THREE ESSAYS ON SUSTAINABLE FINANCE AND CAPITAL MARKETS

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

William Wei Xiong

August 2024

© 2024 William Wei Xiong

ALL RIGHTS RESERVED

THREE ESSAYS ON SUSTAINABLE FINANCE AND CAPITAL MARKETS

William Wei Xiong, Ph.D.

Cornell University 2024

This dissertation contains three separate essays, as in Chapter 1, Chapter 2, and Chapter 3, respectively. The first two chapters study sustainable finance and asset returns, while the third relates to trading mechanisms, activities, and market quality.

In Chapter 1, I investigate whether biodiversity risks are priced in global stock markets by studying 21,248 publicly listed stocks in 117 countries from April 2016 to June 2023. First, I build long-short portfolios of stocks with low and high biodiversity risk exposures to study the "biodiversity alpha." Next, I cross-sectionally analyze company-level biodiversity risk exposures and stock returns to explore the "biodiversity beta." Lastly, I conduct event studies on how biodiversity risk incidents occurring to firms are linked to their stock returns. Overall, the correlation between biodiversity risks and stock returns emerged after the Kunming Declaration in October 2021, and notably in the US.

In Chapter 2, we offer new evidence on how the application of environmental criteria has affected international stock returns. We estimate the market-based realized equity greenium in a cross-section of 21,902 firms from 96 countries between November 2012 and December 2021. We find reliable evidence that green stocks earned higher returns than brown stocks around the world, which was mainly driven by US stocks. This outperformance is associated with lower returns on US energy stocks, but not with higher returns on US technology stocks.

Chapter 3 studies trading pauses on individual stocks under the Limit Up-Limit Down (LULD) Plan, which are key volatility circuit breakers in the US market. Since July 2016, the 10th Amendment to the LULD Plan (A10) has dramatically reduced superfluous trading pauses due to misleading opening prices. Henceforth, the pre-pause liquidity

improves, and there is less room for the post-pause liquidity to increase compared to the pre-pause level. Short-term volatility spikes around trading pauses after A10, and post-pause volatility increases. Post A10, high-frequency quoting peaks closely around trading pauses, especially after trading resumptions. Suggestive evidence indicates that high-frequency quoting is related to improved liquidity around trading pauses, notably after A10 and before trading pauses, but not necessarily linked to increased short-term volatility.

BIOGRAPHICAL SKETCH

In August 2018, Wei (William) Xiong joined Cornell University as a Ph.D. student in finance. During his doctoral studies, he focused on investments, asset management, and empirical asset pricing. His latest research specializes in sustainable finance, addressing the link between environmental issues, such as the loss of biological diversity, and asset returns.

This dissertation is dedicated to my advisor, coauthors, committee members, the Finance Area faculty at Cornell, and my family, friends, and colleagues, along with all those who have supported me throughout this unforgettable journey.

ACKNOWLEDGEMENTS

First and foremost, I deeply appreciate the guidance, advice, and support provided by my advisor and dissertation chair Andrew Karolyi, my committee members Gideon Saar, Jawad Addoum, Yifei Mao, and Nick Guest, and the Finance Area Faculty at Cornell JCB throughout my doctoral studies. I am also grateful to the professors who have educated me, to my fellow Ph.D. students and friends, as well as to the Johnson GSM Ph.D. program DGS Vrinda Kadiyali and GFA Calyn Fisher. The author extends his sincere gratitude to Cornell University, including the Johnson GSM, the JCB, and the Graduate School. I also give my heartfelt thanks to my family and all those who have supported me on this journey.

As for Chapter 1, I am enormously grateful for Andrew Karolyi's insightful advice and unwavering support throughout its development. I am also indebted to Johannes Stroebel, Stefano Giglio, Gideon Saar, Jawad Addoum, Yifei Mao, Nick Guest, David Ng, Kelly Posenau, Alissa Kleinnijenhuis, Lawrence Jin, Scott Yonker, Alan Kwan, Warren Bailey, Mao Ye, Johnny Tang, Minmo Gahng, and Linda Canina, for their valuable insights and suggestions. I thank the seminar participants at Cornell JCB, Tsinghua PBCSF, UCF Orlando, SUNY Binghamton, NTU Singapore, Fudan FISF, SJTU SAIF, SJTU ACEM, PKU PHBS, and Cornerstone Research, and the conference participants at the inaugural New York Fed and NYU Summer Climate Finance Conference (2024). The author extends sincere appreciation to Ying Wu for sharing data on global pricing factors and providing feedback. The author also thanks Cornell JCB and the Finance Area for their support in providing additional data.

Chapter 2 is co-authored with Andrew Karolyi and Ying Wu. I sincerely appreciate their approval to include this as a chapter in my dissertation. Our team deeply appreciates the insightful comments and invaluable feedback from René Stulz, Ľuboš Pástor, Luke Taylor, Jeffrey Wurgler, Malcolm Baker, Daniel Bergstresser, Andrew Ang, Nick Guest, Shaojun Zhang, Julian Kölbel, Lucia Alessi, Jitendra Aswani; conferences participants at the 2023 FMA annual meetings, the 2024 AFA annual meetings, and the 2024 Baruch College Climate Finance and ESG Conference; and seminar participants in the 2023 Cornell Finance Faculty Brown Bag, the Cornell 2030 Project Symposium, and the ESSEC-Amundi Chair on Asset & Risk Management Webinar in June 2024. Special thanks are given to the conference discussants Xiaoqing Eleanor Xu, Laura Starks, and Xi Dong, respectively, for their constructive critiques and valuable suggestions. The authors also express their heartfelt gratitude to Luke Taylor for generously sharing his code and for providing important advice.

Regarding Chapter 3, I express my gratitude for the valuable feedback and suggestions provided by Andrew Karolyi, Maureen O'Hara, Gideon Saar, Scott Yonker, Jawad Addoum, Lawrence Jin, Yifei Mao, Nick Guest, and the attendees of the Cornell Finance PhD Symposium in 2021 and 2022. I thank NYSE for providing the Daily Trade and Quote (DTAQ) data (to Cornell), and NasdaqTrader.com for providing data on the US market trading pauses. The author also extends his appreciation to Craig Holden and Stacey Jacobsen for generously sharing their SAS codes related to the DTAQ data.

TABLE OF CONTENTS

CHAPTER 1

THE WORLD MARKET PRICE OF BIODIVERSITY RISK

In this chapter, I investigate whether biodiversity risks are priced in global stock markets by studying 21,248 publicly listed stocks across 117 countries from April 2016 to June 2023. I first build long-short portfolios of biodiversity-favorable, or "nature-positive" and unfavorable "nature-negative" stocks and uncover a positive "biodiversity alpha" in the US. However, it exists only before the Kunming Declaration in October 2021, and is reversed thereafter by turning negative. No significant "biodiversity alpha" exists outside the US. Next, I examine firm-level biodiversity risk exposures and show that they are positively associated with stock returns worldwide, especially after the Kunming Declaration. This "biodiversity beta" cannot be explained away by carbon emissions or other climate-related issues and environmental issues. Finally, this study shows that firms involved in biodiversity incidents experience higher monthly stock returns in the month of incident(s), particularly after the Kunming Declaration and notably in the US.

1.1 Introduction

"...Biodiversity, and the ecosystem functions and services it provides, support all forms of life on Earth and underpin our human and planetary health and well-being, economic growth and sustainable development..." — Kunming Declaration, October 2021, Part I of the UN Biodiversity Conference (CBD COP 15)

The connection between human economic activities and the well-being of the earth is crucial and complicated. Lately, there has been an increase in attention to the loss of biodiversity, in addition to climate change. During the past three decades, several international agreements have been created, such as the Kyoto Protocol in 1997, and the Paris Agreement in 2015, to reduce greenhouse gas (GHG) emissions and combat global warming. Businesses, financial institutions, and organizations, such as the Task Force on Climate-related Financial Disclosures (TCFD), the Glasgow Financial Alliance for Net Zero (GFANZ), and the Intergovernmental Panel on Climate Change (IPCC), are also taking steps to address the risks that climate change poses. Climate finance has become a vibrant area of research in academia, as pointed out by Starks (2023) in the AFA 2023 presidential address. However, climate change is only one of the crucial factors to consider when it comes to the relationship between human economic activity and our planet's well-being.

Another critical aspect is the loss of biodiversity, together with the efforts needed to conserve it. This will soon become the next major challenge in sustainable finance, which could potentially eclipse the focus on mitigating and adapting to the risks of climate change, even though they are both unprecedented yet interrelated crises. Impactful international organizations to protect biodiversity and nature have been formed over the past decade, such as the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), and the Taskforce on Nature-related Financial Disclosures (TNFD). Recent and influential global agreements aimed at restoring biodiversity include the Kunming Declaration in October 2021, as the fruit of the UN Biodiversity Conference (CBD COP 15) Part I, and the Kunming-Montreal Global Biodiversity Framework (GBF) in December 2022 , which concludes the UN Biodiversity Conference (CBD COP 15) Part II. [1]

So far, finance researchers in academia have not paid enough attention to the connection between biodiversity and finance, such as how biodiversity risks affect asset prices and returns, or how to finance the restoration and protection of biodiversity. Karolyi and Tobin-de la Puente (2023) point out that there had been no articles in top

[1] See: https://www.cbd.int/gbf/

finance journals on the risk of biodiversity loss and finance by 2022. In addition, they call for more research in this area. The goal of this study is to meet this challenge by examining whether and how biodiversity risks are priced in global equity markets in the past decade, which is an equally critical issue compared to the pricing of climate change or carbon transition risk.

Only a few recent working papers have explored biodiversity finance.[2] For example, Rizzi (2022) investigates how loss of natural capital, especially wetlands and protected areas, can impact municipal bond yields. Flammer, Giroux, and Heal (2023), and Junge, Feuer, and Sassen (2023) study how private capital can help finance the conservation and restoration of biodiversity or stop biodiversity loss. Hoepner et al. (2023) find that infrastructure firms that manage material biodiversity risk better have better long-term financing conditions by inspecting their CDS term structure. Other notable articles in biodiversity finance include Cherief, Sekine, and Stagnol (2022) and Kedward et al. (2022).

To my knowledge, the most related work to this article contains Garel et al. (2024), Coqueret and Giroux (2023), and Giglio et al. (2023), which also study the pricing of biodiversity risks. Both Garel et al. (2024) and Coqueret and Giroux (2023) rely on the Corporate Biodiversity Footprint data from the Iceberg Data Lab. Garel et al. (2024) estimate the beta of firms' biodiversity footprints on stock returns, while Coqueret and Giroux (2023) take the long-short portfolio approach to test if there is a biodiversity factor alpha. In contrast, Giglio et al. (2023) provided a few biodiversity risk measures in the United States by building their own data.

This article differs from Garel et al. (2024) and Coqueret and Giroux (2023) in a number of ways. Firstly, in this article, the firm-level risk exposure of land use, as the main driver of biodiversity loss, is linked to stock returns. In contrast, the other two articles

[2]This statement reflects the state of research as of October 2023 when this chapter was drafted, to my best knowledge.

indicate that the climate-related driver of biodiversity loss is playing a key role in stock returns. Garel et al. (2024) and Coqueret and Giroux (2023) mention that even if there is a biodiversity risk premium, it comes from the climate-related driver of biodiversity loss. Instead, I show that the land use driver of biodiversity loss is associated with stock returns.

A second way in which this article contributes to the literature is that I study the MSCI ESG Ratings – Refinitiv Datastream merged data of 21,248 stocks (of 17,002 firms) in 117 countries from April 2016 to June 2023, which covers a much larger number of stocks in a wider range of countries in the world and over a longer time horizon.[3] The corporate biodiversity footprint data from Iceberg Data Lab is detailed, but only covers from 2018 to 2021. Consequently, the monthly returns in Garel et al. (2024) are between 2019 and 2022 (with biodiversity data lagged for 1 year to the returns data). They have 2,025 firms from 32 countries in the final sample after filtering and merging.

The third different aspect is that I explore corporate biodiversity incidents from the RepRisk Premium V2 database from January 2007 to December 2022, and merge it to the MSCI-Datastream data mentioned above for further event studies of the impact of biodiversity incidents on stock returns. This data set of biodiversity incidents has not been studied in the literature to date. It contains actual firm-level risk incidents of biodiversity loss linked to corporate actions, representing a vital means by which to identify channels or links between biodiversity loss and how this risk is priced in equities.

The fourth dissimilarity is that I perform a disaggregated assessment of corporate biodiversity loss risk exposures using granular components of the "E" pillar in MSCI ESG Ratings. In the robust check section of Garel et al. (2023), they also investigate the cross-sectional returns on the MSCI Biodiversity & Land Use (*BLU*) risk exposures matched to

[3]The 117 countries (markets) include sovereign countries and non-sovereign states or regions with valid ISO alpha-2 codes.

firms in their data sample. Likewise, I conduct the same test in the main empirical section, but with a more comprehensive dataset as described above and with other biodiversity-related risk exposures from MSCI. Furthermore, I address the potential issue that the MSCI Biodiversity & Land Use (*BLU*) risk exposure could be overly focusing on the land use as a driver of biodiversity loss while neglecting other environmental drivers, by creating synthetic biodiversity risk exposures that include other drivers, such as water stress, pollutions, wastes, and carbon emissions/footprints, available in the MSCI data. These synthetic measures are based on the IPBES assessment of biodiversity loss drivers and how they link to the goals and targets of the COP 15 Kunming-Montreal Global Biodiversity Framework. Furthermore, to eliminate the concern that biodiversity loss could be the "re-branded" or "re-packaged" climate change or other environmental issues, I empirically show that the land use driver of biodiversity loss is indeed the main driver, which cannot be explained away by other drivers or environmental issues such as climate, pollution, or wastes.

As for the fifth difference, I examine the global stock markets, as well as comparing the US market and the non-US markets for differences, and breaks the observation period into the pre- and post-Kunming Declaration periods in each of the scopes of market. The US results in this article are distinguished from those in the rest of the world, which is not demonstrated in Garel et al. (2024) or in Coqueret and Giroux (2023) as they focus on the US only.[4]

Finally, I adopt both the long-short portfolio "alpha" approach similar to Coqueret and Giroux (2023), and the cross-sectional "beta" approach on corporate biodiversity risk exposures similar to Garel et al. (2023), but for the world, the US, and the non-US world, respectively. Important insights arise from the exercises of cross-validation

[4]Coqueret and Giroux (2023) perform portfolio sorting and apply the long-short portfolios approach in the US markets only, whereas I conduct the long-short portfolio analysis not only in the US market, but also outside the US and in the global market as a whole.

through multiple asset pricing methods.

It is also important to distinguish my work from that of Giglio et al. (2023), their US study of biodiversity risks. Giglio et al. (2023) build several biodiversity measures for the US market at different levels such as the market level and the firm level. Their aggregate-level measures, represented by the Monthly Google Biodiversity Attention Index, and the Daily New York Times Biodiversity Risk Indices, are obtained through textual mining techniques. Their firm-level biodiversity scores are based on analyzing public firms' 10-K disclosure of biodiversity-related sentiments. They also provide industry-level, county-level, and country-level biodiversity scores. Their long-short portfolios are primarily sorted on industry-level risk exposure and in the US market only, while the long-short portfolio in this article is sorted based on various firm-level biodiversity risk exposures for global markets, the US market, and non-US markets. There is a potential concern that portfolios sorted by industry-level biodiversity risks capture industry discrepancies instead of differences in corporate biodiversity risk exposures. My study uses firm-level biodiversity risk exposures based on granular data from the MSCI ESG Ratings Expanded File and corporate biodiversity incidents from RepRisk Premium V2 instead of the self-disclosure biodiversity sentiment from the 10-K files of firms. I also compute the aggregate counts of biodiversity incidents in the US as the aggregate-level measure.

My own study, as well as those of others that examine biodiversity risk pricing, contribute substantially to the broader scope of finance literature on the environmental pillar (as the "E" in ESG) and other environmental issues. Pástor, Stambaugh, and Taylor (2021, 2022) and Karolyi, Wu, and Xiong (2023) study green asset returns. Bolton and Kacperczyk (2021, 2023) and Zhang (2024) investigate carbon risks and returns. In addition to the above, Hsu, Li, and Tsou (2023) study the pollution premium and find that higher toxic emissions are linked with higher returns.

There are four main findings in this study. In the first experiment, I build long-short portfolios on nature-positive (i.e., low-risk) and nature-negative (i.e., high-risk) stocks classified by biodiversity risk exposures. I uncover a positive "biodiversity alpha" in the United States prior to the Kunming Declaration in October 2021.[5] However, it becomes a larger negative alpha after October 2021 such that it cancels the overall alpha during the observation period from April 2016 to June 2023. There is no significant "biodiversity alpha" outside the US either before or after the Kunming Declaration. In general, it does not exist in the global markets as a whole, subsuming the US-specific effect.

The second experiment examines the cross section of stock returns on biodiversity risk exposures, following the Bolton and Kacperczyk (2023) style panel regressions. I find that higher company biodiversity risk exposures are associated with higher stock returns globally. This effect is mainly due to observations made after the Kunming Declaration. There is mixed evidence of whether the correlation between biodiversity risk exposure and stock returns is positive or negative prior to the Kunming Declaration around the world, depending on countries, industries, and time periods of observation. In the US, the relationship between biodiversity risks exposures and stock returns is stronger than in the rest of the world, especially after the Kunming Declaration. The "biodiversity beta" pre-Kunming declaration is negative in the US, but later turns positive and becomes stronger both in importance and in magnitude. Moreover, the "biodiversity beta" in cross-sectional returns cannot be explained by other environmental betas such as the "carbon beta". This applies to the world markets, the US market, and the non-US markets.

In my third experiment, I further examine corporate-related biodiversity risk incidents around the world and link them to stock returns patterns in event time. According to RepRisk Premium V2, biodiversity incidents occur in almost all countries, all industries, and throughout the month of January 2007 to December 2022. Biodiversity incidents and

[5]Throughout this paper, I refer to the biodiversity long-short portfolio alpha as the "biodiversity alpha" or the "PMN alpha", where PMN stands for nature-positive (i.e., low-risk) minus nature-negative (i.e., high-risk). Alternatively, PMN (nature positive-minus-negative) can be viewed as an analogue to the GMB (green-minus-brown) as in Pástor, Stambaugh, and Taylor (2022), and Karolyi, Wu, and Xiong (2023).

the companies involved may vary from time to time, but with an increasing trend around the world, while it is relatively stable in the US. Larger economies or countries with richer biodiversity resources or natural capital tend to experience more biodiversity incidents. The frequency of biodiversity incidents also varies among industries and topic tags (i.e., aspects of biodiversity incidents) in different regions of the world. Biodiversity incidents occur more frequently than other environmental problems such as climate- and pollution-related incidents.

The last experiment links back to the first and the third experiments. The monthly returns and alphas of the PMN portfolio of biodiversity in the US market could be negatively predicted by shocks in monthly total biodiversity incidents of US companies two months ahead. At the enterprise level, after the Kunming Declaration, companies that experience biodiversity incidents in a month have a higher monthly average return than companies that do not in that month. This effect exists throughout the world, but is more significant in the United States than in the rest of the world. The intensive margin of additional incidents is less important than the extensive margin of existence. In addition, companies that encounter biodiversity incidents in one month have increased monthly stock returns compared to their returns in the previous month, compared to companies that do not encounter biodiversity incidents in the same month. This effect is also stronger in the United States during the study period from April 2016 to June 2023.

The remainder of the paper follows this structure. Section 1.2 describes the data, measurements of biodiversity risk exposures, biodiversity incidents, and summary statistics. Section 1.3 discusses the construction of the biodiversity long-short portfolio and the pricing factor tests. Section 1.4 investigates the relations between the cross section of stock returns and firm-level biodiversity risk exposures. Section 1.5 presents the impact of aggregate biodiversity incidents on returns of biodiversity long-short portfolios, and how firm-level biodiversity incidents affect stock returns cross-sectionally. Section 1.6

concludes.

1.2 Data and Descriptive Statistics

1.2.1 MSCI ESG Ratings – Refinitiv Datastream Merged Data

The data cleaning, merging, and filtering processes of the MSCI ESG Ratings – Refinitiv Datastream merged dataset (hereafter, MSCI-Datastream merged) are described in Figure 1.1 and Table 1.2. The coverage of stocks and markets is shown in the Appendix Table 1.A.1.

In addition, Table 1.1 explains the reasoning of choosing the standalone biodiversity-related risk exposures and computing various synthetic biodiversity measures. This article follows the IPBES Assessment of the driving factors of biodiversity loss and the goals of the Kunming-Montreal Global Biodiversity Framework when selecting and constructing biodiversity risk exposures from available and relevant data points in the MSCI ESG Ratings Expanded File.

There are no readily available synthetic biodiversity risk exposures readily available in the MSCI data, while some may be concerned that the *BLU* (Biodiversity & Land Use) risk exposure primarily captures the risk from land use while downplaying the importance of other contributing drivers of biodiversity loss. To address this concern, I created several equal-weighted and unequal-weighted synthetic biodiversity risk exposures, with the consideration of other aspects, such as water stress, pollution and wastes, and impacts on biodiversity loss through climate change, beyond just the land use driving factor. I provide different ranges of inclusion of other biodiversity loss driving factors to mitigate the concern about whether synthetic biodiversity risk exposures are hijacked by risk exposures from other environmental issues such as carbon emissions or climate change. In addition, in Table 1.8, Figure 1.3, and Figure 1.A.1, I compare the land use driver of biodiversity loss against other drivers in the biodiversity risk-sorted portfolio returns and the biodiversity risk exposure beta in the cross-section of stock returns to show their differences. In addition, I improve the contrast between differences between biodiversity loss and other environmental issues by showing topic tags of different types of environmental incidents from RepRisk as described in Section 1.2.3 below.

Regarding the weighting scheme in the unequal-weighted version of synthetic biodiversity risk exposures, there are no detailed guidance or readily available weighting scheme of different underlying standalone risk drivers (exposures). Hence, the weighting schemes in unequal weighted synthetic measures are chosen on the basis of the IPBES assessment report on the contributions of key drivers to biodiversity loss, as well as the simplicity of calculation. The weights do not have to be assigned according to the plan in Table 1.1 Panel D. They may be viewed as a robustness check of the equal-weighted scheme of different biodiversity loss drivers due to different environmental issues.

1.2.2 Global Pricing Factors

The pricing factors used in this article follow the Fama-French-Carhart (FFC) 6 factors, $(Mkt - RF)$, SMB, HML, RMW, CMA and Mom, as in Fama and French (1993, 1998, 2012, 2015, 2017) and Carhart (1997). $(Mkt - RF)$ is the market return excess of the risk-free rate. The size factor is denoted as SMB, while HML stands for the value factor. The profitability and investment factors are RMW and CMA, respectively. The momentum factor is Mom (or UMD, WML) in abbreviation. These 6 factors collectively are referred to as the "FFC 6 factors" in this article, and hence the "FFC 6 factors model". All factors are at the monthly level. The US version of the data is from Ken French's website.[6]

The global version of the FFC 6 factors is from Karolyi and Wu (2018) and Karolyi, Wu, and Xiong (2023). It is computed following the same methodology as the FFC 6 factors for the US, but based on stocks in the major 46 markets in the world. They are highly representative and account for the vast majority of stocks in the global markets. These 46 markets are further grouped into 5 representative regions, North America, Europe, Japan, Asian Pacific, and Emerging Markets, according to their similarities. The North America region contains the United States and Canada. The Europe region is composed of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and UK. Japan stands alone for the Japan stock market because of its uniqueness. The Asia Pacific region contains Hong Kong, Singapore, Australia, and New Zealand. Last but not least, the Emerging Markets include China, India, Indonesia, Malaysia, Philippines, South Korea, Taiwan, Thailand, Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela, Israel, Turkey, Pakistan, South Africa, Czech Republic, Poland, Hungary, and Russia. Similarly, the regional version of the FFC 6 factors is computed based on the stock markets within each region.

1.2.3 RepRisk Premium V2 Biodiversity Incidents

The firm-level biodiversity risk incidents are from the Incidents File (dataset) of the RepRisk Premium V2 database. It contains all kinds of ESG incidents that can be linked to entities such as firms globally from January 2007 to December 2022. Under the Environmental Pillar (as the "E" in ESG), there are 6 issues according to the RepRisk classification. They are "impacts on landscapes, ecosystems, and biodiversity", "local

[6]See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

pollution" (in land and water), "climate change, GHG emissions, and global pollution" (atmospherically), "waste issues", "overuse and wasting of resources", and "animal mistreatment". For brevity, I may refer to them as biodiversity, pollution, climate, wastes, resources, and animal mistreatment incidents in the rest of this article, respectively.

Biodiversity Incidents and Other Environmental Incidents

Table 1.3 Panel A summarizes the total number of firm-level incidents for each environmental issue, in the world, the US, and the non-US world. Each firm is uniquely identified by the "RepRisk ID", and each incident by the "Story ID". An incident can involve multiple firms based in the same or different countries by headquarters. The incidents are aggregated into regions by the headquarters of the involved companies. Therefore, the sum of the US number and the non-US number of incidents can add up to more than the number of incidents in the world.

Biodiversity incidents rank first globally, as well as inside and outside the United States. There were 51, 869 biodiversity incidents in the world from January 2007 to December 2022, which was much more than the total climate incidents of 18,739, or the pollution incidents of 41,321, among the top three. The bottom three are wastes, resources, and animal mistreatment incidents, which are clearly less than those of the top three. Biodiversity incidents in the US account for almost 30% of the world's biodiversity incidents, and it is also about three times the number of US climate incidents. A similar biodiversity-to-climate incidents ratio holds in the world and outside the US. The non-US ranking of different environmental issues is the same as that in the world, while the last two rankings of resources incidents and animal mistreatment incidents are flipped in the US.

Table 1.3 Panel B displays the firm-incident observations across environmental issues, as an incident can involve multiple firms. There are about 3 to 6 times of firm-incident observations relative to incidents counts, which indicates that an environmental incident could involve 3 to 6 firms on average.

The word clouds of the biodiversity issue topic tags in Figure 1.5 can give a bird's-eye view of what falls under biodiversity incidents in general. It can also help visualize the concrete difference between biodiversity and climate or pollution issues in people's prior beliefs.

Furthermore, Figure 1.A.2 gives a straightforward visualized comparison of the topic tags involved in each environmental issue, for the world, the US, and the non-US world, respectively. Moreover, each type of environmental incidents is clearly distinguishable from one another, while some of them are also correlated in terms of shared topic tags. For example, land ecosystems, protected areas, marine/costal ecosystems, and land grabbing are the top-ranked topic tags for biodiversity incidents worldwide. In contrast, greenhouse gas (GHG) emissions, and coal-fired power plants are the most eye-catching ones. Although airborne pollutants and coal-fired power plants are shared across the climate incidents and pollution incidents due to their negative impacts in both territories, pollution incidents also include other aspects such as protected areas and plastics with respect to land and water pollutions. Wastes issues primarily involve wastewater management, nuclear power, as well as plastics. Resources incidents refer to water scarcity, energy management, fracking, and other topic tags. Animal mistreatment topic tags includes animal transportation, fur and exotic animal skins, and endangered species.

Some environmental topic tags, such as the coal-fired power plants, can exist across multiple issues. The upstream coal mining process damages landscapes and habitats for species, which counts into biodiversity issues. Pollution occurs during the transportation of coal to the power plants and includes the toxic emissions after burning. Of course, the power plant emissions also include the much-emphasized greenhouse gases such as carbon dioxide in climate finance research. However, only focusing on the climate or carbon impacts from environmental issues such as coal-fired power plants is an over-simplification of their dimensionality.

The font sizes of the topic tags in the word clouds in Figure 1.5 and Figure 1.A.2 are decided by a combination of the rankings of the topic tags in the relative frequency and the absolute frequency, but leaning toward the relative ranking approach to avoid a too large or too small topic tag visually. Therefore, a large font size means a higher ranking in topic tag frequency, but is not completely proportional to the absolute frequency. The detailed distribution and ranking of biodiversity incidents across topic tags are reported in Table 1.4. Some incidents can involve multiple topic tags.

Biodiversity Incidents Across Industry Sectors

Table 1.5 demonstrates the distribution and ranking of biodiversity incidents across sectors. Mining, oil and gas, utilities, food and beverage, construction and materials are the top 5 sectors with biodiversity incidents in the world, while the top 5 sectors and ranking are slightly different in the US. The least biodiversity incidents are reported in the airlines, tobacco, and gambling sectors. The sectors of technologies and equipment, as well as healthcare, are among the ones with lower incidents. Financial firms and banks are misrepresented in the incidents ranking as their names could also appear in news articles reporting biodiversity incidents involving their clients or companies they held, although they may not be directly involved. However, from a different aspect, this may also post a biodiversity reputational risk for them through incidents-involved companies in other industries that are linked to them financially.

Biodiversity Incidents in Each Month

Figure 1.6 Panel A shows the monthly frequency of biodiversity incidents in the world, the US, and non-US markets, respectively, from January 2007 to December 2022, while panel B shows firms involved in biodiversity incidents each month. The monthly incidents in the US increased slowly from January 2007 to July 2014 and remained relatively stable afterwards with minor fluctuations, and the monthly incidents were all below 200. The increasing of non-US incidents accelerated from about the beginning of 2019 around 200 to the amount of roughly 600 at the end of 2022. Both the increasing trend and the fluctuation of firms involved in biodiversity incidents per month are much more dramatically outside the US, compared to non-US monthly incidents count in Panel A. Monthly firms with incidents increased from about 100 in January 2007 to an oscillating range of 800 to 1600 during the months in 2022. However, the US firms involved in biodiversity incidents increased mildly during the same period and were mostly around the 200-level while never going beyond 600.

Biodiversity Incidents in Each Country

Next, Figure 1.7 contains two pie charts displaying the fractions of biodiversity incidents in all countries indexed by ISO alpha-2 country codes.[7] The distribution in Panel A is by countries of the firm headquarters, while panel B is by countries related to incident. A company can be based in one country but operates in multiple countries, while biodiversity incidents can occur during the economic activities of a company, presumably anywhere on earth. Biodiversity incidents exist in almost all countries. There are 211 countries which had experienced biodiversity incidents from January 2007 to December

[7]These include sovereign countries and non-sovereign states or regions whichever have ISO alpha-2 codes. Therefore, the number of unique alpha-2 codes could be more than the 193 Member States in the United Nations by the time this article is written.

2022 as headquarter countries, while 227 countries had been incident-related countries. The US ranks first in both distribution methods in terms of biodiversity incidents, accounting for about 17% percent of incidents worldwide. The UK (GB) ranks second by company headquarters country for about 8% of biodiversity incidents worldwide, while Brazil (BR) ranks second by incident-related country for about 6% of global biodiversity incidents. These two pie charts suggest that biodiversity incidents tend to occur more frequently in larger economies or countries which are richer in natural capital.

1.3 Biodiversity Long-Short Portfolio Performances

This section studies the long-short portfolios of stocks sorted by various biodiversity risk exposure measures introduced in Table 1.1. The stocks are sorted into terciles of portfolios in the global market, in the US market, and in the non-US market, respectively. The top tercile (high-risk) portfolio is defined as the biodiversity nature-negative portfolio, while the bottom tercile (low-risk) portfolio is the nature-positive portfolio. The biodiversity nature-PMN (hereafter PMN) portfolio is defined as the nature-positive portfolio minus the nature-negative portfolio. And this PMN portfolio construction is performed on the global market, the US market, and the non-US market, respectively. The representative 46 major markets are used as the global market sample and, hence, the major 45 non-US markets for the non-US world.

1.3.1 Biodiversity Nature-PMN Portfolio

Figure 1.2 shows the cumulative returns from April 2016 to June 2023 for the nature-positive and nature-negative portfolios. In Panel A for the global markets, the cumulative returns of the two portfolios remain very close to each other until the

Kunming Declaration in October 2021. Before that, the nature-positive portfolio slightly outperformed the nature-negative portfolio, while the nature-negative portfolio has outperformed the nature-positive one after the Kunming Declaration. Comparing the non-US markets to the US market in Panel B, the nature-negative portfolio has outperformed the nature-positive portfolio since the beginning of the observation period. In contrast, the US nature-positive portfolio had widened its lead over the nature-negative portfolio until October 2021, but there is a dramatic drop in the nature-positive portfolio performance afterward, and hence shrunk the gap.

Furthermore, Figure 1.3 illustrates the evolution of the PMN portfolio. The world PMN portfolio in Panel A mostly remained flat around 0 from June 2016 to October 2021 and experienced a drop after the Kunming Declaration and then stayed around -20% afterward. In Panel B, the non-US world PMN portfolio is always negative and gradually decreased from slightly less than 0 in April 2016 to about -30%. However, strikingly, the cumulative return of the PMN portfolio in the US market went from around 0 in April 2016 to about 50% around October 2021 and then dramatically decreased after the Kunming Declaration to the territory of 0 to 10%.

Panel C and D in Figure 1.3 compare the PMN portfolio based on the *BLU* (Biodiversity & Land Use) risk exposure, the CE (Carbon Emissions) risk exposure, and the PCF (Product Carbon Footprint) risk exposure. This serves as an comparison between biodiversity loss and climate change. And these two issues are clearly different in terms of their impact on portfolio returns according to their different patterns in this figure, for the global market, US market, and non-US markets.

Moreover, Figure 1.4 shows the cumulative returns for PMN portfolios constructed by different biodiversity risk exposures. *BLU* is the standalone biodiversity exposure, while BW, BWTEP, and BWTEPCP are synthetic biodiversity risk exposures as introduced in Table 1.1 with different weighting schemes. The pattern of cumulative PMN portfolio returns for the synthetic measures is similar to that of *BLU* in the global market and the non-US market. There are larger variations across the portfolio by different measures in the US market before the Kunming Declaration due to the different performance from underlying aspects of water stress, pollution and wastes, and carbon emissions and footprints. However, their main patterns are consistent in terms of a gradual increase since April 2016 but a dramatic drop after the Kuning Declaration in October 2021. Their differences mainly lay in the magnitude of the increasing trend before Kuming. In addition, the cumulative returns of the PMN portfolio for the unequal-weighted synthetic biodiversity measures are higher than those of the equal-weighted measures for BWTEP and BWTEPCP, when compared between Panels C and D.

1.3.2 Biodiversity Nature-PMN Performance

In this subsection, I run time-series pricing factor regressions to test the PMN return against other prevalent pricing factors as introduced in Section 1.2.2, which are the global and US versions of the Fama-French 5 factors with the Carhart momentum factor.

Table 1.6 shows PMN factor regression results in the US market, for PMN portfolios constructed on different measures of biodiversity risk exposures. The PMN portfolios sorted on most of the biodiversity risk exposures do not generate a significant abnormal return when including the FFC 6 factors in the regressors, looking at the full sample period from April 2016 to June 2023. The only exception is the PMN portfolios based on the BW measures. However, if adding a post-Kunming Declaration dummy in the regressors to the sample period into the pre-Kunming and post-Kunming periods, there is a positive alpha from 0.4% to 0.75% in different specifications of biodiversity risk exposures with the FFC 6-factor model as in Panel B. However, the post-Kunming alphas are significantly negative and with a much larger magnitude, ranging from -1.14% to -

1.53%.

Furthermore, testing the PMN portfolio sorted by *BLU* risk exposure in models with different combinations of pricing factors, as shown in Table 1.6 Panel C for the US market, the pre-Kunming alpha is significantly negative across all model specifications, ranging from 0.45% to 0.63%. In contrast, the post-Kunming alpha is significantly negative across all models, varying from -1.44% to -1.97%. Similarly, Panel D and E repeat the same tests, as for *BLU* in Panel C, on various synthetic biodiversity measures. The same conclusion holds in most model specifications for various biodiversity measures.

However, things are different outside the US, and hence in the global market. Table 1.7 repeats the same set of tests for the non-US and global markets. Similarly to the US market results, there is no significant alpha during the overall observation period, as shown in Panel C and Panel D. In contrast to the US market results regarding the pre- and post-Kunming Declaration differences, there were no significant alphas either before or after the October 2021 Kunming Declaration. Although only the FFC 6-factor model results are reported in Table 1.7, similar results hold in the unreported tests with different combinations of pricing factors.

1.4 Cross-Sectional Returns and Biodiversity Risk Exposures

This section studies the cross-section of monthly stock returns and biodiversity risk exposures, mostly following the Bolton and Kacperczyk (2023) methodology but with necessary customizations. There are two subsections.

The first subsection compares the effect of firms' *BLU* risk exposures on the cross-sectional stock returns versus those of the other 6 standalone risk exposures based on biodiversity-related MSCI environmental key issues, as introduced in Table 1.1. The goal is to show the BLU (i.e., Biodiversity & Land Use) risk exposure is different from other risk exposures such as CE (Carbon Emissions) in terms of their impact on stock returns. Moreover, the standalone BLU risk exposure is also the core of all other synthetic biodiversity risk exposures. It is important to establish that the BLU risk exposure alone can capture a firm's biodiversity risk exposure, and its influence on stock returns will not be absorbed away by other standalone environmental risk exposures.

The second subsection investigates further into the BLU risk exposure alone by analyzing its correlation with stock returns during the full sample period from April 2016 to June 2023, as well as the pre- and post-Kunming Declaration periods.

1.4.1 Cross-Sectional Returns: BLU vs. Other Biodiversity-Related Risk Exposures

Table 1.8 compares BLU against CE, PCF, WS, TEW, PMW, and EW, as defined in Table 1.1, from the aspects of their impacts on stock returns. All model specifications include the full set of controls similar to Bolton and Kacperczyk (2023) as described in the caption of Table 1.8, as well as all the fixed effects of year-month, country, and ESG industry.

There is a significant and positive beta coefficient on the BLU risk exposure worldwide, as shown in Model (1). Note that all MSCI-based risk exposures are within the range of [0, 10] by construction. Therefore, a 1-point increase in the BLU risk exposure will yield 0.1134 percentage points of increase in monthly stock returns on average during the full sample period. There is no significant beta coefficient on the CE (Carbon Emissions) risk exposure while the magnitude is 0.0523 negatively, as displayed in Model (3).

Putting together the BLU and CE risk exposures as the key regressors in Model (3), the positive effect of *BLU* on returns gets enhanced, as a 1-point increase in the *BLU* risk exposure now correlates with 0.1379 percentage point increase of monthly returns. Interestingly, the beta coefficient on *CE* is now significantly negative, meaning that a 1-point increase in the *CE* risk exposure will now decrease the stock return by 0.0881 percentage point. This shows that the carbon emission risk exposure cannot explain away the impact on stock returns from Biodiversity & Land Use risk exposure. Instead, they are significantly opposite to each other when they exist together in the same model.

Similarly, when performing the pairwise comparison by placing the *BLU* risk exposure with other standalone risk exposures one on one from Model (4) to Model (8), none of them can explain away the significantly positive beta coefficients on the BLU risk exposures, ranging from 0.1138 to 0.1379.

Model (9) uses *BLU* and all other 6 risk exposures as the key regressors together, and still the *BLU* beta coefficient is significantly positive while the magnitude even increases to 0.1387.

So far, Model (1) to Model (9) are all for the global market, including all markets in the merged MSCI-Datastream dataset as described in Figure 1.1 Panel C and the last row in Table 1.2. Model (10) and (11) apply the Model (9) style regression to the US market and the non-US markets, respectively. The same conclusion holds that even the 6 standalone risk exposures together cannot explain away the significantly positive beta coefficient on the *BLU* risk exposure. One distinction is that a 1-point increase in *BLU* risk exposure in the US will increase stock returns by 0.1579 percentage points, which is more than the 0.1322 percentage point increase in non-US markets.

1.4.2 A Closer Look at the Cross-Section of Returns and BLU Risk Exposures

Next, I further examine the cross-sectional returns on the core standalone biodiversity risk exposure *BLU* across different model specifications and with a dummy for the pre- and post-Kunming Declaration periods for potential structural breaks around that influential event on biodiversity. Table 1.9 reports the results for the world, the US, and the non-US world, in Panel A, B, and C, respectively.

Table 1.9 Panel A starts with the global results. Each pair of neighboring models with a smaller odd model number and a larger even model number, such as Model (1) and Model (2), share the same model specifications in terms of controls and fixed effects. The difference is that the even-numbered model, for example, Model (2), also includes a post-Kunming dummy and its interaction term with *BLU*. Since most of models also include the year-month fixed effect, the coefficient on the dummy itself is always 0, so is the standard error of it. For models with the interaction term, the base *BLU* beta coefficient captures the effect of *BLU* biodiversity risk exposure on monthly stock returns, int the period before the Kunming Declaration. The coefficient on the interaction term of the post-Kunming Declaration indicator, After KM, and the *BLU*, captures the change from the baseline beta coefficient to the post-Kunming Declaration beta coefficient. Taking Model (2) for example, the pre-Kunming Declaration beta coefficient on *BLU* is 0.0322 but not significantly different from 0. The post-Kunming beta is 0.2283 significantly more than the pre-Kunming beta. Therefore, it can be viewed as 0+0.2283=0.2283, which means that in a 1-point increase in the *BLU* risk exposure in the post-Kunming period will lead to 0.2283 percentage point increase in monthly returns on average. In addition, Model (1) result indicates that the beta coefficient on the *BLU* risk exposure is positive and significant during the full sample period pre- and post-Kunming. A 1-point increase in *BLU* risk exposure is associated with 0.1134 percentage point increase in average monthly return. Model (1) and Model (2) results indicate that the positive *BLU* beta is primarily coming from the post-Kunming observations, while there is no significant beta pre-Kunming Declaration. The model setup in these two models and their results are consistent with the robustness check results using a small subset of the MSCI *BLU* data as in Garel et al. (2023).

Moreover, going from Model (1) to Model (10) in Table 1.9 Panel A, it is obvious that different inclusion and exclusion of fixed effects will affect the overall sample period BLU beta and the pre-Kunming BLU beta, while little change is on the post-Kunming BLU beta, which is significantly positive and ranges from 0.2283 to 0.2618. Notably, after dropping the country fixed effect, the ESG industry fixed effects and year-month fixed effects as in Model (9) and Model (10), the overall period BLU beta is non-significantly positive, while the pre-Kunming BLU beta is significant negative, while the magnitude is less than 1/3 of that of the post-Kunming BLU beta. A similar pattern shows up in Panel B for the US and Panel C for the non-US markets as well. However, the pre-Kunming BLU beta is all negative throughout different model specifications in the US market, although its significance level varies.

The last model without fixed effects in Table 1.9 Panel B for the United States speaks to the US PMN results in Figure 1.3 and Table 1.6 in Section 1.3. The cross-sectional BLU risk and return relation before Kunming in the United States is "higher risk, lower return," which corroborates the increasing cumulative PMN return or the positive PMN alpha. However, after the Kunming Declaration, the relation has flipped to "higher risk, higher return" or "lower risk, lower return" alternatively. A similar switch in the global market can also be observed in Table 1.9 Panel A Model (10), and Figure 1.2 Panel A.

In Table 1.9 Panel B, the country fixed effects in all models are omitted because there is only the US market. The post-Kunming BLU beta in the US is much stronger than that in the non-US markets, regardless of model specifications.

The results in Table 1.9 and Section 1.3 suggest that biodiversity risk was priced relatively inefficiently before the Kunming Declaration, and was underpriced. In addition, companies with a larger nature-negative impact on biodiversity may be exposed to risks associated with biodiversity loss and other regulatory actions to mitigate their impact. After the Kuning Declaration, forward-looking investors may demand compensation for their biodiversity nature-negative portfolio holdings, which expose them to higher biodiversity risk. That demand may elevate a positive cross-sectional relationship between a firm's stock return and its biodiversity risk exposure, and this corroborates the hypothesis of biodiversity risk premiums in markets after the Kunming Declaration. Similarly, they may also sell down their nature-positive portfolio due to a lower expected return in the future, but not necessarily increase their nature-negative holdings for higher biodiversity risk exposures.

1.5 Impact of Biodiversity Incidents on Stock Returns

This section discusses the relations between RepRisk biodiversity incidents and stock returns in three subsections. The first subsection studies whether the total number of biodiversity incidents in the US can explain or predict the biodiversity PMN factor performance in the US. The second subsection investigates whether the occurrence of biodiversity incidents to firms will affect their stock prices worldwide. The last subsection discusses difference-in-differences analysis on the monthly changes of stock returns for global firms experiencing biodiversity incidents in a month, compared to firms which do not.

1.5.1 The US Biodiversity PMN Factor Performances and Aggregate Biodiversity Incidents

I compute the total number of RepRisk biodiversity incidents involving companies that have their headquarters in the US per month. Next, the prediction error from rolling AR(1) models is applied to the aggregate count of incidents as the measure of biodiversity incident shocks in the US each month from April 2016 to June 2023. The unit of the aggregate incident count is in the hundreds. By trial and error, I also include the lagged 1- and 2-month shocks as the regressors. Adding more lags will not bring additional significance. The results are displayed in Table 1.10.

Panel A of Table 1.10 regresses various versions of biodiversity PMN returns on the lagged 2-month, lagged 1-month, and contemporaneous-month shocks. The results are from Model (1) to Model (7) for the PMN returns based on the standalone BLU and synthetic biodiversity risk exposures as discussed in Table 1.1. Only the coefficients on the lagged 2-month shocks are significant, and the magnitudes range from -0.67 to -0.42 among Model (1) to Model (7). Taking the Model (1) results for example, every 100 more firm-level biodiversity incidents two months ago in the US as a shock in aggregate incidents estimated by the AR(1) model will contribute to a decrease of 0.64 percentage point of PMN returns per month. Models (9) to (15) further test whether the explanatory power only comes from lagged 2-month shocks or biodiversity incidents. This turns out to be the case, and all the coefficients are significant and negative, ranging from -0.72 to -0.40.

Table 1.10 Panel B investigates the PMN alphas instead. Similar results hold as in Panel A. The lagged 2-month shocks are contributing to the decrease of PMN alphas, ranging from -0.66 to -0.53 percentage point decrease per 100 incidents as shocks two months ago, in Model (1) to Model (10) with shocks in the two lagged months and the contemporaneous month. If looking at only the lagged 2-month shocks as displayed in Model (9) and Model (15), the conclusion also holds with a magnitude range from -0.61 to -0.45 percentage point decrease in PMN alpha per 100 incidents in shocks two months ago. One difference compared to Panel A is that the contemporaneous month shock in some models also contributes to the decrease of PMN alpha around -0.40 percentage point.

The fact that only the coefficient on the lagged 2-month version of aggregate biodiversity incidents shocks is significant probably captures the time needed for RepRisk to collect the incidents data and for investors (i.e., users of RepRisk data) to make investment decisions accordingly.

1.5.2 The Cross-Section of Stock Returns and Corporate Biodiversity Incidents

The dataset used in Section 1.5.2 and Section 1.5.3 is the MSCI-Datastream-RepRisk merged data. It is constructed by matching the RepRisk global biodiversity incidents data with the MSCI-Datastream merged dataset from April 2016 to June 2023 as described in Figure 1.1 Panel C and the last row of Table 1.2. The linkage is performed through ISIN codes after calculating how many biodiversity incidents occurred in each month for each ISIN code.

Table 1.11 studies the extensive margin and the intensive margin of the effect of companies experiencing biodiversity incidents on their stock returns. Panel A reports the extensive margin worldwide, following the panel regression in Bolton and Kacperczyk (2023), but including the dummy variable Yes_BI for firms experiencing any biodiversity incidents in a month. The odd-numbered models do not include the interaction term of

Yes_BI and the post-Kunming Declaration dummy $\{AfterKM\}$, while the even-numbered models do. That is, to show the impact of the Kunming Declaration and whether there are differences on the extensive margin of incidents on monthly stock returns. It turns out that, in general, during the full sample period, there is no significant correlation between biodiversity incidents and stock returns, although the magnitude of the coefficient is positive. However, when breaking down the observation period into the pre-Kunming Declaration and post-Kunming Declaration period, things are different. It can be seen that on average if a firm experiences any biodiversity incidents in a month during the post-Kunming Declaration period, its monthly return in that month is about 1.828 to 1.856 percentage points higher than firms which do not, at the 1% significance level.

Similar results hold in Table 1.11 Panel B and Panel C for the US market and non-US markets, respectively, which is that the significantly positive association between biodiversity incidents and monthly stock returns only appears in the post-Kunming Declaration period. However, the magnitude in the US is larger than that in the non-US markets. In the US, after the Kunming Declaration, firms experiencing biodiversity incidents in a month have month returns about 2.868 to 2.877 percentage points higher than other firms in the US which encountered no biodiversity incidents. In contrast, the magnitudes for that correlation in the non-US markets are merely 1.361 to 1.394 percentage points. This indicates that on average, the US markets seem to price biodiversity risk more than the other markets.

Panel D of Table 1.11 examines the intensive margin of the number of biodiversity incidents that a firm has in a month on its monthly stock return, conditional on having at least one biodiversity incident in that month. Due to data availability, this test can only be performed at the global level. It turns out that the intensive margin matters less than the extensive margin, although an additional incident contributes to about 0.227 to 0.233 percentage point increase in monthly returns significantly, the magnitude is much smaller compared to that of the extensive margin as shown in Panel A. This indicates that experiencing additional biodiversity incidents in a short period conditionally, the firm has already experienced one earlier in that month, is only priced incrementally into the firm's return of that month.

1.5.3 Difference-in-Differences of Stock Returns and Corporate Biodiversity Incidents

Relative to the research design in Table 1.11, Table 1.12 has an additional dimension of comparing the monthly return of the focal firms in the focal month to the previous month, rather than only cross-sectionally focusing on the focal month. Table 1.12 adopts a difference-in-differences design to compare the changes in monthly returns for firms experiencing biodiversity incidents in a month with firms that have no incidents. Panel A of Table 1.12 is for the world overall, and it is significant across all regression specifications that firms with biodiversity incidents in a month will have an increased monthly return in that month compared to the previous month for 0.423 to 0.530 percentage points depending on the model, compared to firms that do not encounter any biodiversity incidents in that month. There is no significant difference in the period before or after the Kunming Declaration, as this effect existed even before that.

Table 1.12 Panel B and Panel C repeated the Panel A study on the full sample period for the US and the non-US markets, respectively. Their results are consistent with the world overall sample, but there are slight differences in the magnitude. In the US, the difference-in-differences coefficient is 0.659 without the ESG industry fixed effects, while it is 0.888 with the ESG industry fixed effect. This suggests that there are industrial differences in the strength of this effect. In the non-US world, this coefficient is smaller across three model specifications, ranging from 0.265 to 0.310, and countries seem to matter in the magnitude.

1.6 Conclusion

The risks of loss of biological diversity have been gaining investor attention in global stock markets over the past few years, especially after the Kunming Declaration in October 2021, which is the first part of the UN Biodiversity Conference (COP15). The pricing of biodiversity risks into stock returns is even more notable in the US market.

Estimated by the long-short portfolio approach as of nature-positive and nature-negative portfolios sorted on biodiversity risk exposures, there was a positive "biodiversity alpha" in the US before the Kunming Declaration, but it turned into a strong negative alpha afterward and canceled the overall alpha during the observation period from April 2016 to June 2023. There is no significant "biodiversity alpha" outside the US market either before or after the Kunming Declaration. Hence, neither does it exist in the global market as a whole, overwhelming the US-specific effect.

Investigating into the cross section of stock returns on biodiversity risk exposures, following the Bolton and Kacperczyk (2023) style panel regressions, I find that higher biodiversity risk exposures of firms are associated with higher stock returns globally. This effect is primarily driven by observations after the Kunming Declaration. There is mixed evidence on whether the correlation between biodiversity risk exposure and stock returns is positive or negative before the Kunming Declaration worldwide, depending on countries, industries, and time periods of observations. In the US, the association between biodiversity risk exposures and stock returns is stronger compared to the rest of the world, especially after the Kunming Declaration. The "biodiversity beta" pre-Kunming Declaration was negative in the US, but turned positive afterward and became stronger both in significance and magnitude.

The “biodiversity beta” in the cross-sectional returns cannot be explained away by other environmental betas such as the “carbon beta”. It is held in the global markets, the US market, and the non-US markets.

In addition, I study company-related biodiversity risk incidents worldwide. Biodiversity incidents exist in almost all countries, all industries, and throughout all months from January 2007 to December 2022 according to data available in RepRisk Premium V2. Biodiversity incidents and firms involved can vary from time to time, but with an increasing trend globally, whereas it is relatively stable in the US. Larger economies or countries with richer biodiversity resources or natural capital tend to experience more biodiversity incidents. The frequency of biodiversity incidents also varies across industries and topic tags (or aspects of biodiversity incidents) in different regions of the world. Biodiversity incidents occur more often than other environmental issues such as climate- or pollution-related incidents.

The monthly biodiversity PMN portfolio returns and alphas in the US market could be negatively predicted by shocks in monthly aggregate biodiversity incidents of US-based firms two months ahead. At the firm level, after the Kunming Declaration, firms that experience biodiversity incidents in a month have higher monthly returns on average than firms which do not in that month. This effect exists worldwide, but is more salient in the US than in the rest of the world. The intensive margin of additional occurrences of incidents matters less than the extensive margin of existence. Furthermore, firms that encounter biodiversity incidents in a month have increased monthly stock returns compared to their returns in the previous month, in contrast to firms that did not experience biodiversity incidents in the same month during. This effect is also stronger in the US during the study period from April 2016 to June 2023.

Overall, the biodiversity loss risk may be underpriced globally due to the market inefficiency in its pricing before the Kunming Declaration in October 2021, while the biodiversity risk premium has emerged afterward, especially in the US.

REFERENCES

Bolton, Patrick, and Marcin Kacperczyk, 2021, Do investors care about carbon risk?, *Journal of Financial Economics* 142, 517–549.

Bolton, Patrick, and Marcin Kacperczyk, 2023, Global pricing of carbon-transition risk, *The Journal of Finance* 78, 3677–3754.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *The Journal of Finance* 52, 57–82.

Cherief, Amina, Takaya Sekine, and Lauren Stagnol, 2022, The market effect of acute biodiversity risk: The case of corporate bonds, *SSRN Electronic Journal* .

Coqueret, Guillaume, and Thomas Giroux, 2023, A closer look at the biodiversity premium, *SSRN Electronic Journal* .

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 1998, Value versus growth: The international evidence, *The Journal of Finance* 53, 1975–1999.

Fama, Eugene F., and Kenneth R. French, 2012, Size, value, and momentum in international stock returns, *Journal of Financial Economics* 105, 457–472.

Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F., and Kenneth R. French, 2017, International tests of a five-factor asset pricing model, *Journal of Financial Economics* 123, 441–463.

Flammer, Caroline, Thomas Giroux, and Geoffrey M. Heal, 2023, Biodiversity finance, *SSRN Electronic Journal* .

Garel, Alexandre, Arthur Romec, Zacharias Sautner, and Alexander f Wagner, 2024, Do investors care about biodiversity?, *Review of Finance* .

Giglio, Stefano, Theresa Kuchler, Johannes Stroebel, and Xuran Zeng, 2023, Biodiversity risk, *SSRN Electronic Journal* .

Hoepner, Andreas G. F., Johannes Klausmann, Markus Leippold, and Jordy Rillaerts, 2023, Beyond climate: 'eu taxonomy' criteria, materiality, and cds term structure, *SSRN Electronic Journal* .

Hsu, Po-Hsuan, Kai Li, and Chi-Yang Tsou, 2023, The pollution premium, *The Journal of Finance* 78, 1343–1392.

Junge, Lisa, Yu-Shan Lin Feuer, and Remmer Sassen, 2023, How could the financial sector contribute to limiting biodiversity loss? a systematic review, *SSRN Electronic Journal* .

Karolyi, G. Andrew, and John Tobin-de la Puente, 2023, Biodiversity finance: A call for research into financing nature, *Financial Management* 52, 231–251.

Karolyi, G. Andrew, and Ying Wu, 2018, A new partial-segmentation approach to modeling international stock returns, *Journal of Financial and Quantitative Analysis* 53, 507–546.

Karolyi, G. Andrew, Ying Wu, and William W. Xiong, 2023, Understanding the global equity greenium, *SSRN Electronic Journal* .

Kedward, Katie, Sophus O. S. E. zu Ermgassen, Josh Ryan-Collins, and Sven Wunder, 2022, Nature as an asset class or public good? the economic case for increased public investment to achieve biodiversity targets, *SSRN Electronic Journal* .

Pástor, L'uboš, Robert F. Stambaugh, and Lucian A. Taylor, 2021, Sustainable investing in equilibrium, *Journal of Financial Economics* 142, 550–571.

Pástor, L'uboš, Robert F. Stambaugh, and Lucian A. Taylor, 2022, Dissecting green returns, *Journal of Financial Economics* 146, 403–424.

Rizzi, Claudio, 2022, Nature as a defense from disasters: Natural capital and municipal bond yields, *SSRN Electronic Journal* .

Starks, Laura T., 2023, Presidential address: Sustainable finance and esg issues—valueversusvalues, *The Journal of Finance* 78, 1837–1872.

Zhang, Shaojun, 2024, Carbon returns across the globe, *The Journal of Finance,* forthcoming.

Table 1.1
Biodiversity Loss Drivers and Relevant Risk Exposures in the MSCI ESG Ratings Expanded File

This table indicates the sources and definition of the standalone and synthetic biodiversity risk exposure measures based on the MSCI ESG Ratings Expanded File and the IPBES Assessment / Kunming-Montreal Global Biodiversity Framework. Panel A is based on the Environmental Pillar portion of "Exhibit 1: MSCI ESG Ratings Key Issue Hierarchy" in the MSCI ESG Ratings Methodology guide. The variables directly impacting firm-level biodiversity risk exposures are sandwiched with asterisk marks and enclosed by a textbox. There is no risk exposure score for the "Raw Material Sourcing" key issue in the MSCI ESG Ratings data. "Climate Change Vulnerability" was previously named "Insuring Climate Change Risk." According to MSCI, "Insurance companies are assessed on the physical risk that climate change may pose to insured assets or individuals." The data coverage for this variable is insufficient. "Financing Environmental Impact" also has limited data coverage. MSCI methodology guide states, "Financial institutions are evaluated on the environmental risks of their lending and underwriting activities and their ability to capitalize on opportunities related to green finance." The above two key issues and those under the "Environmental Opportunities" theme are irrelevant to biodiversity risk. Details can be found in the key issue methodology and data dictionary. The "In Use" column indicates whether a key issue risk exposure is used in this study, requiring both relevance and availability from the previous two columns. A blank cell means a "No" indicator. Panel B shows the mapping between the 5 key drivers of biodiversity loss in the IPBES Assessment / Kunming-Montreal Global Biodiversity Framework and the MSCI Environmental Key Issues used in this study. Panel C displays the standalone biodiversity-related risk exposures from MSCI. Panel D depicts the synthetic biodiversity risk exposures which are computed from standalone risk exposures as in Panel C. There are no synthetic biodiversity risk exposures readily available in the MSCI data, nor are there any weights data to compute them. The weight schemes in the unequal-weighted synthetic measures are chosen based on the IPBES Assessment report on the contributions of the key drivers to biodiversity loss, as well as simplicity to compute. The weights do not have to be allocated the way in Panel D.

Panel A: Biodiversity-related Key Issues in the MSCI ESG Ratings Environmental Pillar

Pillar	Themes	Key Issues	Biodiversity Risk Related	Risk Exposure Score Available	In Use
Environmental	Natural Capital	* Biodiversity & Land Use *	Yes	Yes	Yes
		* Water Stress *	Yes	Yes	Yes
		Raw Material Sourcing	-	-	-
	Pollution & Waste	* Toxic Emissions & Waste *	Yes	Yes	Yes
		* Electronic Waste *	Yes	Yes	Yes
		* Packaging Material & Waste *	Yes	Yes	Yes
	Climate Change	* Carbon Emissions *	Yes	Yes	Yes
		* Product Carbon Footprint *	Yes	Yes	Yes
		Climate Change Vulnerability	-	Yes	-
		Financing Environmental Impact	-	Yes	-
	Environmental Opportunities	Opportunities in Clean Tech	-	Yes	-
		Opportunities in Green Building	-	Yes	-
		Opportunities in Renewable Energy	-	Yes	-

Table 1.1
Biodiversity Loss Drivers and Relevant Risk Exposures in the MSCI ESG Ratings Expanded File — *Continued*

Panel B: Mapping from the IPBES / Kunming-Montreal Framework Biodiversity Loss Drivers to MSCI Key Issues

IPBES / Kunming-Montreal Framework Five Direct Drivers of Biodiversity Loss	MSCI ESG Environmental Key Issues	In Use
Changes in Land and Sea Use	Biodiversity & Land Use	Yes
	Water Stress	Yes
Pollution	Toxic Emissions & Waste	Yes
	Electronic Waste	Yes
	Packaging Material & Waste	Yes
Climate Change	Carbon Emissions	Yes
	Product Carbon Footprint	Yes
Direct Exploitation of Organisms	-	-
Invasives Alien Species	-	-

Panel C: Standalone Biodiversity-Related Risk Exposure

Standalone MSCI Biodiversity-Related Risk Exposure	Abbreviation
Biodiversity & Land Use	BLU
Water Stress	WS
Toxic Emissions & Waste	TEW
Electronic Waste	EW
Packaging Material & Waste	PMW
Carbon Emissions	CE
Product Carbon Footprint	PCF

Panel D: Synthetic Biodiversity Risk Exposures Computed from MSCI Data

Synthetic Biodiversity Risk Exposure	Short Name	Composition	Weighting Method	Composite Weight
BW(ew)	B2(ew)	{BLU, WS}	Equal-Weighted	{1/2, 1/2}
BW(uw)	B2(uw)	{BLU, WS}	Unequal-Weighted	{2/3, 1/3}
BWTEP(ew)	B5(ew)	{BLU, WS, TEW, EW, PMW}	Equal-Weighted	{1/5, 1/5, 1/5, 1/5, 1/5}
BWTEP(uw)	B5(uw)	{BLU, WS, TEW, EW, PMW}	Unequal-Weighted	{50%, 25%, 15%, 5%, 5%}
BWTEPCP(ew)	B7(ew)	{BLU, WS, TEW, EW, PMW, CE, PCF}	Equal-Weighted	{1/7, 1/7, 1/7, 1/7, 1/7, 1/7, 1/7}
BWTEPCP(uw)	B7(uw)	{BLU, WS, TEW, EW, PMW, CE, PCF}	Unequal-Weighted	{40%, 20%, 10%, 5%, 5%, 15%, 5%}

Table 1.2
MSCI Key Variables Coverage

This table shows the coverage of firms (as of MSCI Issuer ID) and stocks (as of ISIN) with non-missing observations with 730 days of freshness for each key variable in the MSCI-Datastream merged dataset, respectively, from 2012-11 to 2023-06. It also requires non-missing returns and market capitalization from Datastream. This table, except for the last row, corresponds to Panel B in Figure 1.1. The last row further restricts the sample so that all key variables are non-missing simultaneously, which naturally brings down the time horizon to the range of [2015-10, 2023-06] instead, and it relates to Panel C in Figure 1.1.

MSCI Variable Category	Time Span	# of Obs.	Non-missing # of Obs.	Non-missing Obs. Ratio	# of Firms by ISSUERID	Non-missing # of Firms	Non-missing Firms Ratio	# of Stocks by ISIN	Non-missing # of Stocks	Non-missing Stocks Ratio	Countries with Non-missing Obs.
Environmental (Pillar) _ Score	2012-11 to 2023-06	1,311,567	1,309,785	99.86%	19,707	19,638	99.65%	26,569	26,495	99.72%	122
Environmental (Pillar) _ Weight	2012-11 to 2023-06	1,311,567	1,309,780	99.86%	19,707	19,637	99.64%	26,569	26,494	99.72%	122
Biodiversity & Land Use (Key Issue) _ Exposure Score	2012-11 to 2023-06	1,311,567	965,717	73.63%	19,707	17,373	88.16%	26,569	21,961	82.66%	117
Water Stress (Key Issue) _ Exposure Score	2012-11 to 2023-06	1,311,567	1,139,371	86.87%	19,707	18,600	94.38%	26,569	24,609	92.62%	119
Electronic Waste (Key Issue) _ Exposure Score	2012-11 to 2023-06	1,311,567	923,297	70.4%	19,707	17,055	86.54%	26,569	21,327	80.27%	117
Packaging Material & Waste (Key Issue) _ Exposure Score	2012-11 to 2023-06	1,311,567	923,132	70.38%	19,707	17,044	86.49%	26,569	21,338	80.31%	117
Toxic Emissions & Waste (Key Issue) _ Exposure Score	2012-11 to 2023-06	1,311,567	1,159,430	88.4%	19,707	18,776	95.28%	26,569	24,859	93.56%	119
Carbon Emissions (Key Issue) _ Exposure Score	2012-11 to 2023-06	1,311,567	1,199,105	91.43%	19,707	18,990	96.36%	26,569	25,302	95.23%	119
Product Carbon Footprint (Key Issue) _ Exposure Score	2012-11 to 2023-06	1,311,567	948,209	72.3%	19,707	17,173	87.14%	26,569	21,627	81.4%	117
All non-missing simultaneously	2015-10 to 2023-06	916,602	916,602	100.0%	17,002	17,002	100.0%	21,248	21,248	100.0%	117

Table 1.3
RepRisk Biodiversity and Other Environmental Risk Incidents

This table shows the total count of unique incidents and the total number of firm-incident observations for each RepRisk environmental issue from 2007-01 to 2022-12, in Panel A and B, respectively. Each firm is uniquely identified by the RepRisk ID, and each incident is uniquely identified by the Story ID. Each firm can have multiple incidents recorded in the RepRisk Incident file. And each incident can involve one or multiple firms based in the same or different countries by headquarters location. Therefore, in Panel A, the sum of the US and non-US incident counts can be equal to or more than the world count for each issue. The last three columns rank the environmental issues regionally by the number of incidents and firm-incident observations in each panel, respectively.

Panel A: Incidents by Environmental Issue

RepRisk Environmental Issue	World	US	Non-US	World Ranking	US Ranking	Non-US Ranking
Impacts on landscapes, ecosystems, and biodiversity	51,869	15,348	43,704	1	1	1
Local pollution	41,321	13,723	32,710	2	2	2
Climate change, GHG emissions, and global pollution (atmospheric)	18,739	5,216	15,235	3	3	3
Waste issues	9,831	4,311	7,956	4	4	4
Overuse and wasting of resources	3,083	1,096	2,650	5	6	5
Animal mistreatment	2,547	1,347	1,600	6	5	6

Panel B: Firm-Incident Observations by Environmental Issue

RepRisk Environmental Issue	World	US	Non-US	World Ranking	US Ranking	Non-US Ranking
Impacts on landscapes, ecosystems, and biodiversity	171,730	39,492	132,238	1	1	1
Local pollution	120,601	33,915	86,686	2	2	2
Climate change, GHG emissions, and global pollution (atmospheric)	63,083	18,050	45,033	3	3	3
Waste issues	51,958	12,304	39,654	4	4	4
Overuse and wasting of resources	13,895	2,794	11,101	5	6	5
Animal mistreatment	8,034	3,381	4,653	6	5	6

Table 1.4
RepRisk Biodiversity Incidents Topic Tags Distribution

This table summarizes the distribution of biodiversity incident-firm observations (uniquely indexed by each "Story ID – RepRisk ID" pair) across ESG topic tags in the RepRisk Premium V2 database from 2007-01 to 2022-12. Biodiversity incidents are identified by the RepRisk indicator variable "Impacts on landscapes, ecosystems, and biodiversity." Each incident can involve one or multiple firms. There are 33 biodiversity related ESG topic tags according to the RepRisk Research Scope: Topic Tags data guide (July 2023 version). Different biodiversity incident-firm observations can involve different numbers of biodiversity topic tags. The topic tags are listed in descending order of the world incident-firm observations count. The last three columns rank the topic tags regionally by the total number of biodiversity incident-firm observations involving that topic tag.

RepRisk Biodiversity Incident Topic Tag	World	US	Non-US	World Ranking	US Ranking	Non-US Ranking
Land ecosystems	98,561	22,067	76,494	1	1	1
Protected areas	22,623	3,502	19,121	2	4	2
Marine/Coastal ecosystems	19,050	3,771	15,279	3	3	3
Land grabbing	18,172	2,977	15,195	4	7	4
Palm oil	16,273	3,090	13,183	5	6	5
Endangered species	15,755	3,402	12,353	6	5	6
Coal-fired power plants	12,323	4,003	8,320	7	2	8
Wastewater management	12,133	2,539	9,594	8	10	7
Negligence	10,320	2,835	7,485	9	8	9
Water scarcity	8,142	1,241	6,901	10	12	10
Hydropower (dams)	7,151	734	6,417	11	19	11
Illegal logging	6,268	822	5,446	12	16	12
Fracking	5,932	2,634	3,298	13	9	15
Soy	4,849	1,263	3,586	14	11	14
Forest burning	4,223	593	3,630	15	21	13
High conservation value forests	3,770	517	3,253	16	23	16
Monocultures	3,648	763	2,885	17	18	17
Oil sands	3,558	931	2,627	18	15	18
Arctic drilling	3,046	700	2,346	19	20	19
Genetically modified organisms (GMOs)	2,930	1,163	1,767	20	13	21
Plastics	2,560	781	1,779	21	17	20
Mountaintop removal mining	2,220	1,160	1,060	22	14	25
Deep sea drilling	2,097	519	1,578	23	22	22
Coral reefs	1,590	177	1,413	24	25	23
Offshore drilling	1,355	275	1,080	25	24	24
Abusive/Illegal fishing	874	123	751	26	26	26
Rare earths	655	48	607	27	28	27
Sand mining and dredging	334	37	297	28	29	28
Ship breaking and scrapping	312	19	293	29	31	29
Nuclear weapons	271	53	218	30	27	31
Seabed mining	254	27	227	31	30	30
Chemical weapons	5	0	5	32	33	32
Biological weapons	1	1	0	33	32	33

Table 1.5
RepRisk Biodiversity Incidents Distribution by Sectors

This table shows the total number of biodiversity incidents indexed by unique Story ID in the RepRisk Premium V2 database from 2007-01 to 2022-12 for each RepRisk Sector. Biodiversity incidents are identified by the RepRisk indicator variable "Impacts on landscapes, ecosystems, and biodiversity." Each incident can involve one firm or multiple firms based in the same or different countries by headquarter location. Therefore, the sum of the US and non-US counts can be equal to or more than the world count for a sector. The RepRisk sectors are listed in descending order of the world incidents count. The last three columns rank the sectors regionally by the total number of biodiversity incidents.

RepRisk Sector	World	US	Non-US	World Ranking	US Ranking	Non-US Ranking
Mining	12,894	1,951	11,887	1	6	1
Oil and Gas	12,174	4,331	9,815	2	1	2
Utilities	10,261	2,103	8,504	3	3	3
Financial Services	9,399	1,994	8,081	4	5	4
Food and Beverage	7,030	2,049	6,063	5	4	5
Construction and Materials	6,271	867	5,513	6	10	6
Chemicals	5,873	2,830	3,694	7	2	9
Support Services (Industrial Goods and Services)	5,853	1,640	4,385	8	7	7
Industrial Metals	4,017	361	3,790	9	16	8
Industrial Transportation	3,453	597	2,934	10	13	10
Alternative Energy	2,707	423	2,348	11	15	11
Retail	2,699	963	2,022	12	8	13
General Industrials	2,689	662	2,100	13	12	12
Personal and Household Goods	2,283	782	1,915	14	11	15
Forestry	2,048	115	1,964	15	29	14
Industrial Engineering	1,853	279	1,632	16	21	17
Banks	1,811	343	1,678	17	17	16
Development Banks, Central Banks, and Export Credit Agencies	1,712	922	1,059	18	9	20
Travel and Leisure	1,678	519	1,301	19	14	19
Paper	1,498	209	1,325	20	27	18
Automobiles and Parts	1,057	327	822	21	18	21
Pharmaceuticals and Biotechnology	1,030	306	821	22	20	22
Electronic and Electrical Equipment	691	249	461	23	24	24
Insurance	678	232	495	24	26	23
Software and Computer Services	615	252	406	25	23	26
Aerospace and Defense	498	257	290	26	22	27
Telecommunications	473	62	420	27	30	25
Health Care Equipment and Services	446	307	160	28	19	30
Media	414	157	289	29	28	28
Technology Hardware and Equipment	384	234	228	30	25	29
Airlines	129	25	112	31	32	31
Tobacco	93	41	67	32	31	32
Gambling	24	9	15	33	33	33
*** Unspecified ***	453	79	382	-	-	-

Table 1.6
Performances of Biodiversity Nature-PMN Factors in the US

The table reports the monthly time-series factor regressions of Nature-PMN returns based on various biodiversity risk exposures from 2016-04 to 2023-06 in the US market. Definitions of the biodiversity risk exposures, BLU, BW(B2), BWTEP(B5), and BWTEPCP(B7), with their equal-weighted (ew) and unequal-weighted (uw) variants for synthetic measures, can be found in Table 1.1. The pricing factors follow Fama and French (1993), Carhart (1997), and Fama and French (2015). Mkt-RF is the excess market return. SMB and HML are the size and value factors respectively; similarly, Mom for momentum, RMW for profitability, and CMA for investment. Robust t-statistics are in the parentheses. Significance levels are *** at 1%, ** at 5%, and * at 10%, respectively.

Panel A: FFC 6-Factor Model

Dep. Var.: PMN	(1) BLU	(2) BW(ew)	(3) BWTEP(ew)	(4) BWTEPCP(ew)	(5) BW(uw)	(6) BWTEP(uw)	(7) BWTEPCP(uw)
Constant	0.21	0.41**	0.16	0.04	0.42**	0.30*	0.27
	(1.13)	(2.21)	(0.90)	(0.23)	(2.28)	(1.69)	(1.47)
Mkt-RF	0.05	0.16***	0.05	-0.01	0.14***	0.13***	0.11**
	(1.28)	(3.39)	(1.16)	(-0.31)	(3.26)	(3.22)	(2.45)
SMB	-0.14	-0.25**	-0.11	-0.09	-0.23**	-0.22**	-0.17*
	(-1.60)	(-2.52)	(-1.27)	(-0.98)	(-2.39)	(-2.46)	(-1.74)
HML	0.10	-0.01	0.15**	0.20***	0.01	0.05	0.03
	(1.35)	(-0.16)	(2.32)	(2.86)	(0.19)	(0.72)	(0.42)
Mom	-0.00	-0.04	-0.04	-0.08	-0.04	-0.03	-0.01
	(-0.01)	(-0.65)	(-0.93)	(-1.49)	(-0.87)	(-0.53)	(-0.14)
RMW	-0.23**	-0.29***	-0.27**	-0.28**	-0.32***	-0.30***	-0.27**
	(-2.08)	(-3.15)	(-2.50)	(-2.06)	(-3.57)	(-3.92)	(-2.60)
CMA	-0.59***	-0.49***	-0.39***	-0.39***	-0.53***	-0.58***	-0.46***
	(-4.59)	(-3.77)	(-3.05)	(-3.68)	(-4.24)	(-4.86)	(-3.93)
Observations	87	87	87	87	87	87	87
R-squared	0.45	0.54	0.28	0.28	0.55	0.56	0.44

Panel B: FFC 6-Factor Model with the Post-Kunming Dummy

Dep. Var.: PMN	(1) BLU	(2) BW(ew)	(3) BWTEP(ew)	(4) BWTEPCP(ew)	(5) BW(uw)	(6) BWTEP(uw)	(7) BWTEPCP(uw)
Constant	0.55***	0.74***	0.40**	0.34*	0.76***	0.57***	0.63***
	(2.85)	(3.69)	(2.20)	(1.72)	(3.81)	(3.01)	(3.17)
Post-KM=1	-1.44***	-1.42***	-1.02*	-1.26***	-1.42***	-1.14**	-1.53***
	(-2.79)	(-3.01)	(-1.87)	(-2.96)	(-2.93)	(-2.44)	(-3.46)
Mkt-RF	0.03	0.14***	0.04	-0.03	0.12***	0.11***	0.09**
	(0.79)	(3.20)	(0.84)	(-0.76)	(2.90)	(2.98)	(2.04)
SMB	-0.13*	-0.24***	-0.10	-0.08	-0.22**	-0.21**	-0.16*
	(-1.76)	(-2.67)	(-1.31)	(-1.02)	(-2.53)	(-2.60)	(-1.78)
HML	0.09	-0.02	0.14**	0.19***	0.01	0.04	0.02
	(1.42)	(-0.29)	(2.37)	(3.04)	(0.09)	(0.70)	(0.35)
Mom	-0.01	-0.05	-0.05	-0.09	-0.06	-0.04	-0.02
	(-0.22)	(-0.79)	(-1.02)	(-1.63)	(-1.03)	(-0.64)	(-0.33)
RMW	-0.17*	-0.23**	-0.22**	-0.22*	-0.26***	-0.26***	-0.21**
	(-1.75)	(-2.61)	(-2.21)	(-1.84)	(-3.07)	(-3.46)	(-2.16)
CMA	-0.56***	-0.46***	-0.37***	-0.37***	-0.50***	-0.55***	-0.43***
	(-4.87)	(-3.98)	(-3.02)	(-3.86)	(-4.45)	(-5.05)	(-4.45)
Observations	87	87	87	87	87	87	87
R-squared	0.52	0.59	0.32	0.35	0.60	0.60	0.52

Table 1.6
Performances of Biodiversity Nature-PMN Factors in the US — *Continued*

Panel C: All Models with the Post-Kunming Dummy, for the BLU Measure

Dep. Var.: PMN	(1) BLU	(2) BLU	(3) BLU	(4) BLU	(5) BLU	(6) BLU
Constant	0.63***	0.54**	0.45**	0.47**	0.55***	0.55***
	(2.97)	(2.49)	(2.00)	(2.08)	(2.85)	(2.85)
Post-KM=1	-2.06***	-1.97***	-1.78***	-1.82***	-1.44***	-1.44***
	(-3.00)	(-2.84)	(-2.87)	(-3.05)	(-2.77)	(-2.79)
Mkt-RF		0.06	0.07	0.04	0.03	0.03
		(1.35)	(1.58)	(0.91)	(0.90)	(0.79)
SMB			0.02	-0.01	-0.13*	-0.13*
			(0.22)	(-0.13)	(-1.80)	(-1.76)
HML			-0.19***	-0.20***	0.09	0.09
			(-3.13)	(-3.26)	(1.55)	(1.42)
Mom				-0.08		-0.01
				(-1.07)		(-0.22)
RMW					-0.17*	-0.17*
					(-1.75)	(-1.75)
CMA					-0.56***	-0.56***
					(-4.95)	(-4.87)
Observations	87	87	87	87	87	87
R-squared	0.15	0.17	0.29	0.30	0.52	0.52

Table 1.6
Performances of Biodiversity Nature-PMN Factors in the US — *Continued*

Panel D: All Models with the Post-Kunming Dummy, for the Equal-Weighted Synthetic Measures

D.Var.: PMN	(1) B2(ew)	(2) B2(ew)	(3) B2(ew)	(4) B2(ew)	(5) B2(ew)	(6) B2(ew)	(7) B5(ew)	(8) B5(ew)	(9) B5(ew)	(10) B5(ew)	(11) B5(ew)	(12) B5(ew)	(13) B7(ew)	(14) B7(ew)	(15) B7(ew)	(16) B7(ew)	(17) B7(ew)	(18) B7(ew)
Constant	0.97***	0.78***	0.64***	0.67***	0.73***	0.74***	0.42**	0.33*	0.31	0.34*	0.38**	0.40**	0.25	0.23	0.24	0.28	0.32	0.34*
	(3.98)	(3.04)	(2.91)	(3.08)	(3.59)	(3.69)	(2.07)	(1.71)	(1.55)	(1.68)	(2.12)	(2.20)	(1.23)	(1.11)	(1.14)	(1.33)	(1.62)	(1.72)
Post-KM=1	-2.18***	-1.99***	-1.75***	-1.80***	-1.40***	-1.42***	-1.48**	-1.39**	-1.32**	-1.35**	-1.00*	-1.02*	-1.59***	-1.57***	-1.54***	-1.59***	-1.22***	-1.26***
	(-2.99)	(-2.82)	(-2.95)	(-3.29)	(-2.82)	(-3.01)	(-2.57)	(-2.38)	(-2.20)	(-2.38)	(-1.79)	(-1.87)	(-3.00)	(-2.91)	(-2.80)	(-3.16)	(-2.66)	(-2.96)
Mkt-RF		0.14**	0.17***	0.14***	0.15***	0.14***		0.07*	0.06	0.03	0.05	0.04		0.02	0.00	-0.04	-0.01	-0.03
		(2.37)	(4.01)	(3.11)	(3.59)	(3.20)		(1.69)	(1.37)	(0.66)	(1.15)	(0.84)		(0.46)	(0.02)	(-0.88)	(-0.24)	(-0.76)
SMB			-0.06	-0.10	-0.22**	-0.24***			0.06	0.03	-0.08	-0.10			0.09	0.04	-0.05	-0.08
			(-0.71)	(-1.18)	(-2.56)	(-2.67)			(0.71)	(0.33)	(-1.06)	(-1.31)			(1.10)	(0.60)	(-0.65)	(-1.02)
HML			-0.26***	-0.28***	-0.01	-0.02			-0.06	-0.07	0.16***	0.14**			-0.00	-0.02	0.22***	0.19***
			(-4.32)	(-4.63)	(-0.09)	(-0.29)			(-0.99)	(-1.22)	(2.87)	(2.37)			(-0.05)	(-0.46)	(3.59)	(3.04)
Mom				-0.10		-0.05				-0.09		-0.05				-0.12**		-0.09
				(-1.37)		(-0.79)				(-1.48)		(-1.02)				(-2.05)		(-1.63)
RMW					-0.22**	-0.23**					-0.21**	-0.22**					-0.21*	-0.22*
					(-2.56)	(-2.61)					(-2.14)	(-2.21)					(-1.76)	(-1.84)
CMA					-0.48***	-0.46***					-0.39***	-0.37***					-0.40***	-0.37***
					(-4.28)	(-3.98)					(-3.28)	(-3.02)					(-4.07)	(-3.86)
Observations	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87
R-squared	0.14	0.22	0.44	0.45	0.59	0.59	0.10	0.13	0.14	0.17	0.32	0.32	0.13	0.13	0.14	0.19	0.33	0.35

Panel E: All Models with the Post-Kunming Dummy, for the Unequal-Weighted Synthetic Measures

D.Var.: PMN	(1) B2(uw)	(2) B2(uw)	(3) B2(uw)	(4) B2(uw)	(5) B2(uw)	(6) B2(uw)	(7) B5(uw)	(8) B5(uw)	(9) B5(uw)	(10) B5(uw)	(11) B5(uw)	(12) B5(uw)	(13) B7(uw)	(14) B7(uw)	(15) B7(uw)	(16) B7(uw)	(17) B7(uw)	(18) B7(uw)
Constant	0.96***	0.78***	0.65***	0.68***	0.75***	0.76***	0.75***	0.58**	0.46**	0.49**	0.56***	0.57***	0.78***	0.65***	0.55**	0.57***	0.63***	0.63***
	(4.03)	(3.20)	(2.87)	(3.03)	(3.72)	(3.81)	(3.29)	(2.52)	(2.08)	(2.22)	(2.95)	(3.01)	(3.48)	(2.79)	(2.58)	(2.67)	(3.15)	(3.17)
Post-KM=1	-2.22***	-2.04***	-1.80***	-1.84***	-1.39***	-1.42***	-1.94**	-1.77**	-1.54**	-1.58***	-1.13**	-1.14**	-2.16***	-2.03***	-1.84***	-1.87***	-1.52***	-1.53***
	(-3.01)	(-2.83)	(-2.94)	(-3.28)	(-2.75)	(-2.93)	(-2.62)	(-2.47)	(-2.50)	(-2.78)	(-2.30)	(-2.44)	(-3.56)	(-3.36)	(-3.37)	(-3.66)	(-3.32)	(-3.46)
Mkt-RF		0.14**	0.15***	0.12***	0.13***	0.12***		0.13**	0.14***	0.11**	0.12***	0.11***		0.10**	0.11***	0.09**	0.09**	0.09**
		(2.51)	(3.58)	(2.64)	(3.30)	(2.90)		(2.36)	(3.26)	(2.49)	(3.15)	(2.98)		(2.03)	(2.70)	(1.99)	(2.20)	(2.04)
SMB			-0.02	-0.06	-0.20**	-0.22**			-0.02	-0.05	-0.20**	-0.21**			-0.01	-0.04	-0.16*	-0.16*
			(-0.24)	(-0.74)	(-2.39)	(-2.53)			(-0.18)	(-0.63)	(-2.49)	(-2.60)			(-0.14)	(-0.44)	(-1.77)	(-1.78)
HML			-0.26***	-0.28***	0.02	0.01			-0.24***	-0.26***	0.06	0.04			-0.20***	-0.21***	0.03	0.02
			(-4.15)	(-4.50)	(0.39)	(0.09)			(-3.94)	(-4.16)	(0.96)	(0.70)			(-3.66)	(-3.84)	(0.47)	(0.35)
Mom				-0.11		-0.06				-0.10		-0.04				-0.07		-0.02
				(-1.61)		(-1.03)				(-1.34)		(-0.64)				(-0.95)		(-0.33)
RMW					-0.25***	-0.26***					-0.25***	-0.26***					-0.20**	-0.21**
					(-2.97)	(-3.07)					(-3.42)	(-3.46)					(-2.18)	(-2.16)
CMA					-0.53***	-0.50***					-0.57***	-0.55***					-0.43***	-0.43***
					(-4.74)	(-4.45)					(-5.35)	(-5.05)					(-4.66)	(-4.45)
Observations	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87	87
R-squared	0.15	0.22	0.41	0.43	0.60	0.60	0.12	0.19	0.37	0.39	0.60	0.60	0.17	0.22	0.37	0.38	0.52	0.52

Table 1.7
Performances of Biodiversity Nature-PMN Factors in the World

The table reports the monthly time-series factor regressions of Nature-PMN returns based on various biodiversity risk exposures from 2016-04 to 2023-06 in the representative major 46 markets in the globe. Results are similar if using all the available markets. Definitions of the biodiversity risk exposures, BLU, BW, BWTEP, and BWTEPCP, with their equal-weighted (ew) and unequal-weighted (uw) variants for synthetic measures, can be found in Table 1.1. The pricing factors follow Fama and French (1993), Carhart (1997), and Fama and French (2015). Mkt-RF is the excess market return. SMB and HML are the size and value factors respectively; similarly, Mom for momentum, RMW for profitability, and CMA for investment. The global version of those factors is from Karolyi and Wu (2018), and Karolyi, Wu, and Xiong (2023), and computed based on the major 46 markets. Robust t-statistics are in the parentheses. Significance levels are *** at 1%, ** at 5%, and * at 10%, respectively.

Panel A: Global 46 Major Markets, FFC 6-Factor Model

Dep. Var.: PMN	(1) BLU	(2) BW(ew)	(3) BWTEP(ew)	(4) BWTEPCP(ew)	(5) BW(uw)	(6) BWTEP(uw)	(7) BWTEPCP(uw)
Constant	-0.15	-0.00	-0.14	-0.18	0.00	-0.03	-0.02
	(-0.73)	(-0.02)	(-0.69)	(-0.86)	(0.02)	(-0.15)	(-0.10)
MKR-RF	-0.04	0.00	-0.01	-0.04	0.00	-0.01	-0.02
	(-0.88)	(0.09)	(-0.22)	(-1.07)	(0.03)	(-0.25)	(-0.36)
SMB	-0.10	-0.22**	-0.12	-0.12	-0.22**	-0.23**	-0.20*
	(-0.86)	(-1.99)	(-1.10)	(-1.03)	(-2.03)	(-2.01)	(-1.70)
HML	0.26*	0.15	0.20	0.21	0.18	0.19	0.11
	(1.94)	(1.03)	(1.31)	(1.35)	(1.28)	(1.39)	(0.72)
UMD	-0.04	-0.02	-0.03	-0.03	0.00	0.00	0.00
	(-0.64)	(-0.29)	(-0.41)	(-0.47)	(0.01)	(0.06)	(0.05)
RMW	-0.03	-0.01	-0.11	-0.18	-0.03	-0.04	-0.10
	(-0.16)	(-0.06)	(-0.65)	(-1.02)	(-0.20)	(-0.27)	(-0.53)
CMA	-0.57***	-0.58***	-0.47***	-0.33**	-0.61***	-0.60***	-0.44***
	(-3.71)	(-3.54)	(-2.72)	(-1.99)	(-3.88)	(-3.89)	(-2.75)
Observations	87	87	87	87	87	87	87
R-squared	0.21	0.31	0.19	0.10	0.32	0.29	0.21

Panel B: Global 46 Major Markets, FFC 6-Factor Model, with the Post-Kunming Dummy

Dep. Var.: PMN	(1) BLU	(2) BW(ew)	(3) BWTEP(ew)	(4) BWTEPCP(ew)	(5) BW(uw)	(6) BWTEP(uw)	(7) BWTEPCP(uw)
Constant	-0.04	0.04	-0.09	-0.08	0.05	0.01	0.08
	(-0.17)	(0.18)	(-0.37)	(-0.32)	(0.22)	(0.05)	(0.31)
Post-KM=1	-0.47	-0.20	-0.23	-0.44	-0.20	-0.19	-0.42
	(-1.10)	(-0.52)	(-0.56)	(-1.11)	(-0.49)	(-0.46)	(-1.08)
MKR-RF	-0.04	0.00	-0.01	-0.05	-0.00	-0.01	-0.02
	(-0.94)	(0.06)	(-0.26)	(-1.15)	(-0.00)	(-0.28)	(-0.43)
SMB	-0.10	-0.22**	-0.12	-0.12	-0.22**	-0.23**	-0.20*
	(-0.87)	(-2.01)	(-1.11)	(-1.05)	(-2.05)	(-2.02)	(-1.74)
HML	0.24*	0.14	0.19	0.20	0.17	0.19	0.09
	(1.85)	(0.97)	(1.26)	(1.29)	(1.22)	(1.34)	(0.63)
UMD	-0.05	-0.02	-0.04	-0.04	-0.00	0.00	-0.01
	(-0.79)	(-0.34)	(-0.47)	(-0.58)	(-0.05)	(0.00)	(-0.07)
RMW	-0.00	0.00	-0.10	-0.16	-0.02	-0.03	-0.08
	(-0.02)	(0.00)	(-0.60)	(-0.97)	(-0.14)	(-0.22)	(-0.44)
CMA	-0.54***	-0.57***	-0.45**	-0.30*	-0.60***	-0.59***	-0.41**
	(-3.33)	(-3.26)	(-2.52)	(-1.78)	(-3.56)	(-3.58)	(-2.50)
Observations	87	87	87	87	87	87	87
R-squared	0.22	0.32	0.19	0.11	0.32	0.29	0.22

Table 1.7
Performances of Biodiversity Nature-PMN Factors in the World — *Continued*

Panel C: Non-US 45 Major Markets, FFC 6-Factor Model

Dep. Var.: PMN	(1) BLU	(2) BW(ew)	(3) BWTEP(ew)	(4) BWTEPCP(ew)	(5) BW(uw)	(6) BWTEP(uw)	(7) BWTEPCP(uw)
Constant	-0.37	-0.29	-0.34	-0.34	-0.34	-0.35	-0.28
	(-1.49)	(-1.07)	(-1.29)	(-1.18)	(-1.27)	(-1.32)	(-1.09)
MKR-RF	-0.02	-0.01	-0.01	-0.05	-0.02	-0.03	-0.03
	(-0.27)	(-0.24)	(-0.24)	(-0.85)	(-0.42)	(-0.47)	(-0.45)
SMB	-0.07	-0.09	-0.08	-0.15	-0.09	-0.07	-0.09
	(-0.53)	(-0.73)	(-0.65)	(-1.20)	(-0.71)	(-0.57)	(-0.69)
HML	0.25	0.19	0.12	0.09	0.19	0.18	0.16
	(1.50)	(1.05)	(0.65)	(0.50)	(1.12)	(1.07)	(0.91)
UMD	-0.05	-0.02	-0.03	0.01	-0.01	-0.02	-0.02
	(-0.59)	(-0.26)	(-0.37)	(0.11)	(-0.13)	(-0.25)	(-0.22)
RMW	-0.04	-0.01	-0.05	-0.09	-0.02	0.01	-0.03
	(-0.25)	(-0.05)	(-0.28)	(-0.51)	(-0.13)	(0.06)	(-0.16)
CMA	-0.32	-0.30	-0.16	-0.14	-0.29	-0.28	-0.26
	(-1.60)	(-1.43)	(-0.82)	(-0.67)	(-1.44)	(-1.44)	(-1.29)
Observations	87	87	87	87	87	87	87
R-squared	0.06	0.04	0.02	0.02	0.03	0.03	0.03

Panel D: Non-US 45 Major Markets, FFC 6-Factor Model, with the Post-Kunming Dummy

Dep. Var.: PMN	(1) BLU	(2) BW(ew)	(3) BWTEP(ew)	(4) BWTEPCP(ew)	(5) BW(uw)	(6) BWTEP(uw)	(7) BWTEPCP(uw)
Constant	-0.39	-0.33	-0.38	-0.41	-0.36	-0.38	-0.30
	(-1.33)	(-1.02)	(-1.23)	(-1.17)	(-1.14)	(-1.23)	(-1.02)
Post-KM=1	0.09	0.16	0.18	0.29	0.09	0.15	0.12
	(0.20)	(0.36)	(0.40)	(0.63)	(0.20)	(0.31)	(0.26)
MKR-RF	-0.01	-0.01	-0.01	-0.04	-0.02	-0.03	-0.02
	(-0.26)	(-0.23)	(-0.22)	(-0.81)	(-0.41)	(-0.46)	(-0.43)
SMB	-0.07	-0.09	-0.08	-0.15	-0.09	-0.07	-0.09
	(-0.52)	(-0.72)	(-0.65)	(-1.18)	(-0.71)	(-0.57)	(-0.68)
HML	0.25	0.19	0.12	0.10	0.19	0.19	0.16
	(1.46)	(1.04)	(0.66)	(0.54)	(1.10)	(1.06)	(0.91)
UMD	-0.04	-0.02	-0.03	0.02	-0.01	-0.02	-0.02
	(-0.54)	(-0.21)	(-0.32)	(0.17)	(-0.10)	(-0.21)	(-0.18)
RMW	-0.05	-0.02	-0.06	-0.11	-0.03	0.00	-0.04
	(-0.28)	(-0.09)	(-0.34)	(-0.60)	(-0.16)	(0.02)	(-0.20)
CMA	-0.32	-0.31	-0.17	-0.16	-0.29	-0.29	-0.27
	(-1.55)	(-1.41)	(-0.85)	(-0.74)	(-1.42)	(-1.43)	(-1.28)
Observations	87	87	87	87	87	87	87
R-squared	0.06	0.04	0.02	0.03	0.03	0.03	0.03

Table 1.8
Cross-Sectional Returns and Comparison of MSCI Biodiversity-Related Key Issue Risk Exposures

This table reports the panel regression results of stock returns on different biodiversity-related key issue risk exposures from the MSCI ESG ratings data. The sample period is from 2016-04 to 2023-06. The dependent variable is the stock return. The main independent variables involve risk exposures of BLU, CE, PCF, WS, TEW, PMW, and EW, in different models, and the variable definitions can be found in Table 1.1. The risk exposures and controls are lagged 1 month relative to the dependent variable. All variables are on a monthly frequency. The control variables follow Table 1.9 but are not reported for concision. All models include year-month, country, and the MSCI ESG industry fixed effects. Standard errors (in parentheses) are double clustered at the firm and year level. Significance levels are *** at 1%, ** at 5%, and * at 10%, respectively.

Region	World									US	Non-US
Dep. Var.: Ret.	(1) Return (%)	(2) Return (%)	(3) Return (%)	(4) Return (%)	(5) Return (%)	(6) Return (%)	(7) Return (%)	(8) Return (%)	(9) Return (%)	(10) Return (%)	(11) Return (%)
BLU	0.1134**		0.1379***	0.1131**	0.1189**	0.1228**	0.1150**	0.1138**	0.1387**	0.1579**	0.1322***
	(0.038)		(0.039)	(0.038)	(0.035)	(0.044)	(0.040)	(0.037)	(0.044)	(0.063)	(0.037)
CE		-0.0523	-0.0881**						-0.0905*	-0.1126*	-0.0792
		(0.030)	(0.031)						(0.045)	(0.048)	(0.045)
PCF				0.0046					0.0124	-0.0016	0.0123
				(0.020)					(0.030)	(0.059)	(0.019)
WS					-0.0200				0.0052	0.0064	0.0179
					(0.013)				(0.022)	(0.023)	(0.015)
TEW						-0.0246			-0.0029	0.0175	-0.0197
						(0.023)			(0.027)	(0.039)	(0.027)
PMW							0.0153		0.0109	0.0815	-0.0222
							(0.036)		(0.040)	(0.065)	(0.032)
EW								0.0131	0.0068	-0.0188	0.0190
								(0.016)	(0.017)	(0.033)	(0.018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ESG Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	471433	471433	471433	471433	471433	471433	471433	471433	471433	147763	323670
Adj. R-squared	0.223	0.223	0.223	0.223	0.223	0.223	0.223	0.223	0.223	0.255	0.228

Table 1.9
Cross-Sectional Returns on the BLU Biodiversity Risk Exposure

This table reports the panel regression results of stock returns on the BLU ("Biodiversity & Land Use") biodiversity risk exposure from the MSCI ESG ratings data as introduced in Table 1.1. The sample period is from 2016-04 to 2023-06. The dependent variable is the stock return. The main independent variable is the BLU risk exposure. The indicator variable After KM is a dummy for the era after the October 2021 Kunming Declaration. The main independent variables are BLU and After KM. The risk exposure and controls are lagged 1 month relative to the dependent variable. All variables are in monthly frequency. Control variables, from Ln(MV) to Volatility (12m), follow Bolton and Kacperczyk (2023) whenever possible but with the best options from Refinitiv Datastream instead. For concision, the same set of control variables in Panel B and C are not reported. All models include year-month, country, and the MSCI ESG industry fixed effects. Standard errors (in parentheses) are double clustered at the firm and year level. Significance levels are *** at 1%, ** at 5%, and * at 10%, respectively.

Panel A: World

Dep. Var.: Ret.	(1) Return (%)	(2) Return (%)	(3) Return (%)	(4) Return (%)	(5) Return (%)	(6) Return (%)	(7) Return (%)	(8) Return (%)	(9) Return (%)	(10) Return (%)
BLU	0.1134**	0.0322	0.1143*	0.0355	0.0333	-0.0309	0.0273	-0.0357***	0.0377	-0.0898**
	(0.038)	(0.046)	(0.053)	(0.032)	(0.049)	(0.016)	(0.055)	(0.009)	(0.105)	(0.036)
{After KM}										-2.5595*
										(1.228)
{After KM} x BLU		0.2283**		0.2282**		0.2259**		0.2243**		0.2618**
		(0.088)		(0.083)		(0.088)		(0.084)		(0.090)
Ln(MV)	-0.2311**	-0.2311**	-0.1921*	-0.1926*	-0.1520	-0.1539	-0.1109	-0.1134	-0.1522	-0.1595
	(0.096)	(0.097)	(0.088)	(0.089)	(0.104)	(0.105)	(0.098)	(0.099)	(0.117)	(0.121)
P/B	-0.0545***	-0.0542***	-0.0507***	-0.0503***	-0.0511**	-0.0501**	-0.0466**	-0.0454**	-0.0574*	-0.0521*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.020)	(0.019)	(0.019)	(0.019)	(0.025)	(0.023)
Leverage (TD/TA)	-0.0052**	-0.0051*	-0.0036	-0.0036	-0.0053**	-0.0052**	-0.0041	-0.0041	-0.0058	-0.0070
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Momentum (12m)	-0.0262	-0.0301	-0.0226	-0.0266	-0.0239	-0.0278	-0.0198	-0.0236	-0.0624	-0.1083
	(0.028)	(0.026)	(0.029)	(0.027)	(0.027)	(0.025)	(0.028)	(0.026)	(0.097)	(0.077)
CapEx/TA	-0.0113	-0.0118	-0.0114	-0.0120	-0.0112	-0.0107	-0.0105	-0.0101	-0.0313	-0.0236
	(0.020)	(0.020)	(0.021)	(0.021)	(0.024)	(0.024)	(0.025)	(0.025)	(0.032)	(0.030)
Ln(PPE)	0.1724**	0.1725**	0.1546*	0.1549*	0.1015	0.1037	0.0812	0.0838	0.1503	0.1690
	(0.071)	(0.071)	(0.069)	(0.070)	(0.090)	(0.092)	(0.089)	(0.091)	(0.105)	(0.110)
ROE	0.0298***	0.0295***	0.0288***	0.0285***	0.0287***	0.0283***	0.0273***	0.0269***	0.0326***	0.0334***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Volatility (12m)	0.0746	0.0748	0.0763	0.0763	0.0778	0.0780	0.0813	0.0812	0.1775	0.1907*
	(0.043)	(0.043)	(0.044)	(0.044)	(0.042)	(0.042)	(0.044)	(0.044)	(0.099)	(0.089)
Constant	-0.6887*	-0.6091	-0.8294*	-0.7522	-0.2015	-0.1854	-0.3172	-0.2999	-1.7221	-1.1693
	(0.358)	(0.436)	(0.384)	(0.423)	(0.337)	(0.328)	(0.378)	(0.346)	(1.417)	(1.322)
Year-Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Country F.E.	Yes	Yes	No	No	Yes	Yes	No	No	No	No
ESG Industry F.E.	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Observations	471433	471433	471433	471433	471433	471433	471433	471433	471434	471434
Adj. R-squared	0.223	0.223	0.222	0.223	0.223	0.223	0.222	0.222	0.009	0.014

Table 1.9

Cross-Sectional Returns on the BLU Biodiversity Risk Exposure — *Continued*

Panel B: US

Dep. Var.: Ret.	(1) Return (%)	(2) Return (%)	(3) Return (%)	(4) Return (%)	(5) Return (%)	(6) Return (%)
BLU	0.1243**	-0.0182	0.0317	-0.0776*	0.0410	-0.1501**
	(0.044)	(0.096)	(0.105)	(0.037)	(0.172)	(0.063)
{After KM}						-3.0960*
						(1.608)
{After KM} x BLU		0.4217**		0.4144**		0.4749**
		(0.162)		(0.147)		(0.163)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes	No	No
Country F.E.	-	-	-	-	-	-
ESG Industry F.E.	Yes	Yes	No	No	No	No
Observations	147763	147763	147763	147763	147764	147764
Adj. R-squared	0.255	0.256	0.254	0.255	0.010	0.015

Panel C: Non-US World

Dep. Var.: Ret.	(1) Return (%)	(2) Return (%)	(3) Return (%)	(4) Return (%)	(5) Return (%)	(6) Return (%)	(7) Return (%)	(8) Return (%)	(9) Return (%)	(10) Return (%)
BLU	0.1126**	0.0583	0.0889	0.0348	0.0327	-0.0111	0.0279	-0.0157	0.0378	-0.0660**
	(0.033)	(0.033)	(0.055)	(0.024)	(0.027)	(0.025)	(0.037)	(0.014)	(0.080)	(0.025)
{After KM}										-2.3324*
										(1.082)
{After KM} x BLU		0.1478**		0.1538**		0.1492**		0.1516**		0.1873**
		(0.052)		(0.044)		(0.059)		(0.053)		(0.054)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Country F.E.	Yes	Yes	No	No	Yes	Yes	No	No	No	No
ESG Industry F.E.	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Observations	323670	323670	323670	323670	323670	323670	323670	323670	323670	323670
Adj. R-squared	0.228	0.229	0.228	0.228	0.228	0.228	0.227	0.227	0.009	0.014

Table 1.10

Explaining the Biodiversity PMN Performance in the US by Aggregate Biodiversity Incidents

This table displays the time-series regression results of the MSCI biodiversity PMN performance on the aggregate RepRisk biodiversity incidents count. Panel A is for PMN returns and Panel B is for PMN alphas. Definitions of biodiversity measures, BLU, BW, BWTEP, and BWTEPCP can be found in Table 1.1. The "Δ" operator represents a shock, which is the prediction error from rolling AR(1) models applied on the measure which it applies to. The variable "RRBI Firms HQ US" stands for aggregate counts of RepRisk biodiversity incidents involving firms which have headquarters in the US per month. The unit of the incident count is in the hundreds. Different versions of the AR(1) shock "Δ RRBI Firms HQ US" are used as the regressors, in which "lag 2m" means lagged 2 months, and "lag 1m" for lagged 1 month. The RepRisk data coverage ends at 2022-12. The sample period is from 2016-04 to 2022-12 if there are 81 observations, and 2016-04 to 2023-02 if there are 83 observations, which contains 81 months. Robust t-statistics are in parentheses. Significance levels are *** at 1%, ** at 5%, and * at 10%, respectively.

Panel A: PMN Returns

Dep. Var.: PMN Return	(1) BLU	(2) BW (ew)	(3) BW (uw)	(4) BWTEP (ew)	(5) BWTEP (uw)	(6) BWTEPCP (ew)	(7) BWTEPCP (uw)
Δ RRBI Firms HQ US, lag 2m	-0.64**	-0.62**	-0.65**	-0.58***	-0.67**	-0.42**	-0.62**
	(-2.36)	(-2.25)	(-2.29)	(-3.62)	(-2.50)	(-2.00)	(-2.32)
Δ RRBI Firms HQ US, lag 1m	-0.36	-0.09	-0.15	-0.46	-0.19	-0.33	-0.11
	(-1.10)	(-0.30)	(-0.48)	(-1.65)	(-0.64)	(-1.35)	(-0.42)
Δ RRBI Firms HQ US	-0.31	-0.33	-0.36	-0.27	-0.29	-0.16	-0.18
	(-0.89)	(-0.94)	(-1.02)	(-1.11)	(-0.91)	(-0.64)	(-0.56)
Constant	0.06	0.33	0.30	-0.02	0.14	-0.15	0.20
	(0.24)	(1.22)	(1.13)	(-0.08)	(0.56)	(-0.71)	(0.81)
Observations	81	81	81	81	81	81	81
R-squared	0.07	0.05	0.06	0.09	0.06	0.04	0.05

Dep. Var.: PMN Return	(9) BLU	(10) BW (ew)	(11) BW (uw)	(12) BWTEP (ew)	(13) BWTEP (uw)	(14) BWTEPCP (ew)	(15) BWTEPCP (uw)
Δ RRBI Firms HQ US, lag 2m	-0.63**	-0.67**	-0.70**	-0.55***	-0.72**	-0.40*	-0.65**
	(-2.19)	(-2.33)	(-2.37)	(-3.08)	(-2.51)	(-1.97)	(-2.40)
Constant	0.10	0.39	0.37	0.02	0.22	-0.11	0.24
	(0.41)	(1.48)	(1.40)	(0.12)	(0.86)	(-0.54)	(1.02)
Observations	83	83	83	83	83	83	83
R-squared	0.05	0.04	0.05	0.05	0.05	0.02	0.05

Table 1.10

Explaining the Biodiversity PMN Performance in the US by Aggregate Biodiversity Incidents — *Continued*

Panel B: PMN Returns

Dep. Var.: PMN Alpha	(1) BLU	(2) BW (ew)	(3) BW (uw)	(4) BWTEP (ew)	(5) BWTEP (uw)	(6) BWTEPCP (ew)	(7) BWTEPCP (uw)
Δ RRBI Firms HQ US, lag 2m	-0.56***	-0.53***	-0.61***	-0.66***	-0.61***	-0.53***	-0.59***
	(-3.20)	(-3.64)	(-4.21)	(-5.51)	(-4.55)	(-3.38)	(-3.80)
Δ RRBI Firms HQ US, lag 1m	-0.53	-0.19	-0.29	-0.62*	-0.34	-0.55**	-0.24
	(-1.50)	(-0.64)	(-0.89)	(-1.90)	(-1.20)	(-2.06)	(-0.77)
Δ RRBI Firms HQ US	-0.43**	-0.40**	-0.44**	-0.27	-0.37***	-0.16	-0.26
	(-2.38)	(-2.20)	(-2.34)	(-1.59)	(-2.83)	(-0.89)	(-1.28)
Constant	0.22	0.40**	0.41**	0.12	0.26	0.07	0.31*
	(1.25)	(2.24)	(2.36)	(0.69)	(1.62)	(0.42)	(1.75)
Observations	81	81	81	81	81	81	81
R-squared	0.14	0.10	0.13	0.17	0.14	0.12	0.10

Dep. Var.: PMN Alpha	(9) BLU	(10) BW (ew)	(11) BW (uw)	(12) BWTEP (ew)	(13) BWTEP (uw)	(14) BWTEPCP (ew)	(15) BWTEPCP (uw)
Δ RRBI Firms HQ US, lag 2m	-0.51***	-0.55***	-0.61***	-0.59***	-0.61***	-0.45***	-0.58***
	(-2.82)	(-3.43)	(-3.93)	(-4.30)	(-4.04)	(-2.94)	(-3.58)
Constant	0.23	0.43**	0.43**	0.13	0.30*	0.07	0.32*
	(1.28)	(2.43)	(2.53)	(0.75)	(1.83)	(0.42)	(1.87)
Observations	83	83	83	83	83	83	83
R-squared	0.06	0.06	0.08	0.08	0.09	0.05	0.08

Table 1.11
Corporate Biodiversity Incidents and Monthly Stock Returns

This table reports the panel regression results of monthly stock returns on whether the firm experiences biodiversity incidents (from RepRisk) in that month, indicated by the binary variable Yes_BI. The sample period is from 2016-04 to 2023-06. The dependent variable is the monthly stock return. Indicator variable $\{AfterKM\}$ is a dummy for the era after the October 2021 Kunming Declaration. The main independent variables are Yes_BI and $\{AfterKM\}$. Panel A, B, and C show the extensive margin of experiencing biodiversity incidents in a month, for the world, the US, and the non-US world respectively. Panel D displays the intensive margin of additional biodiversity incidents for the world sample. Control variables, from Ln(MV) to Volatility (12m), are lagged 1 month and following Bolton and Kacperczyk (2023) whenever possible, but with the best options from Refinitiv Datastream instead. In some panels, controls are unreported for concision when indicated. Different regression models have different inclusions of fixed effects (year-month, country, and MSCI ESG industry) as shown at the bottom. Standard errors (in parentheses) are double clustered at the firm and year level. Significance levels are *** at 1%, ** at 5%, and * at 10%, respectively.

Panel A: World (Extensive Margin)

Dep. Var.: Ret.	(1) Return (%)	(2) Return (%)	(3) Return (%)	(4) Return (%)	(5) Return (%)	(6) Return (%)
Yes_BI	0.180	-0.249*	0.154	-0.286	0.144	-0.293
	(0.219)	(0.119)	(0.116)	(0.234)	(0.133)	(0.196)
{After KM} x Yes_BI		1.828***		1.856***		1.852***
		(0.201)		(0.177)		(0.199)
Ln(MV)	-0.164	-0.164	-0.193*	-0.193*	-0.235**	-0.234*
	(0.118)	(0.118)	(0.089)	(0.089)	(0.099)	(0.099)
P/B	-0.051**	-0.051**	-0.051***	-0.051***	-0.055***	-0.055***
	(0.019)	(0.019)	(0.012)	(0.012)	(0.012)	(0.012)
Leverage (TD/TA)	-0.006**	-0.006**	-0.004	-0.004	-0.005*	-0.005*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Momentum (12m)	-0.023	-0.024	-0.022	-0.023	-0.025	-0.026
	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)	(0.028)
CapEx/TA	-0.008	-0.009	-0.010	-0.010	-0.010	-0.011
	(0.021)	(0.021)	(0.020)	(0.020)	(0.019)	(0.020)
Ln(PPE)	0.111	0.111	0.155*	0.155*	0.175**	0.175**
	(0.101)	(0.101)	(0.070)	(0.070)	(0.071)	(0.071)
ROE	0.029***	0.029***	0.029***	0.029***	0.030***	0.030***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Volatility (12m)	0.079*	0.079*	0.077	0.077	0.075	0.075
	(0.041)	(0.041)	(0.044)	(0.044)	(0.043)	(0.043)
Constant	-0.168	-0.167	-0.547	-0.546	-0.401	-0.399
	(0.337)	(0.335)	(0.428)	(0.430)	(0.399)	(0.404)
Year-Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	No	No	Yes	Yes
ESG Industry F.E.	No	No	Yes	Yes	Yes	Yes
Observations	471433	471433	471433	471433	471433	471433
Adj. R-squared	0.223	0.223	0.222	0.223	0.223	0.223

Table 1.11
Corporate Biodiversity Incidents and Monthly Stock Returns — *Continued*

Panel B: US (Extensive Margin)

Dep. Var.: Ret.	(1) Return (%)	(2) Return (%)	(3) Return (%)	(4) Return (%)
Yes_BI	0.187	-0.485*	0.266	-0.412
	(0.330)	(0.247)	(0.205)	(0.391)
{After KM} x Yes_BI		2.868***		2.877***
		(0.411)		(0.392)
Controls	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes
Country F.E.	-	-	-	-
ESG Industry F.E.	No	No	Yes	Yes
Observations	147763	147763	147763	147763
Adj. R-squared	0.254	0.255	0.255	0.255

Panel C: Non-US World (Extensive Margin)

Dep. Var.: Ret.	(1) Return (%)	(2) Return (%)	(3) Return (%)	(4) Return (%)	(5) Return (%)	(6) Return (%)
Yes_BI	0.168	-0.151	0.101	-0.226	0.100	-0.230
	(0.180)	(0.105)	(0.088)	(0.185)	(0.118)	(0.147)
{After KM} x Yes_BI		1.361***		1.376***		1.394***
		(0.212)		(0.183)		(0.205)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	No	No	Yes	Yes
ESG Industry F.E.	No	No	Yes	Yes	Yes	Yes
Observations	323670	323670	323670	323670	323670	323670
Adj. R-squared	0.228	0.228	0.228	0.228	0.228	0.228

Panel D: World (Intensive Margin)

Dep. Var.: Ret.	(1) Return (%)	(2) Return (%)	(3) Return (%)	(4) Return (%)
BI_Counts (> 0)	0.113	0.064	0.121*	0.073
	(0.081)	(0.084)	(0.061)	(0.078)
{After KM} x BI_Counts (> 0)		0.233**		0.227**
		(0.088)		(0.074)
Controls	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes	Yes
ESG Industry F.E.	No	No	Yes	Yes
Observations	14572	14572	14571	14571
Adj. R-squared	0.296	0.296	0.298	0.298

Table 1.12
Difference-in-Differences of Corporate Biodiversity Incidents and Monthly Stock Returns

This table reports the difference-in-differences analysis on stock returns and whether the firm experiences biodiversity incidents (from RepRisk) in that month, indicated by the binary variable Yes_BI. The sample period is from 2016-04 to 2023-06. The dependent variable is the difference in the stock returns between month t and $(t-1)$. The indicator variable $AfterKM$ is a dummy for the era after the October 2021 Kunming Declaration. The main independent variables are Yes_BI and $AfterKM$. Panel A, B, and C show the results for the world, the US, and the non-US world respectively. Control variables, from Ln(MV) to Volatility (12m), are lagged 1 month and following Bolton and Kacperczyk (2023) whenever possible, but with the best options from Refinitiv Datastream instead. In some panels, the controls are not reported for concision when indicated. Different regression models have different inclusions of fixed effects (year-month, country, and MSCI ESG industry) as shown at the bottom. Standard errors (in parentheses) are double clustered at the firm and year level. The significance levels are *** at 1%, ** at 5%, and * at 10%, respectively.

Panel A: World

Dep. Var.: Diff. Ret. [t, t-1]	(1) Diff.Ret.(%)	(2) Diff.Ret.(%)	(3) Diff.Ret.(%)	(4) Diff.Ret.(%)	(5) Diff.Ret.(%)	(6) Diff.Ret.(%)
Yes_BI	0.423***	0.452**	0.466***	0.489**	0.503***	0.530**
	(0.095)	(0.181)	(0.100)	(0.156)	(0.081)	(0.164)
{After KM} x Yes_BI		-0.125		-0.095		-0.112
		(0.450)		(0.461)		(0.450)
Ln(MV)	-0.713***	-0.713***	-0.821***	-0.821***	-0.924***	-0.924***
	(0.095)	(0.095)	(0.107)	(0.107)	(0.115)	(0.115)
P/B	-0.105***	-0.105***	-0.114***	-0.114***	-0.120***	-0.120***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
Leverage (TD/TA)	-0.004**	-0.004**	-0.001	-0.001	-0.003*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Momentum (12m)	0.108*	0.109*	0.115**	0.115**	0.122**	0.122**
	(0.047)	(0.047)	(0.045)	(0.045)	(0.047)	(0.047)
CapEx/TA	-0.034**	-0.034**	-0.022*	-0.022*	-0.028**	-0.028**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Ln(PPE)	0.247***	0.247***	0.403***	0.403***	0.451***	0.451***
	(0.042)	(0.042)	(0.058)	(0.058)	(0.061)	(0.061)
ROE	0.004*	0.004*	0.006**	0.006**	0.006**	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Volatility (12m)	-0.034	-0.034	-0.033	-0.033	-0.044*	-0.044*
	(0.024)	(0.024)	(0.023)	(0.023)	(0.021)	(0.021)
Constant	3.265***	3.265***	1.925***	1.925***	2.300***	2.300***
	(0.494)	(0.494)	(0.370)	(0.370)	(0.403)	(0.402)
Year-Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	Yes	Yes	No	No	Yes	Yes
ESG Industry F.E.	No	No	Yes	Yes	Yes	Yes
Observations	471433	471433	471433	471433	471433	471433
Adj. R-squared	0.218	0.218	0.218	0.218	0.218	0.218

Table 1.12
Difference-in-Differences of Corporate Biodiversity Incidents and Monthly Stock Returns — *Continued*

Panel B: US

Dep. Var.: Diff. Ret. [t, t-1]	(1) Diff.Ret.(%)	(2) Diff.Ret.(%)
Yes_BI	0.659**	0.888***
	(0.217)	(0.227)
Controls	Yes	Yes
Year-Month F.E.	Yes	Yes
Country F.E.	-	-
ESG Industry F.E.	No	Yes
Observations	147763	147763
Adj. R-squared	0.270	0.271

Panel C: US

Dep. Var.: Diff. Ret. [t, t-1]	(1) Diff.Ret.(%)	(2) Diff.Ret.(%)	(3) Diff.Ret.(%)
Yes_BI	0.281**	0.265**	0.310**
	(0.104)	(0.094)	(0.097)
Controls	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes
Country F.E.	Yes	No	Yes
ESG Industry F.E.	No	Yes	Yes
Observations	323670	323670	323670
Adj. R-squared	0.211	0.211	0.212

Panel A: MSCI Data with 730 Days Freshness, 2007-01 to 2023-06

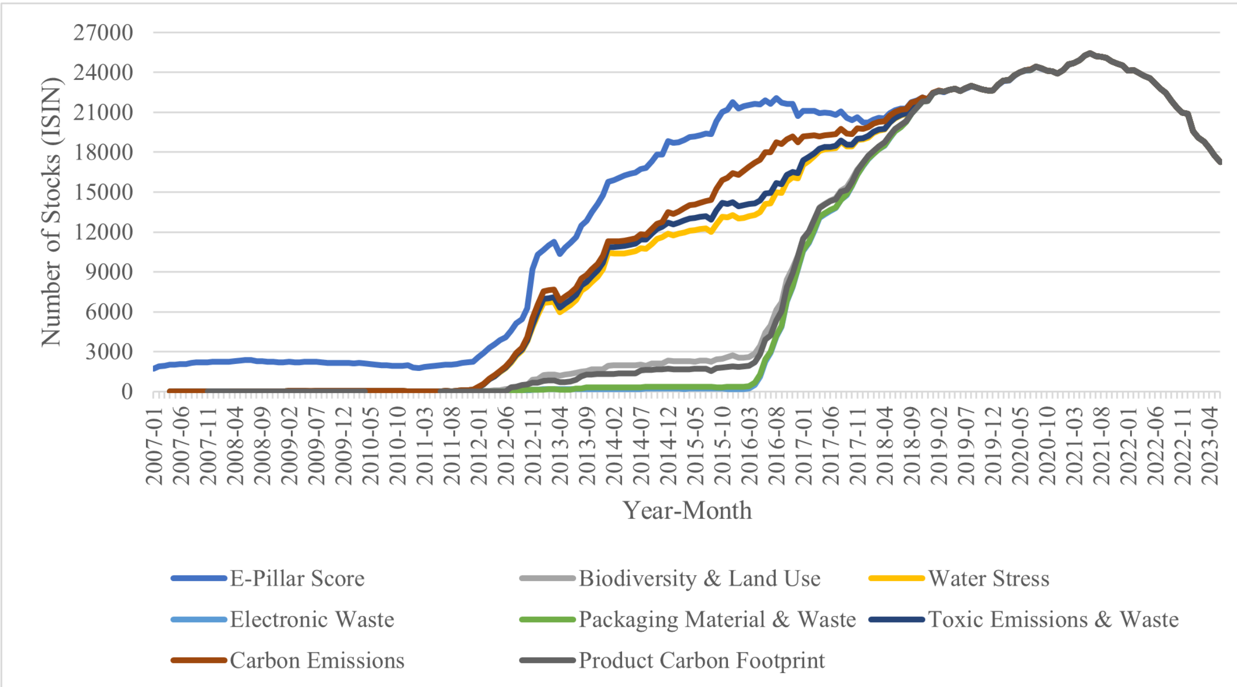
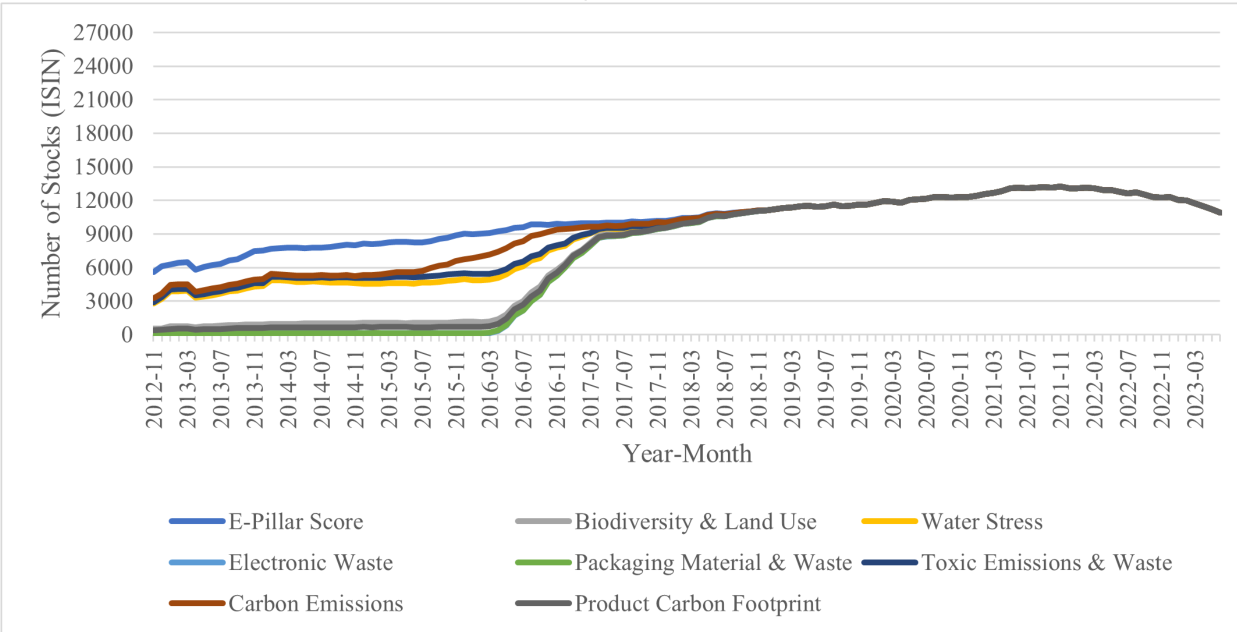


Figure 1.1. Monthly Stock Coverage of Key MSCI Variables. Panel A plots the coverage of stocks (as of ISIN codes) with non-missing values in the environmental pillar score and in each key biodiversity-related risk exposure per month from 2007-01 to 2022-12 (and carried forward to 2023-06) in the MSCI ESG Ratings Expanded File, which is delivered in March 2023. The monthly scores are in effect no more than 730 calendar days after each stock's most recent MSCI EGS Ratings updating date ("IVA_RATING_DATE") per year, and the scores need to be within the [0, 10] range defined by MSCI. The in-effect data is ensured to be carried forward to the first date of each month within 730 calendar days only if no new update is made by MSCI earlier than that. The 2023-01 to 2023-06 monthly data is forward filled with the most up-to-date data in previous months which are still in force. Most of the data within the full sample period is fresh within 1 calendar year. Panel B displays the evolved version from Panel A after merging with stocks in Refinitiv Datastream, which have valid end-of-month returns and end-of-previous-month market capitalizations. Additionally, Panel C requires all the key variables to be non-missing simultaneously, and hence all the lines are overlapped as one lines. Those filters automatically reduce the time range to [2015-10, 2023-06], but the [2015-10, 2016-03] data coverage is too low. Therefore, the data in the empirical analysis starts from 2016-04. See Table 1.1 for the variables explanations. The Environmental Pillar weight coverage is omitted in Figure 1.1 due to overlapping with the Environmental Pillar score.

Panel B: MSCI-Datastream Merged & Filtered Data, 2012-11 to 2023-06



Panel C: MSCI-Datastream Merged & Filtered Data with All Key Variables Non-missing, 2015-11 to 2023-06

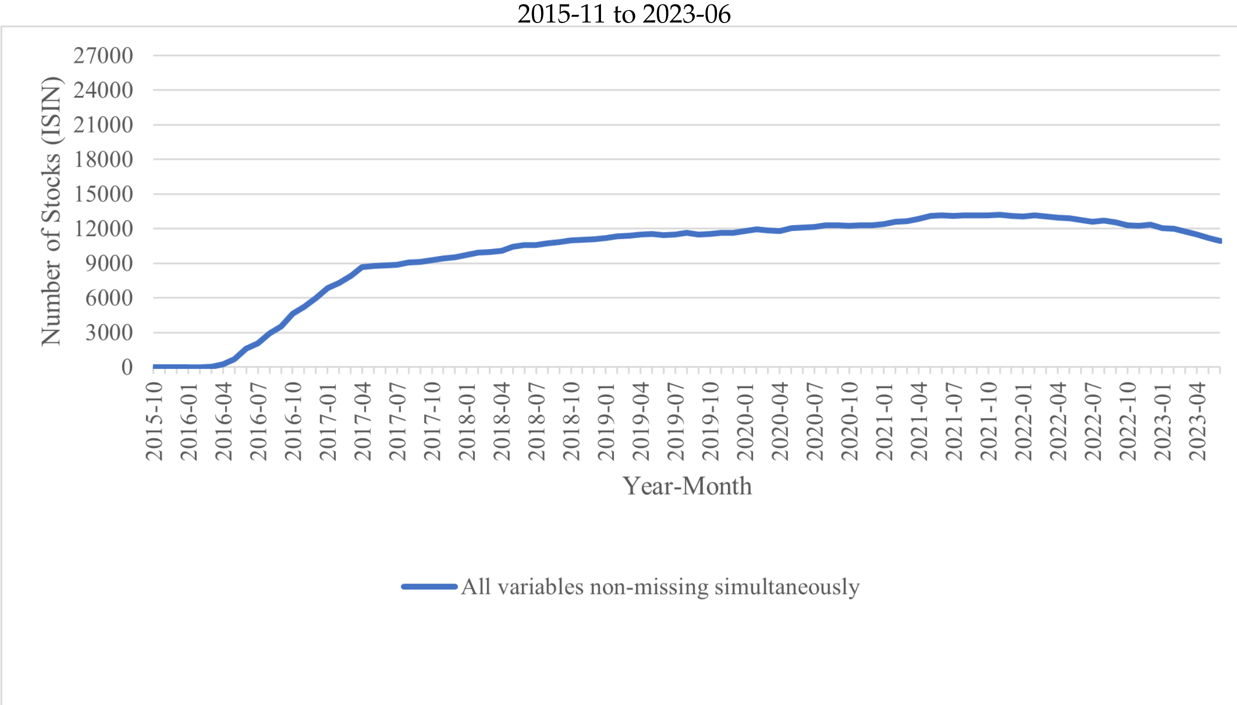
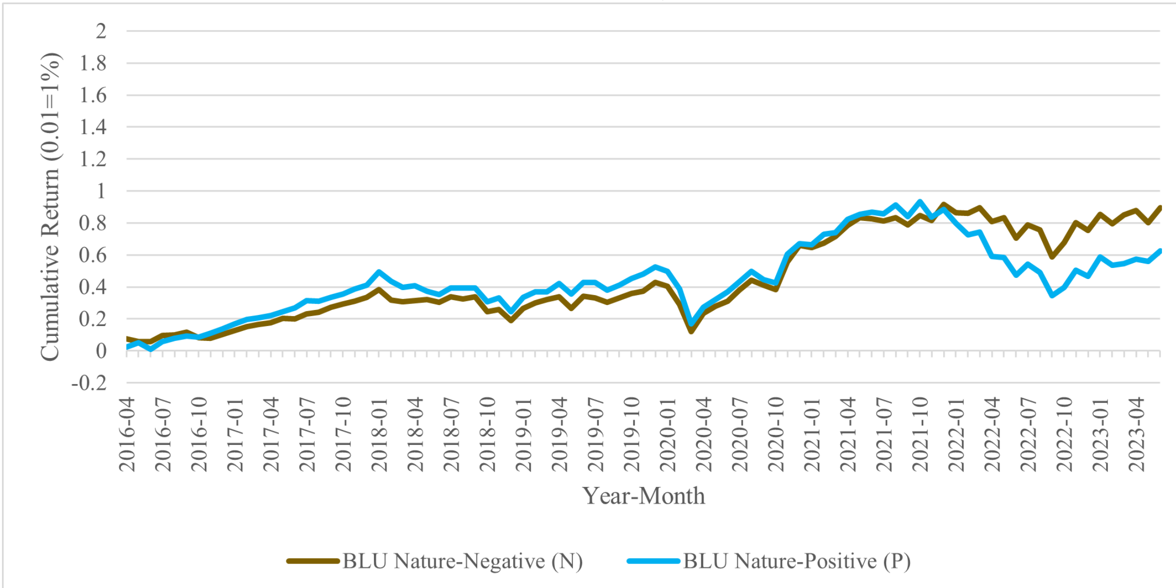


Figure 1.1. Monthly Stock Coverage of Key MSCI Variables. — *Continued*

Panel A: Global 46 Major Markets



Panel B: Non-US 45 Major Markets vs. US Market

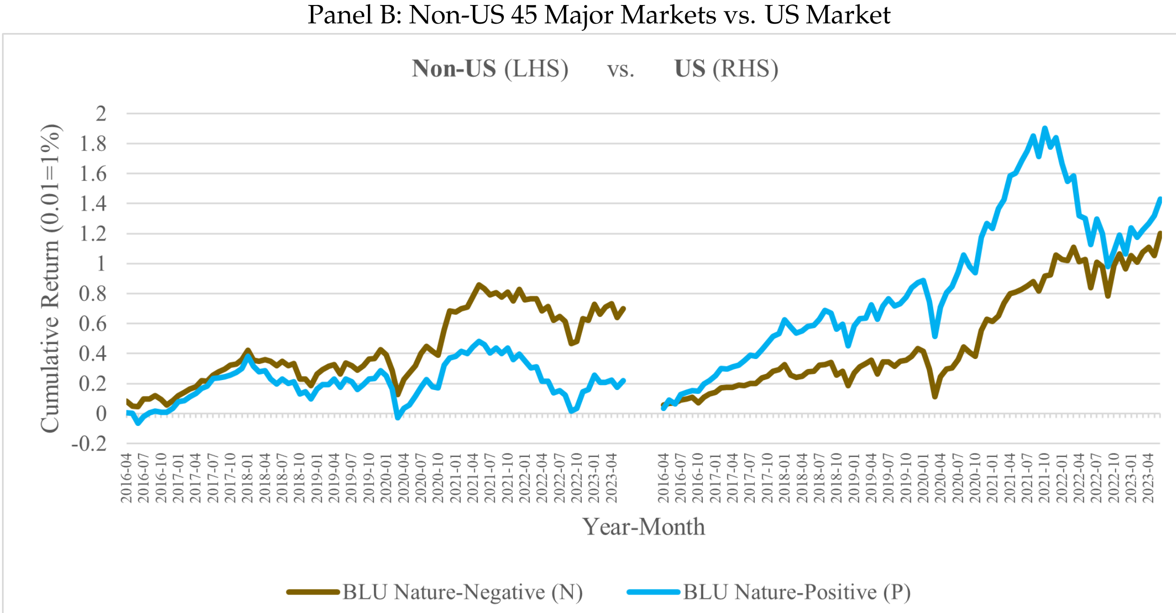
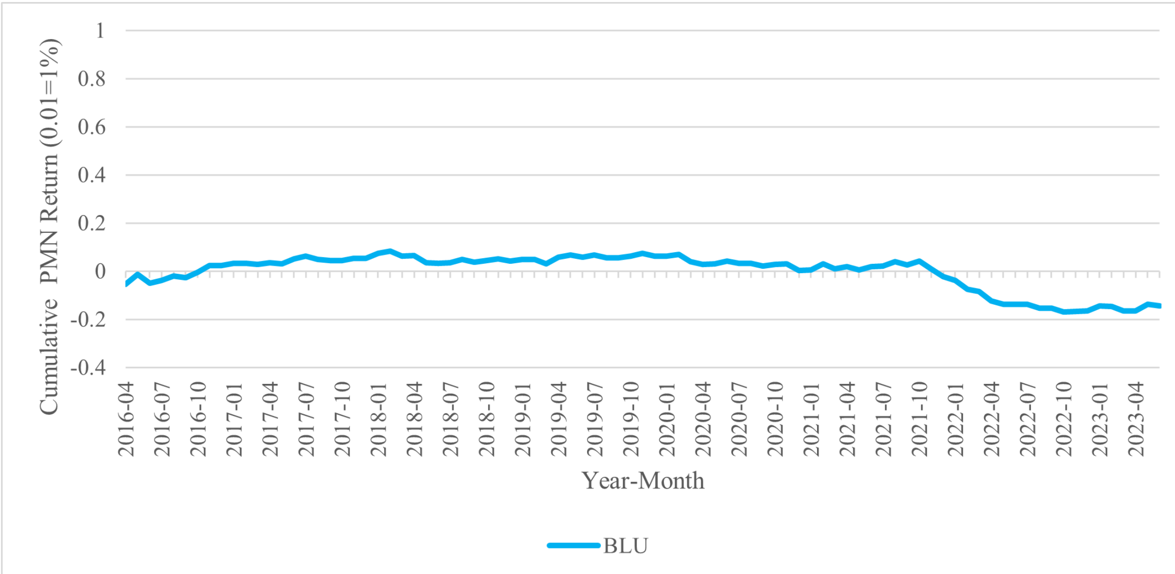


Figure 1.2. Portfolio Returns: BLU Nature-Positive vs. BLU Nature-Negative. This figure shows the cumulative returns of the Nature-Positive portfolio and the Nature-Negative portfolio based on stocks sorted by the BLU biodiversity risk exposure as defined in Table 1.1. Low biodiversity risk exposure means Nature-Positive while high risk for Nature-Negative. The returns are monthly frequency from 2016-04 to 2023-06. The analysis starts from 2016-04 due to data availability. Panel A is for the major representative 46 markets in the globe, while Panel B breaks down the 46 markets into the US market and the 45 major non-US markets. The global pricing factors are also based on these 46 markets as in Karolyi and Wu (2018). Results are very similar if using all the markets included in the MSCI-Datastream merged and cleaned data.

Panel A: Global 46 Major Markets



Panel B: Non-US 45 Major Markets vs. US Market

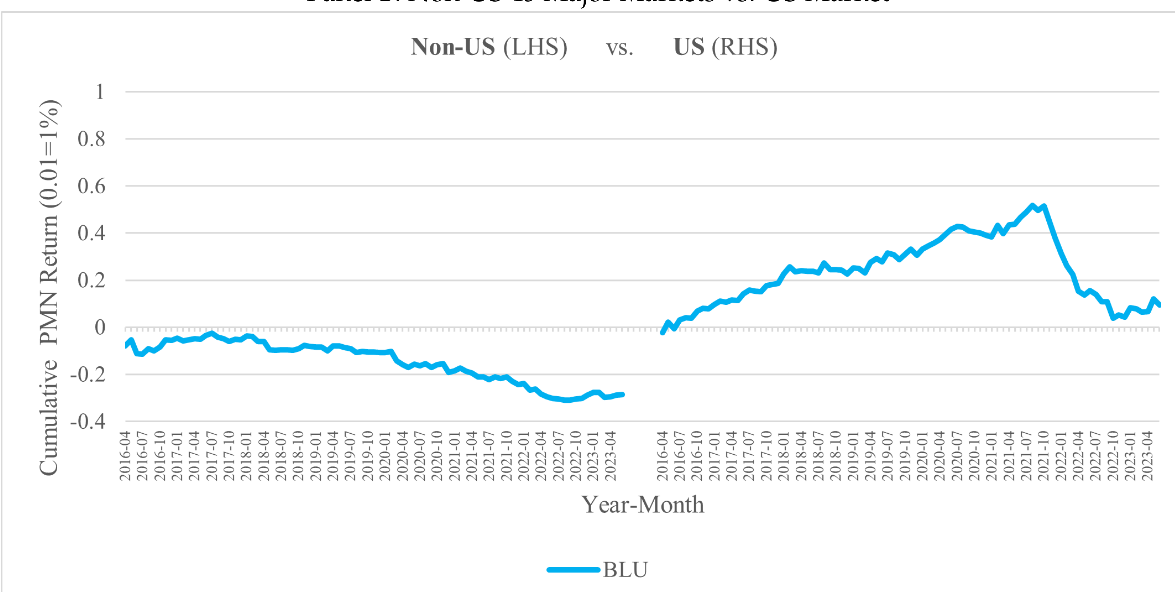
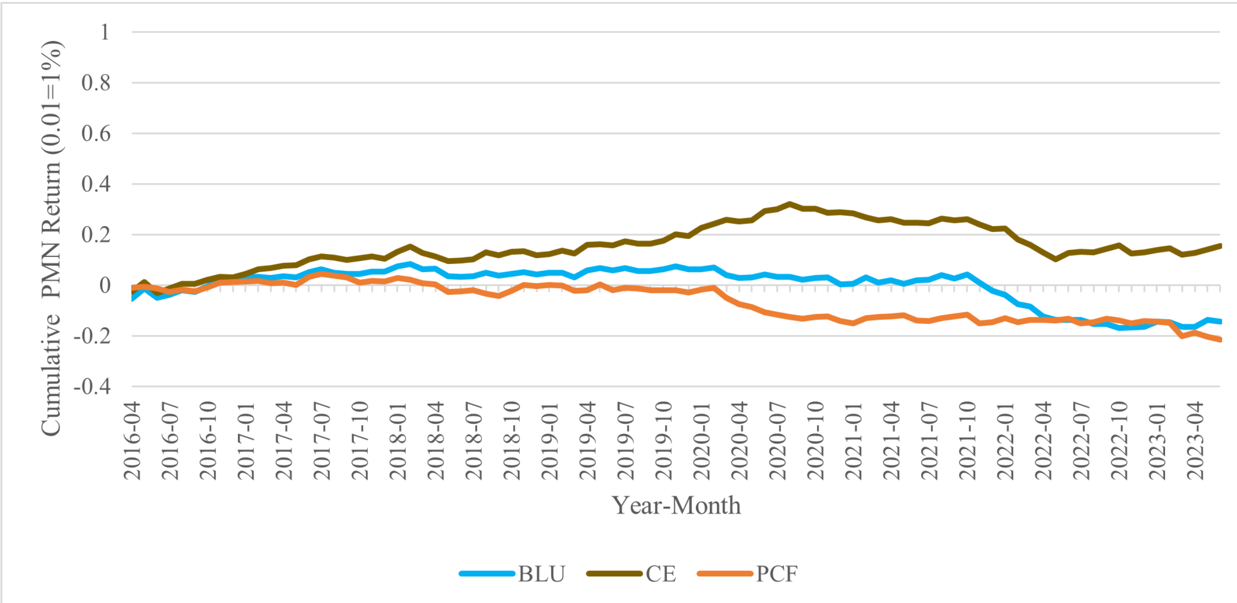


Figure 1.3. BLU Nature-PMN Factor Return. This figure shows the cumulative Nature-PMN (Positive-Minus-Negative) returns based on the BLU biodiversity risk exposure. The returns are monthly frequency from 2016-04 to 2023-06. The analysis starts from 2016-04 due to data coverage rate. Panel A is for the major representative 46 markets in the globe, while Panel B breaks down the 46 markets into the US market and the 45 major non-US markets. The global pricing factors are also based on these 46 markets as in Karolyi and Wu (2018). Results are very similar if using all the markets included in the MSCI-Datastream merged and cleaned data. Panel C and D compare the PMN factors based on BLU (Biodiversity & Land Use), CE (Carbon Emissions), and PCF (Product Carbon Footprint) as defined in Table 1.1.

Panel C: BLU vs. CE vs. PCF — Global 46 Major Markets



Panel D: BLU vs. CE vs. PCF — Non-US 45 Major Markets and the US Market

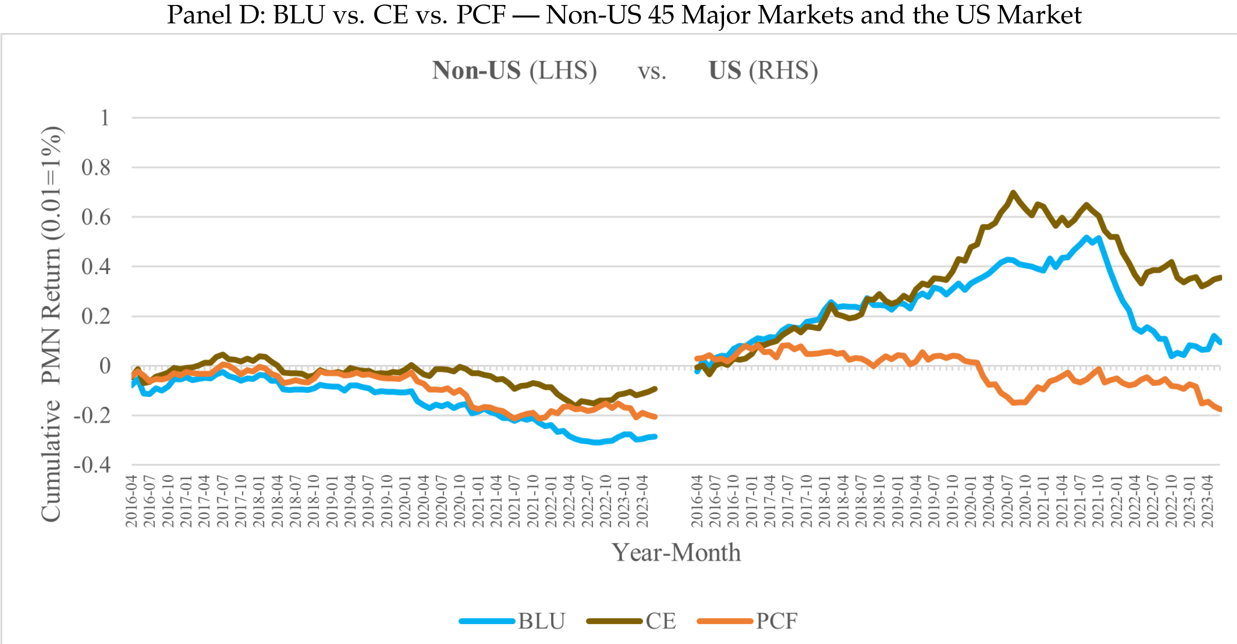
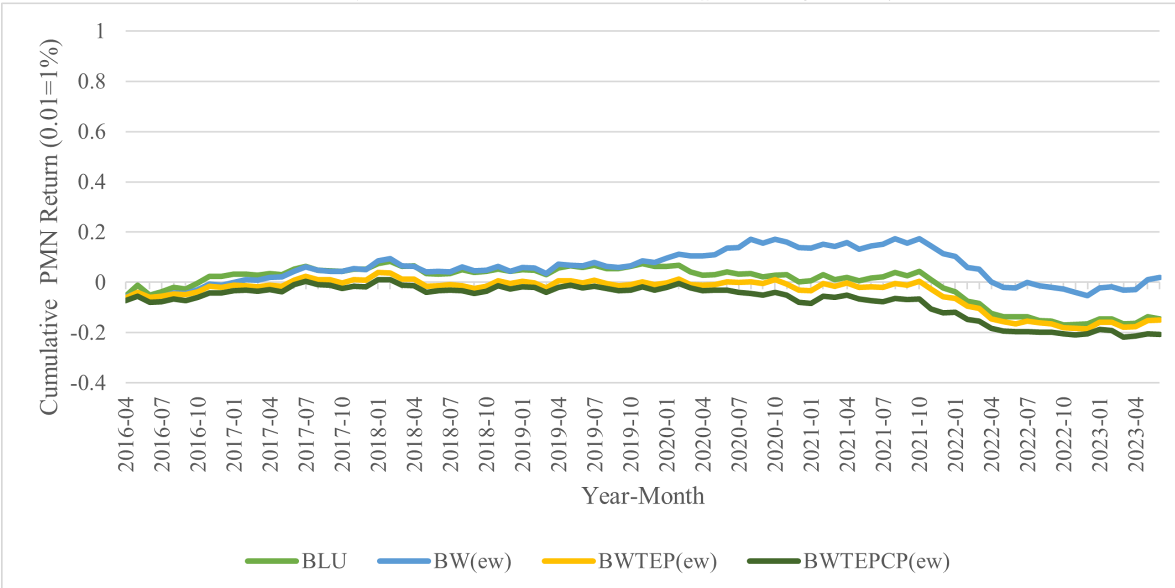


Figure 1.3. BLU Nature-PMN Factor Return. — *Continued*

Panel A: Global 46 Major Markets, with BLU and Equal-Weighted Synthetic Measures



Panel B: Global 46 Major Markets, with BLU and Unequal-Weighted Synthetic Measures

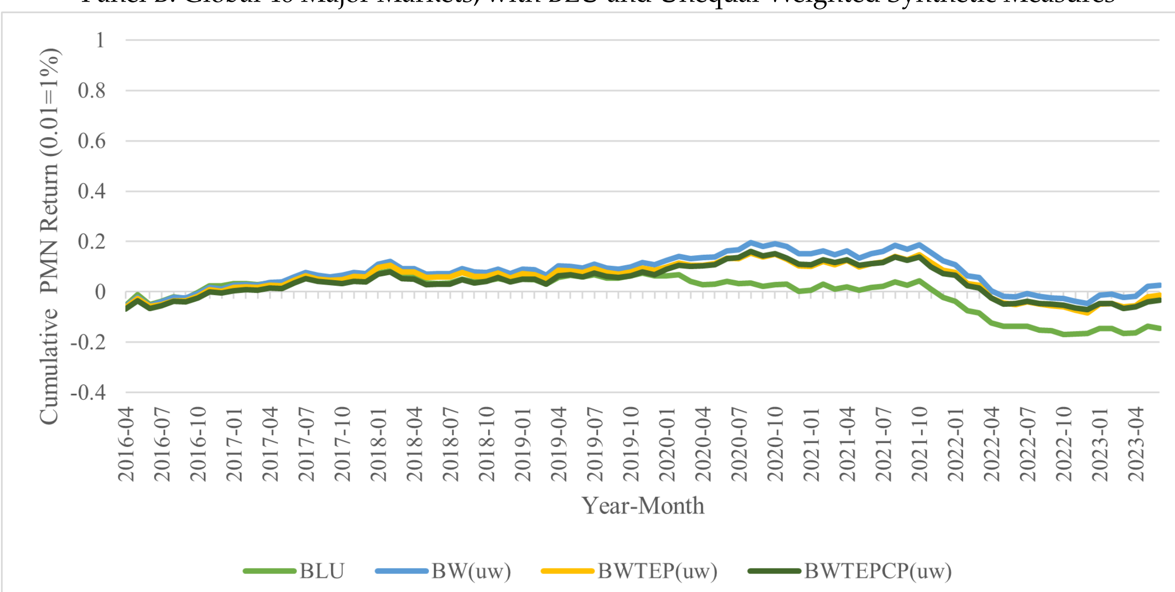
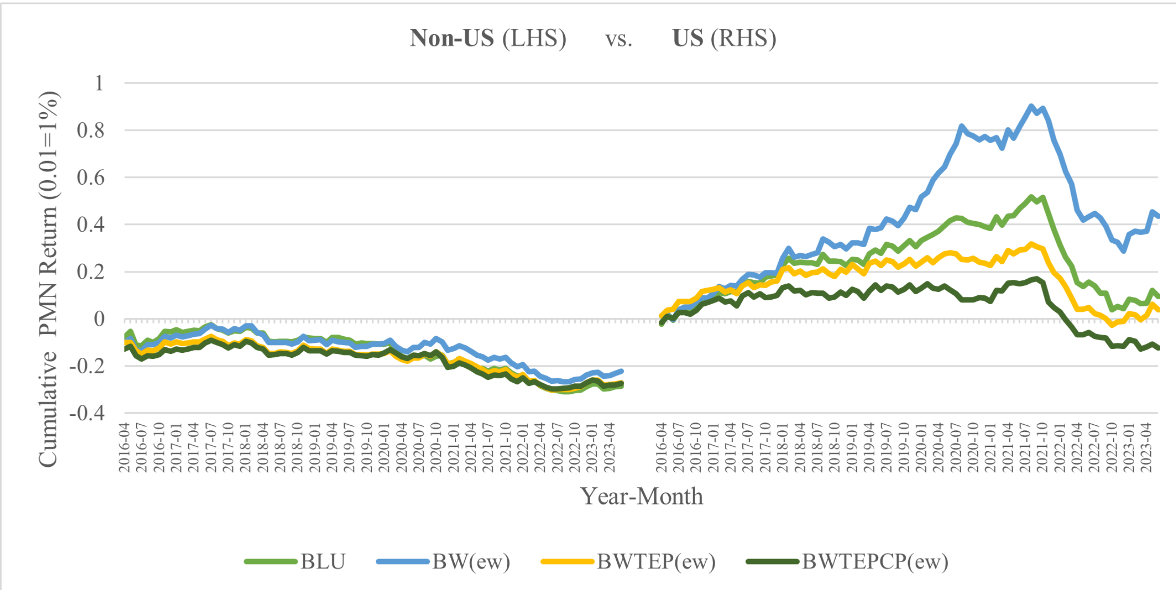


Figure 1.4. Biodiversity Nature-PMN Factor Returns by Various Measures. This figure demonstrates the cumulative Nature-PMN factor returns based on the standalone biodiversity risk exposure BLU and the synthetic biodiversity risk exposures BW, BWTEP, and BWTEPCP by the equal-weighted and unequal-weighted methods as introduced in Table 1.1. Panel A and B are for the global representative 46 major markets, while Panel C and D compare the non-US 45 major markets with the US market. The returns are monthly frequency from 2016-04 to 2023-06. The analysis starts from 2016-04 due to data coverage rate. The global pricing factors are also based on these 46 markets as in Karolyi and Wu (2018). Results are very similar if using all the markets included in the MSCI-Datastream merged and cleaned data.

Panel C: Non-US 45 Major Markets vs. US Market, with BLU and Equal-Weighted Synthetic Measures



Panel D: Non-US 45 Major Markets vs. US Market, with BLU and Unequal-Weighted Synthetic Measures

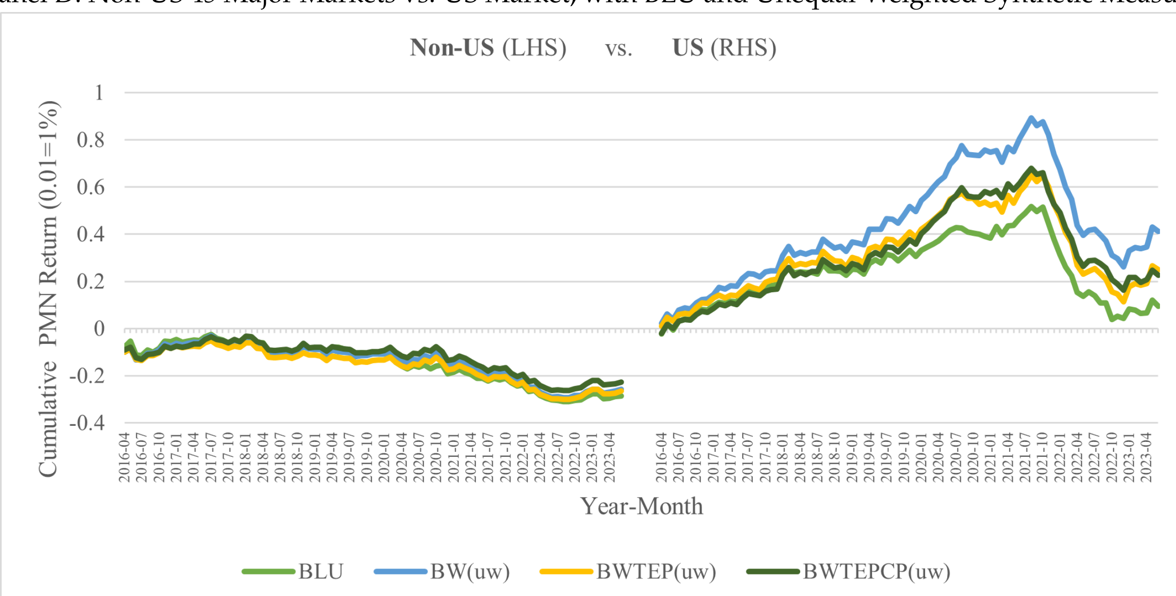


Figure 1.4. Biodiversity Nature-PMN Factor Returns by Various Measures. — *Continued*

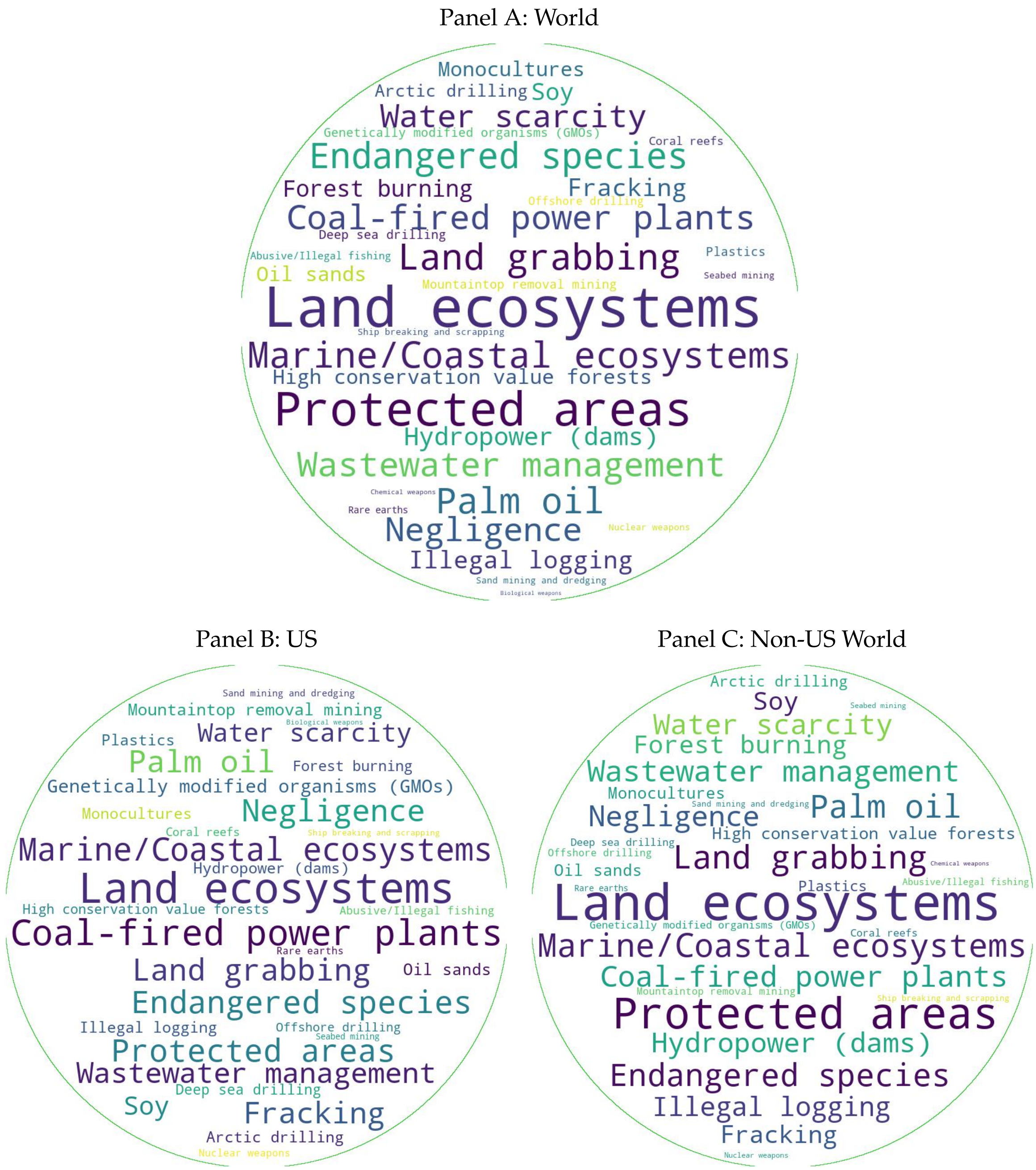
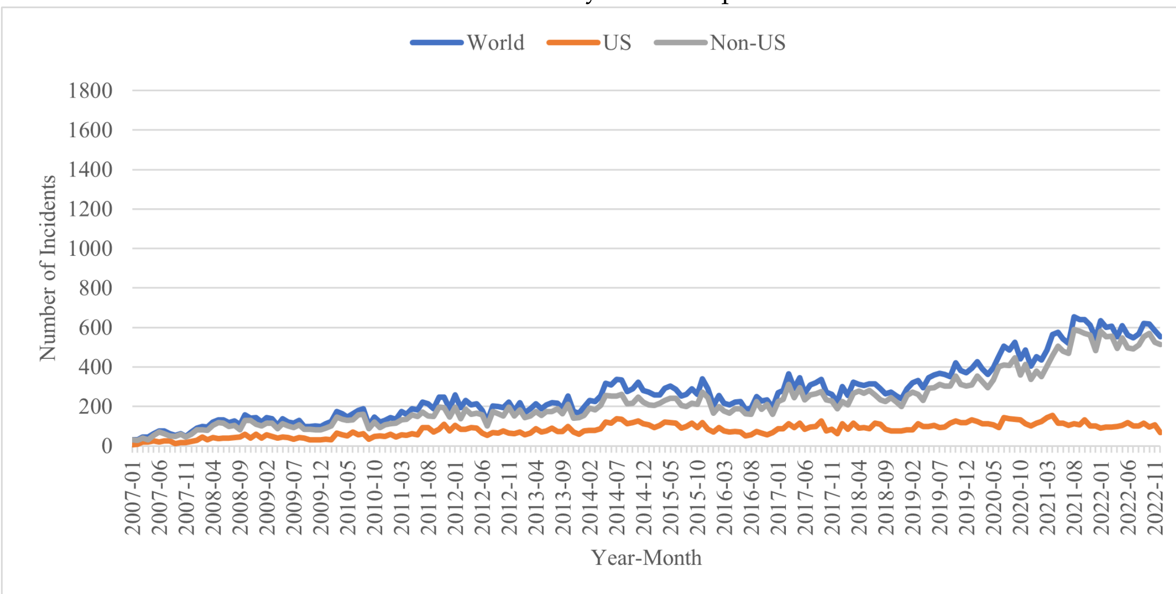


Figure 1.5. Word Cloud of RepRisk Biodiversity Incidents Topic Tags. This figure displays the word cloud of the RepRisk biodiversity incidents topic tags in the RepRisk Premium V2 database from 2007-01 to 2022-12 for the world, the US, and the non-US world in Panel A, B, and C, respectively. Biodiversity incidents are identified by the RepRisk indicator variable "Impacts on landscapes, ecosystems, and biodiversity." There are 33 biodiversity related ESG topic tags according to the RepRisk Research Scope: Topic Tags data guide (July 2023 version). Different biodiversity incident-firm observations can involve different numbers of biodiversity topic tags, and one biodiversity incident can involve a single or multiple firms. Larger font size of a topic tag means a higher number of appearances among the biodiversity incidents.

Panel A: Biodiversity Incidents per Month



Panel B: Firms Involved in Biodiversity Incidents per Month

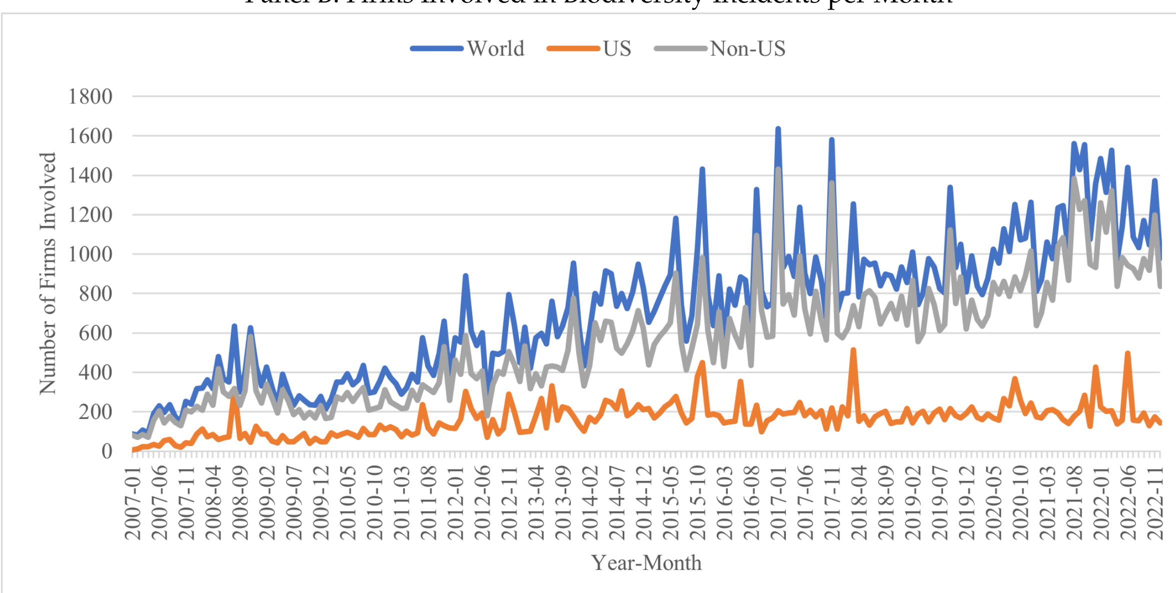
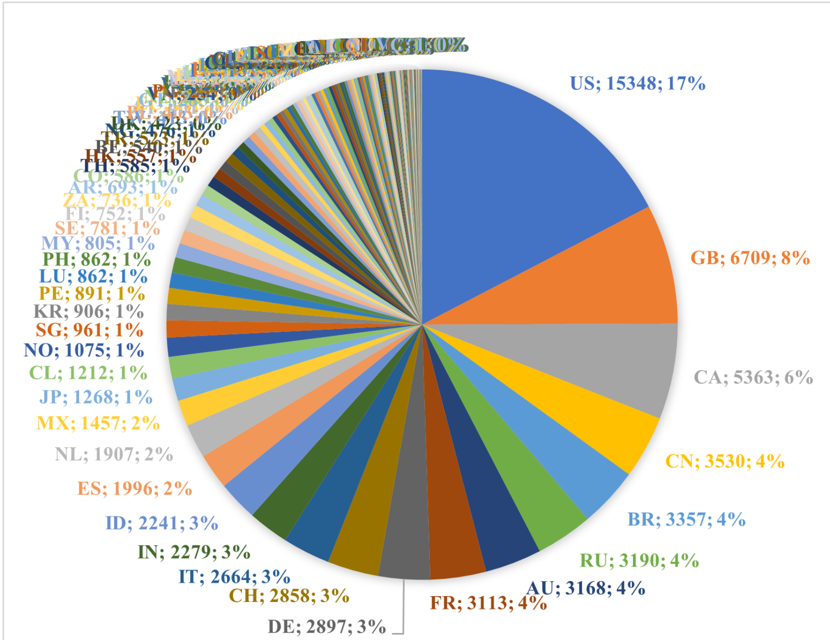


Figure 1.6. RepRisk Biodiversity Incidents and Firms Involved per Month. This figure displays the monthly number of RepRisk corporate biodiversity incidents and firms involved in those incidents from 2007-01 to 2022-12, in Panel A and Panel B, respectively. Biodiversity incidents are identified by the RepRisk indicator variable "*Impacts on landscapes, ecosystems, and biodiversity*." Each incident can involve one firm or multiple firms based in the same or different countries by headquarters location. Therefore, the sum of the US and non-US counts of incidents can be equal to or greater than the world count in any given month.

Panel A: Distribution by Incident Company Headquarters Country



Panel B: Distribution by Incident-Related Country

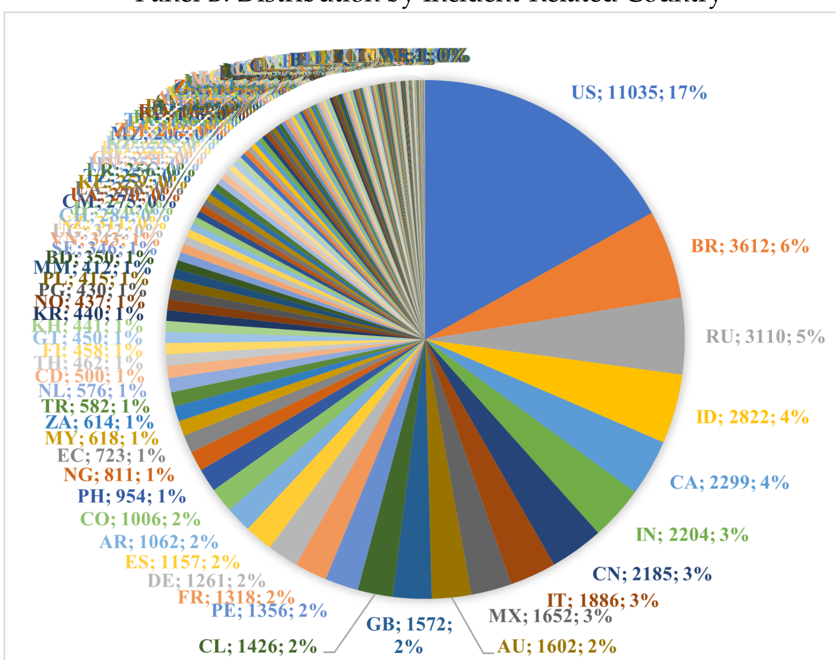


Figure 1.7. RepRisk Biodiversity Incidents Distribution by Countries. This figure displays the distribution of RepRisk corporate biodiversity incidents in each country from 2007-01 to 2022-12, in terms of incident company headquarters countries (211) and of incident related countries (227), respectively, in Panel A and Panel B. The portions are rounded to the nearest integer. ISO3166 alpha-2 country codes are followed by incidents count and ratios.

APPENDIX

Table 1.A.1
Distribution of Stocks across Markets in MSCI-Datastream Merged Data with Non-missing Values in All Key Variables

This table displays the coverage of stocks and markets in the MSCI-Datastream merged dataset. It corresponds to the last row in Table 1.2, which requires all the key MSCI variables to be valid. There are 21,248 unique ISIN codes overall. Among which, 21,032 ISIN codes are linked to one market each; 214 ISIN codes are linked to 2 markets each; 2 ISIN codes are linked to 3 markets each. According to ISIN and ISO documents: (1) "A company changes the country in which it is headquartered: A new ISIN is required only if the company replaces an old security with a new one;" (2) "The first 2 characters (of ISIN) are the alpha-2 country code prefix, as issued per ISO 3166-1, of the country where the issuer of securities (other than debt securities) is legally registered or in which it has legal domicile." In addition, the concept of "country" in this dissertation refers to "stock market", which could be a sovereign country or a non-sovereign state/region with a valid ISO alpha-2 code.

Panel A: Focused 46 Markets

Region	Market	Alpha-2 Code	Stock-Month Obs.	Stocks (ISIN)	Min. Month	Max. Month
North America	United States	US	306,932	6,438	2016-02	2023-06
North America	Canada	CA	37,808	809	2016-04	2023-06
Europe	Austria	AT	4,582	97	2016-05	2023-06
Europe	Belgium	BE	5,106	100	2016-05	2023-06
Europe	Denmark	DK	5,014	106	2016-04	2023-06
Europe	Finland	FI	4,569	115	2016-04	2023-06
Europe	France	FR	20,832	451	2016-03	2023-06
Europe	Germany	DE	21,046	464	2016-03	2023-06
Europe	Greece	GR	825	22	2016-06	2023-06
Europe	Ireland	IE	9,215	214	2016-04	2023-06
Europe	Italy	IT	10,098	217	2016-03	2023-06
Europe	Netherlands	NL	18,981	490	2016-03	2023-06
Europe	Norway	NO	6,556	172	2016-05	2023-06
Europe	Portugal	PT	1,637	36	2016-06	2023-06
Europe	Spain	ES	9,238	209	2016-05	2023-06
Europe	Sweden	SE	18,329	419	2016-04	2023-06
Europe	Switzerland	CH	13,769	268	2016-03	2023-06
Europe	United Kingdom	GB	58,293	1,327	2015-10	2023-06
Japan	Japan	JP	81,661	1,674	2016-04	2023-06
Asia Pacific	Australia	AU	26,758	655	2016-03	2023-06
Asia Pacific	Hong Kong	HK	16,317	496	2016-04	2023-06
Asia Pacific	New Zealand	NZ	4,839	134	2016-05	2023-06
Asia Pacific	Singapore	SG	9,747	261	2016-04	2023-06

Table 1.A.1
Distribution of Stocks across Markets in MSCI-Datastream Merged Data with Non-missing Values in All Key Variables — *Continued*

Panel A: Focused 46 Markets — *Continued*

Region	Market	Alpha-2 Code	Stock-Month Obs.	Stocks (ISIN)	Min. Month	Max. Month
Emerging Markets	Argentina	AR	1,168	43	2016-06	2023-06
Emerging Markets	Brazil	BR	10,193	234	2016-04	2023-06
Emerging Markets	Chile	CL	2,673	68	2016-05	2023-06
Emerging Markets	China	CN	51,947	1,657	2016-03	2023-06
Emerging Markets	Colombia	CO	1,829	43	2016-06	2023-06
Emerging Markets	Czech Republic	CZ	543	17	2016-06	2023-06
Emerging Markets	Hungary	HU	771	23	2016-08	2023-06
Emerging Markets	India	IN	16,483	369	2016-03	2023-06
Emerging Markets	Indonesia	ID	939	26	2016-06	2023-06
Emerging Markets	Israel	IL	3,233	71	2016-05	2023-06
Emerging Markets	Malaysia	MY	6,315	181	2016-05	2023-06
Emerging Markets	Mexico	MX	6,607	178	2016-04	2023-06
Emerging Markets	Pakistan	PK	368	11	2016-10	2023-06
Emerging Markets	Peru	PE	1,559	41	2016-04	2023-06
Emerging Markets	Philippines	PH	1,917	44	2016-08	2023-06
Emerging Markets	Poland	PL	2,585	51	2016-05	2023-06
Emerging Markets	Russia	RU	5,097	149	2016-06	2023-06
Emerging Markets	South Africa	ZA	8,187	178	2016-04	2023-06
Emerging Markets	South Korea	KR	30,976	823	2016-04	2023-06
Emerging Markets	Taiwan	TW	8,960	205	2016-04	2023-06
Emerging Markets	Thailand	TH	3,115	83	2016-06	2023-06
Emerging Markets	Turkey	TR	2,432	102	2016-06	2023-06
Emerging Markets	Venezuela	VE	153	6	2016-12	2022-12

Table 1.A.1
Distribution of Stocks across Markets in MSCI-Datastream Merged Data with Non-missing Values in All Key Variables — *Continued*

Panel B: Other 71 Markets

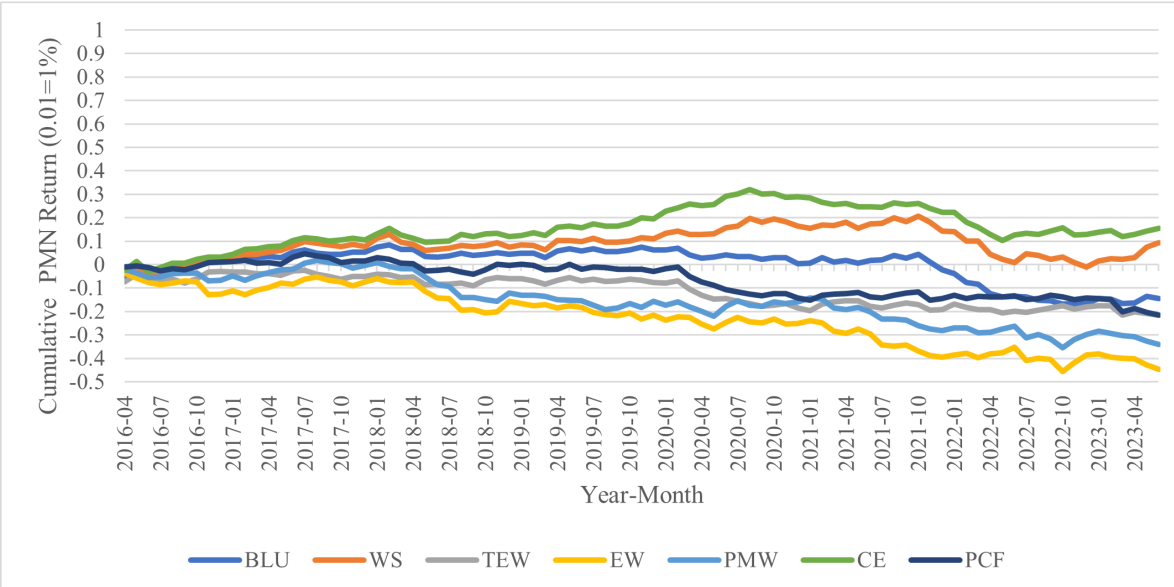
Region	Market	Alpha-2 Code	Stock-Month Obs.	Stocks (ISIN)	Min. Month	Max. Month
Others	Azerbaijan	AZ	48	1	2018-11	2022-10
Others	Bahamas	BS	152	9	2016-06	2023-06
Others	Bahrain	BH	112	6	2017-01	2023-02
Others	Bangladesh	BD	105	4	2016-10	2021-01
Others	Barbados	BB	77	2	2017-01	2023-06
Others	Bermuda	BM	5,122	126	2016-05	2023-06
Others	Bolivia	BO	42	1	2017-05	2020-10
Others	Bulgaria	BG	41	4	2016-06	2023-06
Others	Burkina Faso	BF	87	2	2017-03	2023-06
Others	Cambodia	KH	9	1	2020-08	2021-04
Others	Cayman Islands	KY	9,747	283	2016-04	2023-06
Others	Costa Rica	CR	24	1	2021-07	2023-06
Others	Croatia	HR	54	4	2016-11	2023-05
Others	Curaçao	CW	311	16	2016-10	2023-06
Others	Cyprus	CY	461	20	2016-12	2023-06
Others	Côte d'Ivoire	CI	234	6	2016-10	2022-08
Others	Dominican Republic	DO	75	1	2017-02	2023-06
Others	Egypt	EG	347	12	2016-10	2023-06
Others	El Salvador	SV	54	1	2019-01	2023-06
Others	Estonia	EE	34	3	2018-05	2022-06
Others	Faroe Islands	FO	78	1	2017-01	2023-06
Others	Gabon	GA	48	1	2016-09	2020-08
Others	Georgia	GE	229	9	2016-10	2023-04
Others	Ghana	GH	53	2	2016-07	2021-06
Others	Gibraltar	GI	139	3	2016-08	2023-06
Others	Guatemala	GT	52	1	2018-09	2022-12
Others	Guernsey	GG	1,036	32	2016-05	2023-06
Others	Honduras	HN	26	1	2020-11	2023-04
Others	Isle of Man	IM	325	9	2016-07	2023-06
Others	Jersey	JE	3,253	93	2016-05	2023-06
Others	Jordan	JO	41	3	2017-02	2021-01
Others	Kazakhstan	KZ	315	11	2016-06	2023-06
Others	Kenya	KE	99	3	2017-04	2023-06
Others	Kuwait	KW	366	12	2017-01	2023-06
Others	Latvia	LV	4	2	2019-07	2020-07
Others	Lebanon	LB	48	1	2016-06	2020-05
Others	Liechtenstein	LI	128	6	2019-05	2023-06
Others	Lithuania	LT	68	5	2017-03	2023-06
Others	Luxembourg	LU	12,286	365	2016-03	2023-06

Table 1.A.1
Distribution of Stocks across Markets in MSCI-Datastream Merged Data with Non-missing Values in All Key Variables — *Continued*

Panel B: Other 71 Markets — *Continued*

Region	Market	Alpha-2 Code	Stock-Month Obs.	Stocks (ISIN)	Min. Month	Max. Month
Others	Macao	MO	283	10	2017-02	2023-06
Others	Malawi	MW	7	1	2020-05	2020-11
Others	Mali	ML	40	1	2017-04	2021-06
Others	Malta	MT	326	10	2016-05	2023-06
Others	Marshall Islands	MH	20	3	2019-04	2023-06
Others	Mauritius	MU	496	14	2016-05	2023-06
Others	Monaco	MC	98	3	2019-01	2023-06
Others	Morocco	MA	1,224	25	2016-05	2023-06
Others	Namibia	NA	114	4	2017-03	2023-06
Others	Niger	NE	45	1	2017-04	2021-06
Others	Nigeria	NG	299	10	2016-04	2023-06
Others	North Macedonia	MK	48	1	2016-08	2020-07
Others	Oman	OM	60	2	2017-03	2023-06
Others	Panama	PA	482	17	2016-10	2023-06
Others	Papua New Guinea	PG	109	2	2016-06	2023-06
Others	Paraguay	PY	12	1	2019-05	2020-04
Others	Puerto Rico	PR	606	10	2016-07	2023-06
Others	Qatar	QA	958	24	2016-06	2023-06
Others	Romania	RO	244	9	2016-10	2023-06
Others	Saudi Arabia	SA	3,598	102	2017-05	2023-06
Others	Senegal	SN	69	1	2017-03	2023-06
Others	Serbia	RS	57	3	2016-11	2020-11
Others	Slovakia	SK	449	15	2016-09	2023-06
Others	Slovenia	SI	37	2	2017-07	2020-09
Others	Sri Lanka	LK	101	3	2016-09	2021-07
Others	Tunisia	TN	241	7	2016-06	2023-05
Others	Ukraine	UA	63	2	2018-12	2023-06
Others	United Arab Emirates	AE	2,112	58	2016-05	2023-06
Others	Uruguay	UY	129	4	2018-01	2023-06
Others	Virgin Islands (British)	VG	8,255	279	2016-04	2023-06
Others	Virgin Islands (U.S.)	VI	62	1	2017-11	2022-12
Others	Zambia	ZM	26	1	2017-06	2020-03

Panel A: Global 46 Major Markets



Panel B: Non-US 45 Major Markets vs. US Market

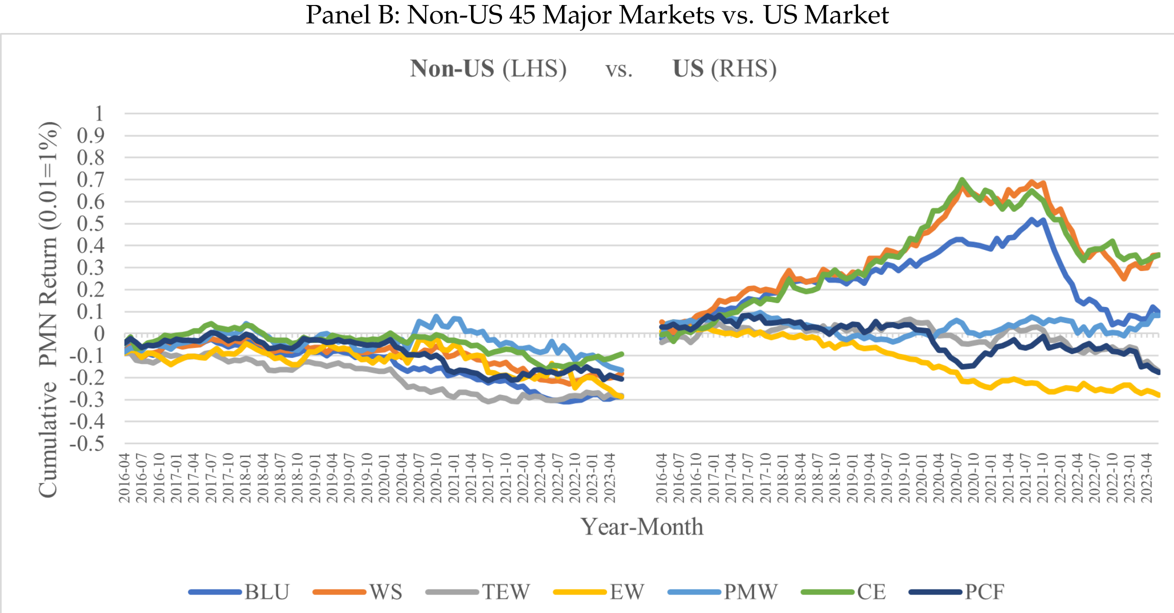


Figure 1.A.1. Nature-PMN Factor Returns Based on Standalone MSCI Risk Exposures. This figure depicts the cumulative Nature-PMN returns of all the standalone biodiversity-related risk exposures introduced in Table 1.1. The returns are monthly frequency from 2016-04 to 2023-06. The analysis starts from 2016-04 due to data coverage rate. Panel A is for the major representative 46 markets in the globe, while Panel B breaks down the 46 markets into the US market and the 45 major non-US markets. The global pricing factors are also based on these 46 markets as in Karolyi and Wu (2018). Results are very similar if using all the markets included in the MSCI-Datastream merged and cleaned data.

Panel A: World

Figure 1.A.2. RepRisk Topic Tags Comparison Across Environmental Incidents. This figure displays the word cloud of the RepRisk topic tags for each of the six environmental incidents from 2007-01 to 2022-12, for the world, the US, and the non-US world, in Panel A, B, and C, respectively. Biodiversity is for the incidents with the full name of "Impacts on landscapes, ecosystems, and biodiversity", Climate for "Climate change, GHG emissions, and global pollution (atmospheric)", Pollution for "Local pollution", Waste for "Waste issues", Animal for "Animal mistreatment" and Resources for "Overuse and wasting of resources". The RepRisk topic tags for each of the six environmental issues are given in the RepRisk Research Scope: Topic Tags data guide (July 2023 version).

Panel B: US

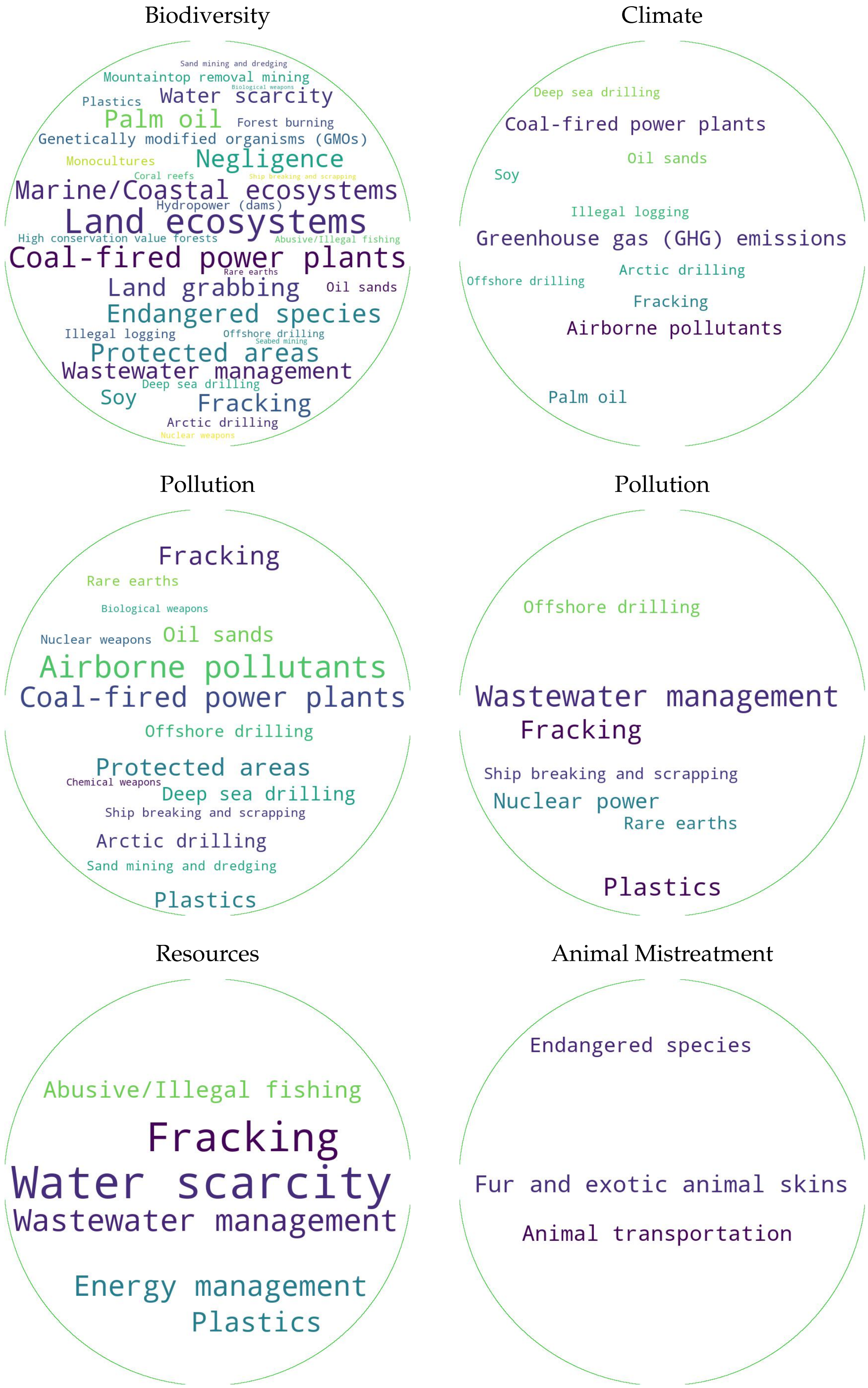


Figure 1.A.2. RepRisk Topic Tags Comparison Across Environmental Incidents. — *Continued*

Figure 1.A.2. RepRisk Topic Tags Comparison Across Environmental Incidents. — *Continued*

CHAPTER 2

UNDERSTANDING GLOBAL GREEN STOCK RETURNS AND RISKS

With G. Andrew Karolyi and Ying Wu [1]

In this chapter, we offer new evidence on how the application of environmental criteria has affected international stock returns. We estimate the market-based equity greenium (in terms of the realized green-minus-brown return spread) in a cross-section of 21,902 firms from 96 countries between November 2012 and December 2021. We find reliable evidence that green stocks earned higher returns than brown stocks around the world, driven by US stocks. This outperformance is associated with lower stock returns of energy firms but not higher returns of technology stocks. Decomposing this outperformance further into five regions, including North America, Europe, Japan, Asia Pacific, and Emerging Markets, demonstrates that the realized equity greenium effect occurs primarily in North America, and during the period before 2016. Most of the equity greenium performance cannot be explained by exposures to return factors prominent in the asset pricing literature.

2.1 Introduction

Sustainable investing, which applies environmental, social, and governance (ESG) criteria in investment decisions, has experienced an impressive development throughout the past two decades. According to the Global Sustainable Investment Review, the total assets under management for sustainable investing reached $35.3 trillion in 2020. The emerging theoretical literature predicts that green assets should have lower expected returns than

[1]This chapter originates from our earlier circulated working paper titled "Understanding the Global Equity Greenium."

brown assets (e.g., Pástor, Stambaugh, and Taylor (2021), Baker et al. (2022)). The reasons include that investors with green tastes are willing to sacrifice financial returns for social benefits, and that green assets are a better hedge against climate risk. However, empirical studies often find inconclusive evidence on the correlation between ESG characteristics and equity returns (Alessi, Ossola, and Panzica (2021), Bolton and Kacperczyk (2021, 2023), Pástor, Stambaugh, and Taylor (2022), Aswani, Raghunandan, and Rajgopal (2023), Zhang (2024)). In this study, we quantify the impact of ESG characteristics on asset prices by exploiting the time-series and the cross-sectional variations of international stock returns. Especially, we focus on the environmental (or greenness) pillar and whether there are notable differences in the greenness-return relation between the equities in the U.S. market and those in the non-U.S. markets.

We examine the pricing dynamics of green equity and their conventional counterparts using a cross-section of 21,902 firms in 96 developed and emerging market countries. We estimate the market-based greenium in terms of the realized return difference between the green and the brown portfolios, sorted by the greenness scores based on the MSCI ESG Ratings data. We follow Pástor, Stambaugh, and Taylor (2022, PST) and assign the greenness measures to individual stocks. Our sample begins in December 2012, when MSCI started to offer a more complete and balanced global data coverage, and ends in December 2021. During this period, the value-weighted portfolio of stocks in the top third of greenness outperformed the bottom third by a cumulative return difference of 70 bps per month. This return spread, which we denote as GMB (green-minus-brown), has a monthly Sharpe ratio of 0.16. This is comparable to the Sharpe ratio of the stock market during this bull market period.

We perform a comprehensive analysis on the time-series and cross-section dynamics of the realized equity greenium effect around the world. Using monthly returns of over 25,000 stocks from 46 countries, we examine whether green stocks have generally performed differently from brown stocks in the first round of global experiments. We find that the strong performance of global GMB returns cannot be explained by exposures to global return factors prominent in the asset pricing literature. Interestingly, brown stocks have started to outperform green stocks since 2022 around the world. Even in the U.S. market, the GMB spread portfolio yield a negative average return of -30 bps per month in 2022. Next, we investigate whether the outperformance of green stocks during November 2012 to December 2021 stems from the undue influence of specific industries. We find that most of the realized equity greenium effect is associated with lower stock returns of energy firms instead of higher returns of technology stocks. In the U.S. market, the global GMB spread portfolio returns has dropped down to only 25 bps per month, which is not significant at the 10% level, if the energy sector is stripped down from the portfolios. In addition, we examine how the GMB returns perform when constructed from regional test asset portfolios. We find that of the five regions (North America, Europe, Japan, Asia Pacific, and Emerging Markets), the GMB returns from North America carry the most weight in the global GMB returns. For North America, its monthly GMB return averages 58 bps, which is significant at the 1% level. In contrast, the monthly GMB returns from the other four regions are rarely distinguishable from zero on the average. There are some critical instabilities on the greenium effect over time and across regions.

The next logical question is whether the ESG risk is priced globally or locally in international stock markets. There exists a long-standing debate in the international asset pricing literature on whether securities are priced locally in segmented markets or globally in a single integrated market (Karolyi and Stulz (2003), Lewis (2011)). Most empirical evidence evaluating partial-segmentation models to date has focused only on whether aggregate market or consumption risks are priced locally or globally. However, more recent research has revealed that the cross section of average returns in global markets is importantly related to firm characteristics, such as size, book-to-market equity ratios or momentum (Bekaert, Hodrick, and Zhang (2009), Hou, Karolyi, and Kho

(2011)). An important debate has emerged over whether the explanatory power of these characteristics arises locally or globally. We are interested in how our answer on the pricing of the ESG risk in international stock markets depends on whether we account for common sources of return covariation related to firm-level attributes so prevalent in equity markets. To answer these questions, we perform a variety of asset pricing tests for a given region of interest. Specifically, we consider a purely global, perfected integrated multi-factor model, a purely local, perfectly segmented multi-factor model, and a partial segmentation hybrid model as suggested in Griffin (2002). We find that the regional GMB alphas are robust to the benchmark models considered in the test. While the performance of the GMB returns varies across regions, there has been shown a relatively stronger performance of the GMB returns in North America. For the other four regions, the performance of the GMB returns depends on whether we account for common sources of return covariation related to firm-level attributes, such as size, value, and momentum.

An interesting feature of the monthly GMB returns is that they have been positive for an extended run, both globally and across region, but then were completely neutralized in the most recent years, especially for the regions of Europe, Asia Pacific, and Emerging Markets. During the subperiod from December 2012 to December 2015, almost all of the five regions experience substantially higher GMB returns. The monthly GMB return averaged 89 bps per month, 49 bps per month, 123 bps per month, and 102 bps per month in North America, Europe, Asia Pacific, and Emerging Markets, respectively. All alphas are statistically significant, regardless of which benchmark model in our study is considered. Their monthly Sharpe ratio of GMB goes up to about 0.45 in three regions (North America, Asia Pacific, and Emerging Markets), and stays at a median level of 0.33 approximately in Europe. All those Sharpe ratios higher than their corresponding stock markets' Sharpe ratios during this bull-market period. In contrast, there is a completely different picture of the GMB performance from January 2016 to December 2021. Green stocks have started to deliver lower returns than brown stocks for three regions except

North America and Japan. The monthly GMB return averaged -34 bps per month, -56 bps per month, and -55 bps per month in Europe, Asia Pacific, and Emerging Markets, respectively. For North America and Japan, the monthly GMB returns averaged 42 bps per month and 7 bps per month, respectively, and none of them is distinguishable from zero. These underperformances cannot be explained by exposures to local return factors prominent in the asset pricing literature either.

We acknowledge, of course, that it is hard to draw a clear line of demarcation between green stocks and brown stocks. However, despite being potentially coarse, such a distinction from the MSCI ESG Ratings data provides a natural framework to test our hypotheses. Moreover, our experiments have yielded encouraging results that can inform subsequent studies.

The rest of this chapter follows this order. Section 2.2 describes the data and the construction of the green, brown, and GMB portfolios. Section 2.3 studies the realized returns of the green, brown, and GMB portfolios in the world, as well as the regional results and industrial comparisons. Section 2.4 conducts robustness checks. Section 2.5 concludes.

2.2 Data and Summary Statistics

We compute stock-level environmental scores based on MSCI ESG Ratings data, following the procedures specified in PST. The MSCI ESG Rating is a successor to the MSCI KLD data. MSCI is documented to be the world's largest provider of ESG ratings (Eccles and Stroehle (2018), Pástor, Stambaugh, and Taylor (2022)). MSCI covers more firms than other ESG raters, such as Asset4, KLD, RobescoSAM, Sustainalytics, and Vigeo Eiris (Berg, Kölbel, and Rigobon (2022)). Furthermore, Berg et al. (2021) find that MSCI's

ESG scores are the least noisy among the eight ESG data vendors that they consider. The MSCI ESG research unit employs more than 200 analysts and incorporates artificial intelligence, machine learning, and natural language processing into its methodology. MSCI generates its ratings based on a variety of sources and updates those ratings at least annually. Due to its comprehensive coverage and advanced methodology, the MSCI ESG Ratings data has been used by more than 1,700 institutional clients around the world.

In particular, we use the MSCI variables "Environmental pillar score" (E_score) and "Environmental pillar weight" (E_weight). E_score is a number between 0 and 10 that measures the firm's weighted average score on 13 environmental issues related to climate change, natural resources, pollution and waste, and environmental opportunities. These scores are designed to measure a company's resilience to long-term environmental risks. E_weight, which is typically constant across firms in the same industry, is a number between 0 and 100 measuring the importance of environmental issues relative to social and governance issues.

Following PST, we compute the unadjusted greenness score of a firm i at the beginning of month t as

$$G_{i,t-1} = -(10 - E\_score_{i,t-1}) \times E\_weight_{i,t-1}/100 \tag{2.1}$$

where $E\_score_{i,t-1}$ and $E\_weight_{i,t-1}$ are from company i's most recent MSCI ratings date before month t, looking back no more than 12 months. The quantity $(10 - E\_score_{i,t-1})$ measures how far the company is from a perfect environment score of 10. The product, $(10 - E\_score_{i,t-1}) \times E\_weight_{i,t-1}$, measures how brown the firm is. To be specific, it is the interaction of how badly the firm scores on environmental issues and how large the environmental impacts are for the typical firm in the industry (i.e., $E\_weight_{i,t-1}$). The initial minus sign converts the measure from brownness to greenness.

The environmental score we use in our analysis is

$$g_{i,t} = G_{i,t} - \overline{G}_t \tag{2.2}$$

where $\overline{G}_t$ is the value-weighted average of $G_{i,t}$ across all firms i. Since we subtract $\overline{G}_t$ from $G_{i,t}$, the environmental score $g_{i,t}$ measures the company's greenness relative to the market portfolio, as in PST. If w_t and g_t denote the vectors containing the weights of the stocks in the market and the $g_{i,t}$ values in month t, then

$$w_t{}' g_t = 0 \tag{2.3}$$

is a condition imposed by Pástor, Stambaugh, and Taylor (2021). Here equations (2.1) to (2.3) are the same as equations (1) to (3) in PST.

We compute $g_{i,t}$ for all stocks with non-missing environmental score data from MSCI and non-missing trading data from Datastream. The sample period begins in December 2012 and ends in December 2021.[2] Our sample begins with all firms with non-missing MSCI ESG Ratings data. We merge MSCI and Datastream using a combination of ISIN, SEDOL, CUSIP, and company name. We filter out those that fail to match the corresponding stocks in the Datastream equity database, for example, private firms or non-equity securities. These filters leave 21,902 firms in 96 countries. To construct our final sample, we confine the list of countries to those in Fama and French (2012) and Karolyi and Wu (2018). As in Fama and French (2012), 23 developed markets are combined into four regions: i) North America, including the United States and Canada; ii) Japan; iii) Asia-Pacific, including Australia, New Zealand, Hong Kong, and Singapore (but not Japan); and iv) Europe, including Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. The remaining 23 markets are combined into

[2]We follow several screening procedures for monthly returns from Datstream as suggested by Ince and Porter (2006) and Hou, Karolyi, and Kho (2011). The starting date of our sample is partly dictated by the availability of the MSCI ESG Ratings data.

Emerging Markets, the fifth region in our tests; it includes Israel, Turkey, Pakistan, South Africa, Czech Republic, Poland, Hungary, Russia, China, India, Indonesia, Malaysia, Philippines, South Korea, Taiwan, Thailand, Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Venezuela. In total, there are 21,198 stocks from 46 countries, referred to as our base sample.[3]

Graph A of Figure 2.1 plots the count of stocks for the base sample. Overall, there is an increasing trend in the coverage of stocks, and especially the total number increased sharply in late 2012 from less than 3,000 to about 8,000. Figure 2.1 also plots the number of stocks on a region-by-region basis. All five regions have experienced a dramatic increase around November 2012. The number of stocks from North America has remained at around 4,000 since the beginning of 2013 while those from the other four regions have continued to rise gradually in the following years. For example, the number of European stocks has increased from roughly 1,400 in January 2013 to more than 2,500 in December 2021. Likewise, the number of stocks from emerging markets has risen from around 1,300 in January 2013 to more than 3,100 in December 2021.

Graph B of Figure 2.1 plots the counts for the U.S. sample only. Here we report two variants, one is on the full U.S. sample and the other on the restricted sample which only includes primary quote and major securities. The restricted sample resembles that in PST, and yields very close results on the count. Graph C of Figure 2.1 plots the count for the global sample excluding the U.S. Consistent with the counts by regions, we notice a very steady increase in the coverage of the non-U.S. stocks with the MSCI ESG Ratings. This rise further justifies the need to conduct more comprehensive research on the impact of the application of ESG criteria on stock returns in the international setting.

[3]Most of the firms and monthly observations are concentrated in the 46 markets considered for our base sample. There are only 704 stocks coming from the other 50 markets and being filtered out here. They account for 3% of the initial sample by count, and their monthly observations account for 2% of the total observations.

2.3 The Equity Greenium

PST documented that green stocks strongly outperformed brown in the U.S. We replicate their study for the U.S. sample and further extend it to the international setting. We examine whether the green stocks have performed differently from the brown stocks for our global sample in the first round of experiments in this section. Next, we examine whether the green stocks have performed differently from the brown stocks for the regional samples in the second round of experiments to follow.

2.3.1 Global Equity Greenium

Figure 2.2 displays the performance of green and brown stocks from November 2012 to December 2021. The connected scatter plot of solid green dots, representing green stocks, shows the cumulative value-weighted return on the portfolio of stocks with greenness scores in the top third. The connected scatter plot of solid brown triangles, representing brown stocks, displays the corresponding cumulative return for stocks with greenness scores in the bottom third. From Graph A which represents the global sample, we see that green stocks strongly outperformed brown stocks in the 2010s, with a cumulative return difference of 70% over our 110-month sample period. We also report the cumulative returns on the GMB portfolio (green-minus-brown) in Figure 2.3 following the calculation procedure in PST. The monthly GMB return averaged 29 bps per month (t-statistic: 1.94), as reported in the first column of Table 2.1.

Among the 46 countries considered in the sample, stocks from the U.S. have created to a monthly GMB returns of, on average, 50 bps (t-statistic: 2.76), as reported in the second column of Table 2.1. The result is consistent with the findings in PST. PST study the GMB portfolio for the period between November 2012 and December 2020 and document a 65 bps per month (*t*-statistic: 3.23) on the GMB portfolio in the U.S. Our replication reaches a 60 bps per month (*t*-statistic: 3.33) on the GMB portfolio in the U.S. when we also limit the sample period from December 2012 to December 2020. Interestingly, brown stocks have strongly outperformed green stocks in the past year of 2021 for the U.S. market. Unlike the first eight years, the GMB portfolio has started to yield negative returns in the U.S. since February 2021. Overall, the downturn has resulted in a -30 bps per month for the past year.

For the remaining 45 countries, the corresponding GMBs yield only 6 bps per month, with a *t*-stat of 0.36, as reported in the third column of Table 2.1. The GMB portfolio performed fairly well during the first eight years, with the average of 14 bps per month, but its performance gets substantially worse afterward in the sense that the monthly return has averaged a negative 58 bps per month in the past year.

Table 2.1 shows that most of the global GMB returns comes from the U.S. sample rather than the remaining 45 countries. For the global GMB portfolio, its Sharpe ratio is 0.16, smaller than the market portfolio's Sharpe ratio of 0.24 but larger than that of the global SMB, 0.07, as well as the global HML portfolio's Sharpe ratio of -0.07. For the U.S. sample, its monthly Sharpe ratio of the GMB portfolio goes up to 0.26. In contrast, the monthly Sharpe ratio of the GMB portfolio only reaches 0.03 for the remaining 45 markets in the sample. Table 2.1 also reports the correlations among the variety of GMB portfolios. The global GMB is closely correlated with both the GMB portfolio in the U.S., with a correlation coefficient of 0.84, and the GMB portfolio in the non-U.S. countries, with a correlation coefficient of 0.89. The U.S. market and the remaining 45 markets are fairly correlated on the GMB portfolios, and the correlation coefficient is 0.53.

Can the strong performance of global GMB returns be explained by exposures to global return factors prominent in the asset pricing literature? To answer this question, the critical research design choice is about the benchmark factor models for global GMB returns. The benchmark models considered here include the global versions of the Capital Asset Pricing model (CAPM), the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Fama and French (2015, 2017) five-factor model, and the Fama-French-Carhart six-factor model (based on the previous two models):

$$r^{\$}_{W,t} - r_{f,t} = \alpha_{W,CAPM} + \beta_W{}' \, [WMKT_t] + \epsilon_t \tag{2.W.1}$$

$$r^{\$}_{W,t} - r_{f,t} = \alpha_{W,FF3} + \beta_W{}' \, [WMKT_t, WSMB_t, WHML_t] + \epsilon_t \tag{2.W.2}$$

$$r^{\$}_{W,t} - r_{f,t} = \alpha_{W,FFC4} + \beta_W{}' \, [WMKT_t, WSMB_t, WHML_t, WMOM_t] + \epsilon_t \tag{2.W.3}$$

$$r^{\$}_{W,t} - r_{f,t} = \alpha_{W,FF5} + \beta_W{}' \, [WMKT_t, WSMB_t, WHML_t, WRMW_t, WCMA_t] + \epsilon_t \tag{2.W.4}$$

$$r^{\$}_{W,t} - r_{f,t} = \alpha_{W,FFC6} + \beta_W{}' \, [WMKT_t, WSMB_t, WHML_t, WMOM_t, WRMW_t, WCMA_t] + \epsilon_t \tag{2.W.5}$$

where $r^{\$}_{W,t} - r_{f,t}$ is the excess return of the global GMB portfolio at time t expressed in dollars relative to the dollar-denominated risk-free rate, $r_{f,t}$. The five models correspond to the CAPM model, the Fama-French 3-factor model (FF3), the Fama-French-Carhart 4-factor model (FFC4), the Fama-French 5-factor model (FF5), and the Fama-French-Carhart 6-factor model (FFC6), respectively. All five models include: $WMKT$, defined as the excess return on the world equity market portfolio, denominated in U.S. dollars, for which the superscript "W" implies that they are constructed from all stocks around the world; $WSMB$, the difference between the returns of globally diversified portfolios of small stocks and big stocks; and $WHML$, the difference between the returns on globally diversified portfolios of high B/M (value) stocks and low B/M (growth) stocks. Eq. (2.W.3) adds $WMOM$ as the difference between the returns of globally diversified portfolios of winner stocks and loser stocks. In Eq. (2.W.4), $WRMW$ is the difference between the returns on globally diversified portfolios of robust operating profitability stocks and weak operating profitability stocks and $WCMA$ is the difference between the returns on globally diversified portfolios of conservative investment stocks and aggressive investment stocks. β_W is a vector of factor loadings that correspond to the respective global factors. The global version of the models could be applied to the global sample, or to each regional sample of the world, when needed.[4]

Panel A of Table 2.2 reports results of regressing the global GMB portfolio returns on various factors. Overall, the strong performance of the global GMB portfolio cannot be explained by exposures to return factors prominent in the asset pricing literature. The factors considered include a market factor (denoted as Mkt-Rf or MKT interchangeably), a size factor (SMB), a book-to-market-equity factor (HML), a momentum factor (MOM or UMD), a profitability factor (RMW), and an investment factor (CMA). Here we consider a variety of the global benchmark models. The first column of the table reports the estimated coefficient as well as the robust t-statistics (in the parentheses) for the global CAPM model, as reported in (1) in the table. The remaining four columns report the estimated results for the global Fama and French (1993) three-factor model (FF3), the global version of the Carhart (1997) four-factor model (FFC4), the global version of the Fama and French (2015, 2017) five-factor model (FF5), and the global version of the Fama and French (2015, 2017) five-factor model augmented with the Carhart (1997) momentum factor (FFC6), respectively, as (2) - (5) from left to right in the table. The alpha of the global GMB is 36 bps per month ($t = 2.37$) for the global CAPM model, 31 bps per month ($t = 2.39$) for the global FF3 model, 29 bps per month ($t = 2.13$) for the global FFC4 model, 30 bps per month ($t = 2.20$) for the global FF5 model, and 28 bps per month ($t = 1.97$) for the global FFC6 model. In all cases, the global GMB's alpha (regression constant) is economically and statistically significant. GMB's lowest alpha in Table 2.1 occurs in Column 5, where we adjust for the global variant of the FFC6 model. Its exposures to the market factor, the size factor, the value factor indicate that the global GMB portfolio tilts toward stocks with negative market beta, large stocks, and growth stocks.

[4] See Table 2.2, Table 2.4, and Table 2.5 Panel A, for example. Consider replacing "W" in the subscript by "i". If applied to the global sample, i means the world. If applied to the US (or non-US) sample, i means the US (or non-US) sample. Similarly, i could also refer to North America, Europe, Japan, Asia Pacific, or Emerging Markets.

Factor model regressions with useful factors should have higher R^2 values. The highest value of the adjusted R^2 in Table 2.1 occurs in Columns 2 and 3, where we adjusted for the global variants of the FF3 model, and of the FFC4 model. This indicates that the market factor, the size factor and the value factor are more useful for explaining time-series variation in the global GMB portfolio returns.

Panel B of Table 2.2 reports results of regressing the GMB portfolio returns in the U.S. on a variety of global benchmark models. In all cases, GMB's alpha in the U.S. is economically large and statistically reliable, ranging from 43 to 54 bps per month, with t-statistics between 2.42 and 2.94. The lowest alpha of the U.S. GMB occurs in column 5, where we adjust for the global FFC6 model. Its exposure to SMB, HML, and UMD indicates that the GMB portfolio in the U.S. tilts toward large stocks, growth stocks, and recent winners. Net of those exposures, the alpha of GMB is 43 bps per month (t = 2.42). The highest alpha of the U.S. GMB occurs in column 1, where we adjust for the global CAPM. The alpha of GMB is 54 bps per month (t = 2.89). The highest value of the adjusted R^2 in Panel B occurs in Columns 3 and 5, where we adjusted for the global variants of the FF3 model and of the FF5 model. This indicates that all the fundamental factors linked to firm characteristics are useful for explaining time-series variation in the U.S. GMB portfolio returns.

Panel C of Table 2.2 reports the regression results for the returns of the GMB portfolio from the remaining 45 markets. In contrast to the results for the global sample and the U.S. sample, the estimates of the GMB alphas decrease substantially for the global sample excluding the U.S., and become insignificantly different from zero in all experiments. For example, the alpha of the GMB portfolio shrinks to an insignificant 9 bps per month in the test of the global version of the FF5 model augmented with the momentum factor. In addition, its exposures to the market factor, the size factor, and the value factor indicate that the GMB portfolio from the other 45 countries tilts toward stocks with negative market beta, large stocks, and growth stocks. This is similar to the results for the global GMB portfolio. The adjusted R^2 values range from 0.04 for the global CAPM to 0.15 for the global FF3 model. This result corroborates the estimates of the exposures, indicating that the market factor, the size factor, and the value factor are the most useful factors in explaining time-series variation in the global GMB portfolio returns excluding the U.S.

The relatively disappointing performance of the GMB portfolio from the non-U.S. markets suggests the need to further explore the sensitivity of our inference on the time-series regression tests to alternative multi-factor asset pricing models. Following a key prescription of Fama and French (2012), we consider the purely local factor model when regressing the GMB portfolio returns in the U.S. on various factors, and report the estimation results in Table 2.3 Table 2.3. All regression tests give qualitatively similar results to those reported in Panel B of Table 2.2. However, by the purely local factor model, the magnitudes of these GMB alphas become smaller, regardless of what estimation models are employed. The lowest alpha of the U.S. GMB occurs in column 3, where we adjusted for the local version for the FFC4 model. Its exposures to the market factor, the size factor, the value factor, and the momentum factor suggest that GMB tilts toward stocks with negative beta, large stocks, growth stocks, and recent winners for the U.S. market. Net of those exposures, the alpha of GMB is 31 bps per month, which is not statistically significant at the 5% level.

At first sight, these results appear at odds with those of PST, who find that green stocks strongly outperformed brown unanimously in the U.S. However, PST's sample period, 2012 to 2020, is shorter than ours, 2012 to 2021. As mentioned earlier, the year 2021 is the period when the GMB portfolio has performed poorly around the world. Without loss of generality, we conduct a subperiod analysis to provide a head-to-head comparison with PST. In this experiment, the sample period is set as the same as that in PST, 2012 to 2020, and we reconduct the time-series regression on the GMB portfolio in the US on various local factors. Panel B of Table 2.3 shows our replication results of PST, and our Panel C of Table 2.3 is exactly a copy of the Table 3 in PST for comparison purpose. It is clear that our replication provides very close results with PST. Like PST. The GMB alpha in the U.S. remains economically large and statistically reliable for all cases. For example, when the local version of the FF5 model is used as the benchmark model, its exposures to the market factor, the size factor, the value factor, the profitability factor, and the investment factor are 0.06, -0.22, -0.13, -0.25, -0.12, respectively, in our replication. PST report that the exposures are 0.04, -0.26, -0.21, -0.39, -0.10, respectively. Further, all of the estimated coefficients come with a similar significance level. They indicate that GMB tilts toward large stocks, growth stocks, and stocks with high profitability. Net of those exposures, we report the alpha of GMB as a value of 43 bps per month (t = 2.41) and PST report a 50 bps per month (t = 2.38). Overall, our replication results reassured us that green stocks did strongly outperform brown in the first eight years but not as well as before during the year 2021.

2.3.2 Industry Equity Greenium

As pointed out by PST, the GMB portfolio has been correlated with two different types of greenness, the greenness of the firm's industry and the relative greenness of the firm within its industry. Does the realized GMB return spread stem from the influence of some specific industries? To investigate this question, we further collect the GICS industry classification data codes from Datastream and merge them with our MSCI ESG Rating datasets. The GICS industry codes classify stocks into eleven general sector categories: (1) Energy, (2) Materials, (3) Industrials, (4) Consumer Discretionary, (5) Consumer Staples, (6) Health Care, (7) Financials, (8) Information Technology, (9) Communication Services, (10) Utilities, and (11) Real Estate. We redo the main experiments on the construction of green and brown portfolios but strip down one sector out of the 11 sectors of stocks in each round of the experiments. Using the energy sector as an example, we first exclude stocks from the energy sector from the complete equity sample and create a refined equity sample which only includes the remaining ten sectors. Then we follow the procedure specified in Section 2.2 and construct a new set of the green portfolio and the brown portfolio, for a given region, which aggregates individual stocks representing all sectors except the sector of energy.[5]

Figure 2.4 displays the performance of green and brown stocks in the industry leave-one-out experiments. Panel A shows the results for the global sample, Panel B shows the results for the U.S. only, and Panel C shows the results for the global sample excluding U.S. For a given region, the left figure demonstrates how the green portfolios and the brown portfolios have performed over time when both portfolios include all sectors of stocks. Using stocks in the energy sector as the representative for the brown stocks, the middle figure reports how the green and brown portfolios have performed if we carve out stocks in the energy sector. Using stocks in the information technology sector as the representative for the green stocks, the right-hand-side graph reports how the green and the brown portfolios have performed if we strip down stocks in the sector of information technology. We also report the cumulative returns on the GMB portfolios in Figure 2.5 for the leave-one-sector-out experiments.

As shown in Figure 2.4 and Figure 2.5, the brown portfolio seems to perform better when we remove all stocks in the energy sector. The US brown portfolio without the energy sector stocks has delivered a much higher return, which almost doubles that of the original US brown portfolio that includes all stocks from the eleven sectors. It indicates that the energy sector, especially in the US, has delivered a lower return, in general, compared to other brown stocks. Therefore, leaving them out would increase the US

[5] We also consider the ICB and TRBC industry classifications in the industry experiments. Our empirical results are very close and consistent cross the three industry systems (GICS, ICB, and TRBC). For the sake of brevity, we mainly report and discuss the results which are based on the GICS industry classification. The results for the other two industry classification are available upon request.

brown return and reduce the GMB spread.

As mentioned in PST, the technology industry, especially “Big Tech”, has delivered higher stock returns in recent years. Then, are our results driven by Big Tech? igure 2.4 and Figure 2.5 indicate that the outperformance of the green portfolio over the brown portfolio does not weaken or disappear when we remove the stocks in the sector of information technology, regardless of which specific region is considered in the experiments. It is clear that we notice a substantial difference between the GMB spread in the U.S. and the GMB spread in the non-U.S. countries. In particular, the U.S. green portfolios have performance substantially better than those in the non-U.S. countries. Are the higher U.S. green returns driven by the higher returns from the large technology companies in the U.S.? Removing the sector of information technology, the U.S. green portfolio continues showing much higher returns than that from the non-U.S. countries. The difference between the U.S. and the global excluding the U.S. are not driven by the undue influence of the technology sector.

Table 2.4 reports the risk-adjusted returns on the global GMB portfolios, the GMB portfolios in the U.S. and the GMB portfolios in the non-U.S. countries when the global FF5 model is considered as the benchmark model.[6] The very left column reports the regression results on the global GMB portfolios. The estimated alpha is 34 bps per month for the complete GMB portfolio including all sectors of stocks, which is very close to 30 bps per month reported in Table 2.2.[7] When we remove the energy sector from the sample, the GMB alpha has decreased to 25 bps per month and it is no longer statistically significant at the 10% level. The weakened GMB performance also occurs in the U.S. sample as well as in the Global excluding U.S. sample. Taking the US sample as an

[6]Table 2.A.1 in the Appendix reports the full set of regression results on the experiments, including the estimated alphas, the estimated coefficients associated with the fundamental factors in the model, as well as the regression fits.

[7]The minor difference is driven by the fact that some stocks in the original data sample have missing GICS codes from Datastream and have to be removed from the portfolio construction in the industry experiments.

example, the GMB alpha has dropped substantially from 49 bps per month (t-statistic: 2.62) to 31 bps per month (t-statistic: 1.63). When we remove the information technology sector from the sample, the GMB alpha has decreased slightly to 32 bps per month, which is still significant at the 5% level for the global sample. In the U.S. the GMB alpha has barely changes, from 49 bps to 50 bps, and both of them are still statistically significant. The stocks in the communication services sector form another group of representative green stocks. The GMB alphas have generally increased and remained reliably significant when we separate the sector of communication services from the complete equity sample. For the global excluding U.S. sample, removing the financial sector helps to increase the GMB alpha from 12 bps per month (t-statistic: 0.70) to 27 bps per month (t-statistic: 1.68). At the same time, the poor GMB performance does not seem to be correlated with some specific sectors. Further, it is worth noting that the substantial difference between the GMB spread in the U.S. and that in the global excluding U.S. still remain in the carving-out sectoral experiments.

Overall, there are three main findings in the industry greenium experiments. First, the realized GMB return spread is associated with the lower returns of energy firms. Second, the equity greenium is not simply a manifestation of premium on technology. Third, the big difference on the GMB spread from one region to another, like from U.S. firms to non-U.S. firms, does not stem from the undue influence of specific industries.

2.3.3 Regional Equity Greenium

To further explore the equity greenium effect, we conduct the second round of experiments. Specifically, how do the GMB returns perform when constructed from equivalent regional test asset portfolios? We construct the spread portfolio that longs the green stocks and shorts the brown stocks for a given region, and examine whether there are some critical instabilities on the equity greenium effect over time and across regions.

Table 2.1 reports the summary statistics for the regional spread portfolios (regional GMBs) for North America, Europe, Japan, Asia Pacific, and Emerging Markets, respectively. The GMB return is 58 bps per month for the region of North America, which is similar with the results in the U.S. It is obvious that excluding North America lowers the global GMB returns so that the monthly GMB returns from the other four regions are hardly significant from zero on the average. For example, we find that the green stocks of European firms earn lower returns than the brown stocks of European firms. The GMB returns averaged -6 bps per month for the entire sample period. Likewise, we find insignificantly negative GMB returns for the region of Emerging Markets, with an average of -2 bps per month. For the regions of Japan and Asia Pacific, the GMB returns share the same sign with those in North America, although the magnitude is much smaller and not reliably different from zero. For example, the average of the monthly GMB in Asia Pacific is only 5 bps and the t-value yields only 0.18. Table 2.1 also reports the correlations among these regional GMBs over time. Most correlations are positive in the sign. For example, the monthly GMB in North America has the correlations as high as 0.52 with the monthly GMS in Europe and down to 0.07 with that in Japan. The exception is the region of Japan, which tends to be negatively correlated with the three regions other than North America. Its correlation runs as -0.04, -0.07, and -0.05 with Europe, Asia Pacific, and Emerging Markets, respectively. Interestingly, the monthly GMB in Emerging Markets seems equally correlated with those in North America (correlation = 0.37), Europe (correlation = 0.36), and Asia Pacific (correlation = 0.38). We also report the cumulative returns on the green portfolio, the brown portfolio, and the GMB portfolio in Figure 2.6 and Figure 2.7.

Is the environmental risk priced globally or locally? And how does our answer depend on whether we account for common sources of return covariation related to firm-level attributes so prevalent in equity markets? There exists a long-standing debate in the international asset pricing literature on whether securities are priced locally in segmented markets or globally in a single integrated market (Karolyi and Stulz (2003), Lewis (2011)). Karolyi and Wu (2018) investigate how reliably multifactor models that include size, value, and momentum factor portfolios capture return covariation globally when factor portfolios are built to allow for (i) only local variation (segmented markets), (ii) global variation (integrated markets), and (iii) both local and global variation in the intermediate case of what they call partial segmentation. Their findings demonstrate how models of partial segmentation achieve the lowest pricing errors and rejection rates relative to the pure segmentation or pure integration models, especially when Emerging Markets are included among the test asset portfolios. To answer the question of whether the ESG risk is priced in a way that depends on the degree of market segmentation or integration, we repeat the time-series regression-based tests of multifactor models above, but on the monthly GMB returns, which are built on a region-by-region basis.

For a given region of interest, we perform three sets of asset pricing tests, which are the regional test, the partial segmentation test, and the global test, respectively. The purely global, perfected integrated multifactor models specified above are examined for the regional GMB portfolios. At the same time, we adopt the purely local, perfectly segmented factor models as the new benchmark for regional test asset portfolios, as suggested in Fama and French (2012) and Karolyi and Wu (2018). The purely local benchmark models considered here include the purely local versions of the CAPM model, the FF3 model, the FFC4 model, the FF5 model, and the FFC6 model:

$$r^{\$}_{i,t} - r_{f,t} = \alpha^{i}_{D,CAPM} + \beta^{i}_{D}{}' \left[DMKT_t\right] + \epsilon_t \tag{2.D.1}$$

$$r^{\$}_{i,t} - r_{f,t} = \alpha^{i}_{D,FF3} + \beta^{i}_{D}{}' \left[DMKT_t, DSMB_t, DHML_t\right] + \epsilon_t \tag{2.D.2}$$

$$r^{\$}_{D,t} - r_{f,t} = \alpha^{i}_{D,FFC4} + \beta^{i}_{D}{}' \left[DMKT_t, DSMB_t, DHML_t, DMOM_t\right] + \epsilon_t \tag{2.D.3}$$

$$r^{\$}_{D,t} - r_{f,t} = \alpha^{i}_{D,FF5} + \beta^{i}_{D}{}' \left[DMKT_t, DSMB_t, DHML_t, DRMW_t, DCMA_t\right] + \epsilon_t \tag{2.D.4}$$

$$r^{\$}_{D,t} - r_{f,t} = \alpha^{i}_{D,FFC6} + \beta^{i}_{D}{}' \left[DMKT_t, DSMB_t, DHML_t, DMOM_t, DRMW_t, DCMA_t\right] + \epsilon_t \tag{2.D.5}$$

where $r^{\$}_{i,t} - r_{f,t}$ is the excess return of the GMB portfolio for region i at time t expressed in dollars relative to the dollar-denominated risk-free rate, $r_{f,t}$. The subscript "D" in the market and factor portfolios implies that they are constructed only from domestic or regional stocks in our experiments. β^i_D is a vector of factor loadings that correspond to the respective local factors.[8]

Table 2.5 reports the regression results on the regional GMB returns, in which the regressions shown in Panel A consider the purely global model as the benchmark model, while the regressions shown in Panel B use the purely local benchmark model. The top-left sections, for both Panel A and Panel B, report the risk-adjusted GMB returns in the region of North America. The regression results on the purely global model are very similar to those reported in Panel B of Table 2.2 for the U.S. market. All GMB alphas in North America are economically large, ranging from 51 to 62 bps per month, at a 1% significance level. When the benchmark model is shifted from the purely global model to the purely local model, the magnitude of the GMB alpha has decreased. Taking the FFC4 model as an example, the risk-adjusted GMB returns have dropped from 51 bps per month to 29 bps per month, although the p-value is still lower than 5%. Furthermore, when the hybrid partial segmentation model is considered in the regressions, a few GMB's alphas turn economically small and hardly reliable. For example, the GMB alpha has further dropped to only 15 bps per month for the FFC4 model, and its p-value is equal to 0.34. At the same time, when we only adjust for the market factor, the alpha is estimated to be 53 bps per month, which is still statistically significant. Admittedly, although the addition of foreign factors to the benchmark model does help reduce the magnitude of the

[8]We consider the partial segmentation model as the third benchmark model for regional test asset portfolios, as suggested in Griffin (2002). Griffin (2002) proposed a variant of the FF3 model of Fama and French (1993) and Fama and French (1998), which includes a market factor, a size factor, and a book-to-market-equity factor, for four countries (the United States, the United Kingdom, Canada, and Japan). He decomposes the global factor model into its domestic and foreign components so that the partial segmentation hybrid model allows domestic and foreign factors to have a different impact on stocks returns. Empirical results show that the regional GMB alphas are generally robust to the benchmark models considered in the test. For the sake of brevity, we report the results for both purely global models and purely local models in Table 2.5.

alphas, it barely yields significant improvements in the model explanatory power. There appears to be only a slight increase in the regression R^2 values.

The middle-left section, for both Panel A and Panel B of Table 2.5, reports the risk-adjusted GMB returns in the region of Europe. The regression results on the purely global model are clearly different from those for North America. All GMB alphas are statistically indistinguishable from zero, regardless of what benchmark model is used. When the purely local factor model is considered as the benchmark model, its exposures to SMB, HML, and UMD indicate that GMB no longer tilts toward large stocks, growth stocks, and recent winners. However, GMB is negatively exposed to the local market factor. When the benchmark model is shifted from the purely local model to the purely global model, the regression R^2 values have increased substantially. Taking the FF3 model as an example, the adjusted R^2 values have been improved from 0.10 for the purely local model to 0.17 for the purely global model. In addition, its exposures to MKT and HML indicate that GMB in Europe tilts toward stocks with negative betas and growth stocks. We the partial segmentation hybrid model is considered as the benchmark model, almost all of the coefficients with respect to the domestic factor are insignificant while most of the coefficients with respect to the foreign factors are statistically reliable. This evidence is consistent with the findings for the purely global factor model in the sense that foreign factors help explain a reliably large proportion of the total variation in the GMB returns for Europe.

The middle-right section of Table 2.5 reports the risk-adjusted GMB returns in the region of Japan. For the estimated coefficients associated with the fundamental factors in the benchmark models, most of the estimations are not distinguishable from zero for the purely global model. When we regress the GMB portfolios returns on the purely local models, the estimations become very similar to those for the region of North America. Its exposure to the local SMB, HML, and CMA indicates that GMB tilts toward large stocks, growth stocks and stocks with high investment in the region of Japan. Net of these exposures, the GMB alphas are not significantly different from zero, regardless of whether the benchmark model is the purely global model or the purely local model. Overall, the realized GMB return spread does not exist in the region of Japan.

The bottom-left section of Table 2.5 shows the regression results on the returns of the GMB portfolio in the Asia-Pacific region. The adjusted R^2 values are generally higher for the purely local models than for the purely global model. When it comes to the coefficients with respect to the fundamental factors, the GMB portfolio in Asia Pacific tilts toward large stocks, growth stocks, and past winners, especially when the purely local model is considered as the benchmark model. Net of these exposures, the alpha of GMB is 2 bps per month for the local CAPM model, 6 bps per month for the local FF3 model, -18 bps per month for the local FFC4 model, and 13 bps per month for the local FF5 model, respectively. In none of these cases, the local GMB alpha (regression constant) is economically large and statistically significant. In all, the inference on the greenium effect in the U.S. does hinge on, to some extent, on the empirical asset pricing models considered in the tests.

The bottom-right section of Table 2.5 shows the regression results on the GMB portfolio returns in the region of Emerging Markets. The adjusted R^2 values are equally small between the purely global models and the purely local model. When the purely local model is used as the benchmark model, the GMB portfolio in Emerging Markets tilts toward stocks with negative market beta and growth stocks. Using the purely global model decreases the GMB alpha, compared to the purely local model. Using the FFC4 model as an example, the model intercept goes down from 14 bps per month for the purely local model to 2 bps per month for the purely global model. Admittedly, neither of them is statistically distinguishable from zero. The prominent return factors in the asset pricing literature help explain the GMB returns in the region of Emerging Markets.

Overall, the performance of the GMB returns varies across regions. We find a stronger performance of GMB in North America. For the other four regions, the performance of the GMB returns depends on whether we account for common sources of return covariation related to firm-level attributes, such as size, value, and momentum.

2.4 Robustness Check

All of our tests up to now have been unconditional and have taken into account the total variation across countries and over the entire period from November 2012 through December 2021. We next investigate how the GMB returns varies over time, on a cross-region basis and on the region-by-region basis. As shown in Figure 2.3 and Figure 2.7, the GMB returns, both globally and regionally, were positive for an extended period but have become neutralized in recent years, especially for the regions of Europe, Asia Pacific, and Emerging Markets.

Panel A of Table 2.6 reports summary statistics on the regional GMB returns between two sub-periods, one is from December 2012 to December 2015 and the other from January 2016 to December 2021. For the first three years of the sample period, green stocks delivered higher returns than brown stocks for almost all regions except Japan. The monthly GMB return averaged 89 bps per month (t-statistic: 2.71), 49 bps per month (t-statistic: 1.99), 11 bps per month (t-statistic: 0.40), 123 bps per month (t-statistic: 2.76), 102 bps per month (t-statistic: 2.73) in North America, Europe, Japan, Asia Pacific, and Emerging Markets, respectively. Accordingly, the monthly Sharpe ratio of GMB increases to 0.45 in three regions (North America, Asia Pacific, and Emerging Markets) and stays at a relatively median level of 0.33 in Europe. The lowest monthly Sharpe ratio occurs in Japan as the level of 0.07. In terms of the correlations among regions, there is still a relatively small comovement in the GMB returns between North America and Europe (a correlation level of 0.54). The next region positively correlated with Europe is Asia Pacific, with a correlation coefficient of 0.40. For both the GMB returns in Asia Pacific and Emerging Markets, they are equally positively correlated with those in other regions except Japan. Similar to the case for the whole sample period, Japan is the region in which the GMB returns behave negatively correlated with the other regions.

As shown in the second half of Panel A, the more recent six years display a different picture on the GMB performance. Green stocks have started to deliver lower returns than brown stocks for three regions except North America and Japan. The monthly GMB return averaged -34 bps per month (*t*-statistic: -1.79), -56 bps per month (*t*-statistic: -1.65), and -55 bps per month (*t*-statistic: -2.34) in Europe, Asia Pacific, and Emerging Markets, respectively. For North America and Japan, the monthly GMB returns averaged 42 bps per month and 7 bps per month, respectively, and none of them is distinguishable from zero. In terms of correlations among regions, the GMB returns in North America have still remained highly correlated with the other four regions. On the other hand, the comovement between Asia Pacific and most of the regions is getting weaker compared with the first three years. Its correlations have dropped from 0.34 to 0.18, from 0.40 to 0.28, and from -0.20 to 0.03 with North America, Europe, and Japan, respectively, while its correlation with Emerging Markets has increased from 0.18 to 0.38.

Panel B of Table 2.6 reports the regression results for the regional GMB returns for the first three years and those for the more recent six years. For the sake of simplicity, here we follow the suggestion of Fama and French (2015) and focus on the local version of the FF5 model. As shown in the top panel for the first three years, there is generally strong GMB performance across regions which cannot be explained by exposures to local return factors prominent in the asset pricing literature. For the region of North America, exposures to MKT, SMB, HML and other factors related to firm-level attributes are quantitatively similar to those reported in Table 2.5. Net of all the exposures, the alpha of the GMB yields a significant 37 bps per month. For the region of Europe, the risk-adjusted GMB returns remain economically large and statistically reliable, with the average level of 54 bps per month, for both the local CAPM model and the local FF3 model. The magnitude of the alphas reduces to 27 bps per month for the local FFC4 model and 42 bps per month for the local FF5 model. The GMB alphas in Japan go as high as 30 bps per month for the local FF5 model and drop to 14 bps per month for the local CAPM. However, all of them are statistically indistinguishable from zero. It should be noted that the monthly GMB has shown much stronger performance in the regions of Asia Pacific and Emerging Markets. Using the local FF5 model as the benchmark model, the alphas of the GMB returns remain 154 bps per month for Asia Pacific, and 142 bps per month for Emerging Markets. Both are significant at the 1% level.

Consistent with the summary statistics shown in Panel A, there is generally weaker GMB performance across region as shown in the bottom rows in Panel B. During the later six years, green stocks seem to underperform brown in the regions of Europe, Asia Pacific, and Emerging Markets. These underperformances cannot be explained by exposures to local return factors prominent in the asset pricing literature. Taking the region of Europe as an example, exposures to the MKT, SMB, HML, RMW, and CMA indicate that the GMB in Europe tilts to stocks with negative market beta. Net of all the exposures, the alpha of the GMB yields a significant -30 bps per month. Likewise, the alpha of the GMB in Emerging Markets yields -51 bps per month, which is significant at the 5% level. However, the GMB alpha remains positive in North America, but the magnitude becomes much smaller, from 37 bps per month to only 5bps per month, in the alpha estimates.

In all, there is strong co-movement on the greenium effect across regions for the first three years of our sample period. Surprisingly, the co-movement has been much weaker since 2016. More importantly, the realized GMB return spreads in Europe, Asia Pacific, and Emerging Markets have disappeared in the sense that green stocks have started to underperform brown stocks in these regions.

2.5 Conclusions

We offer new evidence on how the application of environmental, social, and governance (ESG) criteria has affected international stock returns. We estimate the market-based equity greenium in a cross-section of 21,902 firms from 96 countries. We find reliable evidence that green stocks earned higher returns than brown stocks around the world. This outperformance is associated with lower returns on energy stocks, but not higher returns on technology stocks. Decomposing this outperformance further into five regions, including North America, Europe, Japan, Asia Pacific, and Emerging Markets, demonstrates that the realized green-minus-brown equity return spread mostly occurs in North America and during the period before 2016. Most of the equity greenium performance cannot be explained by exposures to return factors prominent in the asset pricing literature.

Over time, there is strong co-movement in the greenium effect across regions for the first three years of our sample period. Surprisingly, the co-movement gets much weaker starting from 2016. More importantly, the realized green-minus-brown equity return differences in Europe, Asia Pacific, and Emerging Markets have disappeared in the sense that green stocks have started to underperform brown stocks in these regions. The performance of the GMB returns varies across regions. We find a stronger performance of the GMB spread portfolio in the region of North America. For the other four regions, the performance of the GMB returns depends on whether we account for common sources of return covariation related to firm-level attributes, such as size, value, and momentum.

REFERENCES

Alessi, Lucia, Elisa Ossola, and Roberto Panzica, 2021, What greenium matters in the stock market? the role of greenhouse gas emissions and environmental disclosures, *Journal of Financial Stability* 54, 100869.

Aswani, Jitendra, Aneesh Raghunandan, and Shiva Rajgopal, 2023, Are carbon emissions associated with stock returns?, *Review of Finance* 28, 75–106.

Baker, Malcolm, Daniel Bergstresser, George Serafeim, and Jeffrey Wurgler, 2022, The pricing and ownership of us green bonds, *Annual Review of Financial Economics* 14, 415–437.

Bekaert, Geert, Robert J. Hodrick, and Xiaoyan Zhang, 2009, International stock return comovements, *The Journal of Finance* 64, 2591–2626.

Berg, Florian, Julian F Kölbel, Anna Pavlova, and Roberto Rigobon, 2021, Esg confusion and stock returns: Tackling the problem of noise, *SSRN Electronic Journal* .

Berg, Florian, Julian F Kölbel, and Roberto Rigobon, 2022, Aggregate confusion: The divergence of esg ratings, *Review of Finance* 26, 1315–1344.

Bolton, Patrick, and Marcin Kacperczyk, 2021, Do investors care about carbon risk?, *Journal of Financial Economics* 142, 517–549.

Bolton, Patrick, and Marcin Kacperczyk, 2023, Global pricing of carbon-transition risk, *The Journal of Finance* 78, 3677–3754.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *The Journal of Finance* 52, 57–82.

Eccles, Robert G., and Judith Stroehle, 2018, Exploring social origins in the construction of esg measures, *SSRN Electronic Journal* .

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 1998, Value versus growth: The international evidence, *The Journal of Finance* 53, 1975–1999.

Fama, Eugene F., and Kenneth R. French, 2012, Size, value, and momentum in international stock returns, *Journal of Financial Economics* 105, 457–472.

Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F., and Kenneth R. French, 2017, International tests of a five-factor asset pricing model, *Journal of Financial Economics* 123, 441–463.

Griffin, John M., 2002, Are the fama and french factors global or country specific?, *Review of Financial Studies* 15, 783–803.

Hou, Kewei, G. Andrew Karolyi, and Bong-Chan Kho, 2011, What factors drive global stock returns?, *Review of Financial Studies* 24, 2527–2574.

Ince, Ozgur S., and R. Burt Porter, 2006, Individual equity return data from thomson datastream: Handle with care!, *Journal of Financial Research* 29, 463–479.

Karolyi, G. Andrew, and René M. Stulz, 2003, Chapter 16 Are financial assets priced locally or globally?, *Handbook of the Economics of Finance* 1, 975–1020.

Karolyi, G. Andrew, and Ying Wu, 2018, A new partial-segmentation approach to modeling international stock returns, *Journal of Financial and Quantitative Analysis* 53, 507–546.

Lewis, Karen K., 2011, Global asset pricing, *Annual Review of Financial Economics* 3, 435–466.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2021, Sustainable investing in equilibrium, *Journal of Financial Economics* 142, 550–571.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2022, Dissecting green returns, *Journal of Financial Economics* 146, 403–424.

Zhang, Shaojun, 2024, Carbon returns across the globe, *The Journal of Finance*, forthcoming.

Table 2.1
Summary Statistics on the GMB Portfolios

This table reports the summary statistics on the GMB portfolios. The GMB portfolios are for the global sample ("Globe"), for the U.S. only ("U.S."), for the global sample excluding the U.S. ("Globe ex. U.S."), and for five regional samples ("North America", "Europe", "Japan", "Asia Pacific", and "Emerging Markets"), respectively. Section 2.2 provides descriptions of the constructions of the GMB portfolios. The sample period is December 2012 to December 2021.

	Global	U.S.	Global ex. US	North America	Europe	Japan	Asia Pacific	Emerging Markets
Mean returns (%)	0.29	0.50	0.06	0.58	-0.06	0.09	0.05	-0.02
Std. Dev (%)	1.57	1.89	1.64	2.02	1.62	1.60	2.93	2.22
t-statistic	1.94	2.76	0.36	3.01	-0.40	0.56	0.18	-0.10
Sharpe ratio	0.19	0.26	0.03	0.29	-0.04	0.05	0.02	-0.01
Correlation								
Global	1							
U.S.	0.84	1						
Global ex. US	0.89	0.53	1					
North America	0.89	0.97	0.61	1				
Europe	0.73	0.49	0.76	0.52	1			
Japan	0.06	0.08	0.04	0.07	-0.04	1		
Asia Pacific	0.46	0.19	0.58	0.25	0.37	-0.07	1	
Emerging Markets	0.61	0.33	0.75	0.37	0.36	-0.05	0.38	1

Table 2.2
Global GMB Portfolio Alphas

We estimate time-series regressions on the global GMB portfolio. Mkt-Rf is the global excess market return. SMB and HML are the global version of the size and value factors of the Fama and French (1993) model. UMD is the global version of the momentum factor of Carhart (1997). RMW and CMA are the global version of the profitability and investment factors of Fama and French (2015). See Equations (2.W.1) - (2.W.5) in Section 2.3.1 for details of the global model specifications. Returns are in percentage per month. Robust *t*-statistics are in parentheses.

Panel A: Global Sample

	(1)	(2)	(3)	(4)	(5)
Constant	0.36	0.31	0.29	0.30	0.28
	(2.37)	(2.39)	(2.13)	(2.20)	(1.97)
Mkt-Rf	-0.08	-0.06	-0.06	-0.07	-0.07
	(-1.95)	(-1.73)	(-1.70)	(-1.85)	(-1.82)
SMB		-0.21	-0.21	-0.21	-0.22
		(-3.45)	(-3.49)	(-3.20)	(-3.22)
HML		-0.43	-0.40	-0.38	-0.35
		(-6.42)	(-5.26)	(-3.86)	(-3.35)
UMD			0.05		0.05
			(0.84)		(0.82)
RMW				0.03	0.03
				(0.21)	(0.21)
CMA				-0.09	-0.09
				(-0.72)	(-0.71)
Observations	109	109	109	109	109
R-squared	0.03	0.31	0.31	0.31	0.31
Adj. R-squared	0.03	0.29	0.29	0.28	0.27

Table 2.2
Global GMB Portfolio Alphas — *Continued*

Panel B: Sub-sample of the U.S.

	(1)	(2)	(3)	(4)	(5)
Constant	0.54	0.48	0.43	0.48	0.43
	(2.89)	(2.94)	(2.55)	(2.78)	(2.42)
Mkt-Rf	-0.05	-0.02	-0.02	-0.03	-0.02
	(-0.90)	(-0.54)	(-0.50)	(-0.54)	(-0.49)
SMB		-0.22	-0.23	-0.22	-0.23
		(-2.90)	(-3.00)	(-2.67)	(-2.76)
HML		-0.49	-0.43	-0.48	-0.42
		(-5.95)	(-4.60)	(-3.97)	(-3.28)
UMD			0.10		0.10
			(1.43)		(1.42)
RMW				0.00	0.00
				(0.02)	(0.03)
CMA				-0.02	-0.01
				(-0.10)	(-0.09)
Observations	109	109	109	109	109
R-squared	0.01	0.26	0.27	0.26	0.27
Adj. R-squared	0.00	0.24	0.24	0.22	0.23

Panel C: Sub-sample of Global ex. US

	(1)	(2)	(3)	(4)	(5)
Constant	0.15	0.11	0.10	0.11	0.09
	(0.93)	(0.77)	(0.67)	(0.67)	(0.58)
Mkt-Rf	-0.11	-0.09	-0.09	-0.11	-0.11
	(-2.46)	(-2.26)	(-2.24)	(-2.40)	(-2.38)
SMB		-0.15	-0.15	-0.15	-0.16
		(-2.16)	(-2.16)	(-2.04)	(-2.05)
HML		-0.29	-0.28	-0.22	-0.21
		(-3.88)	(-3.24)	(-2.03)	(-1.78)
UMD			0.02		0.02
			(0.35)		(0.34)
RMW				0.02	0.02
				(0.18)	(0.18)
CMA				-0.12	-0.12
				(-0.86)	(-0.85)
Observations	109	109	109	109	109
R-squared	0.05	0.17	0.17	0.18	0.18
Adj. R-squared	0.04	0.15	0.14	0.14	0.13

Table 2.3
GMB Performance in the U.S.

We estimate time-series regressions on the GMB portfolio for the U.S. market. Mkt-Rf is the excess market return for the U.S. market. SMB and HML are the U.S. version of the size and value factors of the Fama and French (1993) model. UMD is the U.S. version of the momentum factor of Carhart (1997). RMW and CMA are the U.S. version of the profitability and investment factors of Fama and French (2015). See Equations (2.D.1) - (2.D.5) in Section 2.3.3 for details of the local model specifications, which are different from those in Panel B of Table 2.2. Returns are in percentage per month. Robust *t*-statistics are in parentheses.

Panel A: U.S. GMB Alphas

	(1)	(2)	(3)	(4)	(5)
Constant	0.50	0.35	0.31	0.39	0.37
	(2.61)	(2.05)	(1.87)	(2.40)	(2.23)
Mkt-Rf	0.00	0.06	0.09	0.08	0.10
	(0.02)	(1.43)	(1.93)	(1.92)	(2.22)
SMB		-0.13	-0.11	-0.25	-0.23
		(-1.91)	(-1.72)	(-3.31)	(-3.04)
HML		-0.26	-0.21	-0.18	-0.15
		(-4.76)	(-3.40)	(-2.78)	(-2.13)
UMD			0.10		0.07
			(1.72)		(1.29)
RMW				-0.28	-0.27
				(-2.97)	(-2.76)
CMA				-0.08	-0.08
				(-0.75)	(-0.71)
Observations	109	109	109	109	109
R-squared	0.00	0.26	0.28	0.32	0.34
Adj. R-squared	-0.01	0.24	0.25	0.29	0.30

Table 2.3
GMB Performance in the U.S. — *Continued*

Panel B: Our Replication of PST (2022) Results

	Mean	(1)	(2)	(3)	(4)	(5)
Constant	0.60	0.62	0.43	0.42	0.43	0.42
	(3.33)	(3.27)	(2.40)	(2.34)	(2.41)	(2.35)
Mkt-Rf		-0.02	0.05	0.07	0.06	0.08
		(-0.36)	(1.07)	(1.49)	(1.33)	(1.63)
SMB			-0.14	-0.12	-0.22	-0.20
			(-1.89)	(-1.62)	(-2.75)	(-2.43)
HML			-0.19	-0.14	-0.13	-0.10
			(-3.07)	(-1.96)	(-1.77)	(-1.24)
UMD				0.09		0.07
				(1.54)		(1.22)
RMW					-0.25	-0.24
					(-2.03)	(-1.90)
CMA					-0.12	-0.09
					(-0.88)	(-0.69)
Observations	97	97	97	97	97	97
R-squared	0.00	0.00	0.17	0.19	0.21	0.22

Panel C: PST (2022) Results

	Mean	(1)	(2)	(3)	(4)	(5) - n.a.
Constant	0.65	0.71	0.50	0.47	0.50	
	(3.23)	(2.91)	(2.23)	(2.14)	(2.38)	
Mkt-Rf		-0.05	0.02	0.05	0.04	
		(-0.78)	(0.32)	(0.87)	(0.77)	
SMB			-0.14	-0.11	-0.26	
			(-1.49)	(-1.23)	(-2.59)	
HML			-0.26	-0.18	-0.21	
			(-3.36)	(-1.99)	(-2.60)	
UMD				0.13		
				(2.00)		
RMW					-0.39	
					(-2.90)	
CMA					-0.10	
					(-0.60)	
Observations	98	98	98	98	98	
R-squared	0.00	0.01	0.19	0.22	0.26	

Table 2.4
Leave-one-sector-out GMB Alphas

We estimate time-series regressions on the global GMB portfolio composed of stocks with valid GICS codes from Datastream. Here we consider the global Fama and French (2015) five-factor model. See Equation (2.W.4) in Section 2.3.1 for details of the model specifications. Alphas are in percentage per month. Robust t-statistics are in parentheses. In addition to the complete GMB portfolio including all sectors of stocks, the 11 leave-one-sector-out GMB portfolios are constructed by using the GICS industry classification system to aggregate individual stocks from the specific region for which the test is performed into 11 groups representing all industries except for Energy, Materials, Industrial, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities, Real Estate, respectively. We report these three cases, the Global, the U.S. and Global excluding U.S., in the table.

		Global		U.S.		Global ex. U.S.	
		Alphas	*t-stat.*	Alphas	*t-stat.*	Alphas	*t-stat.*
All Sectors		0.34	*(2.23)*	0.49	*(2.62)*	0.12	*(0.70)*
All Sectors Except for	Energy	0.25	*(1.70)*	0.31	*(1.63)*	0.08	*(0.47)*
	Materials	0.27	*(1.68)*	0.48	*(2.42)*	0.04	*(0.21)*
	Industrial	0.38	*(2.29)*	0.54	*(2.72)*	0.13	*(0.70)*
	Consumer Discretionary	0.32	*(1.91)*	0.44	*(2.27)*	0.11	*(0.58)*
	Consumer Staples	0.37	*(2.46)*	0.53	*(2.72)*	0.16	*(0.92)*
	Health Care	0.25	*(1.52)*	0.44	*(2.14)*	0.04	*(0.20)*
	Financials	0.50	*(3.57)*	0.56	*(2.77)*	0.27	*(1.68)*
	Information Technology	0.32	*(2.04)*	0.50	*(2.52)*	0.16	*(0.91)*
	Communication Service	0.38	*(2.23)*	0.56	*(2.75)*	0.14	*(0.75)*
	Utilities	0.37	*(2.27)*	0.55	*(2.86)*	0.13	*(0.66)*
	Real Estate	0.34	*(2.19)*	0.50	*(2.59)*	0.13	*(0.69)*

Table 2.5
Regional GMB Alphas

We estimate time-series regressions on the regional GMB portfolios. Panel A reports the regression results using the purely global model as in Equations (2.W.1) - (2.W.4), and Panel B reports those using the purely local model as in Equations (2.D.1) - (2.D.4). See Section 2.3 for details of the model specifications. Returns are in percentage per month. ** denotes significance at the 5% level, and * for the 10% level.

Panel A: Purely Global Model

North America

	(1)	(2)	(3)	(4)
Constant	0.62**	0.55**	0.51**	0.53**
Mkt-Rf	-0.05	-0.02	-0.02	-0.03
SMB		-0.27**	-0.28**	-0.26**
HML		-0.58**	-0.53**	-0.56**
UMD			0.09	
RMW				0.06
CMA				-0.05
R^2	0.01	0.32	0.33	0.32
Adj. R^2	0.00	0.30	0.30	0.29

Europe

	(1)	(2)	(3)	(4)
Constant	0.05	0.01	0.03	0.00
Mkt-Rf	-0.13**	-0.12**	-0.12**	-0.12**
SMB		-0.03	-0.03	-0.02
HML		-0.23**	-0.26**	-0.27**
UMD			-0.04	
RMW				0.03
CMA				0.05
R^2	0.08	0.17	0.17	0.17
Adj. R^2	0.07	0.15	0.14	0.13

Japan

	(1)	(2)	(3)	(4)
Constant	0.08	0.05	0.08	0.08
Mkt-Rf	0.01	0.01	0.01	-0.03
SMB		0.00	0.00	-0.05
HML		-0.13	-0.16*	0.10
UMD			-0.06	
RMW				-0.09
CMA				-0.37**
R^2	0.00	0.03	0.04	0.10
Adj. R^2	-0.01	0.00	0.00	0.06

Asia Pacific

	(1)	(2)	(3)	(4)
Constant	0.07	0.06	-0.09	0.11
Mkt-Rf	-0.03	-0.02	-0.01	-0.02
SMB		-0.12	-0.14	-0.15
HML		-0.18	-0.01	-0.15
UMD			0.28**	
RMW				-0.16
CMA				-0.02
R^2	0.00	0.02	0.06	0.02
Adj. R^2	-0.01	-0.01	0.02	-0.03

Emerging Markets

	(1)	(2)	(3)	(4)
Constant	0.06	0.03	0.02	0.08
Mkt-Rf	-0.09	-0.08	-0.08	-0.10*
SMB		-0.17*	-0.17*	-0.22**
HML		-0.28**	-0.26**	-0.11
UMD			0.02	
RMW				-0.17
CMA				-0.25
R^2	0.02	0.08	0.08	0.11
Adj. R^2	0.01	0.05	0.04	0.06

Table 2.5
Regional GMB Alphas — *Continued*

Panel B: Purely Local Model

North America

	(1)	(2)	(3)	(4)
Constant	0.60**	0.27*	0.29**	0.15
Mkt-Rf	-0.01	0.02	0.01	-0.01
SMB		-0.13**	-0.13**	-0.04
HML		-0.51**	-0.54**	-0.69**
UMD			-0.06	
RMW				0.18*
CMA				0.27**
R^2	0.00	0.55	0.56	0.59
Adj. R^2	-0.01	0.54	0.54	0.57

Europe

	(1)	(2)	(3)	(4)
Constant	0.01	-0.03	0.01	-0.07
Mkt-Rf	-0.13**	-0.11**	-0.11**	-0.10**
SMB		0.05	0.05	0.09
HML		-0.10	-0.13	-0.17*
UMD			-0.04	
RMW				0.06
CMA				0.18
R^2	0.08	0.10	0.10	0.11
Adj. R^2	0.07	0.07	0.07	0.07

Japan

	(1)	(2)	(3)	(4)
Constant	0.09	0.08	0.09	0.10
Mkt-Rf	-0.01	-0.03	-0.03	-0.05
SMB		-0.23**	-0.23**	-0.22**
HML		-0.17**	-0.19**	-0.10
UMD			-0.06	
RMW				0.01
CMA				-0.19*
R^2	0.00	0.10	0.11	0.12
Adj. R^2	-0.01	0.07	0.08	0.08

Asia Pacific

	(1)	(2)	(3)	(4)
Constant	0.02	0.06	-0.18	0.13
Mkt-Rf	0.09	0.05	0.04	0.07
SMB		-0.29**	-0.32**	-0.33**
HML		-0.24**	-0.17	-0.18
UMD			0.19*	
RMW				-0.20
CMA				-0.06
R^2	0.02	0.13	0.16	0.15
Adj. R^2	0.01	0.11	0.13	0.11

Emerging Markets

	(1)	(2)	(3)	(4)
Constant	0.03	0.16	0.14	0.06
Mkt-Rf	-0.08*	-0.11**	-0.12**	-0.15**
SMB		-0.11	-0.12	-0.12
HML		-0.16**	-0.15**	-0.02
UMD			0.04	
RMW				0.02
CMA				-0.20*
R^2	0.03	0.07	0.07	0.10
Adj. R^2	0.02	0.04	0.04	0.05

Table 2.6
Sub-period Experiments on Regional GMBs

We report the summary statistics and estimate time series regressions for two subperiods, from December 2012 to December 2015 and from January 2016 to December 2021. For a given region, the purely local model as in Equation (2.D.4) is considered as the benchmark model. Section 3.2 for details on the model specifications. Returns are in percentage per month. ** denotes significance at the 5% level, and * for the 10% level.

Panel A: Summary Statistics

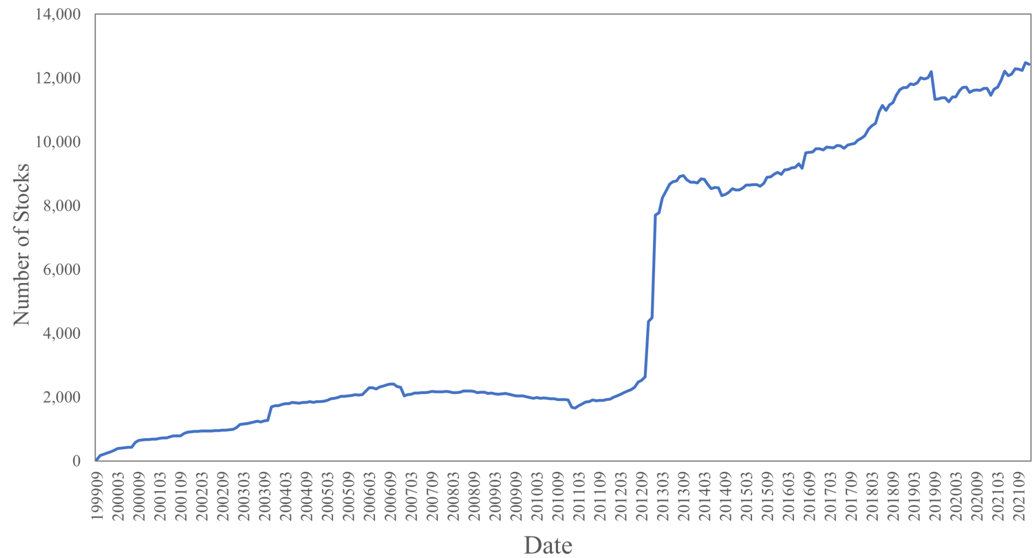
	North America	Europe	Japan	Asia Pacific	Emerging Markets
		Sub-period I: 2012-2015			
Mean returns (%)	0.89	0.49	0.11	1.23	1.02
Std. Dev (%)	2.00	1.49	1.60	2.72	2.27
t-statistic	2.71	1.99	0.40	2.76	2.73
Sharpe ratio	0.44	0.33	0.07	0.45	0.45
		Sub-period II: 2016-2021			
Mean returns (%)	0.42	-0.34	0.07	-0.56	-0.55
Std. Dev (%)	2.02	1.63	1.61	2.87	2.01
t-statistic	1.77	-1.79	0.39	-1.65	-2.34
Sharpe ratio	0.21	-0.21	0.05	-0.19	-0.28
Correlation					
		Sub-period I: 2012-2015			
North America	1				
Europe	0.54	1			
Japan	-0.07	-0.17	1		
Asia Pacific	0.34	0.40	-0.30	1	
Emerging Markets	0.34	0.28	-0.20	0.18	1
		Sub-period II: 2016-2021			
North America	1				
Europe	0.50	1			
Japan	0.14	0.02	1		
Asia Pacific	0.18	0.28	0.03	1	
Emerging Markets	0.36	0.32	0.02	0.38	1

Table 2.6
Sub-period Experiments on Regional GMBs — *Continued*

Panel B: Regional GMB Alphas

	North America	Europe	Japan	Asia Pacific	Emerging Markets
			Sub-period I: 2012-2015		
Constant	0.37*	0.42*	0.30	1.54**	1.52**
Mkt-Rf	-0.05	-0.16*	-0.02	0.04	-0.31**
SMB	-0.12	-0.01	-0.29**	-0.26	-0.47
HML	-0.88**	-0.24	-0.43*	-0.33	-0.23
RMW	0.40**	0.04	-0.39	0.03	0.09
CMA	0.40**	0.75**	0.30	0.32*	-0.25
Observations	37	37	37	37	37
R-squared	0.78	0.26	0.16	0.32	0.17
Adj. R-squared	0.74	0.14	0.03	0.21	0.04
			Sub-period II: 2016-2021		
Constant	0.05	-0.33*	0.04	-0.57*	-0.51**
Mkt-Rf	0.01	-0.13**	-0.06	0.12	-0.11**
SMB	-0.05	0.09	-0.21*	-0.23	-0.24*
HML	-0.56**	-0.11	-0.06	-0.03	0.13
RMW	0.05	0.06	0.05	-0.25*	-0.05
CMA	0.14	-0.02	-0.31**	-0.21	-0.29**
Observations	72	72	72	72	72
R-squared	0.58	0.11	0.19	0.23	0.14
Adj. R-squared	0.54	0.04	0.13	0.17	0.08

Graph A.1: Global Overview



Graph A.2: Count by Region

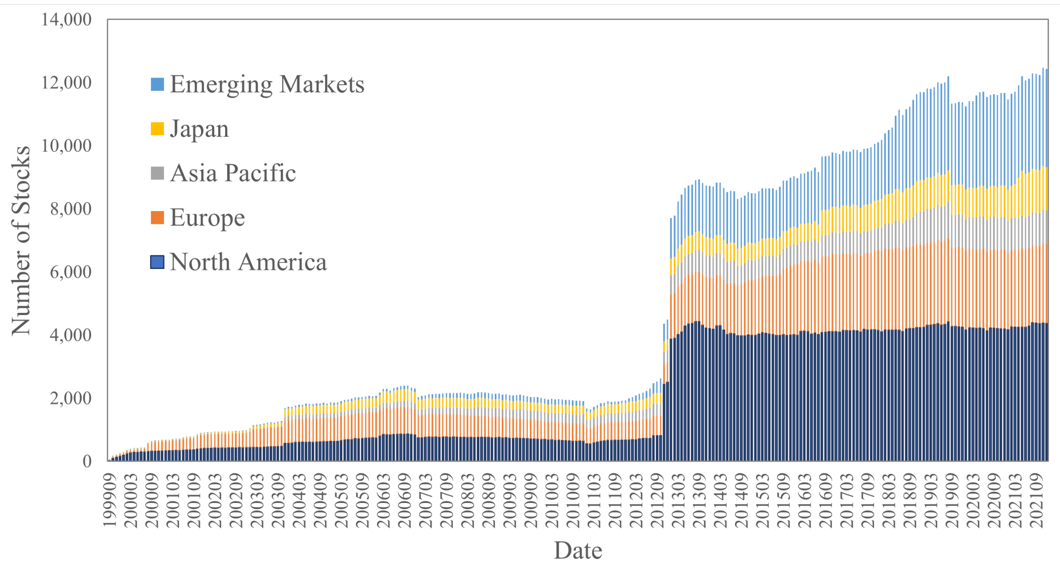
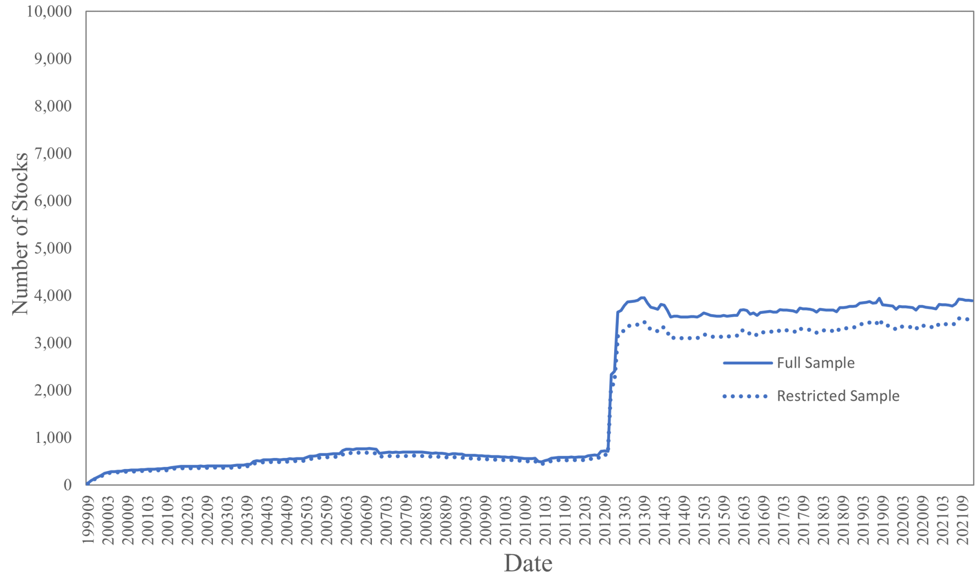


Figure 2.1. MSCI Coverage. The figures plot the number of stocks with non-missing MSCI environmental scores and Datastream trading records from 46 developed and emerging market countries. Graph A shows the counts, overview and by region, for the global sample, Graph B shows the overview for the U.S. Here we report two variants, one is on the full sample and the other on the restricted sample which only includes primary quote and major securities. Graph C shows the count for the global sample excluding U.S.

Graph B: U.S.



Graph C: Globe excluding U.S.

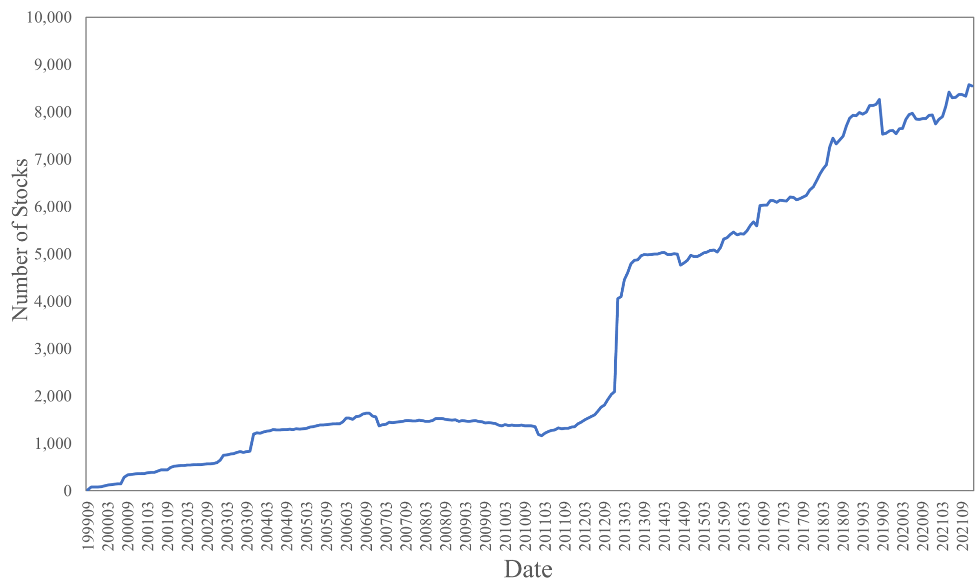


Figure 2.1. MSCI Coverage. —*Continued*

Graph A: Global Overview

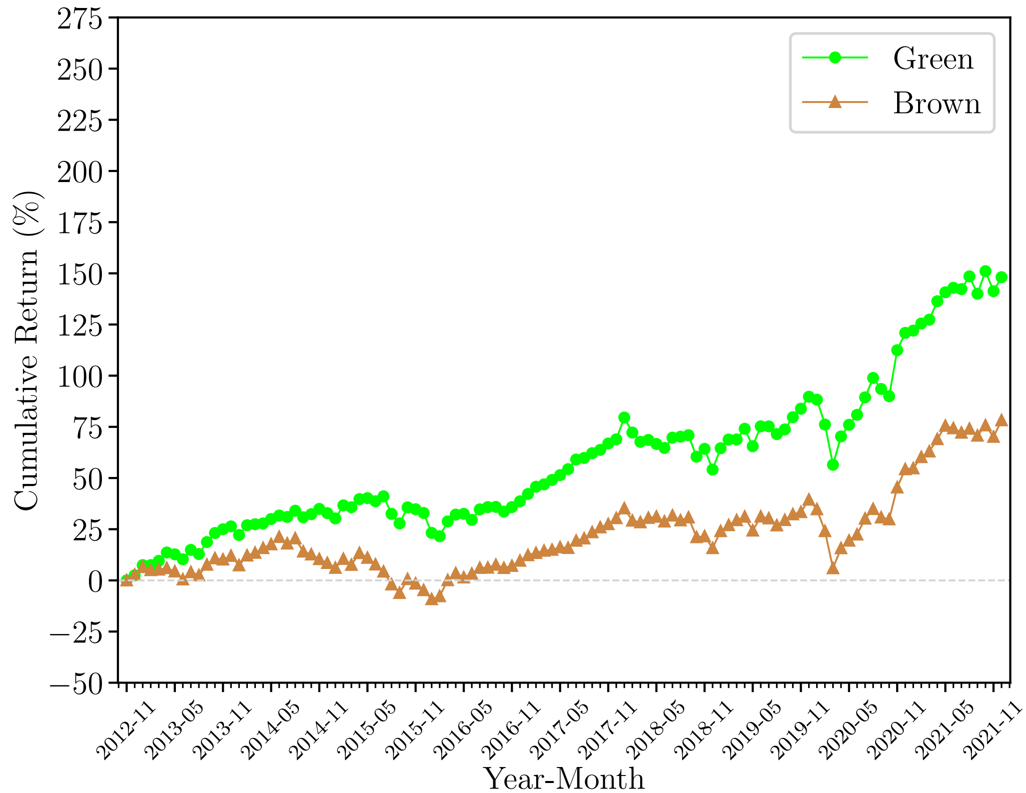
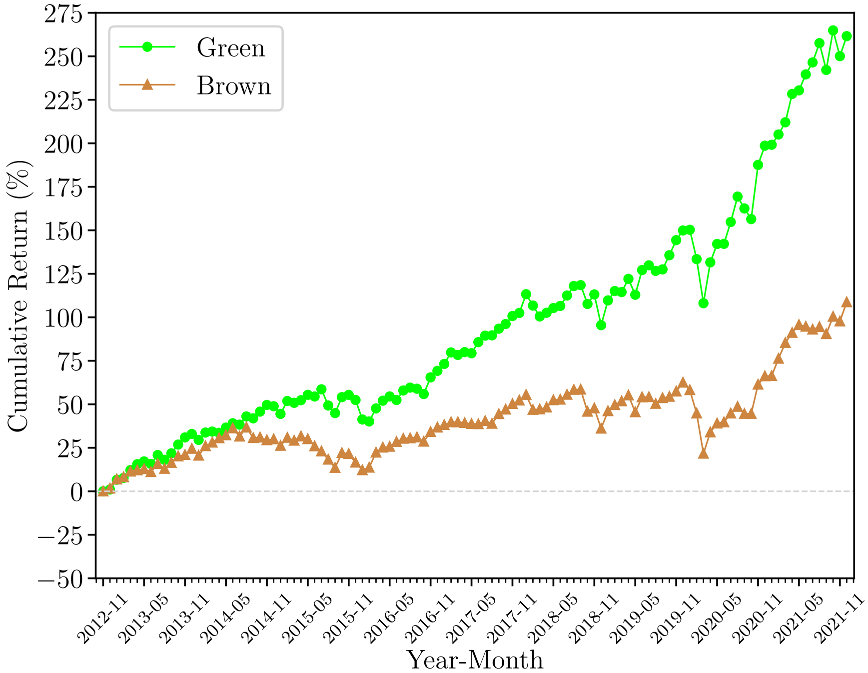


Figure 2.2. Returns on Value-weighted Green and Brown Portfolios. The figures plot the green and brown portfolios. The sample period is between November 2012 and December 2021. The cumulative returns are computed from the Datastream-MSCI merged dataset. Graph A shows the results for the global sample, Graph B shows the results for the U.S. only, and Graph C shows the results for the global sample excluding U.S.

Graph B: U.S.



Graph C: Globe excluding U.S.

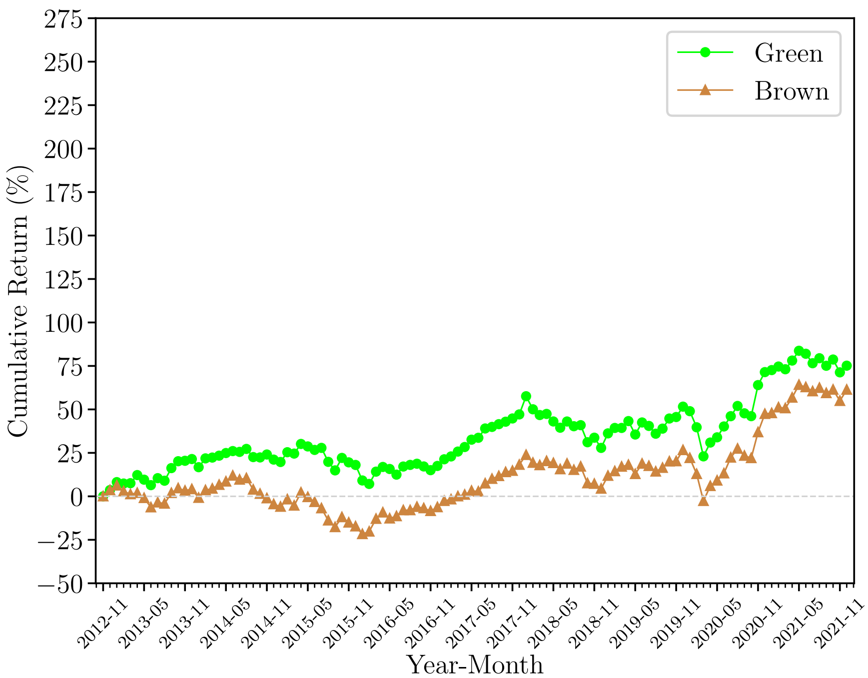


Figure 2.2. Returns on Value-weighted Green and Brown Portfolios. —*Continued*

Graph A: Global Overview

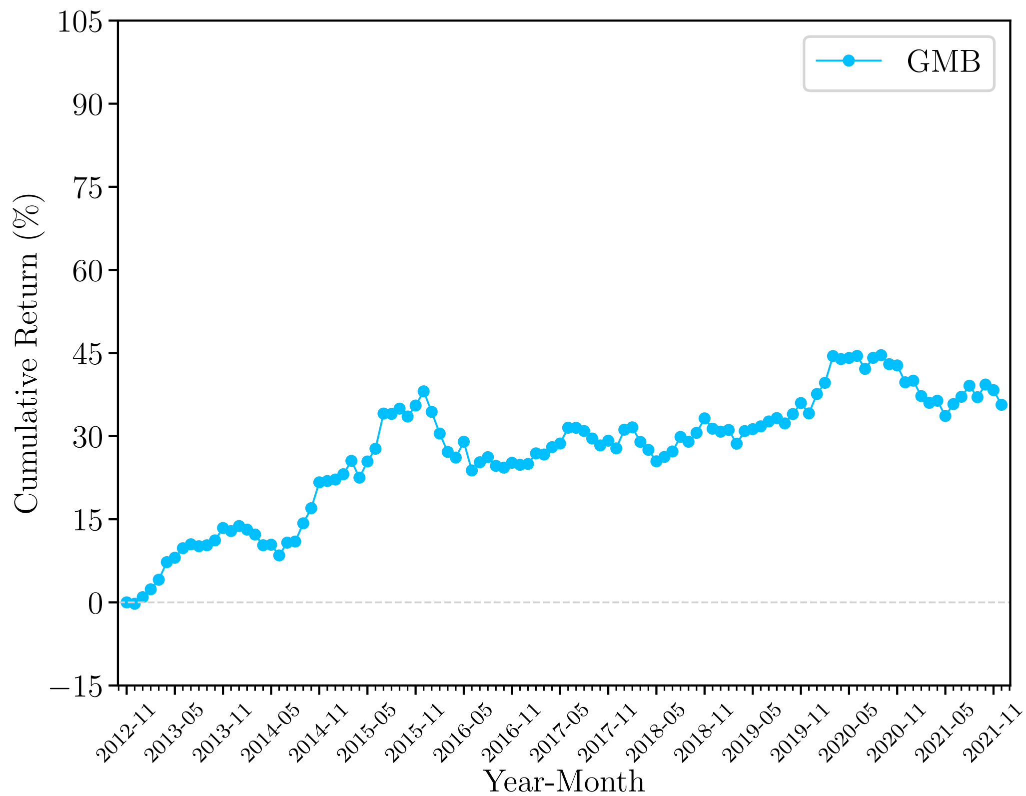
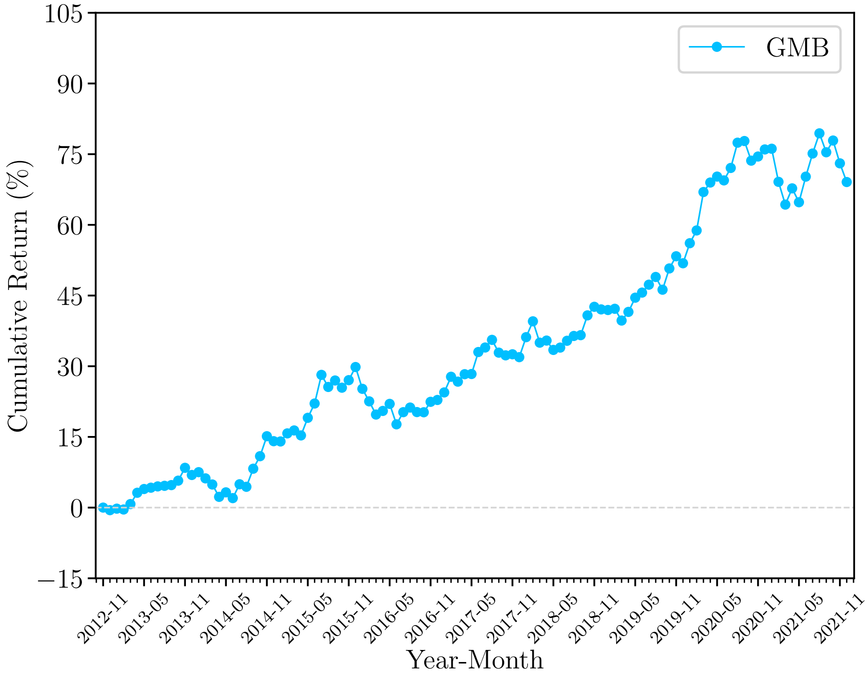


Figure 2.3. Cumulative GMB Returns. The figures plot the cumulative returns on the GMB portfolios. The GMB portfolios long green stocks and short brown stocks. The sample period is between November 2012 and December 2021, and the cumulative returns are computed from the Datastream-MSCI ESG Ratings merged dataset.

Graph B: U.S.



Graph C: Globe excluding U.S.

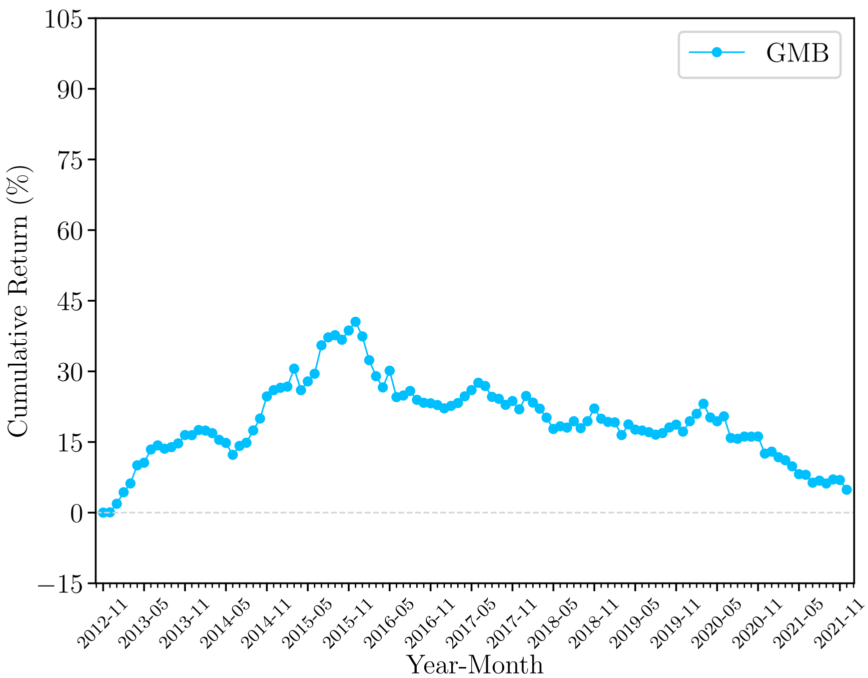


Figure 2.3. Cumulative GMB Returns. —*Continued*

Panel A: Global Overview

Graph A.1: All Sectors | Graph A.2: All Sectors Excluding Energy | Graph A.3: All Sectors Excluding Info. Tech.

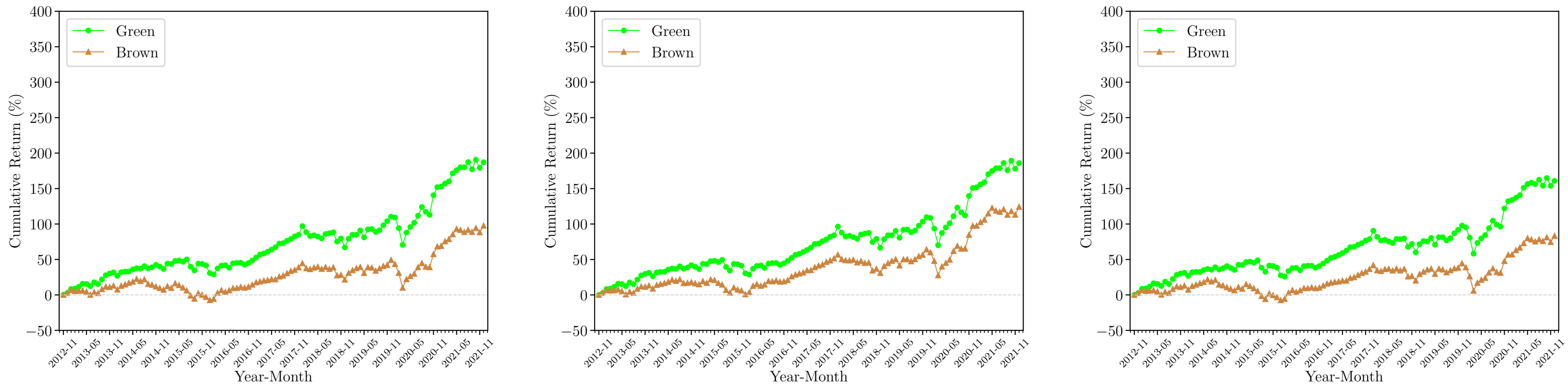
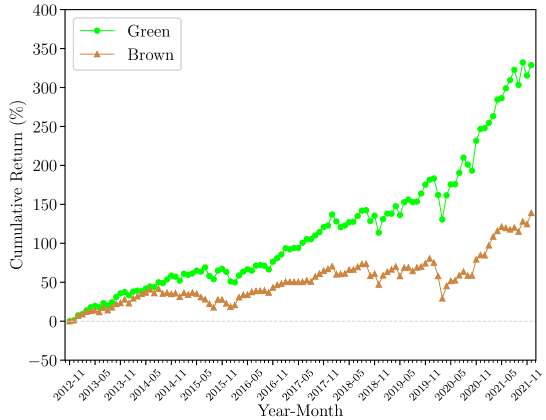


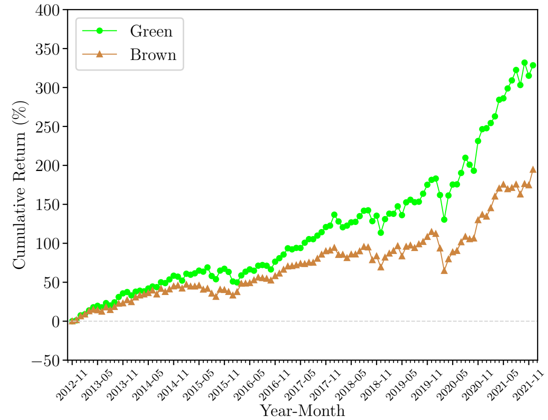
Figure 2.4. Returns on Leave-one-sector-out Green and Brown Portfolios. The graphs display the cumulative returns of the green and brown portfolios, in which the stocks have both valid observations from the Datastream-MSCI merged dataset and valid GICS codes from Datastream. In addition to the complete green and brown portfolios including all sectors of stocks, the two leave-one-sector-out portfolios are constructed by using the GICS industry classification system to aggregate individual stocks representing all industries except for Energy and Information Technology ("Info. Tech."), respectively, for a given region. Panel A shows the results for the global sample, Panel B shows the results for the U.S. only, and Panel C shows the results for the global sample excluding U.S.

Panel B: U.S.

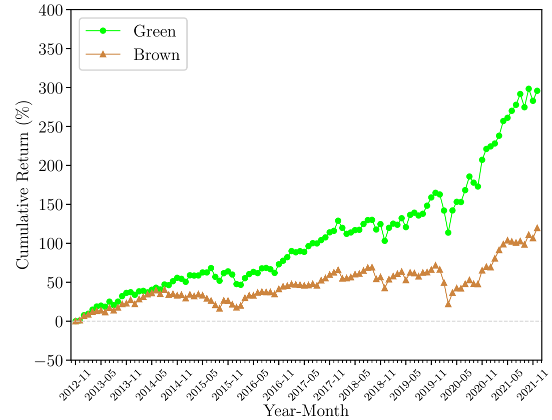
Graph B.1: All Sectors



Graph B.2: All Sectors Excluding Energy

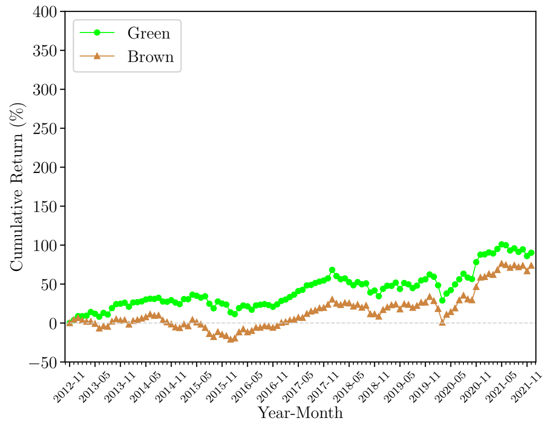


Graph B.3: All Sectors Excluding Info. Tech.

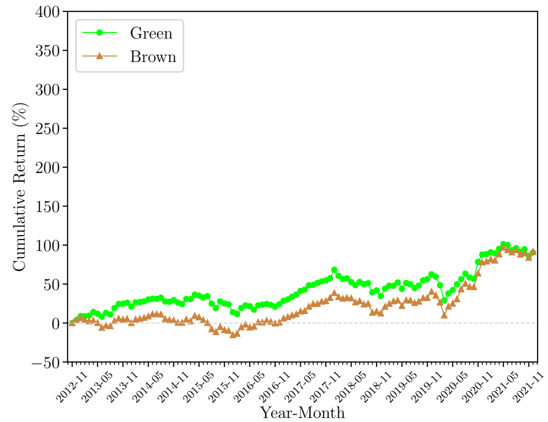


Panel C: Globe excluding U.S.

Graph C.1: All Sectors



Graph C.2: All Sectors Excluding Energy



Graph C.3: All Sectors Excluding Info. Tech.

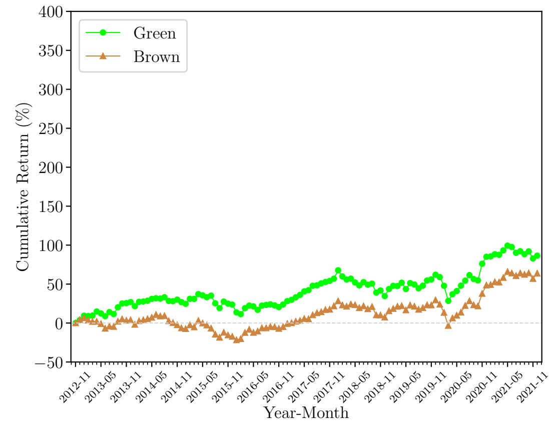
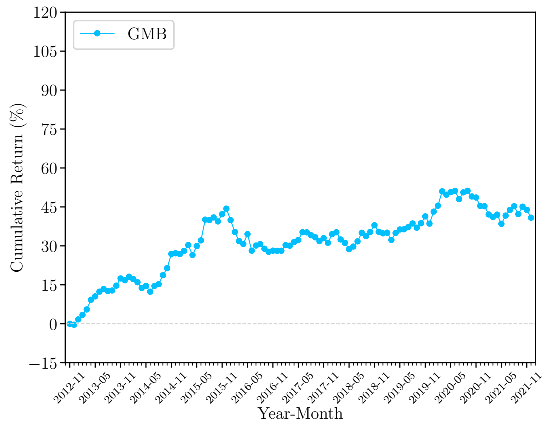


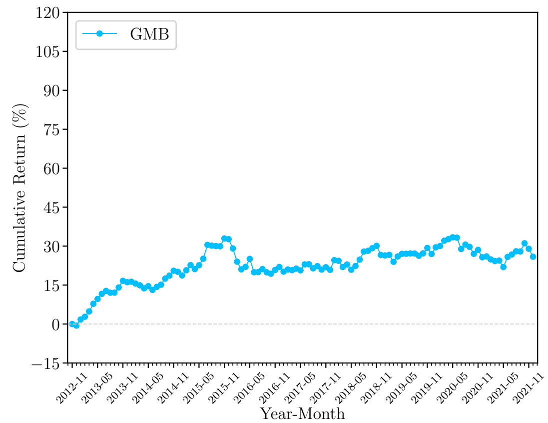
Figure 2.4. Returns on Leave-one-sector-out Green and Brown Portfolios. —*Continued*

Panel A: Global Overview

Graph A.1: All Sectors



Graph A.2: All Sectors Excluding Energy



Graph A.3: All Sectors Excluding Info. Tech.

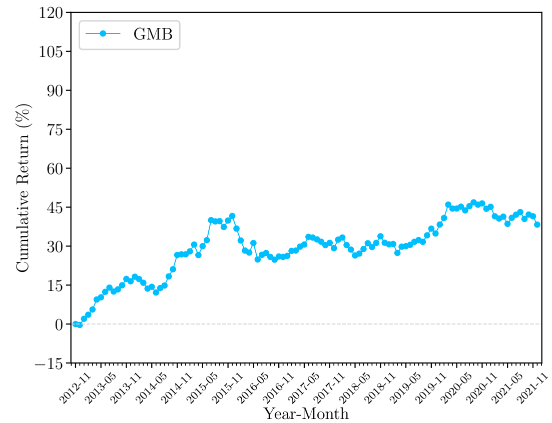
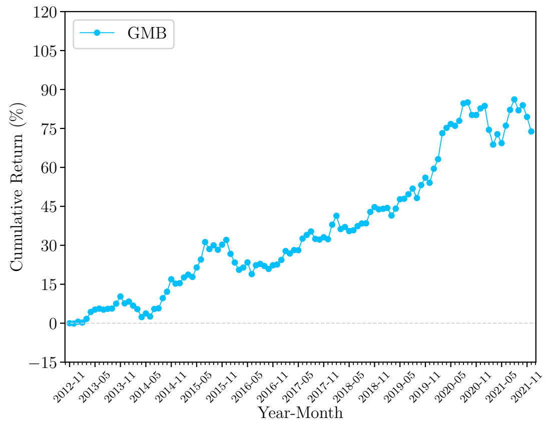


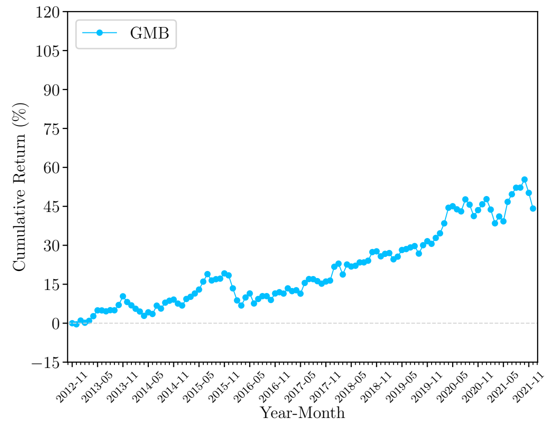
Figure 2.5. Leave-one-sector-out Cumulative GMB Returns. The figures plot the cumulative returns on the GMB portfolios, in which the stocks have both valid observations from the Datastream-MSCI ESG Ratings merged dataset and valid GICS codes from Datastream. In addition to the complete green and brown portfolios including all sectors of stocks, the two leave-one-sector-out portfolios are constructed by using the GICS industry classification system to aggregate individual stocks representing all industries except for Energy and Information Technology ("Info. Tech."), respectively, for a given region. Panel A shows the results for the global sample, Panel B shows the results for the U.S. only, and Panel C shows the results for the global sample excluding U.S.

Panel B: U.S.

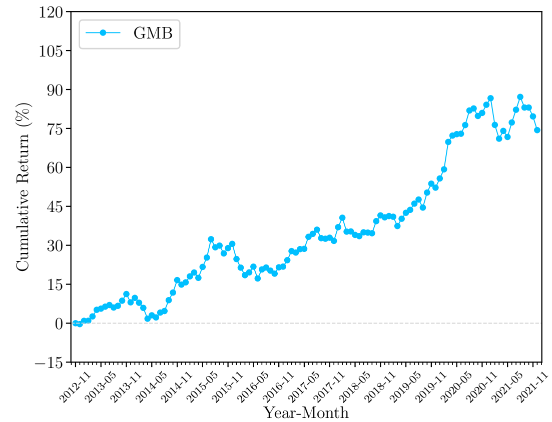
Graph B.1: All Sectors



Graph B.2: All Sectors Excluding Energy

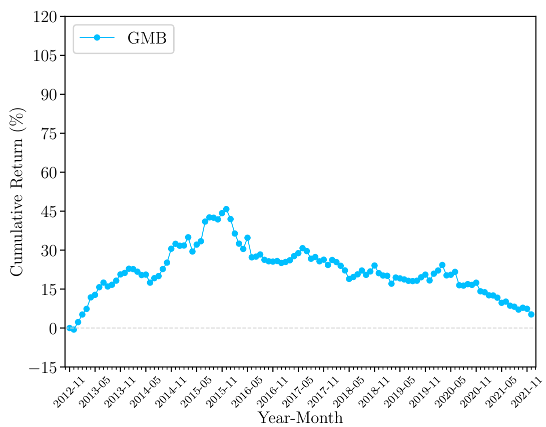


Graph B.3: All Sectors Excluding Info. Tech.

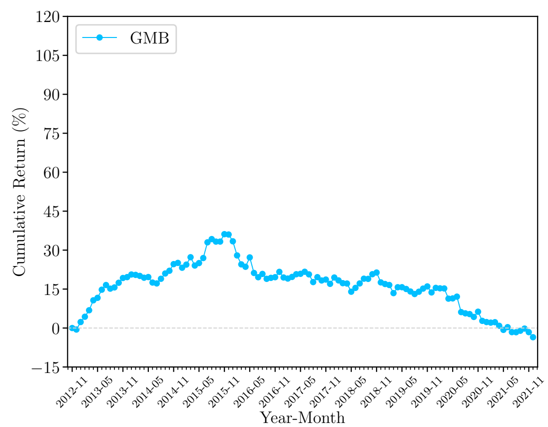


Panel C: Globe excluding U.S.

Graph C.1: All Sectors



Graph C.2: All Sectors Excluding Energy



Graph C.3: All Sectors Excluding Info. Tech.

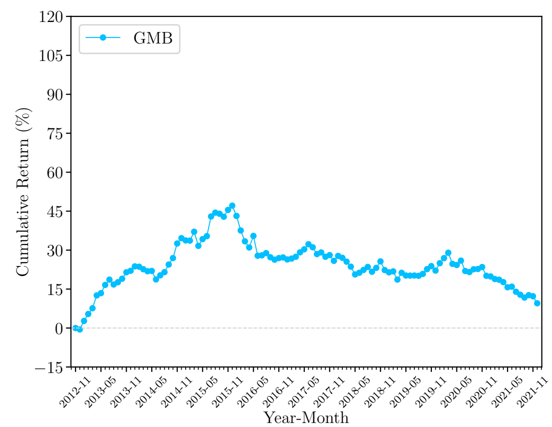


Figure 2.5. Leave-one-sector-out Cumulative GMB Returns. —*Continued*

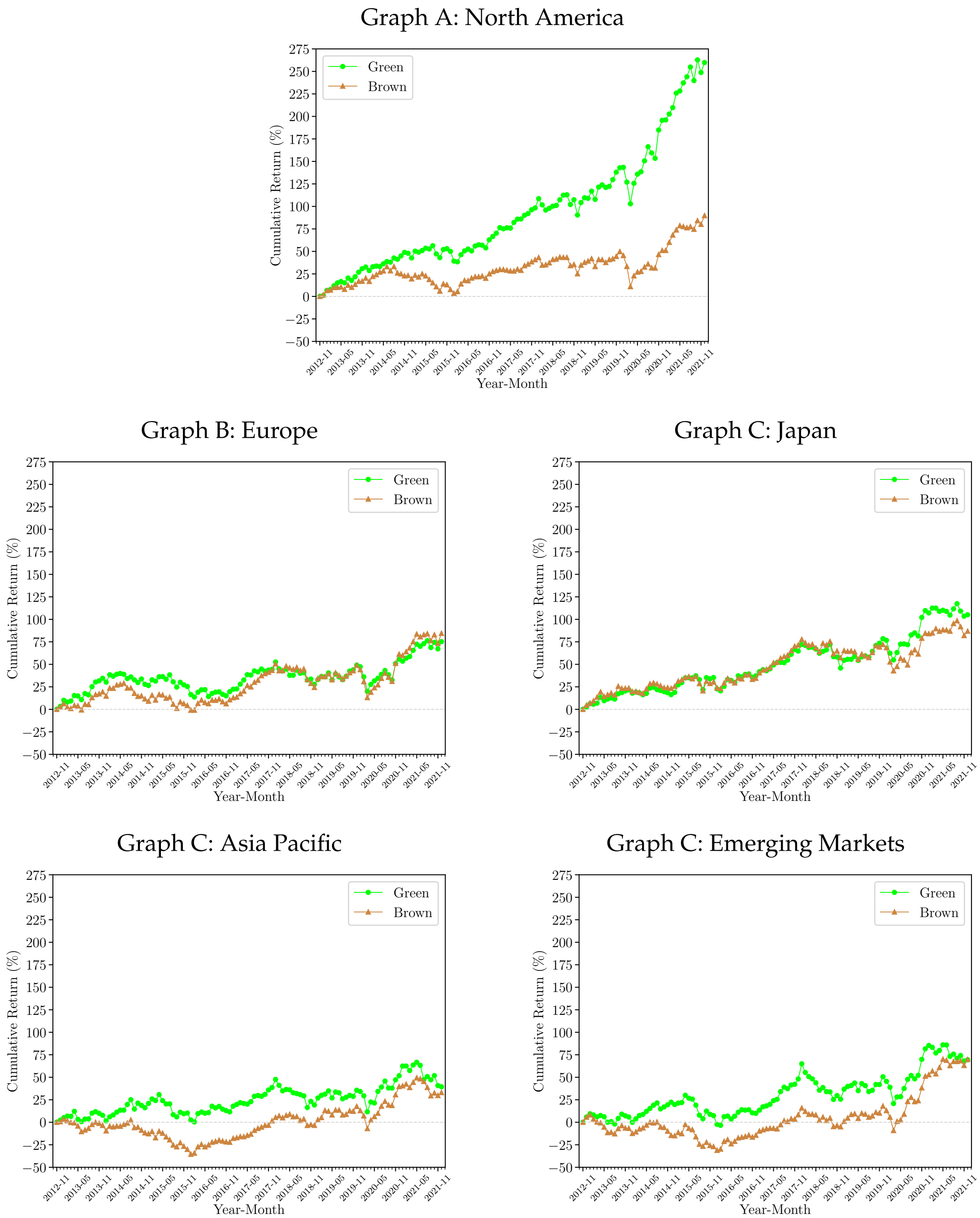


Figure 2.6. Returns on Value-weighted Green and Brown Portfolios by Region. The figures plot the cumulative returns of the green and brown portfolios region by region. The sample period is between November 2012 and December 2021. The cumulative returns are calculated from the merged Datastream-MSCI ESG Ratings dataset.

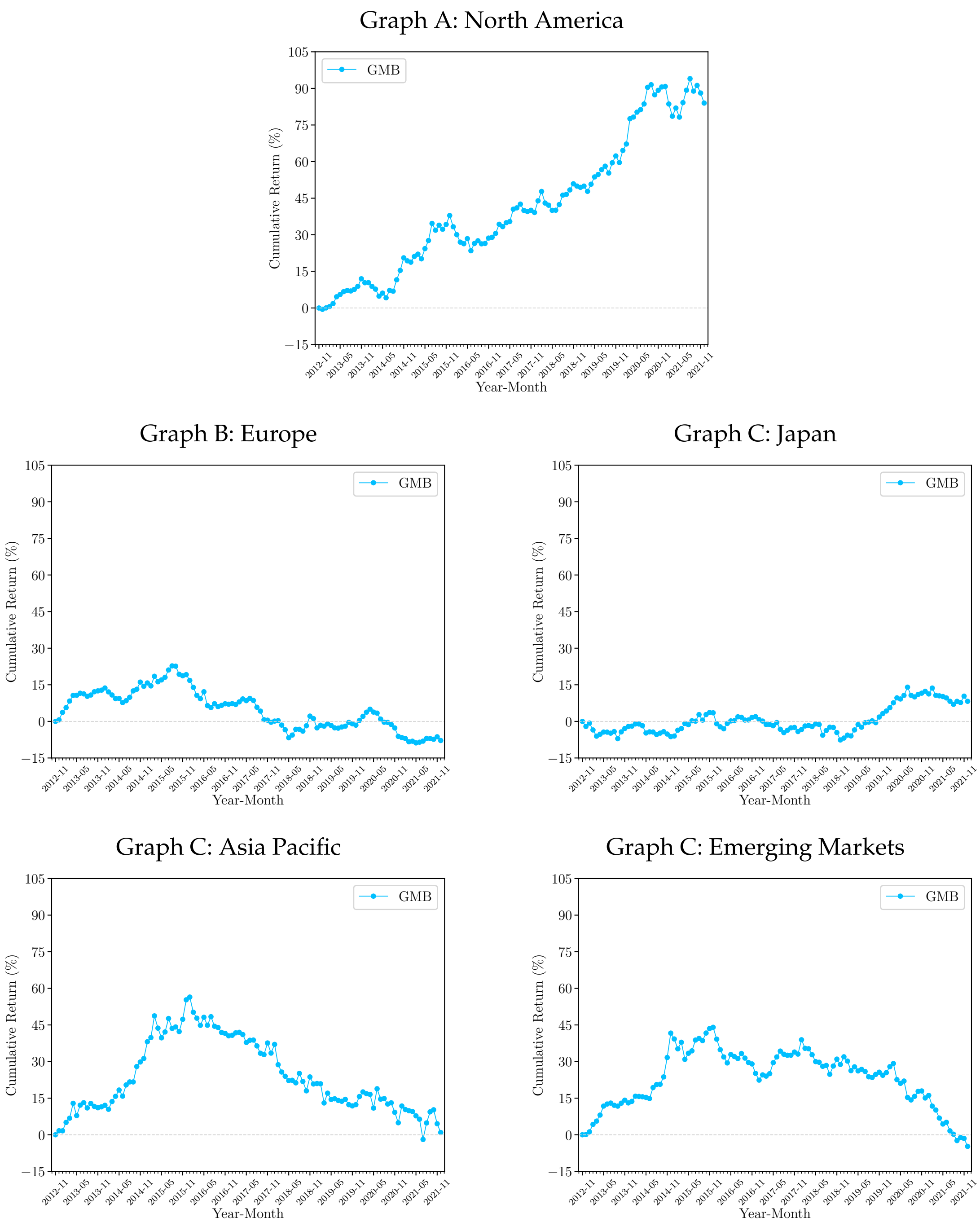


Figure 2.7. Cumulative GMB Returns by Region. The figures plot the cumulative GMB returns region-by-region. The sample period is between November 2012 and December 2021, and the cumulative returns are calculated from the merged Datastream-MSCI ESG Ratings dataset.

APPENDIX

Table 2.A.1
Leave-one-sector-out GMB Alphas

We estimate time-series regressions on the global GMB portfolios that are composed of stocks with valid GICS codes from Datastream. Mkt-Rf is the global excess market return. SMB and HML are the global version of the size and value factors of the Fama and French (1993) model. RMW and CMA are the global version of the profitability and investment factors of Fama and French (2015). See Equations (2.W.4) in Section 2.3.1 for details on the model specifications. Returns are in percentage per month. ** denotes significance at the 5% level, and * for the 10% level.

In addition to the complete GMB portfolio, the 11 leave-one-sector-out GMB portfolios are constructed by using the GICS industry classification system to aggregate individual stocks from the specific region for which the test is performed into 11 groups representing all industries except for Energy, Materials, Industrial, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities, Real Estate, respectively. We report the three cases, the Global, the U.S. and Global excluding U.S., in the table. The list below shows the leave-one-out GICS Sector Name in ascending order with the GICS Sector Code, respectively.

(1): All industries except for Energy (code: 10)
(2): All industries except for Materials (code: 15)
(3): All industries except for Industrial (code: 20)
(4): All industries except for Consumer Discretionary (code: 25)
(5): All industries except for Consumer Staples (code: 30)
(6): All industries except for Health Care (code: 35)
(7): All industries except for Financials (code: 40)
(8): All industries except for Information Technology (code: 45)
(9): All industries except for Communication Services (code: 50)
(10): All industries except for Utilities (code: 55)
(11): All industries except for Real Estate (code: 60)

Table 2.A.1
Leave-one-sector-out GMB Alphas — *Continued*

	Complete GMB	Leave-one-sector-out GMB (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
						Panel : Globe						
Constant	0.34**	0.25*	0.27*	0.38**	0.32*	0.37**	0.25	0.50**	0.32**	0.38**	0.37**	0.34**
Mkt-Rf	-0.07	-0.01	-0.04	-0.07	-0.08*	-0.10**	-0.03	-0.12**	-0.06	-0.05	-0.12**	-0.07
SMB	-0.27**	-0.26**	-0.22**	-0.28**	-0.24**	-0.30**	-0.22**	-0.43**	-0.25**	-0.25**	-0.28**	-0.28**
HML	-0.45**	-0.22**	-0.40**	-0.47**	-0.42**	-0.55**	-0.26**	-0.78**	-0.40**	-0.44**	-0.53**	-0.47**
RMW	0.02	-0.14	0.06	0.02	0.09	0.02	0.07	0.00	0.00	0.01	0.05	0.01
CMA	-0.10	-0.13	-0.15	-0.14	-0.09	-0.06	-0.21	0.03	-0.10	-0.13	-0.01	-0.08
R^2	*0.33*	*0.18*	*0.29*	*0.33*	*0.27*	*0.41*	*0.19*	*0.59*	*0.28*	*0.28*	*0.35*	*0.33*
Adj. R^2	*0.30*	*0.14*	*0.25*	*0.29*	*0.24*	*0.38*	*0.15*	*0.56*	*0.24*	*0.25*	*0.32*	*0.29*
						Panel B: U.S.						
Constant	0.49**	0.31	0.48**	0.54**	0.44**	0.53**	0.44**	0.56**	0.50**	0.56**	0.55**	0.50**
Mkt-Rf	-0.04	0.05	-0.03	-0.02	-0.04	-0.07	0.00	-0.08	-0.03	-0.02	-0.12	-0.03
SMB	-0.26**	-0.20**	-0.22**	-0.29**	-0.25**	-0.27**	-0.26**	-0.35**	-0.24**	-0.25**	-0.28**	-0.27**
HML	-0.53**	-0.19	-0.53**	-0.58**	-0.46**	-0.60**	-0.36**	-0.82**	-0.54**	-0.52**	-0.67**	-0.56**
RMW	0.03	-0.14	0.08	0.03	0.05	0.05	0.06	0.12	0.00	0.02	0.05	0.04
CMA	-0.08	-0.21	-0.11	-0.09	-0.16	-0.04	-0.22	0.07	-0.05	-0.14	0.06	-0.07
R^2	*0.29*	*0.14*	*0.27*	*0.29*	*0.26*	*0.31*	*0.19*	*0.39*	*0.25*	*0.27*	*0.35*	*0.29*
Adj. R^2	*0.25*	*0.10*	*0.24*	*0.26*	*0.22*	*0.28*	*0.15*	*0.36*	*0.22*	*0.23*	*0.31*	*0.25*
						Panel C: Globe ex. U.S.						
Constant	0.12	0.08	0.04	0.13	0.11	0.16	0.04	0.27	0.16	0.14	0.13	0.13
Mkt-Rf	-0.09*	-0.06	-0.04	-0.10**	-0.12**	-0.13**	-0.05	-0.17**	-0.09*	-0.06	-0.12**	-0.10*
SMB	-0.21**	-0.21**	-0.16*	-0.19**	-0.16*	-0.26**	-0.14	-0.38**	-0.21**	-0.19**	-0.21**	-0.21**
HML	-0.27**	-0.10	-0.21*	-0.26*	-0.27*	-0.41**	-0.09	-0.60**	-0.27**	-0.25*	-0.32**	-0.28**
RMW	-0.03	-0.16	-0.03	-0.02	0.11	-0.02	-0.01	-0.06	-0.05	-0.05	-0.01	-0.04
CMA	-0.09	-0.07	-0.13	-0.14	-0.06	-0.05	-0.15	-0.04	-0.10	-0.10	-0.02	-0.07
R^2	*0.16*	*0.08*	*0.11*	*0.16*	*0.15*	*0.25*	*0.05*	*0.45*	*0.16*	*0.12*	*0.16*	*0.16*
Adj. R^2	*0.12*	*0.04*	*0.07*	*0.12*	*0.11*	*0.22*	*0.01*	*0.43*	*0.12*	*0.08*	*0.12*	*0.12*

CHAPTER 3

TRADING PAUSES, HIGH-FREQUENCY ACTIVITY, AND MARKET QUALITY

In this chapter, I study trading pauses on individual stocks under the Limit Up-Limit Down (LULD) Plan, which are key volatility circuit breakers in the US market, designed to prevent future disastrous market events similar to the 2010 Flash Crash. However, unnecessary pauses could harm market quality. Since July 2016, the 10th Amendment to the LULD Plan (A10) has dramatically reduced superfluous trading pauses due to deceptive opening prices. Henceforth, the pre-pause liquidity improves, and there is less room for the post-pause liquidity to increase compared to the pre-pause level. Short-term volatility spikes around trading pauses after A10, and the post-pause volatility increases. Furthermore, it is crucial to understand the role that high-frequency traders play around trading pause. Post A10, high-frequency quoting peaks closely around trading pauses, especially after trading resumptions. Suggestive evidence indicates that high-frequency quoting is related to improved liquidity around trading pauses, notably post A10 and before trading pauses, but not necessarily linked to increased short-term volatility.

3.1 Introduction

An active debate exists among scholars and policy makers about the role and economic consequences of trading pause mechanisms on market quality and price stability. Some believe trading halts (or "circuit breakers") can mitigate volatility, and facilitate liquidity provision. Other beneficial effects include reducing information asymmetry, resolving order imbalances, improving price discovery, and stabilizing prices. In contrast, some others argue that trading pause mechanisms may not reduce volatility but only defer it to the period after the man-made interruption. They also think that enforced pauses may result in magnified shocks and increased volatility. A third school of views takes an intermediate position and emphasizes the origin of volatility from informed trading and uninformed trading. They point out that trading interruptions counter the negative effects from uninformed trading but may harm information dissemination and price discovery when price movements are triggered by informed trading.

The current prevailing stock-level trading pause mechanism in the US market is under the Limit Up-Limit Down (LULD) plan, which contains straddle states, limit states, trading pauses, and clearly erroneous trades. Its predecessor is the single-stock circuit breaker (SSCB) mechanism which was introduced by SEC and FINRA in June 2010, while the LULD Plan was approved in May 2012 and gradually replaced SSCB rules starting from April 2013 in two phases.[1] These rules are introduced to address sudden and extreme price fluctuations of individual stocks across the market in a short time window, as those that occurred during the "Flash Crash" on May 6, 2010. They are designed to protect against extreme price volatility which is potentially harmful to the market, while the LULD Plan is an improved version.[2]

The LULD Plan trading pause is set to prevent individual stocks in the National Market System (NMS) from being traded beyond a certain price band, but it will allow trading to restart if the price deviation is transient. The price band for a stock is calculated by the Securities Information Processors (SIPs) based on an evolving reference price. The initial reference price is decided by the first trade price of a stock on its primary listing exchange if that trade occurs within 5 minutes from market opening. When there is no opening trade satisfying the above criteria, the initial reference price is the midquote of the best bid and ask prices on that stock's primary listing exchange, in the era before the implementation of Amendment 10 to the LULD Plan. However, LULD Plan participants noticed that in the latter case, using the mid-quote of the best bid and ask on the primary

[1] Alternatively, single-stock circuit breakers (SSCB) are also known as single-stock trading pauses (SSTP). And limit-up limit-down pauses may be referred to as LUDP.

[2] See Moise and Flaherty (2017) and Hughes, Ritter, and Zhang (2017).

listing exchange leads to problematic opening reference price. That could start the price band away from the reasonable range of intrinsic price levels and triggers trading pauses even after someone submits a bid or offer quote at a reasonable price close to the intrinsic value.[3]

To address the unrealistic opening reference price issue, Amendment 10 of the LULD Plan came into effect on 18 July 2016 with the approval of the SEC.[4] When a stock's primary listing exchange opens with quotes, now the opening reference price is set to be the previous day's closing price of the stock on its primary listing exchange. If the closing price does not exist, the last sale on the primary listing exchange reported by the SIP will be used instead as the first reference price. In this way, a large amount of unnecessary trading pauses related to the problematic opening reference price could have been avoided, as these trading pauses do not suggest extraordinary market volatility. As documented in Hughes (2017), the occurrence of trading pauses decreased significantly after the implementation of Amendment 10, especially in the 30-minute window from market opening.

This effective regulatory change provided a unique opportunity to study how unneeded trading pauses affect market quality and price stability compared to necessary ones, and whether Amendment 10 has additional beneficial effects on liquidity and volatility. It also created a chance to study whether high frequency traders or strategic liquidity providers step up to fill the gap when there is a mechanism flaw or whether they take advantage of this hole. Hypothetically, they may be able to trigger trading

[3]For example, if a stock has a 20% opening price band expanded from its reference price and there is no opening trading on its primary listing exchange, then the best bid at \$3 and offer at \$19 will make the mid-quote \$11 as the initial reference price, with a lower bound of $\$11\times(1\text{-}20\%)=\$8.8$ and an upper bound of $\$11\times(1+20\%)=\$13.2$. Now, if someone submits a buy order at \$3.5, then the limit state is triggered and the LULD trading pause on this stock is set to happen 15 seconds later (without other changes). Suppose that the closing price on the previous trading day is \$3.5, this quote today at \$3.5 is a reasonable price (based on the previous closing price) while it still triggered the trading pause. That is not sensible. See Hughes (2017) for more discussion of the unrealistic opening reference price issue before Amendment 10.

[4]See Hughes (2017), Amendment 10 order: https://www.sec.gov/rules/sro/nms/2016/34-77679.pdf, and Amendment 10 notice of filing: https://www.sec.gov/rules/sro/nms/2016/34-77205.pdf.

pauses especially in the pre-Amendment 10 (A10) period by exploiting the mechanism defect related to the problematic opening reference price decision. On the other hand, the improved LULD trading pauses mechanism in the post-A10 era may promote high-frequency acitvity around trading pauses in a good way, which is beneficial to market quality. It is intriguing to examine whether high-frequency trading (HFT) activities around trading pauses change after the implementation of Amendment 10, and whether HFT activity is related to market quality improvement and price stability around trading pauses. To my best knowledge, there are no readily available studies investigating the important yet understudied aspects above.

Empirical results in this paper show that, in the pre-A10 era, liquidity measured by percentage quoted spread starts to improve from 14 minutes before trading pauses till 2 minutes before trading pauses, compared to the base bin level 1 hour before trading pauses. It improves even more after trading resumes, and the improvement is significant throughout the 1 hour window after the resumption. However, in the post-A10 era, liquidity improvement, relative to the base bin at 1 hour before trading pauses, starts from 23 minutes after trading resumes and the magnitude is less than half of that of their counterparts in the pre-A10 era. Difference-in-differences results further affirm that the liquidity improvement after trading resumes in the post-A10 era is significantly less than that in the pre-A10 era, for about 8 to 9 percentage points, compared to their base bin levels 1 hour hour before trading pauses, respectively, although the base bin level of liquidity is higher in the post-A10 era.

The short-term volatility measure *HighLow* only increases significantly at the minute just before trading pauses and at the minute right after trading resumes, compared to the base bin level, in the pre-A10 era. However, there are 3 more minute-level bins with a significant increase of *HighLow* before trading pauses and 22 more minute-level bins after trading resumes in the post-A10 era compared to the counterparts of the pre-A10 era. The magnitudes are larger, especially at the $\tau = +1$ minute bin and at the $\tau = -1$ minute bin. Difference-in-differences results also confirm that short-term volatility increases more in the window of a few minutes around trading pauses in the post-A10 era than those in the pre-A10 era relative to their base bin levels, respectively, especially after trading resumes. Especially, in the minute right after trading resumes, the difference in the magnitude of excess short-term volatility relative to the base bin level is the largest, and the post-A10 magnitude is significantly higher.

For high-frequency quote updates $HFQU$, there are a dozen significant 1-minute bins that show an increase from the base bin level an hour before trading pauses in the pre-A10 era. After trading resumes, there are only 3 significant bins with an increase from the base bin level. Among those significant bins around trading pauses, the 1-minute bin right before trading pauses and the 1-minute bin right after trading resumes are much higher than the rest. In the post-A10 era, only the 1-minute bin right before trading pauses and the 1-minute bin right after trading resumes have a significantly higher level of $HFQU$ from the base bin level. And their increased levels of $HFQU$ from the base bin are much higher than their pre-A10 counterparts, especially in the exact minute after trading resumes. Difference-in-differences results further support that the difference between the excess increase of $HFQU$ from base bin level between the post-A10 era and the pre-A10 era is the largest in the minute right after trading resumes, with the post-A10 one being much larger.

High-frequency quote updates are correlated with a decrease in the percentage of quoted spread before and after trading pauses in both the pre-A10 era and the post-A10 era. That implies a liquidity improvement. The magnitude of quoted spread is larger during the hour before trading pauses in both eras. In the post-A10 era both before and after trading pauses, there are more 1-minute bins with a significant decrease of percentage quoted spread from the base bin level than in the pre-A10 era, especially in the hour before trading pauses. This indicates that after the implementation of Amendment 10 to the LULD Plan, high-frequency quoting activity in the 2-hour window around trading pauses correlates more with liquidity improvement than before.

In both the pre-A10 and post-A10 eras, high-frequency quote updates are only positively correlated with short-term volatility *HighLow* in just a few 1-minute bins in the hour before trading pauses and they are all in the $[-25, -1]$ minutes window. After trading resumes, there are a few more bins with significantly positive correlation between high-frequency quote updates and short-term volatility throughout the 1 hour interval in the Pre-A10 era. However, in the post-A10 era, only a handful of bins show a significantly positive correlation, and they are concentrated in the $[+21, +34]$ minutes window. This suggests that, after the implementation of Amendment 10, high-frequency quote updates are less likely to be positively correlated with the increase in short-term volatility during the 2-hour window around trading pauses, especially in the hour after trading resumes.

The remainder of the chapter follows this structure. Section 3.2 reviews the literature on trading pauses and mechanisms in practice. Then testable hypotheses are proposed based on the relevant literature and the purpose of this study. Section 3.3 describes the data, the measurements of liquidity, volatility, and high-frequency activity. Section 3.4 documents the empirical results on the effects of trading pauses on market quality in the pre- and post-Amendment 10 periods. Section 3.5 depicts the evolution of high-frequency quoting activity around trading pauses before and after Amendment 10 and explores its correlation with market quality around trading pauses in the two periods. Section 3.6 concludes.

3.2 Literature Review, Regulatory Rules, and Hypotheses

3.2.1 Theory and Empirical Studies of Trading Halts

The effect of trading halts is debatable. Brady et al. (1988) and Kyle (1988) indicate that they can help ease market tensions with a soothing effect and coordinate market forces. They argue that circuit breakers can reduce volatility, protect liquidity providers, decrease order imbalances, lessen credit risk, promote information processing, facilitate repositioning, and help to cover incurred losses by margins. They believe that the additional level of protection is beneficial to market quality. Consistent conclusions can be found in Greenwald and Stein (1991), claiming that trading halts can assist in balancing immediacy and complete information dissemination among participants in a continuous market. Similarly, Madhavan (1992) states that in times of severe information asymmetry, continuous trading should be replaced by periodic trading instead, which is more practical, allowing accumulation in both liquidity demand and liquidity supply.

In contrast, Fama (1988) pointed out that trading halts can only delay volatility instead of reducing it, causing a spillover effect in the period after trading resumes. Subrahmanyam (1994) states that man-made limits on price changes may aggravate market failures instead of saving them from happening. That paper further claims that trading suspensions induce traders to revoke positions and leave the market, magnifying shocks to stock prices. The mechanism is also known as the magnet effect of price limits, which promotes volatility and propels the stock prices toward the trading suspension threshold.

There can be a middle ground between the above two schools. Harris (1997) divides the causes of volatility into informed and uninformed trading. The former is fundamental, while the latter is transitory. In the circumstance of uninformed trading-driven volatility, trading halts may help to reduce it by absorbing order imbalances. However, when volatility is caused by fundamental trading, the price limits may harm the price discovery and hence the trading halts may prevent necessary information circulation.

Among those undecided theoretical implications, the empirical literature mostly addressed the impact of an earlier mechanism, trading "halts", which differs from the later trading "pauses" or price limits. The former trading "halts" interrupt all activities in the order book and are imposed at the will of exchanges with longer halting intervals. Trading "pauses", however, only restrict trading executions but still allow quoting. In addition, the trading "pauses" are triggered under explicitly known rules, and they span 5 minutes precisely. The existing influential trading "halts" literature include Lee, Ready, and Seguin (1994), Corwin and Lipson (2000), and Christie, Corwin, and Harris (2002), while Harris (1997) and Cho et al. (2003) cover trading "pauses" and prices limits instead.

Lee, Ready, and Seguin (1994) find that the trading volume increases after trading halts. Regarding stock returns after trading resume, Bhattacharya and Spiegel (1998) obtain evidence that return consistency can be obtained after news-induced trading halts, while return reversal occurs after trading halts which are triggered due to order imbalances. Corwin and Lipson (2000) and Christie, Corwin, and Harris (2002), display that the post-halt volatility and bid-ask spreads are at a higher level and can last for two hours or longer. The above studies are based on NYSE data. Meanwhile, Abad and Pascual (2010) study data from the Spanish Stock Exchange and observe an increasing dispersion of the trading volume and mid-quote price during sampling intervals of trading interruptions (i.e., "volatility call auctions"), but they regress to their original levels during the next two hours.

There are some papers on modern automated trading control mechanisms. Zimmermann (2013) focuses on Deutsche Boerse Xetra exchange's volatility interruptions, a mechanism comparable to Nasdaq's trading pauses, and notices that the interruptions have a positive effect on price discovery as the pre-halt price uncertainty decreases. Brogaard and Roshak (2016) study the effects of trading pauses on extreme price movements (EPMs) and compare stock returns in the per-regulation and post-regulation periods. They document that trading pauses can mitigate the degree of extreme price movements while suppressing necessary price reactions.

Hautsch and Horvath (2019) study the effects of trading pauses under the SSCB and LULD mechanisms during the pre-Amendment 10 period on liquidity, volatility, and price discovery in the 120-minute window around trading pauses. The existence of those mechanisms makes the market participant behave differently with the expectation of trading pauses to occur. Trading pauses may facilitate price discovery during the interruption, but hurt price stability and liquidity in the post-pause period. They also find that on average trading pauses fail to calm down the market but instead induced volatility. Although trading pauses may play a protective role in extreme market events, their average negative effects on market quality require additional attention as well.

3.2.2 High-Frequency Activity, Extreme Price Movements, and Market Quality

Hasbrouck and Saar (2013) propose a low-latency trading measure that is a prominent representative of proprietary trading activities by HFT firms, although it could also involve a small portion of agency algorithms. Their measure is intended to capture high-frequency trading behavior and has been further tested and compared with other HFT proxies in Boehmer, Li, and Saar (2018) to show its relative advantage.

The low-latency trading measure by Hasbrouck and Saar (2013) can be taken as a proxy for HFT activity. They use it to study low-latency trading's impact on market quality both in normal times and during turbulent periods with economic uncertainties. Their measure, *RunsInProcess*, is built upon "strategic runs" as a chained sequence of order submissions, cancelations, and executions which are presumably components of a dynamic algorithmic trading strategy, as well as being identifiable through order-level data with public availability. It is calculated as the time-weighted number of "strategic runs" longer than 10 messages in each interval. The measure is highly correlated with the estimates from the Nasdaq 2008-2009 HFT dataset. They find that low-latency trading activity can improve market quality measures in terms of decreasing spreads, increasing depths, and reducing short-term volatility. They also imply that low-latency trading need not harm the interest of long-term investors. Their low-latency trading measure is a publicly available HFT proxy which can be constructed from the Nasdaq TotalView-ITCH data. Researchers can compute the low-latency measure themselves instead of relying on exchanges provided HFT datasets that cover a limited time span.

Boehmer, Li, and Saar (2018) compare the low-latency trading measure *RunsInProcess* with the other three HFT proxies that are computable based on publicly available data to see which may be the best to capture general HFT activity. Those three comparison measures include $Ord2Vol$, $Cancel2Trd$, and *CancelRatio*.[5] The first two have been widely used in HFT and algorithm trading literature such as Hendershott, Jones, and Menkveld (2011), Hagströmer and Nordén (2013), Boehmer, Fong, and Wu (2021). The *CancelRatio* measure is designed to reflect the characteristic of HFT firms which is related to the large amount of orders submitted which are canceled shortly thereafter. The comparison results in Boehmer, Li and Saar (2018) show that *RunsInProcess* is a reasonable HFT activity proxy and has even better performance when time intervals are longer. The $Canel2Trd$ and *CancelRatio* are also doing well, especially during short intervals.

[5]The measures are defined as: (1) $Ord2Vol$:= number of submitted limit orders / (1 + value of trades); (2) $Cancel2Trd$:= number of canceled limit orders / (1 + number of trades); (3) *CancelRatio* := number of canceled limit orders / (1 + number of submitted and canceled limit orders).

Listed below are more papers about the background knowledge of latency and algorithm trading, which are two related factors of low-latency trading.

Looking at data from different markets, Hendershott and Moulton (2011) find that the expansion of automatic expansion and the reduction of execution time lead to decreased liquidity, while Riordan and Storkenmaier (2012) notice that a reduction in latency is accompanied by enhanced liquidity. The latency change may affect the market quality conditional on its impact on the competitions within the liquidity supply side and on how sophisticated the liquidity demanders are, which may help to explain the seemly contradicted results.

Regarding how algorithm trading affects the market, there are papers such as Hendershott, Jones, and Menkveld (2011), Boehmer, Fong, and Wu (2021), Chaboud et al. (2014), Hendershott and Riordan (2013). Especially, Hendershott, Jones, and Menkveld (2011), use the electronic message arrival rate to measure the overall proprietary algorithm and trading algorithm activities, and find that algorithmic trading results in mixed results in different measures of market quality such as spreads and depths. In contrast, Hasbrouck and Saar (2013) find their low-latency trading measure lead to positive results in all their measures of market quality, given that their measure is intended to capture high-frequency proprietary trading as much as possible instead of agency algorithm. In addition, those two papers inspected different data sources in different years with regulation changes, which may contributed to some of the differences in conclusions as well.

Conrad, Wahal, and Xiang (2015) propose a high-frequency quotation measure based on the Daily TAQ data. They calculate "high-frequency quote updates" by counting the number of any changes in prices or sizes of the best bid or offer (BBO) quotes during a given time interval on each exchange and then aggregated across all of them. That does not depend on the official National Best Bid and Offer (NBBO), and the venue selection is endogenous in liquidity-supplying or demanding algorithms. Their measure considers legitimate changes to the tip of the liquidity supply curve of each exchange.

3.2.3 Limit Up-Limit Down Plan and its Amendment 10

The Flash Crash of May 6, 2010 has induced actions from the regulators such as the U.S. Securities and Exchange Commission (SEC) and the U.S. Commodity Futures Trading Commission (CFTC) to prevent future extreme market events and enhance market stability.[6] On June 10, 2010, the SEC and the U.S. Financial Industry Regulatory Authority (FINRA) approve the implementation of the single-stock circuit breaker (SSCB) pilot program to address extraordinary volatility.[7] The SSCB pilot program is supposed to be expired on July 31, 2012, and the SEC approves an improved replacement plan to SSCB on May 31, 2012.[8] The new plan is the National Market System (NMS) Plan to Address Extraordinary Market Volatility, which is also know as the Limit Up-Limit Down (LULD) Plan.[9] The LULD Plan is implemented in different phases, and the full implementation to all stocks is on May 12, 2014.[10]

Briefly speaking, the LULD Plan prohibits trades from happening outside evolving price bands that are formed around reference prices to handle extraordinary market volatility in stocks.[11] For a stock, in general, its reference price in force is dynamically decided based on the previous reference price in force and the preceding 5-minute moving average of transaction prices, except for the initial reference price (that is, opening

[6]See `https://www.sec.gov/news/studies/2010/marketevents-report.pdf`.

[7]See `https://www.sec.gov/rules/sro/finra/2010/34-62251.pdf`.

[8]See `https://www.sec.gov/rules/sro/nms/2012/34-67091.pdf`.

[9]The full details of the LULD mechanism can be found in the original LULD Plan at `https://www.sec.gov/rules/sro/nms/2012/34-67091.pdf`, and in the amendments to the LULD Plan at `https://www.sec.gov/rules/sro/nms.htm`.

[10]More details can be found in Angel (2015), Hughes, Ritter, and Zhang (2017), and Moise and Flaherty (2017).

[11]The stocks in this paper are all NMS securities (including ETFs) in the U.S. securities market.

price) and the reference price after trading pause (that is, reopening price).[12] The reference price and price bands evolve throughout the market hour from 9:30 am to 4:00 pm unless during trading pauses.[13] A price band is formed as the percentage deviations above and below the reference price. The band width is decided by factors such as stock tiers, time of the day, and the previous day closing price.[14] Especailly, the price band during 9:30-9:45 am and during 3:35-4:00 pm is doubled from that during 9:45 am - 3:35 pm as there is usually higher volatility during the open and close.[15] Trades are allowed to occur at quotes within the price band, but not at any bid or offer quote outside the band. If the National Best Offer (NBO) reaches the lower band or the National Best Bid (NBB) reaches the upper band, a limit state is imposed on the stock.[16] The limit state could end if the quote prices are back within the price band. If a limit state lasts for 15 seconds, the stock enters a 5-minute trading pause, and the primary listing exchange could extend the pause for another 5 minutes under certain circumstances.[17] After a trading pause, the trading on the stock reopens according to the reopening rules.[18]

The key component in the LULD mechanism is the reference price. It is recalculated every 30 seconds, but in practice the reference price is not updated unless it deviates from the pro-forma reference price by at least 1%.[19] And, when the market opens, both the

[12]The immediately preceding 5-minute moving average of transaction prices is called the pro-forma reference price.

[13]The time zone in this paper is the Eastern Time, i.e. EDT/EST.

[14]See Footnote 9 and Footnote 10.

[15]However, Amendment 18 removes the doubling rule of price band during 9:30-9:45 am for all stocks, and during 3:35-4:00 pm for all Tier 2 stocks with prices higher than $3. See Table 1 in Moise (2022) and see Amendment 18 in `https://www.sec.gov/rules/sro/nms/2019/34-85623.pdf`.

[16]There is another state called “straddle state”. See Footnote 9 and Footnote 10.

[17]Toward the end of trading hours, the trading resumption or reopening rules could be different, and hence the trading pause lengths. Therefore, it is possible to see that trading pauses last for a different length from 5 minutes or 10 minutes. See Footnote 9 and Footnote 10.

[18]See Footnote 9 and Footnote 10.

[19]The pattern of the reference price looks like a step function, while the pro-forma reference price is the 5-minute moving average of preceding transaction prices which fluctuates continuously. See Figure B.1 in Moise and Flaherty (2017) and Figure 2 in Moise (2022) for more details. And see footnote 12 for the definition of a pro forma reference price

reference price and the pro forma reference price start at the initial reference price. [20]

Therefore, whether the initial reference price is set up in a sensible way has a significant impact on the evolution of reference price and price band, which then determines what kinds of quotes will trigger the limit states and trading pauses. However, the setup mechanism of the initial reference price before the implementation of Amendment 10 is problematic.[21] Before Amendment 10, on a trading day, the first reference price for a stock is the trade price in the opening auction (i.e., opening trade) on its primary listing exchange in the first 5 minutes from market opening. If no such opening trade exists and the stock opens with a quote, the first reference price is the midpoint of the bid and ask quote. [22] The problem is that using the bid and ask midpoint of the opening quote on the primary listing exchange as the opening price results in a skewed initial reference price, especially when the trading interest in that stock is thin or null, which makes it illiquid. That happens if the opening quote bid-ask spread is wide or the quote is skewed, which in turn drives the opening price far away from the stock's fair value. Hence, the midpoint of the opening quote may not represent the true market of that stock, and it is highly affected by "crazy" quotes or "fat fingers".

To fix the problematic quote-based opening price, Amendment 10 redefines the opening price when the stock opens with quotes on its primary listing exchange, based on feedback and backtesting analysis from participants in the LULD Plan.[23] When a stock does not open with a trade in the first 5 minutes, the new opening price is defined as the closing price of the stock on its primary listing exchange on the previous trading day. If

[20]The initial reference price is also called the "first reference price". See the Amendment 10 notice of filling at `https://www.sec.gov/rules/sro/nms/2016/34-77205.pdf` and Amendment 10 order of approval at`https://www.sec.gov/rules/sro/nms/2016/34-77679.pdf`.

[21]More detailed discussion of the problem can be found in Angel (2015) and Hughes (2017) . See also the Amendment 10 notice of filling and the Amendment 10 order of approval as in Footnote 20.

[22]And if there is no such opening trade or quote on the primary listing exchange by 9:35 a.m., the open reference price is the arithmetic mean of the prices of eligible reported transactions for that stock over the preceding 5-minute period across all NMS markets.

[23]See Angel (2015) and see the Amendment 10 notice of filling at `https://www.sec.gov/rules/sro/nms/2016/34-77205.pdf`.

the closing price does not exist, then the last sale on the primary listing exchange will be used. The new opening price should represent the fair value of the stock at the opening, especially for less liquid stocks, in a much more sensible way.

Angel (2015) composes a joint assessment on the LULD mechanism prior to A10 and points out issues such as the problematic opening reference price which induces unnecessary trading pauses especially during the first 30 minutes of market hour.[24] This assessment is prepared for the reference of LULD operating committee and contributes to the making and implementation of Amendment 10 to the LULD Plan. Hughes (2017) studies the real world effect of Amendment 10 and shows that it indeed dramatically reduces unnecessary trading pauses related to the opening price issue, and the decrease of trading pauses in general is also significant.[25]

3.2.4 Testable Hypotheses

Most of the trading pauses in the pre-A10 era are the unnecessary ones in terms of not being indicative of extraordinary market volatility on single stocks. However, the trading pauses in the post-A10 era are more closely in compliance with the spirit of the LULD Plan. The Amendment 10 to the LULD Plan provides an unique opportunity to investigate how different the market quality evolution around the "ought-to-be" trading pauses is from that around the unneeded trading pauses, especially after trading resumptions. It is also a valuable opportunity to comparably study the high-frequency activity around the "ought-to-be" trading pauses and the unneeded ones, and to examine and to examine the influence of high-frequency activity on market quality in those two different scenarios.

[24]See `https://www.sec.gov/comments/4-631/4631-39.pdf`.

[25]Other SEC Division of Economic and Risk Analysis (DERA) white papers also evaluate the LULD mechanism before Amendment 10, such as Moise and Flaherty (2017) and Hughes, Ritter, and Zhang (2017). However, they do not focus on the initial opening reference price issue.

However, there is little documentation in the literature on trading mechanisms or in the high-frequency trading literature on the above important questions. Hence, this paper proposes the following hypotheses and empirically examines them. The results in this paper should be helpful to regulators in re-visiting or making future trading halts and circuit breaker rules, as well as in further understanding high-frequency activity and its impact on market quality.

The first two hypotheses focus on market quality. They investigate the evolution of liquidity and short-term volatility before and after trading pauses and how their post-A10 patterns differ from their pre-A10 patterns.

Hypothesis 1: There is more improvement in post-TP liquidity in the pre-A10 era compared to the post-A10 era, and it is because pre-TP liquidity is lower in the pre-A10 era.

Hypothesis 2: The short-term volatility around trading pauses in the post-A10 era is higher than that in the pre-A10 era, especially after trading pauses.

The next three hypotheses consider high-frequency quoting and its interaction with market quality measures. They explore how high-frequency quoting activity evolves before and after trading pauses, and the difference of that in the pre-A10 era and post-A10 era. They also investigate into the correlation between high-frequency quoting activity and market quality around trading pauses, in terms of liquidity and short-term volatility.

Hypothesis 3: High-frequency quoting activity before and after trading pauses is higher in the post-A10 era than that in the pre-A10 era, especially in the minutes around trading pauses and after trading pauses.

Hypothesis 4: High-frequency quoting activity is positively correlated with liquidity improvement in the 2-hour window around trading pauses, especially before trading pauses, and this correlation is more profound in the post-A10 era than in the pre-A10 era.

Hypothesis 5: High-frequency quoting activity only occasionally positively correlates with short-term volatility in the 2-hour window around trading pauses, and it is even less so in the post-A10 era than in the pre-A10 era, especially after trading pauses.

3.3 Data, Measurement, and Descriptive Statistics

3.3.1 Limit Up-Limit Down Trading Pauses Overview

This paper adopts two ways to access LULD trading pauses data. Following Hautsch and Horvath (2019), the LULD trading pauses data can be obtained from NasdaqTrader.com, which is a website affiliated with Nasdaq. Alternatively, similar to Moise (2022), the LULD trading pauses data can be inferred and extracted from administrative massages files from Daily TAQ.

Figure 3.1 panel (a) depicts the distribution of daily LULD trading pauses and involved stocks in the [-6,+6] calendar months window around the implementation of the LULD Plan Amendment 10. There is a sharp decrease in the frequency of trading pauses occurrence and also in the count of how many stocks experience any number of trading pauses per day after Amendment 10 comes into effect. The decrease actually started a few days before July 18, 2016, according to the trend by the 5-day moving average. In the post-A10 era, both the daily number of trading pauses and the daily number of stocks experiencing trading pauses stay low and never bounce back to the pre-A10 level, with much smaller fluctuations as well. Panel (a) also shows that the pre-A10 daily number of trading pauses is about 40 higher than the daily number of stocks experiencing trading pauses. The pre-A10 daily average count of trading pauses is about 80 while that of stocks experiencing trading pauses is about 40. Also, the frequency of daily trading pauses in the pre-A10 era is much more volatile than that of stocks experiencing trading pauses per day. However, the frequency of daily trading pauses after A10 and the daily number of stocks experiencing trading pauses overlap almost all together, with the frequency of trading pauses slightly higher and more volatile in some days. In general, the frequency of post-A10 trading pauses and the count of stocks experiencing trading pauses are both much less volatile than those in the pre-A10 era. Panel (a) indicates that Amendment 10 successfully reduces the daily occurrence frequency of trading pauses and the stocks experiencing trading pauses per day. It also reduced the ratio of daily trading pauses to stocks experience trading pauses per day. Therefore, in the post-A10 era, there are fewer stocks which are likely to experience trading pauses per day, and a stock is less likely to experience multiple trading pauses on the same day. After the implementation of Amendment 10, there are also fewer day-to-day fluctuations in trading pauses or stocks involved.

Next, Figure 3.1 Panel (b) shows the frequency of monthly trading pauses from the full implementation of the LULD Plan in May 2014 to September 2021, which shows a much longer horizon compared to panel (a).[26] Similar to Panel (a), Panel (b) shows that the frequency of occurrence of monthly trading pauses before A10 is much higher than that in the post-10 era. The pre-A10 average monthly level is about 1000 trading pauses per month, while that in the post-A10 era (but before the Covid-19 outbreak) is approximately in the 100 to 200 range. The decrease in the frequency of trading pause in the post-A10 era is consistent and lasting beyond the first 6 months post-10, until the US Covid-19 outbreak in March 2020. There is an unprecedentedly huge spike in March 2020, indicating that the market is extremely turbulent in that month and that the LULD trading pauses are triggered many times among many stocks, in addition to the

[26]The most recent data update of this study in the current draft covers from May 2014 to September 2021.

four occurrence of the market-wide circuit breaker (MWCB).[27] The monthly occurrence of trading pauses increases in the post-Covid era, and the month-by-month fluctuation is also larger compared to the post-A10 but pre-Covid era. However, the average monthly frequency of trading pauses after March 2020 is still lower than that in the pre-A10 era. In an unreported figure showing the ratio of monthly trading pauses and involved stocks, the ratio is much higher in the pre-A10 era than in the post-A10 era, and it has a clear drop after the implementation of Amendment 10. The pre-A10 ratio fluctuates between 2.8 and 6.5 approximately. The ratio does not bounce back even in the Covid-19 outbreak (in March 2020) and afterwards, and it varies approximately in the range of 1.5 to 4.

In the Appendix, Figure 3.A.1 compares the number of trading pauses with VIX and Equity Market Uncertainty (EMU) and indicates that the dramatic decrease in trading pauses after the implementation of Amendment 10 is not due to changes in market volatility or uncertainty. The effect of Amendment 10 on reducing the occurrence of trading pauses is also documented in Hughes (2017). Figure 3.A.2 plots the monthly market volatility and uncertainty indices, VIX, Equity Market Volatility (EMV), infectious disease EMV, and EMU.[28] Comparing those indices with the monthly trading pause frequency as in Figure 3.1 panel (b), it can be seen that changes in market volatility and uncertainty are not the causes for trading pauses to occur less after the implementation of Amendment 10. Before the Covid-19 outbreak, the post-A10 level of market volatility and uncertainty roughly fluctuated in the same range as the pre-A10 level. There is no significant drop in any of those indices when Amendment 10 comes into effect, but the occurrence of trading pauses is dramatically reduced and stays low until the Covid-19

[27] The four market-wide circuit breaker (MWCB) halts happened on the 9th, 12th, 16th, and 18th of March 2020. See https://www.nyse.com/publicdocs/nyse/markets/nyse/Report_of_the_Market-Wide_Circuit_Breaker_Working_Group.pdf.

[28] The VIX data is from the CBOE website https://www.cboe.com/tradable_products/vix/vix_historical_data/, and it is converted to monthly data from the original daily level data. The EMV and EMU indices are from the Economic Policy Uncertainty website by Scott R. Baker, Nicholas Bloom, and Steven J. Davis, https://www.policyuncertainty.com/. The monthly EMV indices (including the infectious disease EMV) are adopted directly, while the monthly EMU data is converted from the original daily EMU index.

outbreak. In contrast, the March 2020 spike in trading pauses as in Figure 3.1 is driven by Covid-19-induced volatility and uncertainty as in Figure 3.A.2. In addition, Amendment 18 of the LULD plan does not have a significant effect on increasing the frequency of trading pauses, which can be shown in Figure 3.2.

The top panel of Figure 3.2 depicts the daily average intraday quarter-hour evolution of the trading pauses in the [-20, +20] trading days window and [-6, +6] months window before and after the implementation of Amendment 10. In the pre-A10 era, most of the trading pauses happen in the first 30 minutes since market open, i.e. the 9:30-9:45 a.m. and the 9:45-10:00 a.m. quarter-hours. In the top left plot (i.e. the [-20, +20] trading days window), the pre-A10 average count of trading pauses from all stocks is slightly more than 13 in the 9:30-9:45 a.m. quarter-hour interval. Then it increases to slightly less than 21 in the 9:45-10:00 a.m. quarter-hour interval. In the 10:00-10:15 a.m. quarter-hour interval, the daily average of trading pauses drastically drops to about 5.5 and gradually decreases to 2 approximately in the 11:00-11:15 a.m. quarter-hour interval. Afterward, it stays in the 1 to 2 range until 3:00 p.m. and then further decreases toward 0 in the last quarter-hour interval before market closes. It is a similar case in the [-6, +6] months window for the pre-A10 daily average trading pauses. The minor differences are that the 9:30-9:45 a.m. value is about 15 and the 9:45-10:00 a.m. value is approximately 17.5. And the value of 10:00-10:15 a.m. is about 5. That is, the daily averages of the first quarter hour of trading pauses in the [-6, +6] months window is slightly higher than that in the [-20, +20] trading days window, while the peak at the 9:45-10:00 am interval is about 3 trading pauses lower on average per day. The 10:00-10:15 am. level is about half the trading pauses less than that in the [-20, +20] trading days window, and the decrease since then is slightly smoother throughout the day. However, the evolution patterns of the post-A10 daily average of trading pauses are even more similar in the [-20, +20] trading days window and [-6, +6] months window. Both peaks occur in the 9:45-10:00 a.m. interval at around 2.5 trading pauses on average per day, while the 9:30-9:45 a.m. level is approximately 1.5 in the [-20,

+20] trading days window and about one in the [-6, +6] months window. From 10:00 a.m. to market close, the daily average trading pauses stay in the 0 to 1 range and close to the null side, in both windows.

In short, the top panel of Figure 3.2 demonstrates that Amendment 10 significantly reduces the occurrence of trading pauses, especially in the 9:45-10:00 a.m. quarter-hour interval and in the first 30 minutes since market opening. It also reduces the trading pause frequency throughout the rest of the day, but the degree is much smaller because the pre-A10 level of trading pauses after 10 a.m. is much less than the that in the opening half-hour. The eliminated trading pauses by Amendment 10 are the ones linked to the problematic initial reference price issue when stocks open by quotes instead of trades. Those problematic trading pauses in the pre-A10 era are mostly likely to happen in the first hour of trading, especially in the first 30 minutes and after the LULD price band shrinks to half beginning at 9:45 a.m. Amendment 10 has significantly improved the issue and reduced unnecessary trading pauses linked to the previous problematic opening reference price mechanism.

The middle and bottom panel of Figure 3.2 shows that the effect of Amendment 10 on reducing the occurrence of trading pauses in the opening hour is persistent, even in a longer horizon from May 12, 2014 (full implementation of the LULD Plan) to September 30, 2021, beyond the [-20, +20] trading days window and [-6, +6] months window. Similar to what has been shown in the top panel, the effect of Amendment 10 in reducing trading pauses especially in the opening hour is persistent all the way till Feb 2020 when LULD Plan Amendment 18 (A18) comes into effect as well as the March 2020 Covid-19 outbreak. The pre-A10 pattern and the post-A10 but pre-A18 pattern are very similar to those in the top panel, although the pre-A10 highs are slightly lower. In addition, comparing the two plots in the middle panel, it can be seen that Amendment 18 of the LULD Plan (in force in February 2020 as shown in Figure 3.1) slightly increases the number of trading pauses in the 9:30-9:45 a.m. quarter-hour interval by 5 on average per day due to the LULD price band shrinking. In addition, the middle right plot and the bottom plot consider the effect of Covid-19 outbreak in March 2020 on the frequency of trading pauses, by removing March 2020 and by singling out March 2020 respectively. In March 2020, the impact of the Covid-19 outbreak dramatically increases the frequency of occurrence of trading pauses in each of the quarter-hour intervals, especially during the 9:30-11:00 a.m. period. The 9:45-10:00 a.m. and 9:30-9:45 a.m. values are the highest.

3.3.2 Trading Pauses Screening Process

There are 5 filtering and screening steps starting from all LULD trading pauses recorded in the $[-20, +20]$ trading days window to the eligible ones used in the empirical analyses part of this paper. The filters are based on Hautsch and Horvath (2019).

Firstly, each LULD trading pause needs to follow the LULD Plan rules regarding the trading pausing timestamp (i.e. starting time), trading resumption timestamp (i.e. ending time), and time duration of the pause. On a given day, a legitimate LULD trading pause must have its starting time and ending time within the regular trading hours and have a legitimate duration regulated by the rules depending on the starting time.[29] This first filter results in the number of legitimate LULD trading pauses (i.e., "TP events") and the involved stocks (i.e., "TP stocks") as shown in the first row of Table 3.1 Panel (A).

Next, from the remaining trading pauses, only those that last for 5 minutes are kept. That is, for the purpose of unifying comparison since trading pauses with different lengths may have different impacts on market quality and other aspects of interests. This

[29] Most of the LULD trading pauses last for 5 minutes in length. Some can be extended for another 5 minutes. Some other have irregular time lengths. For example, for LULD trading pauses that start towards the market closing time, their ending time may be combined with the market closing time. Some others may have a resumption time recorded after the market closes. Those cases will result in their pause durations being longer than 5 minutes

second screening process leads to the second row in Table 3.1 Panel (A).

Third, to avoid the overlapping effect, if there are multiple trading pauses on a stock on a given day, only those that are 2 hours apart from each other are selected.[30] The remaining eligible TP events and TP stocks after the third filter are demonstrated in the third row of Table 3.1 Panel (A).

The fourth filter requires that the trading pauses need to resume at least 20 minutes before market closes, so as to leave enough minutes after trading resumptions to start the post-TP market quality and other aspects of interests. That screening step results in the counts of TP events and TP stocks in the fourth row of Table 3.1 Panel (A).

Lastly, the fifth filter requires eligible trading pauses to be at least 5 minutes after market opening, which will create at least 5 minutes of measurement units for market quality measures and proxies for other aspects of interest before trading pauses. This fifth filter leads to the last row in Table 3.1 Panel (A).

3.3.3 Time Window around Trading Pauses and Measurement Units of Variables

Following Hautsch and Horvath (2019), the focus time range is 1 hour before trading pauses and 1 hour after trading resumptions. However, what happen during the trading pauses is not covered. The 2-hour window should leave enough time to study how market quality and high-frequency activity evolve towards trading pauses and after trading resumptions, while avoiding the overlapping effects of two nearby trading pauses on the same stock.[31] The time length for each of the bins before and after trading pauses

[30]Christie, Corwin, and Harris (2002) find that the increased level of bid-ask spreads and volatility last for at least 2 hours after trading halts.

[31]See Footnote 30.

could be 1 minutes, 3 minutes, or 5 minutes, which is also referred to as the bin interval in this paper. For 1-minute bins, there will be 60 bins before trading pauses and 60 bins after trading resumes, which constitute the [-60, +60] 1-minute bins window around trading pauses. Similarly, for the 3-minute bins, there will be 20 bins before and 20 bins after trading pauses in the [-20, +20] window composed of 3-minute bins around trading pauses. And for the 5-minute bins, there will be 12 bins fore and 12 bins after trading pauses in the [-12, +12] window composed of 5-minute bins around trading pauses. Note that there is no "bin 0" in any of the window. The current version of this paper focuses on the 1-minute bins. Each bin serves as the time unit upon which the market quality and high-frequency activity measurements are computed.

In this paper, the following notations are used to denote trading pauses and time bins in the 2-hour window around. A unique stock-date-time tuple (s, d, t) identifies a trading pause. The letter s stands for stock, d for date, and t for the time of day when a trading pause occurs. Taking the $[-60, +60]$ window of 1-minute bins around trading pauses, for example, the proxies for variables are measured in each time bin τ, where $\tau = -60, -59, \ldots, -2, -1, 1, 2, \ldots, 59, 60$ are for each 1-minute bin in the $[-60, +60]$ window.[32] Bin "$\tau = 0$" would represent the time when a trading pause is in progress, but this interval of time is not included in the study. Both the notations (s, d, t) and τ will be used as subscriptions in the equations in Section 3.4.1 and Section 3.5.2 to identify trading pauses and bins where the variables are computed.[33]

[32]This is subject to change depending on the bin length. For example, if each bin lasts for 3 minutes instead, then $\tau = -20, -19, \ldots, -2, -1, 1, 2, \ldots, 19, 20$.

[33]See Section 3.4.1 and Section 3.5.2 for more details.

3.3.4 Trading Pauses Sample Summary Statistics

As described in the previous section, the trading pause data is obtained from the DTAQ administrative messages files and from the NasdaqTrader.com via a cross-validation approach. The current version of this paper focuses on LULD trading pauses in the US stock market in the [-20, +20] trading days window around July 18, 2016, the implementation date of Amendment 10.

Table 3.1 summarizes the distribution of trading pauses in the [-20, +20] trading days window around the implementation of Amendment 10, from different aspects. Day 1 is on July 18, 2016, and Day 0 can be considered as the hours after market close on the previous trading day and before market opening time on July 18, 2016. To understand Table 3.1 Panel (A), it is necessary to first understand the filters for selecting eligible trading pauses in this paper, as described in Section 3.3.2.

Table 3.1 Panel (A) displays the count of trading pauses and the count of stocks with trading pauses, after applying each filter cumulatively. The final eligible sample in the $[-20, +20]$ trading days window after applying the 5 filters contains 566 trading pauses in the pre-A10 era and 105 trading pauses in the post-A10 era. Consequently, there are 240 unique stocks involved in the above trading pauses in the pre-A10 era and 60 unique stocks involved in the post-A10 era. Those trading pauses and stocks involved are the ones used in Panel (C) and Panel (D), and throughout the remaining sections in this paper.

Table 3.1 Panel (B) displays the hourly distribution of TP events and TP stocks in the 20 trading days pre-A10 and 20 trading days post-A10 respectively. To account for the filters of 5 minutes after market open and 20 minutes before market close as described above, the first row represents the 9:35-10:00 a.m. interval instead of an hour, and similarly, the last row is for the 3:00-3:40 p.m. interval. The rest of the rows are for each hour from 10:00 a.m. to 3:00 p.m., sequentially. The distribution of trading pauses is highly similar to the top-left plot in Figure 3.2, indicating that the 9:35-10:00 a.m. interval has the most masses and there is a significant drop starting from 10:00 a.m. and gradually decaying throughout the day with minor fluctuations. This pattern applies to both trading pauses in the pre-A10 era and in the post-A10 era, but the post-A10 trading pauses in each interval are much less than their counterparts in the pre-A10 era, especially in the 9:35-10:00 a.m. interval and early hours. This further reinstates the effect of Amendment 10 in reducing the frequency of occurrence of trading pauses that are related to the problematic opening reference price in the pre-A10 era.

Table 3.1 Panel (C) summarizes how many minutes exist before and after fully filtered trading pauses during market hours in the $[-20, +20]$ trading days window around the implementation of Amendment 10. It reflects the happening time of those trading pauses during market hours from a specific angle. In the sample of pre-A10 trading pauses, there are 29.90 of the 1-minute bins before trading pauses on average, and 59.72 of those after trading resumptions. The pre-TP standard deviation of the count of the 1-minute bins is 19.51, while the post-TP standard deviation is 2.90. The means and standard deviations tell that most trading pause events have the complete 60-minute span after trading resumptions, both in the pre-A10 era and post-A10 era. However, they also indicate that most of the trading pause events do not have a complete 60-minute span before trading pauses, and the span varies between different TP events. In the pre-A10 20 trading days, there is on average a nearly 30-minute pre-TP span, but the median is only 16 minutes while the 75th percentile is 59 minutes. That indicates that the majority of pre-TP 1-minute bins span less than 30 minutes in the pre-A10 era and probably concentrated at the 15 to 16-minute range. It further implies that many of the trading pauses occur in the 9:45-9:46 a.m. range, right after the LULD price band shrinks to half of level in the opening 15 minutes.[34] In the post-A10 era, the mean of pre-TP 1-minute bins span is 38.92, which is about 9 minutes longer than in the pre-A10 era. And now the median is 50 of the 1-minute bins with the 75th percentile being 60, while the 25th percentile is now 16. Those indicate that most of the trading pauses in the post-A10 era have a longer pre-TP bins span, and that those trading pauses happen later than their counterparts in the pre-A10 era. The minimum, maximum, and other percentiles validate the above inferences. Panel (C) results further support the effect of Amendment 10 on reducing trading pauses that are linked to a problematic opening reference price, especially those that would occur in the first few quarters.

Table 3.1 Panel (D) describes the actual coverage of the event window of minutes around each trading pause in the pre-A10 and post-A10 eras, respectively. It also depicts the happening time of trading pauses indirectly from a different aspect than that in Panel (C) above. The statistics are produced in this way. First, for each of the 120 time bins in the $[-60, +60]$ minutes window, count how many trading pause events actually cover that 1-minute bin in their 120-minute event windows.[35] There will be 120 counts of trading pauses, 60 in the pre-TP window, and 60 in the post-TP window. Next, compute the time-series summary statistics across the 60 bins in the pre-TP window and across the 60 bins in the post-TP window, respectively. And, the previous two steps are applied to the fully filtered trading pauses in the 20 trading days pre-A10 and in the 20 trading days post-A10, respectively. The above steps result in the 4 rows in this panel. In the pre-A10 era, before trading pauses, there are 282.02 trading pauses involved in a 1-minute bin on average across the 60 bins and the standard deviation is 165.09. The minimum is 141 trading pauses involved in a 1-minute bin, and the maximum is 566 trading pauses

[34] As stated in the captions of Figure 3.1 Panel (C), the timestamps on trading pause and resumption are rarely at 9:35:00 am and 3:40:00 pm sharp. Therefore, the marginal time gap residuals are treated as extra 1-minutes bins when market opens and closes. Hereby, the minimum pre-TP and post-TP bins span are 6 of the 1-minute bins and 21 of the 1-minute bins instead of 5 and 20. And the 16 of 1-minute bins as seen in the 25th and 50th percentiles may actually mean a span of 15 to 16 minutes. And so on and so forth.

[35] Please also refer to the caption in 3.1 Panel (D) for a better understanding.

involved in a bin, which are all the fully filtered trading pauses in the 20 trading days before A10. In the 60 minutes after trading pauses, there are on average 563.37 trading pauses involved in a 1-minute bin with the standard deviation of 2.35. The minimum is 560 trading pauses windows which are involved in a bin and the maximum is 566. That indicates that not all the 120 bins are covered in each of the trading pauses events, especially the earlier bins before trading pauses. However, almost all the 60 bins post-TP are covered in all the trading pauses event windows. In the post-A10 era, there are 105 fully filtered trading pauses, and on average there are 102.77 trading pause windows which cover a bin in the 60 minutes after trading pauses. That is similar to the case in the pre-A10 era, meaning that almost all trading pause event windows cover all the 60 bins after trading resumes. For the 60 bins before trading pauses in the post-A10 era, on average a bin is covered in 68.12 TP event windows, and the standard deviation is 20.84. The bin with the least coverage of the TP event window is covered by 45 TP event windows, while the maximum bin is covered by all 105 TP event windows.

3.3.5 Liquidity Measure and Descriptive Analysis

The main liquidity measure in this study is the percentage quoted spread, which is calculated following the methodology in Holden and Jacobsen (2014).

The $QSpread_\tau$ for each time bin τ (as described in Section 3.3.3) is computed on the basis of all the National Best Bid (NBB) and National Best Ask (NBO) in force in that time bin τ. A stock-date-time tuple (s, d, t) uniquely identifies a trading pause. The letter s stands for stock, d for date, and t for the time of day when a trading pause occurs. The measure is defined for each time bin τ around each trading pause (s, d, t). The stock-date-time tuple (s, d, t) is omitted from the subscripts that follow the formulas for parsimony. For each quote n which has any length of in-force time within bin τ, denote the National

Best Bid as Bid_n, and National Best Ask as Ask_n.[36] Suppose there are N_τ quotes which are ever in force in time bin τ, and the in-force time intervals for each of those quotes are denoted as l_n.

$$MidQuote_n = \frac{(Ask_n + Bid_n)}{2} \tag{3.1}$$

Then, for the time bin τ, the dollar quoted spread and percentage quoted spread are:

$$QSpread_\tau = \frac{\sum_{n}^{N_\tau} (Ask_n - Bid_n)\, l_n}{\sum_{n}^{N_\tau} l_n} \tag{3.2}$$

$$QSpread\,(\%)_\tau = \frac{\sum_{n}^{N_\tau} \left[(Ask_n - Bid_n)\,/MidQuote_n\right] l_n}{\sum_{n}^{N_\tau} l_n} \tag{3.3}$$

Table 3.2 presents the time-series average of the cross-sectional summary statistics for the spread quoted (%). It is based on the [-60, +60] 1-minute bin window around trading pauses. First, the percentage quoted spread is computed for each available bin around each trading pause. Next, the summary statistics are calculated at all the bin levels for qualified trading pauses cross-sectionally.[37] Then, the time-series average is taken across each bin in the pre-TP [-60, -1] interval or the post-TP [+1, +60] interval over the previously acquired bin-level summary statistics. For the time-series average, the data are grouped into four intervals along the pre- and post-A10 dimension and along the pre-

[36]This includes any quote which has a portion of in-force time outside bin t and the other portion of in-force time within bin t. For this type of quote, only the in-force time within the bin t is counted. There can be two scenarios: (1) a quote which becomes in force before the time bin t and is still in force after entering the bin t for a certain period of time; (2) a quote which becomes in force within the time bin t and lasts beyond it.

[37]See Section 3.3 for the filtering process for qualified trading pauses.

and post-TP dimension: (1) pre-A10 and pre-TP, (2) pre-A10 and post-TP, (3) post-A10 and pre-TP, and (4) post-A10 and post-TP. Those correspond to the four rows in Table 3.2.

In the pre-A10 era, the time-series average of pre-TP mean of the bin-level percentage quoted spread is 7.09 which is much larger than 1.65 in the post-TP interval. So is the time-series average of pre-TP median, 1.51, compared to the post-TP median of 0.65. The mean and median indicate that the percentage quoted spread is on average smaller after trading resumes than before trading pauses in the pre-A10 era. That is a preliminary signal of liquidity improvement after trading resumes compared to the level before trading pauses. The time-series average of cross-sectional standard deviation, 13.86, is also much larger in the pre-TP interval than 3.94 in the post-TP interval. It points out that the pre-TP liquidity measured by percentage quoted spread is on average quite volatile across different trading pauses, whereas the post-TP quoted spread is on average much more stabler across trading pauses.

In the post-A10 era, the time-series average of the pre-TP mean is 3.57, which is smaller than its counterpart, 7.09, in the pre-A10 era, but it is larger than the time-series average of the post-TP mean, 1.70, in the post-A10 era. The time-series average of the post-TP mean is similar in the pre-A10 era and the post-A10 era, while the latter is larger by 0.05. The time-series average of the pre-TP median is 1.02 in the post-A10 era, and the post-TP median is 0.70, which is smaller. Compared to their pre-A10 era counterparts, the pre-TP median is smaller by 0.49 while the post-TP median is slightly larger by 0.05. The time-series average of the pre-TP standard deviation, 6.19, is larger than the post-TP standard deviation 3.11. It is also smaller than its counterpart, 13.86, in the pre-A10 era. The time-series average of the post-TP standard deviation in the post-A10 era is 0.83 smaller than its counterpart in the pre-A10 era.

Figure 3.3 Panel (a) compares the cross-sectional mean and median of the percentage quoted spread before and after trading pauses in the pre-A10 and post-A10 periods. It can support the summary statistics in Table 3.2. The post-A10 evolution of the cross-sectional mean in the [-60, +60] 1-minute intervals is stabler than that in the pre-A10 evolution. For the cross-sectional mean at the bin level after A10, there are more fluctuations in the 60-minute pre-TP interval than in the post-TP interval. The triangle-shaped scatter plot of the bin-level percentage quoted spread and its 5-minute moving average (both in grey color) in the left plot of Figure 3.3 Panel (a) also indicates that the pre-TP quoted spread is about 5%-6% higher than the post-TP level, especially in the [-60, -15] minutes window before trading pauses. The evolution of the post-TP percentage quoted spread is less fluctuated from bin to bin while it varies much more dramatically in the [-60, -15] minutes window before trading pauses and quickly decreases thereafter. The pre-A10 cross-sectional mean of the percentage quoted spread is at a higher level at the [-60, -15] minutes interval before trading pauses and is more volatile compared to its post-A10 counterpart. It goes down around 15 minutes before trading pauses and converges to the post-A10 cross-sectional mean evolution. The post-A10 liquidity improvement after trading pauses are not as large as that in the pre-A10 era, because the post-TP liquidity level is much similar to the pre-TP liquidity level in the post-A10 era. However, the improvement in post-TP liquidity in the pre-A10 era is more dramatic, especially compared to the level in the [-60, -15] minutes interval before trading pauses.

There is a spike in the quoted spread in the minute right before the trading pauses in both the mean plot and the median plot, as shown in Figure 3.3 Panel (a). The median plot is less volatile compared to the mean plot, while there is a little hill at the [-30, -15] window before the trading pauses in the pre-A10 era. The post-A10 median plot of percentage quoted spread is almost similar to a flat line except that it slightly goes up right around trading pauses.

Figure 3.3 Panel (b) shows the evolution of the cross-sectional mean and median of the quoted spread in dollar terms. The post-A10 evolution patterns of the post-A10 mean and median are similar to that in the percentage term as in Panel (a), while the post-A10 mean and median evolution patterns have more larger spikes right before trading pauses.

3.3.6 Short-Term Volatility Measure and Descriptive Analysis

The short-term liquidity measure is the *HighLow*, following the spirit of Hasbrouck and Saar (2013), which is computed as the difference of the highest ever in-force mid-quote in the bin τ minus the lowest ever in-force mid-quote in the same bin τ, divided by the mid-point of the highest and the lowest, times 10000. As before, the measure is defined for each time bin τ around each trading pause (s, d, t). The stock-date-time tuple (s, d, t) is omitted from the subscripts that follow the formulas for parsimony. Follow the notations of n and N_τ and the definition of $MidQuote_n$ as in Section 3.3.5, I define *HighLow* in bin τ as below.

$$HighLow_\tau = \frac{\max\limits_{n \in N_\tau}\{MidQuote_n\} - \min\limits_{n \in N_\tau}\{MidQuote_n\}}{\left(\max\limits_{n \in N_\tau}\{MidQuote_n\} + \min\limits_{n \in N_\tau}\{MidQuote_n\}\right)/2} \times 10000 \tag{3.4}$$

Figure 3.4 shows the cross-sectional mean and median of *HighLow* around trading pauses in the pre- and post-Amendment 10 periods, respectively. The plot on the left depicts the evolutions of the minute-by-minute cross-sectional mean in the pre-A10 and post-A10 eras. In the [-60, -10] 1-minute interval before trading pauses, the pre-A10 *HighLow* is mostly higher than the post-A10 *HighLow*. Starting from about 10 minutes before trading pauses, they cross paths, and the post-A10 *HighLow* becomes higher than the pre-A10 *HighLow* mostly. The post-TP cross-sectional mean of *HighLow* is higher in the post-A10 era. The spike during the [-5, +5] 1-minute window around trading pauses in the post-A10 era is also much greater than that in the pre-A10 era. The patterns depicted above indicate that the mean of short-term volatility measured by *HighLow* is higher in the pre-A10 era before about 10 minutes until trading pauses and then it is higher in the post-A10 afterward. The short-term volatility also significantly shoots up during the [-5, +5] 1-minute window around trading pauses in the post-A10 era, then decreases afterward, but stays higher above the level in the pre-A10 era after trading pauses.

Table 3.3 displays the time-series average of the summary statistics for *HighLow* in the minute-level bins before and after trading pauses in the pre-A10 and post-A10 eras. In the pre-A10 era, the time-series average of the minute-level cross-sectional means before trading pauses is 26.47, which is smaller than its counterpart, 18.24, in the interval after trading pauses. The pre-TP median is 4.24 in the pre-A10 era, which is higher than the post-TP median of 2.56. The above statistics suggest that short-term volatility, measured by *HighLow*, decreases after the trading pauses in the pre-A10 era. In other words, the trading pauses in the pre-A10 era seem to have an effect of cooling down short-term volatility on average, after trading resumes, compared to the 1-hour interval before trading pauses. In addition, the time-series average of standard deviation reduces from 51.50 in the pre-TP interval to 33.19 in the post-TP interval. In the post-A10 era, the time-series average of cross-sectional means increases from 21.47 in the pre-TP interval to 30.89 in the post-TP interval; the median increases from 3.51 pre-TP to 14.12 post-TP. Those suggest that, on the contrary, in the post-A10 era, short-term volatility increases after trading pauses. In other words, in the post-A10 era, trading pauses seem to magnify short-term volatility instead of cooling it off. The post-A10 time-series average of standard deviation before and after trading pauses are very similar. The pre-TP standard deviation is 42.17 while the post-TP standard deviation is 42.02.

3.3.7 High-Frequency Quoting Measure and Descriptive Analysis

The key proxy for high-frequency activity in this paper is the measure of high-frequency quote updates $HFQU$ based on Conrad, Wahal, and Xiang (2015). Taking the 1-minute bin as an example, for each 1-minute bin of the [-60, +60] minutes window around a trading pause of a ticker, any changes in the quote price or size of the best bid or best offer are counted on each exchange and aggregated across all exchanges.

There are several merits of using $HFQU$ as a measure of high-frequency activity in this study. First, $HFQU$ is a quote-based proxy for high-frequency activity. The triggering mechanism of LULD trading pauses also depends on quote prices. Therefore, using $HFQU$ as the high-frequency activity proxy can better capture the potential correlation between high-frequency quoting activity and extreme quote price movements, which can trigger trading pauses. Secondly, the $HFQU$ measure can be calculated from the Daily TAQ data, which is the same data source for the main liquidity and volatility measures used in this study. This way, consistency is maintained throughout these different measures and there is no need to concern about the matching rate or data loss when merging different data sources together. Last but not least, $HFQU$ is a relatively straightforward measure to compute and understand, while it can effectively capture high-frequency quotation activity as shown in Conrad, Wahal, and Xiang (2015).

Similar to the liquidity measure and the short-term volatility measure defined in the previous sections, the $HFQU$ measure is also defined for each time bin τ around each trading pause (s, d, t). The stock-date-time tuple (s, d, t) is omitted from the subscripts that follow the formulas for parsimony. Denote each exchange by e and the set of all exchanges as E. Suppose that there are $M_{e,\tau}$ quotes on the exchange e at time bin τ, and each quote q_m is a tuple containing 4 elements, i.e. $q_m = (bid_m, bidsize_m, ask_m, asksize_m)$, where $m, m+1 \leq M_{e,\tau}$. And it is nature to have $q_m \neq q_{m+1}$ if any of the 4 elements is different in this two quotes. For the m^{th} quote on exchange e in time bin τ, note that bid_m is the best bid price; $bidsize_m$ is the best bid size; $ask_m$is the best ask price; $asksize_m$ is the best ask size. As indicated in Conrad, Wahal, and Xiang (2015), they need not to be the national best bid or national best ask.

$$HFQU_{e,\tau} = \sum_{m}^{M_{e,\tau}} \mathbb{1}\{q_m \neq q_{m+1}\} \tag{3.5}$$

$$HFQU_{\tau} = \sum_{e}^{E} HFQU_{e,\tau} \tag{3.6}$$

Figure 3.5 presents the cross-sectional mean and median for each of the 1-minute bins in the [-60, +60] minutes interval around trading pauses, before and after the implementation of Amendment 10.

In the pre-A10 era, the cross-sectional mean of $HFQU$ stays around 10 to 30 during the [-60, -15] minutes window before trading pauses. Then, it goes up from around 15 minutes before trading pauses and climbs to the level around 50 until a spike of approximately 100 occurs 1 minute before trading pauses and follows by another spike around 80 in the minute right after trading resumes. Afterward, it quickly drops to the level close to 50 and goes slightly down to about 40 during the [+1, +60] minutes interval after the trading resumes.

In the post-A10 era, the cross-sectional mean of $HFQU$ is higher than its counterpart in the pre-A10 era, oscillates from about 90 to 25, and stays mostly around 50 during the [-60, -15] minutes window before trading pauses. That suggests that high-frequency quotation activity is higher in the post-A10 era during the [-60, -15] minutes window before trading pauses. Strikingly, the post-A10 cross-sectional mean of $HFQU$ increases about 10 minutes before trading pauses and reaches above 250 in the minute right before trading pauses. It even reaches the 350 level in the minute after trading resumes and quickly declines to about 160 about 5 minutes after trading resumes and then oscillates around 110 till 20 minutes after trading resumes. Afterward, it drops to about 80 and gradually goes town towards 50.

Comparing the evolution of the post-A10 mean and that of the pre-A10 mean of $HFQU$, it is obvious that the mean high-frequency quoting activity is almost consistently higher in the post-A10 era throughout the [-60, +60] 1-minute window before and after trading pauses, except for the short interval of [-15, -10] minutes approximately before trading pauses, where they cross paths and stay close around the level of 50.

As for the median, both the pre-A10 and post-A10 medians stay around 0 until after 20 minutes before trading pauses when they climb up to above 5 and then the post-A10 median shoots up and reaches about 45 in the minute right before trading pauses while the pre-A10 median is at about 35. The post-TP median in the pre-A10 era quickly drops from about 25 in the minute right after trading resume to 5 in a minute later and oscillates around 5 to 10 in the remaining 59 minutes after trading resumes. The median in the post-A10 era is close to 60 in the minute right after trading resumes, and it quickly goes down and oscillates around 35 to 15 during until 10 minutes after trading resumes. It then fluctuates and keeps decreasing to a level between 10 and 5 towards 60 minutes after trading resumes. From the median plot, it is clear that the post-TP median is much higher than the pre-TP median from about 5 minutes before trading pauses to 60 minutes after trading resumes.

It is also obvious that, according to both the mean plot and the median plot, there are huge spikes of high-frequency quoting updates from about 5 minutes before trading pauses and 10 minutes after trading resumes in the post-A10 era. There is only a milder spike 1 minute before trading pauses and 1 minute after trading resumes in the pre-A10 era. In other words, after Amendment 10 implementation, high-frequency quoting update activity dramatically increases right before trading pauses and goes even higher in the minute right after trading resumes then it decays but still remains at a higher level than the pre-TP high-frequency quoting update intensity, and also much higher than its counterparts in the pre-10 era after trading resumes.

Table 3.4 shows the time-series average of the cross-sectional summary statistics of $HFQU$ before and after trading pauses in the pre-A10 and post-A10 eras. In the pre-A10 era, the time-series average of the pre-TP cross-sectional mean is 27.70, which is smaller than its counterpart 39.71 in the post-TP interval. The times-series average of the median also shows an increase from the pre-TP level of 1.85 to 6.73 in the post-TP interval. In the pre-TP interval, the time-series average of standard deviation is 119.73, which slightly increases to 122.27 in the post-TP interval. Those are consistent with what is shown in Figure 3.5. In the post-A10 era, both the pre-TP mean and the post-TP mean are higher than their counterparts in the pre-A10 era. The pre-TP mean is now 60.02 and the post-TP mean is 83.85. Similarly, the pre-TP median is now 2.81 and the post-TP median is 13.10. In other words, both the post-TP mean and median are higher than their pre-TP counterparts in the post-A10 era. In addition, the mean and median in the post-A10 era are higher than those in the pre-A10 era both in the pre-TP interval and in the post-TP interval. The time-series average of the standard deviation in the post-TP interval is 223.51 in the post-A10 era, higher than 155.50 in the pre-TP interval. Overall, these support the observation that the $HFQU$ evolution post A10 is higher than that in the pre-A10 era both before trading pauses and after trading pauses. The $HFQU$ is also more volatile in the post-A10 era around trading pauses, especially after trading resumes.

3.4 Market Quality around Trading Pauses pre and post the Amendment 10

3.4.1 Liquidity around Trading Pauses

This section empirically examines the evolution of liquidity before and after trading pauses in the pre-A10 era and in the post-A10 era. It also compares the difference between the post-A10 and post-A10 liquidity evolution patterns around trading pauses. Whether Amendment 10 induces liquidity improvement in the 2-hour window around trading pauses compared to those in the pre-A10 era is another intriguing question.

The methodology in this section is inspired by Hautsch and Horvath (2019) but is re-designed for the purpose of this research.

The single difference regression is estimated by Eq. (3.9) for trading pauses in the pre-Amendment 10 and post-Amendment 10 periods, respectively. Potential first-order autocorrelations in residuals are corrected using the Prais and Winsten (1954) method. Standard errors are clustered into four consecutive but distinct 30-minute groups per trading pause throughout the $[-60, +60]$ minutes window. This way, the heteroskedastic-consistent variance-covariance matrix is assumed to have no correlation across trading pauses but intra-group correlation is allowed within each of the four half-hour groups per trading pause.

$$y_{(s,d,t),\tau} = \alpha_{(s,d,t)} + \sum_{\tau} \left(\beta_\tau + \beta_\tau^{\mathrm{TP}}\right) D_\tau + \epsilon_{(s,d,t),\tau} \tag{3.7}$$

$$y_{(s,d,t),-1} = \alpha_{(s,d,t)} + \epsilon_{(s,d,t),-1} \tag{3.8}$$

Taking the difference between Eq. (3.7) and Eq. (3.8) yields the single difference regression,

$$y^*_{(s,d,t),\tau} = \sum_{\tau} \left(\beta_\tau + \beta^{\text{TP}}_\tau\right) D_\tau + \epsilon^*_{(s,d,t),\tau} \tag{3.9}$$

where $y^*_{(s,d,t),\tau} \equiv y_{(s,d,t),\tau} - y_{(s,d,t),-1}$ and $\epsilon^*_{(s,d,t),\tau} \equiv \epsilon_{(s,d,t),\tau} - \epsilon_{(s,d,t),-1}$. The subscripts s stands for stock, d for date, and t for the time of day when a trading pause occurs. The definitions of the subscripts (s,d,t) and τ have been introduced in Section 3.3.3 before. A stock-date-time tuple (s,d,t) uniquely identifies a trading pause. For each trading pause, the outcome of interest is measured at each time bin τ, where $\tau = -60, -59, \ldots, -2, -1, 1, 2, \ldots, 59, 60$ are for each 1-minute bin in the $[-60, +60]$ minutes window around trading pauses.[38] Bin "$\tau = 0$" would represent the time when a trading pause is in progress and it is not included in the study. The base bin is the minute one hour before trading pauses happen, i.e. $\tau = -60$. Therefore $y^*_{(s,d,t),\tau}$ captures the relative difference of the outcome variable at bin τ from that at the base bin. The dummy variable D_τ takes value 1 if it is bin τ and 0 otherwise. The sum of coefficients $\left(\beta_\tau + \beta^{\text{TP}}_\tau\right)$ captures a combined effect of high-frequency trends around trading pauses and the impact of trading pauses on the outcome measures at each bin τ, where $\left(\beta_{-60} + \beta^{\text{TP}}_{-60}\right) \equiv 0$ by default for the base bin at $\tau = -60$. Regression results for trading pauses in the pre-A10 and post-A10 eras are estimated separately by Eq. (3.9), corresponding to $\left(\beta_\tau + \beta^{\text{TP}}_\tau\right)_{\text{Pre-A10}}$ and $\left(\beta_\tau + \beta^{\text{TP}}_\tau\right)_{\text{Post-A10}}$ respectively. For the case of the liquidity outcome *QSpread* (%) as the dependent variable, the estimated coefficients are graphically presented in the top and middle panels of Figure 3.6 with different colors for significance levels.

The difference-in-differences regression below extends the single-difference setup from above to illustrate the effect of Amendment 10 on trading pauses.

$$y^*_{(s,d,t),\tau} = \sum_{\tau} \left(\beta_\tau + \beta^{\text{TP}}_\tau\right) D_\tau + \beta_{\text{A10}} \mathbb{1}\{\text{Post A10}\} + \beta^{\text{TP}}_{\text{A10},\tau} \mathbb{1}\{\text{Post A10}\} D_\tau + \epsilon^*_{(s,d,t),\tau} \tag{3.10}$$

[38] See Footnote 32.

When $\mathbb{1}\{\text{Post A10}\} = 0$, Eq. (3.10) resembles Eq. (3.9) but it is for trading pauses before Amendment 10 only; when $\mathbb{1}\{\text{Post A10}\} = 1$, the coefficient β_{A10} indicates the shift in common trends after Amendment 10, while the coefficient $\beta^{\text{TP}}_{\text{A10},\tau}$ captures the effect of Amendment 10 on trading pauses at each bin around. For the liquidity outcome variable $QSpread\,(\%)$ as the dependent variable, the estimated $\beta^{\text{TP}}_{\text{A10},\tau}$ for each bin τ is plotted in the bottom panel of Figure 3.6 with color-differentiated significance levels.

The results of the single differences and difference-in-differences regressions of liquidity measures $QSpread\,(\%)$ are displayed in Figure 3.6. The single differences results in the pre-A10 era can be found in the top panel, while the post-A10 results are in the middle panel.

The top panel presents the single difference results for the pre-A10 period. The vertical bars correspond to the estimated $\left(\hat{\beta}_\tau + \hat{\beta}^{\text{TP}}_\tau\right)_{\text{Pre-A10}}$ as in Eq. (3.9). The base bin is at 60 minutes before trading pauses. The height of the bar represents the magnitude of the estimated coefficients, while the color corresponds to the significance level. Dark blue means significant at the 1% level, medium blue for 5%, light blue for 10%, and white for insignificance (i.e. p-value > 10%). The significance cut-off point is 5% by convention. This top panel shows that there starts to be significant (i.e. at least at the 5% significance level) liquidity improvement from 14 minutes before trading pauses until about 2 minutes before trading pauses, for more than 5 percentage points of decrease in quoted spread from the base bin level. The percentage quoted spread is not significantly different from the base bin level before the interval of $[-14, -2]$ minutes, except that the quoted spread at $\tau = -59$ is slightly higher than the base bin level for about 1 percentage point. The improvement is more so in both magnitude and significance level after trading resumes. After trading resumes, the percentage quoted spread is more than 10 percentage points less than the base bin level 60 minutes before trading pauses, and slowly decreasing toward 12 percentage points less than the base bin level when it is 60 minutes after trading pauses.

The middle panel shows the single difference results from the base bin after the A10 period, measuring how different the percentage quoted spread is at each bin from the base bin level. They are the estimated coefficients $\left(\hat{\beta}_\tau + \hat{\beta}_\tau^{\mathrm{TP}}\right)_{\text{Post-A10}}$ as in Eq. (3.9). At bin $\tau = -59, -58, -57, \text{and} - 56$, the quoted spread increases slightly from the level of the base bin. Afterwards, the bin-level quoted spread is not significantly different from the base level until about 23 minutes after trading resumes. From 23 minutes after trading resumes, the percentage quoted spread is about 3 percentage points less than the base bin level, and going toward 5 percentage points less than the base bin level. The different is significant at at least the 5% level, which indicates a significant improvement in liquidity from 23 minutes after trading pauses and afterward. However, compared to the pre-A10 case, the liquidity improvement starts much later and the magnitude is less dramatic.

The estimated difference-in-differences results, $\hat{\beta}^{TP}_{A10,\tau}$, displayed in the bottom panel show that compared to their base bin levels of percentage quoted spread, respectively, the liquidity improvement after trading resumes in the pre-A10 era is more significant and dramatic than that in the post-A10 era. Note that the pre-A10 and post-A10 eras may not have the same base bin quoted spread levels as indicated in the summary statistics mean and median plots in Section 3.3.5. Since trading resumes, the estimated coefficients are all significant at the level 1% and slightly decrease from about 8 to 6 percentage points throughout the [+1, +60] minute bins. This is because the post-A10 liquidity improvement compared to the base bin liquidity level is much lower than that in the pre-A10 era. Therefore, compared to the pre-A10 liquidity improvement, the post-A10 liquidity appears to be "deteriorating" after trading resumes in the bottom panel, as the difference in the percentage quoted spread from the base-bin spread. However, the middle panel can show that this is actually not the case.

This striking difference in the bottom panel could be caused by two different reasons.

First, the liquidity levels of the base bin in the pre-A10 and post-A10 eras may not be the same. From the left plot in Figure 3.3 Panel (a), it can be seen that the mean percentage quoted spread of the base bin is approximately 5 percentage points lower in the post-A10 era than that in the pre-A10 era. The mean plot in Figure 3.3 Panel (a) also shows that the mean percentage quoted spreads after trading resumes in the pre-A10 era and in the post-A10 era are actually highly overlapped. Secondly, in the post-A10 era, the liquidity level at the bins in [-59, +60] minute interval is less different from the liquidity level at the base bin $\tau = -60$ minutes before trading pauses. However, in the pre-A10 era, there is a dramatic decrease, about 6 percentage points, of quoted spread (i.e., improvement of liquidity) from approximately 15 minutes before trading pauses. Therefore, the bottom panel does not suggest that LULD trading pauses hurt liquidity more after the trading resumes in the post-A10 era compared to those in the pre-A10 era.

3.4.2 Short-Term Volatility around Trading Pauses

To study the impact of trading pauses on short-term volatility around trading pauses in the pre- and post-Amendment 10 eras, the same methodology as in Section 3.4.1 is applied. The dependent variable is now the short-term volatility measures *HighLow*. Figure 3.7 shows the estimated results.

The top panel presents the estimated coefficients $\left(\hat{\beta}_\tau + \hat{\beta}_\tau^{\mathrm{TP}}\right)_{\text{Pre-A10}}$ as in Eq. (3.9) for *HighLow* in the pre-A10 era. It captures on average how different the short-term volatility is from the base bin level at $\tau = -60$ minutes before trading pauses. In the pre-A10 area, the short-term volatility *HighLow* only increases significantly from the base bin level in 1-minute bins just before and after trading pauses. It is close to 40 basis points above the base bin level in the minute before trading pauses and about 35 basis point about the base bin level in the minute right after trading resumes.

The post-A10 results of the estiamted $\left(\hat{\beta}_{\tau} + \hat{\beta}^{\mathrm{TP}}_{\tau}\right)_{\text{Post-A10}}$ are shown in the middle panel. There are more bins showing significantly increased short-term volatility around trading pauses, especially after trading resumes, compared to the significant pre-A10 coefficients. There are 5 significant minute-level bins before trading pauses and 23 bins after trading resumes. The *HighLow* is about 10 basis points lower than the base level at the $\tau = -39$ minute bin. Close to trading pauses, *HighLow* is ranging from about 30 to 90 basis points higher than the base bin level at the $\tau = -5, -3, -2$ and -1 minute bins. That indicates that the short-term volatility increase dramatically since it is 5 minutes before trading pauses in the pre-A10 era. In the 5 minutes after trading resumes, the short-term volatility is even higher. At the 1 minute bin right after trading resumes, *HighLow* is about 130 basis points higher than the level of the base bin. Then it drops to about 40 basis points higher than the base bin level at the $\tau = 2$ minute bin and goes down to about 30 basis points higher than the base level at the $\tau = 5$ minute bin. After 5 minutes from trading resumes, the short-term volatility oscillates around the level of 20 basis points higher than the base level to about 15 basis points higher than the base level until the $\tau = 24$ minute bin. Only the $\tau = 8$ minutes and $\tau = 11$ minutes bins are not significant. The $\tau = 27$ minutes bin is also significantly higher than the base bin, about 18 basis points. In general, in the post-A10 era, short-term volatility *HighLow* rises much higher and dramatically both within a few minutes before trading pauses and after trading resumes. Especially, the positive difference from the base bin level is more profound and longer lasting after trading resumes in the post-A10 era.

The bottom panel displays the estimated difference-in-difference coefficients $\hat{\beta}^{TP}_{A10,\tau}$. The single differences from their respective base bins are denoted as the excess differences. The bottom panel compares how the excess differences in the post-A10 era are different from those in the pre-A10 era. The post-A10 excess differences in the last 3 minutes are about 40 to 60 basis points higher than those in the pre-A10 era. In the first minute after trading resumes, the excess difference is about 100 basis points higher than its counterpart in the pre-A10 era. During the $\tau = 2, 3, 4$, and 5 minute level bins after trading resumes, the excess differences in the post-A10 era are about 50 to 30 basis points higher than their counterparts in the pre-A10 era. Afterwards, occasionally the differences in excess differences are significant at bin $\tau = 10, 13$ and 22 after trading resumes, ranging from 40 to 30 basis points.

The bottom panel shows that a few minutes before and after trading pauses, the post-A10 period short-term volatility increased significantly for about 40 to 100 basis points more in magnitude compared to the pre-A10 periods increase relative to their base bin levels, respectively. Note that the base-bin levels may be different on average in those two periods. According to the mean plot in Figure 3.4, the average base bin *HighLow* is about 30 basis points in the pre-A10 era, while that is about 10 in the post-A10 era, which is about 20 basis point lower. However, the mean plot also demonstrates the pattern that the post-A10 era *HighLow* in the [-10, +10] minute window is much higher than that of the pre-10 era, which is consistent with the results in Figure 3.7. These dramatic differences in excess differences of *HighLow* are both driven by a lower base level for the post-A10 era and a much higher spike around trading pauses in the post-A10 era.

Altogether, Figure 3.4 and Figure 3.7 results suggest that short-term volatility measured by *HighLow* shoot up significantly around trading pauses, especially after trading resumes, in the post-A10 era compared to the pre-A10 era. Cross-sectionally, on average, short-term volatility is lower during the [-60, -10] minute bins before trading pauses in the post-A10 era than in the pre-A10 era, while it is higher during the [-10, +60] minute bins. LULD Plan Amendment 10 might be correlated with an unexpected result in dramatically increasing short-term volatility, starting from a few minutes before trading pauses to a few minutes after trading resumes. Short-term volatility *HighLow* is also higher in the hour after trading resumes compared to that in the pre-A10 era.

3.5 High-Frequency Quoting and Its Role

This section studies the behavior of high-frequency trading and quoting activities before and after trading pauses in the pre-A10 and post-A10 eras. It is intriguing to know how high-frequency activities evolve as trading pauses approach and after trading resumes. Whether high-frequency activities around trading pauses have changed after the implementation of Amendment 10 is also worth investigating. And if so, the possible reasons behind the change are awaiting to be explored.

Another question to be examined in this section is whether high-frequency activities interact or correlate with market qualities around trading pauses. Is a higher high-frequency activity intensity correlated with a higher liquidity provision around trading pauses? Does high-frequency activity induce higher short-term volatility before and after trading pauses? Can high-frequency activity help explain or provide suggestive evidence on the changes of liquidity and volatility around trading pauses in the pre-A10 era and the post-A10 era?

There could also be implications for future regulatory policy making. When the SEC was making Amendment 10, LULD Plan Amendment 10, they did not aim at regulating high-frequency trading or quoting activity around trading pauses. It would be helpful to understand high-frequency trading behavior around trading pauses and anticipate their future behavior and impact on market quality around trading pauses. When updating new LULD Plan trading pause rules, the conditional effects of trading pauses with the presence of high-frequency trading before trading pauses and after trading resumes should be worth considering.

3.5.1 High-Frequency Quoting around Trading Pauses

Section 3.5.1 adopts the same methodology as in Section 3.4.1 to study the evolution of high-frequency quoting activity around trading pauses. The main regressions are the single-difference regressions for the pre-A10 period and post-A10 period, respectively, and difference-in-differences regression for comparing the high-frequency quotations around trading pauses after Amendment 10 implementation and before that. The estimated results are presented in the top, middle and bottom panels of Figure 3.8, respectively.

In the pre-A10 period, compared to the base bin level, the high-frequency quoting measure $HFQU$ starts to rise significantly from the $\tau = -12$ minute bin before trading pauses to the $\tau = -1$ minute bin. There are about 25 to 30 more high-frequency quote updates during the [-12, -2] minute window before trading pauses, compared to the base-bin level in the pre-A10 era. During the exact 1 minute bin right before trading pauses, the excess high-frequency quote updates compared to the base bin level is about 80. Immediately after trading resumes, in the $\tau = 1$ minute bin, the excess $HFQU$ compared to the level of the base bin is about 60 to 70, slightly lower than the level of the 1-minute bin right before trading pauses, but higher than those in the [-12, -2] minute window. Afterward, the excess $HFQU$ is significantly higher than the base-bin level in bins $\tau = 10$ and $\tau = 11$, for about 25 more high-frequency quote updates. The top panel shows that the excess increase of $HFQU$ from the base bin level is concentrated in the [-12, -1] minute window before trading pauses and the minute right after trading resumes, plus two 1-minute bins about 10 minutes later. It is unclear whether the excess $HFQU$ increases before trading pauses contributes to the happening of trading pauses or not. Alternatively, high-frequency traders can frequently update their quotes to provide liquidity and prevent unnecessary trading pauses from occurring. If it is an information-driven trading pause, there may be information involved in the arising $HFQU$ before trading pauses. After trading resumes, the high excess $HFQU$ at the $\tau = 1$ minute bin could represent that high-frequency traders (HFTs) digest information during trading pauses and quickly adjust their position immediately after trading resumes. The excess $HFQU$ at the $\tau = 10$ and $\tau = 11$ may reflect some further adjustments made by HFT.

In the post-A10 period, only the $\tau = -1$ minute bin right before trading pauses and the $\tau = 1$ minute bin right after trading resumes have significant and dramatic excess $HFQU$ compared to the base bin level. The excess $HFQU$ in the minute right before trading pauses is about 170, and it even increased to about 250 in the minute right after trading resumes. These two spikes are much more dramatic than the milder increases in excess $HFQU$ before trading pauses and after trading resumes in the pre-A10 era. And, the differences in magnitude are not induced by differences in the mean base level $HFQU$, as shown in Figure 3.5. The post-A10 base bin level of the mean $HFQU$ is even about 75 higher than that in the pre-A10 era, but the spikes of $HFQU$ are just too dramatic closely before and after trading pauses. This is fascinating as it may suggest that, in the post-A10 era, without those unnecessary trading pauses in the pre-A10 era, HFTs only need to dramatically update their quotes frequently in the minute right before and after trading pauses in a much more efficient manner. The dramatic $HFQU$ right before trading pauses and after trading resumes after more likely to be information-driven in the post-A10 era. It is not clear whether the spike in the minute before the trading pause can be viewed as "triggering" trading pauses or not. This awaits further study.

When comparing the differences after A10 and before A10 as shown in the bottom panel of Figure 3.8, only the 1-minute bins immediately after trading resumes are significantly different in the two eras. In the 1-minute bin after trading resumes, there are much more high-frequency quote updates in the post-A10 period than in the pre-A10 period, relative to their base-bin level at 60 minutes before trading pauses. The difference in excess $HFQU$ levels from their own base bin level is about 200, indicating that there are on average 200 more excess high-frequency quote updates from base bin level in the post-A10 era than in the pre-A10 era. Note that, as described above, the mean plot in Figure 3.5 shows that the mean of the pre-A10 base bin $HFQU$ is about 75 lower than that of the post-A10 era. However, this does not undermine the dramatic differences in excess $HFQU$ in the minute immediately after trading resumes in the post-A10 and pre-A10 eras. It suggests that the revised trading pause mechanism in the post-A10 era can better serve as a window for HFTs to digest information and adjust their positions. They update their quotes significantly more frequently at the minute right after trading resumes without those unnecessary trading pauses in pre-A10. This may suggest a better mechanism for information transmission in the post-A10 era, and now the trading pauses may serve their original purposes better.

3.5.2 High-Frequency Quoting and Liquidity

By comparing Figure 3.3 and Figure 3.5, the evolution patterns of the mean and median around trading pauses are different in percentage quoted spread and $HFQU$, either in the pre-A10 era or in the post-A10 era. It is intriguing and important to empirically inspect the relationship between high-frequency quoting activity and liquidity both before trading pauses and after trading resumptions. In particular, are high-frequency quoting updates positively correlated with liquidity improvement around trading pauses? Does Amendment 10 bring about any changes to the above relation? This section formally studies these questions in detail.

The following regression equation is used to study the correlation between market quality outcomes and high-frequency quoting for each of the 1-minute bin in the [-60, +60] minutes window around trading pauses.

$$y_{(s,d,t),\tau} = \alpha_\tau + \sum_\tau \beta_\tau D_\tau HFQU_{(s,d,t),\tau} + \epsilon_{(s,d,t),\tau} \tag{3.11}$$

The dependent variable y stands for outcome of interest. In this section, it represents the liquidity measured by *QSpread(%)*. The independent variable is the measure of high-frequency activity *HFQU*. Similar to the notations in Eq. (3.7), the subscripts s represent the stock, d the date, and t the time of day when a trading pause occurs. The definitions of the subscripts (s, d, t) and τ have been introduced in Section 3.3.3 before. A stock-date-time tuple (s, d, t) uniquely identifies a trading pause. For each trading pause, the outcome of interest is measured in each time bin τ, where $\tau = -60, -59, \ldots, -2, -1, 1, 2, \ldots, 59, 60$ are for each 1-minute bin in the $[-60, +60]$ minutes window around trading pauses.[39] Bin "$\tau = 0$" would represent the time when a trading pause in progress and it is not included in the study. The dummy variable D_τ takes value 1 if it is bin τ and 0 otherwise. The constant term at each time bin is denoted as α_τ. Standard errors are clustered into four consecutive but distinct 30-minute groups per trading pause throughout the $[-60, +60]$ minutes window, following Hautsch and Horvath (2019). The coefficient β_τ captures how much variation in the outcome variable is associated with changes in the dependent variable $HFQU$ for high-frequency quoting. For liquidity as the outcome variable, the estimated coefficients $\hat{\beta}_\tau$ are plotted in Figure 3.9, with magnitude along the vertical axis and color-coded significance levels. The magnitude of estimated coefficients is scaled up by a multiplier of 100 for better readability. The darker color means higher significance levels or lower p-values. The dark blue is for p-value < 1%, medium blue for p-value < 5%, light blue for p-value ≤ 10%, and transparent for p-value > 10%.

The top panel of Figure 3.9 presents the correlation regression results between the percentage quoted spread $QSpread(\%)$ and the high-frequency quote updates $HFQU$ for each bin during the $[-60, +60]$ minutes window around trading pauses in the pre-A10

[39] This is subject to change depending on the bin length. For example, if each bin lasts for 3 minutes instead, then $\tau = -20, -19, \ldots, -2, -1, 1, 2, \ldots, 19, 20$.

era. Note that only the medium-blue and dark-blue bins are significant at least at the 5% significance level. In the hour before trading pauses, there are 24 significant bins in which high-frequency quote updates are correlated with liquidity improvement. Those significant bins are concentrated in the $[-60, -50]$ minute window and in the $[-25, -1]$ window. The coefficients are negative, and the magnitude spans from 0 to less than 0.04, meaning that one more high-frequency quote update is associated with 0 to less than 0.04 percentage point decrease of quoted spread. This is an obvious drop of the magnitude of the coefficient around 15 minutes before trading pauses, and the liquidity improvement before that is more dramatic. The coefficient pattern in the $[-15, -1]$ minute window before trading pauses is already very similar to that after trading resumes. In the hour after trading resumes, there are 34 bins throughout the $[+1, +60]$ minutes window showing a significant negative correlation between percentage quoted spread and high-frequency quote updates, indicating liquidity improvement. The coefficients are all negative and the magnitude is consistently smaller than 0.01, meaning that one more high-frequency quote update in the 1-minute bin is associate with less than 0.01 percentage point quoted spread decrease. This suggests that even after trading resumes, $HFQU$ is positively correlated with liquidity improvement throughout the hour, with smaller magnitude but more significant 1-minute bins, compared to the hour before trading pauses.

The post-A10 era results are plotted in the bottom panel of Figure 3.9. In the hour before trading pauses, there are 43 bins with significant estimated coefficients, which are negative, and the magnitude ranges from 0 to 0.03. They are mostly evenly spread out during the 1-hour interval before trading pauses. The magnitude of coefficient is larger and more volatile during the $[-60, -10]$ minute interval, while the coefficients in the $[-10, -1]$minute bins mostly fluctuate between 0 and -0.01. The pattern before trading pauses show that, in the post-A10 era, high-frequency quote updates are positively correlated with liquidity improvement in most of the 1-minute bins in the hour before trading pauses, and one more high-frequency quote update is associated with 0 to 0.03 percentage point reduce of quoted spread. After trading resumes, there are 46 bins that are significant. They are all negative and the magnitude is mostly within the 0 to 0.005 range. It indicates that, in the hour after trading resumes, one more high-frequency quote update in a 1-minute bin is associated with a decrease of less than 0.005 percentage points in the quoted spread.

When comparing the post-A10 results with the pre-A10 results, there is a high similarity in the coefficient pattern after trading resumes in both eras. Most of the bins are significant, but the magnitude is small and relatively fluctuating in a stabler range compared to their pre-TP counterparts. That suggests a consistent, stable, but mild positive relation between the high-frequency quote update and liquidity improvements after trading resumes. In the post-A10 era after trading resumes, there are 12 more 1-minute bins that are significant compared to those in the pre-A10 era, indicating that there are more minutes in which $HFQU$ contributes significantly to liquidity improvement, although the overall magnitude in the pkost-A10 era is smaller.

The main difference between the post-A10 and pre-A10 results appears in the hour before trading pauses. There are 43 bins in the post-A10 era that are significant, 19 bins more than those in the pre-A10 era. However, significant bins in the post-A10 era before trading pauses span a smaller range of 0 to -0.03 instead of 0 to -0.04 as in the pre-A10 era. This suggests that there are more minutes during the hour before trading pauses in the post-A10 era that high-frequency quote updates are associated with liquidity improvement, although they may have a smaller magnitude compared to those significant liquidity improvements related to $HFQU$ in the pre-A10 era before trading pauses.

In general, there are more 1-minute bins both before trading pauses and after trading resumes in the post-A10 era such that high-frequency quoting is significantly correlated with liquidity improvement.[40] In some of the 1-minute bins before trading pauses in the pre-A10 era, the magnitude of liquidity improvement associated with high-frequency quote updates is greater than those in the post-A10 era. Figure 3.9 suggests that high-frequency quoting may have a net liquidity provision effect around trading pauses. This effect is more profound in the 2-hour window around trading pauses after the implementation of LULD Plan Amendment 10, and especially in the hour before trading pauses.

The implementation of LULD Plan Amendment 10 may have brought about an unexpected beneficial effect on liquidity improvement conditional on the high-frequency quoting activity in the 2-hour window around trading pauses and resumptions. Figure 3.5 indicates that the high-frequency quotation measure $HFQU$ has been elevated in the post-A10 area throughout the 2-hour window compared to that of the pre-A10 era. The regression plots in Figure 3.9 show that high-frequency quote updates in the post-A10 era are more likely to be significantly associated with improved liquidity in the 2-hour window, and the magnitude of the correlation is greater before trading pauses. However, a higher intensity of $HFQU$ may not be associated with a higher correlation between high-frequency quote updates and quoted spread reduction. The highest average intensity of $HFQU$ shows up around the $[-10, +10]$ minute window around trading pauses as in Figure 3.5, but the largest magnitude of the significant coefficients does not show up during that window in Figure 3.9.

3.5.3 High-Frequency Quoting and Short-Term Volatility

In addition to investigating the relationship between high-frequency quoting and liquidity around trading pauses in the pre-A10 and post-A10 eras, it is also worthwhile

[40]The significance level cutoff is 5%.

to examine the relation between high-frequency quoting and short-term volatility during the same window around trading pauses in those two eras. Both Figure 3.4 and Figure 3.5 appear to show a certain degree of comovement between the short-term volatility measure *HighLow* and high-frequency quote updates $HFQU$, especially in the post-A10 era. First, there is a huge spike closely before trading pauses and after trading resumes in short-term volatility *HighLow*. A similar spike also appears in high-frequency quote updates $HFQU$ in the same interval. The spikes around trading pauses exist in both the pre-A10 era and the post-A10 era, especially in the post-A10 era. Secondly, from about 1 minute before trading pauses to 1 hour after trading resumes, both $HFQU$ and *HighLow* are higher in the post-A10 era than in the pre-A10 era. Do all these indicate that high-frequency quote updates are highly positively correlated with short-term volatility around trading pauses, especially in the $[-10, +10]$ minutes window? Does the implementation of LULD Plan Amendment 10 stimulate high-frequency quoting activity around trading pauses, which in turn drive up the short-term volatility around trading pauses? This section formally investigates these concerns empirically.

Applying the same methodology as in Section 3.5.2, this section studies how short-term volatility in the 2-hour window around trading pauses is correlated to high-frequency quoting in the pre-A10 and post-A10 eras, respectively. The outcome of interest y in Eq. (3.11) is now the short-term volatility measure *HighLow*. The estimated coefficients $\hat{\beta}_\tau$ are shown in Figure 3.10. The magnitude of coefficients are scaled up by a multiplier of 100.

In the pre-A10 era, during the hour before trading pauses, there are only 8 bins with significant coefficients, which are the $\tau = -25, -19, -18, -17, -14, -11, -8$ and -7 minute-level bins. The magnitude of those 8 bins ranges from 0 to less than 0.003, which means that one more high-frequency quote update in a 1-minute bin correlates with an increase of less than 0.003 basis points of short-term volatility *HighLow*. This indicates that high-frequency quote updates are not a notable contributing factor to short-term volatility in the hour before trading pauses. In the hour after trading resumes, there are 20 significant bins, concentrated in the [+8, +26] minutes window and the [+35, +54] minutes window. The range of magnitude is even smaller, ranging from 0 to 0.0015, which means that in these 20 bins, one more high-frequency quote update in a 1-minute bin contributes to an increase of less than 0.0015 basis points in the short-term volatility measured by *HighLow*. After trading resumes, $HFQU$ is more likely to be positively correlated with short-term volatility than before trading pauses, although the magnitude of the correlation is smaller.

In the post-A10 era, there are only 7 bins with significant coefficients before trading pauses, which are the $\tau = -25, -24, -23, -22, -11, -3$ and -1 minute bins. The signs of the coefficients for those significant bins are all positive, and the magnitude ranges from 0 to less than 0.002. That means that one more high-frequency quote update is associated with a less than 0.002 basis point increase of *HighLow* in each of those 7 significant bins before trading pauses. After trading resumes, there are 6 bins with significant coefficients, which are the $\tau = +21, +23, +24, +31, +33$ and $+34$ minute bins. The coefficient signs are all positive and their magnitudes are all less than 0.001. That indicates that one more high-frequency quote update is associated with a less than 0.001 basis point increase of *HighLow* in those 6 significant bins after trading resumes.

Comparing the post-A10 result with the pre-A10 result, it is clear that the number of significant bins is smaller in the post-A10 era both before trading pauses and after trading resumes, especially in the hour after trading resumes. In addition, the magnitude of the coefficients is on average smaller in the post-A10 era. All of these suggest that the positive correlation between high-frequency quote updates $HFQU$ and short-term volatility *HighLow* around trading pauses and resumptions is less profound in the post-A10 era compared to that in the pre-A10 era. Especially after trading resumes, in the post-A10 era, high-frequency quote updates are much less likely to contribute to short-term volatility.

In summary, both in the pre-A10 and post-A10 eras, in the hour before trading pauses, there are only a few bins in which short-term volatility is significantly and positively correlated with high-frequency quoting. During the hour after trading resumes, 1/3 of the 60 bins show a significant and positive correlation between high-frequency quote updates and short-term volatility in the pre-A10 era, but it is much less so after the implementation of the LULD Plan Amendment 10. This suggests that high-frequency quoting is not significantly correlated with short-term volatility most of the time during the [-60, +60] minutes window around trading pauses. After Amendment 10, high-frequency quoting is even less likely to be associated with the increase of short-term volatility either before trading pauses or after trading resumptions.

3.6 Conclusion

Trading pauses under the LULD Plan are the key volatility circuit breakers for individual stocks across the US stock market. Their existence is to prevent events similar to the Flash Crash in May 2010 from happening again, and indeed that kind of event never occurs after the LULD trading pauses came into effect. This mechanism has been subjected to revisions and improvements throughout the years since its implementation in May 2014. Especially, LULD Plan Amendment 10 has dramatically reduced the occurrence of unnecessary trading pauses which are due to problematic opening reference price, while no other LULD plan amendments so far have such a dramatic and consistent impact on the frequency of trading pauses. In addition to the reduction of trading pauses, it is important to examine how market quality around trading pauses changes after the implementation of Amendment 10.

Meanwhile, high-frequency activities and their roles in market quality have been highly debatable since the emergence of high-frequency trading. The relation between high-frequency activities and extreme price movements is an intriguing question, especially the interaction between high-frequency activities and trading pauses on individual stocks. Little has been documented about high-frequency quoting activity around trading pauses and its correlations with market quality in the same window. The implementation of Amendment 10 provides a unique opportunity to study high-frequency activities around unnecessary trading pauses and around necessary trading pauses. It also offers a change to gauge how high-frequency activities around trading pauses have changed after Amendment 10 came into effect, although Amendment 10 was not aimed at altering high-frequency activities around trading pauses.

In conclusion, this paper empirically examines market quality and high-frequency quoting activity around trading pauses in the pre-Amendment 10 era and in the post-Amendment 10 era. In addition, it explores how market quality around trading pauses changes in the two eras and how high-frequency quoting activity is related to the change. The post-trading pauses reduction of illiquidity, measured by the percentage quoted spread, relative to 1 hour before trading pauses, is less after the implementation of Amendment 10 compared to that in the pre-Amendment 10 era. Short-term volatility *HighLow* becomes higher around trading pauses, especially after trading resumptions, in the post-Amendment 10 era than in the pre-Amendment 10 era. High-frequency quote updates $HFQU$ are much higher right before and after trading pauses in the post-Amendment 10 era, particularly after trading resumptions. There are more minutes in the 2-hour window around trading pauses in the post-Amendment10 era that high-frequency quote updates are positively correlated with liquidity improvement, especially before trading pauses. There are fewer minutes in the 2-hour window around trading pauses in the post-Amendment 10 era that high-frequency quote updates are positively correlated with short-term volatility, especially after trading resumptions.

REFERENCES

Abad, David, and Roberto Pascual, 2010, Switching to a temporary call auction in times of high uncertainty, *Journal of Financial Research* 33, 45–75.

Angel, James J., 2015, Limit up – limit down: National market system plan assessment to address extraordinary market volatility, Technical report, Georgetown University.

Bhattacharya, Uttpal, and Matthew Spiegel, 1998, Anatomy of a market failure: NYSE trading suspensions (1974–1988), *Journal of Business & Economic Statistics* 16, 216–226.

Boehmer, Ekkehart, Kingsley Fong, and Juan Julie Wu, 2021, Algorithmic trading and market quality: International evidence, *Journal of Financial and Quantitative Analysis* 56, 2659–2688.

Boehmer, Ekkehart, Dan Li, and Gideon Saar, 2018, The Competitive Landscape of High-Frequency Trading Firms, *The Review of Financial Studies* 31, 2227–2276.

Brady, Nicholas F., James C. Cotting, Robert G. Kirby, John R. Opel, and Howard M. Stein, 1988, *Report of the Presidential Task Force on Market Mechanisms: Submitted to the President of the United States, the Secretary of the Treasury, and the Chairman of the Federal Reserve Board* (U.S. Dept. of the Treasury and U.S. Government Printing Office).

Brogaard, Jonathan, and Kevin Roshak, 2016, Prices and price limits, *Available at SSRN 2667104* .

Chaboud, Alain P, Benjamin Chiquoine, Erik Hjalmarsson, and Clara Vega, 2014, Rise of the machines: Algorithmic trading in the foreign exchange market, *The Journal of Finance* 69, 2045–2084.

Cho, David D., Jeffrey Russell, George C. Tiao, and Ruey Tsay, 2003, The magnet effect of price limits: evidence from high-frequency data on taiwan stock exchange, *Journal of Empirical Finance* 10, 133–168, Emerging Markets S.I.

Christie, William G., Shane A. Corwin, and Jeffrey H. Harris, 2002, Nasdaq trading halts: The impact of market mechanisms on prices, trading activity, and execution costs, *The Journal of Finance* 57, 1443–1478.

Conrad, Jennifer, Sunil Wahal, and Jin Xiang, 2015, High-frequency quoting, trading, and the efficiency of prices, *Journal of Financial Economics* 116, 271–291.

Corwin, Shane A, and Marc L Lipson, 2000, Order flow and liquidity around nyse trading halts, *The Journal of Finance* 55, 1771–1801.

Fama, Eugene F., 1988, Perspectives on october 1987, or, what did we learn from the crash?, Working paper, University of Chicago.

Greenwald, Bruce C., and Jeremy C. Stein, 1991, Transactional risk, market crashes, and the role of circuit breakers, *Journal of Business* 443–462.

Hagströmer, Björn, and Lars Nordén, 2013, The diversity of high-frequency traders, *Journal of Financial Markets* 16, 741–770.

Harris, Lawrence, 1997, Circuit breakers and program trading limits: what have we learned?, Technical report, Wharton School Center for Financial Institutions, University of Pennsylvania.

Hasbrouck, Joel, and Gideon Saar, 2013, Low-latency trading, *Journal of Financial Markets* 16, 646–679, High-Frequency Trading.

Hautsch, Nikolaus, and Akos Horvath, 2019, How effective are trading pauses?, *Journal of Financial Economics* 131, 378–403.

Hendershott, Terrence, Charles M Jones, and Albert J Menkveld, 2011, Does algorithmic trading improve liquidity?, *The Journal of finance* 66, 1–33.

Hendershott, Terrence, and Pamela C Moulton, 2011, Automation, speed, and stock market quality: The nyse's hybrid, *Journal of Financial Markets* 14, 568–604.

Holden, Craig W., and Stacey Jacobsen, 2014, Liquidity measurement problems in fast, competitive markets: Expensive and cheap solutions, *The Journal of Finance* 69, 1747–1785.

Hughes, Paul, 2017, The effect of amendment 10 of the "limit up-limit down" pilot plan, White paper, SEC DERA.

Hughes, Paul, John Ritter, and Hao Zhang, 2017, Limit up-limit down pilot plan and extraordinary transitory volatility, White paper, SEC DERA.

Kyle, Albert S., 1988, Trading halts and price limits, *Review of Futures Markets* 7, 426–434.

Lee, Charles MC, Mark J Ready, and Paul J Seguin, 1994, Volume, volatility, and new york stock exchange trading halts, *The Journal of Finance* 49, 183–214.

Madhavan, Ananth, 1992, Trading mechanisms in securities markets, *the Journal of Finance* 47, 607–641.

Moise, Claudia E., 2022, Circuit breakers, illiquidity, and the covid-19 crisis, Working paper, University of North Carolina at Chapel Hill.

Moise, Claudia E., and Paca Flaherty, 2017, Limit up-limit down pilot plan and associated events, White paper, SEC DERA.

Prais, Sigbert J, and Christopher B Winsten, 1954, Trend estimators and serial correlation, Working paper, Cowles Commission discussion paper Chicago.

Riordan, Ryan, and Andreas Storkenmaier, 2012, Latency, liquidity and price discovery, *Journal of Financial Markets* 15, 416–437.

Subrahmanyam, Avanidhar, 1994, Circuit breakers and market volatility: A theoretical perspective, *The Journal of Finance* 49, 237–254.

Zimmermann, Kai, 2013, Price discovery in european volatility interruptions, *Available at SSRN 2365772* .

Table 3.1
Distribution of Trading Pauses and Stocks around Amendment 10

Panel A: Monthly Trading Pauses and Involved Stocks

This table compares the [-20, -1] and [+1, +20] trading days windows before and after the Limit-Up Limit-Down (LULD) Plan Amendment 10 (A10) comes into force. The implementation date, 18 July 2016, is Day 1. Each row corresponds to a filter for LULD trading pauses (TPs). The row below inherits the filters from the rows above. The last row represents the sample used in the empirical analysis section. *[All legitimate LULD TPs]* means the happening of these TPs follows the rules of the LULD Plan and their resumption time is at 4 pm on the same day. With the next-level filter of the *[5-min length]* length, only TPs lasting 5 minutes are considered for comparison purposes. Furthermore, for *[≥2 hours apart]*, if there are multiple LULD TPs for the same stock-day, only the ones which are at least 2 hours apart from each other are selected. Next, *[≥20 min before mkt close]* means the LULD TPs need to resume at least 20 minutes before market closes (i.e., 4 p.m.). In the final level, *[≥5 min after mkt open]* requires the LULD TPs to be at least 5 minutes after market opening (i.e., 9:30 a.m.).

Cumulative Filters	*LULD TP Events Count*		*Unique LULD TP Stocks Count*	
	Pre A10 (-20 tr days)	*Post A10 (+20 tr days)*	*Pre A10 (-20 tr days)*	*Post A10 (+20 tr days)*
[All legitimate LULD TPs]	1400	199	303	97
& *[5-min length]*	1328	181	281	83
& *[≥2 hours apart]*	716	117	265	68
& *[≥20 min before mkt close]*	715	117	265	68
& *[≥5 min after mkt open]*	566	105	240	60

Panel B: Hourly Distribution of Trading Pauses and Involved Stocks in the Empirical Analysis Sample

This table presents the distribution of Limit-Up Limit-Down (LULD) trading pauses (TPs) and involved stocks in hourly interval across the [-20, +20] trading days around Amendment 10 (A10). The data sample in this table corresponds to the one described in the last row of Panel (a), which is produced by applying all filters. It is also the version used in the empirical analysis section. Note that a stock can have multiple trading pauses across different days in the same hourly interval per day. Therefore, the summation of uniquely involved stocks in the hourly intervals can surpass the total numbers in the last row of Panel (A).

Hourly Interval	*LULD TP Events Count*		*Unique LULD TP Stocks Count*	
	Pre A10 (-20 tr days)	*Post A10 (+20 tr days)*	*Pre A10 (-20 tr days)*	*Post A10 (+20 tr days)*
[9:35am, 10:00am)	362	46	166	24
[10:00am, 11:00am)	90	21	71	18
[11:00am, 12:00pm)	40	12	38	11
[12:00pm, 1pm)	28	6	23	4
[1:00pm, 2:00pm)	18	6	18	6
[2:00pm, 3:00pm)	22	8	21	8
[3:00pm, 3:40pm]	6	6	6	6

Table 3.1
Distribution of Trading Pauses and Stocks around Amendment 10 — *Continued*

Panel C: Cross-Sectional Summary Statistics for 1-Minute Bins Span around Trading Pauses

This table summarizes how many 1-minute bins exist before and after the Limit-Up Limit-Down (LULD) trading pauses (TPs) cross-sectionally before and after Amendment 10 (A10). The maximum span is 60 minutes before and 60 minutes after a LULD TP for the complete [-60, +60] minutes event window around it. The data sample in this table corresponds to the one described in the last row of Panel (A), which is produced by applying all filters. It is also the version used in the empirical analysis section. *A10* is an indicator of whether it is pre-A10 or post-A10. Similarly, *TP* indicates whether it is in the pre-LULD TP or post-LULD TP interval. *Mean*, *SD*, *Skew*, *Kur*t, *Min*, and *Max* represent the mean, standard deviation, skewness, kurtosis, minimum, and maximum. *P5*, *P25*, *P50*, *P7*5, and *P95* represent the 5th, 25th, 50th, 75th, and 95th percentiles, respectively. *N* means the number of LULD TPs. The timestamps on trading pause and resumption are rarely at 9:35:00 am and 3:40:00 pm sharp. Therefore, the marginal time gap residuals are treated as extra 1-minutes bins when market opens and closes. Thus, the minimum pre-TP and post-TP bins span are 6 bins and 21 bins instead of 5 and 20.

A10	*TP*	*Mean*	*SD*	*Skew*	*Kurt*	*Min*	*P5*	*P25*	*P50*	*P75*	*P95*	*Max*	*N*
Pre	Pre	29.90	19.51	0.72	-1.27	6	12.00	16.00	16.00	59.00	60.00	60	566
	Post	59.72	2.90	-11.25	131.71	21	60.00	60.00	60.00	60.00	60.00	60	566
Post	Pre	38.92	21.13	-0.18	-1.81	6	8.60	16.00	50.00	60.00	60.00	60	105
	Post	58.72	5.99	-5.42	30.51	21	54.20	60.00	60.00	60.00	60.00	60	105

Panel D: Time-Series Summary Statistics for Trading Pauses Event Window Coverage per Minute-Bin

This table presents the time-series summary statistics of the Limit-Up Limit-Down (LULD) trading pauses (TP) event window coverage per 1-minute bin in the [-60, +60] minutes window. For instance, the bin of the [-1, 0) minutes before a LULD TP is covered in 566 LULD TP event windows in the pre-Amendment 10 (A10) era, while the bin of [-60, -59) minutes before a LULD TP is only covered in 141 LULD TP event windows in the same era. Those two values also correspond to the *Max* and *Min* during the pre-TP interval in that era. For another example, in the post-A10 era, there are on average 102.77 LULD TP event windows involved, across all the 1-minute bins after a LULD TP. The data sample in this table corresponds to the one described in the last row of Panel (A), which is produced by applying all filters. It is also the version used in the empirical analysis section. *A10* is an indicator of whether it is pre-A10 or post-A10. Similarly, *TP* indicates whether it is in the pre-LULD TP or post-LULD TP window. *Mean*, *SD*, *Skew*, *Kur*t, *Min*, and *Max* represent the mean, standard deviation, skewness, kurtosis, minimum, and maximum. *P5*, *P25*, *P50*, *P7*5, and *P95* represent the 5th, 25th, 50th, 75th, and 95th percentiles, respectively. *N* means the number of 1-minute bins.

A10	*TP*	*Mean*	*SD*	*Skew*	*Kurt*	*Min*	*P5*	*P25*	*P50*	*P75*	*P95*	*Max*	*N*
Pre	Pre	282.02	165.09	0.99	-0.90	141	145.90	164.50	205.50	524.75	566.00	566	60
	Post	563.37	2.35	-0.17	-1.51	560	560.00	561.00	563.00	566.00	566.00	566	60
Post	Pre	68.12	20.84	0.81	-0.96	45	45.95	54.00	59.00	94.25	105.00	105	60
	Post	102.77	2.12	-0.58	-0.79	98	99.00	101.00	103.00	105.00	105.00	105	60

Table 3.2
Time-Series Average of Cross-Sectional Summary Statistics for Quoted Spread

This tables displays the time-series average of the cross-sectional summary statistics for the liquidity measure, Quoted Spread (%). The rows are divided into pre- and post- trading pause (TP) intervals, and pre- and post- Amendment 10 (A10) eras. For example, a "Pre" ("Post") in the A10 column means the adjacent two rows are for the pre-A10 (post-A10) period; and a "Pre" ("Post") in the TP column indicates that the row shows the time-series average of the cross-sectional summary statistics across the 60 minutes bins before (after) trading pauses. The definition of the liquidity measure, the quoted spread (%) follows that in Holden and Jacobsen (2014).

Measure	*A10*	*TP*	*Mean*	*SD*	*Skew*	*Kurt*	*Min*	*P5*	*P25*	*P50*	*P75*	*P95*	*Max*	*N*
Quoted Spread (%)	Pre	Pre	7.09	13.86	317.80	1780.09	0.07	0.18	0.50	1.51	8.74	29.16	71.31	79.18
		Post	1.65	3.94	640.04	5664.29	0.06	0.16	0.38	0.65	1.20	6.67	41.71	268.63
	Post	Pre	3.57	6.19	224.70	783.11	0.02	0.05	0.48	1.02	3.15	17.13	24.46	26.90
		Post	1.70	3.11	418.67	2323.26	0.09	0.30	0.53	0.70	1.36	6.85	20.32	59.75

Table 3.3
Time-Series Average of Cross-Sectional Summary Statistics for HighLow

This tables displays the time-series average of the cross-sectional summary statistics for the short-term volatility measure *HighLow*. The rows are divided into pre- and post- trading pause (TP) intervals, and pre- and post- Amendment 10 (A10) eras. For example, a "Pre" ("Post") in the A10 column means the adjacent two rows are for the pre-A10 (post-A10) period; and a "Pre" ("Post") in the TP column indicates that the row shows the time-series average of the cross-sectional summary statistics across the 60 minutes bins before (after) trading pauses. The definition of the short-term volatility measure *HighLow* follows Hasbrouck and Saar (2013). The values are in basis point.

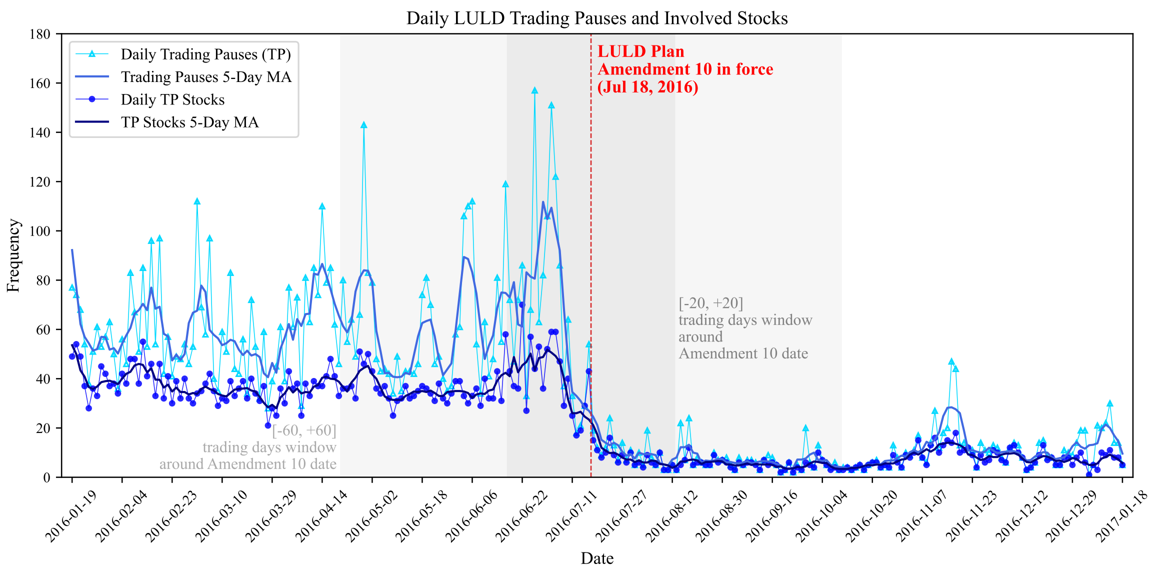
Measure	*A10*	*TP*	*Mean*	*SD*	*Skew*	*Kurt*	*Min*	*P5*	*P25*	*P50*	*P75*	*P95*	*Max*	*N*
HighLow (bps)	Pre	Pre	26.47	51.50	2.64	10.96	0.00	0.00	0.70	4.24	27.03	140.51	254.35	79.18
		Post	18.24	33.19	3.66	25.83	0.00	0.00	0.52	2.56	26.28	76.91	273.38	268.63
	Post	Pre	21.47	42.17	2.77	10.63	0.00	0.03	0.72	3.51	21.93	119.88	186.85	26.90
		Post	30.89	42.02	2.13	9.13	0.00	0.00	1.59	14.12	47.52	113.89	207.46	59.75

Table 3.4
Time-Series Average of Cross-Sectional Summary Statistics for HFQU

This tables displays the time-series average of the cross-sectional summary statistics for high-frequency quotation measure *HFQU*. The rows are divided into pre- and post- trading pause (TP) intervals, and pre- and post- Amendment 10 (A10) eras. For example, a "Pre" ("Post") in the A10 column means the adjacent two rows are for the pre-A10 (post-A10) period; and a "Pre" ("Post") in the TP column indicates that the row shows the time-series average of the cross-sectional summary statistics across the 60 minutes bins before (after) trading pauses. The definition of high-frequency quotation measure *HFQU* follows Conrad, Wahal, and Xiang (2015).

Measure	*A10*	*TP*	*Mean*	*SD*	*Skew*	*Kurt*	*Min*	*P5*	*P25*	*P50*	*P75*	*P95*	*Max*	*N*
HFQU	Pre	Pre	27.70	119.73	8.98	105.48	0.02	0.03	0.20	1.85	13.32	116.18	1634.00	227.08
		Post	39.71	122.27	10.65	168.79	0.00	0.05	0.23	6.73	37.23	171.47	2107.05	488.35
	Post	Pre	60.02	155.50	3.47	16.03	0.03	0.08	0.22	2.81	28.16	376.27	873.27	61.88
		Post	83.85	223.53	5.10	33.68	0.07	0.10	0.35	13.10	67.40	411.02	1686.42	92.77

Panel A: Daily LULD Trading Pauses, [-6, +6] Months around Amendment 10 Implementation



Panel B: Monthly LULD Trading Pauses, 2014-05-01 to 2021-09-30

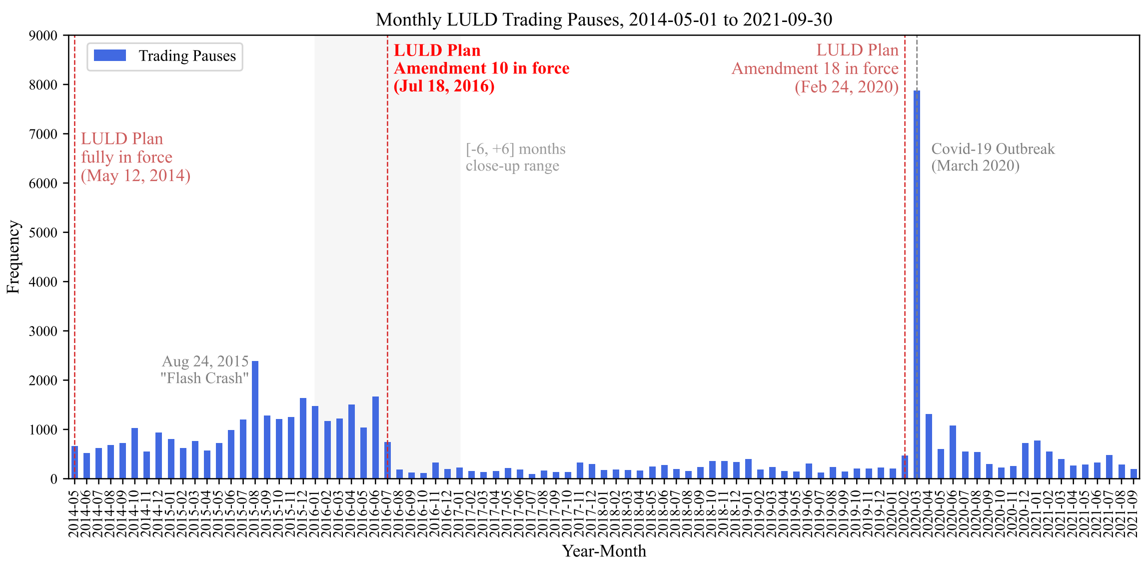


Figure 3.1. Limit Up-Limit Down (LULD) Trading Pauses Frequency. Panel (a) plots the daily number of trading pauses in the U.S. stock market together with the involved stocks which experience trading pauses on that date. It covers the [-6, +6] calendar months window around Amendment 10 implementation on July 18, 2016. The 5-day moving averages (MA) are also plotted to smooth out extreme variations and better reflect the trends. Panel (b) plots the monthly trading pauses count from May 1, 2015 to September 30, 2021. The time span in Panel (a) corresponds to the shaded area of the [-6, +6] months close-up range in Panel (b).

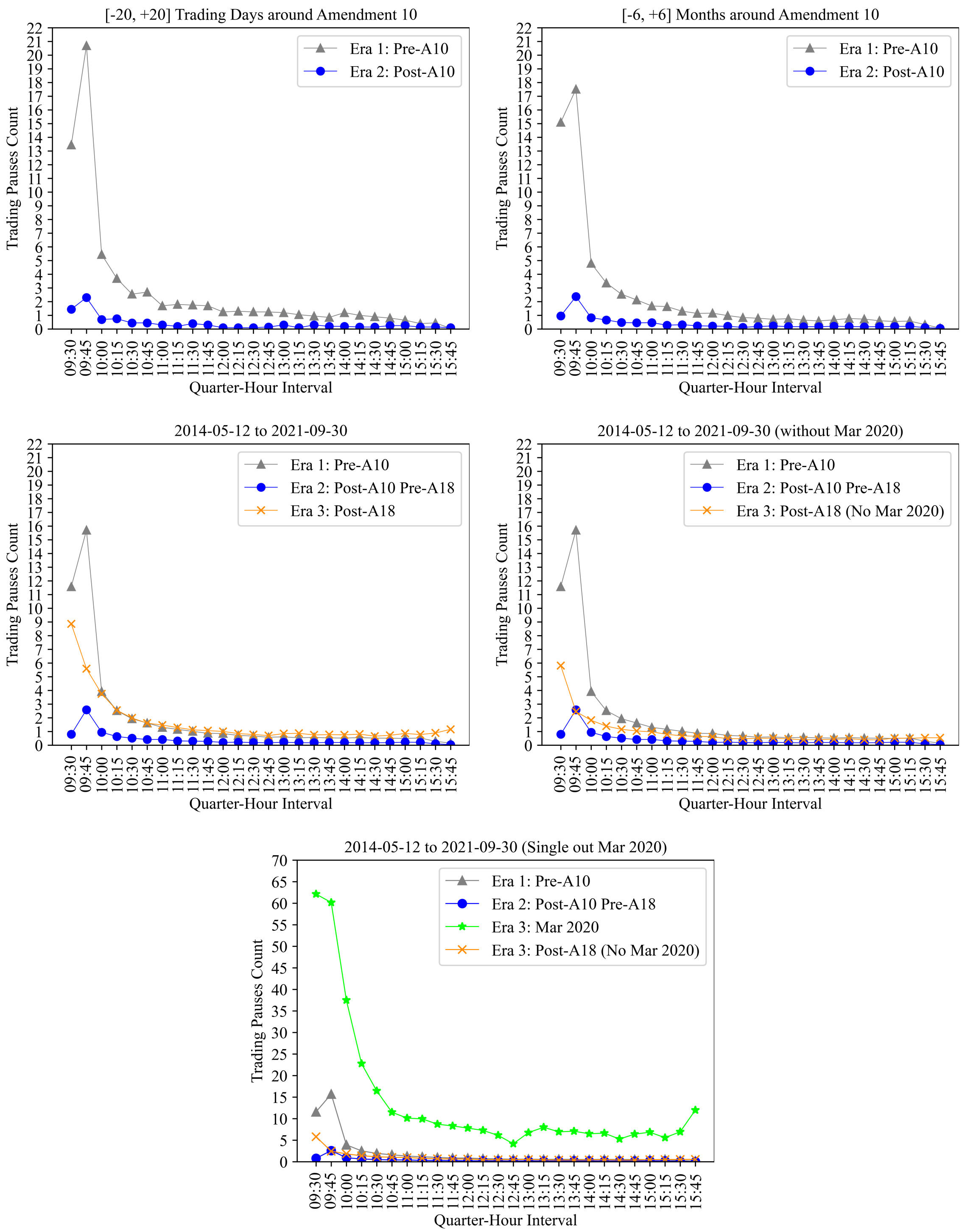
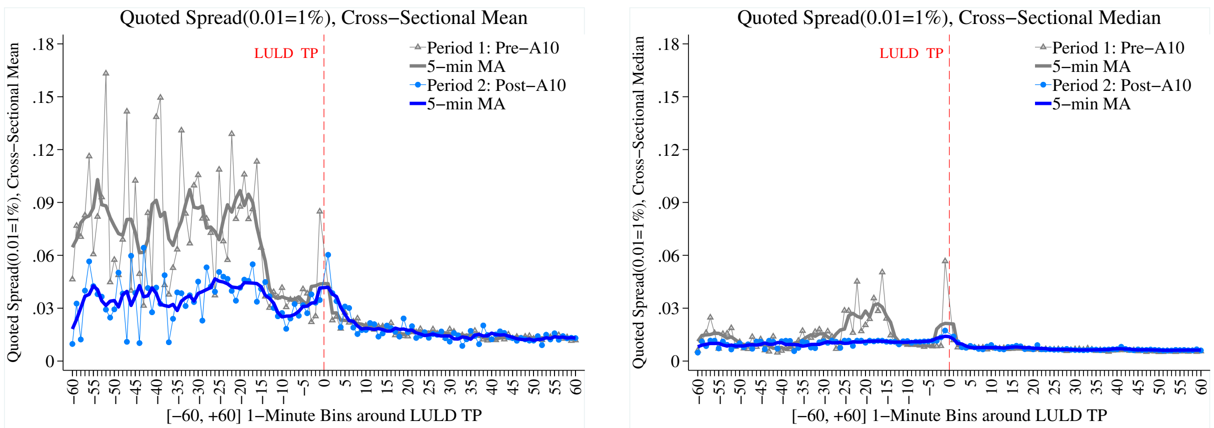


Figure 3.2. Daily Average of Limit Up-Limit-Down Trading Pauses per Quarter-Hour. The top panel plots the daily average occurrence of trading pauses in each quarter hour during market hours, in the [-20, +20] trading days window, and in the [-6, +6] calendar months window, respectively, around Amendment 10 implementation. For example, the "9:30" tick on the horizontal axis represents 9:30-9:45 a.m. The middle panel plots the same content as the top panel, but the time span is from May 12, 2014 (LULD Plan full implementation) to September 30, 2021, and the same period but without March 2020 (Covid-19 outbreak). The bottom panel plots the same content as in the middle panel, but singles out the March 2020 period.

Panel A: Quoted Spread (%)



Panel B: Quoted Spread ($)

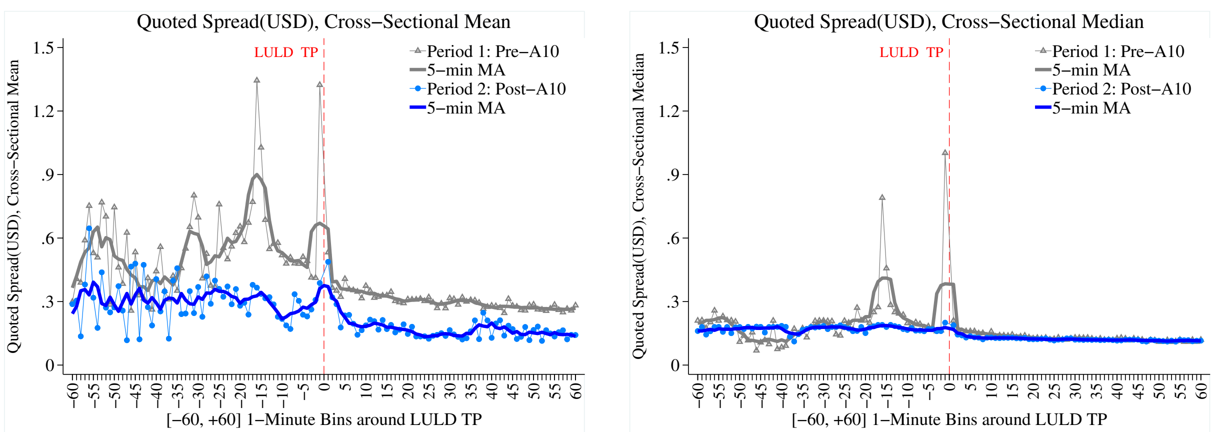
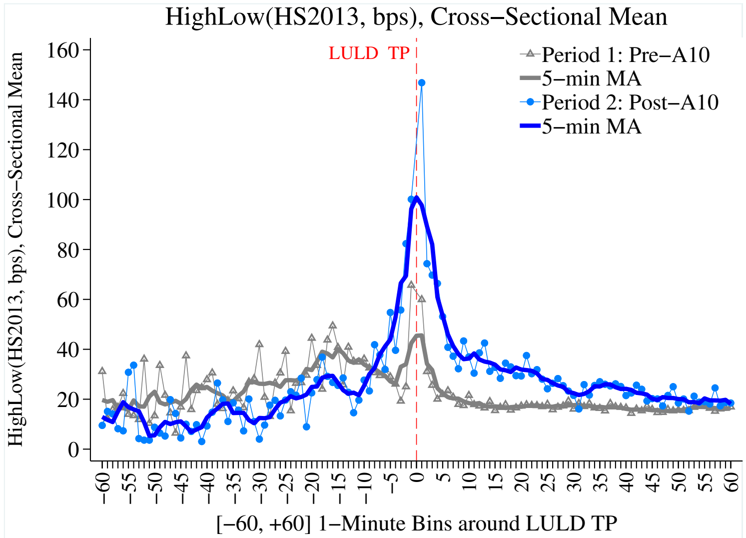


Figure 3.3. Mean and Median of Liquidity Measure: Quoted Spread. This figure plots the minute-by-minute evolution of the cross-sectional mean and median of the liquidity measure Quoted Spread in the [-60, +60] minute bins before and after trading pauses. The 5-minute moving averages (MA) are also included to capture the trend and smooth out extreme variations. Grey color connected-scatters correspond to Quoted Spread around trading pauses in the 20 trading days pre-Amendment 10 while the blue ones are for Quoted Spread around trading pauses in 20 trading days post-Amendment 10. Panel (a) is for Quoted Spread in percentage, while Panel (b) uses Quoted Spread in dollar value.



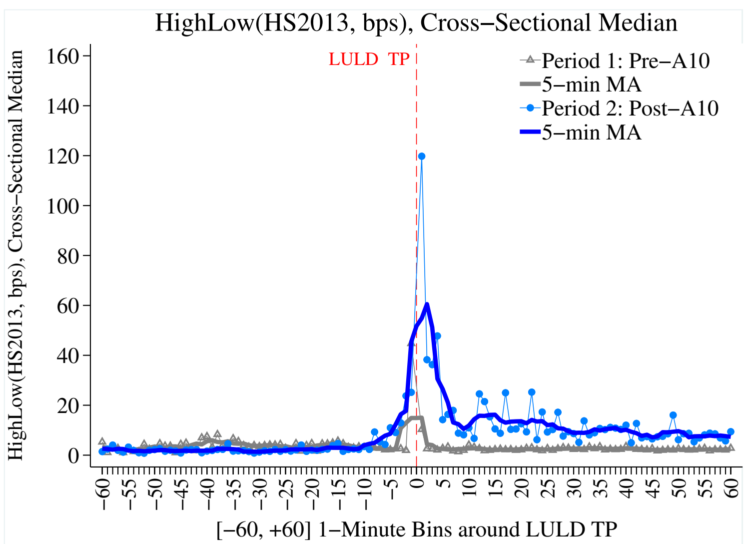


Figure 3.4. Mean and Median of Short-Term Volatility Measure: HighLow. This figure plots the minute-by-minute evolution of the cross-sectional mean and median of the short-term volatility measure *HighLow* in the [-60, +60] minute bins before and after trading pauses. The values are in basis point. The 5-minute moving averages (MA) are also included to capture the trend and smooth out extreme variations. Grey color connected scatters correspond to *HighLow* around trading pauses in the 20 trading days pre-Amendment 10 while the blue ones are for *HighLow* around trading pauses in the 20 trading days post-Amendment 10.

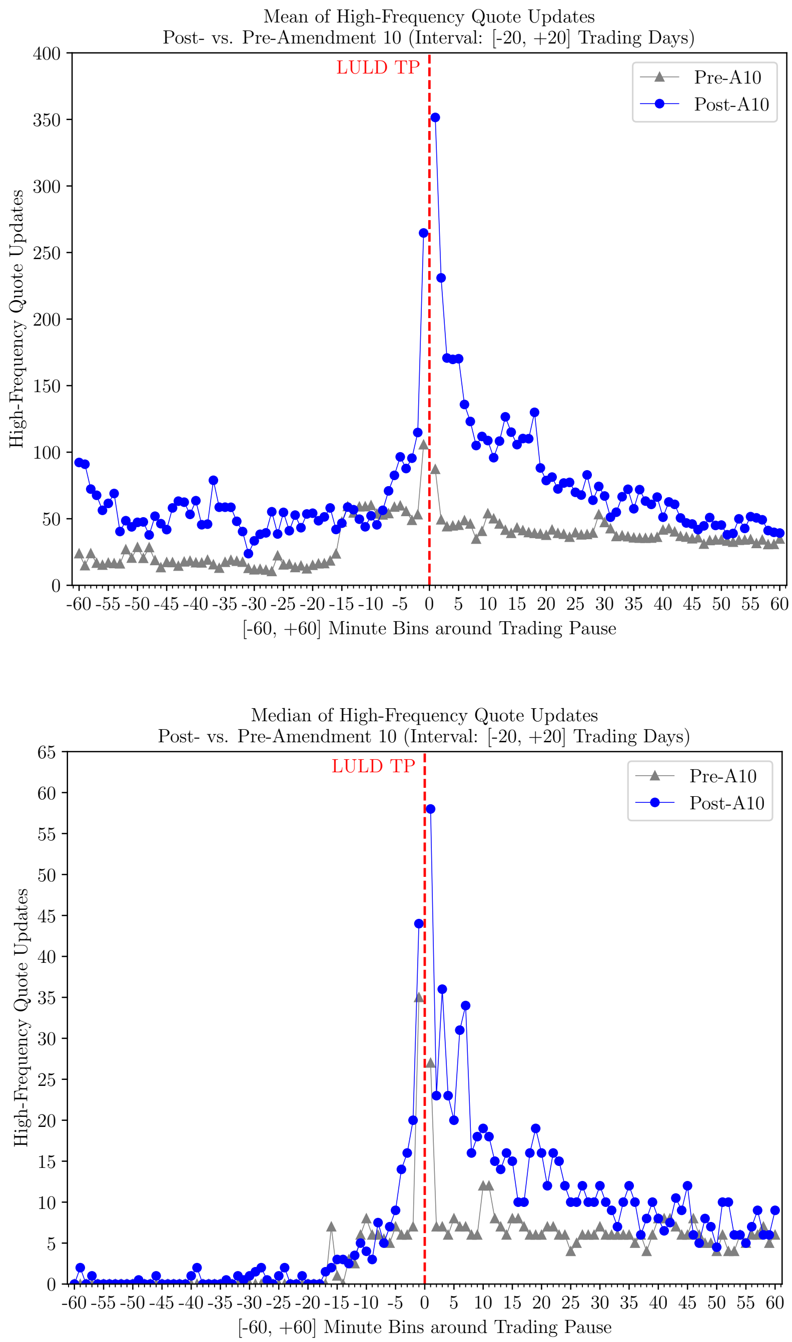


Figure 3.5. Mean and Median of High-Frequency Activity Measure: HFQU. This figure plots the the minute-by-minute evolution of the cross-sectional mean (as in the top panel) and median (as in the bottom panel) of the high-frequency quotation activity measure *HFQU* in the [-60, +60] minute bins before and after trading pauses. The grey color connected scatters correspond to *HFQU* around trading pauses in the 20 trading days pre-Amendment 10 while the blue ones are for *HFQU* around trading pauses in the 20 trading days post-Amendment 10.

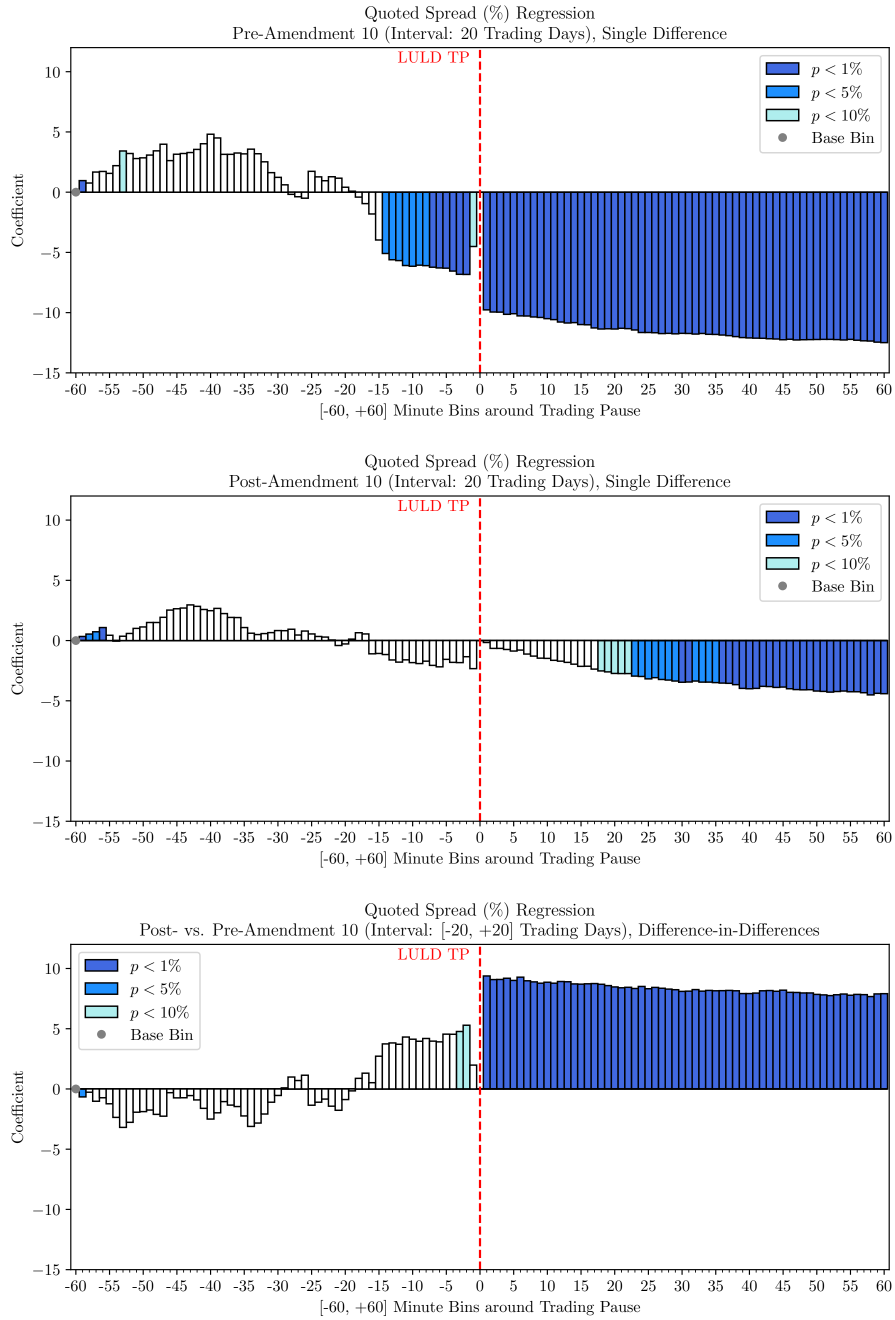


Figure 3.6. Quoted Spread (%) Bin-Level Differences Regressions. The top and middle panels of this figure plot the estimated coefficients $\left(\beta_\tau + \beta_\tau^{\text{TP}}\right)$ as in the single difference Eq. (3.9) for each 1-minute bin in the [-60, +60] minutes window around Limit Up-Limit Down trading pauses (LULD TP) in the pre- and post-Amendment 10 periods respectively. The coefficients capture on average how different the *Quoted Spread* at each 1-minute bin are from the base level 60 minutes before trading pauses. The bottom panel plots the estimated coefficients $\beta_{\text{A10},\tau}^{\text{TP}}$ as in the difference-in-differences Eq. (3.10). The coefficients capture the differences between the post-Amendment 10 and pre-Amendment 10 bin-level differences of *Quoted Spread* relative to their base levels 60 minutes before trading pauses. Darker colors correspond to stricter significance levels (or smaller p-values) as shown in the graph legend. The vertical axis values are in percentage (%).

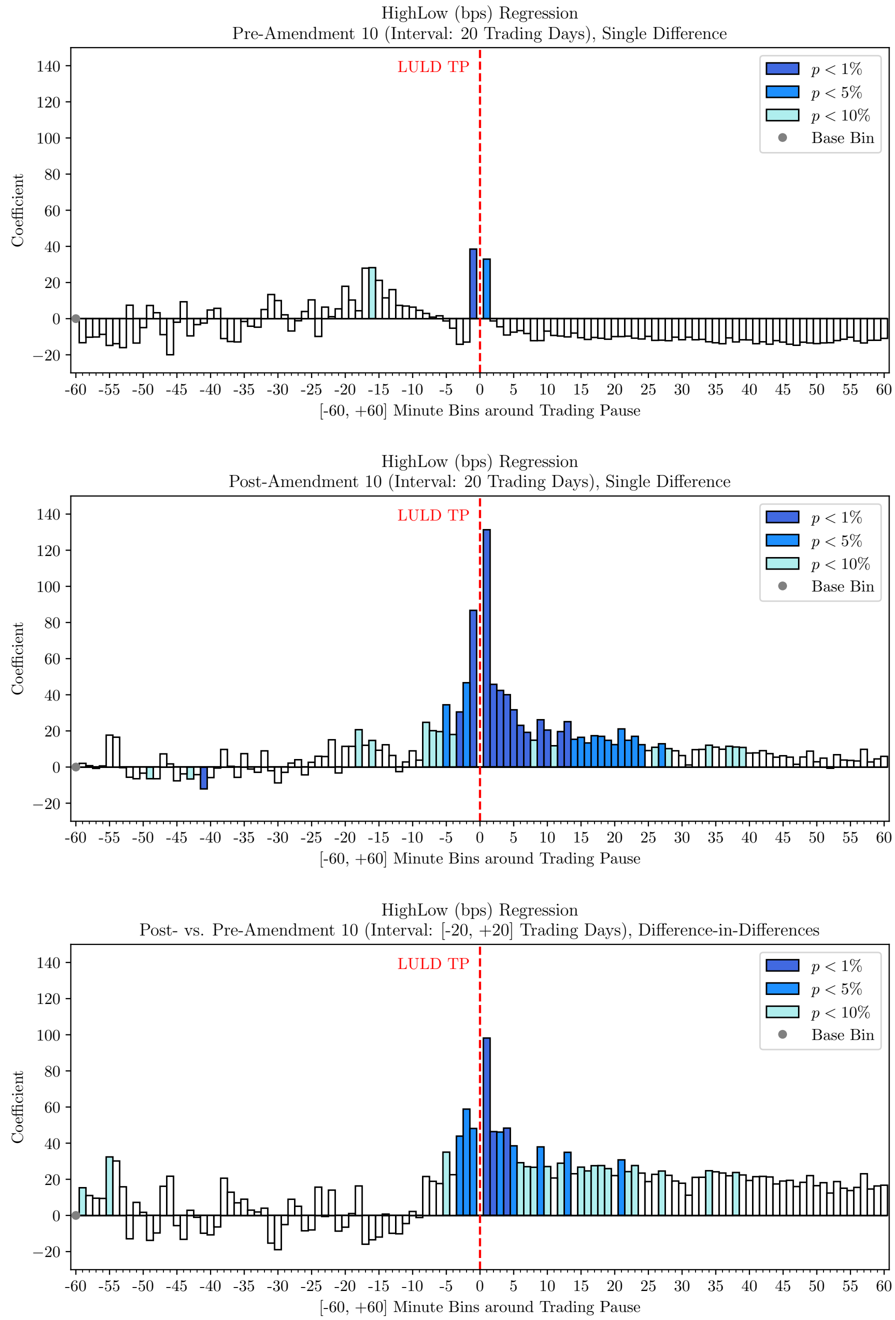


Figure 3.7. HighLow Bin-Level Differences Regressions. The top and middle panels of this figure plot the estimated coefficients $\left(\beta_\tau + \beta_\tau^{\mathrm{TP}}\right)$ as in the single difference Eq. (3.9) for each 1-minute bin in the [-60, +60] minutes window around Limit Up-Limit Down trading pauses (LULD TP) in the pre- and post-Amendment 10 periods respectively. The coefficients capture on average how different the short-term volatility measure *HighLow* at each 1-minute bin are from the base level 60 minutes before trading pauses. The bottom panel plots the estimated coefficients $\beta_{\mathrm{A10},\tau}^{\mathrm{TP}}$ as in the difference-in-differences Eq. (3.10). The coefficients capture the differences between the post-Amendment 10 and pre-Amendment 10 bin-level differences of *HighLow* relative to their base levels 60 minutes before trading pauses. The darker colors correspond to stricter significance levels (or smaller p-values) as shown in the graph legend. The vertical axis values are in basis points (bps).

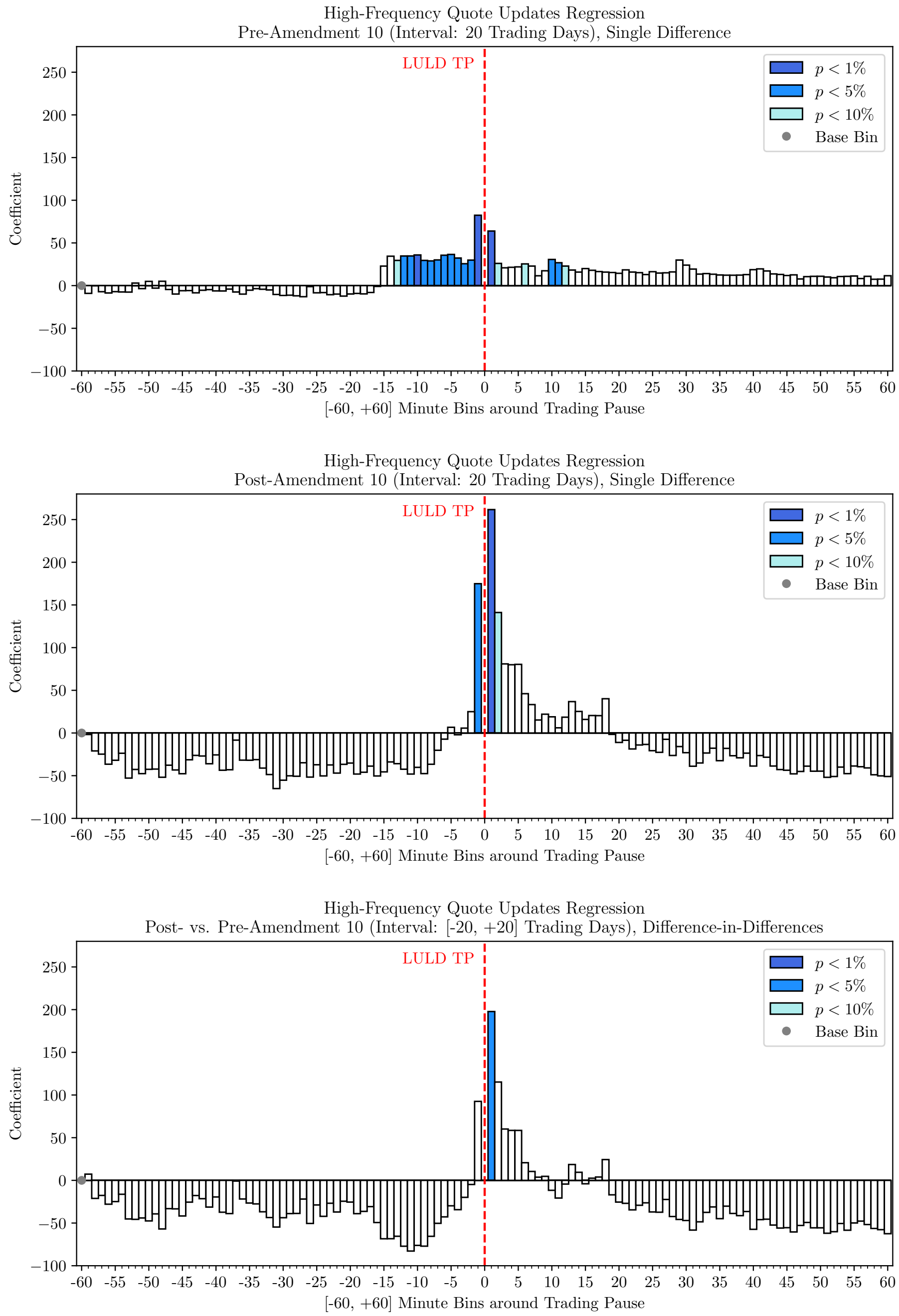


Figure 3.8. High-Frequency Quote Updates Bin-Level Differences Regressions. The top and middle panels of this figure plot the estimated coefficients $\left(\beta_\tau + \beta_\tau^{\mathrm{TP}}\right)$ as in the single difference Eq. (3.9) for each 1-minute bin in the [-60, +60] minutes window around Limit Up-Limit Down trading pauses (LULD TP) in the pre- and post-Amendment 10 periods respectively. The coefficients capture on average how different the *HFQU* at each 1-minute bin are from the base level 60 minutes before trading pauses. The bottom panel plots the estimated coefficients $\beta_{\mathrm{A10},\tau}^{\mathrm{TP}}$ as in the difference-in-differences Eq. (3.10). The coefficients capture the differences between the post-Amendment 10 and pre-Amendment 10 bin-level differences of *HFQU* relative to their base levels 60 minutes before trading pauses. The darker colors correspond to stricter significance levels (or smaller p-values) as shown in the graph legend.

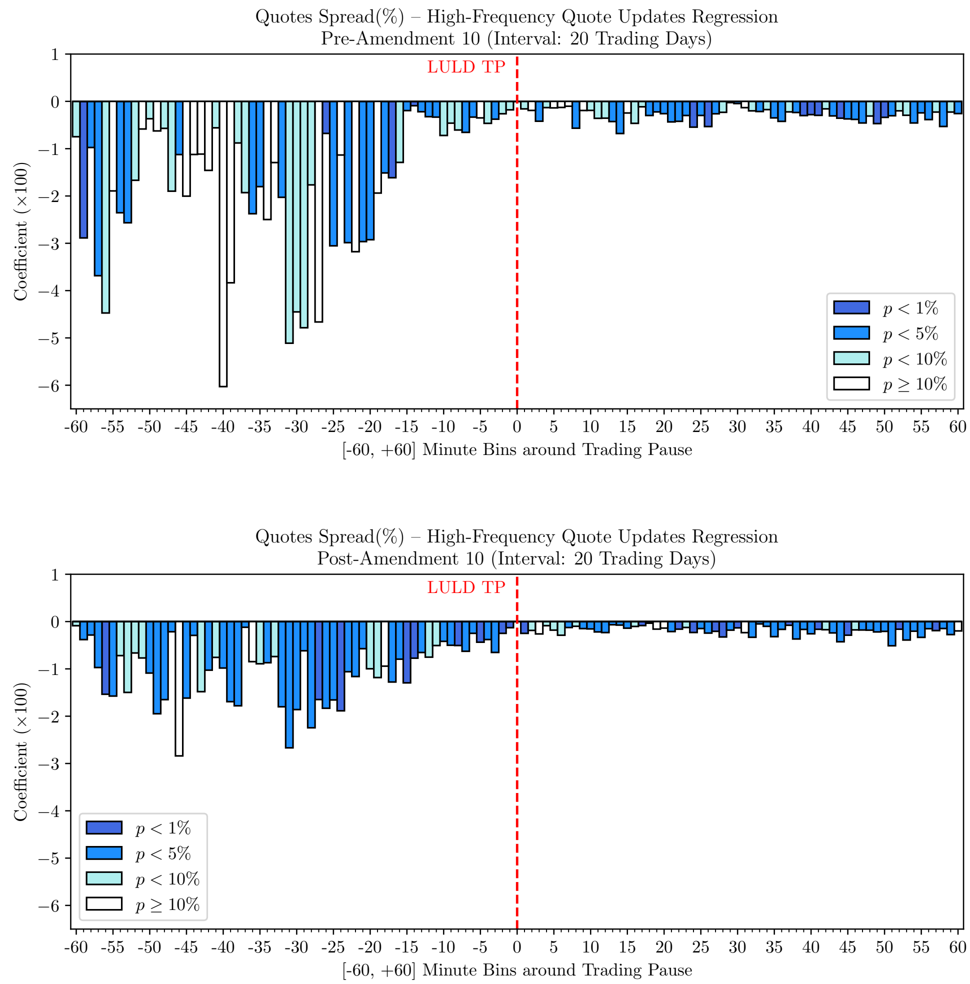


Figure 3.9. Liquidity and High-Frequency Quoting Regression. The top panel plots the estimated regression coefficients when regressing *Quoted Spread* on *HFQU* for each 1-minute bin in the [-60, +60] minutes window around Limit Up-Limit Down trading pauses (LULD TP) in the 20 trading days pre-Amendment 10. The bottom panel plots those estimated coefficients in the 20 trading days post-Amendment 10. The estimated coefficients are scaled up by a multiplier of 100, along the vertical axis. The darker colors correspond to stricter significance levels (or smaller *p*-values) as shown in the graph legend.

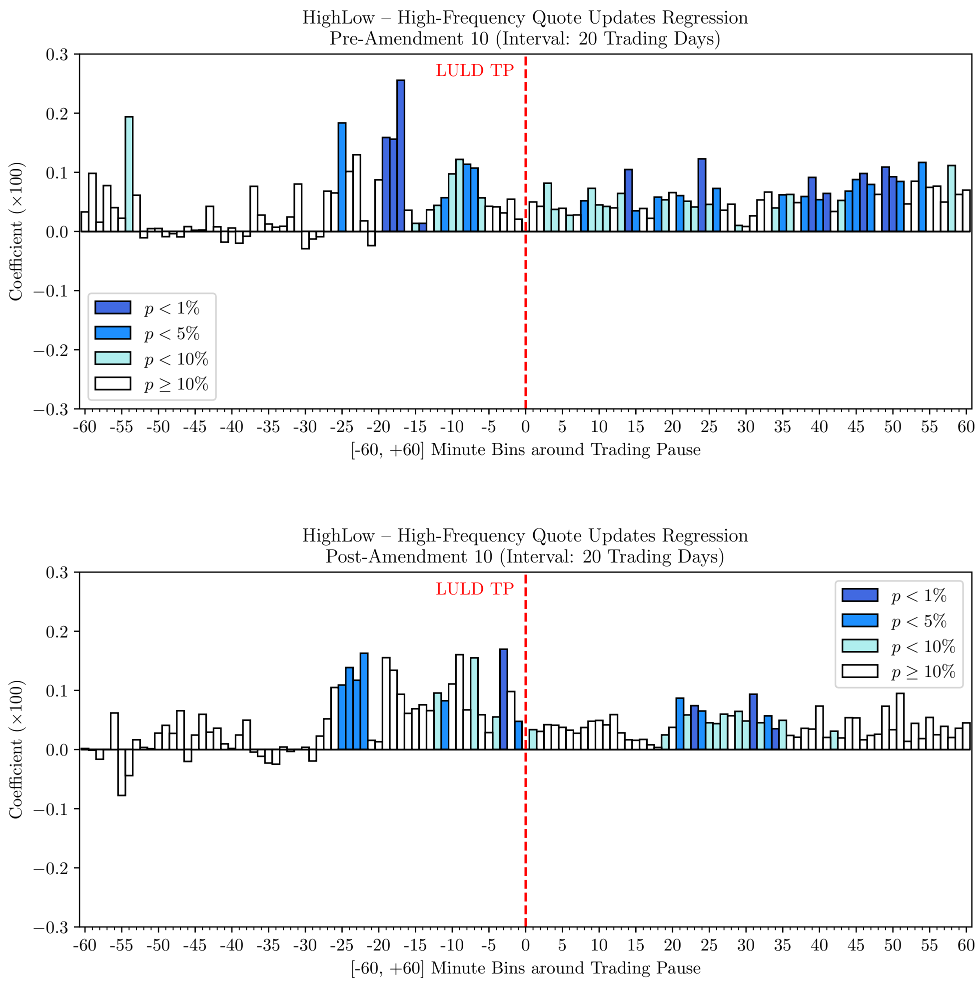


Figure 3.10. Short-Term Volatility and High-Frequency Quoting Regression. The top panel plots the estimated regression coefficients when regressing *HighLow* on *HFQU* for each 1-minute bin in the [-60, +60] minutes window around Limit Up-Limit Down trading pauses (LULD TP) in the 20 trading days pre-Amendment 10. The bottom panel plots those estimated coefficients in the 20 trading days post-Amendment 10. The estimated coefficients are scaled up by a multiplier of 100, along the vertical axis. The darker colors correspond to stricter significance levels (or smaller p-values) as shown in the graph legend.

APPENDIX

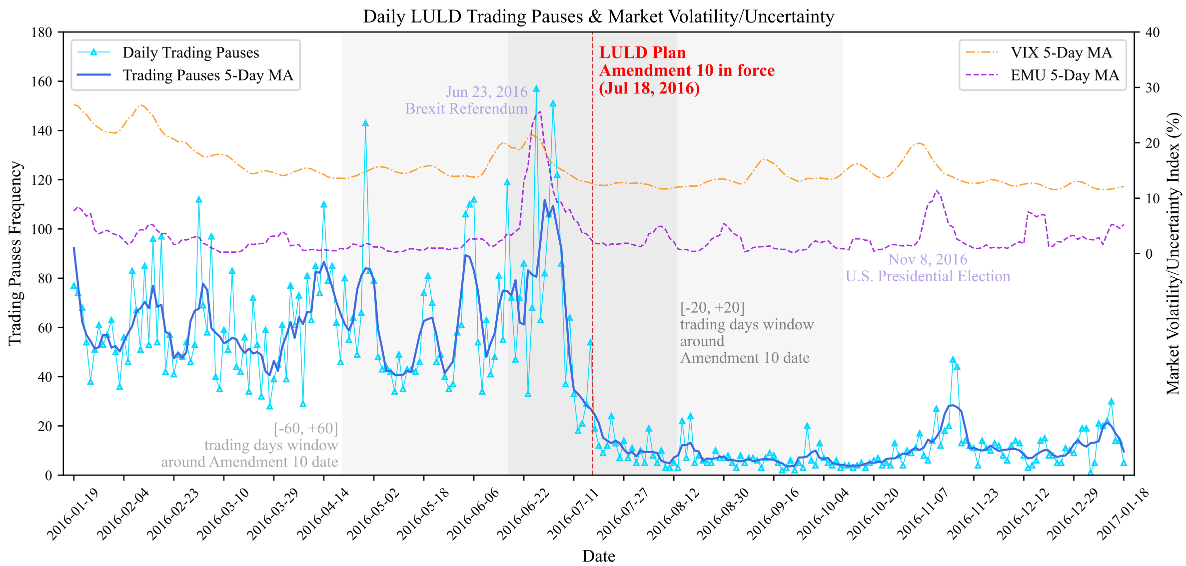


Figure 3.A.1. Daily Limit Up-Limit-Down Trading Pauses and Market Volatility / Uncertainty. This figure plots the daily number of trading pauses in the U.S. stock market together with the involved stocks which experience trading pauses on that date. It covers the [-6, +6] calendar months window around Amendment 10 implementation on July 18, 2016. The 5-day moving averages (MA) are also plotted to smooth out extreme variations and better reflect the trends. The magnitude of trading pauses frequency is indicated on the left hand side axis. This figure also plots the 5-day moving averages (MA) of the VIX and Equity Market Uncertainty (EMU). Their magnitudes are shown along the right hand side axis. This figure supplements Figure 3.1 Panel (a).

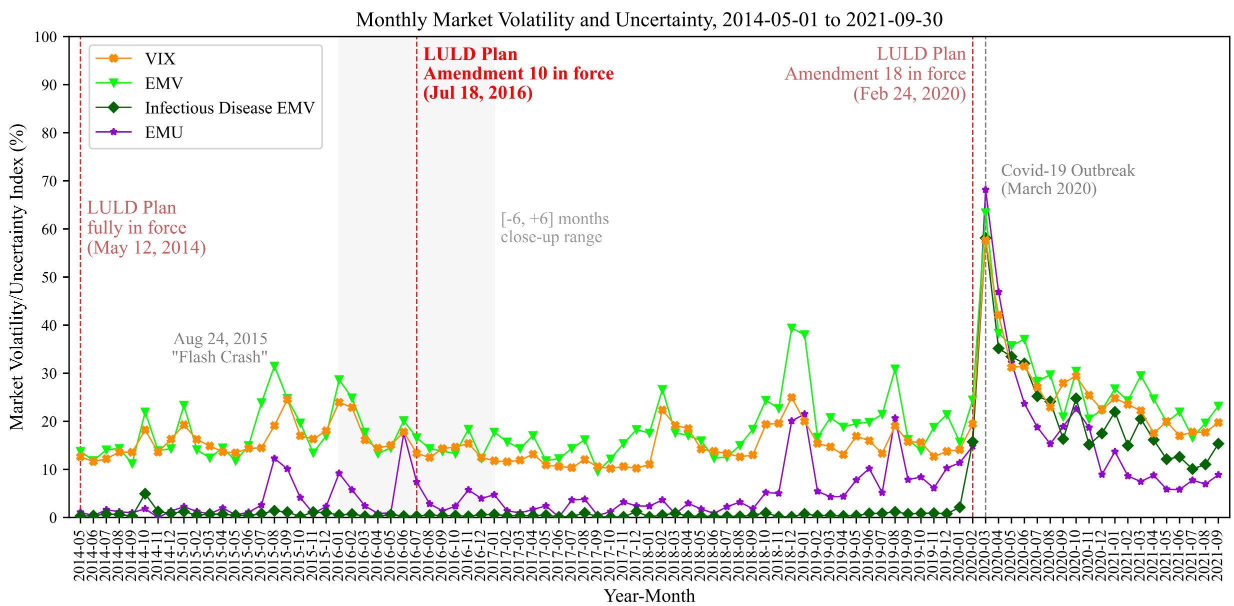


Figure 3.A.2. Monthly Market Volatility and Uncertainty Indices. This figure plots the monthly evolution of market volatility and uncertainty indices from May 2014 to September 2021. They are used for comparison with monthly trading pauses as in Figure 3.1 Panel (b). The vertical axis values are in percentage. The shaded area of the [-6, +6] months close-up range around Amendment 10 implementation corresponds to the entire time span as in Figure 3.1 Panel (a) and also in Figure 3.A.1.