm sizes, I divide the sample into small-cap and large cap-firms to investigate the impact of ESG. The 'high-low strategy' alpha is equivalent to the difference of abnormal returns between high ESG-rating portfolio and low ESG-rating portfolio. Figure 3.6 compares 'high-low strategy' abnormal returns from small and large-cap portfolios under equally-weighed and cap-weighted approaches. In the short and medium runs, the small and large-cap portfolios have negative abnormal returns attributed to the high ESG. The negative effect of ESG on the small-cap portfolios becomes larger as short run goes to medium run while the negative effect of ESG on large-cap portfolio shrinks. In the long run, large-cap portfolios are rewarded by the high ESG-rating with positive abnormal returns from the 'high-low strategy'. Figure 3.6 reinforces the finding that large firms can benefit more from ESG implementation than small firms.

Second, both equally- and cap-weighted portfolios show that ESG acts positively on the abnormal returns for Energy, Basic Materials, Industrials, and Non-cyclical Consumer Goods and Services sectors. Notably, those four sectors are all 'sensitive industries' that are highly likely to cause environmental and social damage. According to definitions from Thomson Reuters Business Classification, Energy sector involves coal mining, oil and gas refining, and uranium processing; Basic Materials sector includes chemicals, metals, and forest products; Industrials contains machinery and equipment and transport infrastructure; Non-cyclical Consumer Goods and Services pertains to alcohol and tobacco supply. Since these sectors are well known to be dangerous to natural and social environments, they gain broader attention and invigilation from the media, the public, and investors. Therefore, those sectors with the 'original sin' making reacting more to ESG and benefit more from it.

In contrast to the second, the third finding shows that ESG imposes a negative effect on the abnormal return in Cyclical Consumer Goods and Services, Telecommunication Services, and Utilities sectors. For the first part, demand for cyclical goods (e.g., automobiles, clothes, furniture, and other durable goods) and services (e.g., hotel, entertainment, media, and publishing) are effected by the business cycles. As a result, financial performance in this sector treads on the heels of the external economic environment, and the effect of ESG may not be strong enough to alter its growing trend. As for Telecommunication and Utilities sector, there is no intuitive explanation for the negative ESG implication on their stock returns. Furthermore, one may challenge the results by arguing that the numbers of the firm for these two sectors chosen in this study (17 and 42) are small relative to that in other sectors (at least 80 firms), therefore, the findings may not be sufficiently representative or reliable. In general, however, one potential reason for the negative relationship between abnormal returns and ESG scores in the long term may be that those three sectors, contrary to the 'sensitive industries' mentioned above, are not likely to cause direct harm to the natural and social environments.

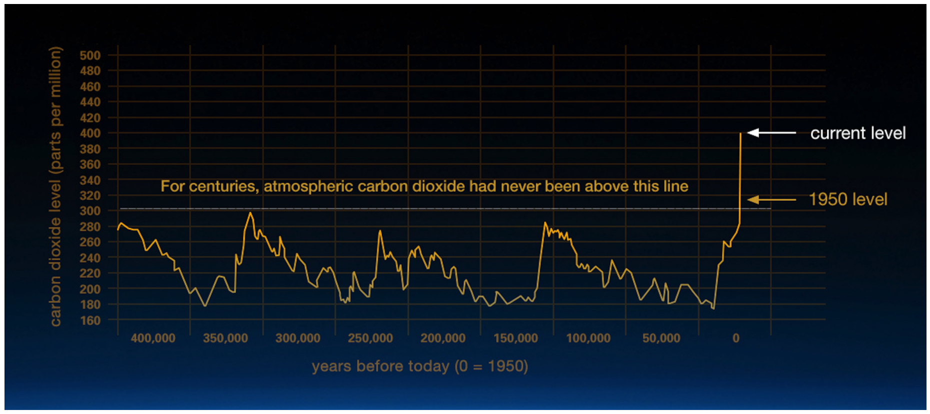
3.6 Conclusion

This essay studies the relationship between CFP and ESG by examining three dimensions: across sectors and firms' sizes and over time horizons. To sum up, the findings from examining the abnormal returns of stock portfolios are consistent with the three hypotheses: sectors, market-cap , and time horizon interactively affect the relationship between ESG performance and stock returns.

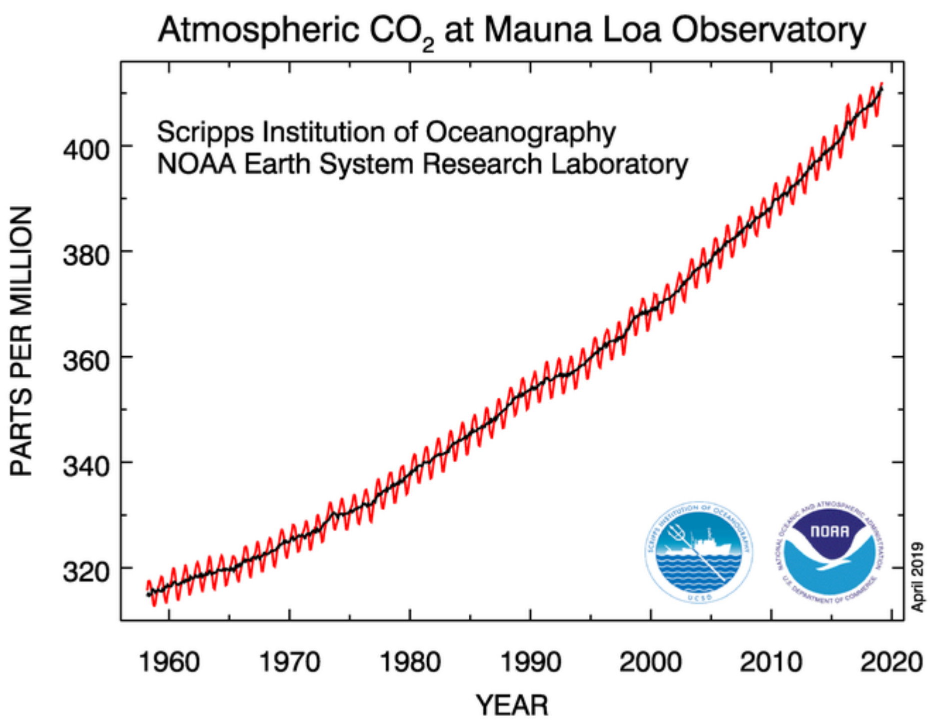
The empirical results suggest that, first, the impact of ESG is different across sectors over different time horizons. In general, ESG has a positive impact on abnormal returns over time for most sectors (Energy, Basic material, Industrials, Non-cyclical Goods and Services, Financials, Healthcare, Technology). The positive (negative) gap of abnormal returns between high and low ESG-rating portfolios increase (decrease) from short run to long run. Among these sectors, the ESG induces positive abnormal returns for more sensitive sectors (oil, gas, chemical, mining, alcohol and tobacco supply etc.), which involve the activities causing environmental and social damages. The public and investors pay more attention to ESG practices of the sensitive sectors than other sectors. Therefore, sensitive firms are impacted more by ESG. This is consistent with a socially responsible asset managers' survey (Maier, 2007). Second, large firms are more exposed to the impact of ESG. Although the short-term payoff may not cover the initial ESG costs, the large firms benefit from

ESG in the long run. Therefore, large firms has more advantages to invest in ESG than small ones do, which explains the ESG scores of large firms are over 36% higher than small firms on average (see Table 3.1). Third, without differentiating sectors and firm sizes, ESG plays a positive role for stock portfolios' performance in the long run. In addition, the high ESG-rating portfolios have lower systemic risk than low ESG-rating counterparts.

One main contribution of this study to the ESG literature is that I utilize the unique ESG rating data to analyze the impact of ESG on stock portfolios across sectors and firm sizes, and over time horizons. ESG, as a comprehensive concept assessing firm's performance from multidimensional perspectives, has been increasingly prevalent in the modern financial market. The findings convey a positive sign of ESG: firms may financially benefit from ESG contribution. It is compatible with the profit-maximizing objective of firms and meanwhile motivates enterprises to be more socially conscious in the process of pursuing economic gains. Such a virtuous circle may also improve the overall efficiency of the financial market in the long run.



(a) Carbon dioxide level traced back 400 thousand years. Source: NASA



(b) Carbon dioxide level from trace back to 1958. Source: NOAA

Figure 3.1: Carbon dioxide level

The data are based on measures of atmospheric samples contained in ice cores. It shows that the level of carbon dioxide emissions has consistently increased since the Industrial Revolution; it broke the historical record (300 parts per million) in the 1950s and kept rapidly growing up to now.

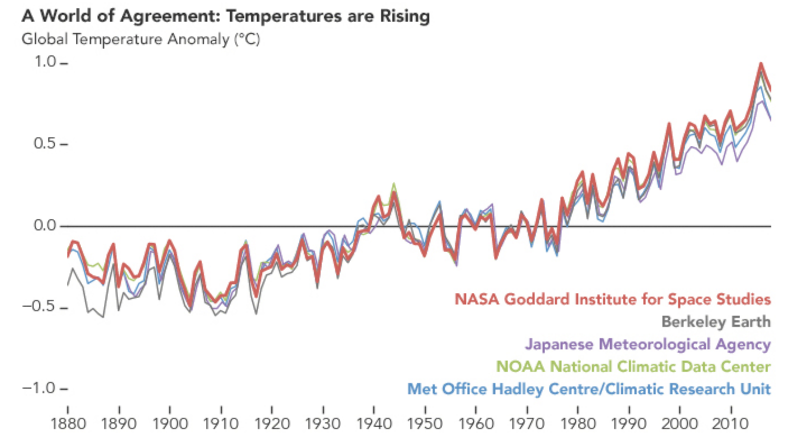


Figure 3.2: Rising temperatures

The lines show yearly temperature anomalies from 1880 to 2014, as recorded by multiple organizations. Despite minor variations from year to year, all four records show similar peaks and valleys. All show rapid warming over the past century, and all indicate the last decade as the warmest.

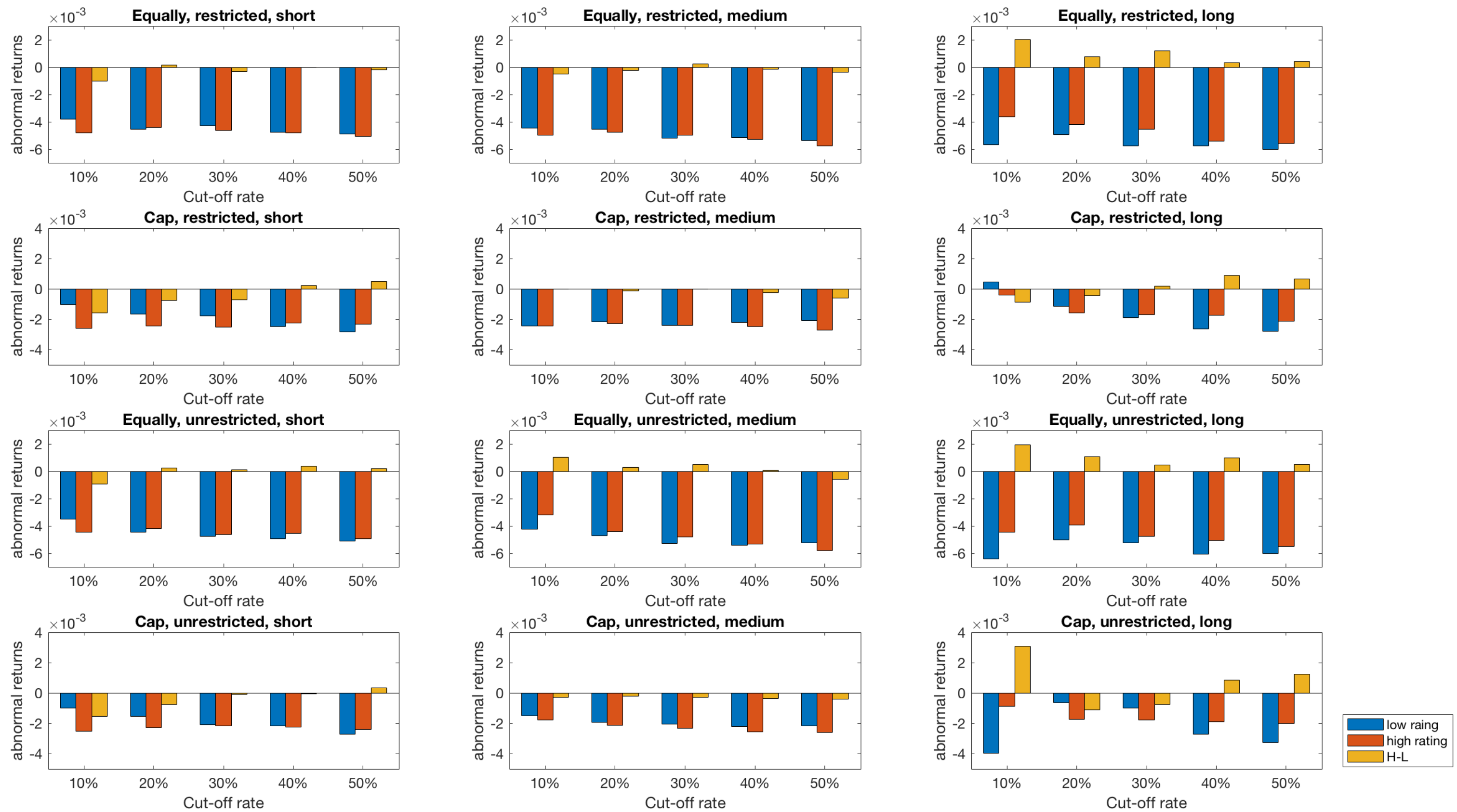


Figure 3.3: Abnormal returns of low ESG, high ESG, and high-low strategy portfolios

The panel on the top two rows are equally, and cap-weighted portfolios for restricted samples; the abnormal returns for equally and cap-weighted portfolios of the unrestricted sample are displayed in the bottom two rows. The columns from left to right represent the short run (1 year), medium run (3 years), and long run (5 years), respectively.

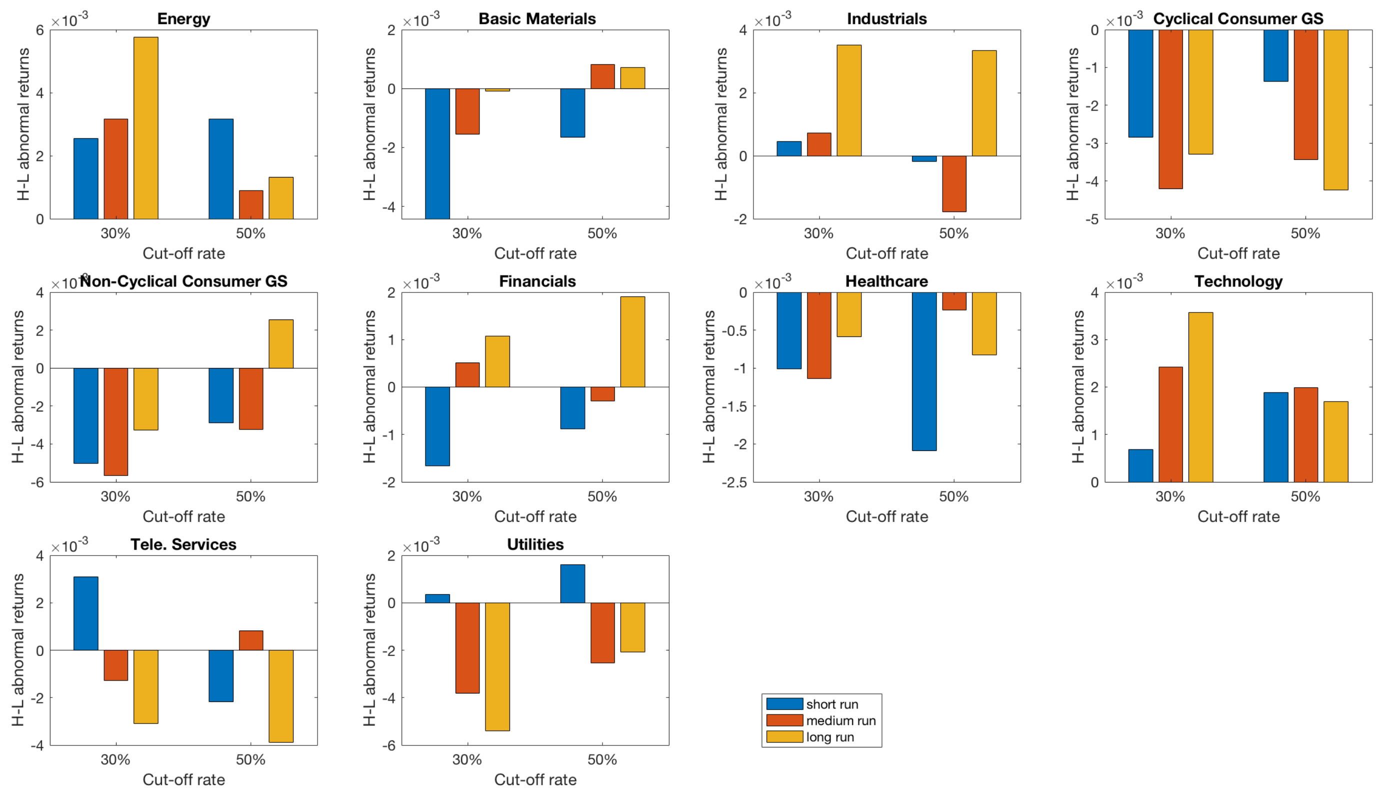


Figure 3.4: High-low strategy abnormal returns of equally-weighted ESG portfolios by sector

This figure exhibits the high-low strategy abnormal returns of equally weighted portfolios for different time horizons by 10 economic sectors. The high-rating portfolios are constructed by the top 30% and 50% of the stocks in each of the sectors; the low ESG rating portfolios consist of the bottom 30% and 50% of the stocks in each of the sectors. The high-low strategy is a trading strategy going long in high rating portfolio and short in low-rating portfolios.

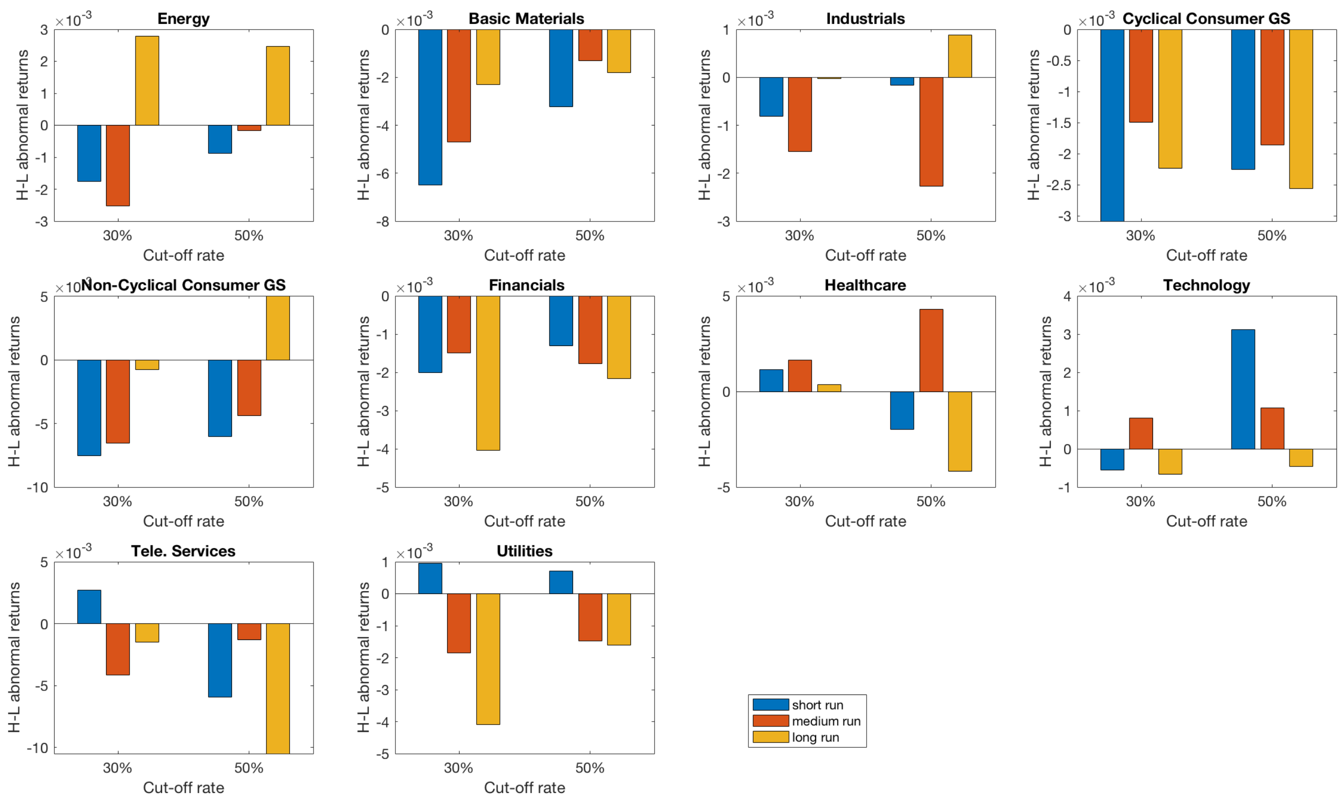


Figure 3.5: Abnormal returns of cap-weighted portfolios by sectors

This figure exhibits the high-low strategy abnormal returns of cap-weighted portfolios for different time horizons by 10 economic sectors. The high rating portfolios are constructed by the top 30% and 50% of the stocks in each of the sectors; the low ESG rating portfolios consist of the bottom 30%, and 50% of the stocks in each of the sector. The high-low strategy is a trading strategy going long in high rating portfolio and short in low rating portfolio.

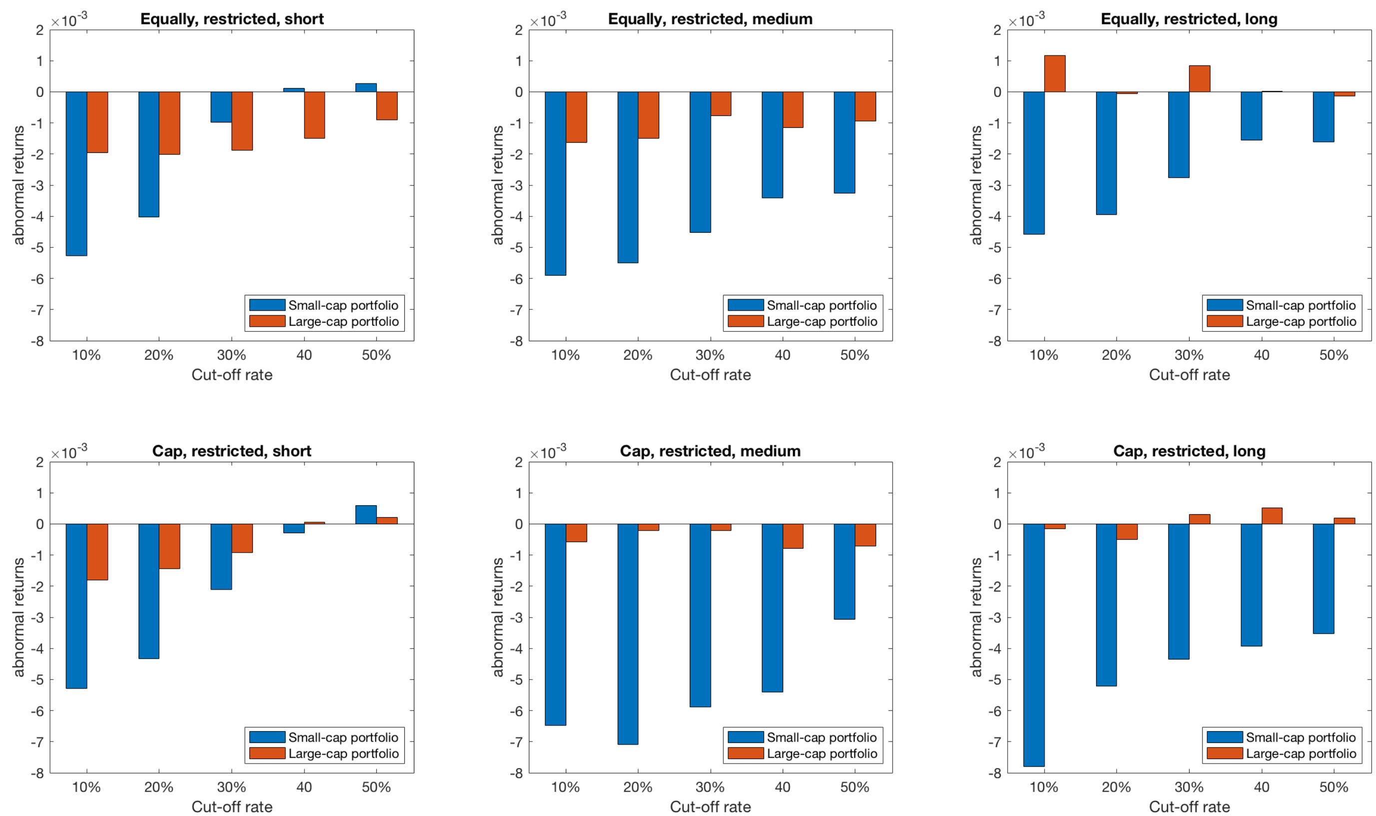


Figure 3.6: The high-low strategy abnormal returns of small-cap and large-cap portfolios

This figure displays the comparison of 'high-low strategy' abnormal returns between small-cap and large-cap portfolios for different weighting approaches, and time horizons. The panels on the top row are abnormal retuns for equally weighted portfolios; the panels on the bottom row are abonormal returns for cap-weighted portfolios. The columns from left to right represent the short run (1 year), medium run (3 years), and long run (5 years), respectively.

Table 3.1: Descriptive Statistics of ESG scores by sectors

	Mean	Min	25%	Median	75%	Max	SD	N
Full Sample								
All	49.86	0.00	37.04	48.04	62.20	97.51	16.50	1508
Energy	52.41	14.53	38.43	51.05	64.58	97.51	17.42	88
Basic.Material	46.11	11.92	34.52	44.07	57.24	84.98	14.79	77
Industrials	48.95	0.00	35.99	47.48	60.36	90.63	16.57	209
Cyclical.Consumer.GS	48.84	11.44	36.49	46.71	60.37	95.22	15.84	226
Non.cyclical.Consumer.GS	51.68	16.72	39.48	50.45	64.68	91.63	15.72	80
Financials	49.24	9.29	36.54	47.10	61.62	93.24	16.64	333
Healthcare	48.66	12.96	35.68	46.30	61.14	89.46	16.21	226
Technology	52.93	0.00	39.35	52.07	65.88	94.07	17.07	210
Tele.services	42.10	20.23	34.22	39.25	47.58	83.87	13.73	17
Utilities	54.20	22.51	41.45	53.06	64.15	91.55	15.40	42
Small-cap Sample								
All	41.62	9.29	31.98	39.51	49.20	86.26	13.20	452
Energy	47.99	17.06	34.17	47.06	62.80	78.95	16.28	20
Basic.Material	38.59	22.02	29.97	35.08	46.14	63.29	10.97	24
Industrials	39.09	17.04	30.34	37.01	45.46	79.69	11.13	53
Cyclical.Consumer.GS	41.92	18.56	32.41	40.00	49.14	78.12	13.23	74
Non.cyclical.Consumer.GS	39.70	16.72	32.00	38.41	46.47	67.50	9.40	22
Financials	40.79	9.29	31.26	39.96	48.04	81.70	12.62	112
Healthcare	40.95	17.73	31.57	38.82	47.04	86.26	12.93	74
Technology	44.64	12.03	33.32	41.95	56.10	84.92	15.43	58
Tele.services	39.94	23.52	34.19	39.94	46.14	53.11	7.74	5
Utilities	44.37	22.51	35.36	45.68	52.46	67.70	11.58	10
Large-cap Sample								
All	56.72	0.00	43.55	57.62	69.87	97.51	16.92	452
Energy	59.53	14.53	44.11	59.64	74.53	97.51	17.81	30
Basic.Material	49.10	11.92	36.26	50.29	62.32	83.99	15.32	26
Industrials	54.83	0.00	41.40	55.00	67.95	90.63	17.42	69
Cyclical.Consumer.GS	55.99	11.44	43.19	56.44	68.90	95.22	15.90	65
Non.cyclical.Consumer.GS	56.31	17.09	44.86	57.59	67.93	91.63	15.40	35
Financials	55.99	13.30	42.36	55.96	70.41	93.24	17.45	91
Healthcare	56.47	17.23	43.05	58.67	70.39	89.46	17.25	49
Technology	60.69	0.00	48.95	62.96	73.14	94.07	16.39	68
Tele.services	62.07	36.93	50.20	56.89	78.03	83.87	15.16	2
Utilities	60.62	24.77	50.41	61.05	72.15	91.55	14.72	17

This table shows the basic statistics of U.S. ESG scores for the full sample, small-cap sample, and large-cap sample by sector. Small-cap sample consists of the bottom 30% of stocks based on the ranking of capitalization. Large-cap sample includes the top 30% of stocks in terms of capitalization. N represents the number of firms in each sector.

Table 3.2: Parameters of equally- and cap-weighted portfolios (unrestricted)

	Low ESG-rating portfolio					High ESG-rating portfolio				
Cutoff	Alpha	MKT	SMB	LMH	MOM	Alpha	MKT	SMB	LMH	MOM
Equally- weighted portfolio										
					Short run					
10%	-0.0035 ***	1.0937 ***	0.3876 ***	0.0791	-0.0779 ***	-0.0045 ***	1.0798 ***	-0.0125	0.0056	-0.0711 ***
20%	-0.0045 ***	1.1049 ***	0.3816 ***	0.0869 **	-0.1050 ***	-0.0042 ***	1.0640 ***	0.0491	0.0607 **	-0.0828 ***
30%	-0.0047 ***	1.1241 ***	0.4042 ***	0.1292 ***	-0.1152 ***	-0.0046 ***	1.0970 ***	0.1143 ***	0.0844 ***	-0.0966 ***
40%	-0.0049 ***	1.1188 ***	0.4109 ***	0.1173 ***	-0.1156 ***	-0.0046 ***	1.1060 ***	0.1582 ***	0.1092 ***	-0.1120 ***
50%	-0.0051 ***	1.1303 ***	0.4025 ***	0.1310 ***	-0.1146 ***	-0.0049 ***	1.1085 ***	0.1993 ***	0.1038 ***	-0.1092 ***
					Medium run					
10%	-0.0042 ***	1.1009 ***	0.3735 ***	0.0608	-0.0755 ***	-0.0032 ***	1.0548 ***	0.0203	0.1352 ***	-0.0518 ***
20%	-0.0047 ***	1.1277 ***	0.3825 ***	0.0851*	-0.0860 ***	-0.0044 ***	1.0646 ***	0.0360	0.0740 ***	-0.0698 ***
30%	-0.0053 ***	1.1508 ***	0.3983 ***	0.1100 ***	-0.1198 ***	-0.0048 ***	1.0935 ***	0.0832 ***	0.0945 ***	-0.1139 ***
40%	-0.0054 ***	1.1498 ***	0.4113 ***	0.1352 ***	-0.1196 ***	-0.0053 ***	1.1073 ***	0.1087 ***	0.0905 ***	-0.1295 ***
50%	-0.0052 ***	1.1333 ***	0.3944 ***	0.1487 ***	-0.1114 ***	-0.0058 ***	1.1229 ***	0.1390 ***	0.0976 ***	-0.1380 ***
					Long run					
10%	-0.0064 ***	1.1067 ***	0.2642 ***	0.1010*	-0.0689 ***	-0.0045 ***	1.0566 ***	0.0287	0.0151	-0.0599 ***
20%	-0.0050 ***	1.0864 ***	0.3266 ***	0.1154 ***	-0.1079 ***	-0.0039 ***	1.0424 ***	0.0397	0.0958 ***	-0.0787 ***
30%	-0.0052 ***	1.1028 ***	0.3541 ***	0.1478 ***	-0.1349 ***	-0.0048 ***	1.0686 ***	0.0799 ***	0.1107 ***	-0.1131 ***
40%	-0.0061 ***	1.1380 ***	0.3671 ***	0.1416 ***	-0.1186 ***	-0.0051 ***	1.0723 ***	0.1297 ***	0.1322 ***	-0.1256 ***
50%	-0.0060 ***	1.1287 ***	0.3470 ***	0.1551 ***	-0.1239 ***	-0.0055 ***	1.0921 ***	0.1688 ***	0.1655 ***	-0.1287 ***
Value weighted portfolio										
					Short run					
10%	-0.0010	0.9683 ***	0.1110 **	-0.0520	0.0030	-0.0025 ***	0.9811 ***	-0.2468 ***	0.0913 ***	0.0283
20%	-0.0015	0.9829 ***	0.1232 ***	-0.0934 **	-0.0300	-0.0023 ***	0.9524 ***	-0.2162 ***	0.0510 **	0.0287 **
30%	-0.0021 ***	1.0249 ***	0.1156 ***	-0.0773 **	-0.0135	-0.0022 ***	0.9743 ***	-0.1955 ***	0.0249	0.0256 ***
40%	-0.0022 ***	1.0371 ***	0.1203 ***	-0.0588*	-0.0132	-0.0022 ***	0.9786 ***	-0.1765 ***	0.0186	0.0146
50%	-0.0027 ***	1.0576 ***	0.1077 ***	-0.0399	-0.0190	-0.0024 ***	0.9914 ***	-0.1564 ***	0.0029	0.0145*
					Medium run					
10%	-0.0015	1.0341 ***	0.0814	-0.1938 ***	-0.0297	-0.0018*	0.9615 ***	-0.2349 ***	0.1232 ***	0.0718 ***
20%	-0.0019*	1.0307 ***	0.1035 **	-0.1097 ***	-0.0331	-0.0021 ***	0.9567 ***	-0.2135 ***	0.0631 ***	0.0635 ***
30%	-0.0020 ***	1.0500 ***	0.1252 ***	-0.1079 ***	-0.0409*	-0.0023 ***	0.9696 ***	-0.1998 ***	0.0364*	0.0459 ***
40%	-0.0022 ***	1.0334 ***	0.1277 ***	-0.0719 **	-0.0424 **	-0.0026 ***	0.9897 ***	-0.1995 ***	0.0247	0.0332 ***
50%	-0.0022 ***	1.0280 ***	0.1216 ***	-0.0383	-0.0350*	-0.0026 ***	0.9940 ***	-0.1783 ***	0.0213	0.0289 ***
					Long run					
10%	-0.0039 ***	1.0905 ***	-0.0154	-0.0143	0.0951 ***	-0.0009	0.9128 ***	-0.2515 ***	0.0034	0.0779 ***
20%	-0.0006	0.9609 ***	0.0664	0.0060	0.0416	-0.0017 **	0.9170 ***	-0.2060 ***	0.0684 **	0.0852 ***
30%	-0.0010	0.9876 ***	0.0676	0.0153	0.0108	-0.0018 ***	0.9217 ***	-0.1812 ***	0.0566 **	0.0555 ***
40%	-0.0027 ***	1.0356 ***	0.0753 **	0.0170	0.0180	-0.0019 ***	0.9351 ***	-0.1695 ***	0.0480 **	0.0367 ***
50%	-0.0033 ***	1.0536 ***	0.0434	0.0466	-0.0075	-0.0020 ***	0.9503 ***	-0.1602 ***	0.0369*	0.0322 ***

This table shows the abnormal returns and the βs from the Carhart four-factor model for the unrestricted samples. The high-rating portfolios are constructed by the top 10%, 20%, 30%, 40%, and 50% of all the stocks; while the low ESG rating portfolios consist of the bottom 10%, 20%, 30%, 40%, 50% of all the stocks. The abnormal returns are produced from two different weighting approaches: equally weighted and cap-weighted portfolios. The short run, medium run and long run represent that the portfolios are constructed based on the ESG ranking at year $t-1$, $t-3$, and $t-5$ respectively. The parameters are estimated using monthly data from 2002.01 to 2018.12. ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively.

Table 3.3: Parameters of equally- and cap-weighted portfolios (restricted)

	Low ESG-rating portfolio					High ESG-rating portfolio				
Cutoff	Alpha	MKT	SMB	LMH	MOM	Alpha	MKT	SMB	LMH	MOM
Equally-weighted portfolio										
					Short run					
10%	-0.0038 ***	1.1142 ***	0.3914 ***	0.0788	-0.0631 ***	-0.0048 ***	1.0633 ***	0.0293	0.0351	-0.0677 ***
20%	-0.0045 ***	1.1056 ***	0.3941 ***	0.1031 ***	-0.1090 ***	-0.0044 ***	1.0720 ***	0.0691 ***	0.0596 **	-0.0776 ***
30%	-0.0043 ***	1.1150 ***	0.3999 ***	0.1236 ***	-0.1139 ***	-0.0046 ***	1.0926 ***	0.1295 ***	0.0826 ***	-0.0974 ***
40%	-0.0048 ***	1.1139 ***	0.4042 ***	0.1233 ***	-0.1172 ***	-0.0048 ***	1.1117 ***	0.1828 ***	0.1014 ***	-0.1084 ***
50%	-0.0049 ***	1.1238 ***	0.3952 ***	0.1268 ***	-0.1145 ***	-0.0051 ***	1.1135 ***	0.2037 ***	0.1106 ***	-0.1058 ***
					Medium run					
10%	-0.0044 ***	1.1424 ***	0.3655 ***	0.0553	-0.0982 ***	-0.0050 ***	1.0707 ***	0.0165	0.0970 ***	-0.0887 ***
20%	-0.0045 ***	1.1305 ***	0.3815 ***	0.0788*	-0.0923 ***	-0.0048 ***	1.0883 ***	0.0350	0.0588*	-0.0991 ***
30%	-0.0052 ***	1.1346 ***	0.4083 ***	0.1084 ***	-0.1072 ***	-0.0050 ***	1.0909 ***	0.0843 ***	0.0888 ***	-0.1196 ***
40%	-0.0051 ***	1.1346 ***	0.3925 ***	0.1362 ***	-0.1115 ***	-0.0053 ***	1.1084 ***	0.1278 ***	0.0749 ***	-0.1351 ***
50%	-0.0054 ***	1.1261 ***	0.3880 ***	0.1500 ***	-0.1180 ***	-0.0057 ***	1.1292 ***	0.1473 ***	0.0951 ***	-0.1342 ***
					Long run					
10%	-0.0057 ***	1.1002 ***	0.2433 ***	0.1549 ***	-0.0497	-0.0036 ***	1.0428 ***	0.0210	0.1052 ***	-0.0652 ***
20%	-0.0049 ***	1.0830 ***	0.3233 ***	0.1324 ***	-0.1014 ***	-0.0042 ***	1.0568 ***	0.0460	0.1087 ***	-0.0698 ***
30%	-0.0057 ***	1.1181 ***	0.3452 ***	0.1452 ***	-0.1228 ***	-0.0046 ***	1.0601 ***	0.1015 ***	0.1473 ***	-0.1226 ***
40%	-0.0058 ***	1.1231 ***	0.3512 ***	0.1565 ***	-0.1152 ***	-0.0054 ***	1.0785 ***	0.1489 ***	0.1455 ***	-0.1300 ***
50%	-0.0060 ***	1.1335 ***	0.3374 ***	0.1658 ***	-0.1237 ***	-0.0056 ***	1.0888 ***	0.1824 ***	0.1492 ***	-0.1308 ***
Value weighted portfolio										
					Short run					
10%	-0.0010	0.9549 ***	0.1394 ***	-0.0966*	-0.0082	-0.0026 ***	0.9777 ***	-0.2321 ***	0.1179 ***	0.0382 **
20%	-0.0017*	0.9854 ***	0.1443 ***	-0.0883 **	-0.0242	-0.0024 ***	0.9596 ***	-0.1809 ***	0.0609 ***	0.0259*
30%	-0.0018 **	1.0238 ***	0.1087 ***	-0.0621*	-0.0171	-0.0025 ***	0.9724 ***	-0.1915 ***	0.0293	0.0339 ***
40%	-0.0025 ***	1.0397 ***	0.1079 ***	-0.0561	-0.0277	-0.0023 ***	0.9786 ***	-0.1766 ***	0.0154	0.0179*
50%	-0.0028 ***	1.0724 ***	0.1048 ***	-0.0628*	-0.0159	-0.0023 ***	0.9852 ***	-0.1565 ***	0.0103	0.0152*
					Medium run					
10%	-0.0024*	1.0863 ***	0.0543	-0.1872 ***	-0.0273	-0.0025 ***	0.9688 ***	-0.2487 ***	0.1235 ***	0.0626 ***
20%	-0.0022 **	1.0493 ***	0.1107 ***	-0.1405 ***	-0.0255	-0.0023 ***	0.9639 ***	-0.2101 ***	0.0707 ***	0.0551 ***
30%	-0.0024 ***	1.0447 ***	0.1231 ***	-0.0732*	-0.0490 **	-0.0024 ***	0.9763 ***	-0.2049 ***	0.0362*	0.0474 ***
40%	-0.0022 ***	1.0304 ***	0.1092 ***	-0.0516	-0.0355*	-0.0025 ***	0.9799 ***	-0.1893 ***	0.0190	0.0379 ***
50%	-0.0021 ***	1.0269 ***	0.1219 ***	-0.0195	-0.0458 ***	-0.0027 ***	0.9955 ***	-0.1820 ***	0.0149	0.0321 ***
					Long run					
10%	0.0005	0.9296 ***	0.0083	0.1228 **	0.1034 ***	-0.0004	0.8877 ***	-0.2103 ***	0.0392	0.0869 ***
20%	-0.0011	0.9716 ***	0.0730	0.0615	0.0528 **	-0.0016 **	0.9109 ***	-0.1945 ***	0.0364	0.0894 ***
30%	-0.0019 ***	1.0230 ***	0.0406	0.0254	0.0111	-0.0017 ***	0.9182 ***	-0.1895 ***	0.0695 ***	0.0630 ***
40%	-0.0026 ***	1.0281 ***	0.0704*	0.0219	0.0149	-0.0017 ***	0.9225 ***	-0.1712 ***	0.0652 ***	0.0441 ***
50%	-0.0028 ***	1.0567 ***	0.0300	0.0508	-0.0031	-0.0021 ***	0.9475 ***	-0.1576 ***	0.0380*	0.0320 ***

This table shows the abnormal returns and the βs from the Carhart four-factor model for the restricted samples. The high-rating portfolios are constructed by the top 10%, 20%, 30%, 40%, and 50% of the stocks in each of the 10 economic sectors, while the low ESG rating portfolios consist of the bottom 10%, 20%, 30%, 40%, 50% of the stocks in each of the 10 economic sectors. The restricted sample approach ensures that the low- and high-rating portfolios contain stocks from different sectors. The abnormal returns are produced from two different weighting approaches: equally weighted and cap-weighted portfolios. The short run, medium run and long run represent that the portfolios are constructed based on the ESG ranking at year $t-1$, $t-3$, and $t-5$, respectively. The parameters are estimated using monthly data from 2002.01 to 2018.12. ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively.

Chapter 4

Financial Impacts of ESG Rating under Different Market Regimes

4.1 Introduction

In 2008, a severe economic crisis swept the world, the main goal for most firms was to survive. Implementing social responsibility, which involve extra costs for firms, thus seemed not to be desirable under such circumstances. However, CRS was not seen as being in jeopardy when economic prosperity was threatened, many firms insisted on maintaining their support for socially responsible activities. During the economic downturn, a leading corporation in imaging equipment and information systems, Canon, kept promoting the reduction of CO_2 emissions through technological innovation and successfully introduced induction heating (IH) fixing technology and on-demand fixing technology into production, increasing resource efficiency and alleviating harm to the environment. The world's largest marketing communications company, WPP, increased its investment in employees' training and wellbeing (from £38.6 million in 2007 to £42.6 million in 2008) to relieve financial burdens on employees due to the worsening economic conditions. The emerging digital business[1] Alibaba also took the lead in socially responsible performance. Under a tough economic environment, it implemented a pay rise plan, promising each of its employees a higher annual bonus in 2008 and higher wage in 2009, to encourage the employees to pull through. One reason for a firm to make time and monetary investment in CSR regardless of intermediate costs during difficult times can be conscientiousness to society. Another possible reason is that CSR can serve as a proactive business strategy that in a fragile economic environment.

Nowadays, CSR has attracted a wide attention from the global market, so the

[1] Alibaba digital business includes e-commerce, retail, local services, entertainment, healthcare, cloud computing, and financial services to consumers and enterprises.

evaluation of CSR contributions has been widely adopted. ESG, which stands for Environmental, Social, and Governance in the capital market that helps the public to assess corporate behaviors and examine firms' subsequent financial performance. Since the beginning of the 21st century, ESG has become a worldwide concern against the backdrop of global climate change and human rights protection. By 2019, the world's largest corporate sustainability initiative—United Nations Global Compact (UNGC)—has attracted more than 13,000 companies from 160 countries to contribute to environmental and social maintenance. Many firms have adopted ESG criteria for their corporate strategies.

In academia, however, the financial impact of ESG issues remains controversial. Studies that are optimistic about the financial consequence of ESG score argue that socially responsible behaviors build trust between a firm and its stakeholders and shareholders, which may help companies manage risks and remedy financial losses in an economic downturn. Nofsinger and Varma (2014) suggest that the effect of ESG rating on mutual funds is positive, as socially responsible mutual funds outperform conventional funds during periods of market crises. Lins et al. (2017) find that firms with high social capital have higher stock returns during the 2008 financial crisis. By studying a large number of countries and industries from 1990 to 2013, Haas and Popov (2019) find that stock markets tend to reallocate investment toward less polluting sectors. On one hand, the skeptics argue that ESG investments generally benefit from a long-run (five years or longer), as ESG costs drag profits down at an early stage (Starks et al., 2017). The short-run (within one year) effect of high ESG rating on companies' financial performance and investors' payoff is still ambiguous. Hence, investing capital and time in ESG maintenance may not be desirable for some firms, especially small businesses, during an economic recession.

By definition, a financial market cycle refers to a period between two latest highs or lows of a common capital benchmark (such as S&P 500). Macroeconomic factors co-move to form different economic regimes. For the stock market, investors often use bull- and bear regimes to characterize the market status: a bull market regime is a positive situation corresponding to a booming economy, while a bear regime is a condition associated with a sluggish economy. According to existing literature, macroeconomic variables are correlated with equity returns and are generally used to imply market regimes. Markowitz (1959), Sharpe (1963), King (1966), Cohen and Pogue (1967), Feeney et al. (1964), Fama and MacBeth (1973), Farrell (1974), Rosenberg and Marathe (1976), Roll and Ross (1980), Arnott (1980), Chen et al. (1986), Fama and French (1993), Fama and French (1996), Jensen et al. (1996) and many others have made distinctive contributions toward using macro factors in asset pricing. In this essay, I select 13 macro variables such as S&P 500 stock price index, 6-month Treasury bill, unemployment rate, etc. that capture the information of market regimes using a machine learning method. Using those macroeconomic variables, I enrich a hidden Markov regime-switching model for asset prices. Market sentiments also can vary between the two regimes. Under a bull market, firms, investors, and consumers feel more confident and thus possess higher expectations for the financial market. In a bear market, however, widespread pessimism and negative market sentiment are more likely to predominate and firms' strategies, investors' investing decisions, and consumers' behaviors tend to be desperate between regimes. Hence, I infer that the impact of ESG ratings on firms' stock returns under a bull regime differs from that under a bear regime. The main conjecture is that the high ESG-rating stocks perform better than low-ESG rating stocks in a bear regime. To estimate differences, I construct high and low ESG-rating stock portfolios and compare their abnormal returns extracted from a regime-switching Carhart four-factor model, based on the high-low strategy.

This essay is organized as follows: Section 2 reviews the recent literature on the financial implications of ESG ratings and proposes the main hypotheses. Section 3 elaborates on methodologies, which contain macroeconomic factor selection via a machine learning method — LASSO (Least Absolute Shrinkage and Selection Operator) and applications of the hidden-Markov regime-switching model and Carhart four-factor model. Section 4 describes data sources of stock portfolios and ESG ratings information. Section 5 illustrates the main findings. Section 6 discusses potential topics in future studies and makes a conclusion.

4.2 Literature Review and Hypotheses

Whether a high ESG-rating generates higher stock returns for a company is still unknown. The literature on the relationship between firms' financial performance and ESG reveals three different views. Please refer to Chapter 3 for literature review.

Although the financial impacts of ESG ratings still remain controversial, a substantial number of studies have realized that the significant role that ESG plays is to help firms to reduce riskiness (Verheyden et al., 2016). In a theoretical context, as Prospect Theory predicts, investors are more sensitive to a loss compared to the same amount of gain. That implies that in a financial market where loss aversion generally dominates gain inclination, investors are willing to protect downside losses from a recessive economy even at the cost of giving up some returns from a thriving market (Kahneman and Tversky, 1979). Due to the asymmetric responses from individuals to losses in bad times and gains in good times, the relationship between stock returns and ESG ratings may well display different patterns in two different market environments — bear- and bull regimes.

Empirically, few studies in the literature conduct regime-switching analysis for ESG's financial implications. However, a relevant field, the socially responsible investment (SRI) research, does address market fluctuations. Nofsinger and Varma (2014) argue that SRI fund portfolios outperform conventional counterparts during the market crisis period despite their underperformance during the non-crisis period, as they shield stocks that are more likely to cause profound-impact negative news regarding social issues and therefore effectively control risks in a faltering economy. Lins et al. (2017) find that, during the economic crisis from 2008 to 2009, the stock returns of firms with higher investment in social capital (measured by CSR performance) are four to seven percentage points higher compared to those with lower social capital accumulation.

Abundant reports have shown evidence on risk-controlling effect from of companies' social responsibility compliance. Boehe and Cruz (2010) and Flammer (2015) find that firms paying close attention to socially responsible behaviors benefit from stronger product differentiation and lower price elasticity of demand. Albuquerque et al. (2012), Pérez and Rodriguez del Bosque (2015), Sen and Bhattacharya (2001), Walsh and Bartikowski (2013) and Xie (2014) all suggest that companies with social responsibility compliance benefit from a higher level of trust and loyalty from customers. A higher survival possibility and a lower threshold to access trade credits are also positive outcomes from ESG compliance by firms (Fatemi et al., 2015). Therefore, I hypothesis that firms can achieve better risk reduction from ESG compliance:

Hypothesis 1: Higher ESG-rating stock portfolios outperform the lower ESG-rating counterpart in bear markets.

Based on the results from Chapter 3, firms' capitalization acts as a key component to address the impact of ESG scores on stock returns. In light of the Fama-French three-factor model, Carhart's four-factor model, and extensive empirical support (Arnott and Hsu, 2008; Bauman et al., 1998; Eun et al., 2008; Switzer, 2010) for superior performance of small-cap stocks over large-cap stocks, I take firm size into consideration when investigating financial impact of ESG ratings. Indeed, small firms are easier to manage and reacting to changes in the external economic environment compared to large firms. Small firms' operations more transparent than large firms'. As a result, small-cap firms with higher ESG scores should be more likely to survive during an economic downturn. Therefore, I hypothesize:

Hypothesis 2: The effect of ESG-rating on stock returns for small-cap firms is positive compared to that for large-cap counterparts in bear markets.

The type of sectors is also a important factor I take into account when examining the relationship between stock returns and ESG scores. As a consequence of sectoral particularities, the distribution of ESG scores may differ across sectors. Please see Chapter 3 for details. Moreover, given a specific sector, the explaining power of ESG-ratings on stock returns in a bull regime is likely to be different from those in a bear regime because even for the same firm, its operations may vary across regimes. Therefore, I hypothesize:

Hypothesis 3: The response of stock returns to a change in ESG ratings in each economic sector is significantly different across bull and bear regimes.

4.3 Theoretical Model

4.3.1 Regime-dependent ESG portfolio construction

To investigate the impact of ESG on stock returns across regimes, I regress the regime-dependent Carhart four-factor model using the data of individual stocks with ordinal ESG ratings. The functional form of the regime-dependent Carhart four-factor model is expressed as:

$$R_{it}-R_{ft} = \alpha_{i,M_t}+\beta_{1i,M_t}(R_{mt}-R_{ft})+\beta_{2i,M_t}SMB_t+\beta_{3i,M_t}HML_t+\beta_{4i,M_t}MOM_t+\epsilon_{i,M_t} \tag{4.1}$$

The mode is an extension of the conventional Carhart four-factor model, which may omit some crucial state-dependent information. Indeed, the normality assumption of the mean regression model has been challenged by the fat-tailed distribution of asset returns. In Equation 4.1, the asset returns follow a mixture of normal distributions with the prior probabilities (see Section 4.3.3 and Equation 4.2) as the mixing coefficients. α_{M_t}, β_{1i,M_t}, β_{2i,M_t}, β_{3i,M_t}, β_{4i,M_t} and ϵ_{i,M_t} are the regime-dependent parameters from Equation (4.1), where M_t is the market regime at time t.

The primary objective is to observe how abnormal returns vary from high to low

ESG-rating portfolios[2] across market regimes. Please see Chapter 3 for the portfolios construction process. To test the hypothesis, I divide stocks into two categories-restricted and unrestricted samples, by sector. In the restricted sample, I respectively rank stocks by ESG ratings from each of 10 sectors[3], rearranging the component of stocks in every group of high/low ESG-rating portfolios to ensure that each proportion of ESG score distribution (top/bottom 10% to 30%) consists of stocks from all 10 sectors. In unrestricted sample, I rank stocks by ESG criteria ignoring the sectors. The sectors are based on Thomson Reuters Business Classification (TRBC)[4], which include Energy, Basic Materials, Industrials, Cyclical Consumer Goods & Services, Non-Cyclical Consumer Goods & Services, Financials, Healthcare, Technology, Telecommunications Services, and Utilities.

I construct stock portfolios using both equally-weighted and cap-weighted methods. The cap-weighted portfolios are constructed by weighting each stock by its market capitalization (higher capitalization implies higher weight). The cap-weighted approach allows me to observe how abnormal returns of large-cap firms differ from small-cap ones with similar ESG rankings.

Moreover, I take market regimes into account when explaining the relationship between stock returns and ESG ratings, as asset returns are unavoidably dependent on the external financial market environment. When an economy is expanding (market at bull regimes), all industries tend to benefit from the upward business trend and therefore result in higher returns. When an economy is encountering a recession (market at bear regimes), all stocks are negatively affected by the market, yielding relatively lower returns. In this essay, I probe whether abnormal returns in the bull regime are significantly different from those in the bear regimes, controlling for ESG cut-off rate, restriction on sectors, and portfolio weights. I use a machine learning method, LASSO, to select candidate economic indicators and then employ the hidden

[2]A stock portfolio in this sense indicates a group of individual stocks with similar ESG scores.

[3]One may explore deeper into TRBC code by dividing the sample into 28 business sectors or 54 industry groups if the sample is large enough.

[4]TRBC is the classification for global companies. It covers 10 sectors, 28 business sectors, 54 industry groups, 143 industries, and 837 activities.

Markov model to identify the market regimes.

4.3.2 Macroeconomic indicators selection using LASSO

McCracken and Ng (2016) provide a macroeconomic database for studying business cycle chronology. It includes 134 macroeconomic variables based on the Federal Reserve Economic Data (FRED). The principle of Occam's Razor states that among several plausible explanations for a phenomenon, the simplest is best. Unnecessary predictors will add noise to the estimation of other quantities. In the presence of "big data", the first question asked is which macroeconomic indicators should be taken into consideration to describe regimes.

In a high dimensional database, especially when the number of variables is much more than the number of observations, traditional linear regression models are not approachable, and variable selections are essential to reduce dimensionality. Therefore, a mechanism that can consider all the variables and select the relevant ones should be utilized. The traditional principal component analysis (PCA) may be a solution, but the number of significant factors is not stable when the size of factors to be estimated is large. In this essay, instead of using a traditional approach such as PCA, or economic reasoning, I use a machine learning method, LASSO to select meaningful macroeconomic indicators to identify market regimes.

LASSO is an regression analysis that operates both variable selection and model estimation by minimizing the residual sum of squares with a penalty on the size of the coefficients. It is first introduced by Tibshirani (1996). Now, LASSO is used to handle machine learning from big data in finance and economics (Belloni et al., 2014; Chinco et al., 2019; Feng et al., 2019; Freyberger et al., 2017; Gu et al., 2019; Han et al., 2019; Kozak et al., 2018; Varian, 2014). The fundamental objective of LASSO is to solve

$$min_{\beta \in \mathbb{R}^p} ||\mathbf{y} - \mathbf{X}\beta||_2 + \lambda ||\beta||_1,$$

where $\mathbf{y} = (y_1, y_2, \cdots, y_n) \in \mathbb{R}^n$ is the response variable, $\mathbf{X} = (X_1, X_2, \cdots, X_n) \in$

$\mathbb{R}^{n\times p}$ is a vector of covariates, $\beta \in \mathbf{R}^p$ is the best fit coefficients, $||.||_m$ is defined as norm ℓ_m. λ is a tuning parameter that controls the size of the penalty. With the norm ℓ_1 term, LASSO performs two major tasks – regularization and variable selection – by solving the objective function. It penalizes (regularization process) certain coefficients for being zero, thereby effectively selecting (variable selection process) a simpler model with fewer covariates. The larger value of the λ, the more coefficients will shrink to zero. In the case of $\lambda = 0$, it reduces LASSO to the least-squares estimation. In practice, λ value is selected by K-fold cross validation (see Bühlmann and Van De Geer (2011),Tibshirani et al. (2015), and Chatterjee and Jafarov (2015)). K-fold cross validation is a statistical sampling procedure. It divides the whole sample into approximate k subsamples. Each k-1 of all k subsamples is used as a training sample to get the best learning results and remaining subsamples as the validation (test) sample. Then, the test results are averaged over the k experiment. The other two commonly used methods for covariates selection are stepwise selection and Ridge regression. However, stepwise selection has many flaws and limitations and, in some cases, can even make the prediction error even worse. Ridge regression can reduce the over-fitting issue and improve prediction error, but cannot perform covariate selection.

4.3.3 Modeling market regimes with time-varying transition probabilities

The macroeconomic factors are modeled by a vector auto-regressive regime-switching model (RS). Let $F_t = (F_{t_1}, F_{t_2}, \ldots, F_{t_J})$ be a set of J macroeconomic indicators. F_{t_j} is used to denote the jth economic indicator at time t. The indicators follow a vector auto-regressive process (VAR):

$$F_t = a_{M_t} + b_{M_t} F_{t-1} + \gamma_{M_t} \mathbb{Z}_t, \tag{4.2}$$

where the coefficients in this process are changing with the switching of the regimes. M_t is a discrete, first-order Markov chain with M regimes. a_{M_t}, b_{M_t}, and γ_{M_t} are a set of model parameters determined by the regime at time t. $a'(a_{1_{M_t}}, a_{2_{M_t}}, ..., a_{j_{M_t}})$ is a vector of regime-dependent intercepts of the linear factor model while b is a regime-dependent matrix of the sensitivities of the macroeconomic indicators at time t to the macroeconomic indicators at time $t-1$ at regime M_t.

$$b_{M_t} = \begin{bmatrix} b_{11M_t} & b_{12M_t} & \cdots & b_{1JM_t} \\ b_{21M_t} & b_{22M_t} & \cdots & b_{2JM_t} \\ \vdots & \vdots & \ddots & \vdots \\ b_{J1M_t} & b_{J2M_t} & \cdots & b_{JJM_t} \end{bmatrix}$$

where $\mathbb{Z}$ is the multivariate independently normally distributed vector of error, $\mathbb{Z} \sim N(0, I_J)$. M_t is inferred from the macroeconomic indicators over time. M_t can only take discrete values such as $M_t = 1, 2, 3, ..., M$.

In contrast to the conventional regime-switching model with a constant transition probability (Hamilton (1989); Davig (2004); Chang (2009); Bollen et al. (2000); Schaller and Norden (1997); Sims and Zha (2006)), I use the time-varying transition matrix in the RS model. Each row of transition probabilities is parameterized using a baseline multinomial logistic model. I use a transition probability model in the spirit of Diebold et al. (1994) and Filardo (1994), the transition probability depends on the lagged covariates.

$$T_{M_{t-1},M_t} = \frac{exp(g_{M_{t-1},M_t})}{1 + exp(g_{M_{t-1},M_t})}, \tag{4.3}$$

$$g_{M_{t-1},M_t} = a_{M_t} + b_{M_t} F_{t-1} \tag{4.4}$$

where T_{M_{t-1},M_t} is the time-varying transition matrix from time $t-1$ at regime M_{t-1} to time t at regime M_t, which follows the multinomial logistic model. F_t is the lagged growth rates of covariates. At each point in time t, the time-varying transition probability is $Pr(M_t = j | M_{t-1} = i, M_{t-2}, \cdots) = Pr(M_{M_t=j} | M_{t-1} = i) = T_{ij,t}$, where $i,\ j \in \{1, 2, \cdots, M\}$. The unconditional expected growth rate of each series from $t-1$ to t is the expectation of regime-dependent expected of that series, with the prior probability $p_t(m)$ in regime m at time t:

$$E(R_t) = E(E(R_t|M_t)) = \sum_{m=1}^{M}(a_{M_t} + F_{t-1}b_{M_t})p_t(m)$$

and the variance-covariance matrix is:

$$V(R_t) = \sum_{m=1}^{M}[(E(R_t) - E(R_t|M_t = m))^2 + \sigma_{M_t}]p_t(m)$$

Optimal Number of Regimes

Since regimes are unobservable, a proper criterion is needed to choose the optimal number of regimes. Intuitively, the likelihood is monotonically increased with the increased number of regimes. The larger the likelihood, the better the model fit for the candidate data. However, too many regimes could create problems of over-fitting or model specification error. Therefore, the number of regimes and the predictability of the model have to be balanced. In this essay, the Bayes information criterion (BIC)(Schwarz, 1978) and Akaike information criterion (AIC)(Sugiura, 1978) are employed to choose the optimal number of regimes. BIC follows

$$BIC(M) = -2\ln(L|M, \Psi(M)) + f(M, \Psi(M))\ln(T),$$

and AIC is given by

$$AIC(M) = -2\ln(L|M, \Psi(M)) + 2 * f(M, \Psi(M)),$$

where M is the number of regimes and L is the likelihood function given the number of regimes. T is the number of observed data points. $\Psi(M) = \{a_{M_t}, b_{M_t}, \gamma_{M_t}\}$ is a set of parameters while $f(M, \Psi(M))$ refers to the number of parameters. By trying different numbers of regimes M, I select the number that can minimize the value of $AIC(M)$ and $BIC(M)$ as the optimal number of regimes.

Since the regimes (M_t) are unobservable, the expectation and maximization algorithm (EM algorithm) will be used to estimate the model parameters. The EM algorithm is an iterative process between E-step (expectation) and M-step (maximization), which is first introduced by Dempster et al. (1977). The EM algorithm is efficient for estimating models that have missing data or unobservable latent variables. The E-step is used to estimate the missing data on regimes, based on observed data and current estimates, by calculating the expected log-likelihood with the updating missing data. The M-step is to maximize the log-likelihood function based on the missing data on regimes found in the E-step. Please see C.1 in Appendix C for the EM algorithm.

4.4 Empirical Results

I use the same ESG-rating data as Chapter 3. Please refer to Chapter 3 for detailed data description, statistics, and explanation. The monthly data cover the ESG rating of more than 2400 U.S. firms from January 2002 to December 2018.

4.4.1 Macroeconomic indicators selection from LASSO

Thirteen macroeconomic indicators are selected from 134 candidates by LASSO. The sample period is from April 1959 to December 2018. For the macroeconomic factors that do not date back to 1959 and other missing data problems, the EM algorithm is employed to address the issue.[5] The descriptive statistic and variable explanations are given in Table 4.1, and the Pearson correlation coefficients are provided in Table 4.2. The selected macroeconomic factors are

- S&P Composite Index
- 6-Month Treasury Bill: Secondary Market Rate
- 10-Year Treasury Constant Maturity Rate
- Value of Manufacturers' New Orders for Consumer Goods Industries

[5] See Section 4.3.3 for the Exception and Maximization Algorithm

- Real Estate Loans, All Commercial Banks
- Industrial Production: Nondurable Consumer Goods
- Industrial Production: Materials
- Civilian Employment Level
- Civilian Unemployment Level
- Average (Mean) Duration of Unemployment
- 3-Month Treasury Bill Minus Federal Funds Rate
- 1-Year Treasury Constant, Maturity Minus Federal Funds Rate
- Consumer Price Index for All Urban Consumers: Commodities

These macroeconomic series are transformed using certain transformation codes[6](e.g., logarithm return, first-order difference). The Equation 4.2 is estimated by fitting the macroeconomic indicators.

4.4.2 Interpretation of regimes

Figure 4.1 shows the AIC and BIC trend according to the number of regimes imposed. For the sample period 1959 to 2018, both AIC and BIC imply that the optimal number of regimes is two.

As the optimal number of regimes is two from AIC and BIC for the sample period 1959 to 2018, the two regimes need to be justified and explained. The statistics of the macroeconomic indicators conditional on regimes are provided in Table 4.3. The factor of S&P composite index has a larger annualized volatility (0.33%) conditional on one regime than the volatility (0.18%) conditional on the other regime. The regime with high market volatility as the bear market and the regime with low market

[6]See Table 4.1 Panel B

volatility as the bull market. Most of the macroeconomic indicators[7] have a pattern of relatively high returns and low volatilities in the bull market regime and the pattern is reversed in the bear market regime.

NBER Justification

The NBER business cycle is used as a justification of the market regimes implied by the hidden Markov regime-switching model.[8] Although they all employ macroeconomic indicators for identification of market regimes and share some similarities in specifying the market regimes (see Figure 4.2), the two approaches are using different methodologies and have key differences. First, NBER declares a recession only if there are significant declines in the major economic activities lasting for more than a few months. Thus, a market crash may not be captured as a recession by NBER. NBER classified the whole year of 1987 as expansion, even with the fact of the "Black Monday" in 1987[9] (see Figure 4.2). The regime-switching model updates the posterior probabilities of market regimes using the Bayesian updating process based on the economic activities month by month; the market regimes can be implied by the posterior probabilities (e.g., a bear regime is defined when the posterior probability is higher than a certain threshold). Therefore, the changes of market regimes implied by the regime-switching model are more frequent than the NBER regimes (see Figure 4.2). Second, the methodology of NBER lacks the ability to predict. NBER records the market regimes based on historical economic activities, retrospectively. The last announcement of the NBER business cycle dating committee in year 2010. This announcement claimed that the U.S economy was out of the recession that occurred

[7]The UEMPMEAN represents Average Duration of Unemployment. In the bear markets, the mean of duration is high, and volatility is low, while the average duration is high and volatility is low in the bull market, which is opposite to the pattern of other factors. Economically, it is true that it is harder to find jobs in the bear market regime and the layoff time of workers is longer than in the bull regime.

[8]NBER uses the terminologies of contraction and expansion, which correspond to bear and bull regimes. For consistency, I will use the bear and bull regimes in throughout.

[9]Black Monday in 1987 was the worldwide (Asia, Europe, U.S, etc.) financial market crisis. The DJIA lost more than 20% of its value, and the FTSE 100 fell more than 23% in two days after the market crash.

in December 2007 and started the expansion in June 2009. The market regime by NBER is classified as the bull until the next announcement in the future. In contrast, the regime-switching model can predict future market regimes by testing the out-of-sample data.

Time-varying Transition Probabilities

As Figure 4.3 shows, the retaining probabilities are high. This indicates that the market is likely to retain a certain regime rather than transitioning to the other regime, which is consistent with the volatility clustering of stock returns. The time-varying transition probabilities provide more information to characterize the turning points of the financial market than the constant transition probability models. The horizontal lines in Figure 4.3 represent the mean of the transition probabilities from one regime to the other. The mean values are

$$\bar{T}_{M_{t-1},M_t} = \begin{bmatrix} \bar{T}_{1,1} & \bar{T}_{1,2} \\ \bar{T}_{21} & \bar{T}_{22} \end{bmatrix} = \begin{bmatrix} 0.5293 & 0.4707 \\ 0.2088 & 0.7912 \end{bmatrix}$$

Over the sample period from 1952 to 2018, the market regimes have a retaining probability of 52.93% (79.12%) at the bear (bull) regime on average; the average transition probability from the bear (bull) to the bull (bear) regime is 47.07% (20.88%). There is a 20% chance for the bull market switching to the bear market for the next period on average while there is more than 47% probability for a bear market switching back to the bull market for the next period on average. This is consistent with historical facts. Over the past few decades, the market experienced several periods of turmoil,[10] yet, most of the time the market is not in recession. The mean value of transition probabilities provides the information.

In fact, transition probabilities are changing over time, depending on the dynamics of the economy. During the early 1980s global economic recession, the time-varying

[10] For example, the 1973 oil crisis, early 1980s recession, Black Monday in 1987, Internet Bubble in 1997, early 2000s recession, global financial crisis in 2008, Chinese stock market crash in 2015.

transition probabilities from the bull to the bear regime (left bottom exhibit of Figure 4.3) are dramatically high (100% at some points), and the transition probabilities from the bear to the bull regime are low. This indicates that the market is expecting to witness a recession, and has a higher probability of staying in the recession during the next period than escaping from it. Before the 2008's global financial crisis, the bull regime's retaining probabilities is more than 80% (the right bottom exhibit of Figure 4.3) and the market is experiencing the bull regime. Approaching 2008, the transition probability from the bull to the bear regime (left bottom exhibit of Figure 4.3) became more substantial, which implies that the market may expect a downturn. With the inception of the 2008 financial crisis, the transition probability from the bull to the bear regime reached to the highest point. Thus, the time-varying transition probability is an important indicator and contains crucial information for understanding the turning points of the market regimes.

4.4.3 ESG portfolio performance across market regimes

In general, ESG ratings have more effects on stock returns in the bear markets than in the bull market. As Figure 4.4 illustrates, such patterns are particularly significant when comparing the top and bottom 10% of stock portfolios by ESG rating. Using an equally-weighted approach, I observe that, under the bear regime, the differences in abnormal returns between high ESG-rating portfolios and corresponding low ESG-rating portfolios are positive. This result is consistent for all cut-off rates in both restricted and unrestricted samples. In contrast, such difference displays a negative sign for each cut-off rate under the bull regime. Those imply that high ESG-rating stocks generally outperform (underperform) low ESG-rating stocks in terms of abnormal returns in a sluggish (booming) market. According to the cap-weighted results, high ESG-rating stocks tend to underperform low ESG-rating ones under both bull and bear regimes. However, I still find that, at the 10% cut-off rate, the performance of high ESG-rating stocks is remarkably lower than that of low ESG-rating stocks in both restricted and unrestricted samples.

Table 4.5 provides the estimated parameters of the regime-switching Carhart four-factor model for stock portfolios across different weighting and sampling approaches. In both regimes, high ESG- and low ESG-rating portfolios underperform the market, resulting in negative abnormal returns. Yet, high ESG- and low ESG-rating portfolios exhibit opposite patterns across the bear and bull regime. For example, the abnormal returns of high ESG-rating portfolios (-0.0029, -0.0033, -0.0037 for cut-off rates 10%, 20%, and 30%) are greater than the abnormal returns of low ESG-rating portfolios (-0.0041, -0.0049, -0.0047 for cutoff rate 10%, 20% and 30%) in bear market, while the alphas of high ESG-rating portfolios are smaller than that of low ESG-rating portfolios in the bull market across cutoff rates. Based on the information above, I find a result consistent with the main hypothesis: higher-rated stock portfolios benefit more from the bear market than the bull market.

Admittedly, higher ESG-rating stock portfolios consistently underperform their lower ESG-rating counterparts in the bull regime despite the fact that higher ESG-ratings are shown to be more attractive in a bear regime. One explanation could be that I only focus on a short-run effect of ESG, which is the impact of ESG rating this year on stock returns next year. Referring to my previous study in Chapter 3 and the literature (Starks et al., 2017), ESG investments are a long-run process since the costs of ESG lead to a conspicuous profit diminution for companies at the beginning, and it takes time for firms to gain from ESG compliance, so that the benefits from ESG are not instant. Therefore, it is reasonable to observe that the low ESG-rating stock portfolios surpass the high-rated ones in short-run abnormal returns. My emphasis in this subsection is to address the positive effect of ESG compliance on firms' stock returns during an economic recession.

Another prominent finding from Table 4.5 is that small-cap firms benefit more from ESG than large-cap firms do in bear market. Equally weighted samples reveal that high ESG-rating stocks perform better than low ESG-rating stocks during an economic contraction. On the contrary, when I employ the cap-weighted approach, the results display that the low ESG-rating portfolios perform better in relation to the high ESG-rating portfolios in terms of abnormal returns under both market regimes. Statistically, based on Table 4.5, high ESG-rating portfolios yield abnormal returns -0.0018, -0.0016, -0.0017 in the bear market and -0.0028,-0.0023, -0.0022 in the bull market for cut-off rates 10%, 20%, and 30%. However, low ESG-rating portfolios, which gain returns -0.0011, -0.0015, -0.00 19 in the bear market and -0.0005, -0.0013, -0.0019 for cut-off rates 10%, 20%, and 30%, respectively, indicate better performance than high ESG-rating stocks. Recall that in the cap-weighted approach, large-cap firms take a higher proportion in portfolios; they have higher explaining power for the results. Comparing the results between portfolios using equally-weight method and the ones using by the cap-weighted approach, I infer that, in an economic downturn, large firms with higher ESG scores yield significantly lower abnormal returns compared to their smaller counterparts. In response to my second hypothesis, the findings conform to my conjecture: a higher ESG-rating equips small-cap firms with a greater ability to withstand stock return losses in the bear market.

To verify the third hypothesis, I compare the financial impact of ESG ratings on stock returns in the bear and bull market regimes across 10 sectors and find notable differences amongst those sectors. Figures 4.5 and 4.6 show the equally- and cap-weighted abnormal returns of high-low strategy portfolios by sectors in the two regimes. In terms of the equally-weighted approach, the high-low strategy abnormal returns are positive in financials, telecommunication services, and utilities sectors for both regimes. This indicates that high ESG-rating portfolios have better financial performance than the low ESG-rating in these three sectors under both market regimes. Among these, financials and utilities sectors have higher abnormal returns in the bear regime (0.0019 and 0.0013) compared to the bull regime (0.0017 and 0.0010). The high-low strategy portfolios in cyclical consumer goods and services sectors show negative abnormal returns in both bear and bull market regimes. Remarkably, Basic Material, Industrials, and Healthcare have positive abnormal returns in the bear market but negative returns in the bull regime. This implies that the high ESG-rating firms in these three sectors outperform (underperform) the low ESG-rating firms in bear (bull) regimes. The cap-weighted approach shows similar results with the exception of industrials and cyclical consumer goods and services. For ease of interpretation, Table 4.6 summarizes the above results in which "good" represents high ESG-rating stocks outperform the low ESG-rating peers in the specific sector and "bad" indicates the opposite. Combining equally-weighted and cap-weighted stock portfolios, I find that the results of only three out of ten sectors — telecommunication services, utilities, and financials—are not affected by market regimes.

Due to variations in operational particularities, properties of products, the elasticity of supply and demand, necessity of negative social externality generation, suppliers and consumers in different sectors hold specific attitudes toward ESG with the shift of market regimes. The findings from the 10 sectors suggest that the effect of ESG-rating on stock returns in a sector given a market regime depends on the level of demand in that sector under that particular market regime (see Table 4.6). For example, the results from both equally-weighted and capital-weighted approach suggest that high ESG-rating portfolios in healthcare sector underperform low ESG-rating portfolios in the bull markets while outperforming the low ESG-rating in the bear markets. Studies in health and labor economics show that economic recession is good for health (Ruhm, 2000). From the perspective of work-leisure choice, people have more time to take care of their health. Thus, the demand for healthcare therefore predictably grows in the bear market. Thus, one explanation of my result is that people pay closer attention to the healthcare sector in economic downturns and tend to choose companies with better reputations. In this case, firms with higher ESG ratings are reasonably more desirable in higher returns than lower ESG-rating ones.

The non-cyclical sector is another example reflecting the role that demand plays in affecting results. In contrast to healthcare, high ESG-rating stocks underperform (outperform) low ESG-rating stocks in the bear (bull) market. Note that the non-cyclical sector consists of necessities of life, including food, beverage, and personal products; in a perfectly competitive market with abundant options for each product, price directly affects demand. In the bear market, household disposable income decreases, and more people suffer from unemployment so they are focus more on prices of products rather than on corporate culture and reputation. In this case, the ESG-rating may not draw attention from consumers and investors.

4.5 Conclusion

Developing sustainable ESG compliance is essential and beneficial in the long run due to various ESG risks (climate change, internal fraud, ethical failure, etc.) in the financial market. There is a strand of literature that reveals a negative link between ESG rating and corporate financial performance. It is likely that initial costs for ESG compliance may cost more in the short term.

This paper investigates the relationship between ESG rating and portfolios' financial return across market regimes. I focus on the short-term horizon, which is the impact of ESG-rating this year on portfolio returns next year. Two market regimes are captured by 13 macroeconomic indicators selected from more than 130 indicators by LASSO. I used the regime to construct the regime-depended ESG portfolios. In the short run, I find a positive relationship between ESG and portfolios' financial performance in the bear market. This finding implies that ESG has a positive impact on firms' financial performance in a sluggish market. The Prospect Theory suggests that investors are more sensitive to a loss compared to the same amount of gain and are willing to protect downside losses from a recessive economy even at the cost of giving up some returns from a thriving market. The outperformance of high ESG-rating portfolios in the bear market suggest that ESG strategy is beneficial not only in the long term but also in a faltering economy. I investigate 10 different economic sectors and find that the effect of ESG rating on stock returns in a sector, given a market regime, depends on the level of demand in that sector under that market regime. There are sectors in which ESG has a negative effect in the bear market. For example, in the bear market, unemployment increases and people tend to have lower incomes, which makes organic food and environmentally friendly products with high ESG-ratings are less attractive to a household. Therefore, in the non-cyclical consumer goods and services sector, high ESG-rating underperforms low ESG-rating stocks in the bear market.

Empirical studies have demonstrated that ESG compliance is a long-term investment. From investors' point of view, nevertheless, ESG also benefits investors and firms in the short run. High ESG-rating portfolios may not produce significant returns compared to low ESG-rating portfolios when the market is booming in the short term, but holding high ESG-rating portfolios helps hedged ESG risks in the bear markets.

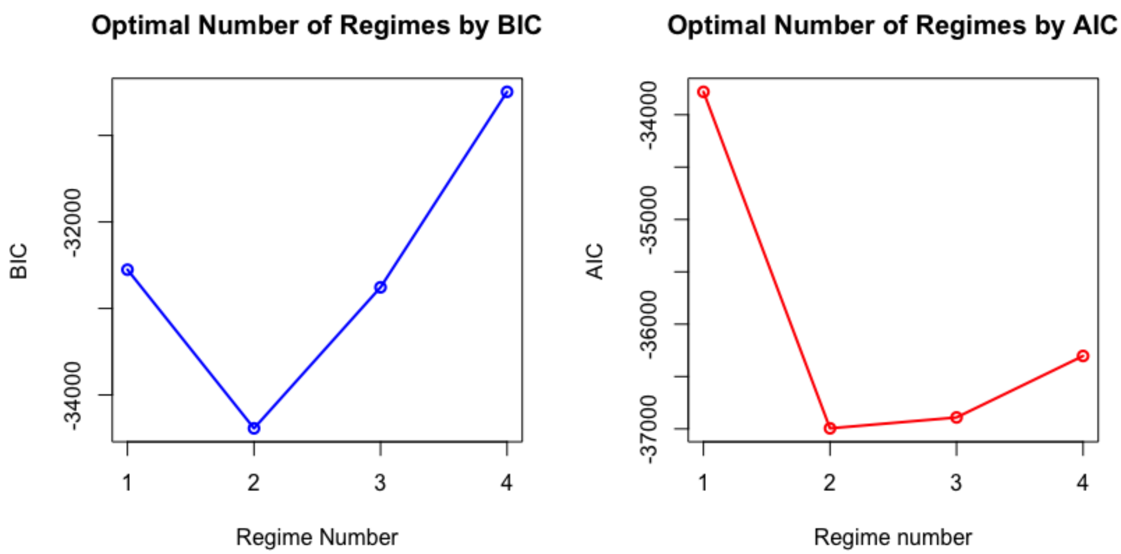


Figure 4.1: The AIC and BIC for alternative number of regimes.

The optimal number of regimes is selected by Bayesian information criterion (BIC) and Akaike information criterion (AIC). AIC and BIC introduce a penalty term for the addition of model parameters to address the issue of overfitting. The left figure shows the BIC values across four regimes, and the right figure exhibits the movements of AIC across regimes. Both AIC and BIC imply that the optimal number of regimes is two.

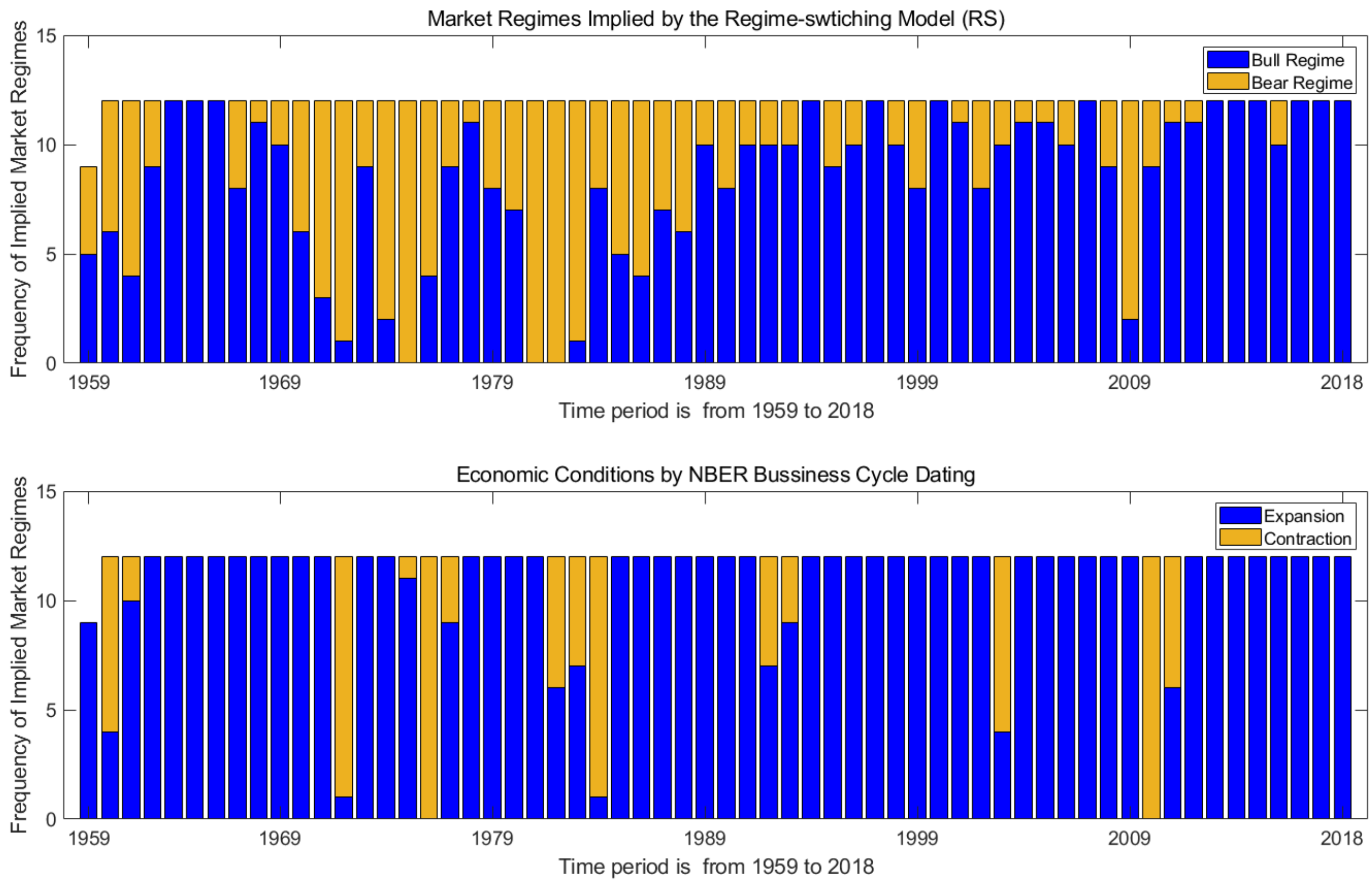


Figure 4.2: The comparison between regime-switching model and NBER.

The top panel shows the frequency of market regimes implied by the hidden Markov regime-switching model (see Section 4.3.3 and Equation 4.2) for each year from 1959 to 2018. The lower figure displays the frequency of economic conditions by NBER business cycle dating for the same time period.

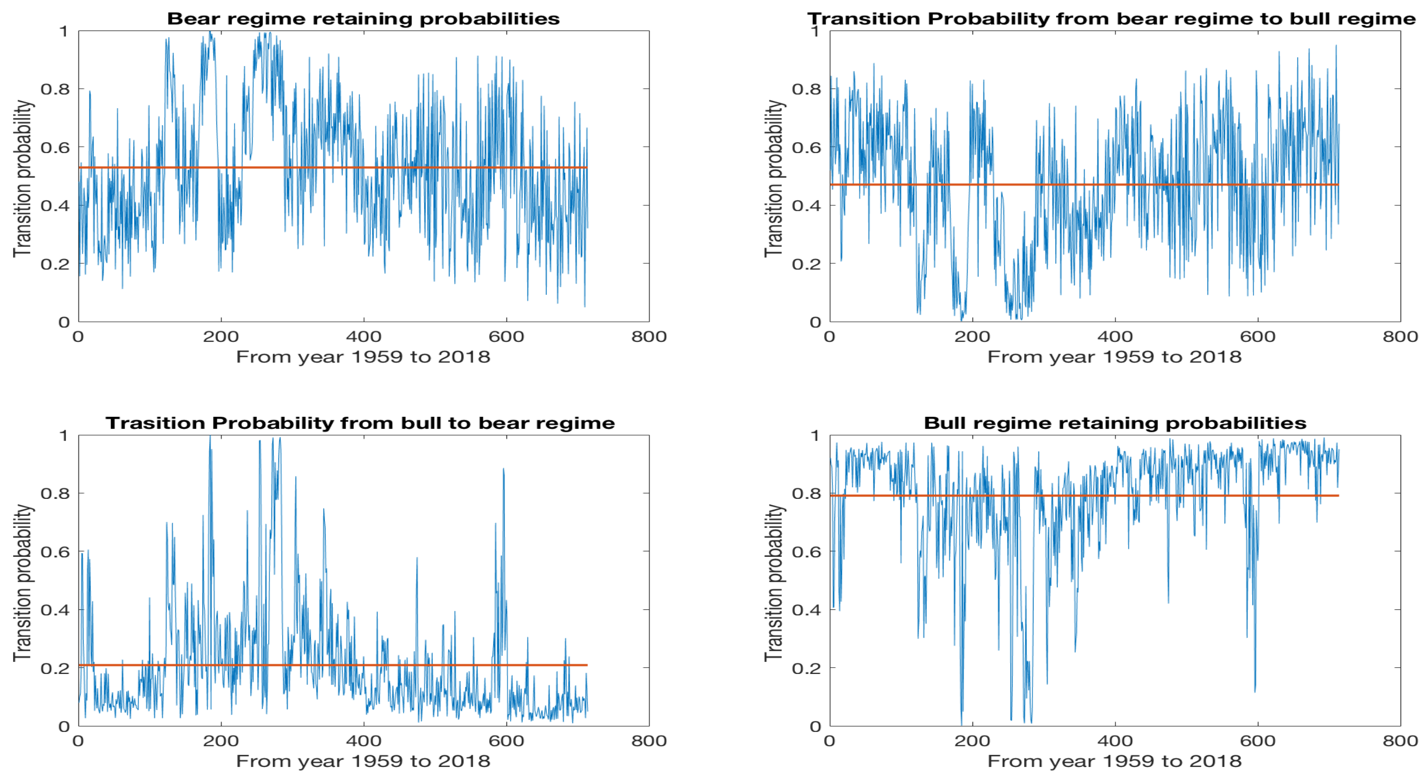


Figure 4.3: The time-varying transition matrix.

The panels exhibit the time-varying transition matrix over time (see Section 4.3.3 and Equations 4.3 and 4.4 for estimation). From top left to bottom right, they are the bear regime retaining probability, the transition probability from bear regime to bull regime, the transition probability from bull to bear regime and the bull regime retaining probability. The horizontal red solid lines (the values are 0.5293, 0.4707, 0.2088, 0.7912 from top left to bottom right, respectively) are the mean of the transition probabilities. The time period is 1959 to 2018.

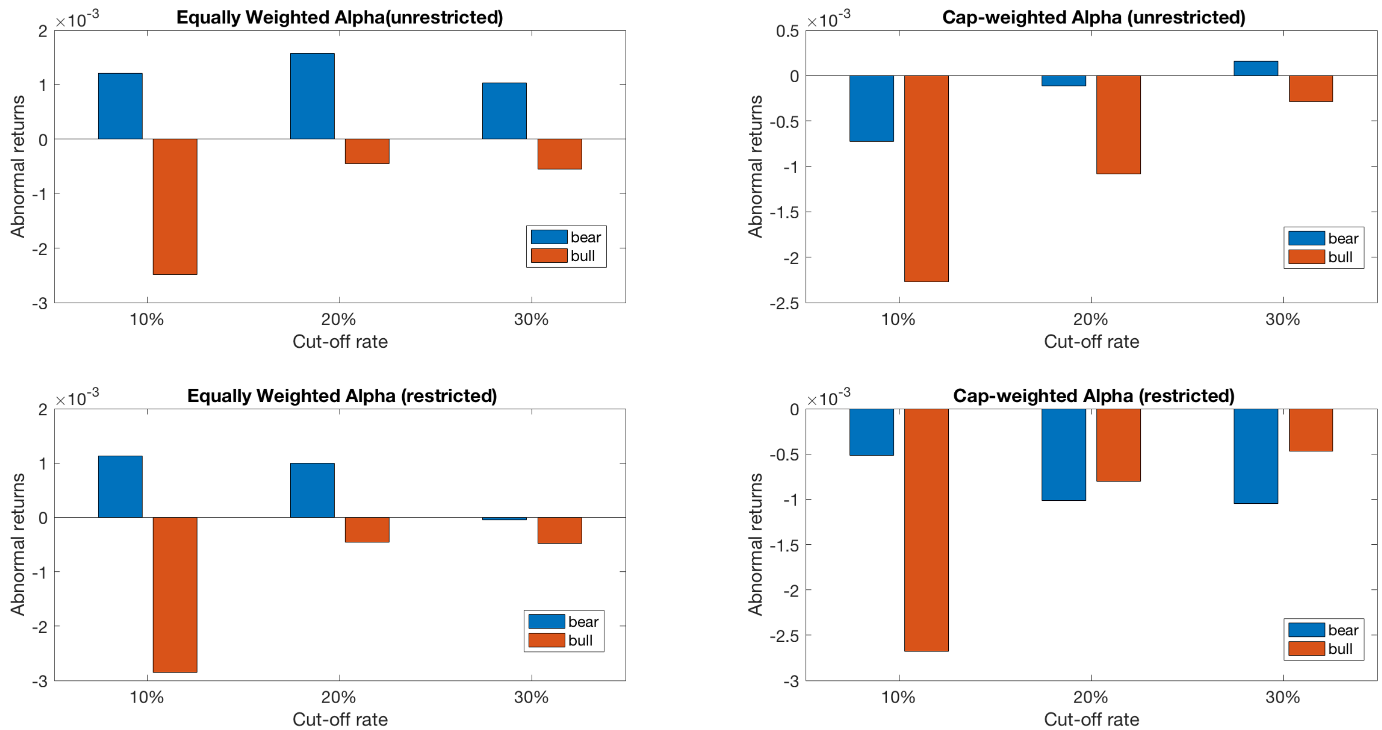


Figure 4.4: Abnormal returns across market regimes

This figure displays the comparison of abnormal returns of high-low strategy portfolios for different samples, portfolio weighting approaches in bear and bull market regimes. The panels on the top row are equally, and cap-weighted portfolios for unrestricted samples; the abnormal returns for equally and cap-weighted portfolios of the restricted sample are displayed on the bottom row.

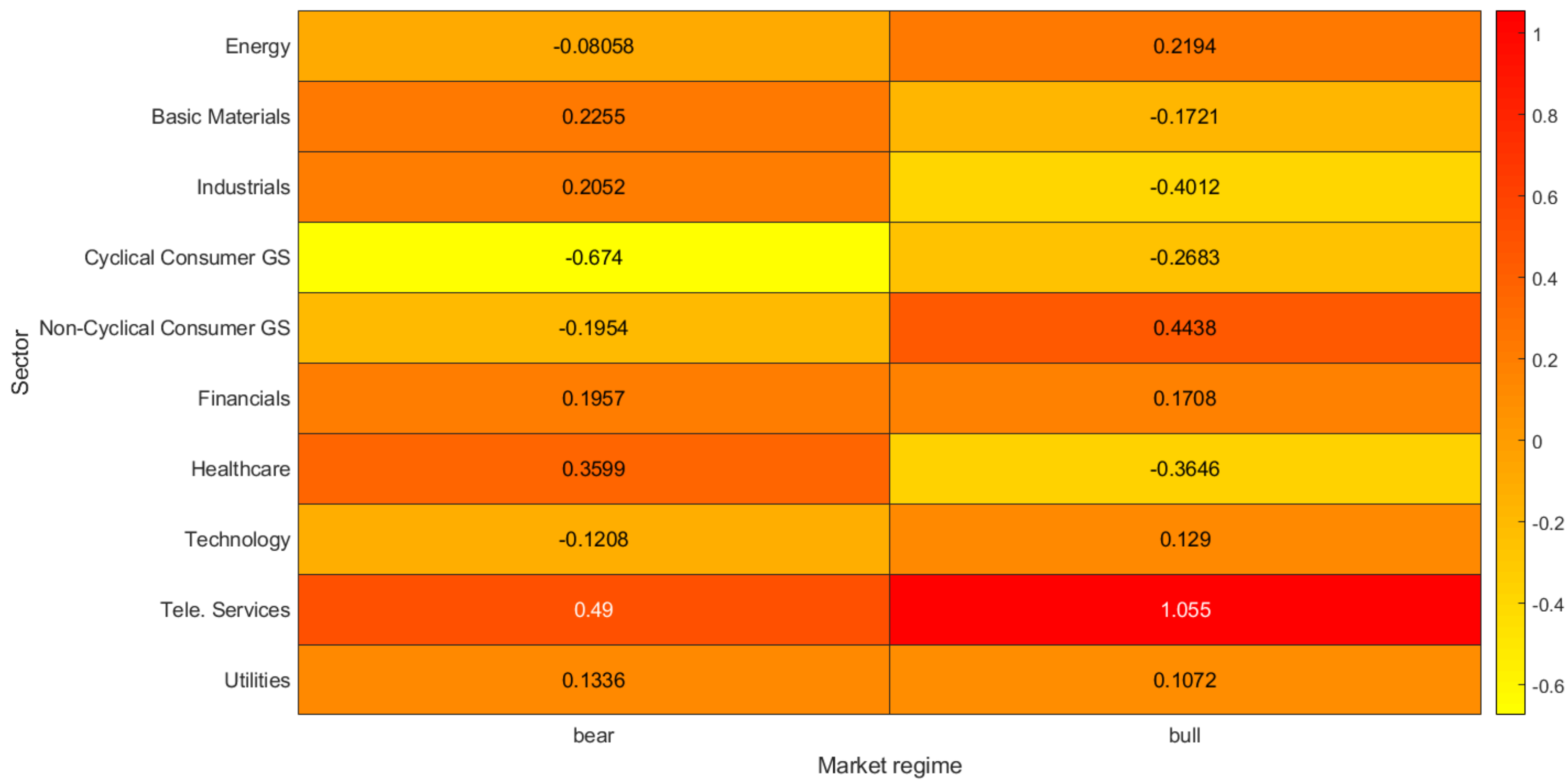


Figure 4.5: Equally-weighted alphas by economic sectors across market regimes

This figure exhibits the high-low strategy abnormal returns of equally weighted portfolios by the economic sectors for both market regimes. The abnormal returns are presented as percentages. The x-axis represents the market regime (left column is bear and right column is bull regime). The y-axis shows the 10 economic sectors. The high-low strategy is a trading strategy going long in high-rating portfolio and short in low-rating portfolio.

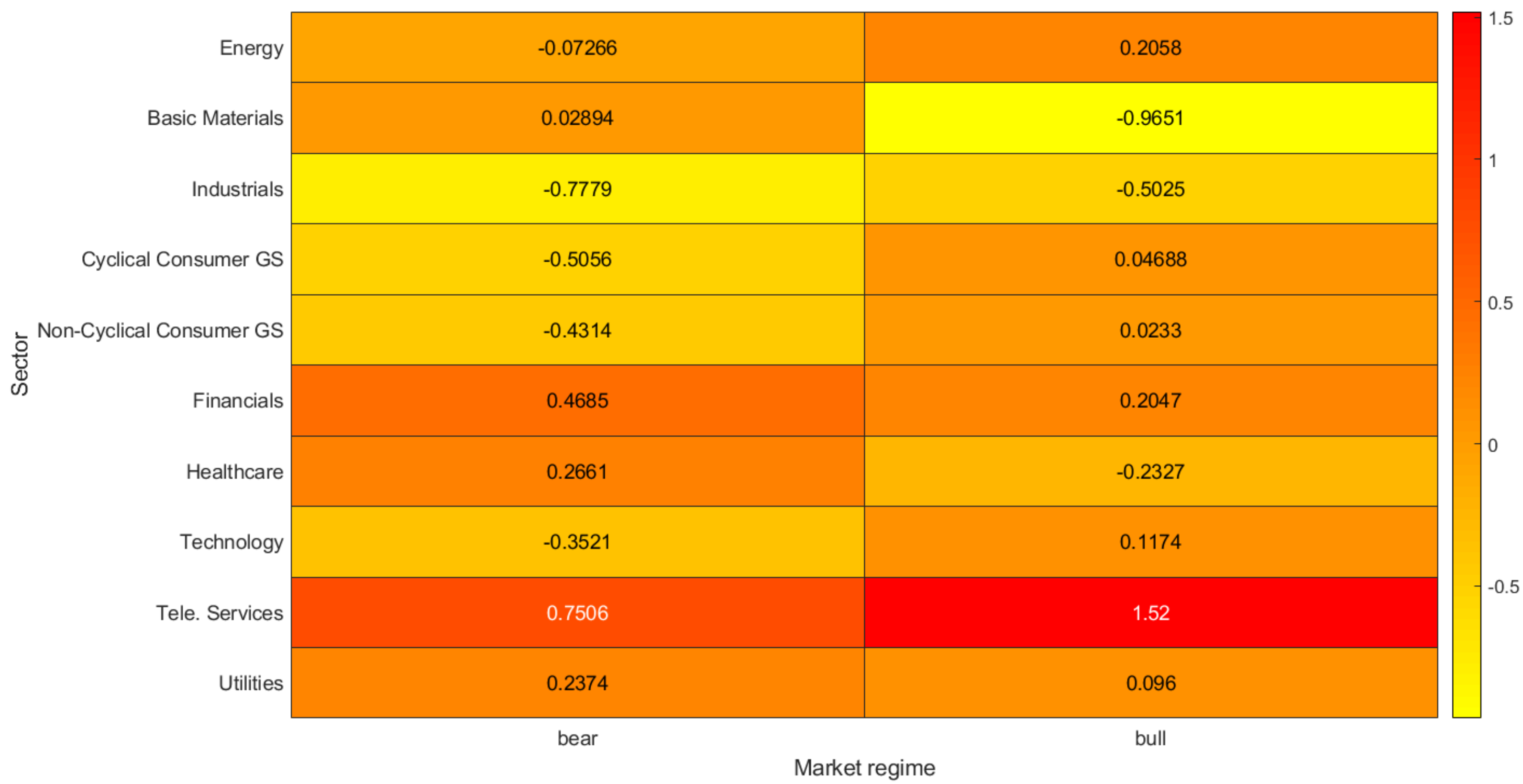


Figure 4.6: Cap-weighted alphas by economic sectors across market regimes

This figure exhibits the high-low strategy abnormal returns of cap-weighted portfolios by the economic sectors for both market regimes. The abnormal returns are presented as percentages. The x-axis represents the market regime (left column is bear and right column is bull regime). The y-axis shows the 10 economic sectors. The high-low strategy is a trading strategy going long in high-rating portfolio and short in low-rating portfolio.

Table 4.1: Descriptive statistics of macroeconomic indicators

Panel A: Descriptive Statistics										
Indicator	Mean	Min	25%	Median	75%	Max	SD	Skewness	Kurtosis	N
S&P 500	0.0055	-0.2280	0.1135	-0.0116	0.0088	0.0273	0.0352	-1.0359	4.1890	714
TB6MS	0.0020	-2.3084	2.1700	-0.0900	0.0100	0.1300	0.3741	-0.3790	9.7300	714
GS10	-0.0015	-1.7600	1.6100	-0.1475	0.0000	0.1500	0.2769	-0.4458	6.3233	714
ACOGNO	0.0066	-0.1046	0.0660	-0.0035	0.0074	0.0166	0.0174	-0.4695	3.4271	714
REALLN	0.0000	-0.0240	0.0313	-0.0017	0.0000	0.0017	0.0041	0.5069	11.0729	714
IPNCONGD	0.0014	-0.0247	0.0247	-0.0035	0.0016	0.0061	0.0075	-0.0288	0.2857	714
IPMAT	0.0022	-0.0790	0.0460	-0.0024	0.0029	0.0074	0.0106	-1.5317	10.4221	714
CE16OV	0.0013	-0.0145	0.0197	-0.0004	0.0013	0.0029	0.0030	0.0565	3.8054	714
UNRATE	-0.0028	-0.7000	0.9000	-0.1000	0.0000	0.1000	0.1793	0.5087	1.7639	714
UEMPMEAN	0.0099	-2.3000	2.5000	-0.3000	0.0000	0.3000	0.6017	0.1124	1.8481	714
TB3SMFFM	-0.4612	-5.3700	1.0700	-0.6775	-0.2350	-0.0500	0.7107	-2.4711	9.0885	714
T1YFFM	0.0590	-5.0000	1.7500	-0.1200	0.1500	0.4400	0.7752	-2.1480	8.5858	714
CUSR0000SAC	0.0000	-0.0347	0.0254	-0.0025	-0.0000	0.0027	0.0053	-0.4172	6.5270	714

Panel B: Description		
Indicator	Transformation	Data Description
S&P 500	$\Delta log(x_t)$	S&P's Common Stock Price Index: Composite
TB6MS	Δx_t	6-Month Treasury Bill: Secondary Market Rate
GS10	Δx_t	10-Year Treasury Constant Maturity Rate
ACOGNO	$\Delta log(x_t)$	Value of Manufacturers' New Orders for Consumer Goods Industries
REALLN	$\Delta^2 log(x_t)$	Real Estate Loans, All Commercial Banks
IPNCONGD	$\Delta log(x_t)$	Industrial Production: Nondurable Consumer Goods
IPMAT	$\Delta log(x_t)$	Industrial Production: Materials
CE16OV	$\Delta log(x_t)$	Civilian Employment Level
UNRATE	Δx_t	Civilian Unemployment Rate
UEMPMEAN	Δx_t	Average (Mean) Duration of Unemployment
TB3SMFFM	x_t	3-Month Treasury Bill Minus Federal Funds Rate
T1YFFM	x_t	1-Year Treasury Constant Maturity Minus Federal Funds Rate
CUSR0000SAC	$\Delta^2 log(x_t)$	Consumer Price Index for All Urban Consumers: Commodities

This table shows the descriptive statistics and description of the selected macroeconomic indicators by LASSO model. The macroeconomic indicators are selected from more than 130 macroeconomic factors. These macro data are organized by McCracken and Ng (2016) based on the FRED database. Panel A shows the basic descriptive statistics of the 15 selected macroeconomic indicators while Panel B exhibits the data transformation of each time series and their descriptions based on the FRED database. The monthly frequency macroeconomic indicators cover the year 1956 to 2018.

Table 4.2: The correlations of the macroeconomic indicators

	S&P 500	TB6MS	GS10	ACOGNO	REALLN	IPNCONGD	IPMAT	CE16OV	UNRATE	UEMPMEAN	TB3SMFFM	T1YFFM	
S&P 500													
TB6MS	-0.11**												
GS10	-0.11**	0.68***											
ACOGNO	0.11**	0.43***	0.37***										
REALLN	-0.05	-0.01	0.01	-0.08*									
IPNCONGD	0.00	0.07	0.02	0.21***	0.08*	-0.01							
IPMAT	0.00	0.19***	0.16***	0.36***	0.07*	0.01	0.24***						
CE16OV	0.02	0.17***	0.14***	0.21***	0.02	0.02	0.07	0.23***					
UNRATE	-0.07	-0.23***	-0.16***	-0.18***	-0.04	-0.06	-0.16***	-0.35***	-0.46***				
UEMPMEAN	0.03	-0.01	0.01	0.09*	0	0.04	0.00	0.03	-0.06	0.02			
TB3SMFFM	0.12**	0.13***	0.09*	-0.21***	0.05	0.12**	0.07	0.20***	0.06	-0.21***	0		
T1YFFM	0.09*	0.14***	0.12**	-0.20***	0.04	0.09*	0.10**	0.18***	0.10**	-0.19***	0	0.85***	
CUSR0000SAC	0.08*	0.05	0.04	0.34***	-0.04	0.09*	0.05	-0.06	0.00	0.01	0.00	0.00	-0.01

This table provides the correlations of the selected macroeconomic indicator. Please refer to Table 4.1 for the description of each indicators. The Pearson's correlation are coefficients computed. ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively.

Table 4.3: Macroeconomic indicator statistics by regimes

	Bear Regime				Bull Regime				
	Mean	SD	Skewness	Kurtosis	Mean	SD	Skewness	Kurtosis	N
S&P500	0.0036	0.0166	-0.5136	2.0387	0.0070	0.0121	-0.0943	0.8741	713
TB6MS	0.0062	0.2735	-0.4722	2.1884	-0.0013	0.1263	-0.7076	4.9344	713
GS10	0.0171	0.1780	-0.3740	1.5955	-0.0053	0.0852	-0.3614	2.2850	713
ACOGNO	0.0066	0.0097	-0.1474	3.7183	0.0063	0.0059	0.3311	3.4693	713
REALLN	0.0001	0.0009	0.3683	1.6774	0.0000	0.0013	-0.0693	3.2941	713
IPNCONGD	0.0013	0.0021	0.1729	0.7339	0.0013	0.0025	-0.0974	0.4927	713
IPMAT	0.0020	0.0051	-1.0690	4.3576	0.0022	0.0048	-1.2073	4.7538	713
CE16OV	0.0015	0.0012	-0.3519	1.1731	0.0013	0.0011	-0.5468	1.7938	713
UNRATE	-0.0048	0.0956	0.9624	4.6122	-0.0042	0.0717	0.9808	4.8433	713
UEMPMEAN	0.0373	0.1421	0.0873	1.2076	0.0006	0.1681	0.1705	1.1777	713
TB3SMFFM	-0.5163	0.6274	-2.3467	7.9147	-0.4486	0.6272	-2.4101	8.2131	713
T1YFFM	0.0188	0.6769	-2.1079	8.0621	0.0678	0.6936	-2.1297	8.2902	713
CUSR0000SAC	-0.0001	0.0021	0.2286	2.7277	0.0000	0.0018	0.1908	1.6292	713

This table shows the regime-dependent statistics of the selected 13 macroeconomic indicators. The description of the indicators can be found in Table 4.1. The monthly frequency macroeconomic indicators cover the years 1956 to 2018, which include 713 data points. The bear market regime corresponds to a relatively low annualized market return of 0.0432 and high annualized market volatility of 0.33%, while the bull regime has a high annualized market return (0.0084) and low annualized market volatility (0.18%).

Table 4.4: The estimated parameters of vector autoregressive regime-switching model

	Alpha	S&P500	TB6MS	GS10	ACOGNO	REALLN	IPNCONGD	IPMAT	CE16OV	UNRATE	UEMPMEAN	TB3SMFFM	T1YFFM	CUSR0000SAC
Bear Regime														
S&P500	0.0001	-0.2590	-0.0069*	-0.0142	0.1114	-1.3079 ***	-0.2518	0.7546 ***	-0.3564	0.0277 ***	-0.0050 **	-0.0004	0.0077 ***	-0.8425 ***
TB6MS	-0.0423	-12.8682 ***	0.0681	0.7098 ***	2.0318	14.0380 ***	-3.7812*	0.2586	0.6827	-0.5996 ***	-0.0265	-0.0259	0.0046	6.8617*
GS10	0.0565 **	-5.6680 **	-0.0933 **	0.6494 ***	1.7400	9.2940 ***	-0.2461	-0.1795	-0.6213	-0.3227 ***	-0.0133	0.1159 ***	-0.1474 ***	8.7367 ***
ACOGNO	0.0037 ***	-0.2036*	0.0040 **	0.0094*	0.1273 **	-0.2455*	-0.2569 ***	0.2870 ***	-0.1551	-0.0091 **	-0.0006	-0.0030 **	-0.0036 ***	-0.0005
REALLN	0.0006 **	0.0046	0.0006	0.0008	-0.0143	-0.0901 **	-0.0056	-0.0438 ***	-0.0332	-0.0021 **	0.0006 **	0.0005*	-0.0002	0.0188
IPNCONGD	0.0011 **	-0.0365	0.0006	0.0069 **	0.0145	-0.1341 **	-0.2353 ***	-0.0053	0.0264	-0.0043 ***	-0.0002	-0.0007	0.0016 ***	0.0129
IPMAT	0.0023 ***	0.0865	0.0017	0.0020	0.0543	0.1479*	-0.1723 ***	0.2787 ***	0.2587 **	-0.0062 ***	0.0006	0.0028 ***	-0.0005	0.2636 ***
CE16OV	0.0017 ***	0.0079	-0.0005	0.0009	0.0017	-0.0608 **	0.0490 ***	0.0548 ***	-0.2214 ***	-0.0026 ***	-0.0008 ***	0.0003	-0.0001	0.0351
UNRATE	-0.0013	0.7252	-0.0173	-0.0841	-0.5107	0.1270	0.1212	-6.6495 ***	-5.0423 **	-0.1040 ***	0.0534 ***	-0.0529 ***	0.0072	-1.2196
UEMPMEAN	0.0500	-4.1179	-0.0149	0.0097	2.1284	12.5125 ***	-2.0240	-3.6975 **	-5.8737	0.4668 ***	-0.1118 ***	0.0331	-0.0104	-7.1696*
TB3SMFFM	-0.1087 ***	-7.2762 **	-0.3225 ***	0.3809 **	-1.5751	5.4815	5.7247 **	-3.2801 **	2.9498	-0.0775	0.0653 **	0.8806 ***	-0.0214	12.6673 ***
T1YFFM	-0.0163	-2.9159	-0.5333 ***	0.4362 **	-1.9995	9.0205*	7.4413 ***	-3.1668*	8.0355	0.0483	0.0596*	0.0347	0.8128 ***	16.2807 ***
CUSR0000SAC	-0.0002	-0.0197	-0.0001	-0.0046 **	-0.0225	-0.1233 ***	0.0427 **	0.0231	-0.0811*	-0.0004	-0.0003	-0.0002	-0.0005	-0.3300 ***
Bull Regime														
S&P500	0.0060 ***	0.2295	-0.0100*	-0.0066	-0.1083	-0.2696	-0.3674 **	0.3845 ***	-0.8231 **	0.0140 **	-0.0046 ***	-0.0023	0.0030	-0.6260 ***
TB6MS	-0.0381 ***	-6.6376 ***	0.2160 ***	0.0289	-0.7599	0.3922	-0.4878	2.4320 **	4.9563*	-0.1726 ***	-0.0151	-0.0456*	0.0289	2.6159*
GS10	0.0023	-2.7013*	-0.0500	0.1803*	0.7439	3.2746 **	-0.2624	0.3191	5.5514 **	-0.0121	-0.0021	0.0461 **	-0.0634 ***	3.4590 **
ACOGNO	0.0036 ***	-0.0344	0.0087 ***	0.0077	-0.0592	-0.1014	-0.0732	0.2708 ***	-0.0750	-0.0024	-0.0011	-0.0050 ***	-0.0002	0.3186 ***
REALLN	0.0001	0.0055	0.0017 **	0.0021	-0.0166*	-0.2779 ***	0.0107	0.0292*	-0.0226	0.0010	-0.0001	0.0001	0.0002	-0.0141
IPNCONGD	0.0008*	0.0678	0.0016	0.0046	-0.0011	-0.1137 **	-0.2551 ***	0.0634 **	0.2294 **	0.0000	-0.0001	-0.0009	0.0022 ***	-0.0638
IPMAT	0.0020 ***	0.0457	0.0025	0.0050	0.0256	-0.1424 **	-0.0167	0.2567 ***	0.2993 **	-0.0038 **	0.0001	0.0022 **	0.0007	0.0328
CE16OV	0.0008 ***	-0.0142	0.0012 **	0.0011	0.0000	-0.0173	0.0275 **	0.0555 ***	-0.1926 ***	-0.0017 ***	-0.0005 ***	-0.0009 ***	0.0009 ***	0.0147
UNRATE	0.0019	-0.7287	-0.0113	-0.0516	0.3137	2.0066*	-0.1681	-5.4963 ***	-4.0778 **	-0.0767 **	0.0341 ***	-0.0245	-0.0118	-0.7282
UEMPMEAN	0.0011	1.9245	-0.2526 **	0.5579*	5.5468 ***	-0.3764	-1.5411	-5.0297 **	-7.7517	0.4966 ***	-0.1272 ***	0.0388	0.0413	-5.8178
TB3SMFFM	-0.0310 **	-5.0995 ***	-0.2835 ***	-0.0819	-0.8648	1.1455	0.7629	0.6395	2.1893	0.0140	-0.0066	0.9038 ***	-0.0274	1.7199
T1YFFM	-0.0011	-4.7706 ***	-0.3677 ***	0.0274	-1.0208*	3.0794*	1.2006	0.2296	6.9729 **	0.0302	-0.0044	-0.0195	0.9000 ***	1.0817
CUSR0000SAC	0.0000	0.0226	-0.0001	-0.0102 ***	-0.0475 ***	0.0006	0.0240	0.0082	-0.0578	0.0008	-0.0006 **	-0.0005	0.0000	-0.1933 ***

This Table displays the estimated parameters from the vector autoregressive (VAR) regime-switching model. The model is defined as $F_t = \alpha_{M_t} + \beta_{M_t} F_{t-1} + \gamma_{M_t}\epsilon_t$ where α_{M_t}, β_{M_t},γ_{M_t} are the regime-dependent parameters and ϵ_t is the multivariate independently normally distributed vector of errors, with zero means and unit standard deviations. the column names represent the 13 macroeconomic variables. ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively.

Table 4.5: Parameters of equally- and cap-weighted portfolios across market regimes

	Low ESG-rating portfolio					High ESG-rating portfolio				
Cutoff	Alpha	MKT	SMB	LMH	MOM	Alpha	MKT	SMB	LMH	MOM
Equally-weighted portfolio (unrestricted sample)										
					Bear market					
10%	-0.0041 ***	1.1532 ***	0.3200 ***	0.0906	-0.0767 ***	-0.0029 ***	1.0925 ***	-0.0084	0.0193	-0.0578 ***
20%	-0.0049 ***	1.1455 ***	0.2950 ***	0.0883*	-0.1159 ***	-0.0033 ***	1.0991 ***	0.0547	0.0582*	-0.0634 ***
30%	-0.0047 ***	1.1800 ***	0.3227 ***	0.1339 ***	-0.1174 ***	-0.0037 ***	1.1264 ***	0.1214 ***	0.0959 ***	-0.0920 ***
					Bull market					
10%	-0.0028 ***	1.0258 ***	0.4387 ***	0.0404	-0.0675 **	-0.0053 ***	1.0680 ***	-0.0165	-0.0036	-0.0802 ***
20%	-0.0040 ***	1.0603 ***	0.4376 ***	0.0735*	-0.0770 ***	-0.0045 ***	1.0318 ***	0.0494*	0.0444*	-0.1032 ***
30%	-0.0045 ***	1.0641 ***	0.4592 ***	0.1057 ***	-0.0954 ***	-0.0050 ***	1.0631 ***	0.1151 ***	0.0665 ***	-0.0884 ***
Equally-weighted portfolio (restricted sample)										
					Bear market					
10%	-0.0050 ***	1.1760 ***	0.3393 ***	0.0830	-0.0551 **	-0.0039 ***	1.1179 ***	0.0389	-0.0533	-0.0471 ***
20%	-0.0048 ***	1.1631 ***	0.3041 ***	0.0975 **	-0.1182 ***	-0.0038 ***	1.1107 ***	0.0945 ***	0.0336	-0.0617 ***
30%	-0.0036 ***	1.1451 ***	0.3171 ***	0.1456 ***	-0.1214 ***	-0.0037 ***	1.1193 ***	0.1497 ***	0.1017 ***	-0.0894 ***
					Bull market					
10%	-0.0026 ***	1.0453 ***	0.4355 ***	0.0351	-0.0698 ***	-0.0055 ***	1.0370 ***	0.0233	0.0766 ***	-0.0885 ***
20%	-0.0042 ***	1.0452 ***	0.4543 ***	0.0877 ***	-0.0781 ***	-0.0046 ***	1.0404 ***	0.0592 ***	0.0571 **	-0.0929 ***
30%	-0.0045 ***	1.0789 ***	0.4498 ***	0.1071 ***	-0.0861 ***	-0.0050 ***	1.0594 ***	0.1235 ***	0.0577 **	-0.0956 ***
Cap-weighted portfolio (Unrestricted sample)										
					Bear market					
10%	-0.0011	1.0084 ***	0.0166	-0.0150	0.0140	-0.0018 ***	1.0183 ***	-0.3328 ***	0.0746 **	0.0465 ***
20%	-0.0015	0.9988 ***	0.0825*	-0.0598	-0.0271	-0.0016 ***	0.9742 ***	-0.2849 ***	0.0605 ***	0.0517 ***
30%	-0.0019 **	1.0545 ***	0.0722*	-0.0408	-0.0127	-0.0017 ***	0.9903 ***	-0.2425 ***	0.0358*	0.0418 ***
					Bull market					
10%	-0.0005	0.9197 ***	0.1711 ***	-0.0982*	-0.0070	-0.0028 ***	0.9564 ***	-0.2002 ***	0.0920 ***	0.0063
20%	-0.0013	0.9573 ***	0.1507 ***	-0.1256 ***	-0.0297	-0.0023 ***	0.9364 ***	-0.1793 ***	0.0342	-0.0063
30%	-0.0019 **	0.9831 ***	0.1472 ***	-0.1154 ***	-0.0031	-0.0022 ***	0.9609 ***	-0.1698 ***	0.0096	0.0018
Cap-weighted portfolio (restricted sample)										
					Bear market					
10%	-0.0018	0.9935 ***	0.1297 **	-0.0483	0.0231	-0.0024 ***	1.0340 ***	-0.3153 ***	0.0713 ***	0.0613 ***
20%	-0.0013	1.0334 ***	0.0595	-0.0806*	-0.0141	-0.0023 ***	0.9933 ***	-0.2328 ***	0.0322	0.0433 ***
30%	-0.0008	1.0399 ***	0.0558	-0.0207	-0.0140	-0.0019 ***	0.9947 ***	-0.2445 ***	0.0448 **	0.0535 ***
					Bull market					
10%	0.0002	0.9019 ***	0.1576 ***	-0.1732 ***	-0.0609	-0.0025 ***	0.9406 ***	-0.1843 ***	0.1259 ***	0.0075
20%	-0.0016	0.9377 ***	0.1970 ***	-0.1118 ***	-0.0281	-0.0024 ***	0.9387 ***	-0.1517 ***	0.0650 ***	0.0005
30%	-0.0021 ***	0.9988 ***	0.1401 ***	-0.0910 ***	-0.0099	-0.0026 ***	0.9519 ***	-0.1616 ***	0.0077	0.0069

This table shows the abnormal returns and the βs from the regime-dependent Carhart four-factor model for unrestricted and restricted samples. The high-rating portfolios are constructed by the top 10%, 20%, and 30% of the stocks in each of the 10 economic sectors, while the low ESG rating portfolios consist of the bottom 10%, 20%, 30% of the stocks in each of the 10 economic sectors. The restricted sample approach ensures that the low ESG- and high ESG-rating portfolios contain stocks from different sectors. The abnormal returns are produced for two different weighting approach portfolios: equally-weighted and cap-weighted portfolios. The parameters are estimated using monthly data from 2002.01 to 2018.12. ***, ** and * denote statistical significance at the 1, 5, and 10% levels, respectively.

Table 4.6: Sector performance across market regimes

		Equally-weighted portfolio	
		bear	
		good	bad
bull	good	Tele. Ser, Utilities, Financials	Energy, Non-cyclical, Technology
	bad	Basic Material, Industrials, Healthcare	Cyclical
		Cap-wighted portfolio	
		bear	
		good	bad
bull	good	Tele. Ser, Utilities, Financials	Energy, Cyclical, Non-cyclical, Technology
	bad	Basic Material, Healthcare	Industrials

This table classifies 10 economic sectors into four groups: high ESG outperforms low ESG in both regimes; high ESG underperforms low ESG in both regimes; high ESG outperforms (underperforms) low ESG in bear regime (bull regime); high ESG outperforms (underperforms) low ESG in bull regime (bear regime). “good” represents outperform, “bad” means underperform.

Chapter 5

Conclusion

The three essays examine asset pricing models in regime-switching and ESG environments. The first essay develops a novel regime-switching option pricing model, in which the underlying asset return volatilities are affected by the macroeconomic environment. According to three commonly used metrics, the option pricing model proposed significantly outperforms the benchmark models (BSM, Hardy and HN). First, the MNZ model has the lowest mean absolute error for both call and put options amongst all comparable models across a broad range of expiration time. Second, the MNZ model has a higher prediction success rate than alternatives. Third, the model exhibits lower mean absolute errors of implied volatilities in relation to the counterparts. These results imply that the option prices predicted by the MNZ model are closer to observed market price statistics compared to BSM, Hardy, and HN models. Since volatility is a critical factor for the option pricing mechanism, the MNZ model considers macroeconomic conditions when identifying market regimes and pricing options. It accounts for more market information and predict prices more accurately than other stochastic volatility models do. Besides, unlike Hardy model, which is incorporated as a special (steady-state) case of the option pricing framework, the posterior probabilities of market regimes in the MNZ model can be updated at each point of time to capture the fluctuation of the capital market.

The second essay studies the effects of ESG rating on corporate stock returns from the perspective of the economic sector, firms size, and time horizon, respectively. The result suggests that those three factors jointly affect the relationship between ESG performance and stock prices: First, for most sectors, the positive (negative) gap of abnormal returns between high- and low-rating portfolios increase (decrease) from short to long run. Among all industries, the sensitive firms, which involve activities triggering environmental and social damage, are more impacted by ESG rating compared to others. Second, large firms are more affected by ESG rating than small ones, because they are more exposed to the public. Third, holding sector and size unchanged, ESG rating tends to generate a positive effect on stock returns in the long run, which implies that ESG investment is a long-term process. This essay applies the unique ESG rating data into the analysis of the impact of ESG on stock portfolios across sectors, firm sizes, and time horizons, which provides a comprehensive interpretation of the financial implications of sustainable corporate behaviors.

The third essay investigates the short run (within one year) ESG-CFP relationship across market regimes. It incorporates machine learning method into a regime-switching model and identifies market regimes from 134 macroeconomic variables. Consistent with the hypothesis, the finding shows that higher ESG rating stock portfolios significantly outperform the lower counterpart in bear markets. The result implies a positive financial effect of ESG in a sluggish economy. Specifically, I study stock portfolios across 10 economic sectors to observe the effect of ESG rating on stock returns in each sector given each market regime. Results suggest that the effect depends on the level of demand. Higher demand in a sector implies that people pay closer attention to it. Thus, in a perfectly competitive market, companies with higher ESG scores are more likely to attract consumers and have better financial performance (our findings for the healthcare sector may serve as an example). The main contribution of this essay is the innovative incorporating machine learning method into a factor model when characterizing the financial impact of ESG rating across market regimes. It fills up a knowledge gap in the existing literature.

For both theoretical development in academia and empirical application in the modern financial market, the asset pricing system is still in the process of improvement. This thesis provides the existing asset pricing framework with more research possibilities. To conclude, this thesis demonstrates the critical role of the regime-switching model in asset pricing study. The financially meaningful result from applying the regime-switching method into an option pricing process helps to increase pricing precision. The economically significant result by adopting regime-switching and machine learning mechanisms into an ESG environment gives support to the construction of a sustainable financial climate.

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Appendix A

Option Pricing under Different Regime Shifts

A.1 Derivation of Recursive Option Pricing Formula

A.1.1 The one-period model

Under the fundamental theorem of asset pricing, if the market is complete and arbitrage free, there is a risk-neutral measurement that the expected future payoffs in all market states are discounted as the asset price. In such a risk-neutral world, I assume that the asset returns follow mixture normal distributions. The one period ($T = 1$, $\delta t = 1$) regime-dependent asset returns follow

$$R_u \sim N((r - \frac{1}{2}\sigma_1^2)\delta t, \sigma_1^2 \delta t) \tag{A.1}$$

$$R_d \sim N((r - \frac{1}{2}\sigma_2^2)\delta t, \sigma_2^2 \delta t) \tag{A.2}$$

where R_u and R_d are the asset returns in regime 1 and regime 2. r is the risk-free rate, σ_1 and σ_2 are the volatility of the asset return in regime 1 and regime 2. δt is the step length while $T = 1$ means that it's a one-period model.

European call option price is defined as

$$C_0 = e^{-rT} E[(S_1 - K)^+] \tag{A.3}$$

$$= p_1 C_0^u + p_2 C_0^d \tag{A.4}$$

where S_1 is the underlying asset price at time $T = 1$ and K is the option strike price, C_0^u and C_0^d are the conditional option prices. p_1 and p_2 are prior probabilities of market regimes 1 and 2.

I define $f_1(x)$ as the density function of the stock price conditional on regime 1 and $f_2(x)$ as the density function of the stock price conditional on regime 2. Thus,

$$p_1 f_1(x) + p_2 f_2(x) \tag{A.5}$$

is the mixture density function of stock price S_1.

$$\begin{aligned}
C_0 &= e^{-rT} E[(S_1 - K)^+] && \text{(A.6)}\\
&= p_1 C_0^u + p_2 C_0^d && \text{(A.7)}\\
&= e^{-rT}([p_1 E(S_1^u - K)^+ | M = 1] + p_2[E(S_1^d - K)^+ | M = 2] && \text{(A.8)}\\
&= e^{-rT} \int_{-\infty}^{+\infty} (S_1 - K)^+ (p_1 f_1(x) + p_2 f_2(x)) dx && \text{(A.9)}\\
&= e^{-rT}[p_1 \int_{-\infty}^{+\infty} (S_0 e^{R_u}) - K)^+ f_1(x) dx + p_2 \int_{-\infty}^{+\infty} (S_0 e^{R_d}) - K]^+ f_2(x) dx] && \text{(A.10)}\\
&= e^{-rT}(p_1 \Delta_1 + p_2 \Delta_2) && \text{(A.11)}
\end{aligned}$$

First, I solve the Δ_1 of equation A.11. Define a new variable $z_1 = \frac{R_u - m_1}{v_1}$, where $m_1 = r\delta t - \frac{1}{2}(\sigma_1^2 \delta t)$ and $v_1 = \sigma_1 \sqrt{\delta t}$. Then the density function of z: $h(z_1) = \frac{1}{\sqrt{(2\pi)}} e^{-\frac{z_1^2}{2}}$

$$\begin{aligned}
\Delta_1 &= \int_{-\infty}^{+\infty} (S_0 e^{R_u} - K)^+ f_1(x) dx && \text{(A.12)}\\
&= \int_{\frac{ln(K/S_0) - m_1}{v_1}}^{\infty} S_0 e^{v_1 z_1 + m_1} h(z_1) dz_1 - K \int_{\frac{ln(K/S_0) - m_1}{v_1}}^{\infty} h(z_1) dz_1 && \text{(A.13)}\\
&= S_0 \int_{\frac{ln(K/S_0) - m_1}{v_1}}^{\infty} \frac{1}{\sqrt{(2\pi)}} e^{(-z_1^2 + 2 z_1 v_1 + 2 m_1)} /2 - K \int_{\frac{ln(K/S_0) - m_1}{v_1}}^{\infty} h(z_1) dz_1 && \text{(A.14)}\\
&= S_0 \int_{\frac{ln(K/S_0) - m_1}{v_1}}^{\infty} \frac{e^{m_1 + v_1^2/2}}{\sqrt{2\pi}} e^{[-(z_1 - v_1)^2]/2} dz_1 - K \int_{\frac{ln(K/S_0) - m_1}{v_1}}^{\infty} h(z_1) dz_1 && \text{(A.15)}\\
&= S_0 e^{m_1 + v_1^2/2} \int_{\frac{ln(K/S_0) - m_1}{v_1}}^{\infty} h(z_1 - v_1) dz_1 - K \int_{\frac{ln(K/S_0) - m_1}{v_1}}^{\infty} h(z_1) dz_1 && \text{(A.16)}
\end{aligned}$$

Then the first integral can be expressed as

$$1 - N[(ln(K/S_0) - m_1)/v_1 - v_1] = N_1[(-ln(K/S_0) + m_1)/v_1 + v_1] \tag{A.17}$$

The second integral can be expressed as

$$1 - N[(ln(K/S_0) - m_1)/v_1] = N_2[-(ln(K/S_0) - m_1)/v_1] \tag{A.18}$$

Thus, substituting $m_1 = r\delta t - \frac{1}{2}(\sigma_1^2 \delta t)$ and $v_1 = \sigma_1\sqrt{\delta t}$ into equation (15),

$$\Delta_1 = S_0 e^{r\delta t} N[\frac{-ln(K/S_0) + (r\delta t - \frac{1}{2}(\sigma_1^2\delta t) + \sigma_1^2\delta t}{\sigma_1\sqrt{\delta t}}] - N[\frac{-ln(K/S_0) + (r\delta t - \frac{1}{2}\sigma_1^2\delta t)}{\sigma_1\sqrt{\delta t}}] \tag{A.19}$$

$$= S_0 e^{r\delta t} N[\frac{ln(S_0/K) + (r\delta t + \frac{1}{2}\sigma_1^2\delta t)}{\sigma_1\sqrt{\delta t}}] - N[\frac{ln(S_0/K) + (r\delta t - \frac{1}{2}\sigma_1^2\delta t)}{\sigma_1\sqrt{\delta t}}] \tag{A.20}$$

$$= S_0 e^{r\delta t} N(d_1^u) - KN(d_2^u) \tag{A.21}$$

where

$$d_1^u = \frac{ln(S_0/K) + (r\delta t + \frac{1}{2}\sigma_1^2\delta t)}{\sigma_1\sqrt{\delta t}} \tag{A.22}$$

$$d_2^u = \frac{ln(S_0/K) + (r\delta t - \frac{1}{2}\sigma_1^2\delta t)}{\sigma_1\sqrt{\delta t}} \tag{A.23}$$

Following the same above process, I can get

$$\Delta_2 = S_0 e^{r\delta t} N(d_1^d) - KN(d_2^d) \tag{A.24}$$

where

$$d_1^d = \frac{ln(S_0/K) + (r\delta t + \frac{1}{2}\sigma_2^2\delta t)}{\sigma_2\sqrt{\delta t}} \tag{A.25}$$

$$d_2^d = \frac{ln(S_0/K) + (r\delta t - \frac{1}{2}\sigma_2^2\delta t)}{\sigma_2\sqrt{\delta t}} \tag{A.26}$$

Following equation A.11 the one period option pricing formula is

$$C_0 = p_1[S_0N(d_1^u) - e^{-rT}KN(d_2^u)] + p_2[S_0N(d_1^d) - e^{-rT}KN(d_2^d)] \tag{A.27}$$

where $d_1^u, d_2^u, d_1^d, d_2^d$ are defined in equations A.22,A.23,A.25,A.26.

A.1.2 The two-period and generalized models

Two-period Model

I derive a two-period model and generalize it to N period model in this section. When T=2, I define a transition probability matrix:

$$p_{ij} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}$$

where p_{ij} is the probability of transferring state i to state j. For example, the probability of staying at state 1 at time $t+1$ is p_{11}; the probability of transferring to state 2 at time $t+1$ is p_{12}. And $p_{11} + p_{12} = 1$; $p_{21} + p_{22} = 1$.

As the optimal number of regimes is two, there are three unique events at time $T = 2$: starting from time $T = 0$, market goes up twice; market either goes up and down or goes down and up; market goes down twice. Conditional on regime M_t, two-period($T = 2, \delta t = 1$) regime-dependent asset return at $T = 2$ follows:

$$R_u^1 + R_u^2 \sim N(2(r - \frac{1}{2}\sigma_1^2)\delta t, 2\sigma_1^2\delta t) \tag{A.28}$$

$$(R_u^1 + R_d^2) \ or \ (R_u^2 + R_d^1) \sim N((2r - \frac{1}{2}\sigma_1^2 - \frac{1}{2}\sigma_2^2)\delta t, (\sigma_1^2 + \sigma_2^2)\delta t \ ) \tag{A.29}$$

$$R_d^1 + R_d^2 \sim N(2(r - \frac{1}{2}\sigma_2^2)\delta t, 2\sigma_2^2\delta t) \tag{A.30}$$

where $R_i^t, \ i \in (u, d), \ t \in (1 \cdots T)$ are independent from each other, thus the covariance of any of two items in R_i^t is zero.

Starting from

$$C_0 = e^{-rT} E[(S_T - K)^+], \ T = 2, \tag{A.31}$$

two-period model can be expressed as

$$C_0 = e^{-rT} \int_{-\infty}^{+\infty} (S_T - K)^+ (p_1 p_{11} f_1(x) + (p_2 p_{21} + p_1 p_{12}) f_2(x) + p_2 p_{22} f_3(x)) dx \tag{A.32}$$

$$= e^{-rT} (p_1 p_{11} \Delta_1 + (p_1 p_{12} + p_2 p_{21}) \Delta_2 + p_2 p_{22} \Delta_3) \tag{A.33}$$

Where

$$\Delta_1 = \int_{-\infty}^{+\infty} (ln(S_0 e^{2R_u}) - K)^+ f_1(x) dx \tag{A.34}$$

$$\Delta_2 = \int_{-\infty}^{+\infty} (ln(S_0 e^{R_u + R_d}) - K)^+ f_2(x) dx \tag{A.35}$$

$$\Delta_3 = \int_{-\infty}^{+\infty} (ln(S_0 e^{2R_d}) - K)^+ f_3(x) dx \tag{A.36}$$

To simplify, I use the notation $R_u + R_d$ to represent $R_u^1 + R_d^2$ and $R_u^2 + R_d^1$; the notation $2R_u$ to represent $R_u^1 + R_u^2$; the notation $2R_d$ to represent $R_d^1 + R_d^2$. $f_1(x)$,$f_2(x)$, and $f_3(x)$ are the density functions of them, correspondingly.

Let's redefine

$$m_1 = 2(r - \frac{1}{2}\sigma_1^2)\delta t \tag{A.37}$$
$$v_1 = \sqrt{2\sigma_1^2\delta t} \tag{A.38}$$
$$z_1 = \frac{2R_u - m_1}{v_1} \tag{A.39}$$

and

$$m_2 = (2r - \frac{1}{2}\sigma_1^2 - \frac{1}{2}\sigma_2^2)\delta t \tag{A.40}$$
$$v_2 = \sqrt{(\sigma_1^2 + \sigma_2^2)\delta t} \tag{A.41}$$
$$z_2 = \frac{R_u + R_d - m_2}{v_2} \tag{A.42}$$

and define

$$m_3 = 2(r - \frac{1}{2}\sigma_2^2)\delta t \tag{A.43}$$
$$v_3 = \sqrt{2\sigma_2^2\delta t} \tag{A.44}$$
$$z_3 = \frac{2R_d - m_3}{v_3} \tag{A.45}$$

Therefore,

$$\Delta_1 = S_0 e^{m_1 + v_1^2/2} \int_{\frac{ln(K/S_0)-m_1}{v_1}}^{\infty} h(z_1 - v_1)dz_1 - K \int_{\frac{ln(K/S_0)-m_1}{v_1}}^{\infty} h(z_1)dz_1 \tag{A.46}$$
$$= S_0 e^{2r\delta t} N(\frac{ln(S_0/K) + (2r\delta t + \sigma_1^2\delta t)}{\sqrt{2\sigma_1^2\delta t}}) - KN(\frac{ln(S_0/K) + (2r\delta t - \sigma_1^2\delta t)}{\sqrt{2\sigma_1^2\delta t}}) \tag{A.47}$$
$$= S_0 e^{2r\delta t} N(d_1^{uu}) - KN(d_2^{uu}) \tag{A.48}$$

and

$$\Delta_2 = S_0 e^{m_2+v_2^2/2} \int_{\frac{ln(K/S_0)-m_2}{v_2}}^{\infty} h(z_2 - v_2) dz_2 - K \int_{\frac{ln(K/S_0)-m_2}{v_2}}^{\infty} h(z_2) dz_2 \tag{A.49}$$

$$= S_0 e^{2r\delta t} N(\frac{ln(S_0/K) + (2r\delta t + \frac{1}{2}(\sigma_1^2 + \sigma_2^2)\delta t)}{\sqrt{(\sigma_1^2 + \sigma_2^2)\delta t}}) - KN(\frac{ln(S_0/K) + (2r\delta t - \frac{1}{2}(\sigma_1^2 + \sigma_2^2)\delta t)}{\sqrt{(\sigma_1^2 + \sigma_2^2)\delta t}}) \tag{A.50}$$

$$= S_0 e^{2r\delta t} N(d_1^{ud}) - KN(d_2^{ud}) \tag{A.51}$$

and

$$\Delta_3 = S_0 e^{m_3+v_3^2/2} \int_{\frac{ln(K/S_0)-m_3}{v_3}}^{\infty} h(z_3 - v_3) dz_3 - K \int_{\frac{ln(K/S_0)-m_3}{v_3}}^{\infty} h(z_3) dz_3 \tag{A.52}$$

$$= S_0 e^{2r\delta t} N(\frac{ln(S_0/K) + (2r\delta t + \sigma_2^2 \delta t)}{\sqrt{2\sigma_2^2 \delta t}}) - KN(\frac{ln(S_0/K) + (2r\delta t - \sigma_2^2 \delta t)}{\sqrt{2\sigma_2^2 \delta t}}) \tag{A.53}$$

$$= S_0 e^{2r\delta t} N(d_1^{dd}) - KN(d_2^{dd}) \tag{A.54}$$

where

$$d_1^{uu} = \frac{ln(S_0/K) + (2r\delta t + \sigma_1^2 \delta t)}{\sqrt{2\sigma_1^2 \delta t}} \tag{A.55}$$

$$d_2^{uu} = \frac{ln(S_0/K) + (2r\delta t - \sigma_1^2 \delta t)}{\sqrt{2\sigma_1^2 \delta t}} \tag{A.56}$$

$$d_1^{ud} = \frac{ln(S_0/K) + (2r\delta t + \frac{1}{2}(\sigma_1^2 + \sigma_2^2)\delta t)}{\sqrt{(\sigma_1^2 + \sigma_2^2)\delta t}} \tag{A.57}$$

$$d_2^{ud} = \frac{ln(S_0/K) + (2r\delta t - \frac{1}{2}(\sigma_1^2 + \sigma_2^2)\delta t)}{\sqrt{(\sigma_1^2 + \sigma_2^2)\delta t}} \tag{A.58}$$

$$d_1^{dd} = \frac{ln(S_0/K) + (2r\delta t + \sigma_2^2 \delta t)}{\sqrt{2\sigma_2^2 \delta t}} \tag{A.59}$$

$$d_2^{dd} = \frac{ln(S_0/K) + (2r\delta t - \sigma_2^2 \delta t)}{\sqrt{2\sigma_2^2 \delta t}}) \tag{A.60}$$

Thus following equation A.32, the price of two-period option is

$$C_0 = p_1 p_{11}[S_0 N(d_1^{uu}) - e^{-rT} K N(d_2^{uu})] \tag{A.61}$$

$$+ (p_1 p_{12} + p_2 p_{21})[S_0 N(d_1^{ud}) - e^{-rT} K N(d_2^{ud}))] \tag{A.62}$$

$$+ p_2 p_{22}[S_0 N(d_1^{dd}) - e^{-rT} K N(d_2^{dd}))] \tag{A.63}$$

where d_1^{uu} d_2^{uu} d_1^{ud} d_2^{ud} d_1^{dd} d_2^{dd} are defined in equations A.55,A.56,A.57,A.58,A.59,A.60.

Generalized Model

After the one-period and two-period model are derived, an T ($T \in (1 \cdots N)$) period model can be generalized. Assuming within time N, there are n periods with market going up and there are N-n periods with market going down. In such a case:

$$d_1^{nu,(N-n)d} = \frac{ln(S_0/K) + Nr\delta t + \frac{1}{2}[n\sigma_1^2 + (N-n)\sigma_2^2]\delta t}{\sqrt{(n\sigma_1^2 + (N-n)\sigma_2^2)\delta t}} \tag{A.64}$$

$$d_2^{nu,(N-n)d} = \frac{ln(S_0/K) + Nr\delta t - \frac{1}{2}[n\sigma_1^2 + (N-n)\sigma_2^2]\delta t}{\sqrt{(n\sigma_1^2 + (N-n)\sigma_2^2)\delta t}} \tag{A.65}$$

Appendix B

Financial Impact of ESG Rating across Sectors and Firm Sizes over Time: New Evidence

B.1 Definitions of ESG Scores by Thomson Reuters

Table B.1: ESG scores explanations by Thomson Reuters

ESG	ESG score types	ESG scores explanation
	ESG Score	ESG Score is an overall company score based on the self-reported information in the environmental, social, and corporate governance pillars.
Environmental	Resource Use Score	Resource Use Score reflects a company's performance and capacity to reduce the use of materials, energy, or water, and to find more eco-efficient solutions by improving supply chain management.

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Table B.1 – *Continued from previous page*

ESG	ESG score types	ESG scores explination
	Emissions Score	Emissions Score measures a company's commitment to and effectiveness in reducing environmental emissions in the production and operational processes.
	Environmental Innovation score	Environmental Innovation Score reflects a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes or eco-designed products.
Social	Management Score	Management Score measures a company's commitment to and effectiveness in following best practice corporate governance principles.

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Table B.1 – *Continued from previous page*

ESG	ESG score types	ESG scores explination
	Shareholders' Score	Shareholders' Score measures a company's effectiveness in the equal treatment of shareholders and the use of anti-takeover devices.
	CSR Strategy Score	CSR Strategy Score reflects a company's practices to communicate that it incorporates the economic (financial), social and environmental dimensions in its day-to-day decision-making processes.
Governance	Workforce Score	Workforce Score measures a company's effectiveness towards job satisfaction, healthy and safe workplace, maintaining diversity and equal opportunities, and development opportunities for its workforce.

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Table B.1 – *Continued from previous page*

ESG	ESG score types	ESG scores explination
Governance	Human Rights Score	Human Rights Score measures a company's effectiveness in respecting the fundamental human rights conventions.
	Community Score	Community Score measures the company's commitment to being a good citizen, protecting public health and respecting business ethics.
	Product Responsibility Score	Product Responsibility Score reflects a company's capacity to produce quality goods and services, incorporating the customer's health and safety, integrity and data privacy.

This table shows the different types of ESG scores and their explination. The information is retrieved from Thomson Reuters (`https://datateamoftheeur.wordpress.com/2018/07/16/new-thomson-reuters-esg-scores-added-to-datastream/`). Those ESG scores are the new added score measurement in 2018.

B.2 ESG Weights by Thomson Reuters

Table B.2: Weights of ESG categories

Pillar	Category	Indicators in Rating	Weights	Pillar Weights
	Resource Use	19	11%	
Environmental	Emissions	22	12%	34%
	Innovation	20	11%	
	Workforce	29	16%	
Social	Human Rights	8	4.50%	35.50%
	Community	14	8%	
	Product Responsibility	12	7%	
	Management	34	19%	
Governance	Shareholders	12	7%	30.50%
	CSR Strategy	8	4.50%	
Total		178	100%	

This table is retrieved from the financial and risk business of Thomson Reuters (see Refinitiv `https://www.refinitiv.com`) and is the measurement weights of Thomson Reuters ESG Scores. The final ESG scores are computed using over 400 different ESG metrics dispersed across 10 categories (resource use, emission, and innovation are the focus of the Environmental pillar; workforce, human rights, community well-beings and product responsibility) under three dimensions (Environmental, Social, and Governance).

Appendix C

Financial Impact of ESG Rating under Different Market Regimes

C.1 Expectation and Maximization Algorithm

I denote the model parameters as $\Phi(M)$ =$\{a_{M_t}$, b_{M_t}, $\gamma_{M_t}\}$, the unobserved regimes over time as M and the observed indicators as X. The EM algorithm can be summarized in the following two steps:

E-step: Set an initial parameter value Φ_0 for the true parameter set Φ, calculate the conditional distribution on regimes, $Q(M) = Pr(M|X;\Phi_0)$, and determine the expected log likelihood, $E_Q\left[\ln Pr(X,M;\Phi)\right]$.

M-step: Maximize the expected log likelihood of joint data of X and M with respect to Φ, to obtain an improved estimate for parameter Φ. The improved estimate is:

$$\Phi_1 = \arg\max_{\Phi}\{E_Q\left[\ln Pr(X,M;\Phi)\right]\}$$

where Φ_1 is the new initial value for the true parameter Φ. The algorithm returns to the E-step after a new estimate is obtained. As the aforementioned processes are going on, the parameters are estimated when the log likelihood is maximized.