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INTRODUCTION TO SPECIAL ISSUE TITLED "CONTEMPORARY FINANCIAL MARKETS AND RISK ANALYSIS"

This special issue of the Journal of Finance and Financial Law delve into contemporary financial markets and risk analysis. The contemporary financial market becomes more complex to serve a greater number of investors and their risk management needs while allocating capital. As a result of this explosion in financial innovation, new financial products have been developed, generating unfamiliar risks for financial market participants. Analyzing the environment requires taking into account a large number of factors. These factors affect international investors directly and indirectly posing new sources of risk, e.g., Global Financial Crisis and Covid-19 economic crisis.

This issue begins with an article on the current state and future prospects of developing a green economy in Afghanistan, concentrating on renewable energy and fossil resources. This study written by Rinat Tantashev and Bahtiyor Eshchanov looks at renewable energy infrastructure, sustainable agriculture, and their challenges and opportunities. Afghanistan has significant potential for a green economy because of its reserves of lithium and rare earth metals, essential for modern green technologies.

The second article written by Carolyne C. Soper and Monika K. Sywak analyze how the Central Bank of the United States, the Federal Reserve System decided to provide greater transparency after the 2008 and impacted the volatility in financial markets, proving that the Federal Open Market Committee (FOMC) announcements did not lead to significant abnormal returns of the analyzed financial instruments – three exchange traded funds and the two volatility indices.

Under the theme of risk and portfolio management needs of investors, Ewa Feder-Sempach depicts the safe-haven concept according to the latest academic literature and distinguishes it from the hedge and diversifier terms that are sometimes used interchangeably by researchers and portfolio managers. This article proposes a few, new approaches to identify and characterize safe-haven assets and to discover the perspective and outline further research in portfolio theory in times of elevated risk.

The authors of the next article Qian Gao and Aleš Kresta discusses similar topics of potential advantages of dynamic portfolio optimization using a multiobjective genetic algorithm to address the challenges of ever-changing market conditions. The results indicate that the multi-objective risk genetic algorithm not only effectively explores the portfolio space but also handles conflicting optimization objectives, thereby enhancing the comprehensiveness and flexibility of investment decisions.

The final article written by Jerchern Lin asks about tail risks that is of central importance to investors. The author developed a novel methodology to decompose return skewness and kurtosis into various systematic and idiosyncratic components and applied it to returns of different fund types to assess the significance of these sources. The results show that hedge funds are subject to higher idiosyncratic tail risks, whereas exchange traded funds exhibit higher systematic tail risks. Such findings can help all fund managers to bolster the portfolio management process.

The articles that have been selected are those that the peer reviewers deemed to be the best papers submitted to the editor, and give insight into a complex investment risk analysis. Although each of the five articles stands solidly on its own merits, I have made an effort to impose a logical structure, motivated by an interest in identifying some of the topical issues around the theme of contemporary financial markets and risk.

I would like to extend my appreciation to the authors who shared their expertise and deep knowledge of finance. I hope that you will find this special issue informative and insightful collection of articles.

Ewa Feder-Sempach
Guest Editor

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GREENING THE ECONOMY IN AFGHANISTAN – ROLE OF THE CRITICAL MINERAL MINING INDUSTRY

Rinat Tantashev[*], **Bahtiyor Eshchanov**[**]

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GREENING THE ECONOMY IN AFGHANISTAN – ROLE OF THE CRITICAL MINERAL MINING INDUSTRY

ABSTRACT

This article explores the current state and future prospects of developing a green economy in Afghanistan, focusing on renewable energy and fossil resources. It also examines regional cooperation and Afghanistan's politico-economic relations with its neighbors, especially Uzbekistan.

Afghanistan has a significant potential for a green economy due to its reserves of lithium and rare earth metals, essential for modern green technologies. The country is rich in renewable energy resources, which could address environmental challenges, reduce fossil fuel dependence, and create new economic opportunities. This study looks into renewable energy infrastructure, sustainable agriculture, and related challenges and opportunities.

The paper starts by providing a literature review which analyzes the data on Afghanistan's geology, economy, and environmental issues. It conducts stakeholder analysis by collecting data on perceptions and expectations from local communities, environmental organizations, and industry experts. The analysis is conducted through reviewing the current mining sector policies and comparing them with successful international models to propose policy reforms.

Key areas for development include expanding renewable energy infrastructure, such as solar and wind power projects, and promoting sustainable agriculture practices. International organizations and donors are supporting these initiatives.

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In conclusion, Afghanistan’s transition to a green economy is viable and beneficial, requiring sustained efforts from the government, international partners, and the private sector. Strategic investments and cooperation can unlock the full potential of Afghanistan’s green economy, contributing to sustainable development and environmental protection.

Keywords: Afghanistan, Uzbekistan, Central Asia, green economy, energy, climate change, regional cooperation.

JEL Class: Q20, Q28, O13, O25, E22.

INTRODUCTION

Afghanistan is a country with vast renewable energy resources, including solar, wind, and hydro power, which present significant opportunities for the development of a green economy. With increasing global concerns about climate change and environmental degradation, transitioning towards a green economy has become imperative for sustainable development. This article examines the prospects and development of a green economy in Afghanistan, highlighting key areas such as renewable energy infrastructure and sustainable agriculture development.

Nowadays, it is clear that a green economy is defined as the one that aims to reduce environmental risks and ecological deficit as well as it aims at sustainable development. It seeks to achieve this development without degrading the environment, and the definition of this type of economy implies thoroughness as the «engine» for sustainable development. Furthermore, it completely covers the environmental, economic, and social perspectives.

It is intended to make a low carbon, asset-efficient and socially comprehensive economy by putting in resources for green development and improving vitality and asset efficiency (UNEP, n.d.).

The economy of Afghanistan has steadily improved in the last decade due to the return of many wealthy emigrants, the modernization of the agriculture sector, and the establishment of more trade routes with neighboring countries. This has also induced the research and programs directed at economic modernization including the implementation of green economy principles in the country (Cuiyun and Chazhong, 2020; Oral et. al., 2021)

One of the key pillars of a green economy in Afghanistan is the development of renewable energy infrastructure. The country has abundant solar and wind resources that can be harnessed to reduce reliance on fossil fuels and improve energy security. The government's Renewable Energy Policy and Action Plan, launched in 2019, outlines strategies to promote renewable energy projects and attract investments in this sector. International organizations and donors have also been supporting renewable energy initiatives in Afghanistan, further boosting the growth of this sector.

In addition to renewable energy, sustainable agriculture plays a crucial role in the development of a green economy in Afghanistan. The country has a long history of agriculture, but traditional farming practices have led to environmental degradation and food insecurity. Transitioning to sustainable agriculture practices, such as organic farming and improved water management, can help enhance food security, increase resilience to climate change, and protect the environment. Supporting small-scale farmers and promoting sustainable farming techniques are essential steps towards achieving a greener agricultural sector.

Agriculture is the backbone of Afghanistan's economy employing 43–52% of its population and contributing to one-third of the national income during 2011–2022 (Trading Economics, 2024a). It is largely based on subsistent farming and envisages the production of various crops, livestock, and horticulture, with a significant potential to drive economic development and enhance food security in the country. Although exact figures are missing, Afghanistan is known to produce a wide variety of cereals, vegetables, melons and gourds. At the same, International Financial Institutes i.e., Asian Development Bank is aiming to develop and expand horticulture and fruit production in the country (ADB, 2024). The country is also known for extensive poppy cultivation, which is seen as the main source of political instability and international condemnation of the country (Al-Jazeera, 2024).

However, despite the high potential, the sector faces numerous serious challenges including political instability, limited infrastructure, climate variability, regulatory uncertainty, and a lack of access to modern technology and markets.

Although 58% of Afghanistan's land is considered agricultural land, the area suitable for crop production comprises about 12% due to underdeveloped irrigation infrastructure and the lack of vital supply chains necessary for establishing farming and agricultural production (Trading Economics, 2024b). This includes irrigated and rain-fed areas where staple crops such as wheat, barley, rice, and maize are grown. Due to frequent droughts and the country's semi-arid climate, only a small portion of arable land is consistently productive, and water scarcity remains a major limitation. Arable land is concentrated in fertile river valleys, such as those around the Kabul, Helmand, and Amu Darya rivers, where irrigation systems support crop cultivation. The country envisages increasing exploitation of its agricultural production potential through the development of internal and riparian rivers, such as the Qosh Tepa canal on the Northern border with Uzbekistan, which is expected to increase the farming land in Northern Afghanistan by 50% (CabarAsia, 2024). This information reveals the huge potential for greening the Afghanistan economy and poses tasks in front of the Afghan society and its political leaders.

While the prospects for a green economy in Afghanistan are promising, there are also challenges that need to be addressed. Limited financial resources, lack of technical expertise, and security concerns pose obstacles to the development of renewable energy infrastructure and sustainable agriculture. Continued support from the government, international partners, and the private sector is crucial for overcoming these challenges and realizing the full potential of a green economy in Afghanistan. By investing in renewable energy projects, promoting sustainable agriculture practices, and fostering collaboration among stakeholders, Afghanistan can pave the way towards a more sustainable and environmentally friendly future.

Energy in Afghanistan is provided by hydropower, followed by fossil fuels, solar power, and imports from the neighboring countries. Approximately 35% of Afghanistan's population has access to electricity. This covers only the major cities in the country, and hence, many rural areas do not have access to 24-hour electricity (UNEP, 2011).

Afghanistan currently generates over 600 megawatts (MW) of electricity from its several hydroelectric plants and uses fossil fuel as well as solar panels. Over 670 MW more is imported from neighboring Iran, Uzbekistan, Tajikistan, and Turkmenistan (DBPedia, n.d.).

Afghanistan has enough opportunity to implement a green economy. In the country's territory, there are strategic reserves not only of lithium – the building element of modern batteries used in the e-vehicle industry and as such, the basis of a new green economy. At the same time, the country possesses abundant rare earth metals and elements necessary for the green technologies' implementation. Nowadays, Chinese entrepreneurs are the first to reach these resources, as shown in the Table 1 (atnNEWS, 2022).

Table 1. Critical minerals in Afghanistan

Mineral	Applications	Estimated Reserves
Copper	Electrical wiring, renewable energy infrastructure	60 million tons
Lithium	Batteries for electric vehicles and electronics	Undiscovered potential, potentially rivaling Bolivia
Rare Earth Elements (REEs)	Magnets, wind turbines, lasers	1.4 million tons
Iron Ore	Construction, steel production	2.2 billion tons
Gold	Jewelry, electronics	Significant, but largely unexplored

Source: own compilation.

It should be noted that over the past decade, the concept of green economy is gaining more and more popularity in the background of the growing and irreversible influence of the anthropogenic factors. As a result, this topic is widely discussed at national, regional, and global levels in all countries across the world.

The history of geological discoveries in Afghanistan refers to the materials of the Soviet geological exploration of the 1980s, found in 2004 by Americans in the national archive.

Based on them, the US Geological Survey first carried out a two-dimensional gravimetric study from an airplane, and after the first promising results a three-dimensional complex one was conducted.

The results were “gathering dust” in the American archives until 2009, a Pentagon group of business projects in the controlled territories arrived from Iraq to Afghanistan. After that, field studies were carried out, and the specified report was compiled (The Washington Post, 2023).

The most significant discovery is probably the world’s largest lithium reserves in the soda salt marshes of Ghazni and neighboring provinces. They may be even more significant than the reserves of Bolivia, which is considered as the world’s largest lithium reserve.

The presence of lithium reserves and rare earth metals in Afghanistan presents significant opportunities for the development of a green economy in the country. These resources are essential to produce electric vehicles, renewable energy technologies, and other green technologies, making them crucial for the transition towards sustainable and environmentally friendly practices.

1. CRITICAL MINERALS AS A SOURCE OF GREEN ECONOMY DEVELOPMENT

Here are some key reasons why the presence of lithium reserves and rare earth metals in Afghanistan can drive the development of a green economy:

- Strategic Resources for Green Technologies:

  Lithium, rare earth metals, and other elements found in Afghanistan are critical components in the manufacturing of batteries, solar panels, wind turbines, and electric vehicles. As the global demand for these green technologies continues to rise, the availability of these resources in Afghanistan positions the country as a potential hub for sustainable energy production and in-novation.
- Economic Growth and Job Creation:

  The extraction and processing of lithium and rare earth metals can create new economic opportunities and employment prospects in Afghanistan. Developing a green economy centered around these resources can stimulate economic growth, diversify the country`s industrial base, and generate revenue through exports of value-added products.
- Energy Security and Independence:

  By harnessing its lithium reserves and rare earth metals to produce renewable energy technologies, Afghanistan can enhance its energy security and reduce dependence on fossil fuels. Investing in green technologies powered by domestically sourced resources can help the country achieve greater energy independence and resilience to external energy shocks.

- Environmental Benefits:
  Transitioning to a green economy based on renewable energy technologies can lead to significant environmental benefits, including reduced greenhouse gas emissions, improved air quality, and protection of natural ecosystems. By leveraging its lithium reserves and rare earth metals for sustainable development, Afghanistan can contribute to global efforts to combat climate change and preserve the environment.
- Technological Innovation and Collaboration:
  The presence of lithium reserves and rare earth metals in Afghanistan offers opportunities for technological innovation, research, and collaboration with international partners in the green technology sector (Shroder, 2015).

By fostering partnerships with industry leaders and academic institutions, Afghanistan can accelerate the adoption of green technologies and position itself as a player in the global green economy.

The existence of lithium reserves and rare earth metals in Afghanistan presents significant opportunities for the development of a green economy that is based on sustainable energy production, economic growth, energy security, environmental protection, and technological innovation.

By capitalizing on these resources and promoting green economic development strategies, Afghanistan can pave the way towards a more sustainable and prosperous future.

However, the authors raise valid points about the potential negative impacts of mineral extraction and processing, as well as the challenges associated with transitioning to a green economy. It is important to consider the social, environmental, and economic implications of resource extraction and ensure that development efforts are conducted responsibly and sustainably.

Indeed, the extraction of valuable minerals can have adverse effects on workers, communities, and ecosystems if not managed properly. It is crucial for Afghanistan to establish robust regulatory frameworks, environmental safeguards, and social responsibility measures to mitigate these risks and ensure that resource extraction activities do not harm local populations or the environment.

Furthermore, transitioning to a green economy requires significant investments in renewable energy infrastructure, technology development, and workforce training. The shift towards sustainable practices may require higher upfront costs and a more labor-intensive approach compared to traditional economic activities. This underscores the importance of strategic planning, capacity building, and international cooperation to support Afghanistan in its efforts to pursue a green development path.

Given the current challenges facing Afghanistan, including political instability, security concerns, and economic hardships, the road to developing a green economy will be challenging.

Addressing these complex issues will require a multi-faceted approach that involves government leadership, private sector engagement, civil society participation, and international support.

While the presence of valuable mineral resources in Afghanistan presents opportunities for economic development, it is essential to approach resource utilization with caution and consider the long-term implications for sustainable growth. By prioritizing responsible resource management, environmental protection, social equity, and green technology innovation, Afghanistan can work towards a more sustainable and inclusive economic future.

In addition, huge reserves of high-quality iron ores (2.2 billion tons), 60 million tons of copper reserves (more than half of Russian reserves) are discovered. Moreover, the location of neodymium, cobalt (used for magnets, special alloys), niobium (used in supercapacitors, superconductors), and other rare earth metals has been confirmed. All of this is of crucial importance to the modern world economy, especially during the current age of transition to green economy (BBC News, 2021).

According to the Washington Post, in a 2010 memo, the Pentagon's Task Force for Business and Stability Operations, which examined Afghanistan's development potential, called the country the "Saudi Arabia of Lithium".

A year later, the U.S. Geological Survey published a map showing the location of major deposits and highlighted the scale of the underground wealth, saying Afghanistan "could be considered as the world's recognized future main source of lithium" (Reuters, 2023).

If China gains control of Afghanistan's pristine lithium and rare earth reserves, it will be a crucial victory in the battle for resources with Europe and the United States.

In 2019, the United States imported 80% of rare earth metals from China. This figure is even higher for the European Union – 98% (The Washington Post, 2023).

There is a collective opinion that Afghanistan's new government (in the example of China) in the future should find balance between future economic growth and environmental protection. Also, they should remember that protecting productivity and improving the environment also equates to developing productivity.

It is expected that with further economic development and improvement of the welfare, the Afghan people will be more conscientious in promoting green, year – round, and low-carbon development.

Like any responsible government, the current Afghan government must fully understand the importance of enforcing ecological "red lines".

With the help of the world community, this country can vigorously develop a circular economy to reduce waste and resource consumption, reuse resources, and recycle waste in production, distribution, and consumption.

2. THE CURRENT SITUATION AND PATHS OF ENERGY SECTOR DEVELOPMENT

The energy sector in Afghanistan faces numerous challenges, including limited access to electricity, reliance on imported energy sources, and vulnerability to supply disruptions. Developing the energy sector in the country is crucial for improving living standards, promoting economic growth, and enhancing energy security.

Furthermore, the transition to a green economy presents opportunities to address these challenges while promoting sustainable development and environmental protection.

One key strategy for developing the energy sector in Afghanistan is to invest in renewable energy sources, such as solar, wind, and hydropower. These sources can provide clean, reliable, and affordable energy while reducing dependence on fossil fuels and mitigating greenhouse gas emissions. By harnessing renewable energy resources, Afghanistan can diversify its energy mix, enhance energy security, and promote environmental sustainability.

In addition to expanding renewable energy capacity, improving energy efficiency is another important aspect of developing the energy sector in Afghanistan. Implementing energy-efficient technologies and practices can help reduce energy consumption, lower costs, and minimize environmental impact. Investing in energy efficiency measures in buildings, transportation, and industry can contribute to a more sustainable and resilient energy system.

Furthermore, enhancing the resilience of the energy infrastructure is essential for ensuring reliable and secure energy supply in Afghanistan. Building robust transmission and distribution networks, upgrading aging infrastructure, and integrating smart grid technologies can help mitigate risks associated with power outages, grid instability, and natural disasters. Strengthening the resilience of the energy sector can support economic development, enhance energy access, and foster sustainable growth.

The development of the energy sector in Afghanistan is intricately linked to the prospects for transitioning to a green economy. By investing in renewable energy, promoting energy efficiency, and enhancing infrastructure resilience, Afghanistan can lay the foundation for a more sustainable and inclusive economic future. A green economy approach can create new opportunities for job creation, innovation, and investment while addressing social and environmental challenges.

By aligning energy sector development with green economy principles, Afghanistan can unlock the potential for sustainable growth, improve quality of life for its citizens, and contribute to global efforts to combat climate change.

The prospects for the development of a green economy in Afghanistan are significant, given the country's abundant renewable energy resources and the growing global focus on sustainability. Here are some key factors that indicate the presence of prospects for the development of a green economy in Afghanistan:

- Renewable Energy Potential:
  Afghanistan has ample solar, wind, and hydro power resources that can be harnessed to meet the country`s energy needs sustainably. The government's commitment to promoting renewable energy projects, as outlined in the Renewable Energy Policy and Action Plan, indicates a strong foundation for the development of a green economy in Afghanistan.
- International Support:
  International organizations and donors have been actively supporting renewable energy initiatives in Afghanistan, providing financial assistance, technical expertise, and capacity building. This external support demonstrates recognition of Afghanistan's potential for green economic development and opens up opportunities for collaboration and investment.
- Sustainable Agriculture Initiatives:
  The transition to sustainable agriculture practices in Afghanistan presents another avenue for green economic development. By promoting organic farming, improving water management, and supporting small-scale farmers, the country can enhance food security, protect natural resources, and create employment opportunities in the agricultural sector.
- Government Commitment:
  The Afghan government has shown a willingness to prioritize environmental sustainability and green economic development through policy initiatives and strategic planning. By continuing to invest in renewable energy infrastructure, promote sustainable agriculture, and create a conducive regulatory environment, the government can further drive the transition towards a green economy.
- Economic Diversification:
  Diversifying the economy through the development of green industries can help reduce dependence on fossil fuels, mitigate climate change impacts, and create new job opportunities in emerging sectors. The shift towards a green economy in Afghanistan has the potential to spur

innovation, attract investments, and drive economic growth in a sustainable manner.

In this way, the presence of abundant renewable energy resources, international support, government commitment, sustainable agriculture initiatives, and the potential for economic diversification all indicate strong prospects for the development of a green economy in Afghanistan. By capitalizing on these opportunities and addressing challenges through collaborative efforts, Afghanistan can pave the way towards a more sustainable and environmentally friendly future.

Notwithstanding with above, Afghanistan is an underdeveloped country with vast renewable and nonrenewable energy resources. Therefore, it has one of the least developed energy generation, transmission and distribution infrastructures. The energy production and consumption rates are low (Chart 1).

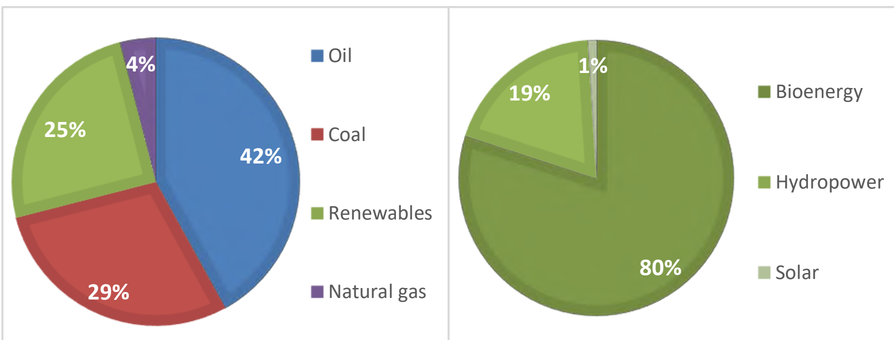

Chart 1. Total Primary Energy Supply in 2021

Source: IRENA (2021).

The country is exploring the potential of deploying modern sources of energy under the auspices of the international financial institutions and donor organizations. The authorities have been chasing a modest and fragmented sustainable energy policy until 2020, however, the generation capacities declined after 2020 (Table 2).

Table 2. Generation capacity and its change in Afghanistan during 2020

Capacity in 2020	MW	%	Capacity change (%) 2015-2020	Capacity change (%) 2019-2020
Non-renewable	277	43	17	0
Renewable	364	57	20	0.2
Hydro/marine	333	52	17	0
Solar	31	5	61	1.8
Wind	0	0	300	0
Bioenergy	0	0		0
Geothermal	0	0		0
Total	641	100	19	-0.1

Source: IRENA (2021).

No new generation capacity was added in 2020. In contrast, the next generation capacity change was +17MW from 2015 till 2020. The figures also indicate that 300MW wind power generation capacity vanished shortly after being commissioned during 2015–2020, not contributing to the overall generation of electricity. Such incidents send negative signals to the local and international stakeholders who are considering investing in renewable power generation in the country (Drishtiias, 2021).

It is believed that the country possesses a significant bioenergy potential. However, the most recent total generation and primary energy consumption capacity figures reveal no contribution from the bioenergy sources.

Along with the biomass sources, off-grid and distributed solar-PV systems have the highest potential in eradicating energy poverty in Afghanistan (IRENA, 2020).

Due to endowment of enormous hydraulic power, solar biomass, wind and geothermal resources, Afghanistan possesses all the necessary conditions to meet the Sustainable Development Goal (SDG) #7 on creating cheap and clean energy access until 2035 (IRENA, 2020).

Among the 20 largest partner countries in foreign economic activity, Uzbekistan has an active foreign trade balance (export exceeds are more than import) with four countries: Afghanistan, Kyrgyzstan, Tajikistan, and Turkey. The remaining 16 countries maintain a passive balance of foreign trade turnover.

That is, Afghanistan is one of the largest sales markets for Uzbekistan. In particular, in 2020, Uzbek export to this country amounted to US$ 776.7 million, while import was 334 times less – only $ 2.3 million. In January–June of 2021, the figures were US$ 350 million and US$ 1.4 million, respectively (IRENA, 2020).

3. OPPORTUNITIES FOR COOPERATION WITH UZBEKISTAN

Opportunities for cooperation with Uzbekistan in the energy sector present a promising avenue for promoting sustainable development and advancing the green economy in Afghanistan. Uzbekistan has made significant strides in developing renewable energy sources, such as solar and wind power, and has also shown a commitment to enhancing energy efficiency and reducing greenhouse gas emissions.

Collaborating with Uzbekistan on energy projects can provide Afghanistan with valuable expertise, technology, and investment opportunities to accelerate the transition to a green economy.

One potential area for collaboration is the development of renewable energy projects, such as solar-PV and wind farms in Afghanistan. Uzbekistan has experience in implementing large-scale renewable energy projects and can share best practices, technical know-how, and financing options with Afghanistan. By partnering with Uzbekistan on renewable energy initiatives, Afghanistan can expand its clean energy capacity, reduce reliance on fossil fuels, and contribute to environmental sustainability.

Another opportunity for cooperation is in energy efficiency. Uzbekistan has implemented energy efficiency programs in various sectors, including residential and public buildings, industry, and transportation, to reduce energy consumption and lower carbon emissions. By sharing knowledge and experiences in energy efficiency measures, Uzbekistan can support Afghanistan in improving energy efficiency standards, promoting sustainable practices, and reducing energy costs.

Furthermore, collaboration with Uzbekistan on enhancing energy infrastructure resilience can help strengthen the reliability and security of the energy sector in Afghanistan.

Uzbekistan has invested in upgrading its energy infrastructure, including transmission and distribution networks, to enhance resilience to natural disasters and other disruptions. By working together on infrastructure development and modernization, Afghanistan can improve energy access, promote economic growth, and build a more resilient energy system.

Establishing cooperation with Uzbekistan in the energy sector can also create opportunities for joint research and innovation in green technologies. Collaborative projects on renewable energy research, technology transfer, and capacity building can foster knowledge exchange, skills development, and technology adoption in Afghanistan. By leveraging Uzbekistan's expertise and resources, Afghanistan can accelerate the adoption of green technologies, drive innovation, and build a competitive advantage in the green economy.

Cooperation with Uzbekistan in the energy sector offers a range of benefits for Afghanistan's development of the green economy. By tapping into

Uzbekistan's experience, resources, and expertise, Afghanistan can advance its clean energy goals, improve energy efficiency, enhance infrastructure resilience, and promote sustainable growth. Establishing partnerships with Uzbekistan can create a win-win situation for both countries, leading to mutual benefits and shared progress towards a more sustainable and inclusive future.

Firstly, the current Afghan government should outline what it means for Afghanistan to strengthen its cooperation with Uzbekistan to "move towards new opportunities" by focusing on green recovery and bringing all stakeholders together.

Then, offer the Afghan leadership to work in this direction, including acting as a coordinator or intermediary, relying on honest business and management principles.

Secondly, under the auspices of development cooperation and donor organizations, a platform to discuss policies on renewable energy, energy efficiency, climate change mitigation, environmental protection, and other aspects, including Afghanistan's transition to a green economy should be created. It will contribute to the further development of society and the economy's resilience and reduce the pressure on the environment.

Finally, formulate priority areas and practical actions to support the Afghan government for green economic recovery after the COVID-19 pandemic to gain more weight in competition for those resources.

For families living in rural Afghanistan, there is no time to waste. Climate change is a genuine and current threat. Moreover, despite being one of the most vulnerable countries in the world to climate change, Afghanistan is one of the least equipped to deal with the consequences: increasing instances of natural disasters and extreme weather, damaging the natural resource base, and putting families' lives at risk.

With the US withdrawal from Afghanistan and the strengthening international sanctions against the Afghan economy, situation in Afghanistan has become more complicated.

For this situation to improve, internal and external legitimization of the current government is required.

However, the Taliban are still delisted. According to M. Kanischev, head of the ANSELM (US) energy efficiency and emission reduction research project, energy transition to the "green" path will require a sharp increase in the production of iron, copper, aluminum, nickel, lithium, cobalt, platinum, and silver, as well as rare earth metals (Ulyev et. al., 2021).

Their production growth can lead to the destruction of soil and rocks.

For example, lithium – one of the most important metals for renewable energy – is mined in more than half of cases in areas where the population already has problems with water supply (Bolivia, Argentina, Australia, Chile). If the extraction is even more intensive, the reservoir pressure will increase.

A striking example is the Atacama Desert in Chile, which is growing, and the oases within it are disappearing. Lithium is mined there, and when it is extracted from the bowels, vast volumes of water are pumped out, which dries up the soil and deprives the nutrition of the local animals. A similar scenario is developing in Bolivia, China, Australia, and other regions where this metal is mined.

Another essential element for batteries is cobalt. The problem with this element is not of an ecological but of a socio-ecological nature.

More than 60% of the world`s cobalt production comes from the Democratic Republic of the Congo (Transport and Environment, 2019). It is mined without violating safety standards, although the metal and its compounds are toxic. Mining is done using forced labor of prisoners and often children.

Ethics and economics do not interact well, but energy transition was not originally based on economic principles, so it is impossible to ignore this.

It is important to acknowledge the environmental and socio-economic challenges associated with the extraction of minerals like lithium and other elements, particularly in regions like the Republic of Congo where mining activities can have detrimental impacts on ecosystems, local communities, and human rights. The inclusion of information on the dangers of lithium mining and other elements serves to highlight the complexities and trade-offs involved in the transition to a green economy, as well as the need for responsible and sustainable practices throughout the supply chain.

Even though minerals like lithium are essential for the development of renewable energy technologies, such as batteries for electric vehicles and energy storage systems, their extraction can have negative consequences if not managed properly. Issues such as water pollution, deforestation, land degradation, and social conflicts are common in mining operations, especially in developing countries where regulatory frameworks and enforcement mechanisms may be weaker.

It is crucial for countries like Afghanistan to consider these challenges and work towards mitigating the environmental and social impacts of mineral extraction.

This may involve implementing strict environmental regulations, promoting transparency and accountability in the mining sector, engaging with local communities and indigenous groups, and exploring alternative mining technologies that minimize harm to the environment.

While environmentally friendly mining technologies for minerals like lithium can be costly and technically challenging, investing in sustainable practices can yield long-term benefits by reducing environmental damage, enhancing social license to operate, and attracting responsible investors.

Collaboration with international partners, such as Uzbekistan or other countries with experience in sustainable mining practices, can also provide valuable insights and support for Afghanistan's efforts to develop a green economy.

Whereas the extraction of minerals like lithium presents environmental and socio-economic challenges, it is essential to address these issues in a holistic manner to ensure the sustainable development of the green economy.

By acknowledging the risks associated with mineral extraction and working towards responsible practices, countries like Afghanistan can harness the potential of these resources while safeguarding the environment and promoting social well-being.

We can visualize the scale of the growth in demand for lithium or cobalt using an example of the car market.

Now there are 1.3 billion cars in the world. Among them, there are only 11.2 million electric vehicles. It is projected that there will be 2.5 billion cars globally by 2050. Let us assume that all the growth will come from electric cars.

One battery for a conventional electric car will need at least 10 kilograms of lithium (1.5–2 times more for Tesla) and 11 kilograms of cobalt. On average, over 20 years, to provide 1.2 billion electric cars with batteries, the annual production of these metals should increase by 600 and 660 thousand tons, respectively (Luong et. al., 2022). Lithium extraction is at most 100 100 000 tons per year, and cobalt is 140 thousand tons.

So, there is a resource base: 80 million tons of lithium, cobalt – 25 million tons, and it is likely to grow, but it will be hardly possible to increase the production of these metals quickly. Furthermore, even more, to make their products safe for the environment.

Moreover, the figures given do not consider the growth in demand for lithium and cobalt for mobile technology and, as well as for solar and wind power plants.

According to M. Astapkovich, Senior Consultant of the Deloitte CIS Sustainability Services Group, the methodology for assessing the environmental impact from the disposal of components for renewable energy sources and batteries for electric vehicles is still being formed (Deloitte, 2024).

At the same time, scientists are actively developing methods for utilizing renewable energy components that have already been built in different parts of the world. He named waste blades from wind turbines and used lithium-ion batteries the most harmful to the environment.

There is information that solar panels create 300 times more toxic waste per unit of energy than nuclear power plants as an example (ibid). Let us suppose over the next 25 years, solar and nuclear power plants produce the same amount of energy, and waste accumulates on two football fields. In that case, nuclear waste will reach the height of Tower of Pisa (52 meters) and solar – the height of two Everest (16 kilometers).

CONCLUSIONS

Thus, the prospects for a critical mineral extraction industry in Afghanistan are promising, as the country has abundant renewable energy resources. Developing economy in Afghanistan could help reduce the country's dependence on fossil fuels, improve energy security, eradicate energy, fuel poverty, and create new job opportunities in the renewable energy sector. One key area for development is the expansion of renewable energy infrastructure, including solar and wind power projects.

The government has already taken steps to promote renewable energy, such as launching the Renewable Energy Policy and Action Plan in 2019. In addition, international organizations and donors have been supporting renewable energy projects in Afghanistan.

Another area with potential for growth is sustainable agriculture. Afghanistan has a long history of agriculture, and transitioning to more sustainable farming practices could help improve food security, increase resilience to climate change, and protect the environment. This could involve promoting organic farming, improving water management, and supporting small-scale farmers.

The development of a critical mineral extraction industry in Afghanistan holds great promise for addressing environmental challenges, reducing dependence on fossil fuels, and creating new economic opportunities.

By harnessing its abundant renewable energy resources and promoting sustainable agriculture practices, Afghanistan can achieve sustainable development while protecting the environment. Continued support from the government, international partners, and the private sector is essential for driving forward the transition towards a green economy in Afghanistan. With concerted efforts and strategic investments, Afghanistan can unlock the full potential of its green economy and pave the way for a more sustainable future.

The government`s efforts to promote renewable energy and sustainable practices, as well as the support from international partners and the private sector, are crucial for realizing the full potential of a green economy in Afghanistan.

It is essential to conduct sectoral review of the sectors of the national economy with a special emphasis on agricultural, power and service sectors. Another priority direction could be the exploration of the human capacity building sector with an aim of facilitating green-economy related training and skill-building.

Overall, establishing practical cooperation in Afghanistan and conducting a coordinated dialogue with the authorities of this country is necessary. Otherwise, the country will not be able to get out of the sectors of the illegal economy and will face an expansion of drug and weapons trafficking.

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TRANSPARENCY OF THE FEDERAL RESERVE, A FORCE OF STABILITY OR VOLATILITY IN FINANCIAL MARKETS POST 2008 AND PRIOR TO COVID-19?

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TRANSPARENCY OF THE FEDERAL RESERVE, A FORCE OF STABILITY OR VOLATILITY IN FINANCIAL MARKETS POST 2008 AND PRIOR TO COVID-19?

ABSTRACT

The purpose of this article is to analyze how the Central Bank of the United States, the Federal Reserve's decision to provide greater transparency after the Financial Crisis of 2008 impacted the volatility in financial markets. This study uses five Chicago Board Options Exchange Volatility Indices as a proxy for overall market volatility and attempts to capture their deviances from expected returns. The event dates identified are when the United States Federal Reserve met and released their "summary of economic predictions".
The methodology deployed uses an event study framework on daily financial market data from the Federal Open Market Committee (FOMC) meeting days, to determine how an increased availability of information impacted financial markets in the period of January 2008 – January 2020.
The results of the empirical analysis do not reveal abnormal returns pre or post the event dates. This finding suggests that the FOMC announcements did not lead to significant abnormal returns of the analyzed assets.
Keywords: Federal Open Market Committee, transparency, Central Bank, monetary policy, financial markets, volatility, market efficiency.
JEL Class: E44, E52, E58, D78, G14.

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INTRODUCTION

In response to the 2008 financial crisis, the United States Federal Reserve increased transparency regarding its decisions on how monetary policy is conducted. In 2011, the Chairman of the Federal Reserve began to hold press briefings four times a year to present the Federal Open Market Committee's (FOMC) current economic projections and to provide additional context for policy decisions. These projections include forecasts for economic growth, unemployment, and inflation. Using daily financial market data from the FOMC meeting days, this research analyzes the movement in various Chicago Board Options Exchange – Exchange Traded Funds (CBOE ETFs) to determine how this increased availability of information impacts financial markets prior to March 2020. This study hypothesizes that the Federal Reserve's increased transparency following the 2008 Financial Crisis, significantly impacts financial markets, as measured by deviations in the Chicago Board Options Exchange Volatility Indices, around the FOMC meeting dates.

This research is significant for both the academic and the professional (industry) audience. Given the volatility in the equity markets and criticism of the Federal Reserve's plan to return a "normal rate" environment post the Great Recession, there is an increased focus on how monetary policy will be conducted. The data points that are provided for each of the years in the forecasts are: the percent change in gross domestic product adjusted for inflation, the unemployment rate, the percent change in the price index for personal consumption expenditures, and the percent change in the price index for PCE excluding food and energy. Beginning in January 2012, the economic projections also include information about policymakers' projections of appropriate monetary policy. These projections support the Federal Reserve's statutory mandate to promote maximum employment and stable prices. This immediate dissemination of information from the Federal Reserve to the public impacts equity markets. This movement can positively or negatively impact investors. One way market participants can gauge investors' fear or concern over these macroeconomic indicators is through the Standard & Poor's stock market index (S&P 500 index). Specifically, the CBOE VIX Volatility Index looks at the 30-day future options to measure how volatile investors believe the market will be. The goal of this research is to further understand how this level of openness to enhance transparency by the Federal Reserve has impacted financial markets.

This study intentionally concluded before the COVID-19 pandemic due to the financial uncertainty that existed during that time. The period of the COVID-19 crisis was characterized by an extreme degree of uncertainty impacting all economies around the globe causing a high level of volatility. Several studies have utilized the event study methodology to examine the COVID-19 pandemic, and the consequent behavior of financial markets (Chevallier, 2020; Cheng, 2020; Bretscher et al., 2020). Findings include that major crisis or risk factors cause rapid and massive financial market reactions (Rai et al., 2020). This current study is structured to eliminate the massive reactions fueled by the COVID-19 crisis on US financial markets, the period analyzed concludes prior to the start of the COVID-19 pandemic.

This paper is organized in the following manner: section one is a literature review, section two discusses the data and methodology, section three is the empirical results and section four presents the conclusion, including other issues to be considered for further research.

1. LITERATURE REVIEW

The specific topic of the Federal Reserve’s transparency has been explored in recent academic literature. Transparency in central banking, particularly by the United States Federal Reserve, has been a focal point of analysis due to its significant implications for financial markets and economic stability both domestically and internationally.

Bauer et al. (2022) contribute to this discourse by developing a novel measure of policy uncertainty based on derivative prices. Their research offers a new lens through which to assess the impact of Federal Reserve announcements and policies. By using derivative prices, Bauer et al. are able to capture market expectations and reactions with high precision, making this measure particularly useful for event studies. Their findings suggest that this new measure can effectively gauge the level of uncertainty and its subsequent impact on market behavior, providing deeper insights into the relationship between Federal Reserve transparency and market stability.

Wang (2019) investigates the effects of Quantitative Easing (QE) announcements on mortgage rates. Wang's study highlights the temporal dynamics of these effects, finding that while short-run impacts are significant, the delayed effects are less pronounced but persist over time. This research challenges previous literature that may have overestimated the overall impact of QE on interest rates. Wang's findings emphasize the importance of considering both immediate and lagged responses in assessing the effectiveness of monetary policy interventions.

In an earlier study, Makenzie et al. (2004) also explore the use of the event study methodology, but with a focus on commodity prices. Their research provides a methodological framework that has been widely adopted in subsequent studies. By analyzing the impact of Federal Reserve announcements on commodity prices, Makenzie et al. offer valuable insights into how different asset classes respond to monetary policy changes. Their work underscores the broad applicability of event study methodologies in evaluating the effects of central bank transparency.

Additional research by Gürkaynak et al. (2005) examines the market's reaction to Federal Reserve statements, emphasizing the importance of clear and transparent communication in managing market expectations. They find that even small changes in wording can have significant effects on asset prices, highlighting the critical role of language and clarity in Federal Reserve communications.

Similarly, Ehrmann and Fratzscher (2007) analyze the global transmission of U.S. monetary policy, demonstrating that transparent and predictable policies help stabilize international markets. Their findings suggest that Federal Reserve transparency not only impacts domestic markets but also has significant global implications, reinforcing the need for clear and consistent communication strategies.

Blinder et al. (2008) provide a comprehensive review of central bank communication, arguing that greater transparency leads to more effective monetary policy by reducing uncertainty and enhancing market participants' understanding of policy intentions. Their work underscores the importance of transparency in achieving desired economic outcomes and improving overall financial stability.

In a recent study, Acosta (2023) examined the role of Federal Reserve transparency as a conduit to make monetary policies more effective. He studied the Federal Reserve Bank's communication transparency by measuring the extent of the similarities between the minutes and transcripts of each FOMC meeting. Acosta's evidence found substantial discrepancies between the minutes and transcript documents suggesting these inconsistencies were not generated intentionally but rather as a result of the difficult task writing of them presents. The study found that the level of minute-transcript similarities fluctuated over the last 40 years with the FOMC meetings transparency increasing over the years. The evidence suggested that high transparency allows the public to better understand implications of monetary policy communications enhancing efficacy of monetary policy.

Boguth et al. (2019) examined scheduled FOMC announcements beginning with the first Press Conference (PC) in April 2011 till September 2017 (27 out of 52 of these announcements were followed by a PC) and derivatives market data to determine whether the hosting of PCs has bearing on financial markets. The authors demonstrated that scheduled PCs substantially impacted market behavior around the FOMC meeting days. The study found that in absence of PCs, the VIX stayed fundamentally the same, while on the meeting days when PCs were held, the VIX declined by 3%. The findings denoted that the markets' perceived uncertainty coincides with the degree of information disclosed during the FOMC announcements suggesting that investors expect more relevant changes to monetary policy on FOMC announcement days with PCs. To level out the perception of all FOMC announcements and increase transparency, the authors recommended holding PCs after every meeting. On June 13, 2018, the Fed announced the change to host PCs after every FOMC meeting which overlapped with the time of the publication of this work (Boguth et al., 2019).

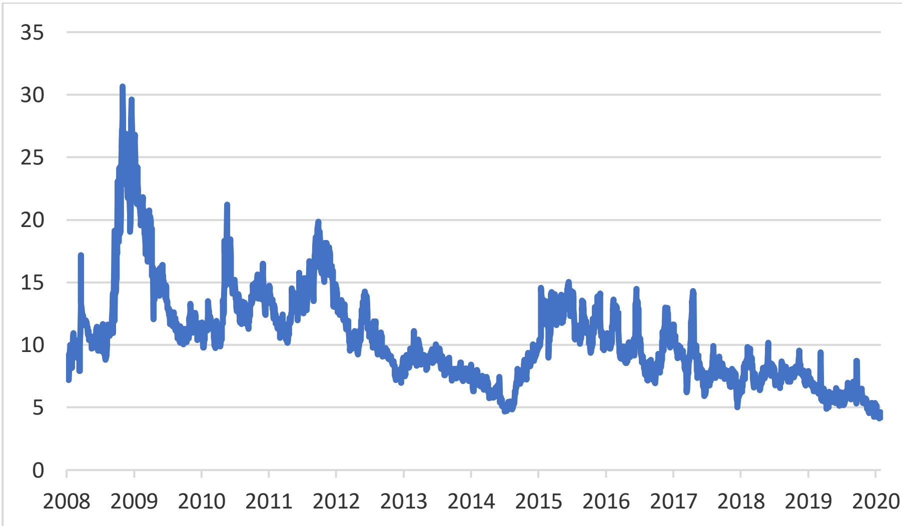
Lubys and Panda (2021) also utilized event study methodology to examine the effects of 2008 to 2016 monetary policies of the Federal Reserve Bank and the European Central Bank unconventional policy announcements, their impact on emerging stock markets and magnitude of similarities. The analysis suggested presence of abnormal returns, however, no significant patterns emerged.

Overall, these studies collectively enhance our understanding of Federal Reserve transparency and its multifaceted impacts on financial markets. The development of novel measures, such as those based on derivative prices, and the nuanced analysis of temporal effects, as seen in Wang's work, are critical advancements in this field. The methodological approaches established by earlier works like Makenzie et al. continue to provide a robust foundation for ongoing research in central bank communication and policy impact assessment.

2. DATA AND METHODOLOGY

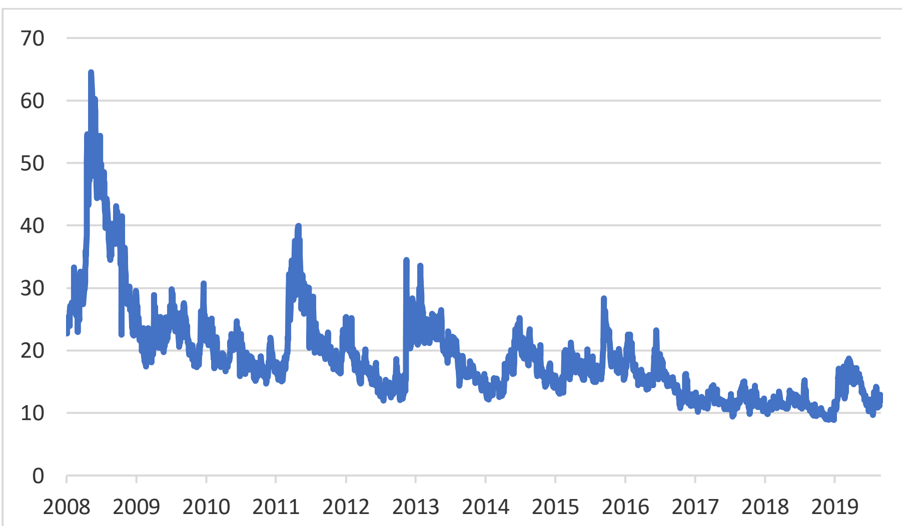
The data for this study covers the period of January 2008 – January 2020, retrieved from the Federal Reserve Bank of Saint Louis (FRED). The event dates are the quarterly dates from the FOMC meetings where the Summary of Economic Predictions (SEP) was released (see Appendix). The objective is to measure the movement in the three exchange traded funds (ETFs) and the two volatility indices. The ETF's analyzed are the CBOE Crude Oil ETF Volatility Index, CBOE Gold ETF Volatility Index, and the CBOE Euro Currency ETF Volatility Index. To monitor overall volatility, we use the CBOE VIX Volatility Index and the CBOE NASDAQ 100 Volatility Index (Figures 1–5).

Figure 1. CBOE Eurocurrency ETF Volatility Index



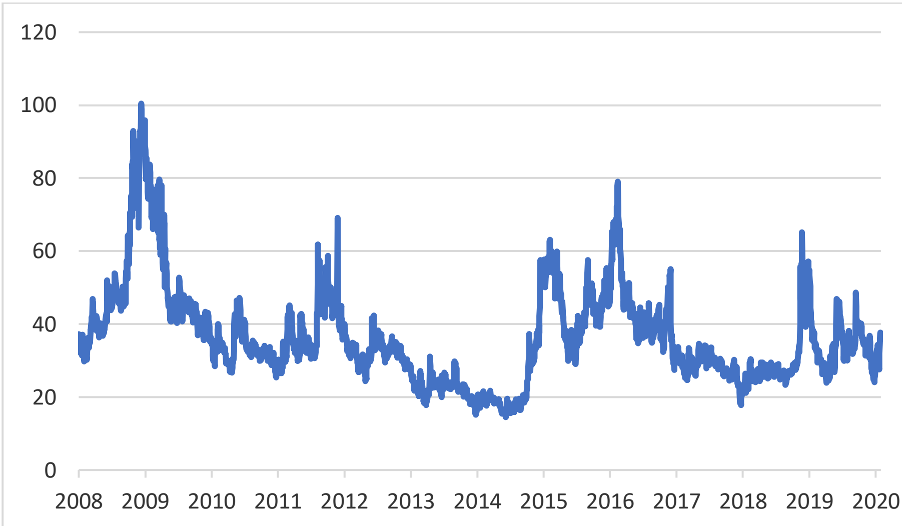
Source: own study based on data from (www1).

Figure 2. CBOE Gold ETF Volatility Index



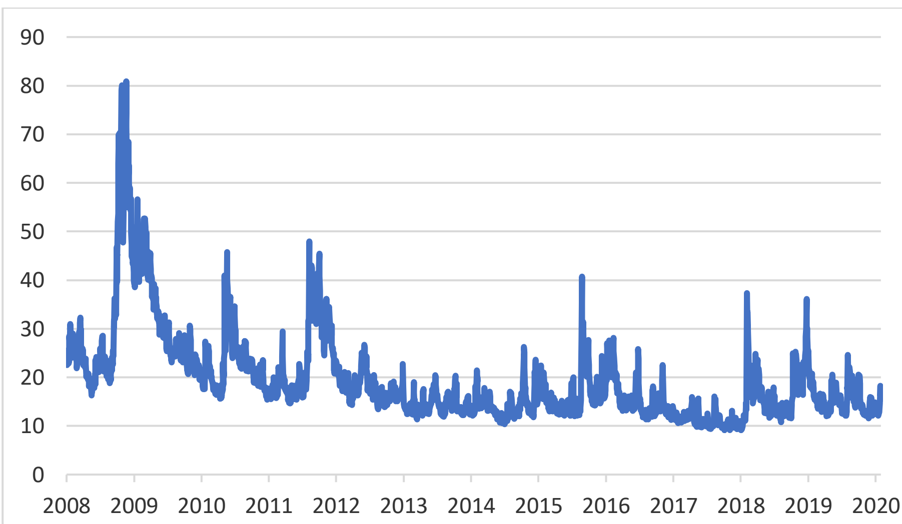
Source: own study based on data from (www2).

Figure 3. CBOE Crude Oil ETF Volatility Index



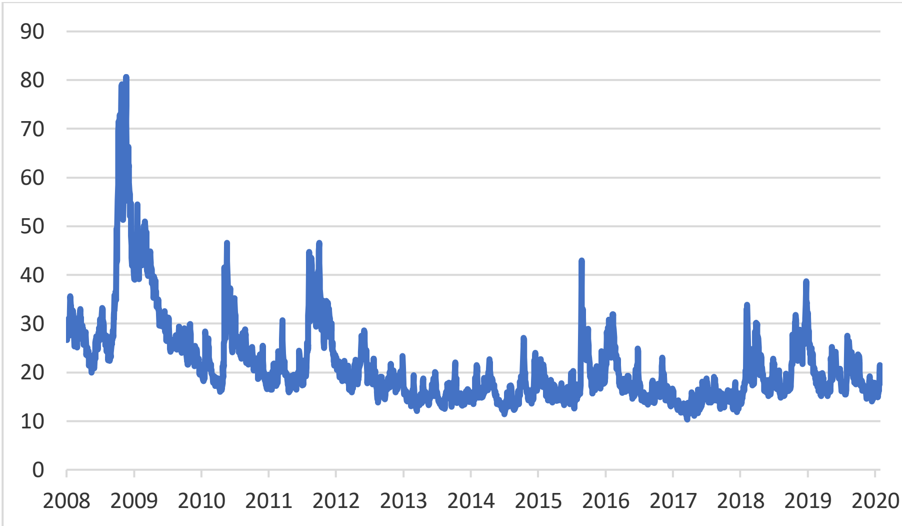
Source: own study based on data from (www3).

Figure 4. CBOE Volatility VIX Index



Source: own study based on data from (www4).

Figure 5. CBOE NASDAQ-100 Volatility Index



Source: own study based on data from (www5).

The variables selected for this study include measures of volatility in the commodity markets, published by the Chicago Board Options Exchange. Calculated as a weighted average of put and call options on the S&P 500 Index, the VIX (Figure 4) is considered as a forecasting indicator of the S&P 500 Index's volatility over a one-month period. VIX is also referred to as the "fear index". Like all indexes, the VIX is not something you can buy directly. Moreover, unlike a stock index such as the S&P 500, you cannot even buy a basket of underlying components to mimic the VIX. Instead, the only way investors can access the VIX is through futures contracts or ETFs (exchange traded funds). While the actual calculations that go into VIX are quite complex, reading the index is rather simple. The number represents the expected percentage range of movement of the S&P 500 – either up or down – over the next year, with a 68% confidence interval (one "standard deviation" in statistics terms). For example, if the VIX is 20, that means: "based on options data for the next 30 days, traders are 68% confident that the S&P 500 will remain within 20% of its present level over the next year".

The CBOE Crude Oil ETF Volatility Index (OVX – Figure 3) measures the market's expectation of 30-day volatility of crude oil prices by analyzing options on the United States Oil Fund (USO). It is often referred to as the "Oil VIX" and reflects the anticipated fluctuations in the price of crude oil, a critical global commodity.

The CBOE Gold ETF Volatility Index (GVZ – Figure 2) measures the market's expectation of 30-day volatility of gold prices by analyzing options on the SPDR Gold Trust (GLD). Known as the "Gold VIX" it provides insights into the expected volatility of gold, which is widely used as a safe-haven asset.

The CBOE Eurocurrency ETF Volatility Index (EVZ – Figure 1) measures the market's expectation of 30-day volatility of the Euro currency by analyzing options on the Currency Shares Euro Trust (FXE). This index offers a view of expected volatility in the Euro, reflecting market sentiment about economic and political events in the Eurozone.

The CBOE NASDAQ-100 Volatility Index (VXN – Figure 5) measures the market's expectation of 30-day volatility for the NASDAQ-100 index, which includes 100 of the largest non-financial companies listed on the NASDAQ stock exchange. Similar to the VIX, it is derived from options prices on the NASDAQ-100 index and indicates the expected volatility of technology-heavy stocks.

3. EMPIRICAL RESULTS

Using the event study methodology, it is determined that there were no abnormal returns during the event period. In stock market trading, abnormal returns are the differences between a single stock or portfolio's performance and the expected return over a set period. Abnormal returns are used to determine a security's or portfolio's risk-adjusted performance when related to the overall market or a particular index. Abnormal returns can be either positive or negative.

The event study methodology is a widely used approach in finance to assess the impact of specific events on stock prices. Among many other studies, Soper and Sywak (2019) used the event study methodology to analyze the impact of federal minimum wage change announcement on the stock market returns examining abnormal returns of publicly traded major employers. By comparing the actual returns during the event period to the expected returns, researchers can isolate the effect of the event from other market movements. Expected returns are typically estimated using a market model, which relates the returns of the security to the returns of a market index.

Contrary to expectations, this empirical analysis using the event study methodology does not reveal abnormal returns pre or post the event dates. This finding suggests that the Federal Open Market Committee (FOMC) announcements did not lead to significant deviations from the expected returns of the stocks or portfolios under study. One possible explanation for this result is market efficiency, which posits that financial markets quickly and accurately incorporate all available information into asset prices.

The Efficient Market Hypothesis (EMH) suggests that any new information, such as FOMC announcements, is rapidly assimilated by the market. Particularly, Fama et al. (1969) stated that financial markets function efficiently, and defined market to be informationally efficient in view of that stock prices integrate all relevant information. Therefore, any potential abnormal returns would be quickly nullified as market participants adjust their expectations and trading strategies almost instantaneously. This rapid incorporation of information can result in the absence of detectable abnormal returns in the periods immediately following the announcement.

Furthermore, the lack of abnormal returns pre or post the event dates may indicate that investors had already anticipated the FOMC's decisions based on prior information and market expectations. In such cases, the actual announcement serves merely to confirm what the market had already priced in, resulting in minimal immediate impact on stock prices.

Additionally, the results could also reflect the transparency and communication strategies employed by the Federal Reserve. Over the years, the Fed has increasingly aimed to reduce uncertainty by providing clear guidance and setting market expectations through forward guidance and other communication tools. This preemptive approach helps to mitigate any shock effects that might otherwise lead to abnormal returns.

The absence of abnormal returns around the FOMC announcement dates, as revealed by the event study methodology, underscores the efficiency of financial markets in processing and reacting to new information. It also highlights the effectiveness of the Federal Reserve's transparency measures in managing market expectations and ensuring stability in financial markets.

CONCLUSIONS

This study analyzes four CBOE ETF Volatility Funds and their deviance from expected returns before and after each time the Federal Reserve met and released their "summary of economic predictions" from January 2008 to January 2020.

The empirical analysis does not support the hypothesis, as the results indicate that there were no significant abnormal returns observed before or after the FOMC meeting dates. This suggests that the increased transparency from the Federal Reserve did not lead to measurable changes in market volatility during the study period. Since 2008, investors have looked for methods to understand volatility in the financial markets. It is important to recognize that this increased transparency occurred in response to the Great Recession, however, the investigation of potential shocks to the funds provides vital information to market participants. Further analysis into market trends can allow those impacted the foresight to adjust their portfolios accordingly to withstand this volatility.

One interpretation of these results is that the impact of the Federal Reserve predictions translates to returns in a period beyond ten days before the actual change. Another factor to consider is that the predictions released are discussed and anticipated well before the actual availability date. The efficient-market hypothesis states that it should be impossible to outperform the overall market through expert stock selection or market timing, and that the only way an investor can possibly obtain higher returns is by chance or by purchasing riskier investments.

For the next stage of this research a more diverse group of financial instruments could be utilized. Another aspect to consider is whether to use the FOMC meeting dates where the Federal Reserve only discussed changes in the fed-funds target rate. This study attempts to identify abnormal returns around the dates of the FOMC announcements on economic predictions, although the results were insignificant, the authors argue there is enough significance to warrant further research and provide valuable information to market participants.

DISCLOSURE STATEMENT

The authors report no conflicts of interest.

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APPENDIX:

FOMC Meeting Dates that include the Summary of Economic Predictions (SEP)

1/30/2008	6/23/2010	12/12/2012	6/17/2015	12/13/2017
4/30/2008	11/3/2010	3/20/2013	9/17/2015	3/21/2018
6/25/2008	1/26/2011	6/19/2013	12/16/2015	6/13/2018
10/29/2008	4/27/2011	9/18/2013	3/16/2016	9/26/2018
1/28/2009	6/22/2011	12/18/2013	6/15/2016	12/19/2018
4/29/2009	11/2/2011	3/19/2014	9/21/2016	3/20/2019
6/24/2009	1/25/2012	6/18/2014	12/14/2016	6/19/2019
11/4/2009	4/25/2012	9/17/2014	3/15/2017	9/18/2019
1/27/2010	6/20/2012	12/17/2014	6/14/2017	12/11/2019
4/28/2010	9/3/2012	3/18/2015	9/20/2017	

Source: own study based on data from (www6).

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PORTFOLIO MANAGEMENT IN TIMES OF ELEVATED RISK. SAFE-HAVEN AND HEDGE ASSETS IN CAPM SETTING

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PORTFOLIO MANAGEMENT IN TIMES OF ELEVATED RISK.
SAFE-HAVEN AND HEDGE ASSETS IN CAPM SETTING

ABSTRACT

The purpose of the article. The purpose of the article is to present the safe-haven concept according to the latest academic literature and distinguish it from the hedge and diversifier terms that are sometimes used interchangeably by researchers and portfolio managers. The ultimate goal of the paper is to place the safe-haven and hedge assets in the portfolio theory setting by introducing the negative beta parameter as stated in the Capital Asset Pricing Model. According to the literature, this article proposes a few approaches to identify and characterize safe-haven assets and to discover the perspective and outline further research in the portfolio theory.
Methodology. The work uses the method of descriptive and comparative analysis of literature, i.e., Systematic Literature Review (SLR). This method is used to present scientific overview of portfolio management when uncertainty rises to identify safe-haven and hedge assets.
Results of the research. This paper aims to characterize and identify three main types of assets helping investors to reduce the portfolio risk: safe haven, hedge, and diversifier. It introduces an improved analytical framework of beta parameter and drawdown beta concept to contribute to the rapidly expanding research on portfolio theory. Lastly it depicts a trade-off effect, which is stronger in-crisis performance of safe-haven assets. The returns of safe-haven assets are more positive when the stock market returns are more negative that may safeguard the financial system.
Keywords: safe-haven assets, hedge, diversifier, CAPM, beta.
JEL Class: C10, F30, F31, G11, G15.

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INTRODUCTION

The extreme recent events of the COVID-19 pandemic crisis, the Russian invasion of Ukraine and the Israeli–Palestinian conflict highlighted the demand to manage the portfolio risk sparked by unprecedented market conditions. Unexpected market breakdowns caused global stock markets frequently fluctuated and led to a cross-market spillover of financial risks. These last events manifested that the risk could spread to other financial markets by a rapid information transfer. As a consequence, international investors and portfolio managers cannot ignore the existence of market spillovers and need to find appropriate assets or risk diversification methods in view of the returns on the investment portfolio. Therefore, traditional investment strategies could not remain effective in the face of high geopolitical risk and it is crucial to identify safe-haven and hedge assets when crisis events occur. Recently, there has been a growing body of research analyzing safe-haven and hedge attributes of different financial assets like gold, bitcoin and other reserve currencies and lastly commodities (He et al., 2018: 30–37, Feder-Sempach et al., 2024).

Altogether, gold, reserve currencies like the Japanese yen and Swiss franc, some debt instruments, as well as commodities, are considered popular safe havens for international stock markets. However, the conclusions on the safe haven and hedge abilities of above mentioned assets have not reached a consensus, making it difficult for investors to compare the performances of different assets that are labelled ‘safe’ when extreme events occur mainly because of the spillover risk (Wang et al., 2022: 1–16).

The purpose of the article is to present the safe-haven concept according to the latest academic literature and distinguish it from the hedge and diversifier terms that are sometimes used interchangeably by researchers and portfolio managers. The main objective is to place the safe-haven assets in the portfolio theory setting by introducing the negative beta parameter according to the Capital Asset Pricing Model (CAPM) by adding the drawdown beta concept and contribute to rapidly expanding research on identifying safe-haven assets thoroughly.

1. THE CONCEPT OF SAFE-HAVEN ASSETS

The safe haven literature is large and it is still growing. The rising global uncertainty amplifies the demand for safe-haven assets because the term 'safe haven' refers to investments that are expected to retain or increase in value during times of market upheaval. These assets are desired by investors who want to reduce their exposure to losses when markets are volatile. A flight to safety ensues as a way to avoid a potential portfolio drawdown. Typically, safe havens are characterized by their liquidity, stability, and ability to hedge against market downturns. They are not risk-free financial assets but are considered to offer protection against systemic risks that can cause widespread losses in other asset classes portfolio. Theoretically, this concept is usually perceived as a hiding place, meaning that investors can protect wealth during the market crisis. However, the safe-haven effect is generally present in developed financial markets (Baur and McDermott, 2010: 1886–1898).

There is a significant relationship between the safe assets and safe-haven assets regarding the level of risk and return. The empirical safe-haven literature proposes two almost independent strands: a safe-haven strand, and a safe assets strand (Baur et al., 2021)[1]. Primarily, the term safe haven was used to refer to an asset with low risk and high liquidity (Upper, 2000), making it similar to a safe asset but these two terms are different in nature. Safe assets are safe over a long period of time regardless of crisis, whereas a safe-haven attribute is a short-lived phenomenon identified only during the market collapse. Safe assets are uncorrelated with other assets' returns on average, while safe haven assets are negatively correlated with other asset returns during a market crisis (Bogołębska et al., 2024). See the Figure 1 depicting differences between safe-haven assets, safe assets and risky assets.

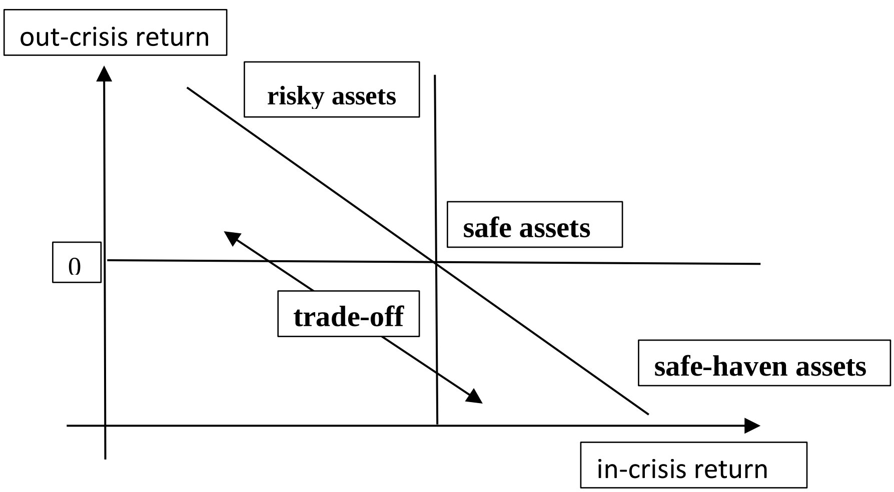

Figure 1. Trade-off across assets

Source: Baur et al. (2021).

[1] According to Baur et al. (2021) three almost independent strands have emerged in the literature: a safe-haven strand, a safe assets strand and a flight to quality strand. Flight to quality emphasizes investors' movements from stocks to bonds in response to negative market shocks.

According to Figure 1 the safe haven property comes at a cost when market rises conversely to risky asset performance that comes at a cost when market falls. The trade-off shows that the positive returns of safe-haven assets in a crisis come at the cost of lower or negative returns in non-crisis periods in compliance with economic and financial theory (Baur et al., 2021).

There is a large and growing number of research trying to indicate established or potential safe-haven assets. Most of the identification strategies are based on the average return during the adverse market conditions or crisis periods. Nonetheless, the definition of a safe-haven asset remains controversial in academic literature and the safe-haven investments are usually distinguished from hedge and diversifiers.

The ability to hedge risk is often a central consideration for international investors during rising uncertainty. Diversification and hedging are often considered as dominant investment strategies in financial markets. Ultimately, a safe haven is defined as a security that is negatively correlated with stock market returns in the case of a market crash. This feature is contrasted with a hedge property, which is defined as a security that is uncorrelated with the stock market on average (Baur and Lucey, 2009). According to Baur and McDermott (2010: 1886–1898) "a strong (weak) safe haven is defined as an asset that is negatively correlated (uncorrelated) with another asset or portfolio in certain periods only, e.g., in times of falling stock markets. A strong (weak) hedge is defined as an asset that is negatively correlated (uncorrelated) with another asset or portfolio on average". Similarly to a safe haven "a strong (weak) hedge is defined as an asset that is negatively correlated (uncorrelated) with another asset or portfolio on average". Above features of two types of asset properties include the length of the effect whereas hedge attribute holds on average and safe-haven attribute only during the declining stock market.

Baur and Lucey (2009), followed by Baur and McDermott (2010: 1886–1898), introduced a precise terminology showing the distinction between the safe-haven and hedge terms, previously considered to be a function of safe-haven assets, and adding one more, i.e. diversifier meaning an asset that is positively, but not perfectly correlated with another asset on average (see Table 1).

Table 1. Strong and weak safe-haven and hedge and diversifier definition

Name of the feature	Definition
Strong safe haven	An asset is a strong safe haven when it is negatively correlated with the stock market during periods of market distress
Weak safe haven	An asset is a weak safe haven when it is uncorrelated with the stock market during periods of market distress
Strong hedge	An asset is a hedge when it is negatively correlated with the stock market on average (not only during times of financial distress)
Weak hedge	An asset is a hedge when it is uncorrelated with the stock market on average (not only during times of financial distress)
Diversifier	An asset is a diversifier when it is positively but not perfectly correlated with the stock market on average (not only during times of financial distress)

Source: own elaboration based on the cited literature and Feder-Sempach et al. (2024).

There are several assets that are mostly classified as safe havens: gold (Baur and Lucey (2009), sometimes silver and other commodities (Cifarelli and Paladino, 2015: 1–15), reserve currencies (Ranaldo and Söderlind, 2009), public debt instruments (Kaul and Sapp, 2006: 760–779), defensive stocks, and recently, cryptocurrencies, such as Bitcoin (Li and Miu, 2023: 367–385). Recently, Rizvi et al. (2022: 106396) investigated the safe-haven properties of Green, Islamic, and Crypto assets against gold and treasury securities. They revealed that both Green and Islamic Bonds only act as safe-haven assets during the normal market condition which in contrast to a safe-haven definition stating that a safe-haven effect works during the market downturns. Traditional US Treasuries, cryptocurrencies, and gold emerged as safe-haven assets under bearish or extreme volatility periods legitimizing their safe-haven attribute.

1.1. Gold and precious metals

Gold has a substantial, safe haven property in every economic condition (Boubaker et al., 2020: 123093; Akhtaruzzaman et al., 2021: 105588; Triki and Ben Maatoug, 2021: 101872). Primarily, gold is considered a safe-haven asset, helping investors to reduce risk during uncertain periods but other precious metals such as silver, platinum, and palladium are still gaining importance. Gold has traditionally been considered a safe-haven asset against exchange rates, highlighting its monetary asset role (Batten et al., 2010). Nowadays, gold has retained its traditional monetary role as a store of value while it no longer plays a central role in the contemporary monetary system. It has a significant symbolic value that distinguishes it from other precious metals because it played a central role in the history of the monetary system. Gold ended its primary role in the international monetary system after the collapse of the Bretton Woods system in

1971 but still it is a part of most central banks' foreign-exchange reserves (Bie and Henneberg Pedersen, 1999).

One of the first articles analysing the safe-haven attribute of gold was proposed by Baur and Lucey (2009) and Baur and McDetmott (2010: 1886–1898), who found that gold was a strong safe haven for most developed markets during the peak of the Global Financial Crisis (GFC). Gold has always been considered as a safe-haven asset because it is negatively correlated with the economic cycle and usually provides positive returns during crises (Bouri et al., 2020). The safe-haven and hedge attribute of gold was analyzed against G7 stock markets (Shahzad et al., 2020), or US real estate stocks in the long and short run (Raza et al., 2018) and developed and emerging markets. Shahzad et al. (2019: 322–330) studied the role of Bitcoin, gold and commodities for stock indices and gold, and the commodity index can be considered as a weak safe-haven asset in some cases. Bekiros et al. (2017: 317–334) examined the hedging and diversification roles of gold for the BRICS markets proving that gold acts as a hedge and safe-haven asset for BRICS stocks in both crisis and non-crisis periods.

Contrary to gold and sometimes silver, platinum and palladium are usually classified as industrial metals (Vigne et al., 2017) but platinum may be useful as a safe haven in periods of extreme stock market declines (McCown and Shaw, 2017: 328–337). Their high economic value and ability to maintain this value even during financial downturns make precious metals, especially gold and silver, safe-haven assets (Starr and Tran, 2008: 416–436). The interactions between precious metals and stock indices are not homogenous, what is more, they differ across countries. This can be attributed to different properties of these commodities with the emphasis on significantly different demand and supply fundamentals, as well as the size and complexity of financial markets, creating different spillover mechanisms.

Azimli (2022: 102679) analyzed the dynamic connectedness of asset classes among four commodities: copper, iron, gold, and silver and ten major global stock indices. The results indicate that silver outperforms gold as a safe-haven asset in the post-COVID 19 period. Lucey and Li (2015) find evidence that during extreme stock and bond market distress in the United States, silver, platinum, and palladium act as a safe haven contrary to gold. On the other hand, Sikiru and Salisu (2021: 2199–2214) indicate that only gold acted as a safe haven during the COVID-19 among precious metals. Mujtaba et al. (2023: 2381–2414) examine the hedge and safe-haven properties of four commodity classes (precious metals, energy, agriculture, and livestock), for the United States and China at an equity index and sectoral level. Their findings indicate that precious metals are weak safe havens for all equity sectors of China and the USA. What is more, this property is limited. Additionally, in case of China, precious metals provide a weak hedge to the majority of sectors and the Shanghai Composite Index (SCI). Gençyürek and

Ekinci (2023: 297–321) investigate the role of precious metals as diversifier, hedgers and safe-haven assets in the stock markets of BRICS and Turkey. They find that all of the four metals are effective risk management instruments, except for hedging strategy. Moreover, to mitigate risk, investors should increase the weight of precious metals in their portfolio, except for gold. These studies confirm that precious metals are too distinct to be considered a single asset class. Conventionally, gold and silver are perceived as substitutes of money (Batten et al., 2010), and they are treated as a store of value and a medium of exchange (Jain and Ghosh, 2013). Their safe-haven characteristics are well documented in the academic literature stressing gold prominence in investment and monetary debates (O'Connor et al., 2015).

1.2. Currencies

The list of safe-haven currencies is consistent with the list of main reserve currencies, i.e., the US dollar, the euro, the Swiss franc, and the Japanese yen exhibiting the dominant position of the US dollar followed by the euro (Lu et al., 2024: 3–5). Accordingly, the determinants of safe-haven currency status are compatible with the determinants of international currencies (Bogołębska et al., 2019: 65–81). Nevertheless, the global structure of foreign exchange reserves does not explain the strong representation of the yen and the franc as safe-haven assets and overestimates the role of the common European currency euro.

In the literature on safe-haven currency drivers, the emphasis is on the structural characteristics of the economy. Habib and Stracca (2012: 50–64) showed that only a few country-specific characteristics, such as the net foreign asset position and the size of the stock market, and in the case of advanced countries, the interest spread compared to the US, are somewhat systematic drivers of safe-haven currency behaviour. Additionally, Masujima (2019) indicated that above mentioned drivers are not permanent and they might change strongly. The results of the panel regression suggest that the determinants of safe havens shifted from external sustainability factors, such as current account surplus to market-driven factors, such as carry trade opportunity and high liquidity during and after the financial crisis. The results also highlight the increasing effects that changes the monetary policy stance and investors' willingness to avoid risk and invest in safe-haven assets (Feder-Sempach et al., 2024).

Much empirical research confirms the different patterns of safe-haven currency behaviour. Ranaldo and Söderlind (2009) showed that the Swiss franc, along with the yen and the euro, has significant safe-haven characteristics and moves inversely with international equity markets and foreign exchange trends. Coudert et al. (2014) found that only the yen and the US dollar exhibited safe-haven properties observed in advanced and emerging financial markets.

What is worth stressing is the currency's safe haven status that may change over time, e.g., the Swiss franc appreciates against the euro in response to increases in global risk but depreciates against the dollar, the yen and the British pound, (Grisse and Nitschka, 2015: 153–164). Recently, an innovative study was conducted by Feder-Sempach et al. (2024) stating that safe-haven effects work differently for gold and the yen; hence, the Japanese yen seems to act as the strongest safe haven across all stock indices. According to the latest research of Changrong et al. (2024: 101013), no East Asian currency has a safe-haven attribute under geopolitical risk and trade policy uncertainty. However, the Japanese yen maintains its status against VIX index, (Lee et al., 2024: 119–134).

Nowadays, new potential safe-haven assets are studied, namely cryptocurrencies and Bitcoin. The fast growing cryptocurrency market has succeeded in attracting the attention of investors and financial institutions. The cryptocurrency protocol is based on the voluntary participation and it is not subject to any control and allows everyone to accumulate and transfer value in a currency that resists price manipulation (Chemkha et al., 2021: 71–85). Bitcoin is a decentralized digital currency, independent of any political centres, neither governments nor central banks. For that reason, Bitcoin and other cryptocurrencies can be considered a potential safe-haven asset but the literature suggests that Bitcoin fulfilled this role to a limited extent at most.

However, empirical studies are skeptical about the prospects for cryptocurrencies as safe haven assets. Bouri et al. (2017) examined whether bitcoin can act as a hedge and a safe haven for major world stock indices, bonds, oil, gold, the general commodity index, and the US dollar index. The empirical results indicate that bitcoin is a poor hedge and it is suitable for diversification purposes only. However, it serves as a strong safe-haven against weekly extreme down-movements in Asian stocks. They also show that bitcoin and safe-haven properties vary between horizons. Bitcoin's status as a safe haven is partly inconsistent with the literature. Choi and Shin (2022) and Będowska-Sójka and Kliber (2021: 101390) showed that, unlike gold, bitcoin prices decline in response to financial uncertainty shocks. This is in contrast to the safe-haven quality of gold. This complex economic phenomenon could be explained by bitcoin prices' fact that the responses to economic shocks are different from those of gold, instead behave like commodities such as crude oil (Gronwald, 2019: 86–92). Apparently, the main outcome of the current literature is that bitcoin should not enter the discussion as a potential safe-haven asset (Smales, 2019: 385–393). All in all, the US dollar is still considered the best safe-haven currency for short- and medium-term investments (Tronzano, 2023: 273), followed by the Japanese yen and the Swiss franc.

1.3. Public debt instruments and defensive stocks

Debt instruments issued by the public sector are considered safe havens because they provide high-quality income regardless of economic uncertainty (Baur and Lucey, 2009). Usually, international investors tend to have more confidence in debt instruments issued by governments of advanced economies, starting with the US treasuries issued by the global reserve currency issuer. High quality sovereign bonds are the best example of safe-haven assets because of their lower volatility and the high expected creditworthiness of their issuers. Debt instruments issued by the US, UK, German, and Japanese governments can act as safe-haven assets because of the high-quality returns and risk-free label (Bogołębska et al., 2024). Usually, long-term Treasury bonds act as safe-haven assets and improve the strategy performance during markets upheavals (Kaczmarek et al., 2022: 101610).

Connolly et al. (2005) showed a negative relation between the uncertainty measures and the future correlation of stock and bond returns. They stated that bond returns tend to be high (low), relative to stock returns, during the days when implied volatility increases (decreases) substantially and during the days when stock turnover is unexpectedly high (low). These findings prove that the diversification benefits increase with rising uncertainty of the stock market showing the safe-haven properties of bonds. According to Baur and McDermott (2013), who analyzed the two most prominent safe-haven assets – US Treasury bonds and gold suggests that both bonds and gold tend to act as safe-haven assets following stock market crises. However, these assets appear to differ in the timing of their responses to crisis events and gold is a stronger safe haven. Usually, assets such as 10-year Treasuries issued by advanced economies have safe-haven attributes.

Contrary to popular belief, some stocks can play the role of safe-haven assets. Investors interested in reducing their risk during economic downturns can also choose defensive stocks or namely safe stocks to provide stable earnings and consistent returns. Safe stocks are the stocks whose price is relatively stable and feature little or no response to the market decline, e.g., Apple stocks passed the crisis of 2008 quite easily. Defensive companies deliver products considered necessities – things consumers buy even during a crisis hence, they are less prone to cyclical effects and recessions. Typically, defensive stocks provide dividends regardless of economic prosperity when they are issued by well-established companies. It may be explained by their low correlation with the overall stock market, which results in a beta parameter lower than one. Last studies by Yousaf et al. (2023: 101844) analysed the FAANA (Facebook, Apple, Amazon, Netflix and Alphabet) stocks acting as hedge, diversifier, and safe haven against four alternative assets: gold, US treasury bonds, the US dollar and bitcoin. This study showed that most of the FAANA stocks acted as weak or strong safe havens against gold, bonds, bitcoin and the US dollar. Moreover, few FAANA stocks had a strong safe-haven attribute against the US treasury bonds and the US dollar during the COVID-19 pandemic crisis. Ultimately, above mentioned studies have a different perspective because it examines the FAANA stock as safe-havens and fills the gap in safe-haven research by changing the commonly used patterns (Bogołębska et al., 2024: 24).

2. MANAGING PORTFOLIO RISK ACCORDING TO CAPM

Harry Markowitz (1952: 77–91) launched modern portfolio theory with the idea of creating the most efficient portfolio by reducing volatility and the risk of losses by choosing assets that are potentially negatively correlated. This theory introduces a systematic approach to build and manage the investment portfolio in the long run. He advocates that the way to choose a portfolio and reduce risk is to diversify. The concept of diversification means spreading investments across a range of assets to reduce risk, including stocks, bonds, and alternative assets like commodities. He proposed how investors should combine assets into a portfolio that would provide the best possible combination of risk and return, i.e. the highest potential rate of return for a given level of risk or that would minimise the risk for a given level of return (Bogołębska et al., 2024: 25–35). Portfolio diversification is widely used in international investments. The idea is to create a pool of different assets with weak or negative correlations, allowing investors to minimise their losses if unforeseen events occur. Nowadays, widespread advanced technological improvements help international investors build a portfolio with a minimum risk (Bhuiyan et al., 2023).

First, investors should consider the relationship between different investment opportunities, including all types of assets and all international markets. It is vital to consider the entire spectrum of investments because the returns of all these investments interact. Second, portfolio theory assumes that investors are risk averse, meaning that when given a choice between two assets with equal rates of return, they will choose the one with the lowest level of risk. Therefore, the relationship between return and risk is expected to be positive. For that reason, investors are willing to accept a greater risk in search of a higher return (Reilly and Brown, 1997). Markowitz proposed a basic portfolio model, showing that the variance of the rate of return was a significant measure of portfolio risk. He derived the portfolio risk formula using the portfolio variance, and this formula indicates the importance of diversification in reducing the total portfolio risk (Miziołek et al., 2020: 41–45). Markowitz defined the efficient frontier as the highest expected return for a given level of risk, or the lowest risk for a given expected return. The efficient frontier represents the trade-offs between risk and return, and is used to identify portfolios that follow the investors' risk tolerance and investment goals.

A simpler method for portfolio selection is the single-index model proposed by Sharpe (1964: 425–442). According to this model, returns on a security can be represented by the performance of a single factor-market index. Sharpe proposed the concept of a single market index, stating that a security's performance has a correlation with the performance of the market index. In the Sharpe model, the crucial measure is beta, which shows the sensitivity of individual assets to market movements. The use of a single index market model calls for estimates of the beta parameter for individual financial assets that could potentially be included in a portfolio. The single index market model is used to estimate beta parameters, which can be used to assess risk. To estimate the risk measured by beta, investors use the regression model. This regression line is called the security characteristic line. It is defined as the best-fit regression line through a scatter plot of the rate of return for individual risky assets and for the market portfolio over a designated period (Bogołębska et al., 2024: 26–27). The relation is depicted in Figure 2.

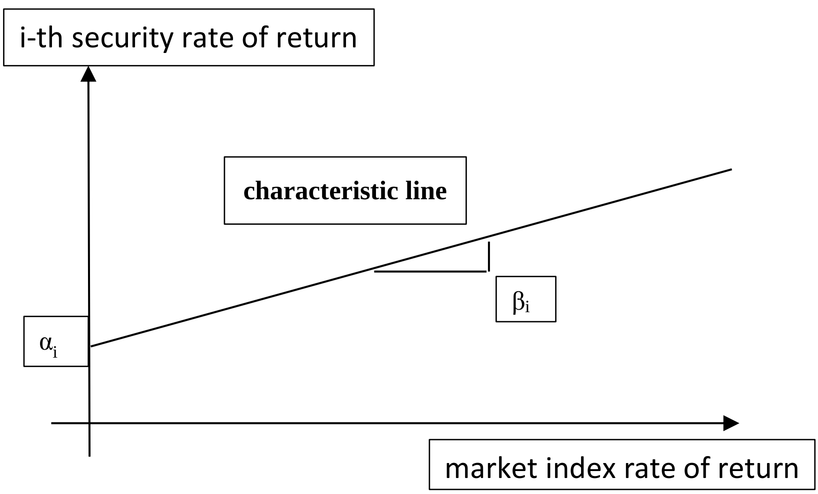

Figure 2. Security characteristic line

Source: Elton and Gruber (1995: 138).

Figure 2 shows that the intercept of the regression line is the alpha parameter, while the slope of the line is the beta parameter. Beta is a measure of volatility with reference to the general market. The beta parameter is used as an indicator of risk, and its value can be as a systematic risk measure:

β <0 – a beta of less than zero indicates that an asset has an inverse relationship with the market. Those assets tend to increase in price when the general market prices fall, and they are potential safe-haven and hedge assets.

0<β<1 – a beta of less than one indicates that an asset return moves less than the market return; there is a lower systematic risk than the market. Defensive stocks have a beta of less than one. Those are potential diversifiers.

β =1 – a beta equal to one indicates that an asset's return is fully correlated with the returns in the market itself. Adding an asset to a portfolio with a beta of 1.0 does not add any risk.

β >1 – a beta greater than one indicates that the asset's return moves higher than the market return; there is a higher systematic risk than the market. Aggressive stocks have a beta greater than one (Bogołębska et al., 2024: 28).

The beta parameter plays a central role in modern finance as a measure of asset risk. In the context of CAPM, beta denotes the volatility, or systematic risk, of a security or an asset compared to the market. It is used in the CAPM formula as a measure of systematic risk to give an investor the expected return (Dębski et al., 2016: 75–92, Feder-Sempach and Szczepocki, 2022: 46).

According to Baur and Lucey (2009), followed by Baur and McDermott (2010), a safe-haven asset is negatively correlated with another asset during a market crisis; hence, these assets have negative beta parameters to hold their value during market turbulence, and they can reduce risk, see Table 2.

Table 2. Beta parameter and asset's properties

Asset Properties	Beta
Safe haven	Negative or 0 beta in times of financial crisis or bear market conditions
Hedge	Negative or 0 beta on average, bull and bear market conditions
Diversifier	Beta over 0 but not equal to 1 on average, bull and bear market conditions

Source: own elaboration based on the cited literature and Bogołębska et al. (2024).

Following the classification presented in Table 2, the correlation of different assets can be replaced by the beta parameter that determines whether diversification works. The beta parameter shows how one asset moves compared to another, which, in this case, is used to depict the different properties of a financial asset (Bogołębska et al., 2024: 28–29).

To show a bigger picture of safe-haven assets, Baur et al. (2021) used the quantile regression to analyze the returns of potential safe-haven assets during different market conditions including crisis. They found a trade-off effect, which is stronger in-crisis performance of safe-haven assets and weaker out-crisis performance and vice versa for risky assets. Thus, the safe-haven effect is stronger in extreme lower and upper quantiles than in center quantiles, which is graphically depicted in Figure 3.

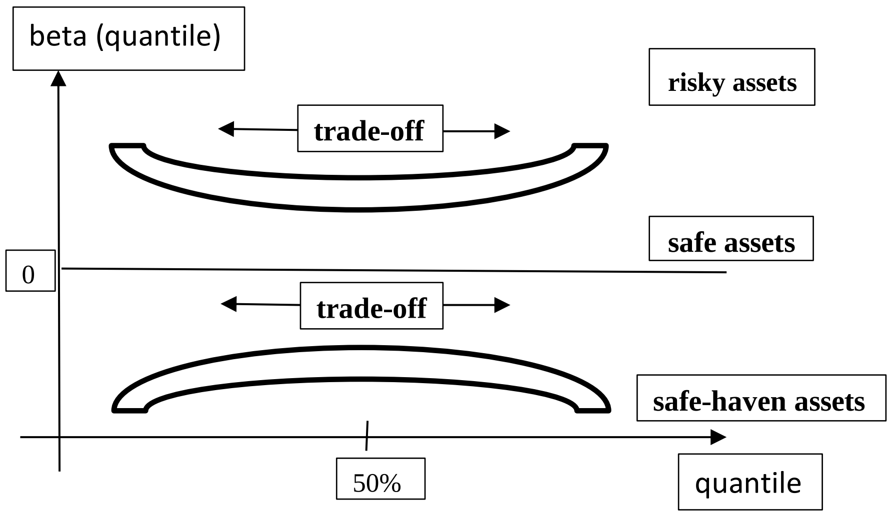

Figure 3. Beta parameter across quantiles

Source: Baur et al. (2021).

Risky assets move with the market, in particular when the market goes up or down. Therefore, their beta parameter is expected to be positive. Information insensitive safe assets have beta equals to zero. In contrast, safe-haven assets move opposite the market when the market goes down, their beta is expected to be negative for lower quantiles. This inverted u-shape curvature of conditional quantile estimates shows that safe-haven effect is stronger in extreme lower and upper quantiles than in center quantiles. Safe-haven assets do not increase in price constantly, but only when the market falls (Baur et al., 2021).

Recently, various techniques have been proposed with the latest drawdown based risk measures called Conditional Drawdown-at-Risk Beta (CdaR Beta) introduced by Zabarankin et al. (2014: 508–517) and Expected Regret of Drawdown Beta (EroD Beta) proposed by Ding and Uryasev (2022: 1265–1276). These two innovative risk measures, like the standard or traditional beta, relate the returns of an asset to the returns of the market, but are based on the concept of drawdowns: the decline in the value of an asset from a peak to a subsequent low. Drawdown betas are more sensitive to market distress during unexpected events and can work as safe-haven assets identifier by having greater informative power.

CONCLUSIONS

During the times of rising uncertainty, it becomes crucial to portfolio managers to look for assets that are negatively correlated or uncorrelated with the main components of the portfolio to limit their exposure to losses in the event of market turmoil. Thus, a safe-haven investment has the potential to protect investors and offset losses in the event of COVID-19 pandemic crisis, the Russian invasion of Ukraine and the Israeli-Palestinian conflict.

There is a list of different assets having the safe-haven attribute. Gold is regarded as an effective instrument protecting stock market investment from a decline thus a strong safe-haven asset. Precious metals are considered safe-haven assets due to their ability to hedge and offset the risk of the financial markets. Reserve currencies, the US dollar, Swiss franc, Japanese yen are common examples of safe-haven assets. They strengthen or hold their value in times of global economic uncertainty caused by economic downturns or political tensions. The US dollar stands out as the best safe-haven currency, while Swiss franc and Japanese yen are perceived as a longstanding safe-haven asset (Baltensperger and Kugler, 2016: 1–30; Zheng-Zheng et al., 2024: 119–134). The role of bitcoin as a safe-haven asset is also under discussion. Some analyses showed that bitcoin can act as potential safe-haven asset, mostly during the COVID-19 pandemic crisis – strong safe-haven asset properties (Yan et al., 2022: 415). In times of crisis, the US government debt could be viewed as a safe-haven investment because of the strong economic fundamentals of the United States and the US financial market prominence (Hager, 2016: 557–580).

There are three types of asset attributes helping investors to reduce the risk: safe haven, hedge, and diversifier. Acknowledging these different properties of financial assets can potentially help to understand complex relationships over investment holding periods and adverse market conditions to build an optimal portfolio. The definition of safe-haven, hedge and diversifying assets has been incorporated into portfolio theory by the beta parameter and the asset properties specification according to CAPM. The correlation of different assets can be replaced by the beta parameter that determines whether diversification works. The beta parameter shows how one asset moves compared to another, which, in this case, is used to depict the safe-haven, hedge and diversifying assets. The new concept of drawdown based risk measure called drawdown beta might be also helpful in reducing the overall volatility and portfolio risk. Additionally, to analyze the returns of potential safe-haven assets during different market conditions, including crisis the trade-off effect is analyzed, which is stronger in-crisis performance of safe-haven assets and weaker out-crisis performance. Returns of safe-haven assets are more positive the more negative the market returns are which may have a stabilizing effect on the overall financial system.

The ability to identify safe-haven and hedge assets is relevant to portfolio managers and all investors using an active approach to manage portfolio risk. This article comprises the most relevant research articles to manage the portfolio in times of elevated risk according to the portfolio theory and CAPM.

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EMPIRICAL STUDY OF MULTI-OBJECTIVE RISK PORTFOLIO OPTIMIZATION BASED ON NSGA-II

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EMPIRICAL STUDY OF MULTI-OBJECTIVE RISK PORTFOLIO OPTIMIZATION BASED ON NSGA-II

ABSTRACT

The purpose of the article. The application of multi-objective optimization in portfolio management has gained significant attention in asset management. This study aims to uncover the potential advantages of dynamic portfolio optimization using a multi-objective genetic algorithm to address the challenges of ever-changing market conditions.

Methodology. By incorporating multi-objective optimization, this paper comprehensively examines three key portfolio objectives: minimizing two risk types and maximizing returns. The approach involves constructing portfolios, initializing the population using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), and employing crossover and mutation steps to achieve Pareto optimality. Additionally, this study compares the performance of two risk minimization strategies through traditional portfolio backtesting.

Results of the research. The results indicate that the multi-objective risk genetic algorithm not only effectively explores the portfolio space but also handles conflicting optimization objectives, thereby enhancing the comprehensiveness and flexibility of investment decisions. However, its performance depended on the chosen risk measurement methods, and the backtesting returns were unstable.

Keywords: portfolio optimization, risk measure, multi-objective, NSGA-II, empirical study.

JEL Class: C52, C61, G11.

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INTRODUCTION

Portfolio optimization remains a critical task, requiring the effective allocation of asset weights to manage investments efficiently. Traditional portfolio optimization methods typically focus on a single objective, such as maximizing returns or minimizing risk (standard deviation). However, real-world investment scenarios often involve multiple conflicting objectives, rendering the complexity of multi-objective optimization beyond the capabilities of conventional single-objective approaches (Chiam et al., 2008).

The introduction of genetic algorithms (GA) has enabled addressing these complex issues. Nonetheless, research on applying non-dominated sorting genetic algorithm II (NSGA-II) to optimize under real market data and complex constraints still needs to be completed. Therefore, this paper aims to use NSGA-II for three-objective optimization and to compare these results with traditional minimum-risk optimization methods through backtesting using real data.

Based on this, the paper is organized as follows: Section 1 is the literature review, which provides a detailed discussion of the application of NSGA-II in portfolio optimization. Section 2 provides a concise overview of NSGA-II and details the multi-objective optimization process undertaken. Additionally, the risk measurement methods utilized in this study are described in detail. Furthermore, Section 3 presents and compares the optimization results obtained using real-world data. Finally, the work and findings are summarized in the conclusion.

1. LITERATURE REVIEW

The application of multi-objective genetic algorithms in portfolio optimization falls into three areas. First, improvements to the genetic algorithm itself, including modifications or the use of non-traditional parameters. Second, the hybridization of multiple algorithms for optimization. Lastly, empirical comparisons of optimization results were obtained using different algorithms. It is important to note that these three types of applications are not mutually exclusive and are often combined (Ertenlice and Kalayci, 2018).

For instance, Liu et al. (2017) integrated the affinity propagation algorithm to generate a set of portfolio candidates. They employed a genetic algorithm to optimize the Sharpe ratio-based objective function, achieving an optimal portfolio strategy with higher returns and lower risk. Lou (2023) introduced more refined selection strategies, dynamic mutation parameters, and initialization optimizations to the NSGA-II algorithm and used Monte Carlo Markov Chain (MCMC) to perform ten-year portfolio forecasts, resulting in enhanced outcomes. Similarly, Chen et al. (2018) utilized group balance and Sharpe ratio to identify

Pareto-optimal solutions. The screening of similar stocks within a group can also be carried out using the mixed K-value clustering method, which can mix multiple algorithms.

Pal et al. (2021) applied clustering and a variable-length NSGA-II for dynamic adjustments, with results indicating a higher return rate than the benchmark index. To address potential issues of nonlinearity and discontinuity in quadratic programming, Deb et al. (2011) coupled NSGA-II with clustering and local search procedures, improving the accuracy of the proposed method.

Comparing different algorithms' performance, applicability, and empirical effectiveness is also critical. Kaucic et al. (2019) observed that negatively skewed assets are prematurely excluded in cases of skewed and fat-tailed returns. Their results across five datasets indicate that the enhanced NSGA-II outperformed other methods. Similarly, Anagnostopoulos and Mamanis (2011) compared five evolutionary algorithms and tested the effectiveness of steady-state evolution in mean-variance optimization with cardinality constraints, finding that NSGA-II demonstrated strong performance and was well-suited for large-scale problems.

However, Mishra et al. (2009) found that multi-objective particle swarm optimization (MOPSO) outperformed NSGA-II, and indicator based evolutionary algorithm (IBEA) was shown to be closer to the actual Pareto front compared to NSGA-II (Bhagavatula et al., 2014). These findings suggest two possibilities: either NSGA-II may lag behind newer algorithms (Liagkouras and Metaxiotis, 2018), or the empirical results produced by NSGA-II may be unstable (Fortin and Parizeau, 2013).

Evaluating NSGA-II under realistic data and constraints is essential, as strategies and objectives greatly influence outcomes. Yang (2006) noted that in multi-objective models, uncertainty reduces risk tolerance and stabilizes portfolio weights, creating a preventive effect. Macedo et al. (2017) found that using technical indicators with trading strategies impacts the efficient frontier, optimizing asset allocation and enhancing robustness against transaction costs and market shifts. Meanwhile, broader constraints, such as cardinality and budget limits, should be addressed while highlighting transaction costs and estimation errors as critical challenges in portfolio optimization and rebalancing (Meghwani and Thakur, 2017).

2. METHODOLOGY

The methodology section introduces the risk measurement methods and portfolio optimization techniques. Finally, this research presents the NSGA-II algorithm, outlining its process and key concepts. This section discusses the standard deviation as a measure of risk, which measures the dispersion of data points relative to the mean (Markowitz, 1952). The formula is as follows:

$$\sigma_{ij} = cov(R_i, R_j), \tag{1}$$

$$\sigma_p = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij}}, \tag{2}$$

where:
the portfolio consists of n assets;
σ_{ij} is the covariance of the return R_i and R_j;
σ_p is the standard deviation of the portfolio;
w_i is the weight of each asset i;
w_j is the weight of each asset j.

Next, Conditional Value at Risk (CVaR) is the average potential loss exceeding the Value at Risk (VaR) at a given significance level, providing a more comprehensive measure of extreme risk. The formula is shown in Equation (4):

$$VaR_\alpha = inf\{x \in \mathbb{R}: P(L \geq x) \leq \alpha\}, \tag{3}$$

$$CVaR_\alpha = \frac{1}{\alpha} \int_{VaR_\alpha}^{\infty} L\, f(L) dL\,, \tag{4}$$

where:
inf means the lower bound;
Let L be the random variable representing portfolio loss;
α denote the significance level, 5% in this paper;
the function $f(L)$ represents the probability density function of the loss L.

According to the two risk measurement methods mentioned above, this study can construct a three-objective portfolio based on the two risk measure methods, as illustrated in Equation (5):

$$\begin{aligned} Objective:\ \ Max\ \ & \mu_p = \sum_{i=1}^{n} w_i \mu_i\,, \\ Min\ \ & \sigma_p, \\ Min\ \ & CVaR_\alpha, \\ Subject\ to: \quad & \sum_{i=1}^{n} w_i = 1\,, \\ & w_i \geq 0, \qquad i = 1, 2, \ldots, n, \end{aligned} \tag{5}$$

where:
μ_p is the expected return of the portfolio;
μ_i is the expected return of a single asset.

The formula is analogous to traditional portfolio optimization methods. In subsequent comparisons, this study will construct portfolios with a single risk to obtain the results of backtested cumulative returns. Next, this section will introduce the NSGA-II. Figure 1 provides its pseudocode to illustrate the overall process.

Algorithm 3 NSGA-II algorithm

procedure NSGA-II($\mathcal{N}', g, f_k(\mathbf{x}_k)$) ▷ $\mathcal{N}'$ members evolved g generations to solve $f_k(\mathbf{x})$
    Initialize Population $\mathbb{P}'$
    Generate random population - size $\mathcal{N}'$
    Evaluate Objective Values
    Assign Rank (level) Based on Pareto dominance - *sort*
    Generate Child Population
      Binary Tournament Selection
      Recombination and Mutation
    for $i = 1$ to g **do**
        for each Parent and Child in Population **do**
            Assign Rank (level) based on Pareto - *sort*
            Generate sets of nondominated vectors along PF_{known}
            Loop (inside) by adding solutions to next generation starting from the *first* front until $\mathcal{N}'$ individuals found determine crowding distance between points on each front
        end for
        Select points (elitist) on the lower front (with lower rank) and are outside a crowding distance
        Create next generation
            Binary Tournament Selection
            Recombination and Mutation
    end for
end procedure

Figure 1. NSGA-II pseudo code diagram

Source: Coello et al. (2007: 93).

Figure 1 illustrates the pseudocode of the NSGA-II, an algorithm designed to optimize multiple objectives through several key steps. Initially, the algorithm generates an initial population and evaluates the objective function values for each individual. Next, it ranks the individuals using non-dominated sorting and calculates the crowding distance. The algorithm then employs binary tournament selection to choose parents for crossover and mutation operations. Subsequently, the parent and offspring populations are merged, followed by non-dominated sorting, to select the best individuals for the next generation based on Pareto ranking and crowding distance. This process is repeated until a specified number of generations is reached, resulting in a set of near-optimal non-dominated solutions.

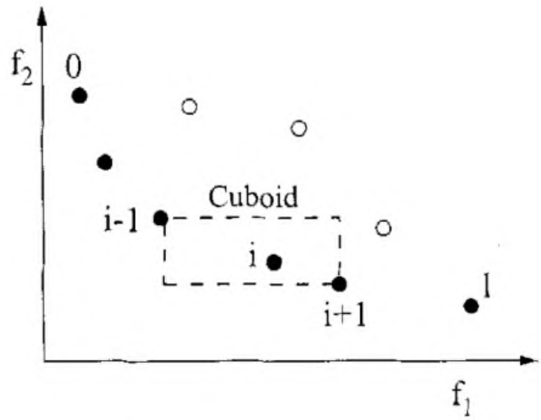

Figure 2. Illustration of crowding distance calculation

Source: Deb et al. (2002: 185).

Figure 2 illustrates how crowding distance helps maintain solution diversity. From a geometric perspective, the figure demonstrates how the algorithm calculates crowding distance based on differences in objective values within a two-dimensional objective space. Using two objective functions as an example, the black and white dots in the figure represent two non-dominated fronts. For a given solution i, the crowding distance is estimated by calculating the differences in objectives between this solution and its nearest neighbors $i - 1$ and $i + 1$ within the same non-dominated front. This distance metric reflects the density of solutions around i. It aids the algorithm in distributing selected solutions evenly along the Pareto front, thereby avoiding convergence to a narrow region and preserving solution diversity.

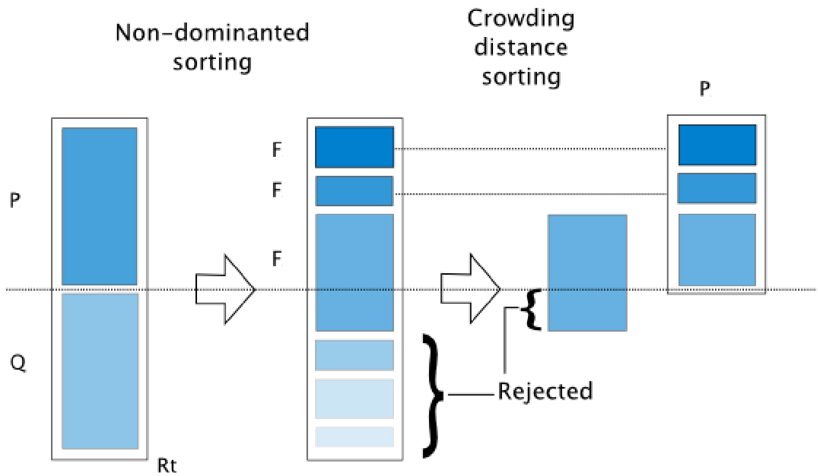

Figure 3. Illustration of elite sorting strategy

Source: Deb et al. (2002: 186).

Figure 3 illustrates the selection process in the NSGA-II algorithm, highlighting the critical roles of elitism and crowding distance in the optimization process. The initial population is merged with the offspring population Q_0, resulting in a combined population of size $2N$. The algorithm first applies fast, non-dominated sorting to this combined population, dividing it into multiple fronts and calculating the crowding distance for each individual. Priority is given to selecting individuals from the first front, representing optimal Pareto solutions.

If the required number of individuals still needs to be chosen, the algorithm selects from subsequent fronts. To ensure diversity in the solution space, individuals within the same front are chosen based on their crowding distance, providing a wide distribution across the objective space. This selection strategy enables NSGA-II to explore the solution space effectively while identifying solutions close to the global optimum.

After constructing a portfolio, evaluating the risk-return profile of the investment strategy using several key performance metrics is essential (Zhou et al., 2022). Among these, the Sharpe ratio, Sortino ratio, Maximum Drawdown (MDD), and Calmar ratio are widely recognized for their effectiveness in capturing different performance dimensions. Their respective calculation methods are detailed in Equations (6–9).

MDD is a measure of the largest peak-to-trough decline in portfolio value during a given period, reflecting the worst-case loss an investor could face (Almahdi and Yang, 2017). It is defined as:

$$MDD = max\left|\frac{V_t - V_{peak}}{V_{peak}}\right|, \tag{6}$$

where:
V_t is the portfolio value at time t;
V_{peak} is the highest portfolio value observed up to t.

A lower MDD indicates better capital preservation. For simplicity, the risk-free rate is considered as the minimum expected return. The formulas for the performance ratios share a similar structure:

$$Sharpe = \frac{R_p - R_f}{\sigma_p}, \tag{7}$$

$$Calmar = \frac{R_p - R_f}{MDD}, \tag{8}$$

$$Sortino = \frac{R_p - R_f}{\sigma_p^-}, \tag{9}$$

where:
R_p is the portfolio return;
R_f is the risk-free rate;
$R_p - R_f$ is the excess return;
σ_p is the portfolio standard deviation;
σ_p^- is the portfolio semi-deviation.

The Sharpe ratio, Calmar ratio, and Sortino ratio are essential indicators for evaluating the risk-adjusted performance of a portfolio. The Sharpe ratio assesses a portfolio's efficiency by comparing its excess return to total risk, offering a comprehensive view of risk-adjusted returns. The Calmar ratio focuses on the relationship between excess return and MDD, emphasizing the portfolio's ability to generate returns while minimizing the risk of significant capital loss. Meanwhile, the Sortino ratio refines the Sharpe ratio by isolating downside risk-returns falling below a specified target – providing a more targeted evaluation of risk relative to adverse outcomes.

3. EMPIRICAL RESULTS

To simplify the complexity of the application and enhance practical feasibility, this research performs the optimization using the NSGA-II framework implemented in the Pymoo library (Blank and Deb, 2020). The optimization utilizes daily data of Dow Jones Industrial Average (DJIA) constituent stocks from January 1, 2018 to December 31, 2023. To maintain ease of use, this study used the default optimization parameters provided by Pymoo, except for setting the population size to 200 and the number of generations to 600. The risk-free rate is set to 2%.

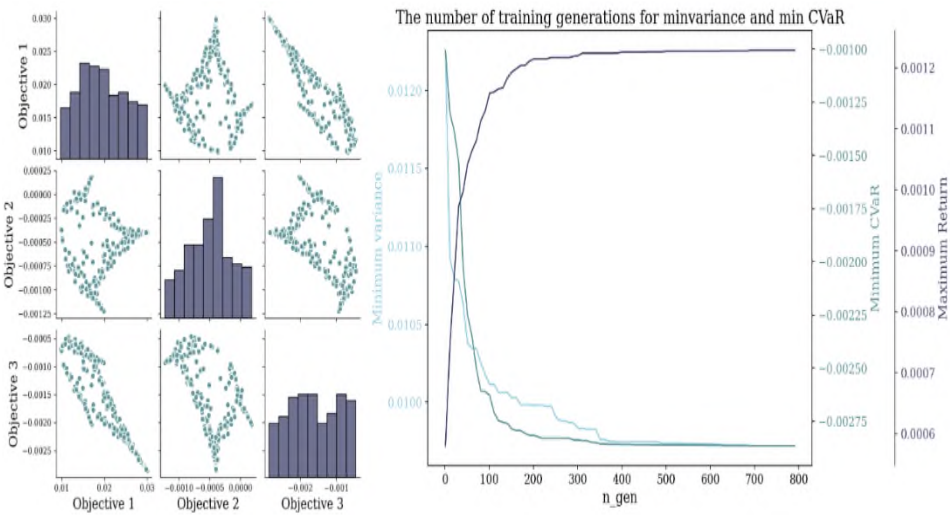

Figure 4. NSGA-II and Monte Carlo portfolio optimization results

Source: derived from calculations.

Subplot 1 displays scatter plots of Pareto optimal solutions obtained from NSGA-II for various objectives in Figure 4. The diagonal histograms represent the density distributions of each objective's values. The observed dispersion reflects the complexity of real data, which prevents perfect optimization and results in the selection of relatively superior points.

Subplot 2 illustrates the stabilization of minimum variance and minimum CVaR after about 600 iterations, indicating convergence. This stabilization provides a solid foundation for comparing NSGA-II with traditional methods, ensuring the results are well-validated for assessing its relative performance.

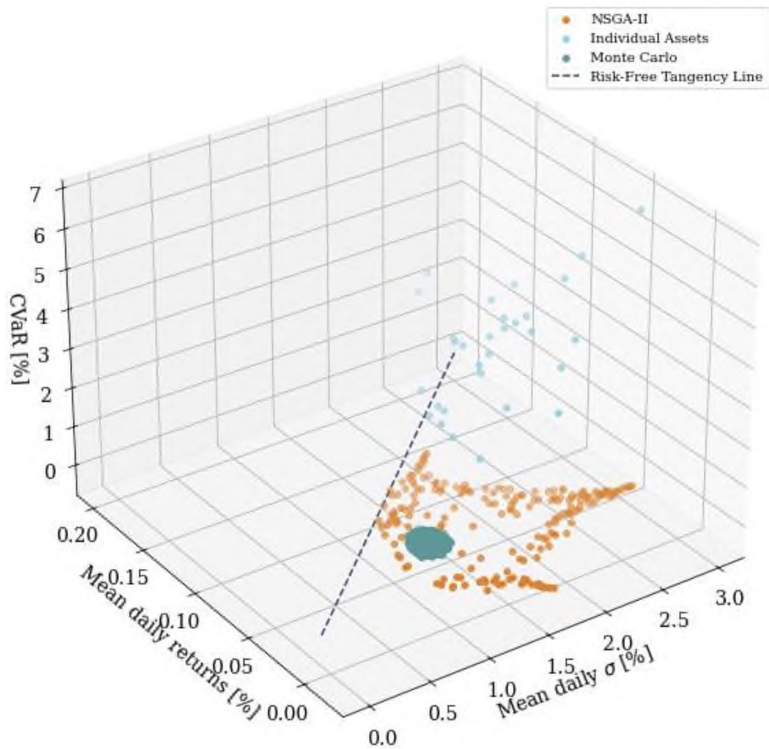

Figure 5. NSGA-II and Monte Carlo portfolio optimization results

Source: derived from calculations.

As shown in Figure 5, the Pareto optimal solution set obtained from NSGA-II demonstrates significantly greater expansiveness than the 100,000 Monte Carlo simulations. This indicates that NSGA-II explores a broader solution space to identify higher-quality, non-dominated solutions and more effectively balances multiple conflicting objectives while handling complex constraints. Consequently, NSGA-II offers a more comprehensive and precise approach to portfolio optimization. Next, the portfolio optimization backtest results are shown in Figure 6.

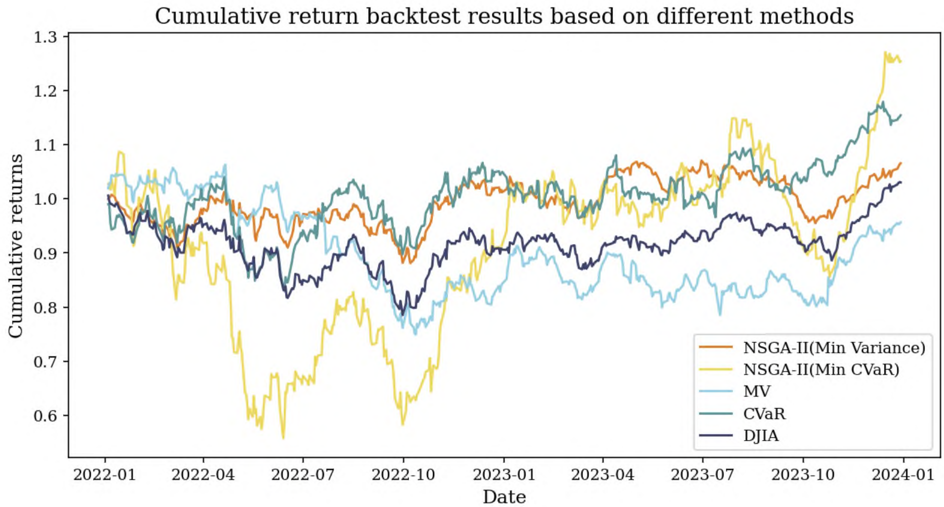

Figure 6. Cumulative return backtest results based on different methods

Source: derived from calculations.

As shown in Figure 6, the constructed portfolios remained relatively stable throughout the backtesting period. The NSGA-II portfolios consistently outperformed the index, particularly those optimized for minimum variance and traditional minimum CVaR. However, the NSGA-II portfolio optimized for minimum CVaR experienced relatively large fluctuations and underwent three significant drawdowns. On the other hand, the classical minimum variance portfolio failed to surpass the index for consecutive 14 months, maintaining negative returns. This indicates that portfolios constructed using traditional methods may have limited ability to sustain returns, and achieving optimal results may require selecting the optimization method based on the chosen risk measure. The performance of each portfolio can be seen in Table 1.

Table 1. Performance table for evaluating different portfolios

Portfolio	Cum	Mean	Sharpe	Calmar	Sortino	MDD
MV	0.956	-0.004	-0.125	-0.081	-0.206	0.295
CVaR	1.212	0.126	0.439	0.376	0.694	0.283
NSGA-II(MV)	1.061	0.038	0.141	0.141	0.244	0.130
NSGA-II(CVaR)	1.254	0.187	0.438	0.343	0.707	0.487
DJIA	1.030	0.028	0.050	0.037	0.083	0.219

Note: Cum represents the cumulative return, Mean refers to the average daily annualized return, and MDD denotes the maximum drawdown.

Source: derived from calculations.

Table 1 presents the key performance metrics for several portfolios. Except for the MV portfolio, the optimized portfolios outperform the benchmark index across most indicators. However, the two CVaR-based portfolios exhibit greater MDD, indicating significant capital losses during specific periods. Notably, the Sortino ratio, which accounts for downside risk, is the highest among all portfolios, underscoring their robust risk-adjusted performance. Despite the higher drawdown, the superior performance of the NSGA-II (CVaR) portfolio across other metrics makes it the most attractive option overall.

In contrast, the classical MV portfolio demonstrates a maximum drawdown of 0.295, indicating insufficient risk management. Its other performance significantly needs to catch up to the other optimized portfolios, with returns failing to justify the level of risk undertaken. Therefore, the MV portfolio is not a favorable choice, particularly in high-risk contexts, where its inadequate returns highlight its inefficiency. These findings suggest that while the NSGA-II (CVaR) portfolio exhibits specific vulnerabilities in capital preservation, its overall performance renders it the most compelling option for portfolio selection.

DISCUSSION

This study provides a significant value by integrating the NSGA-II algorithm into portfolio optimization, showcasing its potential to balance conflicting objectives such as risk and return. By comparing traditional minimum CVaR optimization with multi-objective approaches, the research highlights how advanced algorithms can improve portfolio performance and expand the scope of risk management strategies. However, the study has notable limitations, including its reliance on historical data and the assumption of market stationarity, which may not fully capture future market dynamics.

The instability of the NSGA-II portfolio optimized for minimum CVaR during the backtesting process might stem from the algorithm's reliance on historical data and its tendency to prioritize short-term performance trade-offs. NSGA-II's stochastic nature, while beneficial for exploring diverse solutions, may introduce noise, leading to suboptimal selections under certain market conditions.

By contrast, traditional minimum CVaR optimization directly minimizes extreme losses, offering more consistent risk management, albeit at the expense of flexibility. This raises the question of whether NSGA-II's exploratory capabilities can be adjusted or augmented–such as integrating robust optimization techniques–to mitigate instability while maintaining its innovative strengths.

Future research could delve into the underlying algorithmic mechanisms driving these differences, particularly under varying market conditions. Additionally, it would be valuable to incorporate considerations such as transaction costs or liquidity constraints, or to explore alternative optimization objectives to enhance portfolio performance.

CONCLUSIONS

This paper used NSGA-II for multi-objective optimization with different risk measures and compared the results with traditional backtesting methods. The findings indicate that the Pareto solutions obtained through NSGA-II have a relative advantage over those from Monte Carlo methods. However, the cumulative returns from backtesting depend on the chosen risk measures. This suggests that multi-objective optimization is feasible in empirical tests, but further evaluation metrics for the portfolio must be considered.

Additionally, this study observed that the results of multi-objective algorithms may vary with parameter adjustments, indicating potential instability in cumulative returns during empirical testing. Another concern is how long the optimized portfolio can maintain relatively stable returns, implying that the holding period of the portfolio requires careful consideration.

The findings of this study provide valuable insights for empirical portfolio optimization and highlight several issues that need attention. Although multi-objective optimization and NSGA-II have been extensively studied, further empirical evidence may be necessary to ensure their consistent ability to maintain low-risk levels and generate returns in real-world scenarios.

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DISCLOSURE STATEMENT

The authors report no conflicts of interest.

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TAIL RISKS ACROSS INVESTMENT FUNDS

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TAIL RISKS ACROSS INVESTMENT FUNDS

ABSTRACT

The purpose of the article. Managed portfolios are subject to tail risks, which can be either index level (systematic) or fund-specific. Examples of fund-specific extreme events include those due to big bets or fraud. This paper studies the two components in relation to compensation structure in managed portfolios.
Methodology. A novel methodology is developed to decompose return skewness and kurtosis into various systematic and idiosyncratic components and applied it to the returns of different fund types to assess the significance of these sources. In addition, a simple model generates fund-specific tail risk and its asymmetric dependence on the market, and makes predictions for where such risks should be concentrated. The model predicts that systematic tail risks increase with an increased weight on systematic returns in compensation and idiosyncratic tail risks increase with the degree of convexity in contracts.
Results of the research. The model predictions are supported with empirical results. Hedge funds are subject to higher idiosyncratic tail risks and Exchange Traded Funds exhibit higher systematic tail risks. In skewness and kurtosis decompositions, the results indicate that coskewness is an important source for fund skewness, but fund kurtosis is driven by cokurtosis, as well as volatility comovement and residual kurtosis, with the importance of these components varying across fund types. Investors are subject to different sources of skewness and fat tail risks through delegated investments. Volatility based tail risk hedging is not effective for all fund styles and types.
Keywords: Tail Risk, Systematic Risk, Idiosyncratic Risk, Coskewness, Cokurtosis, Copula, Tail Dependence, ETFs, Closed-end Funds, Mutual Funds, Hedge Funds, Compensation.
JEL Classification: G01, G11, G12.

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INTRODUCTION

It is well-known that financial asset returns exhibit asymmetry and fat-tailedness. Mandelbrot (1963) and Fama (1965) provide theoretical arguments and empirical evidence that price changes follow stable Paretian distributions. Along with the observation of time-varying volatility, asymmetric volatility, and volatility clustering by Bekaert and Wu (2000) and others, financial economists have been trying to find sources that contribute to the skewness and kurtosis in returns data, both conditionally and unconditionally. Facts about non-normality and jumps in returns and volatility reinforce the importance of higher order moments. Most importantly, financial markets do crash, as in 1929, Black Tuesday in 1987, the Asian financial crisis in 1997, Long-Term Capital Management in 1998, the dot-com bubble burst in 2000, and the recent financial crash of 2008. Tail risks are important and relevant.

Tail risks are of central importance to investors. A large negative event can significantly reduce portfolio value and the literature has tried to model this[1]. Large drawdowns in wealth due to extreme events in the last decade lead investors to fear another market crisis. To cope with investors' fears for extreme events, the fund industry has recently developed volatility-based tail risk hedging funds. Managed futures have also become a popular alternative investment class as investors seek broad diversification.

Tail risks can complicate investors' economic decisions. Samuelson (1970) points out that mean-variance efficiency becomes inadequate when higher moments matter for portfolio allocation. Harvey et al. (2010) emphasize the importance of higher moments in portfolio allocation. Cvitanić et al. (2008) show that ignoring higher moments in portfolio allocation can imply welfare losses and overinvestment in risky assets. If investors have preference for higher moments, they will demand a higher rate of return to compensate for negative tail risks.

A lack of diversification in investor holdings due to trading constraints or market frictions suggests that investors will care about not only systematic tail risks, but also idiosyncratic tail risks in their portfolio returns. Idiosyncratic risk is theoretically uncorrelated with market risk. However, higher moments of idiosyncratic shocks can be correlated with systematic shocks. Similarly, the covariance risk between the higher moments of systematic shocks and idiosyncratic shocks can be priced.

[1] In recent literature on portfolio choice and delegated principal-agent problems, many models incorporate a VaR constraint to limit downside risk. The motivation behind downside risk is that investors are concerned with losses in extreme events and thus they will demand compensation for such extreme, but rare risks, and consider these risks in their investment decisions.

Given that most investors delegate their wealth to fund managers and care about tail risks, it is important to understand the structure of tail risks in managed portfolios and look for solutions to prevent extreme downside risk. For example, if investors are not aware of tail risks hidden in managed portfolios, dynamic trading and negatively skewed trading strategies can improve fund performance in view of mean and variance, but induce great downside risk.

The investment funds in this study include closed-end funds (CEFs), exchange-traded funds (ETFs), open-ended funds (OEFs), and hedge funds (HFs). In the finance literature, few have looked at the link between tail risks and returns across different types of funds. However, different fund types are subject to different rules and regulations. Importantly, different fund types are subject to different compensation schemes and agency costs. These differences lead to different tail risk exposures.

Conventionally, investors regard HFs as high risk investment products due to the lack of transparency and loose regulation. Hedge fund managers often claim that certain hedge fund strategies can be used to hedge tail risks. This paper addresses four questions:

1. Are tail risks in hedge funds systematically different from other types of investment funds?
2. Are tail risks in managed portfolios well diversified?
3. Do hedge funds offer an alternative for investors to hedge tail risks?
4. Can compensation structure explain the heterogeneity in the sources of tail risks across fund types?

Two empirical methods are used to document differences in tail risks across investment funds. First, the frequency of monthly returns exceeding 3 and 5 standard deviations from the mean ("three and five sigma" events) is counted. The results show that the probabilities of tail returns exceed those under normal distributions. The frequencies across fund types are not statistically different. These results imply that on average, investors suffer from the occurrence of a "three sigma" event every two years, regardless of fund types. Second, skewness and kurtosis are used as tail risk measures. Empirical findings support the presence of conditional skewness and kurtosis in financial assets (Hansen, 1994; Harvey and Siddique, 1999; Jondeau and Rockinger, 2003). Except fixed income ETFs, all fund types have negative skewness and excess kurtosis.

Skewness and kurtosis are decomposed into systematic versus idiosyncratic tail risks. The results show that HFs are subject to higher idiosyncratic tail risks, but ETFs exhibit higher systematic tail risks. The decomposition of skewness shows that coskewness is an important source of skewness across fund types. Kurtosis for ETFs and OEFs mainly comes from cokurtosis, but CEFs and HFs have the largest components in volatility comovement and residual kurtosis, respectively. Thus, the decomposition reveals that there are interesting differences in tail risks across fund types that is not revealed by counting outliers. Idiosyncratic cokurtosis is consistently the least important contributing factor to kurtosis across fund styles and types. Overall, the combined contribution of cokurtosis and volatility comovement exceeds more than 50% of kurtosis across fund types.

The decomposition results suggest that:

(1) investors cannot diversify tail risks in traditional investment funds, including HFs, because most of their skewness and tail risks come from coskewness, cokurtosis, and volatility comovement;

(2) an effective tail risk hedging mechanism should consider fund performance relative to extreme market movements in return, volatility, and skewness. A volatility-based tail risk hedging fund or a fund offering negative correlation with broad asset classes is not likely to be sufficient;

(3) the decomposition of tail risks may reflect the trading strategies undertaken by a fund type.

This paper further ties fund managers' compensation schemes with tail risks and tries to understand the decomposition of tail risks across fund types. The literature on agency costs, incentive contracts and the fund flow-performance relationship examine fund managers' risk-taking behavior. Brennan (1993) proposes an agency based model with relative performance and suggests that option-like compensation can induce skewness in fund returns. Motivated by relative performance measures and convex payoff structures, fund managers may take fund-specific tail risks (big bets) endogenously.

A simple model is designed to illustrate how fund managers adjust systematic and idiosyncratic tail risks in response to the weight on compensation relative to a benchmark (the return decomposition effect) and to the importance of incentive compensation (the convexity effect). A normal shock for the benchmark, a negatively skewed shock for the fund-specific big bet, and their asymmetric tail dependence by the copula to generate nonzero covariance risks between the higher moments of the two assets are implemented into the model. The model predicts the following: first, the more the compensation depends on systematic returns, the more systematic risk the fund managers would take. This action would increase total fund skewness and decrease total fund kurtosis. Second, when the weight on the incentive contract increases, the increased convexity encourages fund managers to take big bets and funds exhibit lower skewness and higher kurtosis.

The rest of the paper proceeds as follows. Section I explains how fund strategies affect tail risks. Section II offers descriptions of and comparisons across different types of investment funds. Section III describes the model to produce tail returns and risks in response to the weight between systematic/idiosyncratic risk and the convexity in compensation across fund types. Section IV outlines the data.

Section V explains empirical methods. Section VI presents empirical results. Section VII presents a robustness analysis.

1. HOW FUND STRATEGIES IMPACT TAIL RISKS

Two strategies that traditional fund managers use to outperform benchmarks or peers are stock picking and beta timing. These two strategies have their own implications for fund tail risks. If market factors are skewed and fund managers use aggressive bets on beta timing, fund returns can be skewed[2]. Time-varying betas can induce time-varying systematic skewness risk. Alter-natively, a fund can follow a strategy of holding asset classes or compositions of assets different from the benchmark and achieve good stock selection to have better performance. If a fund manager relies on stock selection to generate alpha, idiosyncratic tail risk of the fund reflects the tail risks of the stocks the fund focuses on. The turnover of individual stocks in managed portfolios can also cause time-varying fund tail risks.

Fund risk can be decomposed into systematic and idiosyncratic components. Funds' systematic tail risk comoves with the market. Kraus and Litzenberger (1976) provide theoretical and empirical evidence that unconditional systematic skewness matters for market valuation. Harvey and Siddique (2000) extend the study to conditional skewness. Dittmar (2002) concludes that conditional systematic kurtosis is relevant to the cross-section of returns. If fund managers want to increase funds' systematic coskewness, in expectation of an upswing in the market, they can add positively coskewed financial assets. Adding an asset with positive coskewness, such as out-of-money options, makes the fund more right skewed. Buying or selling options on the market or individual security options will affect the skewness of the managed portfolio relative to the market (Leland, 1999). Harvey and Siddique (2000) document that abnormal returns from momentum strategies result from buying assets with negative coskewness (winners) and shorting assets with positive coskewness (losers). Therefore, a contrarian trading strategy, i.e. buying losers and sell winners, can increase fund skewness. Similarly, fund managers can increase portfolio kurtosis by adding assets with high cokurtosis.

Another mechanism that fund managers can use to increase overall portfolio skewness and kurtosis operates through idiosyncratic skewness and kurtosis. Some financial assets with specific characteristics, such as small-cap stocks, illiquid foreign securities, convertible bonds, may have more skewed distributions. Adding these assets can make investment funds more skewed.

[2] In an ICAPM setting with conditional volatility, Engle and Mistry (2007) study negative skewness in priced risk factors - Fama and French factors and Carhart's momentum factor.

Likewise, foreign currencies have fatter tails than stocks or bonds. Currency fund managers can adjust the level of kurtosis via currency exposure.

In addition to what a fund manager trades (where), trading strategies (how) can also result in fund tail risks. However, trade positions in fund holdings disclosure may disguise the magnitude of skewness and fat tail risks. For example, a fund manager bets on two assets to converge to one price. A merger arbitrage manager bets on the completion of a merger by buying the target firm and selling the bidding firm. An event driven manager trades on corporate events that can affect share prices, such as restructurings, recapitalizations, spin-offs, etc. A pairs trading strategy is based on relative mispricing's of two assets in the same sector. A statistical arbitrage trade captures pricing inefficiencies between securities. These strategies create a short position on a synthetic put option, i.e. if desired events do not occur, the loss can be substantial.

The short volatility trades above are one type of negatively skewed bet. A negatively skewed trade is characterized by a concave function of the underlying price level, which delivers steady profits with low volatility most of the time. For example, a fund manager can collect premiums by shorting put options. However, extreme events can wipe out all those gains. Examples are covered call writing, short derivative positions, short vega option strategies, leveraged positions, illiquid trades, etc. Dynamic trading strategies of a HF manager can improve Sharpe ratios at the expense of significant tail risks (Leland, 1999). Goetzmann et al. (2007) argue that fund managers can manipulate performance through dynamic trading.

2. COMPARISONS ACROSS INVESTMENT FUNDS

Financial institutions offer a wide variety of financial products to meet investors' needs. This study examines four fund types: CEFs, ETFs, OEFs, and HFs. An OEF issues and redeems shares at net asset value (NAV) at market close each day in response to investors' demands. The NAV of an OEF is calculated directly from the prices of stocks or bonds held in the fund. An OEF is required to report its NAV by 4 pm Eastern Standard Time, and trades on OEFs can only be legally executed end of the day when NAVs are determined.

Unlike an OEF, a CEF has a finite number of shares traded on an exchange. A fixed number of shares are sold at the initial public offering (IPO) and investors are not allowed to redeem shares after the IPO. Due to a set amount of shares traded on the exchanges, a CEF can be traded at a premium or a discount relative to the value of its portfolio. Numerous studies have attributed unrealized capital gains, the liquidity of the assets held, agency costs, and irrational investor sentiment as possible reasons for the CEF discount. Since redemptions of shares are restricted, a CEF is able to invest in less liquid securities than an OEF. About

80% of CEFs are income oriented and most CEFs are leveraged (Cherkes et al., 2009). A CEF can borrow additional investment capital by issuing auction rate securities, preferred shares, long-term debt, reverse-repurchase agreements, etc. Therefore, a CEF can have higher risks and earn higher returns from illiquidity premiums, active management, and leverage.

ETFs, like CEFs, are traded on a stock exchange. However, market prices of an ETF diverge from its NAV in a very narrow range. Since major market participants can redeem shares of an ETF for a basket of underlying assets, if the prices of an ETF deviate too much from its NAV, an arbitrage opportunity takes place. Moreover, most ETFs passively track their target market indices. But some ETFs, in contrast to mutual funds, are designed to provide 2 or 3 times leverage on the benchmarks. Leveraged ETFs have return characteristics similar to options in terms of amplifying investment returns, but no preset expiration dates.

Mutual funds and ETFs are under SEC regulations, but HFs face minimal regulations by the SEC. Only HFs with more than $100,000,000 in assets are required to register as investment advisors and report holding information through 13-F filings. Therefore, HF managers are generally free to employ dynamic trading strategies (Fung and Hsieh, 1997). Management fees on HFs are between 1.5% and 2% of assets under management and performance fees are asymmetric and on average 20%. Like CEFs, HFs can invest in illiquid assets due to lockups and redemption notification periods (Aragon, 2007). HFs further suffer from smoothed returns (Asness et al., 2001). Getmansky et al. (2004) show that serial correlation in HF returns can be explained by illiquidity exposure and smoothed returns. In addition, HF managers use leverage to increase capital efficiency and investment returns. In short, illiquidity, leverage, high-water marks, investment flexibility, asymmetric performance fees, lack of transparency, and redemption requirements may increase HFs' tail risk exposures.

Convexity affects tail risks. HF managers are compensated by high-water mark contracts. The compensation is calculated as 20% of profits in excess of high-water marks only if previous losses are fully recovered. This option-like compensation can induce HF managers to take idiosyncratic bets to turn around fund performance. An OEF manager receives compensation based on assets under management. Sirri and Tufano (1998) and Chevalier and Ellison (1997) find a nonlinear relationship between fund flow and past performance. Asymmetric return chasing by investors can create incentives for OEF managers to take big bets to improve returns relative to the markets. In addition, relative performance evaluation to a benchmark or peers can motivate a mutual fund manager to take idiosyncratic bets to climb up in the rankings. The compensation for ETF managers depends more on systematic fund returns because they are generally evaluated based on how closely they track the benchmarks. As such, systematic tail risks are more important for ETF managers. Overall, the compensation structure can impact on a fund manager' tail risk taking behavior and induce fund tail risks from heterogeneity in asset classes.

In summary, differences in fund characteristics, such as active management, redemptions, regulations, transparency to investors, agency costs, etc., may lead to differences in tail distributions across fund types. Most importantly, the model predictions propose that heterogeneity in compensation structure can explain heterogeneity in tail risks across fund types because compensation structure is linked to a fund manager's tail risk taking and optimal allocation among asset classes and risks.

3. THE MODEL

3.1. Return Dynamics and Tail Dependence

A fund manager facing an exogenous compensation structure is modelled. The model predicts how the compensation structure can induce systematic and idiosyncratic skewness and kurtosis in fund returns. The manager chooses an optimal allocation between a benchmark and a negatively skewed bet on idiosyncratic returns. The model predictions are used to explain tail risks across fund types.

Suppose that a fund manager faces a stylized portfolio choice problem today at time t between a benchmark and a big bet. The benchmark exposure captures market timing and the big bet captures selectivity and tail-risk management. Assume the joint distribution of returns of the two assets are independent and identically distributed (*i.i.d*) through time and their complete moments and joint distribution are observable before the allocation is updated. Thus for $j = 1, \ldots, t$, the fund's return dynamics is modeled as follows:

$$R_{i,t+1} = w * R_{p,t+1} + (1 - w) * R_{BB,t+1} \tag{1}$$

where:
$R_{i,j}$ is the return at time $t + 1$ for fund i,
$R_{p,j}$ and $R_{BB,j}$ are the returns of the benchmark and the big bet at time j,
w is the optimal weight that maximizes expected wealth at time t and $w \in [0, 1]$[3].

For simplicity, subscript j and $t + 1$ are dropped in the following analysis. A fund manager's strategies on beta timing and security selection do not only affect the magnitude of systematic and idiosyncratic components of returns. Even if both components are uncorrelated, the higher moments of one component and

[3] For robustness, the model is also tested with $w \in [-1, 1]$ to allow a fund manager to short sell.

the mean and variance of the other component are not necessarily uncorrelated, and this correlation is modelled below.

The benchmark represents the systematic risk of a fund and suffers from macroeconomic shocks. The benchmark is assumed to follow a normal distribution and satisfy zero residual tail risks[4]. In the empirical work, equal-weighted portfolios of funds are constructed by using funds within the same style and beta-weighted exogenous factors as proxies for benchmarks. The weight on the benchmark captures a fund manager' market timing strategy at time *t*.

The big bet reflects fund-specific risk or microeconomic shocks. Fund managers often engage in security selection, undertaking idiosyncratic risk to generate alpha. Simonson (1972) provides evidence for speculative behavior of mutual fund managers. HF managers commonly engage in negatively skewed bets (Taleb, 2004). A negatively skewed bet is characterized as a trade that has a large chance of making gains but a very small chance of losing big money. Examples are arbitrage trading strategies, leveraged trades, short (derivatives) positions, illiquid assets, credit related instruments, syndicated loans, pass-through securities, etc. Big bets can endogenously generate tail risks and induce asymmetric payoffs in investment funds. Moreover, trades that endogenously generate left tail risks can help fund managers manipulate performance measurement (Goetzmann et al., 2007).

Additional motivations to model the big bet as a negatively skewed bet are the following. First, fraud or ponzi schemes follow negatively skewed distributions. For instance, Benard Madoff's hedge funds made a succession of considerable gains, but once he was charged with fraud, fund performance plummeted. The return distribution is negatively skewed. Second, due to the negative price of risk for skewness, the big bet captures exposure to a non-benchmark asset that are possibly rewarded with a positive expected return. Third, the negatively skewed shock captures left-tail risk or crash risk. Crash risk arises from a low probability event that produces large negative returns. Fourth, the combination of the benchmark and the big bet under aforementioned assumptions can assure fund returns to be close to normal or negatively skewed. This is consistent with what we observe in the data.

Big bets are idiosyncratic because if a fund manager wants to camouflage a fund's trading, will use a trading strategy or an asset isolated from market movement. For example, frauds are fund-specific. Moreover, greater tail risks are associated with higher risk premiums. Fund managers have a wide variety of securities to select for negatively skewed trades, compared to some benchmarks,

[4] The benchmark can also be assumed to be positively or negatively skewed, as long as the tail risks from the benchmark are lower than the big bet. The benchmark has limited tail risks since a underperforming firm in the benchmark will be replaced and investors do not observe benchmarks to blow up. Leverage on the benchmark will not yield downside risk as severe as individual assets.

based on their expertise and research. For instance, illiquidity premiums are associated with stock options due to wider bid-ask spreads than index options. The downside risk of short volatility trades on individual securities is higher than the benchmarks because of higher idiosyncratic volatility. Due to compensation structure, fund managers may have incentives to camouflage fund alpha by taking idiosyncratic big bets with significant tail risks. Titman and Tiu (2010) find that HFs deviating from systematic factors provide abnormal returns or higher Sharpe ratios.

The literature on pay-performance well documents managerial risk-taking behavior in response to performance relative to a benchmark (e.g. Murphy, 1999). Brown et al. (1996) find that mid-year losers tend to increase fund risk in the latter part of the year. Chevalier and Ellison (1997) conclude that mutual fund managers alter fund risk towards the end of year due to incentives to increase fund flows. Kempf and Ruenzi (2008) find that mutual funds adjust risk according to their relative ranking in a tournament within the fund families.

To capture the bet having a low probability of blowing up, but a large chance of winning, the skewed t-distribution is used to model the big bet[5]. In this study, the marginal distribution of the big bet follows the skewed t-distribution with $\lambda = -0.6$ (skewness) and $\nu = 7$ (degree of freedom) to generate negative skewness and excess kurtosis. Both parameters are in the reasonable range from the aforementioned empirical papers. Since only unexpected shocks matter for unexpected returns, both the benchmark and the big bet are standardized to be mean zero and variance one.

There are alternatives to endogenously generate fund tail risks with an idiosyncratic big bet. For instance, one can add jumps in asset prices and volatility to generate skewness and kurtosis. Another approach is to model a mixture of normal distributions in returns and volatility. Both approaches require more assumptions on parameter specifications than the skewed t. As far as is known, the parameter values for funds are not well documented. For example, there is little evidence on the frequency of jumps and jump sizes in investment funds.

The dependence structure between the benchmark and the big bet can impact fund tail risks. The change of the moments and the return distribution of a fund depends on the covariance, coskewness, and cokurtosis risk between the benchmark and the big bet. For example, Boguth (2010) models state-dependent

[5] The generalized skewed t-distribution is first suggested by Hansen (1994) and is applied to model time-varying asymmetry and fat-tailedness by Jondeau and Rockinger (2003) and Patton (2004). Theodossiou (1998), Daal and Yu (2007) show that the skewed t-distribution provides a better fit for financial asset returns in both the U.S. and emerging markets than GARCH-jump models. Recent studies also adopt the skewed t-distribution to model asset returns and extend its applications in asset allocation, risk management, credit risk, and option pricing (e.g. Aas and Haff, 2006, Dokov et al., 2007).

idiosyncratic variance and its correlation with the mean and variance of a systematic factor to induce fund skewness and kurtosis. Recent studies have also documented asymmetric tail dependence among financial assets (Longin and Solnik, 2001; Ang and Chen, 2002).

The tail dependence between the benchmark and the big bet is modelled by a T-Copula[6]. The bivariate copula is the joint distribution of two marginal distributions. Financial asset returns tend to comove together more strongly in bad economic states than good ones. The copula models asymmetric joint risks among financial assets. Its application includes credit default risk, catastrophic risk for insurers, systemic risk among financial institutions, etc (Frey et al., 2001; McNeil et al., 2005). T-Copula is adopted because of its prominence in the tail dependence literature. Results are based on tail dependent parameter $\kappa = 0$[7].

The model setup follows Patton (2004). He studies the optimal conditional weight between a big-cap and a small-cap portfolio under various tail dependence structures. To solve the optimal weight for two given assets, it is necessary to estimate the conditional mean and variance. Unlike his study, my focus is on the unconditional weight and the benchmark and the big bet to be any specific financial assets are not restricted. Because the differences in tail risks between these two assets are emphasized, two arbitrary standardized financial assets are adopted[8]. If two specific financial assets, such as S&P 500 and a stock option on Citibank, are interested, the standardized time-series by their respective volatilities can be multiplied and their respective means can be added back to derive the optimal unconditional weight of these two specific assets. One example with mutual fund data is shown in the robustness analysis section.

This allocation problem reflects a fund manager's ability to adjust systematic and idiosyncratic tail risk. For example, market-neutral HFs have low systematic tail risk but high idiosyncratic tail risk. ETF or index funds have high systematic tail risk, but relatively low idiosyncratic tail risk. In daily fund management, fund managers can adopt market-timing or stock-picking strategies to decide the allocation between systematic and idiosyncratic returns. In a multi-period setting, a fund manager can disguise fund performance by betting on negatively skewed assets or investing strategies.

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[6] Normal and Rotated Gumbel copula is also tested for a robustness check. Normal copula has zero tail dependence and Rotated Gumbel copula has lower tail dependence only.

[7] Results hold for $\kappa = 0.5$ and 0.9, reflecting different levels of covariance, coskewness, cokurtosis risk between the benchmark and the big bet.

[8] Kan and Zhou (1999) is followed to standardize the systematic factor to simulate asset returns.

3.2. Characterization of Compensation Structure and Optimization Problem

A combination of a linear and a convex compensation contract is considered. The linear contract is based on a fund manager's systematic and fund-specific returns with the nonnegative allocation weight α and 1 − α, respectively[9]:

$$W_{linear} = \alpha\big(wR_p\big) + (1 - \alpha)\big((1 - w)R_{BB}\big) \tag{2}$$

where α is specified in the incentive contract. The return decomposition parameter α reflects the weight of the systematic component on the compensation. For larger α, the manager's compensation depends more on the systematic component of returns.

A fund manager's total compensation may also depend on the convex payoff:

$$W_{opt} = 1 + max(\varphi(R_i + K), 0) \tag{3}$$

and W_{linear}, weighted by nonnegative g and 1 − g, respectively:

$$W = gW_{opt} + (1 - g)W_{linear} =$$
$$= g(max(\varphi(R_i + K), 0) + (1 - g)\big[\alpha\big(wR_p\big) + (1 - \alpha)\big((1 - w)R_{BB}\big)\big] \tag{4}$$

where the incentive fee φ is subject to high-water marks and commonly quoted as 20% in the HF industry. Fund managers receive incentive fees only if fund value exceeds the highest value the fund has previously achieved. The convexity parameter g is exogenously given and varies across fund types. The larger the g, the more convex the compensation. K measures the cumulative losses up to time t and is modeled as:

$$K_t = min(0, K_{t-1} + R_t) \tag{5}$$

directly model the option-like payoff like HFs, instead of using an arbitrary fixed K. An arbitrary K may reflect implicit convexity faced by fund managers, such as tournaments or fund-flow performance relations, but it is too arbitrary to justify a specific value to K. To the best of available information, there are no empirical studies that estimate the range of K across funds. Furthermore, incentive fees in the mutual fund industry are calculated based on cumulative performance over previous periods as well. Elton et al. (2003) show that fulcrum fees can always be

[9] Ramakrishnan and Thakor (1984) show that in the presence of moral hazard, contracts will depend on both systematic and idiosyncratic risks.

converted to non-negative incentive fees. Nonetheless, a fixed K = 1% is used as a robustness check.

This setup for managerial compensation is very stylized so that it can be applied to different types of investment funds. HF managers are measured against high-water marks and thus $g = 1$. For ETFs and index funds, tracking errors are critical in performance measurement and no convex payoff applies to compensation[10]. Therefore, α and g are 1 and 0, respectively. Because actively managed OEFs are subject to implicit optionality, such as fund-flow performance relations and "tournaments", the compensation should depend on a combination of total fund returns and fund-specific returns ($0 < \alpha, g < 1$). CEFs are subject to discounts, which can be regarded as the moneyness of an option that investors sell to the management. Both α and g are between 0 and 1 for CEFs. The setup implicitly captures relative performance in ETFs, CEFs, OEFs, and absolute performance in HFs. The order of the magnitude of α (index tracking) across fund types is ETFs, CEFs or OEFs, and HFs; the effect of g (convexity) is in the order of HFs, OEFs or CEFs, and ETFs.

In summary, Table 1 shows how the model for the different fund types is applied.

Table 1. Parameters used across different fund types

	ETFs	Index	Active OEFs	CEFs	HFs
α	1	1	∈ (0,1)	∈ (0,1)	∈ (0,1)
g	0	0	∈ (0,1)	∈ (0,1)	1
K	NA	NA	Cumulative *	NA	Cumulative
φ	NA	NA	< 1% *	NA	20%

* if applicable (Elton et al., 2003).

Source: Elton et al., 2003.

Following Patton (2004), fund managers are assumed to optimize his/her wealth for the period t + 1 using returns observed up to time t to form expectations. Under the assumption of i.i.d returns, the optimal weight can be solved by maximizing the sum of utility functions up-to-date.

$$W = argmaxE_t[U(W_{t+1})] = argmax\frac{1}{t}\sum_{j=1}^{t} U(W_j) \qquad (6)$$

Where W_j is the manager's total compensation at time j. For simplicity, the subscript j is dropped in the following notation.

The non-normal fund returns and option-like compensation structure lead to nonlinearity and non-normality of total wealth W. The utility below follows

[10] Kim (2010) shows that the flow-performance relation is weak for index funds.

Mitton and Vorkink (2007) and Boguth (2010) and captures the higher moments of wealth.

$$U(W) = E(W) - \frac{1}{2\tau_2}Var(W) + \frac{1}{3\tau_3}Skew(W) - \frac{1}{12\tau_4}Kurt(W) \qquad (7)$$

where τ_2, τ_3, and τ_4 are risk tolerance for the second, third, and fourth moments of W. The central moments are defined as $Var(W) = E[W - E(W)]^2$, $Skew(W) = E[W - E(W)]^3$ and $Kurt(W) = E[W - E(W)]^4 - 3Var(W)^2$. The main results use τ_2 = 1.5, τ_3 = 0.15, and τ_4 = 0.015. The parameters of risk tolerance for the second, third, and fourth moments under this utility is translated into relative risk aversion between 5 and 10 under the power utility[11]. The initial wealth is set to be 1 because the optimal allocation does not depend on the initial wealth under this utility.

The positive sign of the third term denotes the manager's preference for skewness. The negative sign of the fourth term corresponds to the manager's dislike of kurtosis. This type of utility captures the manager's concern for skewness and kurtosis relatively to dispersion.

Since the distribution of fund returns in this model is not solely determined by mean and variance and managerial compensation is convex, the utility taking account of the probability distribution of wealth up to the fourth moments is used. Fund managers are assumed to value skewness and kurtosis. A convex contract is not desirable for a fund manager who is neutral to risks or cares only about mean and variance. Hemmer et al. (2000) show that the incentive contract should be more convex when skewness is increased, and the amount of convexity depends on the risk aversion. The return generating process and asymmetric dependence structure guarantees skewness and kurtosis in wealth. Fund skewness and kurtosis cannot be diversified away in this model. The preference for higher moments ensures fund managers consider tail risks in the asset allocation between the benchmark and the big bet according to compensation structure.

Career concern and "tournament" also support the preference for higher moments. As Taleb (2004) states, "Does one gamble dollars to win a succession of pennies (negative skewness) or one risks a succession of pennies to win dollars (positive skewness)?" Although the conventional utility theory suggests that a rational manager would prefer positive skewness and dislike excess kurtosis, most funds are negatively skewed and fat-tailed. One reason can be career concerns. If a fund manager takes a positively skewed bet, the probability of

[11] According to Kane (1982), the skewness ratio and kurtosis ratio for the power utility are equal to 1+γ and (1+γ)(2+γ), where γ is the relative risk aversion and skewness (kurtosis) ratio reflects preference for the third (fourth) moment relative to aversion to variance. Thus, the range of skewness ratio is between 6 and 11 and kurtosis ratio is between 42 and 132 for γ = 5 and 10. Parameters for risk tolerance used in the model suggest skewness ratio and kurtosis ratio to be 10 and 100, respectively.

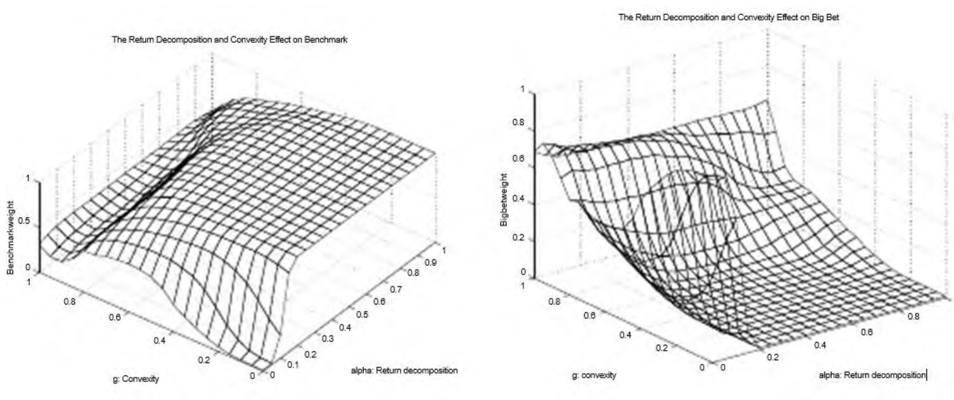
failures is too high to stay in the business. From the "tournament" perspective, if a fund underperforms its peer, the fund manager may choose to gamble with a large probability of considerable losses, but a tiny probability of huge gains. Large losses can blow up the fund. On the other hand, an outperforming fund may take a negatively skewed bet instead because of a very tiny probability of losses and frequent gains.

3.3. MONTE CARLO RESULTS

Since the optimization problem above has no closed-form solution, Patton (2004) is followed to numerically solve the asset allocation problem. The details are in the Appendix A.

Figure 1 presents the optimal weights of the benchmark and the big bet. Figure 2 shows the snapshot of the optimal weights with respect to α and g, i.e. the return decomposition and convexity effect. Figure 3 displays the optimal skewness and kurtosis of a fund.

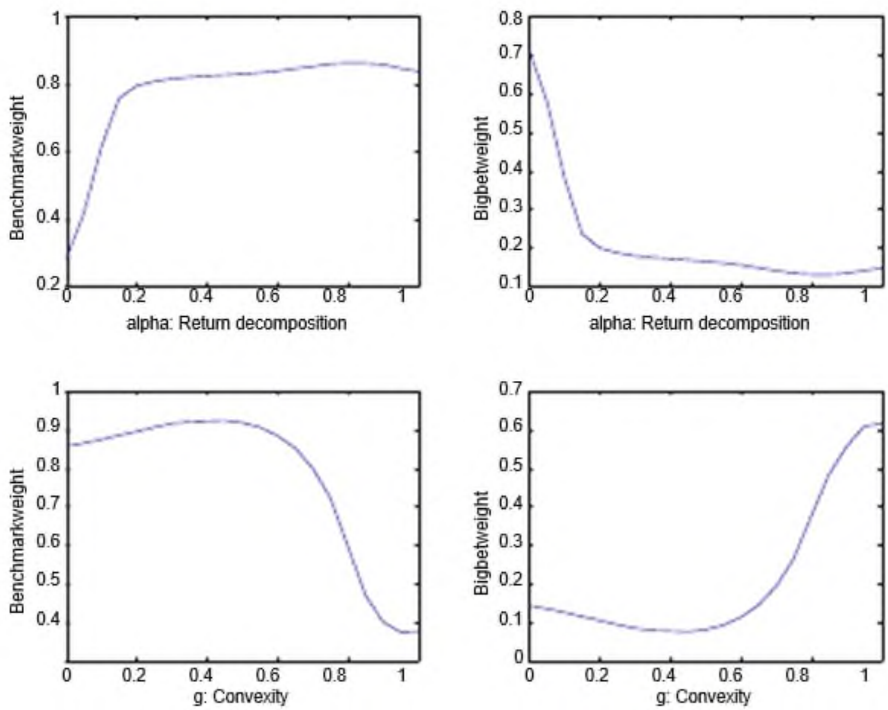
Figure 1. The Optimal Weight of the Benchmark and Big Bet



Source: own study based on the model outputs.

The return decomposition parameter α and the convexity parameter g are the weight of the systematic return and convex payoff in managerial compensation, respectively. Z-axis is the optimal weight on the benchmark.

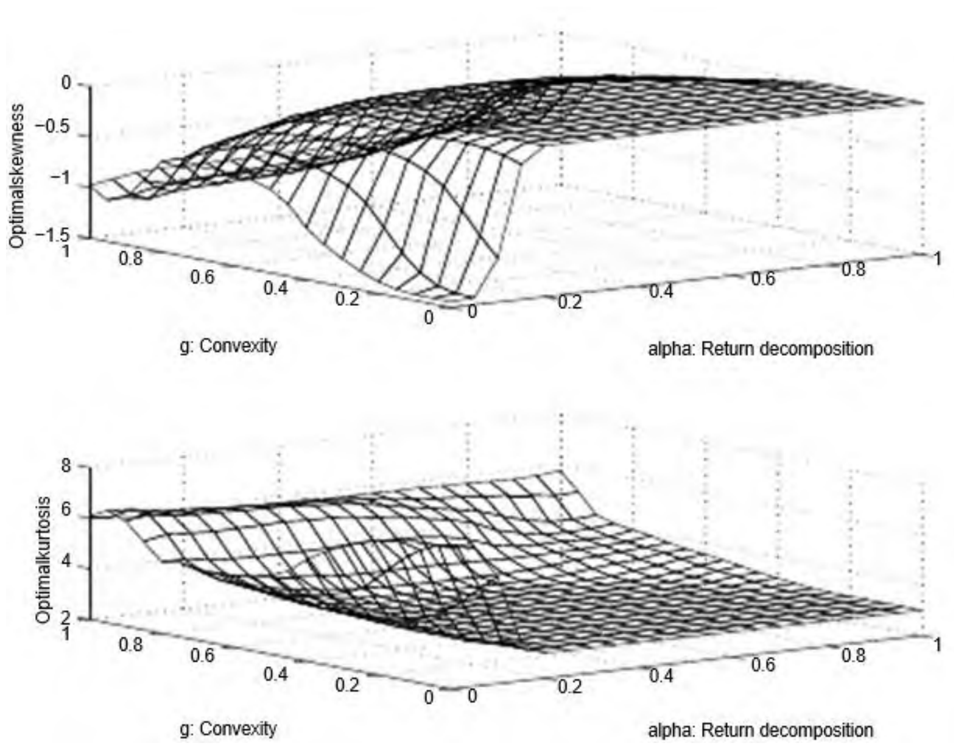
Figure 2. The Return Decomposition and Convexity Effect on the Optimal Weights of the benchmark and the Big Bet



Source: own study based on the model outputs.

The graphs on the top panel show the return decomposition effect on the benchmark (left) and the big bet (right). The graphs on the bottom panel show the convexity effect on both assets. The snapshot is taken by averaging weights across all g and α for each α on the x-axis and g on the y-axis, respectively.

Figure 3. The Optimal Fund Skewness and Kurtosis



Source: own study based on the model outputs.

The model predicts that as convexity in the contract increases (i.e. g increases), fund managers will increase weights on the idiosyncratic big bet and thus reduce fund skewness and increase fund kurtosis. On the other hand, if a fund managers' compensation ties more to the systematic returns (i.e. α increases), more weight will be allocated to the benchmark to increase fund skewness and reduce fund kurtosis.

The incentive to take the idiosyncratic big bet is to risk the possibility of negatively skewed outcomes in exchange for improving the fund's expected alpha for the next period. Consider two types of fund managers in the economy: conservative and aggressive. A fund manager whose compensation depends more on the systematic component of returns (i.e. a larger α) can be viewed as the conservative one. An ETF fund manager is one example. The conservative fund manager face a linear contract and tail risks have symmetric impact on managers. Thus, simply trades the benchmark and has no incentive to improve alpha and trade idiosyncratic big bets since trading big bets does not increase utility. On the contrary, when a fund manager is endowed with a more convex compensation scheme (i.e. a larger g), fund managers care about the upside and downside differently. An aggressive fund manager prefers idiosyncratic big bets that improve or camouflage the short-term performance at the cost of increased left tail risks. HFs are the example. Convexity generally increases skewness, but the introduction of a negatively skewed bet can mitigate the convexity effect.

One intriguing implication from the model is that if the compensation structure depends mostly on idiosyncratic returns with little convexity (i.e. α and g are both very low), the model suggests that a fund manager will invest mostly in the idiosyncratic big bet to increase expected returns and undertake tail risks. However, it is hard to find this type of compensation structure since the compensation structure should be based on any signals that informs about managers' actions (Holmstrom, 1979). Most funds' compensation relies on convexity and systematic returns to some degrees.

In summary, Figure 1 shows the predictions for the tail risks for the different fund types. HFs' skewness and kurtosis come mostly from the idiosyncratic component of returns because the convex compensation is associated with $g = 1$. The increased weight on the idiosyncratic big bet lowers the skewness and raises the kurtosis of a HF. ETFs, represented by higher α and lower g, are subject to higher systematic tail risks. Figure 3 shows that ETFs exhibit less negative skewness and lower kurtosis. OEFs and CEFs are associated with α and g between 0 and 1. As such, their weights of the idiosyncratic components in total fund skewness and kurtosis are between HFs and ETFs.

4. THE DATA

The ETFs, OEFs, CEFs, and HFs in this study are investment funds managed in the U.S. The list of ETFs and CEFs domiciled in the U.S. are screened from the Morningstar database, including both live and dead funds. Monthly returns of ETFs and CEFs from the CRSP monthly stock return table are merged with the list of funds from Morningstar database by dates and tickers. ETFs and CEF returns start from 1993 and 1929, respectively. Monthly OEF returns are from CRSP U.S. survivorship-free mutual fund database and start in 1962. The HF sample is constructed from the HFR database, starting in 1996. The data period for all four fund types ends in 2008.

Groups of funds are formed by styles for analysis. ETFs and CEFs are grouped by Morningstar styles[12]. OEFs are grouped by CRSP style codes[13]. HFs are grouped by HFR main strategies[14]. Table I (in Appendix) summarizes univariate statistics of "average" funds across fund styles and types. By "average", it means that statistics for individual funds in the same group are averaged to represent "average" or individual fund statistics.

HFs are the most negatively skewed. ETFs are the least negatively skewed and fixed income, ETFs have positive skewness. The level of skewness in OEFs and CEFs is between HFs and ETFs. The kurtosis of HFs (ETFs) is close to that of CEFs (OEFs). The model fully predicts the tail risks in HFs and ETFs. The tail risks in HFs increase because increased convexity in compensation motivates fund managers to take more big bets (negatively skewed bets). The tail risks in ETFs declines because the increased weight on compensation relative to the benchmark induces a ETF manager to increase loadings on the benchmark, which bears lower left tail risk. There are variations in tail risks across fund styles within the same fund type. It can be observed from the variation of the significance level of the Jarque-Berra test.

5. EMPIRICAL DESIGN

5.1. Frequency of Tail Returns

If an investment fund is well diversified, the distribution of returns should be close to normal, i.e. its skewness is zero and kurtosis is 3. However, Table I (in Appendix) suggests that tail returns and risks do exist in investment funds. One direct approach is to measure the frequency of tail returns in a given fund.

Tail returns of an individual fund are defined as its monthly returns above or below a cutoff stated of observing one jump conditional on a large log-return. He concludes that as far into the tail as 3.5 standard deviations, a large observed log-return can still be produced by Brownian noise. A large log-return above 3.5

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[12] Equity ETFs: Global, Currency, Sector, Balanced, Bear Market, Commodities, Large/Mid/Small Cap, Growth/Value, and Others. Fixed Income ETFs: Global, Sector, Long Term, Intermediate Term, Short Term, Government, High Yield, and Others. Equity CEFs are Global, Balanced, Sector, Commodities, Large/Mid/Small Cap, Growth/Value, and Others. Fixed Income CEFs are Global, Sector, Long Term, Intermediate Term, Short Term, Government, High Yield, and Others.

[13] Equity funds are classified as Index, Commodities, Sector, Global, Balanced, Leverage and Short, Long Short, Mid Cap, Small Cap, Aggressive Growth, Growth, Growth and Income, Equity Income, and Others. Fixed income funds are classified as Index, Global, Short Term, Government, Mortgage, Corporate, and High Yield. The classification methodology is in Appendix A.

[14] Equity Hedge, Event-Driven, Fund of Funds, HFRI Index, HFRX Index, Macro, and Relative Value. Descriptions of these investment strategies are available from HFR (www1).

standard deviations in a finite time would help identify at least one jump. A fund with a high frequency of monthly returns exceeding 5 standard deviations suggests that jumps can be identified in the fund returns. As such, 3 and 5 standard deviations are used as thresholds to determine tail returns.

Funds' monthly returns are decomposed into systematic and idiosyncratic components and compute the percentage of monthly systematic and idiosyncratic returns exceeding 3 and 5 standard deviations of the means of respective distributions.

Let $COUNT_{i,t_i}$ be one if fund *i* is monthly return on month *ti* is greater than 3 or 5 standard deviations from the mean. The test statistics of the frequency of tail returns for fund *i* is derived by assuming that $COUNT_{i,t_i}$ follows the Bernoulli distribution and the sequence of $COUNT_{i,t_i}$ is independent and identically distributed, i.e. $COUNT_{i,t_i}$ is 1 with probability p and 0 otherwise on each month. Thus, at the individual fund level, the frequency of tail returns and its test statistics can be represented as follows:

$$X_i = \frac{1}{I_i}\sum_{t_i=1}^{T_i} COUNT_{i,t_i} \sim N\left(p, \frac{p(1-p)}{T_i}\right) \tag{8}$$

where T_i is the number of monthly returns for fund *i* and t_i = (1, 2, ..., T_i) ∈ T_i. At the style or type level,

$$Y_s = \frac{1}{N_s}\sum_{i=1}^{N_s} X_i \sim N\left(p, \frac{1}{N_s^2}\left(\sum_i \frac{p(1-p)}{T_i} + \sum_i \sum_{j\neq i} \rho_{tail}\sqrt{\frac{p(1-p)}{T_i}}\sqrt{\frac{p(1-p)}{T_j}}\right)\right) \tag{9}$$

where N_s is the number of funds in the style or type s, ρ_{tail} is calculated as follows. If the returns of different funds in the same style or type s are jointly within 3 standard deviations from their respective means in month t, i.e. $COUNT_{i,t}$ = 0 for all fund *i* in the style or type s in month *t*, those returns are dropped to compute correlations. Then correlations between different funds in the same style or type to derive ρ_{tail} are averaged. ρ_{tail} reflects correlation between funds at the extreme states.

To compare any two fund styles or types (Y_s and Y_r) at the aggregate level:

$$Y_s - Y_r \sim N\big(0, var(Y_s) + var(Y_r) - 2cov(Y_s, Y_r)\big) \tag{10}$$

$$cov(Y_s, Y_r) = \frac{1}{N_s N_r} \sum_i \sum_j \rho_{tail}\sqrt{\frac{p(1-p)}{T_i}}\sqrt{\frac{p(1-p)}{T_j}} \tag{11}$$

Table II (in Appendix) presents the frequencies of monthly returns exceeding 3 and 5 standard deviations from the mean across fund types. The frequency of raw tail returns ranges from 1.78% (CEFs) to 1.10% (OEFs) and 0.13% (CEFs) to 0.01% (ETFs) for the 3 and 5 standard deviations, respectively[15]. Both ranges exceed the probability of 3 and 5 sigma events under the normal distribution, i.e. 0.27% and less than 0.0001%, respectively. This result substantiates the presence of tail risks in managed portfolios.

For all fund types, the null hypothesis that a 3(5) standard deviation event occurs 4%(1%) per month is not rejected at 1% significance level. This suggests that on a monthly basis, all four fund types are subject to a 3(5) sigma event with 4%(1%) probability. In view of economic significance, investors who delegate investment decisions to fund managers still face 3 “sigma” event approximately every two years.

The frequencies of idiosyncratic tail returns are less varied across fund types than systematic tail returns. At the 3 standard deviations, CEFs have the highest frequency of tail returns on both return components[16]. ETFs show high frequency of systematic tail returns, but lowest frequency of idiosyncratic tail returns. The frequencies of both systematic and idiosyncratic tail returns at the 5 standard deviations follow the same order as raw tail returns. The test statistics associated with the hypothesis that the occurrence of systematic/idiosyncratic returns exceeding 3(5) standard deviations from the mean equals to 4%(1%) per month are not significant at 1% significance level. The classic portfolio theory suggests that idiosyncratic tail risks can be diversified away by increasing the number of assets. It is interesting to see that managed futures suffer from both systematic and idiosyncratic tail risks at similar frequency.

Investors suffer more systematic risks by investing in ETFs, but more idiosyncratic risks in HFs and OEFs. The high frequencies of idiosyncratic tail returns in CEFs and HFs imply that both fund types have high tracking errors, and their managers trade on individual assets with high idiosyncratic risks to increase performance. ETFs exhibit higher frequency of systematic tail risks than HFs and OEFs since tracking errors or idiosyncratic risks should be minimized for ETFs.

T-tests of differences in frequencies of tail returns (raw, systematic, and idiosyncratic) fail to reject the hypothesis that funds in different fund types have the same frequency at 1% significance level, except for equity CEFs and ETFs at the 3 standard deviations. This indicates that investors should be aware of 3 and 5 sigma events not only for HFs, but for all four types of investment funds.

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[15] Results for 2 standard deviations are also available upon request. Across fund types, the frequency of raw tail returns ranges from 4.74% and 5.6%; the frequencies of both systematic and idiosyncratic tail returns are very close to 5%.

[16] One concern is that the recording of the last return due to delisting varies across data vendors. One reason for CEFs to have higher a frequency may be due to traded price discounts. However, the order of frequencies across fund types still hold if the last observation is removed from the analysis.

The frequencies of tail returns are further broken down by right and left tails. The striking finding is that most tail returns come from the left tails. This evidence supports the importance of downside risk and the prevalence of negative skewness and leptokurtosis across fund types.

5.2. Systematic and Idiosyncratic Tail Risk

5.2.1. THE BENCHMARKS

Different fund styles and types have different levels of systematic risk and are exposed to different risk factors. Therefore, a broad-based index is not the appropriate benchmark to decompose risk into systematic and idiosyncratic components across fund styles and types. CEF returns are subject to discounts and Lee et al. (1991) show that changes in discounts are correlated with small firm returns. The discounts resemble market-to-book ratios and Thompson (1978) show that discounts predict the expected returns of CEFs. ETFs track market indexes and are most sensitive to market factors directly associated with the benchmarks they track. Because OEFs follow long-only strategies, standard asset classes may be appropriate market factors. HFs have no benchmarks, and fund managers tend to maximize total fund returns due to high watermark provisions. In addition, different HF styles pursue different directional/nondirectional trades and dynamic trading strategies, and differ in option-like payoffs. These HF characteristics lead to distinctive risk profiles among HFs, compared to other fund types.

Inappropriate factors may lead to a misleading measure of systematic and idiosyncratic risk decomposition. If the chosen market factors don't appropriately explain the variations of systematic components of returns, too much idiosyncratic risk is mistakenly identified. Then empirical results will spuriously show fund skewness and kurtosis mostly come from the idiosyncratic component of returns.

The equal-weighted portfolios of funds are used to decompose systematic and idiosyncratic components of returns. This follows many studies on fund performance (e.g. Grinblatt and Titman, 1994; Brown et al., 1999; Ackermann et al., 1999). The advantages of using portfolios of funds within the same style as a benchmark include the following: portfolios of funds are readily observable and capture diversification effects to isolate idiosyncratic returns of funds within the style[17]. Second, many fund managers in the same style make similar bets or share similar trading strategies. Therefore, funds in the same style may be exposed to

[17] The k^{th} order moment of portfolios of funds is $O(\frac{1}{n^{k-1}})$. As n → ∞, $E[R_p - E(R_p)]^K = E[\frac{1}{n}R_i - \frac{1}{n}E(R_i)]^K = \frac{1}{n^k}E[R_i - E(R_i)]^K \leq \frac{n}{n^k}$

the same common factors (Hunter et al., 2010). The benchmark can capture a common component in the variation over time and across funds within the group.

In addition, return characteristics and distributions differ across fund styles and types and the portfolios of funds capture distinctive differences. For example, HFs exhibit nonlinearities in returns and the magnitudes of nonlinearities differ across HF styles. An index constructed of the funds in the same style captures style-specific returns.

Third, a fund manager is regarded as providing valuable services when the investment opportunity set is expanded by the trading strategies of the fund. Therefore, a benchmark should share common assets with the fund. For example, if the Janus Balanced Fund trades growth stocks and U.S. Treasuries, both types of securities should be included in the benchmark. The portfolios of funds represent a joint set of reference assets for funds with the same trading strategy.

Fourth, portfolios of funds create a peer group of managers who pursue the same style. Thus, portfolios of funds have the highest correlations with funds in the same style and represent asset classes in that style. Fund managers are increasingly evaluated relative to a benchmark specific to their styles, instead of a broad-based benchmark. An inappropriate benchmark can induce incorrect measurement of relative performance. For example, a small-cap fund manager may underperform relative to a broad market index, but overperform relative to a small stock benchmark.

5.2.2. THE DECOMPOSITION

The following regression is run to decompose the systematic and idiosyncratic components of risks:

$$R_{i,t} - E(R_i) = \beta_i \left(R_{p,t} - E(R_p)\right) + u_{i,t} \tag{12}$$

where $R_{i,t}$ and $R_{p,t}$ are returns for fund *i* and portfolios of funds *p* at time *t*. The portfolios of funds are constructed based on the investment styles outlined in section IV. $\beta_i \left(R_{p,t} - E(R_p)\right)$ and $u_{i,t}$ stand for the systematic and idiosyncratic component of de-meaned returns for fund *i*. Both components are orthogonal to each other.

The simple linear regression in (12) is advantageous to study systematic and idiosyncratic tail risks[18]. Under the single factor model, the skewness of r_i can be decomposed as follows:

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[18] If the quadratic terms are added to (12), i.e. $R_{i,t} - E(R_i) = \alpha_i + \beta_i(R_{p,t} - E(R_p)) + \gamma_i(R_{p,t} - E(R_p))^2 + \varepsilon_{it}$ the skewness decomposition becomes $E(r^3) = \beta_i^3 E({r_p}^3) + 3\beta_i E\left(r_p {\varepsilon_i}^2\right) + E({\varepsilon_i}^3) + \left[3\beta_i^2 \gamma_i E\left({r_p}^4\right) + 3\beta_i \gamma^2 E\left({r_p}^5\right) + 3\gamma_i E\left(({r_p}^2 {\varepsilon_i}^2\right) +\right.$

$$E(r_i^3) = E[(\beta_i r_p + u_i)^3] =$$
$$\underbrace{\beta_i^2 cov(r_i, r_p)^2 + 2\beta_i^2 cov(u_i, {r_p}^2)}_{\text{COSKEW}} + \underbrace{3\beta_i cov({u_i}^2, r_p)}_{\text{ISOCKEW}} + \underbrace{E(u_i^3)}_{\text{RESSKEW}} \quad (13)$$

where r_i and r_p are de-meaned returns, i.e. $r_i = R_i - E(R_i)$ and $r_p = R_p - E(R_p)$ According to (13), the skewness decomposition consists of three parts: coskewness (COSKEW), idiosyncratic coskewness (ICOSKEW), and residual skewness (RESSKEW). Since both COSKEW and ICOSKEW contain β and covary with the market, they are different forms of systematic skewness. RESSKEW represents idiosyncratic tail risk. Note that coskewness in this study is defined as the sum of two covariance terms – the covariance of fund returns with market volatility and the covariance of fund residuals with market volatility. The latter is small under the assumption of orthogonality between the systematic and idiosyncratic components in the one-factor regression.

Moreno and Rodríguez (2009) show that coskewness is managed and the coskewness policy is persistent over time. In their remark, "managing coskewness" refers to having a specific policy regarding the assets incorporated into the fund's portfolio to achieve higher or lower portfolio coskewness. If a manager consistently adds assets with negative coskewness to reduce fund skewness, the fund will exhibit negative coskewness and investors will demand a higher risk premium.

The idiosyncratic coskewness, i.e. the covariance between idiosyncratic volatility and market returns, is advocated by Chabi-Yo (2009). Chabi-Yo (2009) proves that idiosyncratic coskewness is equivalent to a weighted average of individual security call and put betas. He shows that in a single factor model, during market upswings ($r_p > 0$), ICOSKEW is positive and the idiosyncratic risk premium is negative; during market downswings ($r_p < 0$), ICOSKEW is negative and the idiosyncratic risk premium is positive. In other words, stocks whose option betas with high sensitives to market returns have low average returns because they hedge against market upswings and downswings. Out-of-money options written on these stocks have large betas or higher sensitivities with market returns. Investors prefer options written on stocks with lottery-like returns. The

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$3\gamma_i^2 E({r_p}^4 \epsilon_i) + 6\beta_i\gamma_i E(({r_p}^3 \varepsilon_i) + \gamma_i^3 E(({r_p}^6)] = COSKEW + ICOSKEW + RESSKEW$ +other higher moments. Similarly, the kurtosis decomposition expands as $E(r_i^4) = \beta_i^4 E({r_p}^4) + 4\beta_i E(r_p {\varepsilon_i}^3) + E({\varepsilon_i}^4) + 4\beta_i^3\gamma_i E({r_p}^5) + 6\beta_i^2\gamma_i^2 E({r_p}^6) + 4\beta_i\gamma_i^2 E({r_p}^5) + \gamma^4 E({r_p}^8) + 4\epsilon_i 3\beta^2\gamma_i E({r_p}^4) + 3\beta_i\gamma^2 E({r_p}^5) + \gamma^3 E({r_p}^6) + 6\epsilon^2[2\beta_i\gamma_i E({r_p}^3) + \gamma^2 E({r_p}^4)] + 4[\beta_i E(r_p{\varepsilon_i}^3) + \gamma_i E({r_p}^2{\varepsilon_i}^3)] = COKURT + ICOKURT + RESKURT + VOLVOMV$ + other higher moments. The components in this study can also be extracted under the quadratic assumption.

idiosyncratic coskewness explains two market anomalies. First, Ang et al. (2006 and 2009) document that stocks with high idiosyncratic volatility have low expected returns. Second, idiosyncratic coskewness helps explain the empirical finding that distressed stocks have low returns (Chabi-Yo and Yang, 2009).

Note that $cov(u_i^2, r_p)$ is equivalent to $cov[E(u_i^2|r_p), r_p]$ or $E[E(u_i^2|r_p), r_p]$. This decomposition implies that the sign and the magnitude of ICOSKEW depends on the risk-return relation and the level of conditional heteroscedasticity. Skewed fund returns can be generated through conditional heteroscedasticity. If an asset has high idiosyncratic conditional heteroscedasticity, negatively correlated with market returns, adding this asset to a fund will impart negative skewness through a large negative ICOSKEW.

Mitton and Vorkink (2007) and Barberis and Huang (2008) document that idiosyncratic skewness is priced and its relation with expected returns is negative. Boyer et al. (2010) empirically test the negative relation between idiosyncratic skewness and expected returns.

The decomposition of kurtosis is derived as follows:

$$E(r_i^4) = E[(\beta_i r_p + u_i)^4] = \beta_i^3 \underbrace{cov(r_i, r_p{}^3) + 3\beta_i^3 cov(u_i, r_p{}^3)}_{\text{COKURT}} + 6\underbrace{\beta_i^2 E(r_p{}^2 u^2)}_{\text{VOLCOMV}} + \underbrace{4\beta_i cov((u_i^3, r_p)}_{\text{ICOKURT}} + \underbrace{E(u_i^4)}_{\text{RESKURT}} \quad (14)$$

This decomposition displays four sources of fund kurtosis: cokurtosis (COKURT), comovements of volatility (VOLCOMV), idiosyncratic cokurtosis (ICOKURT), and residual kurtosis (RESKURT). COKURT, VOLCOMV, and ICOKURT are exposed to the market and are classified as systematic tail risks. RESKURT is considered as idiosyncratic tail risk. The importance and validity of cokurtosis on asset returns are documented by Dittmar (2002).

The cokurtosis of an asset can impact the total kurtosis of the fund. Investors dislike fat-tails in returns and thus demand a positive risk premium on an asset with large kurtosis. Such an asset will increase the total kurtosis of the fund. If a manager constantly adopts the strategy of buying positive cokurtosis assets, the fund will show a large weight on cokurtosis in the kurtosis decomposition. In addition, since cokurtosis reflects the covariance between market skewness and individual fund returns, a fund with positive cokurtosis indicates a positive relation between the fund return and the skewness of the market returns.

The VOLCOMV term is the comovement of shocks to fund conditional volatility and market volatility. The negative relationship between these two shocks can reduce the kurtosis level of funds. Since investors prefer assets with lower kurtosis, fund managers can add assets, whose volatility moves oppositely to market volatility to achieve this goal. For example, a fund manager can engage trades on variance swaps, VIX options, or VIX futures to reduce exposure to market volatility in extreme markets.

The concept of comovement of volatility is often applied across international markets (Hamao et al., 1990; Susmel and Engle, 1994). The comovement of volatility between the market and a fund can be interesting as well. Fund managers are known to use market-timing and market volatility timing strategies (Treynor and Mazuy, 1966; Merton and Henriksson, 1981; Busse (1999). From the hedging perspective, if an investor's portfolio is exposed to the market, adding a fund which comoves with market volatility can be suboptimal due to kurtosis. Since kurtosis is the variance of the variance, a fund manager can add assets with high volatility comovements with the market to increase the kurtosis of the fund. When a fund exhibits a large VOLCOMV component, it is inferred that using comovements of volatility is a common strategy for the fund.

Following Chabi-Yo (2009), I refer to the covariance between idiosyncratic skewness and market returns as idiosyncratic cokurtosis. Like idiosyncratic coskewness, idiosyncratic cokurtosis can be interpreted as a weighted average of individual security call and put betas. For a single factor model, market upswings imply positive option betas and thus positive idiosyncratic cokurtosis.

$cov\left(u_i^3, r_p\right)$ can be rewritten as $cov[E(u_i^3 | r_p), r_p]$ or $E[E(u_i^3 | r_p), r_p]$ The idiosyncratic cokurtosis is implicitly embedded with a skewness-return relation and the magnitude of conditional heteroscedasticity. Conditional heteroscedasticity is a property of residual returns and kurtosis in fund returns can be induced by conditional heteroscedasticity from different assets. If fund managers prefer funds being less fat-tailed, in expectation of an increase in market returns, they can add assets with high idiosyncratic skewness covarying negatively with market returns. A trading strategy involving small cap stocks is one example.

Chabi-Yo (2009) extends his analysis to higher moments and concludes that risk premium on higher moments is driven by individual security call and put betas. Although the risk premium on idiosyncratic kurtosis is not well documented in the literature, a fund with a larger weight on idiosyncratic kurtosis implies that the manager has more flexibility in what and how to trade. For example, since HF managers constantly use high leverage and dynamic strategies, and are able to invest in a wider class of assets, HFs should exhibit a larger weight on RESSKEW and RESKURT.

The components in skewness and kurtosis decompositions are summarized below:

Table 2. Summary of Higher Moment Covariance Risks[19]

Components	Economic Interpretation	Type of Risk	Likely to be Driven by Compensation/ Fund Type
COSKEW	Covariance between fund returns and market volatility	Systematic	Systematic (α=1)/ ETFs
ICOSKEW	Covariance between fund volatility and market returns		
RESSKEW	Idiosyncratic skewness held in the fund	Idiosyncratic	Convex (g=1)/ HFs
COKURT	Covariance between fund returns and market skewness	Systematic	Systematic (α=1)/ ETFs
VOLCOMV	Covariance between fund volatility and market volatility		
ICOKURT	Covariance between fund skewness and market returns		
RESKURT	Idiosyncratic kurtosis held in the fund	Idiosyncratic	Convex (g=1)/ HFs

∗ α (g) is the weight in compensation relative to benchmark (convex payoff).

Like beta risk, investors should concern themselves with different sources of tail risks. Investors fear those “black swans” that cause widespread disruption, and the components from skewness and kurtosis decompositions can help them identify the sources of tail risks in their portfolios. Market crashes cause not only spikes in market volatility, but also declines in market returns and skewness. COSKEW and VOLCOMV (ICOSKEW and ICOKURT) measure fund movement against market volatility (market returns). COKURT refers to the relation between fund performance and market skewness.

Investors always try to diversify risks across styles or types of funds. If investors want to hedge their investments against “black swans”, they should measure these components to identify the needs and choose an effective tail risk hedging mechanism accordingly. For instance, if a portfolio faces potential tail risks when economies skid, gold and treasuries are good hedging tools. On the other hand, if the significant portion of tail risks in a fund comes from COSKEW or VOLCOMV, one should look for volatility-based tail risk hedging mechanism, such as long-short strategies or managed futures.

[19] The simulated results from section 3 show that if a fund’s systematic (idiosyncratic) tail risks are increased with the weight in compensation relative to benchmark (convexity), COSKEW and COKURT (RESSKEW and RESKURT) are the main contributors, and ICOSKEW and ICOKURT contribute the least to fund tail risks. In other words, the model predicts that COSKEW and COKURT drive the systematic tail risks in ETFs and RESSKEW and RESKURT drive the idiosyncratic tail risks in HFs.

5.2.3. GMM ESTIMATION FOR SKEWNESS AND KURTOSIS DECOMPOSITIONS

The error terms of the time-series regression in (12) may suffer from heteroscedasticity, autocorrelation, and non-normality, and thus result in inefficient β coefficients and biased OLS standard errors. Furthermore, funds in the same group share commonalities in risk and strategies, and thereby the error terms may be correlated across funds and subject to possible fixed effects and clustering. Hansen's (1982) generalized method of moments (GMM) is the most robust estimation technique to allow for heteroscedasticity, autocorrelation, non-normality, and cross-sectional correlation in error terms. As such, GMM methodology is adopted to estimate the components from skewness and kurtosis decompositions.

The parameters for the skewness decomposition are β_i, μ_i, μ_p, $COSKEW_i, ICOSKEW_i$and $RESSKEW_i$ for i = *1...N* . N is the number of funds in the same fund style or type. μ_p is the expected return for the portfolio of funds. μ_i is the expected return for fund i. Following equation (12) and (13) moment conditions for skewness are the following:

$$r_{i,t} = R_{i,t} - \mu_i \tag{15}$$

$$r_{p,t} = R_{p,t} - \mu_p \tag{16}$$

$$u_{i,1t} = (R_{p,t} - \mu_p)u_{i,t} \tag{17}$$

$$u_{i,2t} = COSKEW_i - \beta_i^3 r_{p,t}{}^3 - 3\beta_i^2(r_{p,t}{}^2 u_{i,t}) \tag{18}$$

$$u_{i,3t} = ICOSKEW_i - 3\beta_i(r_{p,t}u_{i,t}^2) \tag{19}$$

$$u_{i,4t} = RESSKEW_i - u_{i,t}^3 \tag{20}$$

Similarly, the following moment conditions are used to estimate $\beta_i, \mu_i, u_p,\ COKURT_i$, $ICOKURT_i, VOLCOMV_{i,} RESKURT_i$in the kurtosis decompositinin equation (12) and (14).

$$r_{i,t} = R_{i,t} - \mu_i \tag{21}$$

$$r_{p,t} = R_{p,t} - \mu_p \tag{22}$$

$$u_{i,1t} = (R_{p,t} - \mu_p)u_{i,t} \tag{23}$$

$$u_{i,2t} = COKURT_i - \beta_i^4 r_{p,t}{}^4 - 4\beta_i^2 \left(r_{p,t}{}^3 u_{i,t}\right) \tag{24}$$

$$u_{i,3t} = VOLCOMV_i - 6\beta_i \left(r_{p,t}{}^2 u_{i,t}^2\right) \tag{25}$$

$$u_{i,4t} = ICOKURT_i - 4\beta_i \left(r_{p,t} u_{i,t}^3\right) \tag{26}$$

$$u_{i,5t} = RESKURT_i - u_{i,t}^4 \tag{27}$$

6. EMPIRICAL RESULTS

Table III (in Appendix) reports the skewness decomposition across fund types. The first column (EW portfolio skewness) is the total skewness for the equal-weighted portfolios of funds. The second column (individual skewness) is the average of total skewness across all funds in a given style. Individual funds' coskewness (COSKEW), idiosyncratic coskewness (ICOSKEW), and residual skewness (RESSKEW) are reported as the proportion of total fund skewness and they are denoted as COSKEW (%), ICOSKEW (%), and RESSKEW (%), respectively. All values at the style level are calculated as the equal-weighted average across all funds within the same style. Style averages are reported at the bottom of the fixed income styles, equity income styles, and all fund styles. FI Average is the average of statistics across fixed-income fund styles. EF Average is the average of statistics across equity fund styles. Group Average is the average of statistics across all fund styles.

Managed portfolios have negative skewness and excess kurtosis at both aggregate and individual fund levels. Note that the equal-weighted portfolio skewness and average fund skewness can be different, although for fixed income funds, both values are close. Equal-weighted portfolios of funds are constructed using all observations in a given month, but the number of funds changes over time. High attrition can make the distributions of the equal-weighted portfolios of funds negatively skewed. HFs are one example. Likewise, fund birth rates can affect the number of funds in a given month, and thus impact the distributions of the equal-weighted portfolios.

COSKEW is an important source of skewness across fund types. The proportions of CEF skewness are almost equal in the three components of skewness. The individual COSKEW, ICOSKEW, and RESSKEW are 40.48%, 33.32%, and 26.21%, respectively. Around 80% of ETF skewness is from COSKEW. OEF skewness mostly comes from COSKEW (71.17%) and HFs have a percentage of 65.93% on COSKEW. The large fractions of COSKEW in fund skewness suggest that market volatility has a strong impact on fund returns, and fund skewness risks are not diversified. Across fund types, HFs display the highest percentage on RESSKEW (44.29%). This can reflect the asset classes HFs invest in, and the leverage and dynamic strategies HFs can undertake.

Most fixed income and equity fund styles have the largest component in COSKEW. Relative to fixed income CEFs and ETFs, fixed income OEFs have a highly negative percentage on ICOSKEW, and a highly positive percentage on RESSKEW. The negative percentage on ICOSKEW means that fund volatility decreases when market return drops. The hedging gains from ICOSKEW are counteracted by negative RESSKEW. This suggests that fixed income OEF managers use trading strategies that bear high idiosyncratic skewness risk or trade negatively skewed assets with high turnover. Equity ETFs and OEFs consistently have the highest percentages in COSKEW. Equity CEFs' percentage on three skewness components are close. This suggests that equity fund managers engage in trades or assets that make a big marginal contribution to the skewness of the market portfolio.

Panel E of Table III (in Appendix) provides the t-statistics on the comparison of the proportion of each component in fund skewness across fund types. The F-test of differences in the fractions of RESSKEW (%) show that all four fund types differ in RESSKEW (%). CSKEW (%) in ETFs and MFs are significantly different from CEFs or HFs. ICOSKEW (%) is more significant in CEFs and ETFs than OEFs. HFs' RESSKEW (%) is statistically significant than other fund types. This suggests that the sources of fund skewness differ across fund types, and not a single tail risk hedging strategy can work for all types of fund investors. For example, OEF investors can opt for tail risk hedging strategies based on ICOSKEW to reduce exposures to COSKEW.

The sign and magnitude of each skewness component can be determined by multiplying individual COSKEW (%), ICOSKEW (%), and RESSKEW (%) by the average fund skewness. CEFs, ETFs, OEFs, and HFs all have negative COSKEW and negative RESSKEW. This result denotes that investment fund returns and the market volatility move in opposite directions and fund managers add individual assets with negative skewness or fund-specific strategies generate negatively skewed payoff. Negative skewness is associated with high risk premiums. During crises, jumps in market volatility reduce fund skewness and negatively skewed bets can blow up. Investors can suffer from high skewness risk hidden in managed portfolios.

The sign of ICOSKEW depends on the correlation between a fund's idiosyncratic volatility and market returns. The relation can be positive or negative, and thus can be used to offset COSKEW. For example, large positive ICOSKEW means that assets' idiosyncratic risks in the fund are positively correlated with market returns. During crises, drops in returns yield positive skewness in fund returns and offset negative COSKEW. Empirical studies show that small growth firms have high idiosyncratic volatility; large value firms are low idiosyncratic volatility stocks. Thus, ICOSKEW is more negative in the former.

OEFs and HFs have a negative sign on ICOSKEW (%) (positive values of ICOSKEW), but CEFs and ETFs have a positive sign on ICOSKEW (%) (negative values of ICOSKEW). HFs and OEFs have a positive relations between a fund's idiosyncratic volatility and market returns, but ETFs and CEFs have negative relations. That combined with the magnitude of ICOSKEW can reflect the asset characteristics a fund trades. The comparison of ICOSKEW suggests that HFs and CEFs prefer small growth stocks and ETFs and OEFs prefer large value stocks.

Table IV (in Appendix) presents results from the kurtosis decomposition. Individual components are reported as percentages of total fund kurtosis – COKURT (%), VOLCOMV (%), ICOKURT (%), and RESKURT (%). The average ETF and OEF fund has excess kurtosis below 3 and CEFs and HFs exhibit large kurtosis. This result confirms the analysis on the frequencies of tail returns. Fixed income funds have more kurtosis than equity funds. In particular, equity ETFs and equity OEFs show less fat-tailedness than other fund types.

COKURT (41.4%) and VOLCOMV (35.62%) contribute the most to the kurtosis of CEFs, including fixed income and equity CEFs. COKURT (67.46%) is the most important contributor to the kurtosis of both fixed income and equity ETFs. Fixed income and equity OEFs have the highest percentage on COKURT as well. HFs depend on RESKURT (39.60%) the most, and then VOLCOMV (33.81%). These results suggest that funds are subject to different types of systematic fat tail risks, and an effective tail risk hedging should reduce exposures an investor faces the most. Morever, the fractions of combined COKURT and VOLCOMV exceed more than 50% of fund kurtosis, and it implies that too much systematic fat tail risk is not diversified away in funds as suggested by the portfolio theory. Since HFs have the highest percentage in residual tail risks (RESSKEW and RESKURT) across fund types, this confirms that HF managers commonly use idiosyncratic assets to improve performance. Across all fund styles and types, ICOKURT has minimal influence on total fund kurtosis.

Similar to skewness, a fund manager's trading strategies are reflected in COKURT, VOLCOMV, ICOKURT, and RESKURT. Results show that managed portfolios have positive COKURT, positive VOLCOMV, and positive RESKURT, suggesting fund returns and volatility are positively correlated with market volatility and skewness and idiosyncratic assets in funds are fat-tailed. When a fund manager has constantly trade illiquidity or volatility based products, such as VIX options or futures, the percentage on VOLCOMV will be high. HFs are one example. On the other hand, if a fund manager mostly trades assets in the benchmark, COKURT can have a high percentage. ETFs are one example. The high percentage in RESKURT can reflect a fund manager's flexibility in stock picking. Agency costs and compensation structure give a manager incentives to take tail risks (low skewness and high kurtosis) to generate risk-adjusted returns over time.

Panel E of Table IV (in Appendix) summarizes the t-statistics associated with the comparison of the proportion of each kurtosis component across fund types. COKURT (%) in fund kurtosis are ranked from high to low as OEFs, ETFs, CEFs, and HFs, and pairwise comparisons show statistical differences. Interesting, RESKURT (%) yields the opposite ranking, i.e. HFs, CEFs, ETFs, and OEFs. VOLCOMV (%) is the highest in CEFs and statistically different from other fund types. The sources of fat tail risks are more heterogeneous across fund types than those of skewness risks. These results support the argument that volatility based tail hedging is not effective for all fund types since COKURT, VOLCOMV, and RESKURT reflect different types of covariance risks with extreme market movements in market returns, volatility, and skewness.

The comparison of the same style across fund types exhibits some differences in the skewness and kurtosis decomposition. For instance, equity global OEFs have the largest component in COSKEW, but most of skewness of equity global CEFs come from RESSKEW. Although COSKEW contributes the most to long-short strategies, long-short OEFs rely more on COKURT, but equity hedge HFs face more fat tail risks from RESKURT. The inconsistency shows that different fund types rely on trading strategies that induce different levels of systematic and idiosyncratic skewness and fat tail risks, even their fund objective is the same.

The skewness and kurtosis decomposition help understand the trading strategies commonly used by fund managers and priced risks across fund types. If a fund manager tends to add negatively coskewed assets to increase expected returns, one would observe negative COSKEW in the fund. If a fund manager often chooses assets with high idiosyncratic volatility or negative idiosyncratic skewness, the fund will exhibit higher percentage on ICOSKEW or ICOKURT. If the skewness or kurtosis of a fund comes mostly from the idiosyncratic component of returns, one can conclude that the fund uses individual assets to increase fund expected returns. If a fund's common trading strategy is to rely on volatility comovement between the assets and the market, the source of kurtosis of the fund will mostly come from VOLCOMV.

More importantly, the examination of each component from the skewness and kurtosis decomposition conclude that managed funds are subject to different sources of tail risks. This has several important implications. First, it is hard to diversify tail risks in managed portfolios. Because COSKEW, COKURT, and VOLCOMV contribute to most tail risks and they all have the same signs and similar magnitudes for all fund types, fund returns and volatility of all fund types will move towards the same direction when market volatility jumps or market skewness declines drastically. Heterogeneity in the percentage of components across fund styles suggests that investors can select a specific style and fund type to match their needs to hedge tail risks. Moreover, the fund industry claims that HFs can be used to hedge tail risks because of the flexibility in asset classes and trading strategies. Equity hedge and macro HFs do have less negative skewness, but style averages show that most HF styles are still subject to tail risks, especially idiosyncratic tail risks. For example, fund of hedge funds invest in a variety of different hedge funds, but their idiosyncratic tail risks are not well reduced (skewness of -0.459 and excess kurtosis of 0.588).

Second, the measures of these components help investors examine tail risks in their investment portfolios. The appropriate tail risk hedging fund should match investors' risk profiles on these components. Like hedging beta risk, investors can look for low beta securities or industries to reduce systematic risk. For instance, if an investor's portfolio consists of low COSKEW and high VOLCOMV, s/he should look for a tail risk hedging fund that offers fund returns positively correlated with market volatility and fund volatility negatively correlated with market volatility to reduce systematic tail risks.

Third, a one-size-fits-all tail risk hedging mechanism does not work for all funds. A fund negatively correlated to investors' portfolios is not sufficient to hedge tail risks. The fund industry has been launching volatility-based tail risk hedging funds, which guarantee a convex payoff to the upside during periods of market crisis. However, an effectively tail risk hedging mechanism should consider how fund returns and volatility respond to extreme movements in market returns, volatility, and skewness. These components capture different sources of tail risks, and thus policy makers and fund managers should examine these components on any funds.

Measurement errors are associated with estimation of skewness and kurtosis. All funds are kept with at least 12 monthly returns. This causes a trade-off between survivorship bias and measurement errors. The components in the kurtosis decomposition have higher statistical significance than those in the skewness decomposition. RESKURT and VOLCOMV are statistically significant at 5% for most fund styles and types. On the other hand, three components of the skewness decomposition yield low statistical significance.

Based on model predictions, across fund types, HFs (ETFs) should be subject to idiosyncratic risk the most (least). The compensation structure of ETFs is tied to systematic returns with no convexity. Some OEFs are subject to explicit incentive fees and their assets have been growing (Elton et al., 2003). Moreover, the fund-flow performance relation is convex for OEFs. The implicit convexity for CEFs may come from fund tournament or price premium/discount relative to net asset values. The compensation structure for CEFs depends more weight on idiosyncratic returns than ETFs, because of active management in CEFs and index-tracking in ETFs. The percentage of RESSKEW for HFs, OEFs, CEFs, and

ETFs are 44.29%, 26.21%, 31.27%, and 5.74%, respectly. For the kurtosis decomposition, HFs, OEFs, CEFs, and ETFs have the percentage of RESKURT as follows: 39.60%, 23.45%, 11.91%, and 10.30%. These results conincide with the model predictions.

The total fund skewness from low to high is HFs, OEFs, CEFs, and ETFs. This ranking is predicted by the model. The total fund excess kurtosis for CEFs is the highest, but only slightly above HFs. Figure 2 suggest that it is possible if the α (the return decomposition parameter) and g (the convexity parameter) for CEFs on average is close to 0. OEFs have the lowest kurtosis, but very close to ETFs. The model fails to predict the result of total fund kurtosis, but it can be attributed to the assumed range of α and g for OEFs.

The order of skewness holds across fixed-income funds, but the result for kurtosis is mixed across equity funds. The percentages for fixed-income funds across ETFs, CEFs, and OEFs are 7.62%, 11.33%, and 73.23%, respectively, for the skewness decomposition. The kurtosis decomposition also shows that fixed-income ETFs have the lowest weight (13.30%) on the idiosyncratic component. Equity ETFs have the percentage on RESSKEW and RESKURT – 4.48% and 8.29%, respectively, but equity OEFs have the lowest percentage on RESKURT.

The empirical results and model predictions are in line with Starks (1987). She concludes that the "symmetric" contract does not necessarily eliminate agency costs, but it better aligns the interests between investors and managers than the "bonus" contract. Since ETFs use a symmetric contract and HFs use a bonus contract, the alignment of interests is worse for HFs but agency costs still exist in both funds. This implication is reflected in the differences in skewness and kurtosis between these two types of funds. ETFs are less negatively skewed and fat-tailed. HFs are more negatively skewed and more leptokurtic. ETFs are subject to more systematic tail risks, and HFs are subject to more idiosyncratic tail risks.

7. ROBUSTNESS ANALYSIS

7.1. An Application of the Model on Mutual Funds

All moments in the model in section IV are standardized. One set of parameters from mutual funds is applied to the model. Brown, Goetzmann, Ibbotson, and Ross (1992) simulate mutual fund returns by the following:

$$R_{i,j} = r_f + \beta_i(R_{p,j} - r_f) + \epsilon_{i,j} \tag{28}$$

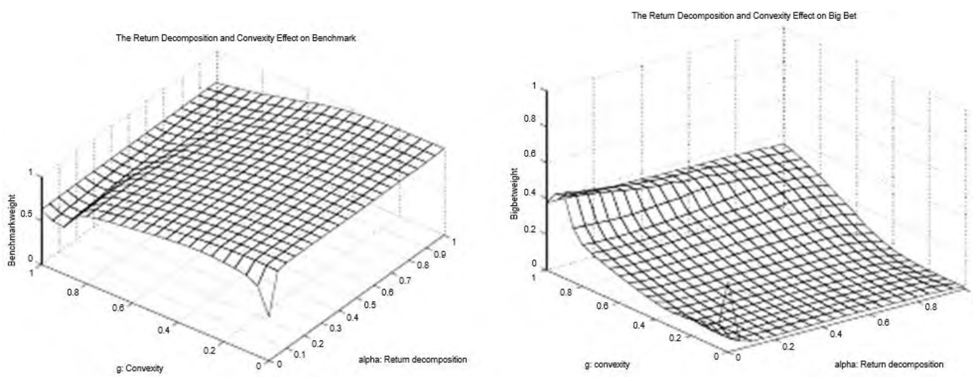
where the risk free rate is 0.07 and the risk premium is assumed to be normal with mean 0.086 and standard deviation 0.208. β_i follows the normal distribution with mean 0.95 and standard deviation 0.25 cross-sectionally. The idiosyncratic term $\varrho_{i,j}$ is assumed to be normal with mean 0 and standard deviation σ_i. The relationship between nonsystematic risk and βi is approximated as:

$$\sigma_i^2 = k(1-\beta_i)^2 \tag{29}$$

The value of k is 0.05349. Note that $\beta_i(R_{p,j} - r_f)$ and $\in_{i,j}$ are equivalent to $r_{p,j}$ and $r_{BB,j}$ in the model, representing systematic and idiosyncratic components of returns. These parameters are implemented in the model and display the model's predictions for the relation between the return decomposition (convexity) effect and the optimal weight on the market portfolio and the big bet in Figure 4.

To summarize, the model predictions hold in a qualitatively similar manner. Convexity induces fund managers to take idiosyncratic big bets and increased weights in compensation relative to a benchmark cause fund managers to invest more in the benchmark and thus yield more systematic tail risks.

Figure 4. The Optimal Weight of the Benchmark and Big Bet



Source: own study based on the model outputs.

The return decomposition parameter α and the convexity parameter g are the weight of the systematic return and convex payoff in managerial compensation, respectively. Z-axis is the optimal weight.

7.2. Autocorrelation

Stale pricing or serial correlation of returns has the most significant impact on HFs among fund types. Due to the unique characteristics of HFs, such as limited regulations and the lockup and notice periods, HF managers have more flexibility in trading illiquid assets. Since current prices may not be available for illiquid assets, HF managers commonly use past prices to estimate them. As a result, the presence of illiquid assets can lead to significant serial correlation on HF returns. This link is supported by Getmansky et al. (2004), who conclude that illiquidity and smoothed returns are the main source of serial correlation in HFs. The existence of serial correlation in returns can affect HF performance and statistics (Lo, 2002; Jagannathan et al., 2010).

Following Asness et al. (2001) and Getmansky et al. (2004), let the true but unobserved demeaned return satisfy the following regression:

$$r_{i,t}^* = \beta_i^* r_{p,t} + u_{i,t}^*,\ E(u_{i,t}) = 0, r_{p,t}\ and\ u_{i,t}^*\ are\ i.i.d.$$

Three lags are used to model autocorrelations of the observed demeaned returns. The observed demeaned return $r_{i,t}$is thus modelled as:

$$r_{i,t} = \theta_0 r_{i,t}^* + \theta_1 r_{i,t-1}^* + \theta_2 r_{i,t-2}^*$$

$$= \beta_i^*(\theta_0 r_{p,t} + \theta_1 r_{p,t-1} + \theta_2 r_{p,t-2})$$

$$+ \Big(\theta_0 u_{i,t}^* + \theta_1 u_{i,t-1}^* + \theta_2 u_{i,t-2}^*$$

$$= \beta_{0,i}\theta_0 r_{p,t} + \beta_{1,i}\theta_1 r_{p,t-1} + \beta_{2,i}\theta_2 r_{p,t-2} + \eta_{i,t}$$

$$= (\beta_{0,i} + \beta_{1,i} + \beta_{2,i}\Big)\big(R_{p,t} - \mu_p\big) + \tilde{u}_{i,t}$$

The last equation is used by Asness et al. (2001) to compute the “summed beta” Sharpe ratios for HFs. They estimate coefficients by the second to last equation and consider the summation of three coefficients as the true beta. They therefore compute the “summed beta” residuals as:

$$\tilde{u}_{i,t}^* = r_{i,t} - \tilde{\beta}_i^* \left(R_{p,t} - \mu_p\right)$$

where $\tilde{\beta}_i^*$ is the true or “summed beta”, i.e. $\tilde{\beta}_i^* = \beta_{0,i} + \beta_{1,i} + \beta_{2,i}$. The same approach is followed to construct moment conditions. GMM moment conditions are modified as follows. For skewness decomposition:

$$r_{i,t} = R_{i,t} - \mu_i$$

$$r_{p,t} = R_{p,t} - \mu_p$$

$$u_{i,1t} = (R_{i,t} - \mu_i - \beta_{0,i}\big(R_{p,t} - \mu_p\big) - \beta_{1,i}\big(R_{p,t-1} - \mu_p\big) - \beta_{2,i}(R_{p,t-2} - \mu_p))(R_{p,t} - \mu_p)$$

$$u_{i,2t} = (R_{i,t} - \mu_i - \beta_{0,i}(R_{p,t} - \mu_p) - \beta_{1,i}(R_{p,t-1} - \mu_p) - \beta_{2,i}(R_{p,t-2} - \mu_p))(R_{p,t-1} - \mu_p)$$

$$u_{i,3t} = (R_{i,t} - \mu_i - \beta_{0,i}(R_{p,t} - \mu_p) - \beta_{1,i}(R_{p,t-1} - \mu_p) - \beta_{2,i}(R_{p,t-2} - \mu_p))(R_{p,t-2} - \mu_p)$$

$$u_{i,4t} = COSKEW_i - \widetilde{\beta}_i^{*3} r_{p,t}^3 - 3\widetilde{\beta}_i^{*2}(r_{p,t}^2 \tilde{u}_{i,t}^*)$$

$$u_{i,5t} = ICOSKEW_i - \widetilde{\beta}_i^{*}(r_{p,t} \tilde{u}_{i,t}^{*\,2})$$

$$u_{i,6t} = RESSKEW_i - \tilde{u}_{i,t}^3$$

For kurtosis decomposition:

$$r_{i,t} = R_{i,t} - \mu_i$$

$$r_{p,t} = R_{p,t} - \mu_p$$

$$u_{i,1t} = (R_{i,t} - \mu_i - \beta_{0,i}(R_{p,t} - \mu_p) - \beta_{1,i}(R_{p,t-1} - \mu_p) - \beta_{2,i}(R_{p,t-2} - \mu_p))(R_{p,t} - \mu_p)$$

$$u_{i,2t} = (R_{i,t} - \mu_i - \beta_{0,i}(R_{p,t} - \mu_p) - \beta_{1,i}(R_{p,t-1} - \mu_p) - \beta_{2,i}(R_{p,t-2} - \mu_p))(R_{p,t-1} - \mu_p)$$

$$u_{i,3t} = (R_{i,t} - \mu_i - \beta_{0,i}(R_{p,t} - \mu_p) - \beta_{1,i}(R_{p,t-1} - \mu_p) - \beta_{2,i}(R_{p,t-2} - \mu_p))(R_{p,t-2} - \mu_p)$$

$$u_{i,4t} = COKURT_i - \tilde{\beta}_i^{*4} r_{p,t}^4 - 4\tilde{\beta}_i^{*3}(r_{p,t}^3 \tilde{u}_{i,t}^*)$$

$$u_{i,5t} = VOLCOMV_i - \widetilde{6\beta}_i^{*2}(r_{p,t}^2 \tilde{u}_{i,t}^{*\,2})$$

$$u_{i,6t} = CONSKT_i - 4\tilde{\beta}_i^{*}(r_{p,t} \tilde{u}_{i,t}^{*\,3})$$

$$u_{i,7t} = RESKURT_i - \tilde{u}_{i,t}^4$$

The decomposition results (%) for skewness and kurtosis are reported in Table V (in Appendix). Overall, the tail risk decompositions are robust to autocorrelation. The weight on RESSKEW increases slightly and the weight on RESKURT stays almost the same. COSKEW and RESSKEW are still the top two contributors to HF skewness. The components of VOLCOMV and RESKURT occupy the most weights in HF kurtosis. More interestingly, in contrast to the finding in Asness et al. (2001) that beta risk increases after stale prices are adjusted, idiosyncratic tail risks for HFs slightly increase. This may suggest that stale pricing helps identify true idiosyncratic tail risks undertaken by HF managers.

7.3. Exogenous Systematic Factors

Different fund types are subject to different exogenous systematic factors due to risk characteristics. ETFs are passive and index-tracking, and therefore returns are highly correlated with market factors. The premiums on CEFs are related to market risk, small-firm risk, and book-to-market risk (Lee et al., 1991; Swaminathan, 1996; Pontiff, 1997). Carhart (1997) shows that momentum plays an important role in mutual fund performance. Non-linearities in HF returns may suggest some systematic factors representing option-like payoffs (Fung and Hsieh, 2001; Agarwal and Naik, 2004).

Following the literature, Fama-French 3-factor model is used for equity ETFs and CEFs, Carhart 4-factor model for equity OEFs and Fung and Hsieh 7-factor model for HFs. For bond funds, two more Barclay bond indexes are added – the Barclay U.S. government/credit index and corporation bond index. Fama-French 3-factors are value-weighted market excess returns, and two factor-mimicking portfolios SMB and HML. SMB and HML measure the observed excess returns of small caps over big caps and of value stocks over growth stocks. Carhart adds the momentum factor on top of Fama-French 3-factors. The momentum factor is constructed by the monthly return difference between one-year prior high over low momentum stocks. Fung and Hsieh 7-factors include the equity and bond market factor, the size spread factor[20], the credit spread factors[21], and three lookback straddles on bond futures, currency futures, and commodity futures.

For simplicity, this paper adopts the single-factor model to illustrate economic intuitions on components of skewness and kurtosis decompositions. Beta-weighted time series of aforementioned factors are constructed to decompose systematic and idiosyncratic tail risks. Table VI and VII (in Appendix) show the results[22].

First, COSKEW contributes the most to total fund skewness, except HFs. COKURT is the most contributing source to total fund kurtosis for ETFs and OEFs. In addition, HFs (ETFs) have the largest (smallest) weight on RESSKEW

[20] Wilshire Small Cap 1750 - Wilshire Large Cap 750 return.

[21] Month-end to month-end change in the difference between Moody's Baa yield and the Federal Reserve's 10-year constant-maturity yield.

[22] Equal-weighted exogenous factors are also constructed, but across all fund types and styles, RESSKEW and RESKURT consistently have the highest percentages among all components in both skewness and kurtosis decompositions. This result reflects that equal-weighted exogenous factors do not appropriately capture time-variation in systematic tail risks and implies that investors can diversify tail risks across fund types. A further analysis on the correlation between equal-weighted portfolios of funds and equal-weighted exogenous factors shows that the decomposition of the systematic and idiosyncratic tail risks is sensitive to the chosen benchmarks, i.e. low correlation between the endogenous and exogenous benchmarks implies the increased percentage of RESSKEW and RESKURT. All results are available upon request.

and RESKURT. Second, RESSKEW and RESKURT tend to be higher for fixed income funds when beta-weighted exogenous factors are used. This spurious result may be induced by missing bond factors, such as a high-yield index or a global bond index.

7.4. Year 1996-2008

The starting period of four fund types differs in this study. However, the time-variation of economic states, such as changes in yields and business cycles, may impose differential impacts on "economy-wide" shocks on funds. Using the same time intervals for all four fund types can ascertain that all funds are subject to the same economic shocks at any time. If the pattern of skewness and kurtosis decomposition holds, the percentage of each component should be robust to the same starting period. Therefore, all investment funds are restricted to have the same starting date as HFs and perform GMM on this subsample of data.

The main inferences remain qualitatively unchanged, when the dataset for all funds is restricted between the period from 1996 to 2008 only. Note that this period also excludes the 1987 stock market crash. COSKEW contributes the most to the skewness of all fund types. COKURT and VOLCOMV are the two largest components in kurtosis decomposition for CEFs, ETFs, and OEFs. HFs' kurtosis comes mostly from the VOLCOMV and RESKURT. At the style level of each fund type, few fund styles have different proportions in skewness and kurtosis decompositions. It may imply that each component is time-varying at the style level. However, at the aggregate fund type level, the percentage on each component stays the same. In addition, HFs (ETFs) have the largest (least) weights on idiosyncratic tail risks.

CONCLUSIONS

Different styles and types of managed portfolios execute different strategies and objectives. Traditional fund managers can make investment decisions based on returns and volatility of different individual assets. They can also adjust exposure to systematic factors or asset classes, such as size, book-to-market, or momentum. However, many stylized facts on financial asset returns refute the validity of the mean-variance framework, and market-timing and stock-picking strategies can induce systematic and idiosyncratic tail risks.

This study shows that managed portfolios are subject to tail risks. The frequency of tail returns shows that CEFs and HFs are subject to more total tail risks. ETFs show a disparity in the frequency between the systematic and idiosyncratic tail returns. Therefore, fund managers may manage systematic and idiosyncratic tail risks through investing in assets with desired properties and tail risks. For instance, a manager can generate abnormal returns by adding assets with negative coskewness or positive cokurtosis or selecting negatively skewed or positively kurtosised assets. The skewness and kurtosis decompositions show the mechanisms fund managers may use to manage tail risks.

Skewness and kurtosis decompositions introduce economically important components. These components reflect fund returns and volatility with respect to extreme movements in market returns, volatility, and skewness. Skewness is decomposed into coskewness, idiosyncratic coskewness, and residual skewness. Coskewness and idiosyncratic coskewness are relatively important in the total fund skewness, but all three components do not show statistical significance. Kurtosis can be decomposed into four components – cokurtosis, volatility comovement, idiosyncratic cokurtosis, and residual kurtosis. The volatility comovement and residual kurtosis contribute the most to the total fund kurtosis at a statistically significant level. Results of the skewness and kurtosis decompositions are robust to benchmarks used.

The fund tail risks are linked to compensation structure across fund types through a simple model. There are two main determinants of compensation schemes – the decomposition between the systematic and idiosyncratic returns (return decomposition effect), and the convexity or degree of optionlike payoffs (convexity effect). The model predicts that the increased weight on systematic returns can increase market exposure, and in turn increase total skewness and decrease total kurtosis. In addition, increased convexity can increase idiosyncratic tail risks, and thus reduce asymmetry and raise fat-tailedness. Empirical results confirm both predictions.

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APPENDICES

Appendix A

A.1 THE NUMERICAL PROCEDURE FOR THE OPTIMIZATION PROBLEM

A fund manager solves for the optimal unconditional weight based on returns up to time t. Steps are the following:

(a) Generate 10,000 jointly independent random variables (U,V) from the T-Copula.

(b) Solve for the optimal weight:

$$w = argmax \frac{1}{t}{}_{j=1}^{t} U(W_j)$$

(c) Simulate step (a) to (c) 1000 times.

A.2 CONDITIONING BIASES AND BENCHMARKS

The literature has documented the following biases in fund datasets and they might differ across fund types and bias results on tail risks.

Incubation bias is referred to as fund families start several new funds, but only open funds that succeed in the evaluation period to the public. Evans (2007) shows that incubated mutual funds outperform non-incubated funds. Incubation creates upward bias on fund returns and thus increase skewness and reduce kurtosis. In addition, when a fund enters to the database, its past return history is automatically added to the database. The addition of past returns causes backfilling bias and it can bias fund skewness upwards and kurtosis downwards.

For OEFs, returns before the fund inception date are deleted to avoid incubation bias. This step follows from Evans' (2007) initial approach since the complete list of mutual fund tickers and their creation dates from NASD are not accessible. Fund returns for the first year are also deleted to remove backfill bias. For HFs, returns before the inception date are dropped to remove incubation bias. Aggarwal and Jorion (2010) use the data field "date added to database" in TASS dataset and find the median backfill period is 480 days. The same approach is adopted to clean out back-filled HF returns.

Stale prices mean that reported asset prices do not reflect correct true prices, possibly due to illiquidity, non-synchronous trading, or bid-ask bounce. These characteristics can cause serial-correlation in returns. HFs suffer from this bias the most, and are adjusted for stale prices in the robustness analysis.

If a study includes only funds that survive until the end of the sample period, survivorship bias occurs. The survival probability of funds depends on past performance (Brown and Goetzmann, 1995). Managers who take significant risk and win will survive. Therefore, the database is left with high risk and high return surviving funds. The survivorship bias imparts a downward bias to risk, and an upward bias to alpha (e.g. Carhart, 1997; Blake and Timmermann, 1998). It also induces more positive skewness and less fat-tailedness.

CEFs may suffer also from survivorship bias, due to the commonly observed discounts on traded prices. The discounts may lead to liquidation or reorganization ("open-ending") and leave the dataset with surviving funds. Although the exit rate for ETFs is low, survivorship bias might still affect their tail risks. To avoid survivorship bias, the lists of ETFs and CEFs are downloaded from the Morningstar survivorship free database. OEFs are taken from the CRSP survivorship free database.

The survivorship bias is more complex for HFs. HFs may decide to stop reporting because of liquidation or self-selection (Ter Horst and Verbeek, 2007; Jagannathan et al., 2010). Liquidation refers to underperforming funds exiting the database. Self-selection is associated with a fund's decision to be included in the database. For instance, outperforming HFs have less incentives to report performance to attract new investors and fund managers may switch to another data vendor for marketing purposes. Both live and dead hedge fund returns are combined from HFR to eliminate survivorship bias.

The look-ahead bias arises when funds are required to survive some minimum length of time after a reference date. One type of look-ahead bias applicable to this study is the look-ahead benchmark bias (Daniel et al., 2009). Since the time series of styles are not kept in the database, funds that change styles over time may suffer from look-ahead benchmark bias. This omission can bias risk-adjusted returns and tail risks. The portfolios of funds for OEFs are constructed look-ahead bias free. Monthly returns are used only after the beginning of the assigned style. No ex-post style returns are used.

ETFs and CEFs are subject to look-ahead bias as well since no data vendors keep the history of their classification codes. However, it is unlikely these funds will change investment styles through time, given their fund characteristics[23].

Investment funds with less than twelve months of returns are excluded and all investment funds maintain the same investment strategy for at least twelve months. Fund managers are usually evaluated at the end of year and the minimum of 12 observations offer sufficient degrees of freedom for GMM estimation[24].

[23] ETFs are index funds and CEFs do not allow the redemption of shares after IPO.

[24] Two mutual funds (CRSP Fund ID 031241 in fixed income index and 01108 in fixed income government) and two HFs (HFR Fund ID 17393 and 21981 in relative value) are removed from this study manually because the percentages on the components in skewness and kurtosis decompositions by GMM estimation are so large that the average weights across individual funds are heavily skewed. All four funds have no monthly returns outside 3 standard deviation from the

Nevertheless, attempts to control these ex-post conditional biases may be imperfect. By construction, HFs might still suffer limited look-ahead benchmark bias and no change of styles in ETFs and CEFs is assumed. Lack of NASD data might leave backfill bias in the mutual fund sample. In addition, it is known that the coverage of HFs has little overlap across different data vendors. Relying on only HFR data may not represent the whole HF industry.

HFR provides main and sub strategy classification codes for HFs. Main strategy classification codes is used. Style classification codes for ETFs and CEFs are from Morningstar. The Morningstar classification codes for ETFs and CEFs are commonly used on many financial websites and easily accessible to investors. For OEFs, style classification codes in the CRSP mutual fund database are used. The database uses five different classification codes to cover disjoint time periods. POLICY codes are used before 1990. CRSP uses WIESENBERGER (WB OBJ) codes between 1990 to the end of 1992. Strategic Insight Objective (SI OBJ) codes cover from 1993 to September, 1998. Lipper Objective (Lipper OBJ) codes are used up to 2008. Most recent funds are classified by Thomson Reuters Objective (TR OBJ) codes.

Benchmark data are from the following sources. Market excess returns, SMB and HML factors are obtained from Ken French's website[25]. The momentum factor is downloaded from CRSP. The seven HF factors[26] are downloaded from David Hsieh's website[27]. The Barclay U.S. government/credit index (LHGVCRP) and corporate bond index (LHCCORP) are downloaded from Datastream.

A.3 OPEN-ENDED FUND STYLES

Funds with the following style codes are considered fixed income funds - POLICY in B&P, Bonds, Flex, GS, or I-S; WB OBJ in I, S, I-S, S-I, I-G-S, I-S-G, S-G-I, CBD, CHY, GOV, IFL, MTG, BQ, BY, GM, or GS; SI OBJ in BGG, BGN, BGS, CGN, CHQ, CHY, CIM, CMQ, CPR, CSI, CSM, GBS, GGN, GIM, GMA, GMB, GSM, or IMX; Lipper Class in 'TX' or 'MB'; Lipper OBJ in EMD, GLI, INI, SID, SUS, SUT, USO, GNM, GUS, GUT, IUG, IUS, ARM, USM, A, BBB, or HY; and TR OBJ in AAG, BAG, GLI, BDS, GVA, GVL, GVS, UST, MTG, CIG, or CHY. Funds with holdings in bonds and cash less than 70% at the end of the previous year are further screened out.

mean. Removing these four funds has minimal effects on the univariate statistics of the style that they belong to.

[25] www2.

[26] The equity and bond market factor, the size spread factor, two credit spread factors, and three lookback straddles on bond futures, currency futures, and commodity futures.

[27] www3.

Fixed income funds (FI) are classified as Index, Global, Short Term, Government, Mortgage, Corporate, and High Yield. Index funds (FI Index) are selected by matching the string “index” with the fund name. Global funds are coded as SI OBJ in BGG or BGN, Lipper OBJ in EMD, GLI, or INI, or TR OBJ in AAG, BAG, or GLI.

Short term funds are coded as SI OBJ in CSM, CPR, BGS, GMA, GBS, or GSM, Lipper OBJ in SID, SUS, SUT, USO, or TR OBJ in BDS. Government funds are codes as POLICY in GS, WB OBJ in GOV or GS, SI OBJ in GIM or GGN, or Lipper OBJ in GNM, GUS, GUT, IUG, or IUS, or TR OBJ in GVA, GVL, GVS, or UST. Mortgage funds are coded as POLICY WB OBJ in MTG, GM, SI OBJ in GMB, Lipper OBJ in ARM or USM, or TR OBJ in MTG. Corporate funds are coded as POLICY in B&P, WB OBJ in CBD,BQ, SI OBJ in CHQ, CIM, CGN, CMQ, Lipper OBJ in A, BBB, or TR OBJ in CIG. High Yield funds are coded as POLICY in Bonds, WB OBJ in I-G-S, I-S-G, S-G-I, BY, CHY, SI OBJ in CHY, Lipper OBJ in HY, TR OBJ in CHY. Other funds are funds that are classified as bond funds but do not meet the criteria above.

Similarly, the following codes are used to screen out equity funds – POLICY in Bal, C&I, CS, Hedge, or Spec; WB OBJ in G, G-I, I-G, AAL, BAL, ENR, FIN, GCI, GPM, HLT, IEQ, INT, LTG, MCG, SCG, TCH, UTL, AG, AGG, BL, GE, GI, IE, LG, OI, PM, SF, or UT; SI OBJ AGG, BAL, CVR, ECH, ECN, EGG, EGS, EGT, EGX, EID, EIG, EIS, EIT, EJP, ELT, EPC, EPR, EPX, ERP, FIN, FLG, FLX, GLD, GLE, GMC, GRI, GRO, HLT, ING, JPN, OPI, PAC, SCG, SEC, TEC, or UTI; Lipper Class in EQ; Lipper OBJ in SP, SPSP, AU, BM, CMD, NR, FS, H, ID, S, TK, TL, UT, CH, CN, CV, DM, EM, EU, FLX, GFS, GH, GL, GLCC, GLCG, GLCV, GMLC, GMLG, GMLV, GS, GSMC, GSME, GSMG, GSMV, GNR, GTK, IF, ILCC, ILCG, ILCV, IMLC, IMLG, IMLV, IS, ISMC, ISMG, ISMV, JA, LT, PC, XJ, B, BT, CA, DL, DSB, ELCC, LSE, SESE, MC, MCCE, MCGE, MCVE, MR, SCCE, SCGE, SCVE, SG, G, GI, EI, EIEI; and TR OBJ in AAD, AAG, AGG, BAD, BAG, CVT, EME, ENR, EQI, FIN, FOR, GCI, GLE, GPM, GRD, HLT, MID, OTH, SMC, SPI, TCH, UTL. Funds with holdings in bonds and cash less than 70% at the end of the previous year are further screened out.

Equity funds (EF) are classified as Index, commodities, Sector, Global, Balanced, Leverage and Short, Long Short, Mid Cap, Small Cap, Aggressive Growth, Growth, Growth and Income, Equity Income, and Others. Index funds (EF Index) are identified by finding the match of the string “index” within the fund name or funds with Lipper OBJ in SP or SPSP, or TR OBJ in SPI.

Commodities funds are coded as WB OBJ in ENR, GPM, PM, SI OBJ in GLD Lipper OBJ in AU, BM, CMD, NR, or TR OBJ in ENR, GPM. Sector funds are codes as POLICY in Spec, WB OBJ in FIN, HLT, TCH, UTL, SF, UT, SI OBJ in FIN,HLT, Lipper OBJ in FS, H, ID, S, TK, TL, UT, or TR OBJ in FIN, HLT, OTH, TCH, UTL. Global funds are coded as POLICY in C&I, WB OBJ in INT, GE, IE, SI OBJ in ECH, ECN, EGG, EGS, EGT, EGX, EID, EIG, EIS, EIT, EJP, ELT, EPC, EPX, ERP, FLG, GLE, JPN, PAC, Lipper OBJ CH, CN, DM, EM, EU, GFS, GH, GL, GLCC, GLCG, GLCV, GMLC, GMLG, GMLV, GS, GSMC, GSME, GSMG, GSMV, GNR, GTK, IF, ILCC, ILCG, ILCV, IMLC, IMLG, IMLV, IS, ISMC, ISMG, ISMV, JA, LT, PC, XJ, TR OBJ in EME, FOR, GLE. Balanced funds are coded as POLICY in Bal, WB OBJ in AAL, BAL, BL, SI OBJ in BAL, CVR, FLX, Lipper OBJ in B, BT, CV, FLX, or TR OBJ in AAD, BAD, AAG, BAG, CVT. Leverage and short funds are coded as POLICY in Hedge, WB OBJ in OI, SI OBJ in OPI, or Lipper OBJ in CA, DL, DSB, ELCC, SESE. Long short funds are coded as Lipper OBJ in LSE. Mid cap funds are coded as WB OBJ in GMC, Lipper OBJ in MC, MCCE, MCGE, MCVE, TR OBJ in MID. Small cap funds are coded as WB OBJ in SCG, Lipper OBJ in MR, SCCE, SCGE, SCVE, SG, or TR OBJ in SMC. Aggressive growth funds are coded as WB OBJ in GI, GCI, SI OBJ in AGG, or TR OBJ in AGG. Growth funds are coded as WB OBJ in G,LG, SI OBJ in GRO, Lipper OBJ in G, or TR OBJ in GRD. Growth and income funds are coded as WB OBJ in GI, GCI, SI OBJ in GRI, Lipper OBJ in GI, or TR OBJ in GCI. Equity income funds are coded as WB OBJ in EI, IEQ, Lipper OBJ in EI, EIEI, or TR OBJ in EQI. Other funds are funds that are classified as equity funds but do not meet the criteria above.

Appendix – Tables

TABLE I. SUMMARY STATISTICS

This table reports summary statistics for average funds across fund styles and types. Nofunds is the total number of funds. Nobs is the average number of nonmissing time series observations of average funds. Each statistic for a style is reported as the cross-sectional average of statistics of individual funds in the same style. Mean is the average mean, std is the average standard deviation, skewness is the average skewness, kurtosis is the average excess kurtosis, ρ_1 is the average first order sample autocorrelation, ρ_2 is the average second order sample autocorrelation, and ρ_3 is the average third order sample autocorrelation. Reported statistics are in percentage per month. JB is the Jarque Bera p-value for test for normality. JB test statistic is $\frac{Nobs}{6}\left(Skewness^2 + \frac{Kurtosis^2}{4}\right)$. LQ is the Ljung-Box q statistics for the test of lag-3 autocorrelation.
LQ test statistic is $Nobs(Nobs+2)\sum_{j=1}^{3}\frac{\rho_j}{Nobs-j}$. FI Average is the average of statistics across fixed-income fund styles. EF Average is the average of statistics across equity fund styles. Group Average is the average of statistics across all fund styles.

Style	Nofunds	Nobs	Mean	Std	Skewness	Kurtosis	Min	Max	JB	ρ_1	ρ_2	ρ_3	LQ
Panel A: Closed-End Funds													
FI Global	26	133	0.185	5.953	−0.602	6.080	−26.00	20.33	< 0.05	−0.043	−0.002	−0.122	0.2713
FI Sector	29	151	0.309	6.214	−0.399	4.611	−22.48	22.33	< 0.05	−0.033	0.028	−0.057	0.4299
FI Long Term	26	129	−0.580	7.356	−1.224	8.322	−31.50	19.77	< 0.05	−0.065	0.091	−0.020	0.1992
FI Intermediate Term	25	259	0.803	5.759	0.203	5.443	−19.15	26.50	< 0.05	−0.097	−0.025	−0.045	0.145
FI Short Term	6	114	0.584	3.777	−0.912	4.361	−15.76	10.52	< 0.001	−0.061	−0.002	0.058	0.1801
FI Government	13	120	0.451	2.963	−0.185	2.305	−9.37	9.78	0.0679	−0.067	−0.012	0.028	0.3736
FI High Yield	47	142	−0.377	6.545	−0.620	3.708	−24.05	19.95	< 0.05	0.075	0.048	−0.003	0.357
FI Others	23	73	−0.685	4.672	−1.656	6.415	−19.71	10.70	< 0.001	0.259	0.186	0.013	0.0643
FI Average	24	140	0.086	5.405	−0.675	5.156	−21.00	17.49	< 0.05	−0.004	0.039	−0.019	0.2526
EF Balanced	46	110	−0.695	7.329	−0.780	4.193	−24.99	20.72	0.0693	0.112	0.021	−0.058	0.3177
EF Global	92	122	−0.145	9.955	−0.059	2.725	−29.53	31.94	0.1199	0.060	0.017	−0.031	0.4727
EF Sector	17	157	0.153	7.142	−0.162	4.424	−23.74	28.19	< 0.05	0.064	−0.002	−0.035	0.2411
EF Commodities	20	125	−1.214	9.109	−1.136	4.279	−32.94	18.95	< 0.05	0.056	0.188	0.010	0.2806
EF Large Cap	59	145	−0.272	6.438	−0.698	5.530	−23.44	20.71	0.0828	0.104	0.001	−0.024	0.361
EF Mid Cap	11	152	0.169	7.198	−0.258	4.565	−22.40	20.36	< 0.05	0.038	−0.071	−0.056	0.3546
EF Small Cap	6	161	0.611	12.124	−0.138	3.321	−31.95	51.28	< 0.05	0.110	0.017	−0.019	0.4631
EF Growth	18	97	0.200	8.482	−0.480	4.707	−24.89	28.51	< 0.05	0.101	−0.030	−0.042	0.3682
EF value	19	63	−0.584	6.251	−0.996	3.886	−21.98	14.63	0.053	0.099	0.025	−0.073	0.4109
EF Others	32	65	−1.318	10.111	−1.426	5.649	−38.08	20.11	0.1106	0.164	−0.050	−0.004	0.3635
EF Average	32	120	−0.310	8.414	−0.613	4.328	−27.39	25.54	0.0645	0.091	0.011	−0.033	0.3633
Style	Nofunds	Nobs	Mean	Std	Skewness	Kurtosis	Min	Max	JB	ρ_1	ρ_2	ρ_3	LQ
Group Average	29	129	−0.134	7.077	−0.640	4.696	−24.55	21.96	< 0.05	0.049	0.024	−0.027	0.3141
Panel B: ETFs													
FI Global	2	14	−0.218	6.383	−0.314	2.910	−15.61	12.82	0.2702	0.084	−0.341	−0.209	0.1995
FI Sector	3	22	0.677	1.680	0.826	1.841	−2.61	4.98	0.1073	0.360	−0.367	−0.287	0.0708
FI Long Term	2	49	0.631	3.407	0.945	7.720	−8.81	13.33	< 0.001	0.223	−0.475	−0.297	< 0.01
FI Intermediate Term	6	28	0.464	2.001	0.585	3.537	−4.08	6.13	< 0.05	0.227	−0.392	−0.183	0.1196
FI Short Term	3	21	0.437	0.969	−0.252	2.156	−2.00	2.66	0.1579	0.163	−0.207	−0.062	0.2098
FI Government	12	44	0.927	3.990	0.526	1.444	−8.12	11.55	0.4384	0.115	−0.050	0.024	0.2719
FI High Yield	2	17	−1.562	6.988	0.654	2.636	−13.97	16.36	0.2087	0.051	−0.233	−0.504	0.0681
FI Others	2	40	0.409	2.477	−1.078	3.699	−7.78	5.74	< 0.01	0.176	−0.239	−0.130	0.2464
FI Average	4	29	0.221	3.487	0.236	3.243	−7.87	9.20	0.1517	0.175	−0.288	−0.206	0.1484
EF Balanced	5	14	−1.728	4.575	−0.215	1.968	−10.87	7.97	0.1928	0.150	−0.351	−0.284	0.0631
EF Global	108	56	−1.117	7.917	−0.733	2.404	−24.24	15.27	0.192	0.268	−0.046	−0.059	0.2524
EF Sector	111	42	−0.939	6.346	−0.726	1.687	−18.51	11.23	0.2064	0.161	−0.148	−0.093	0.2482
EF Commodities	47	38	−0.939	10.759	−0.892	1.430	−29.54	16.56	0.1325	0.253	0.129	−0.003	0.2758
EF Large Cap	82	51	−0.956	5.537	−1.310	2.842	−18.78	7.67	< 0.05	0.284	−0.116	−0.028	0.1816
EF Mid Cap	55	40	−1.496	7.450	−1.194	2.648	−23.77	10.13	0.1149	0.298	−0.116	−0.077	0.1537
EF Small Cap	35	50	−1.269	6.874	−1.327	2.731	−24.21	8.64	< 0.05	0.231	−0.138	−0.175	0.1783
EF Growth	46	47	−1.457	7.245	−1.068	1.884	−22.61	10.35	0.1382	0.290	−0.017	−0.099	0.2181
EF value	46	51	−0.843	5.699	−1.413	3.579	−20.47	8.19	< 0.05	0.239	−0.189	−0.050	0.1512
EF Bear Market	40	22	1.624	10.706	0.676	1.142	−15.53	26.78	0.2369	0.170	−0.288	−0.206	0.1844
EF Currency	10	29	0.197	3.486	−0.670	3.786	−10.02	7.36	0.0801	0.284	0.091	0.016	0.3396
EF Others	82	48	−1.555	8.767	−0.737	1.749	−24.44	16.49	0.1675	0.162	−0.172	−0.118	0.2887
EF Average	55.583	41	−0.873	7.113	−0.801	2.323	−20.25	12.22	0.1294	0.233	−0.113	−0.098	0.2113
Group Average	34.95	36	−0.436	5.663	−0.386	2.691	−15.30	11.01	0.1383	0.209	−0.183	−0.141	0.1861
Panel C: Open-Ended Funds													
FI Index	32	95	0.508	1.252	−0.034	1.378	−3.14	4.21	0.2657	0.136	−0.096	0.065	0.2406
FI Global	303	87	0.381	2.367	−0.556	3.739	−8.00	6.47	0.1495	0.181	−0.114	−0.038	0.1798
FI Short Term	645	76	0.287	0.763	−0.890	5.023	−2.07	2.28	0.2501	0.242	0.084	0.124	0.1684

Style	Nofunds	Nobs	Mean	Std	Skewness	Kurtosis	Min	Max	JB	ρ_1	ρ_2	ρ_3	LQ
FI Government	727	93	0.464	1.124	− 0.138	1.311	− 2.88	3.60	0.1831	0.210	0.016	0.117	0.2543
FI Mortgage	219	81	0.399	0.898	− 0.420	2.018	− 2.33	2.69	0.2976	0.191	0.002	0.138	0.2589
FI Corporate	798	74	0.421	1.285	− 0.580	2.578	− 3.81	3.63	0.2704	0.142	− 0.090	0.043	0.2166
FI High Yield	944	87	0.361	2.338	− 1.174	5.553	− 9.41	6.04	0.1161	0.224	− 0.112	− 0.094	0.1069
FI Others	619	79	0.623	1.006	0.286	3.412	− 2.32	3.60	0.2316	0.425	0.378	0.334	0.1669
FI Average	536	84	0.431	1.379	− 0.438	3.126	− 4.24	4.07	0.2205	0.219	0.009	0.086	0.199
EF Index	838	79	− 0.177	5.149	− 0.966	2.850	− 17.75	10.37	0.1072	0.199	− 0.066	− 0.013	0.2642
EF commodities	238	78	0.340	8.826	− 0.516	1.585	− 27.06	20.58	0.1587	0.085	0.050	0.065	0.2728
EF Sector	1331	69	− 0.322	6.933	− 0.371	1.268	− 18.82	15.72	0.2876	0.137	− 0.051	− 0.059	0.3842
EF Global	3373	78	− 0.115	5.884	− 0.796	2.245	− 19.52	12.36	0.1489	0.237	0.024	0.008	0.2393
EF Balanced	988	80	0.134	3.096	− 1.098	3.332	− 11.16	6.03	0.1121	0.192	− 0.065	0.003	0.274
EF Leverage and Short	675	62	− 0.099	6.231	− 0.287	1.597	− 16.50	14.93	0.2483	0.119	− 0.051	− 0.059	0.336
EF Long Short	80	22	− 1.774	4.877	− 0.980	1.439	− 14.30	5.24	0.1843	0.293	− 0.061	− 0.109	0.2205
EF Mid Cap	1331	63	− 0.335	5.942	− 0.919	2.579	− 19.61	11.80	0.1253	0.229	− 0.050	− 0.051	0.2213
EF Small Cap	1970	68	− 0.183	6.207	− 0.741	1.930	− 19.66	13.03	0.1336	0.170	− 0.053	− 0.132	0.2247
EF Aggressive Growth	247	46	1.493	6.072	− 0.734	2.067	− 17.52	13.05	0.1803	0.059	− 0.094	− 0.036	0.5208
EF Growth	4586	73	− 0.141	5.145	− 0.812	2.114	− 16.50	10.24	0.1826	0.186	− 0.047	− 0.023	0.3083
EF Growth and Income	2459	70	− 0.160	4.494	− 0.883	2.169	− 14.83	8.48	0.1484	0.165	− 0.073	− 0.027	0.3286
EF Equity Income	509	55	− 0.208	4.233	− 0.782	2.041	− 13.09	8.05	0.2366	0.140	− 0.095	− 0.026	0.327
EF Others	1758	65	1.267	5.362	− 0.498	1.994	− 15.42	12.90	0.2147	0.062	− 0.044	− 0.093	0.4216
EF Average	1456	65	− 0.020	5.604	− 0.742	2.086	− 17.27	11.63	0.1763	0.163	− 0.048	− 0.039	0.3102
Group Average	1121	72	0.144	4.067	− 0.631	2.465	− 12.53	8.88	0.1924	0.183	− 0.028	0.006	0.2698
Panel D: Hedge Funds													
Equity Hedge	2367	48	0.399	5.051	− 0.299	2.001	− 12.87	12.30	0.2928	0.102	0.015	− 0.019	0.3381
Event-Driven	585	56	0.381	3.241	− 0.618	4.071	− 9.32	8.23	0.1682	0.262	0.102	0.057	0.209
Fund of Funds	1194	46	0.091	2.625	− 0.981	2.951	− 7.83	4.82	0.2097	0.272	0.159	0.064	0.2403
HFRI	75	137	0.612	2.925	− 1.115	6.471	− 11.69	9.49	< 0.05	0.302	0.148	0.073	0.1028
HFRX	27	46	− 0.425	2.337	− 1.709	6.048	− 9.27	2.80	0.1688	0.273	0.182	0.049	0.1318
Macro	810	45	0.470	4.562	0.012	2.006	− 10.38	11.74	0.3267	0.054	− 0.052	− 0.044	0.3471
Relative Value	786	46	0.241	2.991	− 1.208	7.001	− 10.18	5.84	0.146	0.265	0.100	0.073	0.2289
Style	Nofunds	Nobs	Mean	Std	Skewness	Kurtosis	Min	Max	JB	ρ_1	ρ_2	ρ_3	LQ
Group Average	835	60	0.253	3.390	− 0.845	4.364	− 10.22	7.89	0.1945	0.219	0.093	0.036	0.2283

TABLE II. FREQUENCY OF TAIL RETURNS ACROSS FUND TYPES

Tail returns are defined as monthly returns exceeding (+/−)5 and (+/−)3 standard deviations from the means. The frequency of tail returns of a fund is calculated as the count of tail returns divided by its total number of monthly returns. The test statistics is calculated by assuming the distribution of the counts of tail returns to be Bernoulli and *i.i.d*. Total fund returns are further decomposed into systematic and idiosyncratic components to calculate the frequency of systematic and idiosyncratic tail returns. Results are reported in three rows for each fund type. The first row is the frequency of total tail returns. The second row is the frequency of systematic tail returns. The third row is the frequency of idiosyncratic tail returns. The cross cell by the same fund type represents the average frequency of tail returns across funds in that fund type. The cross cell of two different fund types is the difference in frequency of tail returns between two fund types. T-values are in the parenthesis based on the test hypothesis of zero frequency.

CEFs/ETFs/OEFs/HFs refer to closed-end funds/exchange-traded funds/ open-ended funds/hedge funds, respectively.

Panel A: All Funds

		CEFs		ETFs		OEFs		HFs	
		5std	3std	5std	3std	5std	3std	5std	3std
	Total	0.132(-0.47)	1.775(-1.54)	0.123(0.21)	0.617(1.33)	0.086(0.04)	0.672(0.45)	0.055(0.03)	0.609(0.50)
CEFs	Systematic	0.139(-0.47)	1.885(-1.46)	0.137(0.23)	0.462(0.99)	0.109(0.06)	0.814(0.55)	0.093(0.06)	0.788(0.64)
	Idiosyncratic	0.095(-0.49)	1.076(-2.02)	0.087(0.15)	0.426(0.92)	0.035(0.02)	0.212(0.14)	0.032(0.02)	0.156(0.13)
	Total			0.009(-0.34)	1.158(-1.25)	-0.037(-0.06)	0.056(0.10)	-0.068(-0.04)	-0.008(-0.01)
ETFs	Systematic			0.002(-0.34)	1.423(-1.13)	-0.028(-0.05)	0.352(0.72)	-0.044(-0.02)	0.326(0.22)
	Idiosyncratic			0.007(-0.34)	0.650(-1.47)	-0.052(-0.09)	-0.214(-0.45)	-0.055(-0.03)	-0.270(-0.18)
	Total					0.046(-0.39)	1.102(-1.53)	-0.031(-0.08)	-0.063(-0.21)
OEFs	Systematic					0.030(-0.40)	1.071(-1.55)	-0.016(-0.03)	-0.026(-0.01)
	Idiosyncratic					0.059(-0.39)	0.864(-1.66)	-0.003(-0.00)	-0.056(-0.22)
	Total							0.077(-0.50)	1.165(-1.95)
HFs	Systematic							0.046(-0.51)	1.097(-2.00)
	Idiosyncratic							0.063(-0.50)	0.920(-2.12)

Panel B: Fixed Income Funds

		CEFs		ETFs		OEFs	
		5std	3std	5std	3std	5std	3std
	Total	0.199(-0.49)	1.967(-1.59)	0.159(0.05)	1.173(0.48)	0.052(0.02)	0.867(0.36)
CEFs	Systematic	0.234(-0.47)	2.054(-1.53)	0.193(0.06)	1.715(0.70)	0.127(0.04)	0.930(0.38)
	Idiosyncratic	0.146(-0.52)	1.265(-2.14)	0.106(0.03)	-0.288(-0.12)	-0.016(-0.01)	-0.034(-0.01)
	Total			0.041(-0.28)	0.793(-1.21)	-0.107(-0.03)	-0.306(-0.13)
ETFs	Systematic			0.041(-0.28)	0.339(-1.38)	-0.066(-0.02)	-0.785(-0.33)
	Idiosyncratic			0.041(-0.28)	1.553(-0.92)	-0.122(-0.04)	0.254(0.11)
	Total					0.147(-0.26)	1.099(-1.13)
OEFs	Systematic					0.106(-0.27)	1.124(-1.12)
	Idiosyncratic					0.162(-0.26)	1.299(-1.05)

Panel C: Equity Funds

		CEFs		ETFs		OEFs	
		5std	3std	5std	3std	5std	3std
	Total	0.085(-0.41)	1.642(-1.35)	0.078(0.40)	0.464(3.06)	0.065(0.04)	0.552(0.48)
CEFs	Systematic	0.074(-0.42)	1.769(-1.28)	0.074(0.38)	0.285(1.88)	0.064(0.04)	0.724(0.64)
	Idiosyncratic	0.059(-0.42)	0.946(-1.75)	0.053(0.28)	0.346(2.28)	0.026(0.02)	0.191(0.17)
	Total			0.007(-0.34)	1.178(-1.22)	-0.013(-0.01)	0.088(0.13)
ETFs	Systematic			0.000(-0.34)	1.484(-1.09)	-0.010(-0.01)	0.439(0.54)
	Idiosyncratic			0.006(-0.34)	0.600(-1.47)	-0.028(-0.03)	-0.156(-0.20)
	Total					0.020(-0.36)	1.091(-1.35)
OEFs	Systematic					0.010(-0.36)	1.044(-1.37)
	Idiosyncratic					0.033(-0.35)	0.756(-1.51)

TABLE III. SKEWNESS DECOMPOSITION BY EQUAL-WEIGHTED PORTFOLIOS ACROSS FUND STYLES AND TYPES

This table summarizes the skewness decomposition by using equal-weighted portfolios of funds as market portfolio. EW portfolio skewness is the skewness for the equal-weighted portfolios of funds formed by funds in the same styles. Individual skewness is the cross-sectional average of skewness of individual funds in each style. Skewness is the third central moment about the mean and computed as $E\frac{(r_i^3)}{\sigma_i^3}$. r_i and σ_i are the demeaned return and standard deviation of fund *i*. COSKEW, ICOSKEW, and RESSKEW refer to the following components in the skewness decomposition:

$$E\left(r_i^3\right) = \underbrace{\beta_i^2 cov\left(r_i, r_p^2\right) + 2\beta_i^2 cov\left(u_i, r_p^2\right)}_{\text{COSKEW}} + 3\beta_i \underbrace{cov\left(u^2, r_p\right)}_{\text{ICOSKEW}} + \underbrace{E\left(u_i^3\right)}_{\text{RESSKEW}}$$

where $r_p$is the demeaned return for the market portfolio. Individual COSKEW, ICOSKEW, and RESSKEW are the average of estimated values from the above equation by GMM across individual funds and reported as the percentage of the skewness of demeaned fund returns $E\left(r_i^3\right)$ FI and EF stand for fixed income and equity funds, respectively. Numbers in parentheses are t-statistics associated with a null hypothesis of zero raw coskewness, idiosyncratic coskewness, and residual skewness in the respective columns. FI Average is the average of statistics across fixed-income fund styles. EF Average is the average of statistics across equity fund styles. Group Average is the average of statistics across all fund styles. Panel E, F, and G summarize the t-statistics on the comparisons of the percentage of each component between any two fund types based on fixed income, equity, and total funds, respectively. F test reports the p-value of the test of differences in mean estimates on the percentage of each component across four fund types in parentheses.

			Systematic		Idiosyncratic
Styles	EW Port Skewness	Individual Skewness	Individual COSKEW (%)	Individual ICOSKEW (%)	Individual RESSKEW (%)
Panel A: Closed-End Funds					
FI Global	− 1.512	− 0.602	122.89	− 12.21	− 10.67
			(− 0.65)	(− 0.29)	(0.32)
FI Sector	− 0.754	− 0.399	105.95	− 6.07	0.12
			(− 0.60)	(− 0.41)	(− 0.10)
FI Long Term	− 0.339	− 1.224	57.37	40.49	2.14
			(− 0.33)	(− 0.61)	(0.19)
FI Intermediate Term	0.749	0.203	− 6.31	116.74	− 10.43
			(0.43)	(0.32)	(− 0.22)
FI Short Term	− 0.419	− 0.912	27.74	63.65	8.61
			(− 0.73)	(− 1.20)	(− 0.03)
FI Government	− 0.262	− 0.185	32.15	36.76	31.09
			(− 0.14)	(− 0.31)	(− 0.59)
FI High Yield	0.296	− 0.620	70.36	4.62	25.01
			(− 0.88)	(− 0.16)	(− 0.49)
FI Others	− 2.273	− 1.656	43.16	12.03	44.81
			(− 1.16)	(− 0.65)	(− 0.10)
FI Average	− 0.564	− 0.675	56.66	32.00	11.33
			(− 0.51)	(− 0.41)	(− 0.13)
EF Balanced	− 0.157	− 0.780	72.21	25.29	2.49
			(− 0.99)	(− 0.45)	(0.22)
EF Global	0.598	− 0.059	16.66	70.76	12.59
			(− 0.74)	(0.61)	(0.36)

Styles	EW Port Skewness	Individual Skewness	Systematic: Individual COSKEW (%)	Systematic: Individual ICOSKEW (%)	Idiosyncratic: Individual RESSKEW (%)
EF Sector	− 0.896	− 0.162	53.60	19.99	26.41
			(− 0.99)	(0.30)	(− 0.24)
EF Commodities	0.508	− 1.136	50.18	66.73	− 16.90
			(− 0.69)	(− 0.38)	(0.01)
EF Large Cap	2.306	− 0.698	3.07	− 28.21	125.15
			(− 1.01)	(− 0.25)	(− 0.14)
EF Mid Cap	0.247	− 0.258	− 67.72	77.61	90.10
			(− 0.41)	(− 0.25)	(− 0.47)
EF Small Cap	0.833	− 0.138	68.26	9.26	22.48
			(− 1.26)	(1.39)	(− 0.89)
EF Growth	0.789	− 0.480	51.55	− 19.30	67.76
			(− 1.11)	(0.26)	(− 0.67)
EF Value	− 0.834	− 0.996	− 13.76	97.39	16.37
			(− 1.11)	(− 0.50)	(− 0.47)
EF Others	− 1.830	− 1.426	41.24	24.17	34.59
			(− 1.07)	(− 0.33)	(0.18)
EF Average	0.156	− 0.613	27.53	34.37	38.10
			(− 0.94)	(0.04)	(− 0.21)
Group Average	− 0.164	− 0.640	40.48	33.32	26.21
			(− 0.75)	(− 0.16)	(− 0.17)
Panel B: ETFs					
FI Global	− 1.016	− 0.314	59.64	39.26	1.10
			(− 0.55)	(0.93)	(0.00)
FI Sector	0.924	0.826	103.91	− 5.69	1.79
			(1.20)	(− 0.47)	(− 0.32)
FI Long Term	1.178	0.945	122.79	− 20.81	− 1.98
			(0.94)	(− 0.97)	(0.21)
FI Intermediate Term	0.650	0.585	85.66	5.04	9.30
			(0.75)	(− 0.86)	(0.37)
FI Short Term	0.445	− 0.252	46.24	25.57	28.20
			(0.27)	(− 1.18)	(− 0.34)
FI Government	0.024	0.526	− 45.66	123.15	22.51
			(− 0.01)	(0.83)	(0.20)
FI High Yield	0.531	0.654	106.86	− 6.95	0.09
			(0.66)	(− 1.15)	(0.48)
FI Others	− 1.143	− 1.078	101.51	− 1.50	− 0.01
			(− 1.33)	(1.54)	(0.49)
FI Average	0.199	0.236	72.62	19.76	7.62
			(0.24)	(− 0.17)	(0.14)
EF Balanced	− 0.041	− 0.215	76.95	12.18	10.87
			(− 0.48)	(0.52)	(0.54)
EF Global	− 0.967	− 0.733	87.30	4.00	8.70
			(− 1.33)	(0.34)	(0.38)
EF Sector	− 0.716	− 0.726	71.30	27.25	1.45
			(− 1.07)	(− 0.50)	(0.19)

Styles	EW Port Skewness	Individual Skewness	Systematic: Individual COSKEW (%)	Systematic: Individual ICOSKEW (%)	Idiosyncratic: Individual RESSKEW (%)
EF Commodities	− 0.751	− 0.892	81.85	18.00	0.15
			(− 1.61)	(− 0.40)	(− 0.08)
EF Large Cap	− 0.743	− 1.310	87.54	12.13	0.33
			(− 1.55)	(− 1.11)	(0.07)
EF Mid Cap	− 1.071	− 1.194	88.21	10.39	1.41
			(− 1.46)	(− 1.07)	(0.06)
EF Small Cap	− 1.023	− 1.327	94.84	5.52	− 0.36
			(− 1.53)	(− 1.23)	(− 0.13)
EF Growth	− 0.121	− 1.068	94.54	5.37	0.09
			(− 1.72)	(− 0.78)	(− 0.09)
EF Value	− 0.560	− 1.413	93.09	6.51	0.40
			(− 1.57)	(− 0.77)	(0.03)
EF Bear Market	0.917	0.676	62.21	17.30	20.50
			(1.00)	(0.88)	(0.46)
EF Currency	− 1.362	− 0.670	105.81	− 11.26	5.45
			(− 0.60)	(0.10)	(− 0.35)
EF Others	− 0.321	− 0.737	75.58	19.59	4.82
			(− 1.16)	(− 0.47)	(0.01)
EF Average	− 0.563	− 0.801	84.93	10.58	4.48
			(− 1.09)	(− 0.37)	(0.09)
Group Average	− 0.258	− 0.386	80.01	14.25	5.74
			(− 0.56)	(− 0.29)	(0.11)
Panel C: Open-Ended Funds					
FI Index	− 0.167	− 0.035	100.30	3.62	− 3.92
			(− 0.16)	(0.04)	(− 0.19)
FI Global	− 0.849	− 0.556	85.77	− 66.27	80.50
			(0.06)	(− 1.13)	(0.13)
FI Short Term	− 0.333	− 0.890	45.00	− 142.57	197.57
			(− 0.51)	(− 0.35)	(− 0.38)
FI Government	− 0.158	− 0.138	69.42	8.48	22.10
			(− 0.67)	(0.24)	(− 0.01)
FI Mortgage	− 0.315	− 0.420	80.90	2.53	16.57
			(− 0.58)	(− 0.29)	(− 0.04)
FI Corporate	− 0.963	− 0.580	113.87	− 33.19	19.32
			(− 0.69)	(− 0.11)	(0.07)
FI High Yield	− 0.776	− 1.174	− 32.05	− 7.75	139.80
			(− 1.00)	(− 0.51)	(0.06)
FI Others	− 0.095	0.286	48.69	− 62.56	113.86
			(0.00)	(0.06)	(0.41)
FI Average	− 0.457	− 0.439	63.99	− 37.22	73.23
			(− 0.44)	(− 0.25)	(0.01)
EF Index	5.493	− 0.966	95.55	2.39	2.05
			(− 1.45)	(0.01)	(− 0.33)
EF commodities	0.155	− 0.516	87.41	23.22	− 10.63
			(− 1.07)	(0.07)	(− 0.15)

Styles	EW Port Skewness	Individual Skewness	Systematic: Individual COSKEW (%)	Systematic: Individual ICOSKEW (%)	Idiosyncratic: Individual RESSKEW (%)
EF Sector	− 0.569	− 0.371	83.74	3.99	12.27
			(− 0.73)	(− 0.20)	(0.04)
EF Global	− 0.918	− 0.796	83.73	9.82	6.45
			(− 1.24)	(− 0.01)	(− 0.00)
EF Balanced	− 0.472	− 1.098	88.85	17.72	− 6.57
			(− 1.23)	(− 0.40)	(− 0.13)
EF Leverage and Short	2.351	− 0.287	19.62	29.08	51.30
			(− 0.48)	(− 0.06)	(− 0.26)
EF Long Short	− 1.658	− 0.980	76.09	− 1.42	25.33
			(− 1.69)	(− 0.72)	(− 0.26)
EF Mid Cap	− 0.494	− 0.919	84.11	11.02	4.87
			(− 1.13)	(− 0.56)	(0.06)
EF Small Cap	− 0.490	− 0.741	103.62	− 7.17	3.54
			(− 1.07)	(− 0.41)	(0.07)
EF Aggressive Growth	− 0.405	− 0.734	101.10	− 5.18	4.08
			(− 1.05)	(0.68)	(0.07)
EF Growth	− 0.695	− 0.812	81.57	14.60	3.83
			(− 1.30)	(− 0.31)	(− 0.00)
EF Growth and Income	− 0.997	− 0.883	96.89	0.93	2.18
			(− 1.30)	(− 0.31)	(− 0.14)
EF Equity Income	− 0.944	− 0.782	91.69	1.25	7.07
			(− 0.93)	(− 0.79)	(0.06)
EF Others	− 0.567	− 0.498	− 40.20	143.89	− 3.70
			(− 0.85)	(0.73)	(0.07)
EF Average	− 0.015	− 0.742	75.27	17.44	7.29
			(− 1.11)	(− 0.16)	(− 0.07)
Group Average	− 0.176	− 0.631	71.17	− 2.44	31.27
			(− 0.87)	(− 0.20)	(− 0.04)
Panel D: Hedge Funds					
Equity Hedge	− 0.302	− 0.299	46.67	17.42	35.91
			(− 0.36)	(− 0.25)	(0.04)
Event-Driven	− 1.899	− 0.618	53.84	21.50	24.67
			(− 0.63)	(− 0.60)	(0.06)
Fund of Funds	− 1.000	− 0.981	42.13	10.99	46.88
			(− 0.93)	(− 0.92)	(− 0.32)
HFRI	− 1.074	− 1.115	157.06	− 95.69	38.63
			(− 0.64)	(− 0.79)	(− 0.17)
HFRX	− 2.257	− 1.709	110.83	− 23.03	12.20
			(− 0.57)	(− 1.70)	(− 0.71)
Macro	0.378	0.012	19.74	− 20.42	100.68
			(0.14)	(0.14)	(0.04)
Relative Value	− 4.219	− 1.208	31.24	17.85	51.04
			(− 0.45)	(− 0.62)	(− 0.23)
Group Average	− 1.482	− 0.845	65.93	− 10.20	44.29
			(− 0.49)	(− 0.68)	(− 0.18)

Panel E: All Funds

	Component	ETFs	OEFs	HFs
CEFs	COSKEW	−3.19	−3.42	0.01
	ICOSKEW	1.38	2.71	1.52
	RESSKEW	1.67	0.66	−1.23
ETFs	COSKEW		−1.12	6.03
	ICOSKEW		2.31	0.68
	RESSKEW		−2.46	−4.24
OEFs	COSKEW			5.04
	ICOSKEW			−1.15
	RESSKEW			−2.67

F test of equality: COSKEW (p=0.256) ICOSKEW (p=0.960) RESSKEW (p=0.070)

Panel F: Fixed Income Funds

	Component	ETFs	OEFs
CEFs	COSKEW	1.22	−0.54
	ICOSKEW	−0.71	1.67
	RESSKEW	−0.05	−2.18
ETFs	COSKEW		−1.36
	ICOSKEW		1.82
	RESSKEW		−1.37

F test of equality: COSKEW (p=0.979) ICOSKEW (p=0.903) RESSKEW (p=0.853)

Panel G: Equity Funds

	Component	ETFs	OEFs
CEFs	COSKEW	−3.21	−2.67
	ICOSKEW	1.38	1.15
	RESSKEW	1.57	1.50
ETFs	COSKEW		0.07
	ICOSKEW		0.03
	RESSKEW		−0.25

F test of equality: COSKEW (p=0.830) ICOSKEW (p=0.970) RESSKEW (p=0.538)

TABLE IV. KURTOSIS DECOMPOSITION BY EQUAL-WEIGHTED PORTFOLIOS ACROSS FUND STYLES AND TYPES

This table summarizes the kurtosis decomposition by using equal-weighted portfolio of funds as market portfolio. EW portfolio kurtosis is the kurtosis for the equal-weighted portfolios of funds formed by funds in the same styles. Individual kurtosis is the cross-sectional average of kurtosis of individual funds in each style. Kurtosis is the fourth central moment about the mean and computed as $E\frac{(r_i^4)}{\sigma_i^4} - 3$. r_i and σ_i are the demeaned return and standard deviation of fund i. COKURT, VOLCOMV, ICOKURT, and RESKURT refer to the following components in the kurtosis decomposition:

$$E(r_i^4) = \beta_i^3 \underbrace{cov(r_i, r_p^3) + 3\beta_i^3 cov(u_i, r_p^3)}_{\text{COKURT}} + 6\beta_i^2 \underbrace{E(r_p^2 u^2)}_{\text{VOLCOMV}} + 4\beta_i \underbrace{cov(u^3, r_p)}_{\text{ICOKURT}} + \underbrace{E(u_i^4)}_{\text{RESKURT}}$$

where r_p is the demeaned return for the market portfolio. Individual COKURT, VOLCOMV, ICOKURT, and RESKURT are the average of estimated values from the above equation by GMM across individual funds and reported as the percentage of the kurtosis of demeaned fund returns $E(r_i^4)$. FI and EF stand for fixed income and equity funds, respectively. Numbers in parentheses are t-statistics associated with a null hypothesis of zero raw cokurtosis, idiosyncratic cokurtosis, volatility comovement, and residual kurtosis in the respective columns. FI Average is the average of statistics across fixed-income fund styles. EF Average is the average of statistics across equity fund styles. Group Average is the average of statistics across all fund styles. Panel E, F, and G summarize the t-statistics on the comparisons of the percentage of each component between any two fund types based on fixed income, equity, and total funds, respectively. F test reports the p-value of the test of differences in mean estimates on the percentage of each component across four fund types in parentheses.

Styles	EW Port Kurtosis	Individual Kurtosis	Systematic			Idiosyncratic
			Individual COKURT (%)	Individual VOLCOMV (%)	Individual ICOKURT (%)	Individual RESKURT (%)
Panel A: Closed-End Funds						
FI Global	11.897	6.080	52.09	37.14	− 3.27	14.04
			(1.12)	(2.10)	(0.19)	(2.60)
FI Sector	3.395	4.611	19.84	41.68	5.24	33.24
			(0.90)	(1.77)	(0.63)	(2.86)
FI Long Term	7.365	8.322	43.68	37.20	− 2.08	21.20
			(0.66)	(1.88)	(0.05)	(2.06)
FI Intermediate Term	5.568	5.443	29.75	44.91	2.92	22.42
			(1.12)	(2.21)	(0.76)	(3.24)
FI Short Term	1.814	4.361	12.36	54.30	3.88	29.47
			(0.35)	(1.58)	(0.39)	(2.35)
FI Government	2.390	2.305	14.97	38.31	8.46	38.25
			(1.20)	(2.13)	(0.83)	(2.51)
FI High Yield	5.445	3.708	47.57	36.53	− 5.41	21.32
			(1.56)	(2.27)	(− 0.04)	(2.59)
FI Others	11.743	6.415	67.79	22.50	− 0.54	10.25
			(1.36)	(1.73)	(0.21)	(2.20)
FI Average	6.202	5.156	36.01	39.07	1.15	23.77
			(1.03)	(1.96)	(0.38)	(2.55)
EF Balanced	5.747	4.193	51.43	34.53	− 1.24	15.29
			(1.40)	(1.96)	(0.29)	(2.50)
EF Commodities	5.801	2.725	30.94	40.01	3.98	25.07
			(1.33)	(2.21)	(0.48)	(2.84)
EF Global	4.882	4.424	18.35	41.89	3.87	35.89
			(0.96)	(2.04)	(0.21)	(2.40)
EF Sector	5.754	4.279	34.19	43.47	− 6.02	28.36
			(1.19)	(1.82)	(− 0.41)	(2.27)
EF Large Cap	27.479	5.530	45.49	39.45	− 0.17	15.23
			(1.30)	(1.85)	(0.27)	(2.62)
EF Mid Cap	2.958	4.565	29.65	36.43	5.81	28.10
			(0.99)	(1.92)	(0.52)	(2.51)
EF Small Cap	5.238	3.321	5.27	76.14	− 16.61	35.21
			(− 0.43)	(1.89)	(− 0.47)	(3.32)
EF Growth	6.635	4.707	22.20	50.27	− 5.23	32.76
			(0.39)	(1.64)	(0.01)	(2.77)
EF Value	4.680	3.886	56.87	37.22	− 1.57	7.48
			(1.38)	(1.91)	(− 0.13)	(2.06)
EF Others	7.017	5.649	58.66	33.23	− 0.44	8.55
			(1.18)	(1.92)	(0.51)	(2.24)
EF Average	7.619	4.328	35.30	43.26	− 1.76	23.19
			(0.97)	(1.92)	(0.13)	(2.55)
Group Average	6.989	4.696	35.62	41.40	− 0.47	23.45
			(1.00)	(1.94)	(0.24)	(2.55)

Styles	EW Port Kurtosis	Individual Kurtosis	Systematic Individual COKURT (%)	 Individual VOLCOMV (%)	 Individual ICOKURT (%)	Idiosyncratic Individual RESKURT (%)
Panel B: ETFs						
FI Global	3.555	2.910	52.77	31.84	8.92	6.47
			(0.89)	(1.27)	(0.15)	(2.18)
FI Sector	2.002	1.841	92.65	8.34	− 1.43	0.45
			(1.77)	(2.01)	(0.03)	(1.97)
FI Long Term	9.208	7.720	82.56	16.75	0.16	0.54
			(1.35)	(1.47)	(0.25)	(1.60)
FI Intermediate Term	4.283	3.537	66.89	30.30	− 0.64	3.46
			(1.29)	(1.61)	(− 0.35)	(2.16)
FI Short Term	0.890	2.156	36.00	34.02	− 1.95	31.93
			(0.80)	(1.14)	(0.12)	(2.26)
FI Government	0.123	1.444	7.41	28.26	0.77	63.56
			(0.65)	(1.16)	(0.35)	(2.47)
FI High Yield	2.787	2.636	94.35	5.68	− 0.05	0.02
			(1.39)	(2.51)	(− 0.13)	(2.00)
FI Others	4.516	3.699	98.79	1.20	0.01	0.01
			(1.57)	(2.14)	(− 0.22)	(1.87)
FI Average	3.421	3.243	66.43	19.55	0.72	13.30
			(1.21)	(1.66)	(0.03)	(2.06)
EF Balanced	1.408	1.988	61.75	28.67	0.07	9.50
			(1.24)	(2.09)	(0.17)	(1.73)
EF Global	2.524	2.404	69.21	22.32	1.84	6.63
			(1.45)	(2.27)	(0.15)	(2.60)
EF Sector	2.259	1.687	48.06	33.30	− 0.38	19.01
			(1.16)	(2.02)	(0.04)	(2.42)
EF Commodities	3.222	1.430	69.22	23.32	1.37	6.10
			(1.56)	(2.03)	(0.07)	(2.23)
EF Large Cap	1.559	2.842	79.38	17.94	− 0.28	2.96
			(1.50)	(2.31)	(− 0.28)	(2.36)
EF Mid Cap	3.267	2.648	79.32	15.20	− 0.51	5.98
			(1.35)	(1.96)	(0.05)	(2.31)
EF Small Cap	2.240	2.731	90.59	9.41	− 0.56	0.56
			(1.51)	(2.29)	(− 0.09)	(2.47)
EF Growth	1.453	1.884	81.83	15.01	− 0.03	3.19
			(1.70)	(2.28)	(0.21)	(2.62)
EF Value	2.537	3.579	79.72	17.24	− 0.44	3.48
			(1.40)	(2.24)	(0.16)	(2.43)
EF Bear Market	0.970	1.142	48.28	38.85	− 1.11	13.99
			(1.26)	(1.83)	(− 0.01)	(2.24)
EF Currency	3.894	3.786	55.12	26.71	0.19	17.99
			(0.94)	(1.60)	(0.31)	(2.24)
EF Others	0.489	1.749	55.47	32.84	1.62	10.08
			(1.45)	(2.27)	(0.04)	(2.63)
EF Average	2.152	2.323	68.16	23.40	0.15	8.29
			(1.38)	(2.10)	(0.07)	(2.36)
Group Average	2.659	2.691	67.47	21.86	0.38	10.30
			(1.31)	(1.93)	(0.05)	(2.24)

Styles	EW Port Kurtosis	Individual Kurtosis	Systematic Individual COKURT (%)	Systematic Individual VOLCOMV (%)	Systematic Individual ICOKURT (%)	Idiosyncratic Individual RESKURT (%)
Panel C: Open-Ended Funds						
FI Index	0.545	1.412	75.50	20.03	− 1.91	6.38
			(2.17)	(2.30)	(− 0.13)	(2.42)
FI Global	5.778	3.739	35.55	52.03	− 4.35	16.76
			(1.11)	(2.29)	(0.10)	(2.56)
FI Short Term	1.911	5.023	16.24	71.25	− 20.75	33.20
			(0.47)	(1.94)	(− 0.33)	(2.20)
FI Government	0.430	1.311	56.88	26.83	− 1.82	18.10
			(1.97)	(2.18)	(0.18)	(2.65)
FI Mortgage	0.966	2.018	60.27	27.10	0.48	12.15
			(1.99)	(2.38)	(0.13)	(2.17)
FI Corporate	4.220	2.578	69.02	25.31	− 1.93	7.60
			(1.79)	(2.54)	(− 0.15)	(2.17)
FI High Yield	4.850	5.553	72.90	21.01	− 0.03	6.12
			(1.58)	(2.28)	(0.27)	(2.34)
FI Others	2.824	3.412	18.32	21.92	− 0.95	60.71
			(0.56)	(1.36)	(0.14)	(2.84)
FI Average	2.690	3.131	50.59	33.18	− 3.91	20.13
			(1.45)	(2.16)	(0.03)	(2.42)
EF Index	87.572	2.850	77.95	18.13	− 0.77	4.69
			(1.69)	(2.57)	(− 0.14)	(2.44)
EF Commodities	4.114	1.585	66.37	25.43	− 0.66	8.86
			(1.57)	(2.62)	(0.05)	(2.52)
EF Sector	2.142	1.268	44.65	37.35	1.03	16.97
			(1.70)	(2.32)	(0.25)	(2.68)
EF Global	3.287	2.245	73.89	20.49	0.54	5.08
			(1.69)	(2.75)	(0.15)	(2.79)
EF Balanced	2.151	3.332	73.09	21.10	− 0.83	6.64
			(1.55)	(2.49)	(0.25)	(2.56)
EF Leverage and Short	23.537	1.597	44.92	38.01	− 0.47	17.54
			(1.39)	(2.12)	(0.34)	(2.33)
EF Long Short	2.791	1.439	67.59	24.49	2.43	5.48
			(1.36)	(2.09)	(0.07)	(2.49)
EF Mid Cap	1.336	2.579	76.03	21.74	− 1.06	3.28
			(1.65)	(2.43)	(0.10)	(2.55)
EF Small Cap	1.097	1.930	73.92	24.35	− 1.25	2.98
			(1.70)	(2.55)	(− 0.03)	(2.56)
EF Aggressive Growth	0.730	2.067	71.61	19.73	0.58	8.08
			(1.39)	(2.54)	(0.04)	(2.55)
EF Growth	2.198	2.114	73.00	21.60	0.11	5.30
			(1.86)	(2.62)	(0.16)	(2.61)
EF Growth and Income	2.785	2.169	82.80	14.39	− 0.06	2.87
			(1.80)	(2.69)	(0.07)	(2.55)
EF Equity Income	3.010	2.041	79.60	17.44	− 0.21	3.17
			(1.74)	(2.52)	(0.09)	(2.57)
EF Others	1.857	1.994	66.75	23.17	0.11	9.97
			(1.41)	(2.54)	(0.08)	(2.58)
EF Average	9.901	2.086	69.44	23.39	− 0.04	7.21
			(1.61)	(2.49)	(0.11)	(2.56)
Group Average	7.279	2.466	62.59	26.95	− 1.45	11.91
			(1.55)	(2.37)	(0.08)	(2.50)

Styles	EW Port Kurtosis	Individual Kurtosis	Systematic			Idiosyncratic
			Individual COKURT (%)	Individual VOLCOMV (%)	Individual ICOKURT (%)	Individual RESKURT (%)
Panel D: Hedge Funds						
Equity Hedge	2.004	2.001	17.56	34.18	1.08	47.17
			(0.64)	(1.50)	(0.29)	(2.45)
Event-Driven	6.907	4.071	23.59	31.03	3.75	41.64
			(0.73)	(1.58)	(0.49)	(2.25)
Fund of Funds	4.186	2.951	44.53	33.21	2.35	19.91
			(1.17)	(1.95)	(0.37)	(2.31)
HFRI	4.018	6.471	33.21	42.58	− 0.29	24.50
			(0.98)	(2.14)	(0.70)	(2.90)
HFRX	8.220	6.048	50.56	27.05	1.26	21.13
			(0.69)	(1.88)	(0.65)	(2.27)
Macro	0.134	2.006	7.28	22.82	2.96	66.95
			(0.61)	(1.21)	(0.29)	(2.32)
Relative Value	25.845	7.001	7.27	45.82	− 8.80	55.89
			(0.42)	(1.07)	(0.20)	(1.96)
Group Average	7.330	4.364	26.28	33.81	0.33	39.60
			(0.75)	(1.62)	(0.43)	(2.35)

Panel E: All Funds

	Component	ETFs	OEFs	HFs
CEFs	COKURT	− 13.38	− 21.59	12.11
	VOLCOMV	10.31	13.76	6.78
	ICOKURT	− 0.23	1.38	− 2.63
	RESKURT	8.38	11.51	− 18.67
ETFs	COKURT		− 3.45	33.55
	VOLCOMV		1.78	− 7.07
	ICOKURT		2.95	− 4.12
	RESKURT		1.96	− 37.51
OEFs	COKURT			106.32
	VOLCOMV			− 20.94
	ICOKURT			− 13.28
	RESKURT			− 73.00

F test of equality: COKURT ($p < 0.001$) VOLCOMV ($p < 0.001$) ICOKURT ($p < 0.001$) RESKURT ($p < 0.001$)

Panel F: Fixed Income Funds

	Component	ETFs	OEFs
CEFs	COKURT	−0.99	−4.17
	VOLCOMV	3.16	3.19
	ICOKURT	−0.20	2.89
	RESKURT	−0.82	0.33
ETFs	COKURT		−0.35
	VOLCOMV		−2.01
	ICOKURT		1.10
	RESKURT		1.08

F test of equality: COKURT ($p=0.002$) VOLCOMV ($p=0.053$) ICOKURT ($p=0.042$) RESKURT ($p=0.535$)

Panel G: Equity Funds

	Component	ETFs	OEFs
CEFs	COKURT	−12.31	−19.29
	VOLCOMV	8.84	12.46
	ICOKURT	0.16	0.67
	RESKURT	7.18	10.30
ETFs	COKURT		−5.81
	VOLCOMV		4.23
	ICOKURT		1.12
	RESKURT		4.86

F test of equality: COKURT ($p< 0.001$) VOLCOMV ($p< 0.001$) ICOKURT ($p=0.207$) RESKURT ($p< 0.001$)

TABLE V. AUTOCORRELATION-ADJUSTED SKEWNESS AND KURTOSIS DECOMPOSITION OF HEDGE FUNDS

This table summarizes the skewness and kurtosis decompositions by using equal-weighted portfolio of funds as market portfolio, after being adjusted for stale prices. The 3-lag autocorrelated observed return process is identified as

$$r_{i.t} = (\beta_{0,i} + \beta_{1,i} + \beta_{2,i})r_{p,t} + u_{i,t}$$

$r_{i.t}$ and $r_{p,t}$ are demeaned return for fund i and market portfolio. Substitute the true $\tilde{\beta}_i^* = \beta_{0,i} + \beta_{1,i} + \beta_{2,i_i}$in the equation of $r_{i.t} = \tilde{\beta}_i r_{p,t}$ to derive and compute the skewness and kurtosis decompositions. Numbers in parentheses are t-statistics associated with a null hypothesis of zero raw coskewness, idiosyncratic coskewness, residual skewness, cokurtosis, idiosyncratic cokurtosis, volatility comovement, and residual kurtosis in the respective columns. Group Average is the average of statistics across all fund styles.

Panel A: Skewness Decomposition			
	Systematic		Idiosyncratic
Styles	Individual COSKEW (%)	Individual ICOSKEW (%)	Individual RESSKEW (%)
Equity Hedge	23.66	36.20	43.21
	(− 0.32)	(− 0.28)	(0.04)
Event-Driven	50.84	21.25	27.54
	(− 0.54)	(− 0.59)	(0.08)
Fund of Funds	44.63	21.19	35.23
	(− 0.95)	(− 0.79)	(− 0.30)
HFRI	141.69	− 49.19	8.05
	(− 0.75)	(− 0.40)	(− 0.26)
HFRX	66.09	− 15.20	52.80
	(− 0.83)	(− 1.36)	(− 0.25)
Macro	42.53	− 99.38	157.81
	(0.11)	(0.12)	(0.05)
Relative Value	32.20	22.77	45.39
	(− 0.37)	(− 0.60)	(− 0.18)
Group Average	57.38	− 8.91	52.86
	(− 0.52)	(− 0.56)	(− 0.12)

Panel B: Kurtosis Decomposition				
	Systematic			Idiosyncratic
Styles	Individual COKURT (%)	Individual VOLCOMV (%)	Individual ICOKURT (%)	Individual RESKURT (%)
Equity Hedge	9.77	48.98	− 11.54	52.88
	(0.50)	(1.20)	(0.22)	(2.15)
Event-Driven	10.18	51.51	− 6.23	44.51
	(0.50)	(1.26)	(0.25)	(2.06)
Fund of Funds	37.69	43.03	− 2.42	21.82
	(1.04)	(1.66)	(0.33)	(2.04)
HFRI	36.99	34.96	4.50	23.57
	(1.07)	(1.91)	(0.69)	(2.80)
HFRX	52.37	21.01	1.58	25.76
	(0.90)	(1.53)	(0.25)	(2.25)
Macro	− 9.27	60.95	− 35.47	84.24
	(0.27)	(0.82)	(0.14)	(1.95)
Relative Value	− 5.57	67.05	− 21.31	60.21
	(0.27)	(0.95)	(0.07)	(1.82)
Group Average	18.88	46.79	− 10.13	44.71
	(0.65)	(1.33)	(0.28)	(2.15)

TABLE VI. SKEWNESS DECOMPOSITION BY BETA-WEIGHTED EXOGENOUS FACTORS

Beta-weighted factors are constructed from Fama-French 3-factors, Carhart 4-factors, Fung-Hsieh 7-factors, and 2 bond factors. Equity CEFs and ETFs use the beta-weighted Fama-French 3-factors. Equity open-ended funds and hedge funds use the beta-weighted Carhart 4-factors, and Fung-Hsieh 7-factors, respectively. Bond CEFs, ETFs, and open-ended funds use two more bond indexes in addition to the factors used in their equity counterparts – the Barclay U.S. government/credit index and corporation bond index. The weights to construct beta-weighted factors depend on the respective betas on each factor. Betas are estimated by regressing fund excess returns on factor excess returns. EW portfolio skewness is the cross-sectional average of skewness of beta-weighted factors. Individual skewness is the cross-sectional average of skewness of individual funds in each style. Skewness is the third central moment about the mean and computed as $E\frac{(r_i^3)}{\sigma_i^3} - 3$. r_i and σ_i are the demeaned return and standard deviation of fund i. COSKEW, ICOSKEW, and RESSKEW refer to the following components in the skewness decomposition:

$$E(r_i^3) = \beta_i^2 \underbrace{cov(r_i, r_p^2) + 2\beta_i^2 cov(u_i, r_p^2)}_{\text{COSKEW}} + 3\beta_i \underbrace{cov((u_i^2, r_p)}_{\text{ISOCKEW}} + E\underbrace{(u_i^3)}_{\text{RESSKEW}}$$

where r_p is the demeaned return for the market portfolio. Individual COSKEW, ICOSKEW, and RESSKEW are the average of estimated values from the above equation by GMM across individual funds and reported as the percentage of the skewness of demeaned fund returns E[r3]. FI and EF stand for fixed income and equity funds, respectively. Numbers in parentheses are t-statistics associated with a null hypothesis of zero raw coskewness, idiosyncratic coskewness, and residual skewness in the respective columns. FI Average is the average of statistics across fixed-income fund styles. EF Average is the average of statistics across equity fund styles. Group Average is the average of statistics across all fund styles.

Fund Type	EW Port Skewness	Individual Skewness	Systematic: Individual COSKEW (%)	Systematic: Individual ICOSKEW (%)	Idiosyncratic: Individual RESSKEW (%)
Panel A: Closed-End Funds					
FI Average	− 0.772	− 0.675	24.66 (− 0.35)	38.56 (− 0.59)	36.75 (− 0.47)
EF Average	− 1.274	− 0.613	45.51 (− 0.96)	32.98 (− 0.64)	22.14 (0.28)
Group Average	− 1.051	− 0.640	36.24 (− 0.69)	35.46 (− 0.62)	28.63 (− 0.05)
Panel B: ETFs					
FI Average	0.162	0.236	59.63 (0.15)	15.40 (− 0.39)	22.25 (0.82)
EF Average	− 1.170	− 0.801	82.55 (− 1.14)	13.16 (− 0.22)	3.85 (0.22)
Group Average	− 0.637	− 0.386	73.38 (− 0.62)	14.06 (− 0.28)	11.21 (0.46)
Panel C: Open-Ended Funds					
FI Average	− 0.352	− 0.439	22.56 (− 0.12)	29.67 (− 0.38)	50.24 (− 0.37)
EF Average	− 0.919	− 0.742	90.53 (− 1.11)	5.69 (− 0.19)	3.85 (0.11)
Group Average	− 0.712	− 0.631	65.81 (− 0.75)	14.41 (− 0.26)	20.72 (− 0.06)
Panel D: Hedge Funds					
Group Average	0.928	− 0.845	27.81 (− 0.45)	23.88 (− 0.68)	47.80 (− 0.29)

TABLE VII. KURTOSIS DECOMPOSITION BY BETA-WEIGHTED EXOGENOUS FACTORS

Beta-weighted factors are constructed from Fama-French 3-factors, Carhart 4-factors, Fung-Hsieh 7-factors, and 2 bond factors. Equity CEFs and ETFs use the beta-weighted Fama-French 3-factors. Equity open-ended funds and hedge funds use the beta-weighted Carhart 4-factors, and Fung-Hsieh 7-factors, respectively. Bond CEFs, ETFs, and open-ended funds use two more bond indexes in addition to the factors used in their equity counterparts – the Barclay U.S. government/credit index and corporation bond index. The weights to construct beta-weighted factors depend on the respective betas on each factor. Betas are estimated by regressing fund excess returns on factor excess returns. EW portfolio kurtosis is the cross-sectional average of kurtosis of beta-weighted factors. Individual kurtosis is the cross-sectional average of kurtosis of individual funds in each style. Kurtosis is the fourth central moment about the mean and computed as $E\frac{(r_i^4)}{\sigma_i^4} - 3$. r_i and σ_i are the demeaned return and standard deviation of fund i. COKURT, VOLCOMV, ICOKURT, and RESKURT refer to the following components in the kurtosis decomposition:

$$E(r_i^4) = \beta_i^3 \underbrace{cov\left(r_i, r_p^3\right) + 3\beta_i^3 cov\left(u_i, r_p^3\right)}_{\text{COKURT}} + 6\beta_i^2 \underbrace{E\left(r_p^2 u^2\right)}_{\text{VOLCOMV}} + 4\beta_i \underbrace{cov\left((u_i^3, r_p\right)}_{\text{ICOKURT}} + E\underbrace{(u_i^4)}_{\text{RESKURT}}$$

where r_p is the demeaned return for the beta-weighted factors. Individual COKURT, VOLCOMV, ICOKURT, and RESKURT are the average of estimated values from the above equation by GMM across individual funds and reported as the percentage of the kurtosis of demeaned fund returns $E\left(r_i^4\right)$. FI and EF stand for fixed income and equity funds, respectively. Numbers in parentheses are t-statistics associated with a null hypothesis of zero raw cokurtosis, idiosyncratic cokurtosis, volatility comovement, and residual kurtosis in the respective columns. FI Average is the average of statistics across fixed-income fund styles. EF Average is the average of statistics across equity fund styles. Group Average is the average of statistics across all fund styles.

Fund Type	EW Port Kurtosis	Individual Kurtosis	Systematic Individual COKURT (%)	 Individual VOLCOMV (%)	 Individual ICOKURT (%)	Idiosyncratic Individual RESKURT (%)
Panel A: Closed-End Funds						
FI Average	3.603	5.156	7.83	24.45	14.74	52.48
			(0.62)	(1.43)	(1.09)	(2.48)
EF Average	4.228	4.328	23.92	36.83	7.02	29.90
			(1.01)	(1.75)	(0.74)	(2.54)
Group Average	3.950	4.696	16.77	31.33	10.45	39.94
			(0.84)	(1.61)	(0.89)	(2.52)
Panel B: ETFs						
FI Average	1.832	3.243	25.53	39.35	0.01	35.18
			(0.65)	(1.36)	(0.15)	(2.12)
EF Average	2.329	2.323	68.89	21.03	1.88	7.81
			(1.40)	(2.14)	(0.27)	(2.44)
Group Average	2.130	2.691	51.55	28.36	1.13	18.76
			(1.10)	(1.82)	(0.22)	(2.31)

Fund Type	EW Port Kurtosis	Individual Kurtosis	Systematic Individual COKURT (%)	 Individual VOLCOMV (%)	 Individual ICOKURT (%)	Idiosyncratic Individual RESKURT (%)
Panel C: Open-Ended Funds						
FI Average	2.806	3.131	14.08	28.12	2.28	55.82
			(0.47)	(1.53)	(0.39)	(2.73)
EF Average	2.153	2.086	73.20	19.80	0.36	6.23
			(1.65)	(2.54)	(0.15)	(2.70)
Group Average	2.390	2.466	51.70	22.82	1.06	24.26
			(1.22)	(2.17)	(0.23)	(2.71)
Panel D: Hedge Funds						
Group Average	3.664	4.364	17.07	34.68	1.46	46.83
			(0.55)	(1.36)	(0.47)	(2.46)

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