An Investigation of ETF Flows: Asset Allocation Perspectives

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การศึกษาเงินทุนเคลื่อนย้ายของ ETFs ผ่านมุมมองการจัดสรรสินทรัพย์

น.ส.บุณยาพร วงศ์สวัสดิ์กุล

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาศิลปศาสตรมหาบัณฑิต
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บุณยาพร วงศ์สวัสดิ์กุล : การศึกษาเงินทุนเคลื่อนย้ายของ ETFs ผ่านมุมมองการจัดสรรสินทรัพย์ . (An Investigation of ETF Flows: Asset Allocation Perspectives) อ.ที่ปรึกษาหลัก : ผศ. ดร.พงศ์ศักดิ์ เหลืองอร่าม

บทความนี้ศึกษาผลกระทบของการจัดสรรสินทรัพย์ต่อเงินทุนเคลื่อนย้ายของ ETF โดยใช้การวิเคราะห์การถดถอยแบบ Fixed-effect panel regression ครอบคลุมเดือน ต.ค. 2551 ถึง ก.ค. 2562 ขอบเขตการลงทุนประกอบด้วย ETF ที่จดทะเบียนในตลาดหลักทรัพย์สหรัฐฯ 9 ชนิด แบ่งเป็น 5 กลุ่มสินทรัพย์ การปรับน้ำหนักการลงทุนรายเดือนของแต่ละ ETF ในพอร์ตคำนวนจากกลยุทธ์การหาพอร์ตการลงทุนที่เหมาะสม 5 กลยุทธ์ แบ่งเป็นแบบค่าเฉลี่ยและความแปรปรวนของพอร์ต และแบบบนฐานความเสี่ยง ผลการศึกษาพบว่าการปรับน้ำหนักการลงทุนของกลยุทธ์การหาพอร์ตการลงทุนแบบบนฐานความเสี่ยงอธิบายการเคลื่อนย้ายเงินทุนระหว่างกลุ่มสินทรัพย์ได้อย่างมีนัยยะสำคัญ บ่งชี้ว่านักลงทุนมีเป้าหมายเพื่อรักษาเสถียรภาพของความผันผวนของพอร์ตมากกว่าการมุ่งเน้นผลตอบแทนสูงสุด บทความนี้ศึกษาต่อถึงความสัมพันธ์ระหว่างเงินทุนเคลื่อนย้ายและราคาของ ETF ในช่วง flight-to-quality และพบว่าการเคลื่อนไหวของเงินทุนเคลื่อนย้ายนำหน้าการเคลื่อนไหวของราคา

สาขาวิชา	เศรษฐศาสตร์และการเงินระหว่างประเทศ	ลายมือชื่อนิสิต ....
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This study investigates impacts of asset allocations on ETF flows across asset classes in a panel form, utilizing fixed-effects panel regression. The period of study covers October 2008 to July 2019. The investment universe contains 9 U.S.-listed ETFs, classifying into 5 asset classes. Monthly asset allocations are obtained from 5 optimization strategies based on mean-variance and risk-based optimizations. The findings indicate that asset allocations of risk-based optimization strategies significantly explain fund flows across asset classes. It implies that ETF market participants attempt to stabilize portfolio volatilities rather than maximize portfolio expected returns or risk-adjusted returns. This study further analyses relations between ETF flows and returns during flight-to-quality episodes and find that flows lead returns.

Field of Study:	International Economics and Finance	Student's Signature ....
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Boonyaporn Wongsawatgul

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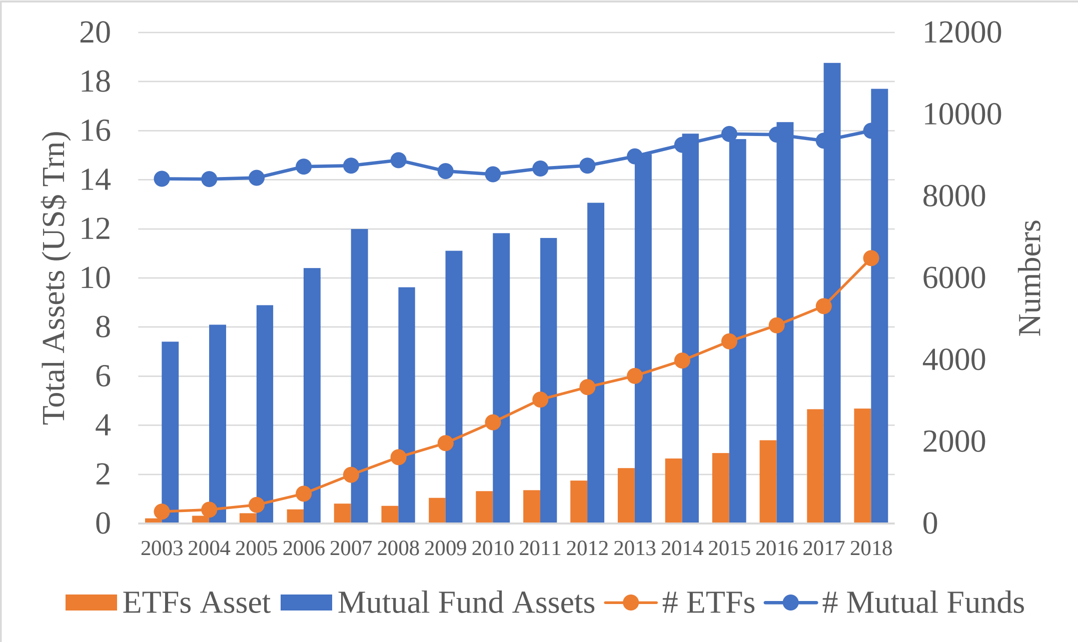
CHAPTER 1: INTRODUCTION

1.1 Background and Stylized Facts

Mutual funds have been dominant investment vehicles in global financial markets for many years. Recently, the role of exchange-traded funds (ETFs) has been in the spotlight particularly since the global financial crisis a decade ago as shown in figure 1. The diagram depicts total asset under management (AUM) of mutual funds and ETFs, as well as number of mutual funds and ETFs from 2003 to 2018. The AUM and number of ETFs have accelerated since 2007, whereas the data of mutual funds have plateaued. An ETFs was first designed as a passive investment vehicle that replicate the performance of an index. Afterward, the ETF universe had been expanded from equity to non-equity, from the U.S. domicile to other regions, and from index mimic to complex investment strategies, leveraging, as well as reversal direction of index movements (Lettau and Madhavan (2018); Miffre (2007)). ETFs offer liquidities of investments in low-liquid asset classes, e.g. bonds, as well as offshore investments. Hence, ETFs extend opportunities of portfolio diversifications, thereby enhance portfolio performances even beyond employing mutual funds. These samples of advantages support a popularity of ETFs not only among institutional investors, but also individual market participants.

Given the rising role of ETFs and the capability of high-liquid international investments, an investigation of ETF flows is relevant for global investors and policymakers, in particular, as massive and volatile portfolio flows could propel economic distortions, financial contagion, and policy challenges (Ahmed and Zlate (2014); Gelos (2011)). Previous literatures analyze ETFs in the case of, for example, price discovery, price efficiency, global asset allocation and performances compared to mutual funds, flow-return and flow-price relations, and financial stability. Nevertheless, literature of determinants of ETF flows is hardly found.

***Figure 1**: Total assets and number of mutual funds and ETFs from 2003 to 2018*



Source: Statista

Determinants of fund flows are typically classified into two core criteria, macro and micro levels. From a macro landscape, empirical evidence finds significant effects of shifts in macroeconomic environments, financial conditions, and monetary policy shocks on mutual fund flows (e.g. Banegas, Montes-Rojas, and Siga (2016); Chalmers, Kaul, and Phillips (2013); Jank (2012); Kroencke, Schmeling, and Schrimpf (2015)). An examination of fund flows through micro perspectives, nonetheless, is overlooked. It is important to note that ETF flows and even mutual fund flows are usually examined through one asset class at a time (e.g. Clifford, Fulkerson, and Jordan (2014); Jank (2012)), or many asset classes separately (e.g. Banegas et al. (2016); Chalmers et al. (2013)), implying that all asset classes have persistent relations, or algebraically constant correlations, over the periods of study even during shifts in macroeconomic environment and financial conditions. Table 1 exhibits correlations of monthly returns and monthly fund flows between U.S. equity ETF (SPY) and U.S. aggregate bond ETF (AGG), as well as the relations between U.S. equity ETF and other economies (EFA for developed countries excluding U.S. and Canada, and VWO for emerging markets). The fund-flow correlations are not significant for all security pairs, whereas the return correlations are all significant, except for the equity-bond pair. These correlations represent the fixed relations over the period.

***Table 1**: Correlations of monthly net fund flows and returns between U.S. equity ETF, U.S. bond ETF, and other economies' equity ETFs between January 2006 and July 2019*

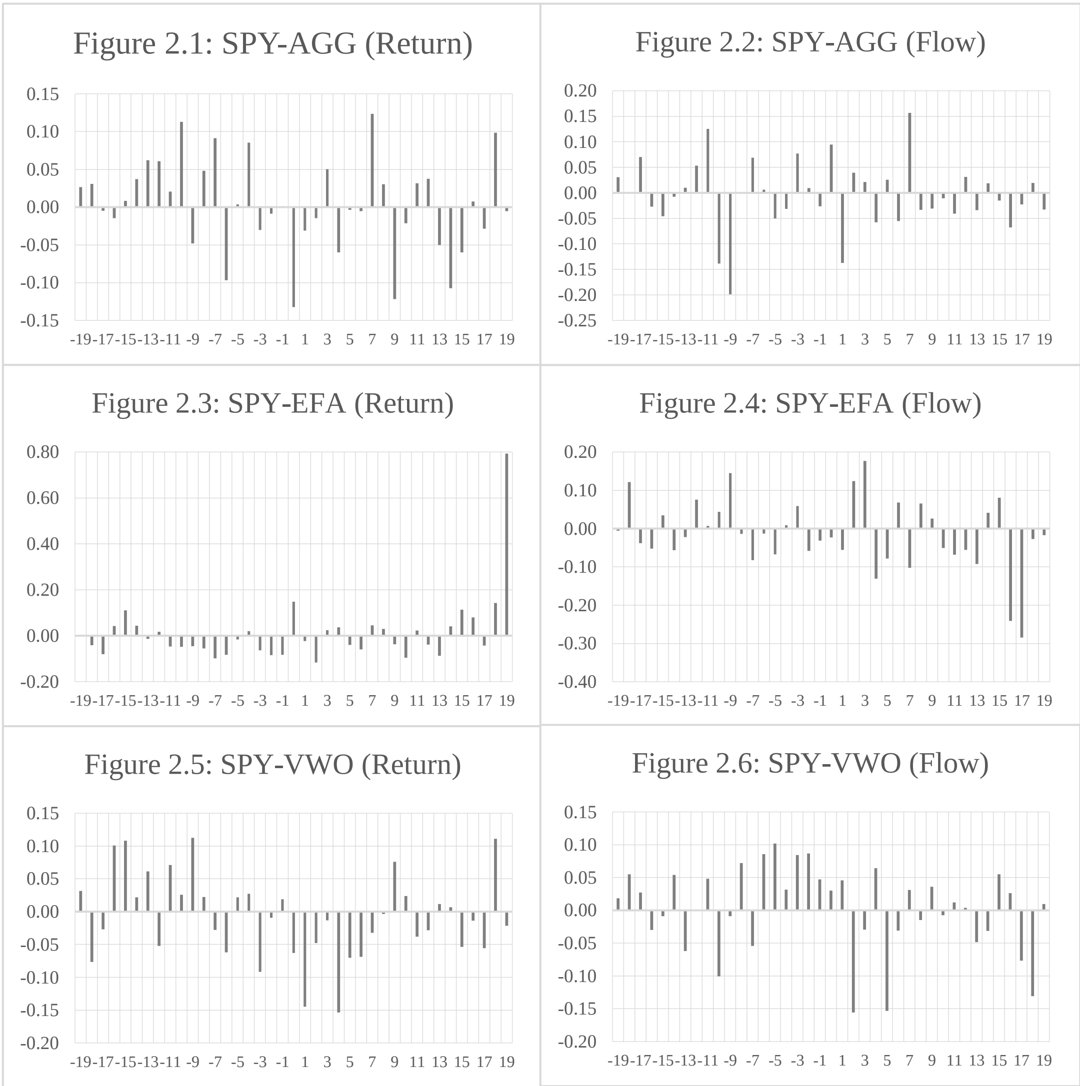
Correlation	SPY-EFA	SPY-VWO	EFA-VWO	SPY-AGG
Net Fund Flow	-0.0233	0.0303	-0.0320	0.0949
Return	0.8953	0.7908	0.8721	0.0477

Source: Bloomberg and author's calculation
SPY is U.S. equity ETF, EFA is developed market ETF, VWO is emerging market ETF, and AGG is U.S. aggregate bond ETF

In fact, price performances, returns, and relations of different asset classes vary over time according to economic, monetary, and business cycles (e.g. Fisher, Maymin, and Maymin (2015); Sheikh and Sun (2012)). To verify the findings, figure 2 displays cross-correlations among pairs of ETFs, measuring relations between two time series at different periods. Many ETF pairs undoubtedly demonstrate contrary relations at different lags. For example, figure 2.4 illustrates that cross-correlation of the U.S. equities and developed-market equities (SPY-EFA) fund flows is significantly positive at lag 9 but significantly negative at lag 16 and 17.

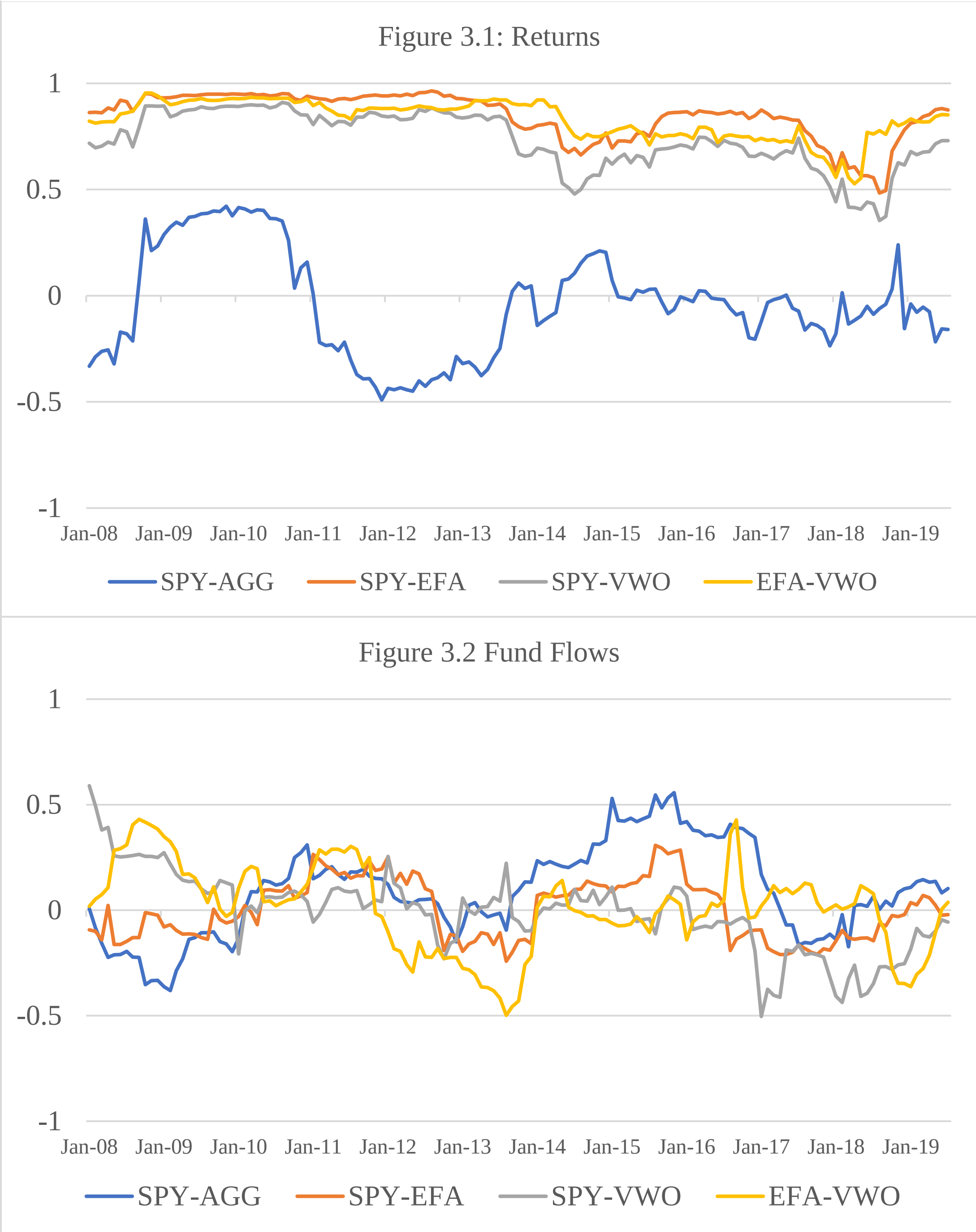
Another dimension of correlations, a dynamic correlation, is also examined. Figure 3.1 and 3.2 demonstrate dynamic correlations of returns and fund flows with a 24-month rolling window, respectively. The dynamic correlation of return across asset classes, U.S. equities and U.S. aggregate bonds (SPY-AGG), apparently fluctuates between positive and negative territories: Returns of equity and bond could move both correspondingly and conversely over time. However, the relations within asset class – a pair of U.S. equities and developed market equities (SPY-EFA), and a pair of U.S. equities and emerging-market equities (SPY-VWO) – are significantly and consistently positive. In terms of fund flows, dynamic correlations of all three pairs fluctuate, indicating that fund flows flee from one asset and flood into the others in some periods, while they move into both assets during other periods. Besides, magnitudes of relations of different asset pairs are variety as equity-bond dynamic-correlation waves are broader than the equity pairs.

***Figure 2**: Cross-correlation functions from January 2006 to July 2019*



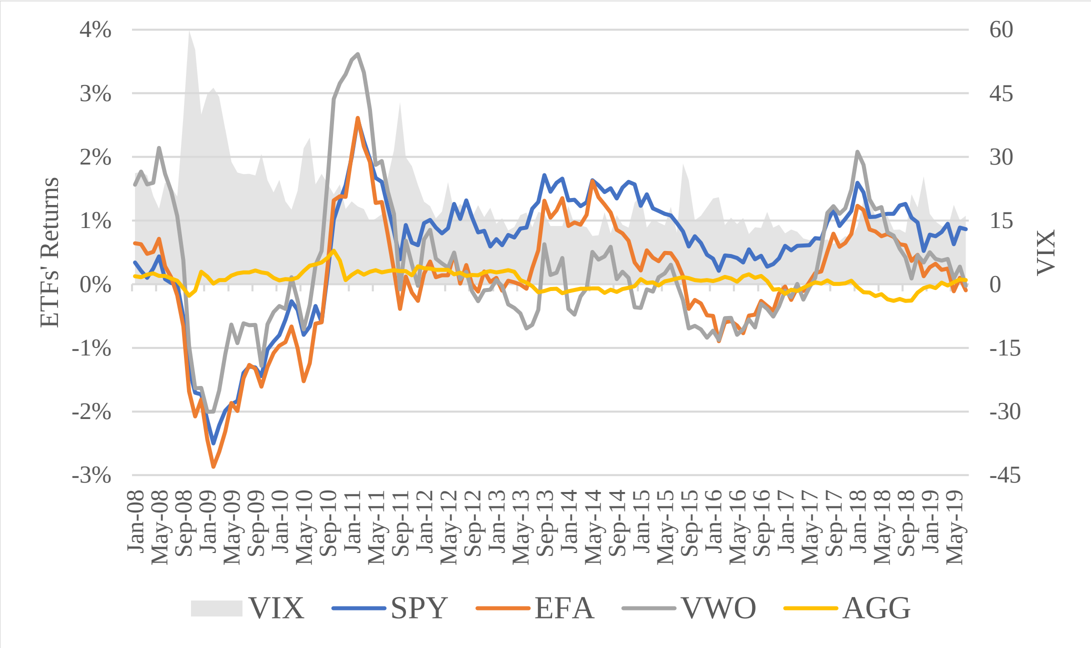
Source: Bloomberg and author’s calculation
SPY is U.S. equity ETF, EFA is developed market ETF, VWO is emerging market ETF, and AGG is U.S. aggregate bond ETF

***Figure 3**: Dynamic correlations with 24-month rolling window of returns and fund flows from January 2008 to July 2019*



Source: Bloomberg and author's calculation
SPY is U.S. equity ETF, EFA is developed market ETF, VWO is emerging market ETF, and AGG is U.S. aggregate bond ETF

***Figure 4**: Monthly returns with 24-month rolling window from January 2008 to July 2019*



Source: Bloomberg and author's calculation
SPY is U.S. equity ETF, EFA is developed market ETF, VWO is emerging market ETF, and AGG is U.S. aggregate bond ETF

The above observations correspond to the empirical findings that different asset classes behave differently during different economic and financial environments. In times of calm circumstances, risky assets, e.g. equities, generally outperform less risk assets, e.g. bonds and money markets, as relatively high-risk assets are offset by relatively high returns. Conversely, less risk assets are the outperformers during periods of financial market turbulences as investors search for protections rather than profits. Figure 4 emphasizes these events. During the global financial crisis in 2008-2009, the volatility index (VIX), gauging volatility of S&P 500 index, had surged to almost 60. Accordingly, the three equity ETFs (SPY, EFA, and VWO) generate negative rolling returns as much as 3 percent. Whereas U.S aggregate bond ETF (AGG) produces slightly positive returns, apparently outperforming the risky ETFs. When the crisis eased afterward, the VIX had declined and the equity ETFs had outpaced. Occurrences when returns of less risk assets beat returns of risky assets are called flight-to-quality phenomenon as investors move toward less risk assets during high volatility times (Gubareva & Borges, 2016).

On top of that, the surveillance somewhat relates to the foundations of the portfolio management framework. Portfolios that reallocate in response to macroeconomic and financial environments, or the so-called dynamic and tactical asset allocation, significantly outperform buy-and-hold strategies (Jensen and Mercer (2003); (Sheikh & Sun, 2012); (Chalmers et al., 2013); (Uhl, Pedersen, & Malitius, 2015)). Given the manifest advantages and widespread adoptions of portfolio diversification, asset allocation, and portfolio rebalancing, market participants practically consider multi-asset classes contemporaneously. As such, these observations induce an interest of investigating fund flows of many asset classes in an aggregate form simultaneously, or in a form of panel data, as well as effects of asset allocation and portfolio rebalancing on contemporaneous ETF flows.

Literature analyzing asset allocation and portfolio rebalancing generally utilizes mean-variance optimization (MVO), introduced by Markowitz in 1952, to construct optimal portfolios. Despite prevalent practices, MVO has been criticized on some restrictions when implementing, for example, MVO portfolios contain risk exposures mostly from equity risks. In recent years, the risk-based optimizations have gained popularity among financial institutions, especially after the global financial crisis in 2008. The crux of the risk-based optimizations is to enhance risk diversifications of a portfolio rather than allocate investing money. Empirically, several results demonstrate that risk-adjusted returns of risk-parity portfolios outperform other traditional portfolio strategies (Anderson, Bianchi, and Goldberg (2012); Asness, Frazzini, and Pedersen (2012); Chaves, Hsu, Li, and Shakernia (2010)).

All in all, the observations of the linkage among different relations of asset classes over time, shifts in macroeconomic environments and financial conditions, portfolio management strategies, as well as the rising role of ETFs and the scarcity of literature exploring determinants of ETF flows, motivates the objectives of this paper. This study, therefore, primarily investigates ETF flows across asset classes in a contemporaneous form through a micro view of asset allocations. To perform a comparison and provide broad perspectives of asset allocations in an ETF landscape, this study employs both MVO and risk-based strategies. In addition, as the definition of flight-to-quality episodes is based on asset returns, it is interesting to examine movements of net fund flows in response to movements of returns during the phenomenon in order to broaden the investigation of ETF flows as well.

1.2 Objective

This study aims to investigate determinants of ETF flows. The first investigation is the impacts of asset allocations, or changes in weights of securities in a portfolio, on fund flows across asset classes in a contemporaneous form. Asset allocations and portfolio rebalancing incorporate mean-variance optimization (MVO) and risk-based optimization strategies. The second investigation is the corresponding movements between ETF returns and fund flows during flight-to-quality episodes.

1.3 Scope

This paper covers the period from October 2008 to July 2019 with a monthly frequency. The study utilizes the fixed-effects panel regression to examine the effects of asset allocations on ETF flows. The scope of ETF flows is U.S.-listed ETFs, including equities, bonds, commodities, real estates, and money markets. The investment universe consists of the U.S. equity (SPY), developed-market equity (EFA), emerging-market equity (VWO), U.S aggregate bond (AGG), Non-U.S. bond (BWX), real estate (VNQ), commodities (DBC), gold (GLD), and money markets (SHV). The portfolio constructions and asset allocations are based on two widespread strategies – the mean-variance optimization (MVO) and the risk-based optimization. The objectives based on MVO include (1) maximum expected returns, (2) maximum Sharpe ratio, and (3) minimum volatility, which is also classified as a risk-based optimization. The risk-based objectives incorporate (4) risk parity and (5) maximum diversification. All five portfolios are long only, full investment, and rebalanced at the end of a month using 250-day rolling window.

The other independent variables are classified into two categories, macroeconomic surprises and financial conditions. Macroeconomic surprises consist of Citigroup Economic Surprise Index of the U.S. (ESI^{US}), European Union (ESI^{EU}), global (ESI^{GL}), and emerging markets (ESI^{EM}) as proxies for surprises in economic data releases. Financial conditions include Fed funds future (FFF) as a proxy for prospects of market participants on future path of the Federal reserve's policy rates, and Bloomberg Financial Condition Index of the U.S. (FCI^{US}), European Union (FCI^{EU}), the U.K. (FCI^{UK}), and Asia ex-Japan (FCI^{AXJ}), capturing the overall stress in money markets, bond markets, and equity markets.

CHAPTER 2: LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

2.1 Literature Review

Exchange-traded funds (ETFs) are ones of the most influential financial innovations in the past decade. An ETF, by definition, is an investment vehicle that replicates the performance of an index. The first ETF, labeled as SPY, was designed to track the performance of the S&P500 index. It was launched in 1993 and has become the world largest ETF. An ETF was initially created as a passive investment vehicle. Ultimately, the ETF universe has expanded from equity to non-equity, from the U.S. domicile to other regions, and from index mimic to complex investment strategies, leveraging, as well as reversal direction of index movements.

ETFs are often compared to mutual funds. Due to more cutting-edge financial instruments, ETFs are superior for many reasons. In terms of liquidity, unlike buying and selling at day-end NAVs as mutual funds, ETFs can be traded intraday. Processes of real-time price tracking are organized by the creation-redemption mechanism. ETFs also have lower costs and more tax efficient than mutual funds. The foremost superiority is that ETFs supply for investment opportunities and diversifications globally in such a way that enhance portfolio performances beyond what mutual funds could as evidenced by a North-West shift in the efficient frontiers and an improved risk-adjusted returns, or the so-called Sharpe ratio (Agrrawal (2013); Huang and Lin (2011); Miffre (2007)).

Despite of that, ETFs have been criticized somewhat on, for example, price efficiency, price discovery, and amplifications of financial market fluctuation (Ben-David, Franzoni, and Moussawi (2018); Williams, Converse, and Levy-Yayati (2018); Lee, Hsu, and Lee (2016); Levy and Lieberman (2013)). Greater numbers of ETF ownerships cause underlying securities to be more volatile and less price efficient. The finding of Buckle, Chen, Guo, and Tong (2018) indicates that changes in ETF prices lead prices of underlying securities to change rather than vice versa. In addition, Williams et al. (2018) find that international capital flows via ETFs have enlarge the size of effects as a result of global financial cycle in emerging markets even more sensitive than flows of mutual funds. Nevertheless, the superiorities remain outweigh and, eventually, ETFs have been used broadly among market participants, both institutional and individual investors.

The rising role of ETFs in global financial markets raises curiosity of drivers of ETF flows. Prior to the era of ETFs, mutual funds have been dominant for decades. Correspondingly, previous literature mainly studies mutual fund flows. Most literature delves into mutual fund flows through macro perspectives, classifying into monetary and macroeconomic catalysts, and with different time horizons. Empirical results indicate that macroeconomic environments (e.g. growth of Gross Domestic Product (GDP), industrial production, retail sales, housing indicators, IS manufacturing survey indicators, and inflation (CPI)), financial conditions (e.g. returns of S&P 500 index, default spreads, term spreads, the Treasury-Eurodollar spread (TED), the volatility index (VIX)), and monetary policy shocks (e.g. unexpected decisions of Federal Funds Rates, and Federal Funds Futures) could significantly explain movements of mutual fund flows. Empirically, economic downturns, financial market turbulence, and unexpected loosening monetary policy induce flows to move out of risky assets, e.g. equity, toward low-risk assets, such as money market and bond mutual funds.

Banegas et al. (2016) exploit structural VAR to study the effects of monetary policy shocks on mutual fund flows of equity and bond. They conclude that unexpected tightening monetary policy decisions induce cash flows to move out of bonds and into equities. Kroencke et al. (2015) scope the investigation on the period of FOMC meetings. The result demonstrates that flows move into the U.S. equities in the week before and during the week of the Fed’s meetings. Moreover, the Fed’s monetary easing triggers flows away from the U.S. and move into international assets. On the macroeconomic fundamental front, Chalmers et al. (2013) separately explore four major asset classes – equity, bond, money market, and foreign equity – and find that prospects of economic downturns and financial market turmoil, represented by a decrease in term spread, an increase in default spread and TED spread, prompt investors to move away from risky equity funds and turn to low-risk money market funds. Jank (2012) further finds the positive co-movement between asset returns and its flows, indicating common reactions to macroeconomic news. For a micro-level, although various literatures studying asset allocation are available, an assessment of the relation between asset allocation and movements of fund flows is inadequately inspected.

In contrast to the studies of mutual fund flows, literature determining ETF flows is hardly found. Clifford et al. (2014) is the first literature that delves into drivers of ETF flows. They research determinants of equity ETF flows focusing on, first, ETF characteristics, which are in common with mutual fund determinants, e.g. fund size (logs of total net assets), expense ratio, and portfolio turnover, and second, trading characteristics, which are essential determinants of ETF flows that differ from mutual fund flows, e.g. price-to-NAV ratio, spread, and volume. They find that high trading volume, small spread, and high price-to-NAV ratios (or premiums) significantly increase flows into equity ETFs.

Additionally, they analyze the role of returns in affecting ETF flows and surprisingly find that return chasing behaviors of ETF investors remain exist as found in mutual fund investors even though ETFs were created to be passive investment vehicles. The return chasing behaviors imply that returns lead flows. Other examinations that detect ETF flows are also related to flow-return field but are inspected via a reversal relation, i.e. ETF flows perform as independent variables. However, their findings are not harmonized. As opposed to the result from Clifford et al. (2014), Brown, Davies, and Ringgenberg (2019) find that ETF flows significantly foretell returns, while Staer (2017) concludes that a positive relation between flows and returns, named as price pressure, will be followed by a negative relation between lagged flows and returns, labeled as price reversal. Thus, flow-return relations of ETFs remain vague.

Observably, to the best of my knowledge, the studies of mutual fund flows and ETF flows are either in the form of one asset class at a time (e.g. Clifford et al. (2014); Jank (2012)) or many asset classes separately (e.g. Banegas et al. (2016); Chalmers et al. (2013)). In fact, there are empirical findings indicate that individual asset classes response differently to diverse economic and financial regimes. Thus, price performances, returns, and relations of different asset classes vary over time as

Sheikh and Sun (2012) labeled “non-linear relationship”. Fisher et al. (2015) address that equities outperform in times of low inflation and high growth. Fixed-income securities perform well when growth and inflation are low. Commodities are outstanding during periods of high inflation and high growth.

During recovery and growth phases, or calm market circumstances, risky assets typically outperform relatively low-risk assets as higher risks would be offset by higher expected return. However, in the periods of economic downturns and financial market turbulences, low-risk and less risky assets, e.g. government bonds and money markets, outperform risky assets, e.g. equities. These occurrences are called flight-to-quality phenomenon as investors search for shelters toward less risky investments and temporarily abandon risky assets in order to protect their wealth rather than produce it (Gubareva & Borges, 2016). Consequently, returns of less risky assets beat returns of risky assets. The phenomenon is somewhat related to the finding of macro-determinants of mutual fund flows mentioned previously that economic downturns, financial market turbulences, and unexpected loosening monetary policy induce flows to move out of risky assets toward low-risk assets. It should be noticed that flight-to-quality phenomenon are described rely on asset returns, not fund flows.

These postulates underpin the foundation of portfolio management, asset allocation, and portfolio rebalancing; there is no single static asset allocation that resilient to all environments. Portfolios that readjust allocations according to shifts in economic and financial regimes, or the so-called dynamic and tactical asset allocation strategies, significantly outperform buy-and-hold strategies (Jensen and Mercer (2003); Sheikh and Sun (2012); Chalmers et al. (2013); Uhl et al. (2015)). Previous literature analyzing asset allocation and portfolio rebalancing basically adopts the mean-variance optimization (MVO). MVO has been the foundation of portfolio optimization in the modern portfolio theory (MPT) since the initiation by Markowitz in 1952. MVO proposes that an investor allocates weights of asset classes within a portfolio by trading off risks and expected returns. Moreover, MVO suggests that diversification could enhance portfolio performance. Empirical evidence in an ETF sphere reiterates that well-diversified portfolios, both across asset classes and across nations, efficiently enhance risk-adjusted returns. (Huang and Lin (2011); Miffre (2007); Agrrawal (2013)).

Regardless of a widespread utilization, MVO has been criticized on restrictions of practical implementations. Virtually, risks of equities are higher than those of bonds, and portfolios based on MVO heavily contain equities, thereby exposing high risks. As performances of individual asset classes, as well as their correlations, are highly related to economic and monetary cycles, risk contributions of each asset class to a portfolio vary over time, generating volatilities of risk exposures. Furthermore, an accurate estimation of the expected returns and covariances is practically difficult (Chaves et al., 2010). In turn, other strategies have developed for overcoming the practical hurdles, including the risk-based optimization strategies.

There are three major sorts of objectives under risk-based optimization strategies, namely, minimum volatility, risk parity, and maximum diversification (Clark, Silva, & Steven, 2013). The crux of risk parity is to allocate risk contributions to a portfolio risk of individual asset classes equally, not an allocation of capitals as suggested by MVO. The objective of maximum diversification is to maximize the ratio of weighted-average asset volatilities to portfolio volatility, equalizing the marginal contributions of each asset to portfolio risk as minimum variance portfolios. Therefore, risk-based portfolios predominantly contain low-risk asset classes, e.g. bonds and money markets (Asness et al. (2012); Chaves et al. (2010)). As a result, the characteristics of risk-based portfolios are low risks and low expected returns.

To improve the performance of a portfolio, investors could exploit leverage, which consequently generates new risks in the portfolio. Despite risks of leveraging, the historical performances, measured by risk-adjusted returns or the so-called Sharpe ratio, of risk parity portfolio, for example, have been widely proved to outperform traditional portfolios, including MVO, equal weighting, and 60/40 equities/bonds (Chaves et al. (2010); Anderson et al. (2012); Asness et al. (2012); Fisher et al. (2015)). Distinct from MVO, a risk-based portfolio construction requires only standard deviations and covariances of returns. An estimation of expected returns is excluded. An irrelevance of expected return projection makes risk-based strategies more practical.

According to the manifest advantages and widespread adoptions of asset allocation, portfolio diversification, and portfolio rebalancing, coupled with the evidence that different asset classes act differently in different economic environments, market participants practically consider multi-asset classes simultaneously. Nevertheless, literature exploring movements of fund flows in a contemporaneous form, as well as assessing effects of asset allocations on fund flows remains scarce and are even more hardly found in the ETF landscape. Consequently, the objective of this study is to primarily investigate ETF flows in a contemporaneous form and concentrate on micro determinants, i.e. asset allocations. In addition, the evidence that mutual fund flows flee from risky assets toward low-risk assets during chaotic circumstances has linkages with flight-to-quality phenomenon, which was described based on asset returns. Thus, this study further inspects corresponding movements between net fund flows of the ETFs and their returns during flight-to-quality episodes.

2.2 Conceptual Framework

2.2.1 Modern portfolio theory (MPT)

Modern portfolio theory (MPT) is a framework that underpins investment strategies and portfolio management since the introduction. The foundation of MPT was established by Markowitz in 1952. He proposed a framework of mean-variance analysis to construct an optimal portfolio. The mean-variance optimization (MVO) explains that a risk-averse investor allocates different risky assets in a portfolio based on a trade-off between risks and expected returns, which are estimated from historical data. When an investor requests more expected returns, more risk levels are unavoidably accepted. Therefore, objectives of optimal portfolio allocation are either maximizing expected returns for a given level of accepted risk or minimizing risks for a given level of expected return. A portfolio expected return, and a portfolio volatility, or standard deviation, are measured from the following formulas.

(i) Portfolio expected return

$$E(r_p) = \sum_{i=1}^{n} w_i E(r_i)$$

where $E(r_p)$ = expected return of portfolio

w_i = weight of asset *i* in portfolio

$E(r_i)$ = expected return of asset *i*

(ii) Portfolio volatility or standard deviation

$$\sigma_p = \sqrt{w' \sum \mathrm{w}}$$

where σ_p = volatility or standard deviation of portfolio

w' = transpose weight matrix (weights of all assets in portfolio)

$\sum$ = a covariance matrix

w = a matrix of allocated weights

Possible combinations of different risky assets are plotted in a risk-return diagram, representing as X marks in figure 5. The optimal combinations – portfolios with maximum expected returns for a given risk level, or minimum risks for a given expected returns – locate on a single hyperbola above the other possible choices called an efficient frontier, illustrating in figure 5. Since investors often allocate their wealth not only to risky assets, risk-free asset was introduced into the model. Returns of risk-free assets (R_f) lie on a vertical axis of the risk-return diagram as it is risk-free. An optimal portfolio of risky and risk-free assets is then discovered from a tangent between a risk-free expected return and an efficient frontier, which is called Capital market line (CML). An optimal portfolio at a tangent point generates the maximum risk-adjusted return, or Sharpe ratio, named after William Sharpe, who formulated this in 1966. The formula is presented below

(ii) Sharpe ratio

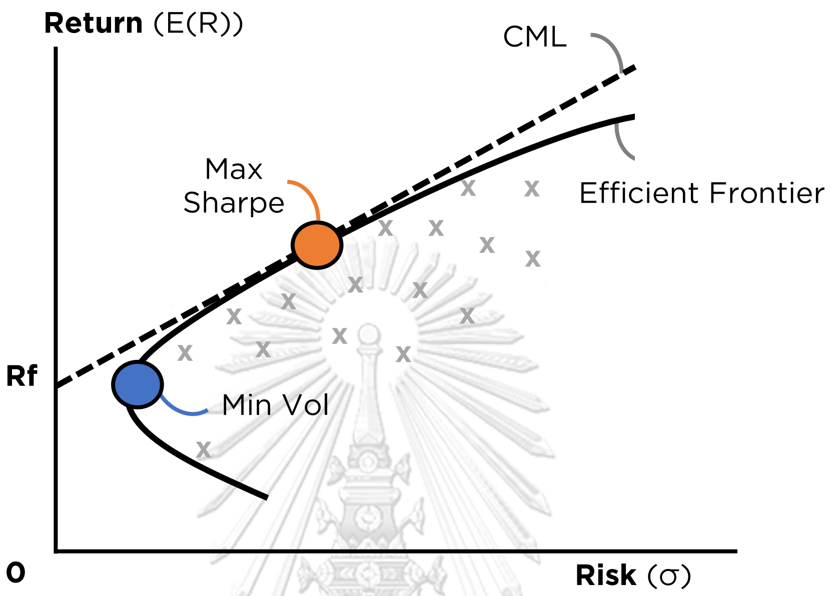
$$Sharpe\ Ratio = \frac{E(r_p) - r_f}{\sigma_p}$$

where $E(r_p)$ = expected return of portfolio

r_f = return of risk-free asset

σ_p = volatility or standard deviation of portfolio

***Figure 5**: Risk-return diagram and efficient frontier*



MPT classifies risks into two components, systematic risk and unsystematic risk. Systematic risk, or market risk, is inherent to the overall market. Hence, this type of risk is inevitable, whereas unsystematic risk exists in a specific company or industry. These risks could be reduced by diversification. In turn, MPT indicates the benefits of portfolio diversification – more diversified portfolios could mitigate risk exposures and enhance Sharpe ratio. Different asset classes that are less correlated could mitigate systematic risk. Different securities within the same asset class that are less correlated could curtail unsystematic risk likewise. As such, a portfolio containing assets that are less correlated would gain benefits of diversification, calling it a well-diversified portfolio. Correlations between assets are obtained from the following formula.

(iv) Correlation of returns between different asset classes

$$\rho_{ij} = \frac{Cov(I,J)}{\sigma_i \sigma_j}$$

where ρ_{ij} = correlation between asset i and j

σ_i and σ_j = volatilities of asset i and j

$\sum$ = a covariance matrix

$Cov(I,J)$ = covariance between asset i and j, calculated by

$$Cov(I,J) = \frac{\sum_{t=1}^{N}[(I_{i,t} - \bar{I})(J_{j,t} - \bar{J})]}{n-1}$$

where $I_{i,t}$ and $J_{j,t}$ = return of asset i and j at time t

$\bar{I}$ and $\bar{J}$ = average return of asset i and j

n = number of assets

There are 4 major steps to construct a portfolio; (1) capital allocation, (2) asset allocation, (3) security selection, and (4) portfolio rebalancing. The first step is capital allocation. An investor proportionate wealth into risky assets and risk-free assets. Asset allocation and securities selection are an investment strategy that allocates proportions of each asset and securities within that asset in a portfolio to balance risks and expected returns coordinating to an investor's risk tolerance, investment goals and period. The fundamental of asset allocation is that different assets behave differently in different economic and financial conditions. Accordingly, risk-return characteristics of each asset are diverse. Correlations among assets are also different, not perfectly correlated, and vary over time, reiterating the benefits of well-diversified portfolios.

Three major asset allocation strategies are prevailing, i.e. strategic asset allocation, dynamic asset allocation, and tactical asset allocation. Strategic asset allocation generates standstill asset weights of an optimal portfolio for a long-term investment period. The weights are not adjusted even economic environments shift. To maintain the original weights, the method of rebalancing is adopted. Dynamic asset allocation also creates an initial optimal portfolio. Unlike strategic asset allocation, dynamic asset allocation allows investors to reallocate or rebalance their asset proportions over time, corresponding to different economic conditions. Tactical asset allocation is the most resilient strategy among these three. Investors could operate portfolios more actively and frequently.

2.2.2 Push-pull framework

The push-pull framework has been academically used to explain cross-border portfolio flows. Push factors refer to common international determinants, e.g. global liquidity, global risk appetite, and monetary and fiscal policies in advanced economies. In contrast, pull factors are country-specific determinants, e.g. economic growth, inflation, real interest rate, current accounts, fiscal balances, and sovereign ratings. According to changes in economic circumstances and financial conditions, the importance of push and pull factors in driving flow movements shift over time (Fratzscher, 2012). Besides, different countries diversely respond to common shocks due to heterogenous macroeconomic fundamentals and other pull factors.

CHAPTER 3: DATA AND METHODOLOGY

3.1 Data

The period of study covers October 2008 to July 2019 with a monthly frequency. The investigation of asset allocations of ETFs in explaining ETF flows across asset classes utilizes fixed-effects panel regressions. The main data source is Bloomberg, except for ETF price data that are obtained from Yahoo Finance. The dependent variable is the panel of net values of ETF flows of individual ETFs (FLOW) in the portfolio. The investment universe involves major asset classes and regions. ETFs representing these asset classes are selected based on the longest availability of historical price and fund-flow data. The universe contains 5 asset classes, incorporating equities, bonds, commodities, real estates, and money markets. The selected securities include 9 U.S.-listed ETFs, namely, the U.S. equity (SPY), developed-market equity (EFA), emerging-market equity (VMO), U.S aggregate bond (AGG), Non-U.S. bond (BWX), real estate (VNQ), commodities (DBC), gold (GLD), and money markets (SHV). The interested independent variables are the panel of changes in weights of individual ETFs in the portfolio, or portfolio reallocations (AA). Details of the ETFs in this study are presented in table 2.

Other independent variables are selected according to previous literature, classifying into macroeconomic surprises and financial conditions. Macroeconomic surprises consist of Citigroup Economic Surprise Index of the U.S. (ESI^{US}), European Union (ESI^{EU}), global (ESI^{GL}), and emerging markets (ESI^{EM}) as proxies for surprises in economic data releases. Financial conditions include changes in implied Fed funds future (FFF) as a proxy for prospects of market participants on future path of the Federal reserve's policy rates, and Bloomberg Financial Condition Index of the U.S. (FCI^{US}), European Union (FCI^{EU}), the U.K. (FCI^{UK}), and Asia ex-Japan (FCI^{AXJ}). The variables included in the panel regression are summarized in table 3.

The Citigroup Economic Surprise Indices gauge surprised in economic news and data of actual releases versus median of Bloomberg consensus survey in terms of weighted historical standard deviations of the data. The indices are calculated daily in a rolling three-month window. A positive reading indicates that the data on average beat consensus, whereas a negative value designates that the data on average below estimations. The index contains data of change in non-farm payrolls, unemployment rate, trade balance, GDP, retail sales ex-autos, TIC net portfolio flows, durable goods orders, core CPI, and industrial production.

The Bloomberg Financial Condition Indices track the overall stress in money markets, bond markets, and equity markets. The values of indices are calculated as Z-scores, which measure the number of standard deviations that daily financial conditions lie above or below the average of financial conditions. The index is an equally weighted sum of three major sub-indexes: money market indicators, bond market indicators, and equity market indicators (Rosenberg, 2009). Each major sub-index is then made up of a series of underlying indicators, which receive an equal weight in that sub- index. Money market indicators consists of Ted spread, commercial paper/T-bill spread, and Libor-OIS spread. Bond market indicators consists of investment-grade corporate/Treasury spread, muni/Treasury spread, swaps/Treasury spread, high yield/Treasury spread, and agency/Treasury Spread. Equity market indicators consists of S&P 500 share prices and VIX index.

The implied Fed funds futures is calculated from 100 subtracted by Fed funds futures (or FF1 Bloomberg ticker), and FFF is changes in these implied Fed funds futures.

***Table 2**: ETFs included in the investment universe*

Symbol	Name	Detail	Asset Class
SPY	SPDR S&P 500 ETF	Tracking a market-cap-weighted index of US large- and midcap stocks selected by the S&P Committee.	US equity
EFA	iShares MSCI EAFE ETF	Tracking large- and mid-capitalization developed market equities, excluding the U.S. and Canada.	DM equity
VWO	Vanguard FTSE Emerging Markets ETF *Figure 1* *Figure 2*	Tracking the return of the FTSE Emerging Markets All Cap China A Inclusion Index, investing in stocks of companies located in emerging markets around the world, such as China, Brazil, Taiwan, and South Africa	EM equity
AGG	iShares Core U.S. Aggregate Bond ETF	Tracking the investment results of an index composed of the total U.S. investment-grade bond market.	US bond
BWX	SPDR Bloomberg Barclays International Treasury Bond ETF	Tracking a market-value weighted index of investment grade fixed-rate government bonds issued by countries outside the U.S.	Non-US bond
VNQ	Vanguard Real Estate ETF	Tracking the return of the MSCI US Investable Market Real Estate 25/50 Index, investing in stocks issued by real estate investment trusts (REITs), companies that purchase office buildings, hotels, and other real property	Real estate
DBC	Invesco DB Commodity Index Tracking Fund	Tracking an index of 14 commodities. It uses futures contracts to maintain exposure and selects them based on the shape of the futures curve to minimize contango	Commoditie s
GLD	SPDR Gold Trust	Tracking the gold spot price, less expenses and liabilities, using gold bars held in London vaults	Gold
SHV	iShares Short Treasury Bond ETF	Tracking the investment results of an index composed of U.S. Treasury bonds with remaining maturities between one month and one year	Money markets

Sources: SPDR, iShares, Vanguard

***Table 3**: Variables included in the panel regression*

Data	Measurement	Source
ETF flows	Fund flow data of 10 ETFs in the investment universe	Bloomberg
ETF daily prices	Daily prices of 9 ETFs in the investment universe	Yahoo Finance
Macroeconomic shocks of the U.S.	Citigroup economic surprise index of the United States	Bloomberg
Macroeconomic shocks of the EU	Citigroup economic surprise index of the European Union	Bloomberg
Macroeconomic shocks of global economies	Citigroup economic surprise index of global economies	Bloomberg
Macroeconomic shocks of EMs	Citigroup economic surprise index of emerging countries	Bloomberg
Fed funds futures	Generic 1st Fed funds Future (FF1)	Bloomberg
Financial conditions of the U.S.	Bloomberg financial condition index of the United States	Bloomberg
Financial conditions of the EU	Bloomberg financial condition index of the European Union	Bloomberg
Financial conditions of the U.K.	Bloomberg financial condition index of the United Kingdom	Bloomberg
Financial conditions of Asia ex-Japan	Bloomberg financial condition index of Asia ex-Japan	Bloomberg

3.2 Methodology

3.2.1 Portfolio optimization

The investigation begins with the calculation of month-end reallocations or change in weights of each ETFs in the portfolio, denoted as AA in the equation, which are obtained by employing R programming. Since there are various strategies of portfolio optimizations applying in the real world, this study determines five well-known optimization objectives, categorizing into mean-variance optimization (MVO) and risk-based optimization strategies. The objectives based on MVO consist of (1) maximum expected return, (2) maximum Sharpe ratio, and (3) minimum volatility, which is also classified as a risk-based optimization. The risk-based objectives incorporate (4) risk parity and (5) maximum diversification. All five portfolios are long only, full investment, and rebalanced at the end of a month using 250-day rolling window. It is important to note that portfolio optimizations and rebalancing in this study are conducted by using only historical prices without considering costs of implementations. Objective functions of five optimization strategies are described below.

(i) Maximum expected return optimization

Maximum expected return optimization is the first MVO-based strategy. The approach concentrates only on one dimension – portfolio expected returns. It aims to maximize portfolio returns, or weighted average of securities in a portfolio regardless of portfolio volatilities, representing as the equation below.

$$E(r_p) = \sum_{i=1}^{n} w_i E(r_i)$$

where $E(r_p)$ = expected return of portfolio

w_i = weight of asset *i* in portfolio

$E(r_i)$ = expected return of asset *i*

(ii) Maximum Sharpe ratio optimization

The second MVO-based strategy is maximum Sharpe ratio, or risk-adjusted return. It remains focusing on returns but take the volatility dimension into account. Sharpe ratio represents average portfolio returns excessing a risk-free rate per a unit of portfolio volatility as shown below.

$$Sharpe\ Ratio = \frac{E(r_p) - r_f}{\sigma_p}$$

where $E(r_p)$ = expected return of portfolio

r_f = return of risk-free asset

σ_p = volatility or standard deviation of portfolio

(iii) Minimum volatility optimization

The third MVO-based strategy, which is also classified as one of risk-based optimization, is minimum volatility optimization. This strategy, in contrast, concentrates only on minimizing portfolio volatilities, or standard deviation of a portfolio regardless of portfolio returns, representing as the following equation.

$$\sigma_p = \sqrt{w'\Sigma \mathrm{w}}$$

where σ_p = volatility or standard deviation of portfolio

w' = transpose weight matrix (weights of all assets in portfolio)

Σ = a covariance matrix

w = a matrix of allocated weights

Portfolio volatilities also be the leading roles in risk parity and maximum diversification optimizations, but pinpoint different perspectives.

(iv) Risk parity

The plain vanilla risk parity targets at equalizing risk contributions of each security in a portfolio. This study adopts twenty-day volatilities, or standard deviations, of each ETF as inputs. The weights are calculated from a ratio of reciprocals of standard deviations of an ETF to a summary of reciprocals of standard deviations of every ETF in the portfolio. The formulas are exhibited below.

$$RC_i = w_i\sigma_i \quad , \quad w_i = \frac{\frac{1}{\sigma_i}}{\sum_{j=1}^{n}\frac{1}{\sigma_j}}$$

where RC_i = risk contribution of asset *i*

w_i = weight of asset *i* in portfolio

σ_i = volatility or standard deviation of asset *i*

(v) Maximum diversification

Maximum diversification pursues the most diversified portfolio. The objective function is maximizing a diversification ratio, which is the ratio of weighted average of volatilities to the portfolio volatility, presenting as the following equation.

$$D(W) = \frac{w'\sigma}{\sigma_p}$$

where $D(W)$ = diversification ratio

w' = transpose weight matrix (weights of all assets in portfolio)

σ = volatility or standard deviation of all assets in portfolio

σ_p = volatility or standard deviation of portfolio

Monthly weights of individual ETFs in the portfolio are derived according to these objective functions. Changes in these weights are the variable AA. Since there are five different sets of AA variables according to the five optimization strategies, five panel regressions with different AA are computed separately. Therefore, this study not only investigates whether asset allocations could explain ETF flows, but also which optimization strategy is able to explain the flows.

3.2.2 ETF flows and asset allocation

Fixed-effects panel regression is utilized to inspect the relation between asset allocations and ETF flows of the securities within the portfolio. The regression is a balanced panel and consist of 9 cross sectionals (i), covering 9 ETFs in the investment universe. As presented in section 3.1, the dependent variables are net fund flows of the 9 individual ETFs in a panel form ($FLOW_{i,t}$). The interested independent variables are asset allocations, or monthly changes in weights, of the 9 ETFs ($AA_{i,t}$). The are 5 sets of asset allocations as this study applies 5 different portfolio optimization strategies, describing in section 3.2.1. Therefore, 5 panel regressions with different set of AA are examined. Both dependent and interested independent variables are in a panel form, whereas other independent variables are in a form of time series, classifying into macroeconomic factors and financial factors. Macroeconomic factors incorporate economic surprise index of the U.S. (ESI^{US}), European Union (ESI^{EU}), global (ESI^{GL}), and emerging markets (ESI^{EM}). Financial factors comprise of changes in implied Fed funds future (FFF), financial condition index of the U.S. (FCI^{US}), European Union (FCI^{EU}), the U.K. (FCI^{UK}), and Asia ex-Japan (FCI^{AXJ}). The regression is presented below.

$$FLOW_{i,t} = \alpha_i + \beta_1 AA_{i,t} + \beta_2 ESI_t^{US} + \beta_3 ESI_t^{EU} + \beta_4 ESI_t^{GL} + \beta_5 ESI_t^{EM} + \beta_6 FFF_t + \beta_7 FCI_t^{US} + \beta_8 FCI_t^{EU} + \beta_9 FCI_t^{UK} + \beta_{10} FCI_t^{AXJ} + \varepsilon_t$$

3.2.3 Identification of flight-to-quality occurrence

This study further concentrates on the periods when investors flee from risky assets and move into less risk assets due to financial market turbulences and economic downturns. These periods are named as flight-to-quality phenomenon. Flight-to-quality events in this study follow the definition and methodology of Gubareva and Borges (2016). The phenomenon is described as periods when less risk assets outperform risky assets. The proposed total return-based framework, therefore, parallels the definition. The advantage of this framework is that it could identify specific timeframe of the beginning and the end of each flight-to-quality occurrence using total returns of risky and less risk assets. The original framework utilized daily total return data. Since this study adopts monthly frequency in all sections, the framework is applied with monthly returns instead. The risky asset in this study is U.S. equities (SPY) and U.S. aggregate bonds (AGG) represent the less risk asset.

The input data are monthly prices (denoted as Index) of SPY and AGG from September 2008 to July 2019. The first step is generating 45-month rolling windows for the dataset, where the latest month is month number 1 (M1) and the oldest month is month number 45 (M45). Every M1 is defined as an anchor date (AD). The second step is computing returns of each securities between AD and M_k, where k is month number 2 to 45. The formula is presented below.

$$R_{(AD-k,AD)}^{Index} = \frac{Index_{(AD)}}{Index_{(AD-k)}} - 1$$

The third step is calculating return differences (ΔR) between the less risk asset (AGG) and the risky asset (SPY), presented as the following formula.

$$\Delta R_{k(AD)} = R_{(AD-k,AD)}^{AGG} - R_{(AD-k,AD)}^{SPY}$$

The fourth step is searching for maximum and minimum points of return differences. The maximum (minimum) points are where the slope of return differences shifts from positive (negative) to negative (positive) sloping. Months with minimum return differences are defined as initial months (IM) and months with maximum return differences are denoted as end months (EM). A period between IM and the following EM is counted as one episode. Episodes that have return differences greater than or equal to five percent are defined as flight-to-quality episodes.

3.2.4 ETF flows during flight-to-quality episode

To extend the investigation of ETF flows, this section aims to inspect movements of ETF flows corresponding to movements of their returns during flight-to-quality episodes. As mentioned in the previous section, prices of risky assets plunge while prices of less risk assets rise during flight-to-quality occurrences. Nevertheless, the relation between ETF prices and fund flows remain unclear. This section, therefore, examines whether flight-to-quality months, measured by securities returns, could explain movements of fund flows within the same period.

The flight-to-quality months, following section 3.2.3, would be placed in the regression as dummy variables. All initial months, end months, as well as months in between the episodes, take on a value 1, whereas the other months take on a value 0. Hence, value 1 of dummy variables represent flight-to-quality months. The flight-to-quality dummy is placed in the regression as $\mathrm{D_t}$, presenting in the equation below.

$$FLOW_{i,t} = \alpha_i + \beta_1 AA_{i,t} + \beta_2 ESI_t^{US} + \beta_3 ESI_t^{EU} + \beta_4 ESI_t^{GL} + \beta_5 ESI_t^{EM} + \beta_6 FFF_t + \beta_7 FCI_t^{US} + \beta_8 FCI_t^{EU} + \beta_9 FCI_t^{UK} + \beta_{10} FCI_t^{AXJ} + \beta_{11} D_t + \varepsilon_t$$

CHAPTER 4: EMPIRICAL FINDINGS

4.1 Examination of the ETFs in the universe

ETFs in this study are selected to represent varieties of asset classes within the portfolio. Each asset class has distinctive characteristics, which vary over time according to macroeconomic and financial circumstances. This section, therefore, demonstrates different characteristics of ETFs in the study through expected returns, volatilities, as well as their correlations during the period of study. Figure 6 illustrates cumulative return indices of the ETFs from October 2008 to July 2019. The most outstanding performer is SPY (U.S. equity), generating the highest cumulative returns of 150 percent, followed by GLD (gold), VNQ (real estate), VWO (emerging market equity), EFA (developed market equity), AGG (U.S. aggregate bonds), BWX (non-U.S. bonds), SHV (money markets), and DBC (commodities), respectively. GLD, the second-best performer, generates cumulative returns only one-third of the winner'. The cumulative returns of SHV have hovered around 100 over the period. DBC, on the other hand, is the only one that never reach a positive territory.

During the global financial crisis in 2008-2009, GLD had produced the highest cumulative returns, followed by VWO, BWX, AGG, and SHV, respectively. These ETFs, which are generally considered as low-risk asset classes except VWO, had generated positive cumulative returns even in the financial market rout. VWO, the only risky asset among the others, was temporarily perceived as a shelter as the crisis had emerged from developed countries. The worst performer was VNQ as the U.S. mortgage market was the origin of the disaster. All other risky assets; DBC, SPY, and EFA, had undoubtedly created losses. In the periods of recovering and growing after the crisis, the outperformers during the crisis; GLD and VWO, had weaken. Instead, the then losers had outpaced, particularly SPY and VNQ. These occurrences had proved that low-risk or safe assets outperform during turbulent times, while risk assets outperform in recovering and growing periods.

***Figure 6**: Cumulative return indices of ETFs in the portfolio from October 2008 to July 2019*

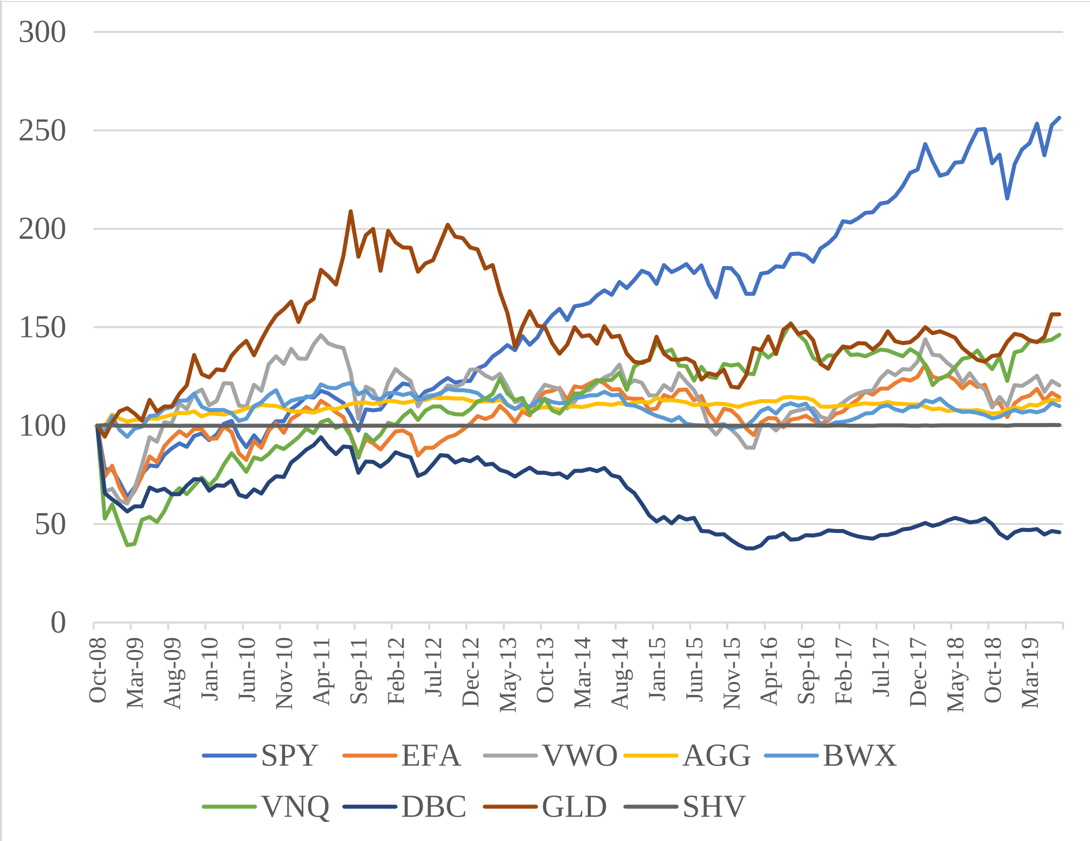


***Table 4**: Annualized returns, annualized standard deviations (SD), annualized Sharpe ratios, and maximum drawdowns of the ETFs from October 2008 to July 2019*

ETFs	**Ann. Return (%)**	**Ann. SD (%)**	**Ann SR (%)**	**Max Drawdown (%)**
SPY	*9.0814	14.8158	*0.6130	-36.2617
EFA	1.2558	18.1288	0.0693	-38.4014
VWO	1.7351	21.7724	0.0797	-39.5268
AGG	1.1256	3.7184	0.3027	-7.4589
BWX	0.8773	8.5805	0.1022	-19.1668
VNQ	3.5681	*23.9530	0.1490	-60.7072
DBC	-6.9388	18.6490	-0.3721	*-62.3783
GLD	4.2264	17.7656	0.2379	-42.9102
SHV	0.0267	0.1635	0.1636	-0.3527

* denoted as the greatest value of each column

Figure 7*: Risk-return scatter of the ETFs in annualized forms cover October 2008 to July 2019*

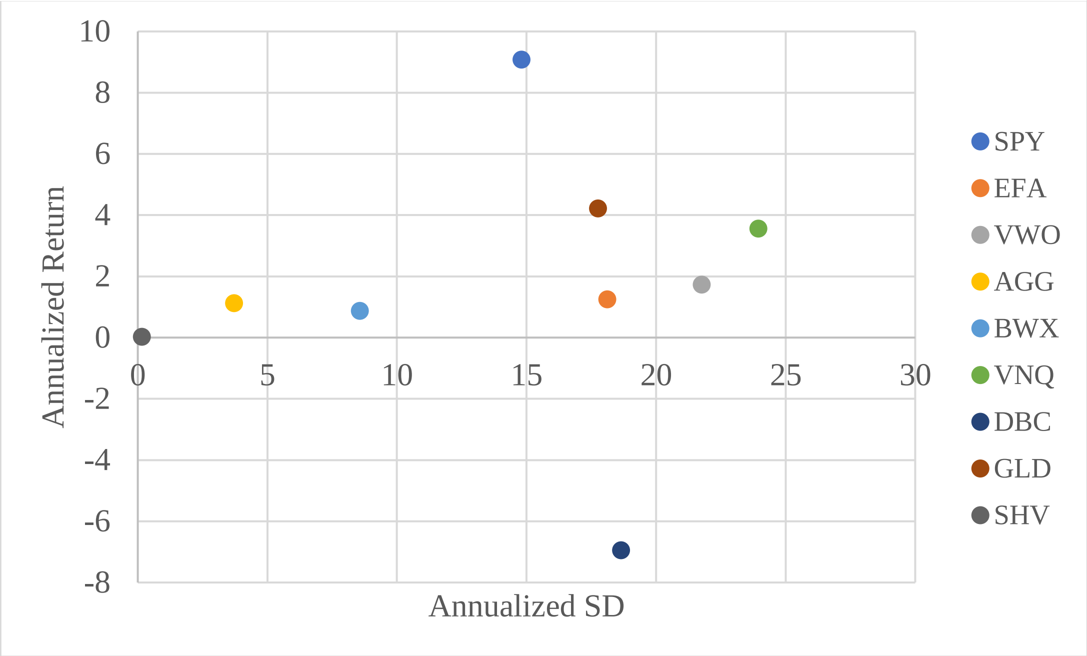


Table 4 and figure 7 demonstrates various static values representing the whole period of study. From a return perspective, the ETF ranking of annualized returns correspond to cumulative return indices. On a volatility front, or annualized standard deviations (SD), VNQ ranks first, followed by VWO, DBC, EFA, GLD, SPY, BWX, AGG, and SHV, respectively. These rankings reiterate the trade-off between risks and returns. To take both expected returns and volatilities into account, an annualized Sharpe ratio is then computed. Sharpe ratio exhibits excess returns of risky assets over risk-free rates per a unit of volatility, or a risk-adjusted returns. Note that Sharpe ratio in this study does not incorporate risk-free rate into the formula for the sake of simplicity. Through a risk-adjusted return perspective, SPY also be the best performer, followed by AGG, GLD, SHV, VNQ, BWX, VWO, EFA, and DBC. Relatively low-risk assets, e.g. AGG and SHV, beat those relatively high-risk assets, e.g. VWO and DBC, when consider expected returns and volatilities simultaneously.

Another method that indicate a magnitude of return fluctuation is maximum drawdown. Maximum drawdown measures the largest peak-to-trough of returns, or the range between the highest gain and the lowest loss. DBC produces the largest maximum drawdown of approximately negative 62 percent, followed by VNQ, GLD, VWO, EFA, SPY, BWX, AGG, and SHV. The bottom two create only negative 7 percent and 0.3 percent, respectively, which are far less than the biggest three. Unsurprisingly, most of ETFs that have high-fluctuated returns are high-volatile asset classes.

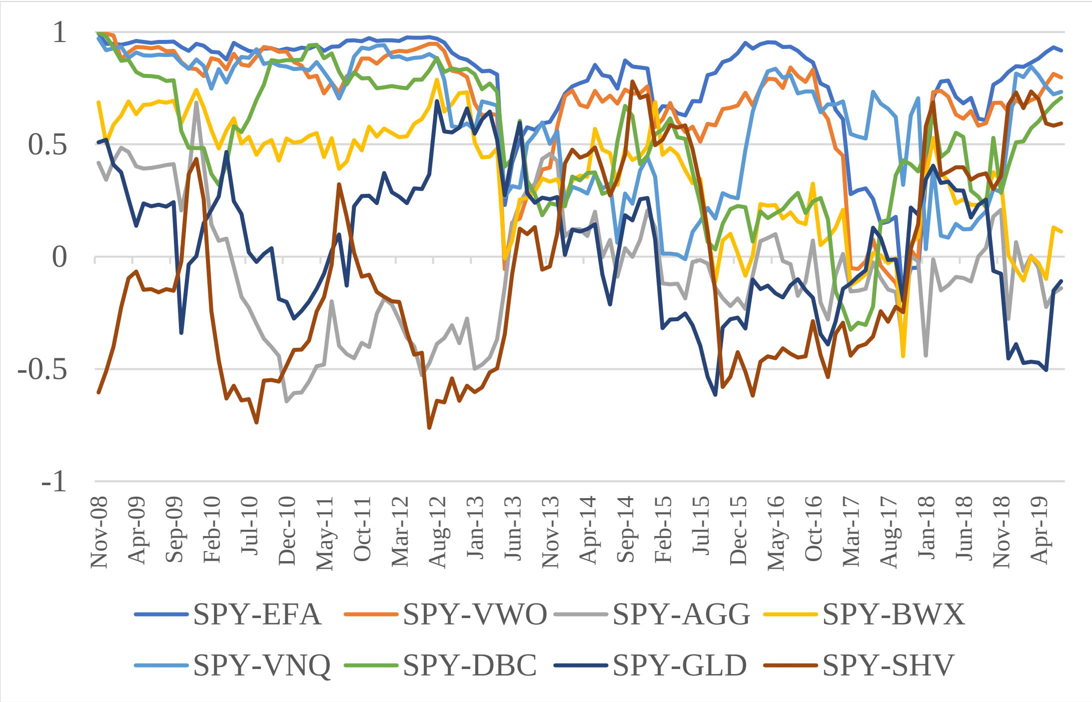
Correlation is also examined as it is a crucial variable in the process of portfolio diversification. From table 5, equity ETFs of the three economies (SPY, EFA, and VWO) are highly positively correlated, evidenced by correlations that exceed 0.8, which are greater than a significant benchmark of more than absolute 0.5. The three economies also have strength relations with real estate (VNQ) and commodities (DBC). Other pairs of ETFs have vague relations, or they are not significantly related, indicating as correlations that less than absolute 0.5.

Table 5*: Correlations of monthly returns among the ETFs from October 2008 to July 2019*

	SPY	EFA	VWO	AGG	BWX	VNQ	DBC	GLD	SHV
SPY	1								
EFA	0.89	1							
VWO	0.80	0.88	1						
AGG	0.04	0.17	0.16	1					
BWX	0.03	0.07	0.05	0.09	1				
VNQ	0.72	0.69	0.62	0.33	0.06	1			
DBC	0.54	0.57	0.62	-0.06	0.12	0.32	1		
GLD	0.03	0.11	0.27	0.40	0.16	0.08	0.38	1	
SHV	-0.10	-0.10	-0.12	0.18	0.03	0.01	-0.06	0.11	1

It is important to note that the correlations exhibiting in table 5 are static values of the full period. In fact, as mentioned in the introduction section, correlations among asset classes and securities vary over time. Therefore, dynamic correlations are examined to observe movements of correlations during the period. Figure 8 depicts dynamic correlations between SPY and other ETFs in the universe. The diagram indicated that most of relations among the pairs are not persistent. The dynamic correlations fluctuate between positive and negative territories, and shift between significant and non-significant levels.

***Figure 8**: Dynamic correlations of monthly returns with 12-month rolling window between SPY and the other ETFs from November 2008 to July 2019*



In addition, table 6 demonstrates 4 criteria of dynamic correlations among all ETF pairs in this study as a percentage of the total 129 periods. The 4 criteria include relations that are positive, negative, significantly positive, and significantly negative. A positive relation and a negative relation are a rolling correlation that greater than 0 and less than 0, respectively. A significant relation is a rolling correlation that exceed absolute 0.5. There are only 2 out of 36 pairs that have consistent relations over the period: the pairs of EFA-VWO and VWO-BWX are continuously positive. The both pairs are also the most significantly positive, evidenced by 96.12 percent and 89.92 percent of significantly positive periods to the total periods. SPY-EFA and SPY-VWO are also significantly positive most of the time, indicated by 89.92 percent and 84.50 percent of significantly positive periods to the total periods.

In the negative territory, the negative correlations of AGG-DBC, SPY-AGG, and SPY-SHV are the most frequent. However, only the relation between SPY and SHV is the most frequently significant: periods that the relations are significantly negative occur 18.60 percent. Other pairs that the relations are significantly negatively correlated are VNQ-SHV, EFA-SHV, and VWO-SHV. It should be noticed that Risky assets such as equities and REITs are significantly negatively correlated to low-risk assets only money markets.

In summary, even though the static correlation of equities of the three economies among each other, the equities and real estate, as well as the equities and commodities are significantly positively correlated, there is a time when a norm relation has broken. Furthermore, securities within the similar asset class, as well as familiar regions, are highly correlated most of the time. These observations emphasize a crucial role of dynamic asset allocations and portfolio rebalancing in enhancing expected returns as well as curtailing risk exposures of a portfolio.

Table 6*: Percentages of 4 criteria of dynamic correlations of monthly returns with 12-month rolling window among the ETFs from November 2008 to July 2019*

ETF Pair	Positive (%)	Negative (%)	*Sig. Pos. (%)	*Sig. Neg. (%)
SPY-EFA	97.67	2.33	89.92	0.00
SPY-VWO	93.02	6.98	84.50	0.00
SPY-AGG	36.43	63.57	0.78	3.88
SPY-BWX	89.92	10.08	36.43	0.00
SPY-VNQ	99.22	0.78	68.99	0.00
SPY-DBC	95.35	4.65	52.71	0.00
SPY-GLD	57.36	42.64	9.30	2.33
SPY-SHV	39.53	60.47	13.18	18.60
EFA-VWO	100.00	0.00	96.12	0.00
EFA-AGG	54.26	45.74	19.38	3.10
EFA-BWX	98.45	1.55	62.79	0.00
EFA-VNQ	89.92	10.08	58.14	2.33
EFA-DBC	90.70	9.30	58.14	1.55
EFA-GLD	62.79	37.21	13.95	0.00
EFA-SHV	48.06	51.94	21.71	12.40
VWO-AGG	64.34	35.66	13.95	2.33
VWO-BWX	100.00	0.00	89.92	0.00
VWO-VNQ	89.15	10.85	55.04	0.00
VWO-DBC	88.37	11.63	62.02	0.78
VWO-GLD	86.82	13.18	31.78	0.00
VWO-SHV	56.59	43.41	28.68	10.85
AGG-BWX	96.90	3.10	48.06	0.00
AGG-VNQ	76.74	23.26	41.09	0.78
AGG-DBC	30.23	69.77	0.00	7.75
AGG-GLD	89.92	10.08	34.11	0.00
AGG-SHV	74.42	25.58	20.93	0.00
BWX-VNQ	89.92	10.08	46.51	0.00
BWX-DBC	84.50	15.50	40.31	0.00
BWX-GLD	94.57	5.43	56.59	0.00
BWX-SHV	73.64	26.36	28.68	2.33
VNQ-DBC	72.87	27.13	30.23	6.20
VNQ-GLD	65.12	34.88	4.65	0.78
VNQ-SHV	48.06	51.94	10.08	16.28
DBC-GLD	79.84	20.16	37.21	0.00
DBC-SHV	60.47	39.53	13.95	6.98
GLD-SHV	69.77	30.23	22.48	3.88

* Sig. Pos. and Sig. Neg. stand for significantly positive and significantly negative dynamic correlations, respectively

4.2 Portfolio optimizations and rebalancing

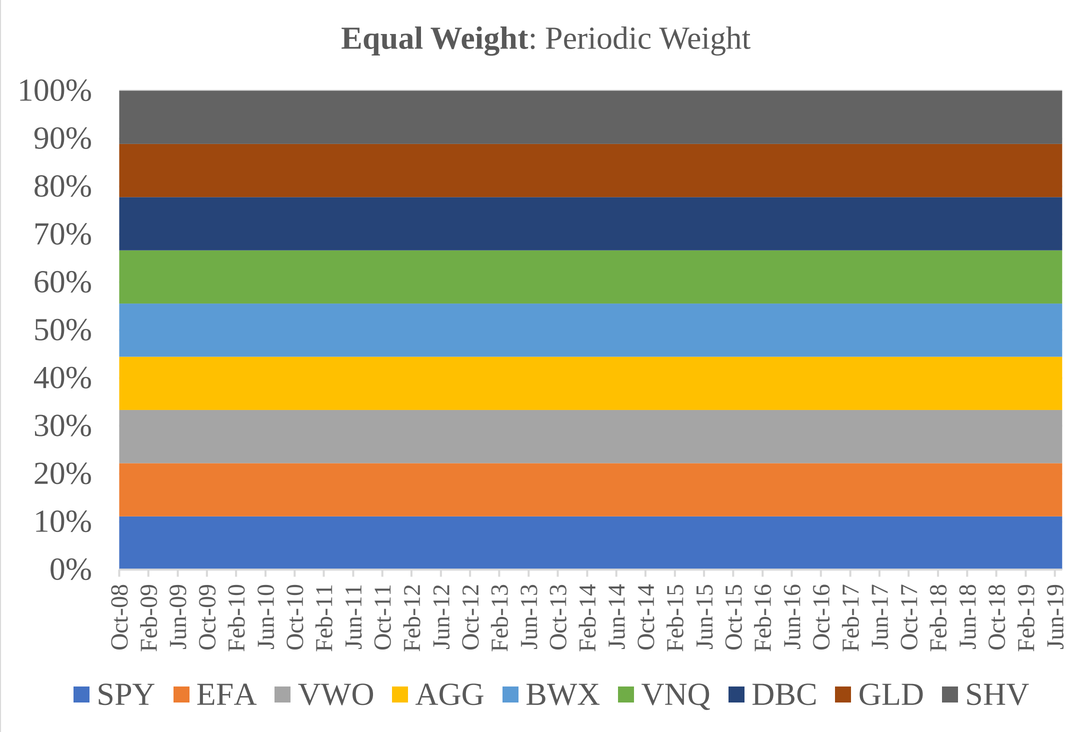
The asset reallocations, or monthly changes in weights of each ETF in the portfolio, are the interested independent variable in this study. There are 5 sets of asset allocations as the weights are obtained from five objectives of portfolio optimizations. The five objectives incorporate (1) maximum expected return, (2) maximum Sharpe ratio, (3) minimum volatility, (4) risk parity, and (5) maximum diversification. The first three objectives are based on mean-variance optimization (MVO) strategy, whereas the latter three are risk-based strategies. Minimum volatility objective could be categorized into both strategies. All five portfolios apply monthly rebalancing with 250-day rolling windows. By using ETF daily prices since October 2007, the results of periodic weights are obtained from October 2008 to July 2019. The five portfolio strategies are compared to the benchmark portfolio; the equal-weighted portfolio, allocating individual ETFs equally over time. Figure 9 illustrates monthly weights and risk contributions of the five portfolio strategies in order to compare dynamic investing money contributions and risk contributions accordingly. Note that risk contributions of each ETFs to a portfolio are computed from weighted 20-day volatilities.

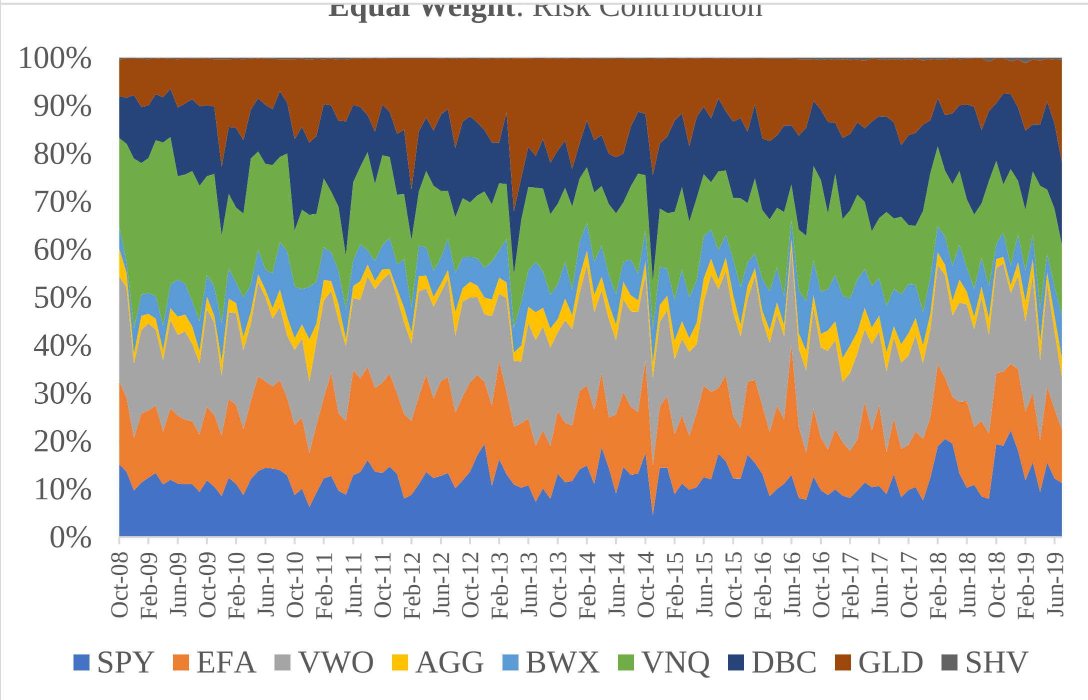
The diagrams obviously distinguish characteristics between return-based and risk-based portfolios. Return-based objectives – optimization strategies that consider expected returns – are portfolios with the objectives of maximum expected return and maximum Sharpe ratio, or risk-adjusted returns. Both portfolios usually contain relatively high-volatile assets, e.g. SPY, VNQ, GLD, and VWO, paralleling the annualized standard deviations in section 4.1. Although maximum Sharpe ratio portfolio often weighs on high-volatile assets, there are times when majority of the portfolio is low-volatile assets as the optimization objective incorporates both expected returns and volatilities. Additionally, the two portfolios confront more dramatic shifts in securities when rebalance than the risk-based portfolios, including minimum volatility portfolio, risk parity portfolio, and maximum diversification portfolio. Portfolios with risk-based objectives, which take only risk perspectives into account, predominantly weigh on relatively low-volatile assets. The three portfolios persistently comprise SHV more than a half, followed by AGG. As a result, shifts in weights of the risk-based portfolios are smoother than the return-based portfolios.

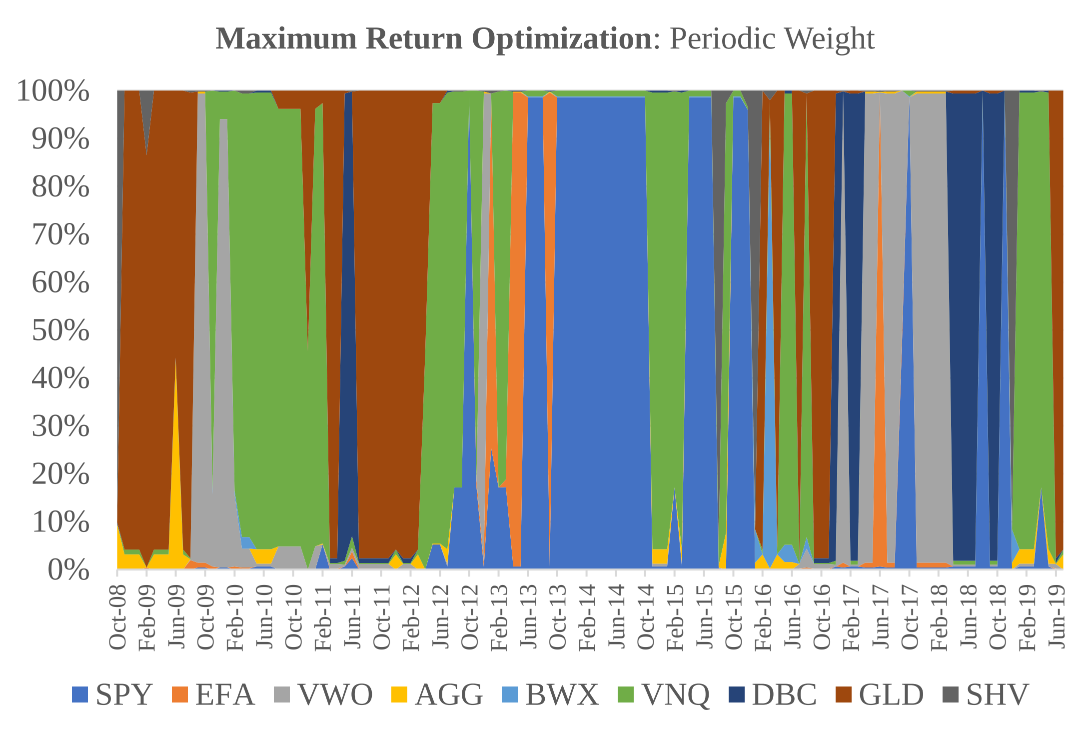
Nevertheless, these money weights do not coincide with risk contributions. The most obvious evidence is the risk contributions of equal-weighted portfolio. Investing money of the benchmark portfolio is allocated equally, but risk contributions of equal-weighted securities are not equal as high-volatile assets contribute volatilities to a portfolio much greater than low-volatile assets. Low-volatile securities such as SHV and AGG contribute very small amounts of risks to the benchmark portfolio. Return-based portfolios comprise high-volatile assets in general. Therefore, risk contributions of maximum return portfolio and maximum Sharpe ratio portfolio slightly differ from periodic weights but remain confront dramatic shifts of core risk distributions from different securities. These evidences induce some market participants to shift their focus from traditional cash allocations to risk allocations in order to balance risk contributions of a portfolio instead.

In contrast to equal-weighted portfolio, the risk parity portfolio contains an equal risk contribution. Likewise, the other risk-based portfolios, minimum volatility and maximum diversification portfolios, incorporate more balance and well-diversified risk contributions than the two return-based portfolios. The portfolios usually hold SPY by less than 5 percent, but it contributes almost 40 percent to total portfolio risks. Whereas the portfolios weigh on SHV approximately 80 percent, but it contributes less than 50 percent of portfolio risks. Thus, common characteristics of risk-based portfolios are containing low-risk assets while generating less cumulative returns than return-based strategies. The utmost advantage of risk-based optimizations beams especially during financial market turmoil. The NAVs of the five portfolios in figure 10 also reiterate the benefit that risk-based portfolios help protecting investors' wealth much better than return-based portfolios.

***Figure 9**: Monthly weights and risk contributions of the five optimization strategies from October 2008 to July 2019*






Maximum Return Optimization: Periodic Weight
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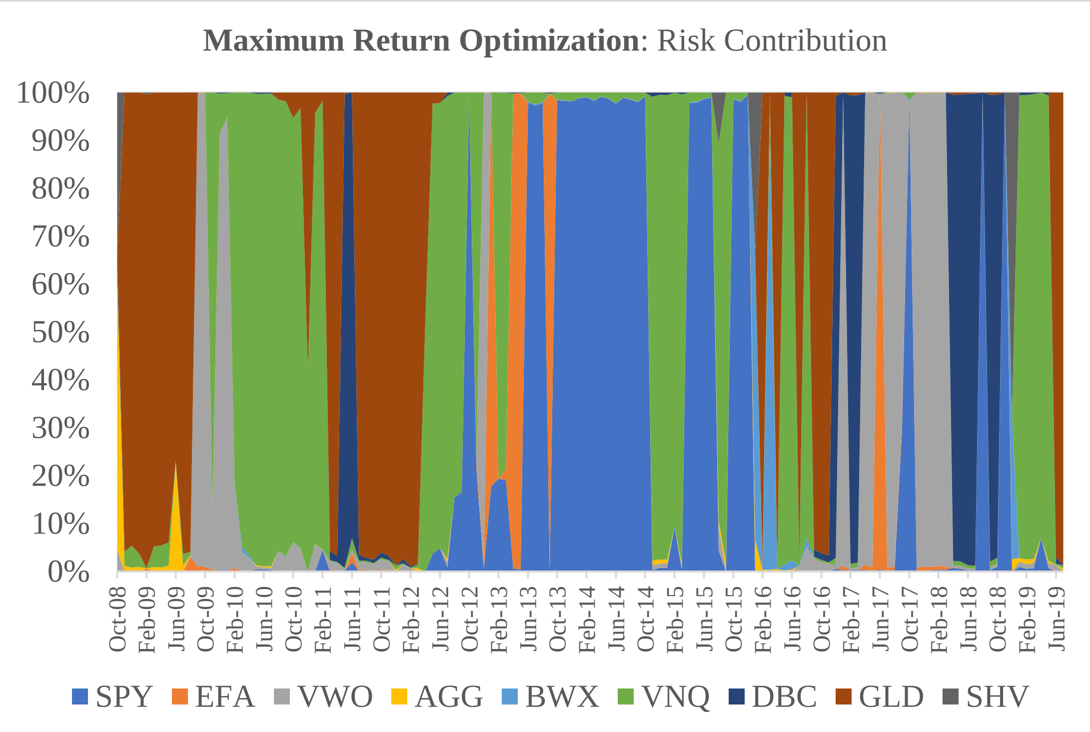
SPY EFA VWO AGG BWX VNQ DBC GLD SHV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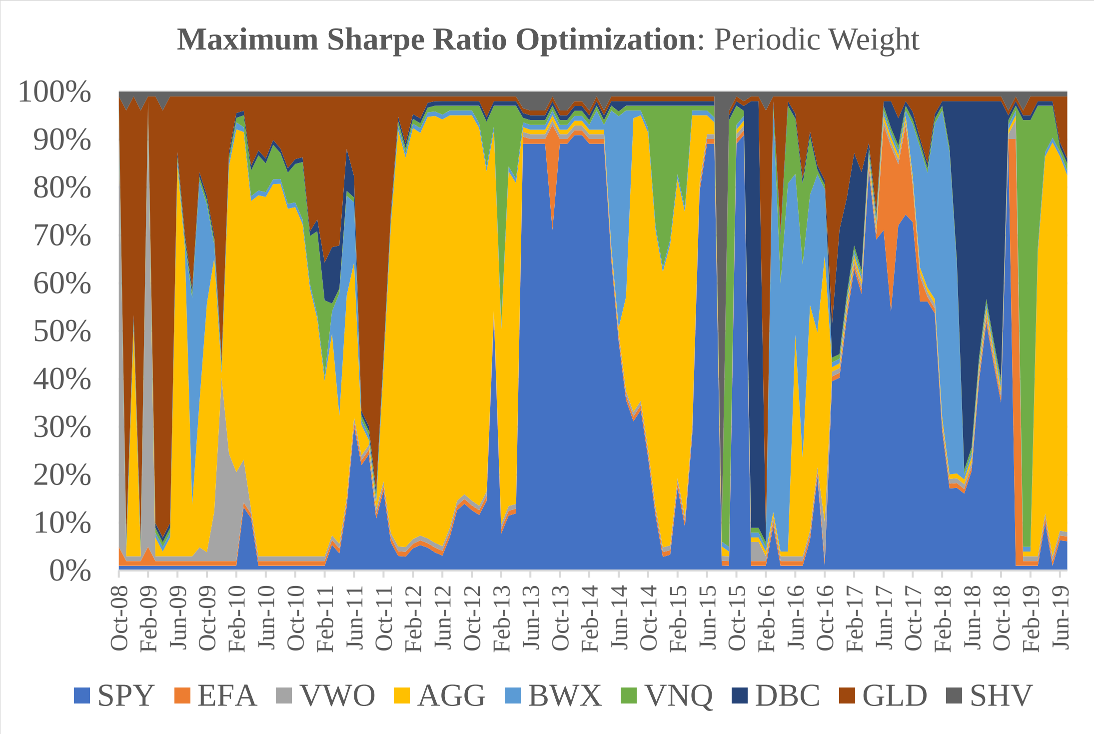
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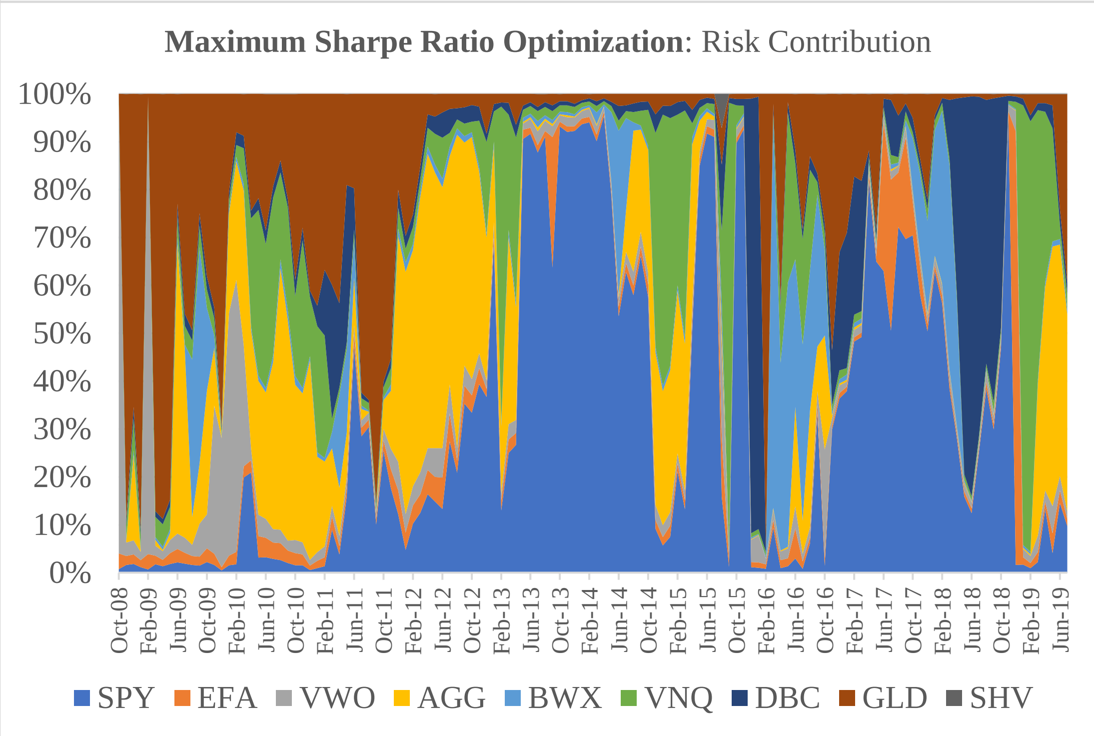
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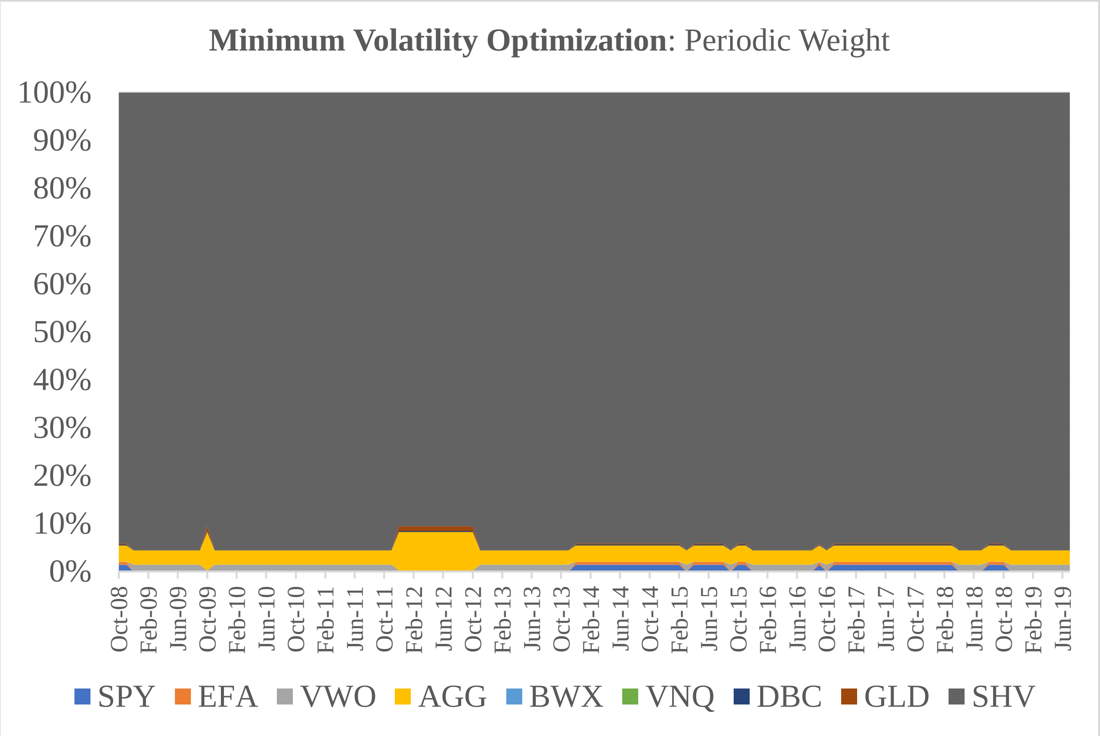
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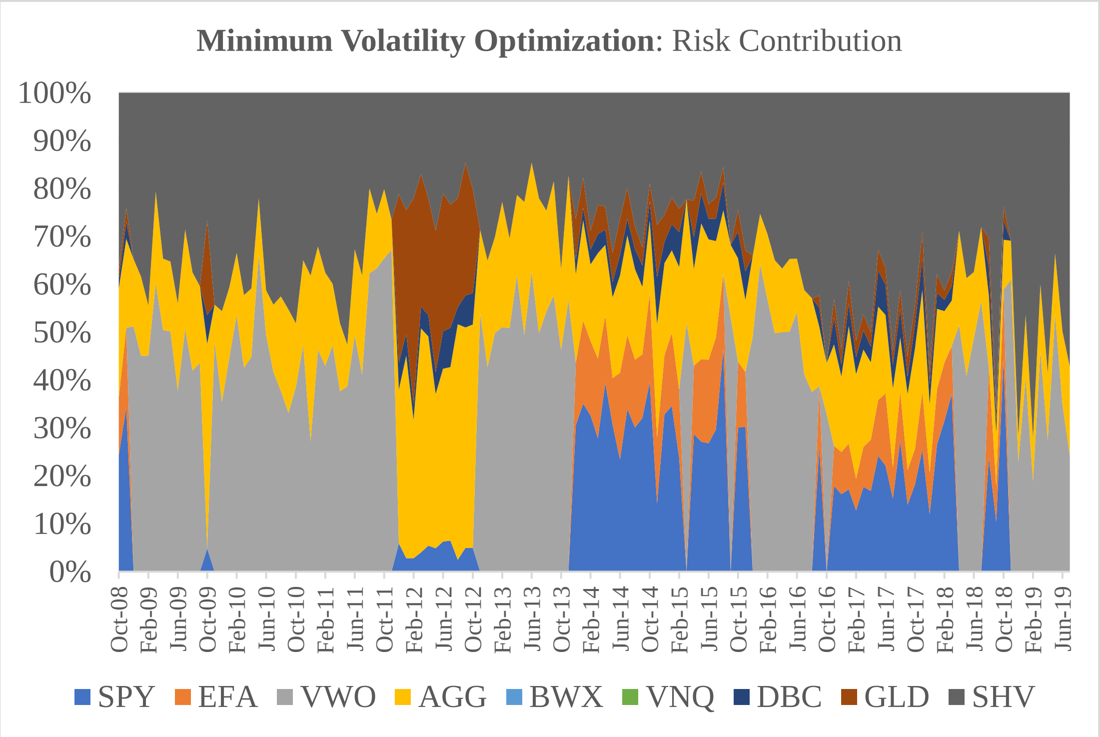
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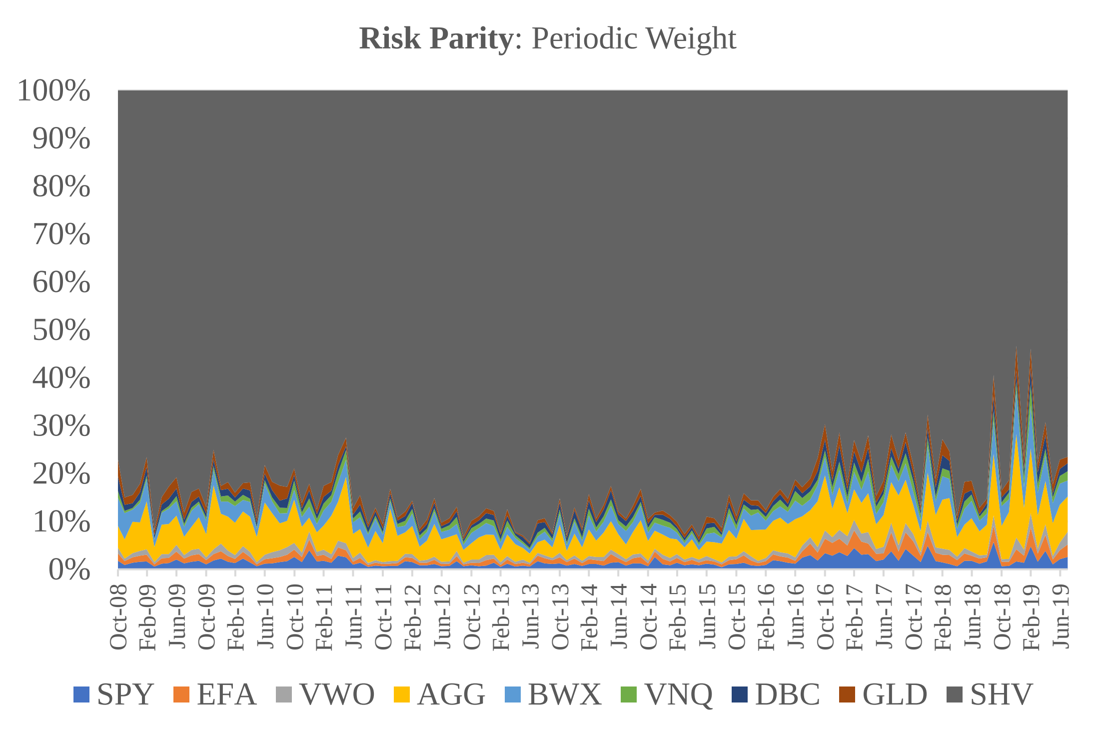
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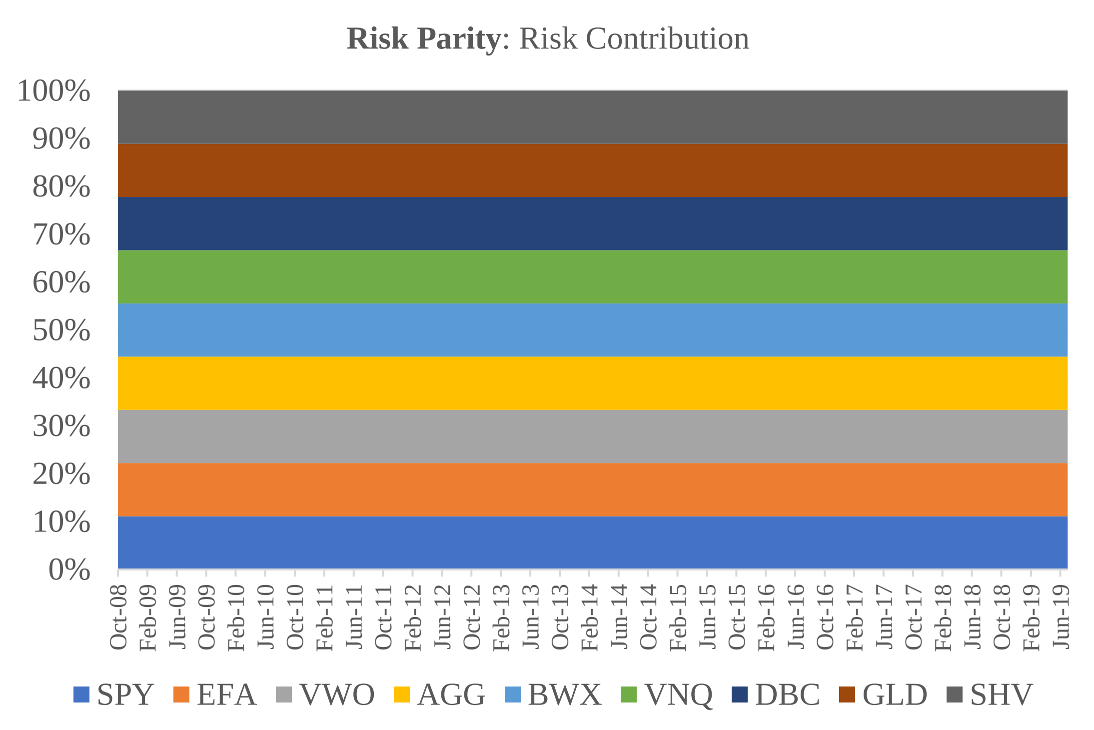
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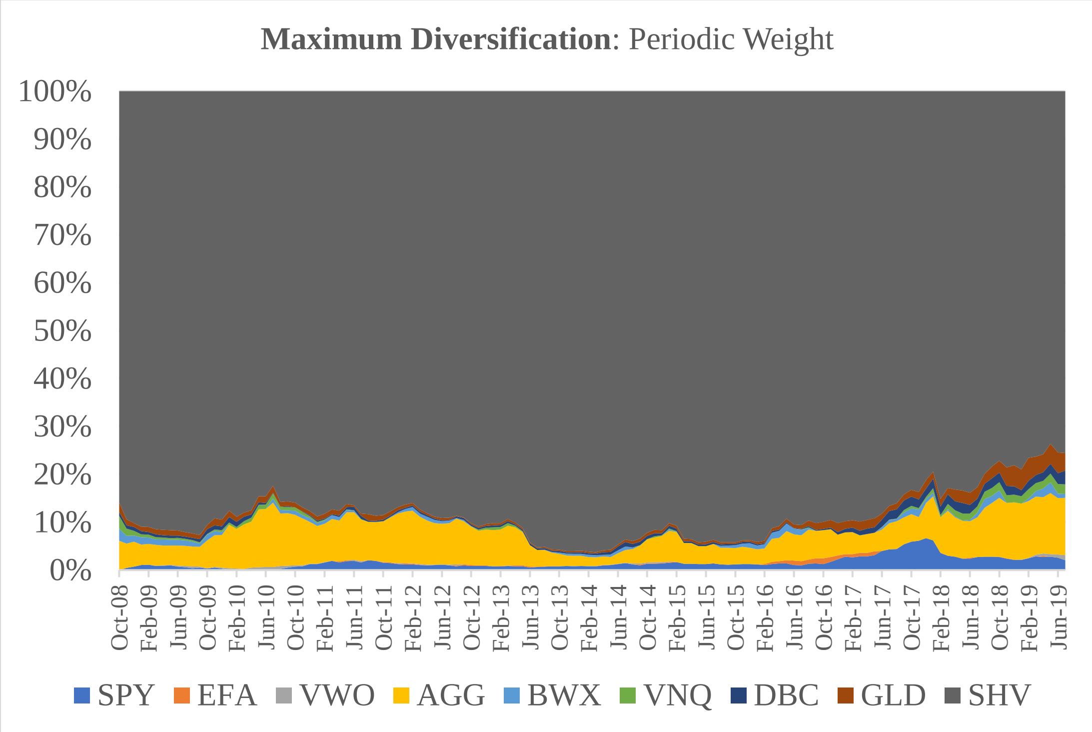
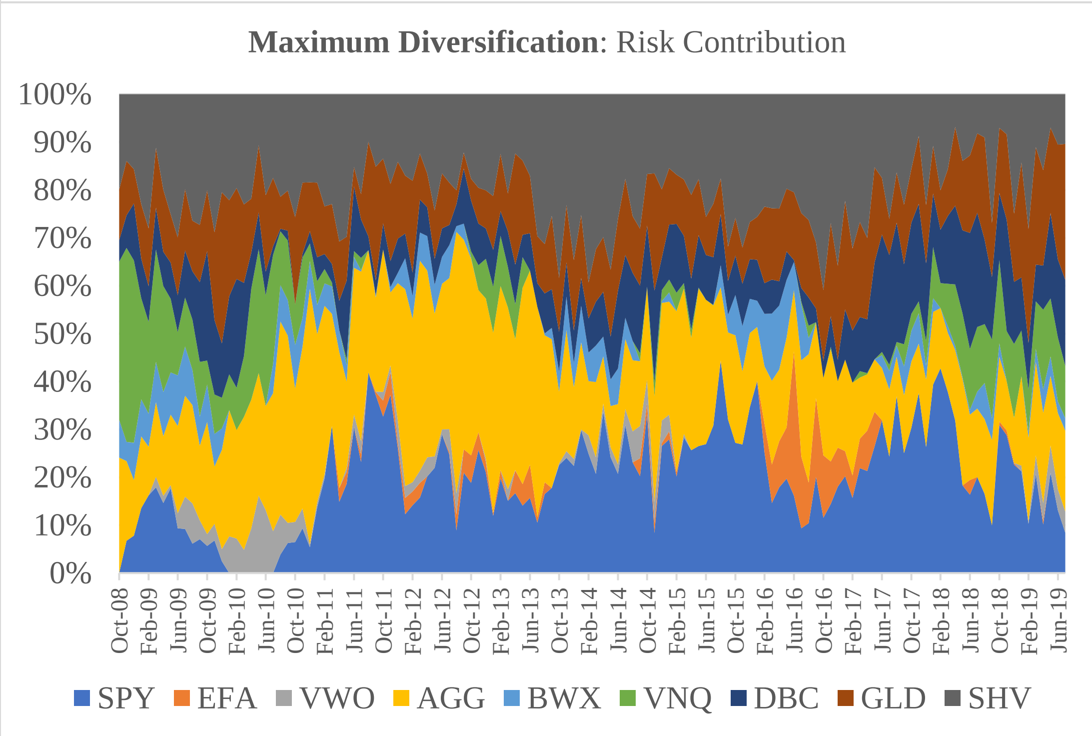




In terms of portfolio performances, figure 10 displays cumulative return indices, or periodic net asset values (NAV) of 100 units of investing money, of the five portfolios and the benchmark portfolio. Maximum return portfolio (Max Ret) produces the highest cumulative return index of 747.68, followed by maximum Sharpe ratio portfolio (Max SR), equal-weighted portfolio (EW), risk parity portfolio (RP), maximum diversification portfolio (Max DV), and minimum volatility portfolio (Min Vol), which generate cumulative return indices of 254.65, 135.08, 108.28, 104.21, and 101.93, respectively. The NAV of the champion is almost 3 times more than the first runner-up and is over 7 times of the last. The ranking apparently discriminates return-based and risk-based strategies. The return-based objectives; maximum expected return portfolio and maximum Sharpe ratio portfolio, are the only two that beat the benchmark portfolio.

The bottom diagram of figure 10 enlarges the cumulative return indices of the three risk-based portfolios; minimum volatility, risk parity, and maximum diversification, as their performances are far less than the top three. Among risk-based peers, risk parity portfolio is the outperformer, creating NAV approximately 1 time more than the last. Nevertheless, during financial market turbulences such as the global financial crisis, the return-based portfolios produces larger cumulative losses than the risk-based portfolios. NAVs of maximum Sharpe ratio portfolio and equal-weighted portfolio reduce to the lowest of 73.65 and 73.91, respectively. Whereas risk parity portfolio, maximum diversification portfolio, and minimum volatility portfolio reach the lowest NAVs of 95.50, 97.99, and 99.31, respectively.

A measurement of drawdown provides another dimension of losses. It measures the size between the latest lowest loss and the recorded highest gain. Figure 11 shows drawdowns of the five portfolios and the bottom chart magnifies the movements of the three risk-based portfolios. As expected, the risk-based portfolios curtail peak-to-trough movements more efficiently than the return-based portfolios. For the maximum drawdown, as represented in table 7, maximum Sharpe ratio generates the highest maximum drawdown among the peers of 26.35 percent, followed by the benchmark portfolio of 26.10 percent, maximum return portfolio of 14.15 percent, risk parity portfolio of 4.10 percent, maximum diversification portfolio of 2.01 percent, and minimum volatility of 0.69 percent. Corresponding to the decreases in NAVs, all portfolios generate maximum drawdowns during the global financial crisis in 2008-2009 except for the maximum return portfolio, where maximum drawdown occur at the end of 2011. For the whole period, the benchmark portfolio produces the largest average drawdown of 4.22 percent, followed by maximum return portfolio, maximum Sharpe ratio portfolio, risk parity portfolio, maximum diversification portfolio, and minimum volatility portfolio, which generates average drawdowns of 2.43 percent, 2.28 percent, 0.63 percent, 0.28 percent, and 0.11 percent, respectively.

Performances in an annualized form, presenting in table 7 and figure 12, are consistent with the time-series perspectives previously. Among the peers, maximum return portfolio creates the highest annualized returns of 20.45 percent, followed by maximum Sharpe ratio portfolio of 12.13 percent, equal-weighted portfolio of 4.50 percent, risk parity portfolio of 1.03 percent, maximum diversification portfolio of 0.53 percent, and minimum volatility portfolio of 0.22 percent. In terms of volatilities, the ranking of annualized standard deviation parallels the ranking of annualized returns. To incorporate both return and volatility dimensions, annualized Sharpe ratios are computed. All five portfolios outpace the benchmark. Maximum return portfolio produces the highest annualized Sharpe ratio of 1.31, followed by maximum Sharpe ratio portfolio of 0.90, maximum diversification portfolio of 0.65, risk parity of 0.62, minimum volatility of 0.58, and the benchmark portfolio of 0.40.

***Figure 10**: Cumulative return indices or NAV of the benchmark portfolio and the five portfolio strategies from October 2008 to July 2019*

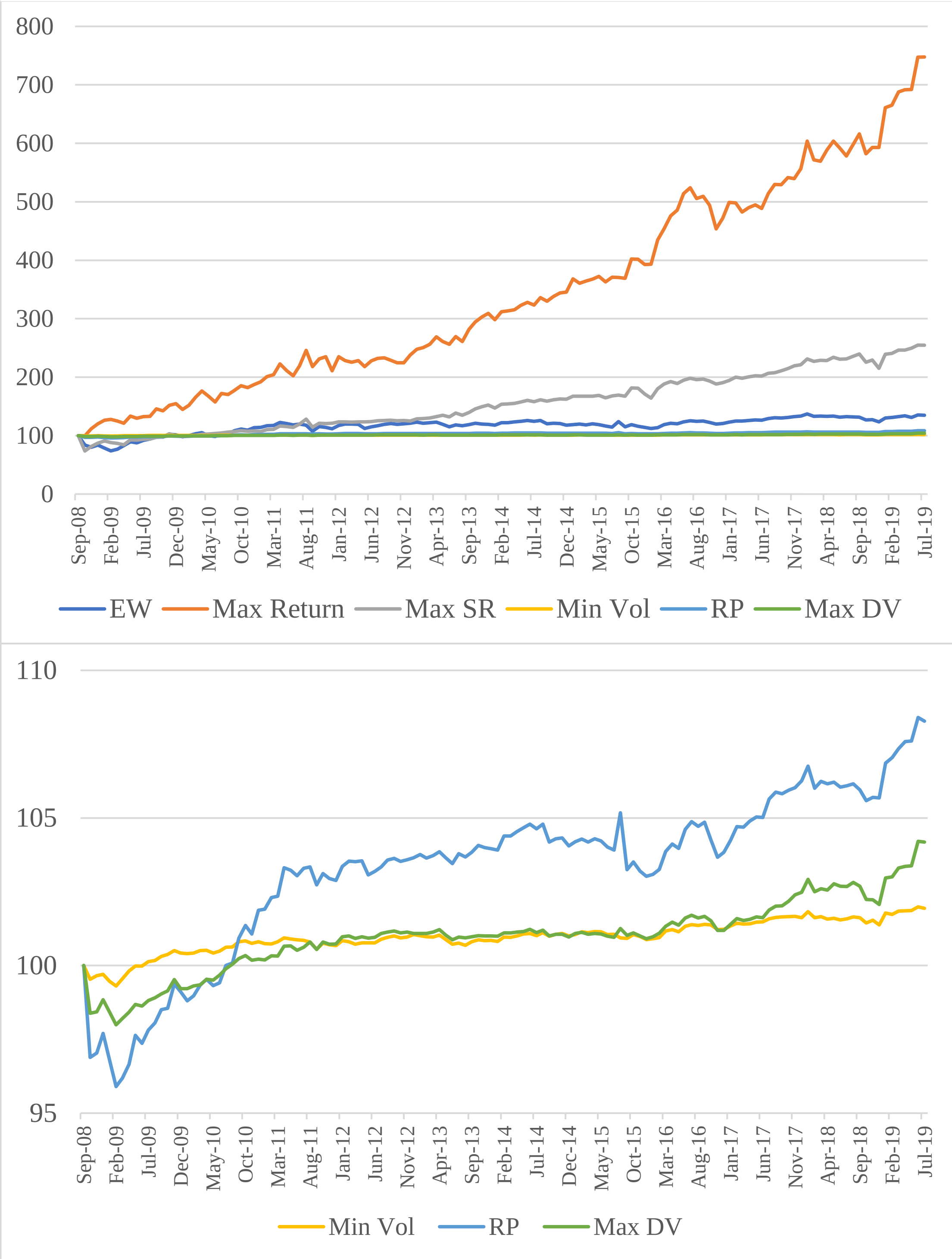


Figure 11*: Drawdowns of the five portfolio strategies from October 2008 to July 2019*

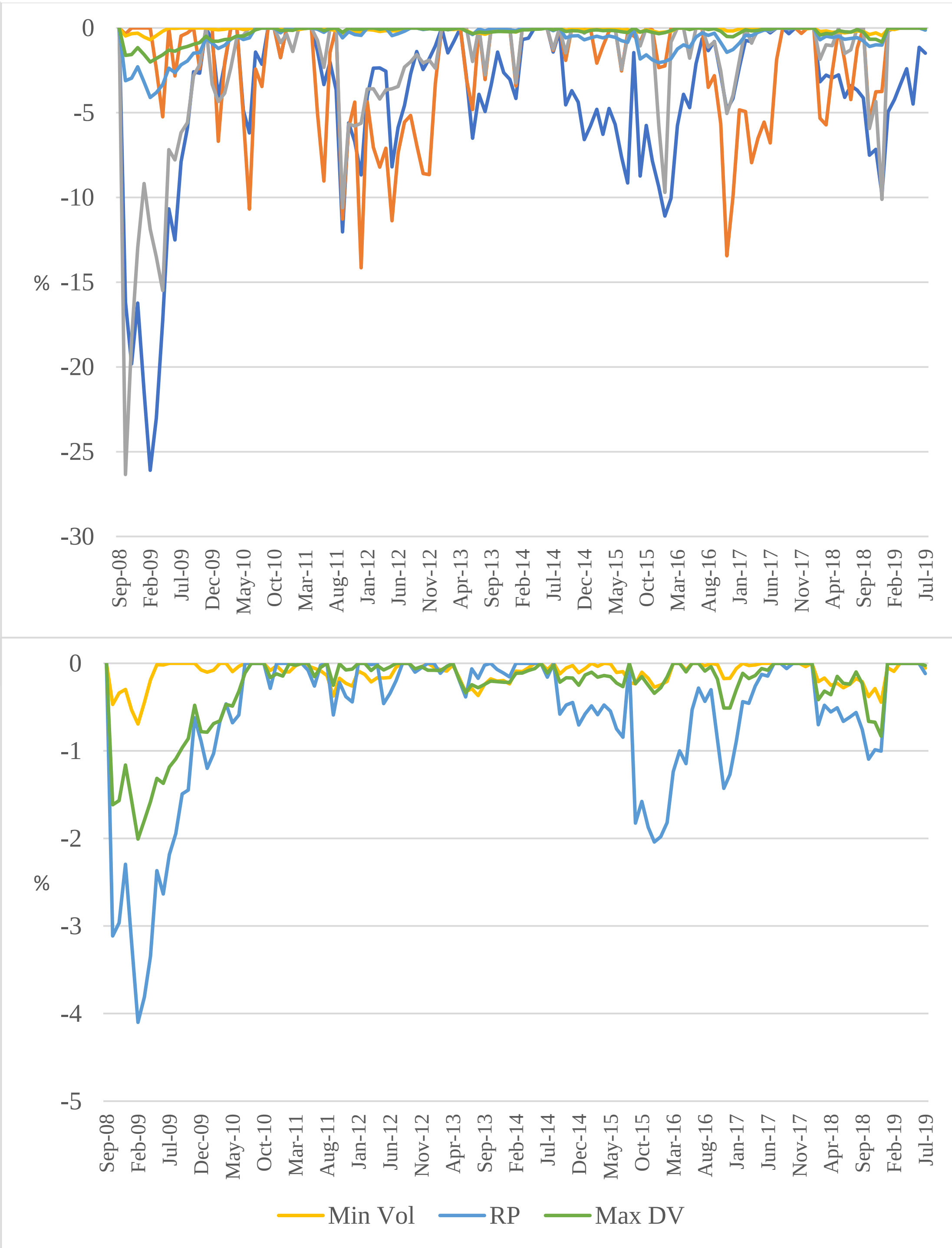


***Figure 12**: Risk-return scatter of the five portfolio objectives and the benchmark portfolio in annualized forms cover October 2008 to July 2019*

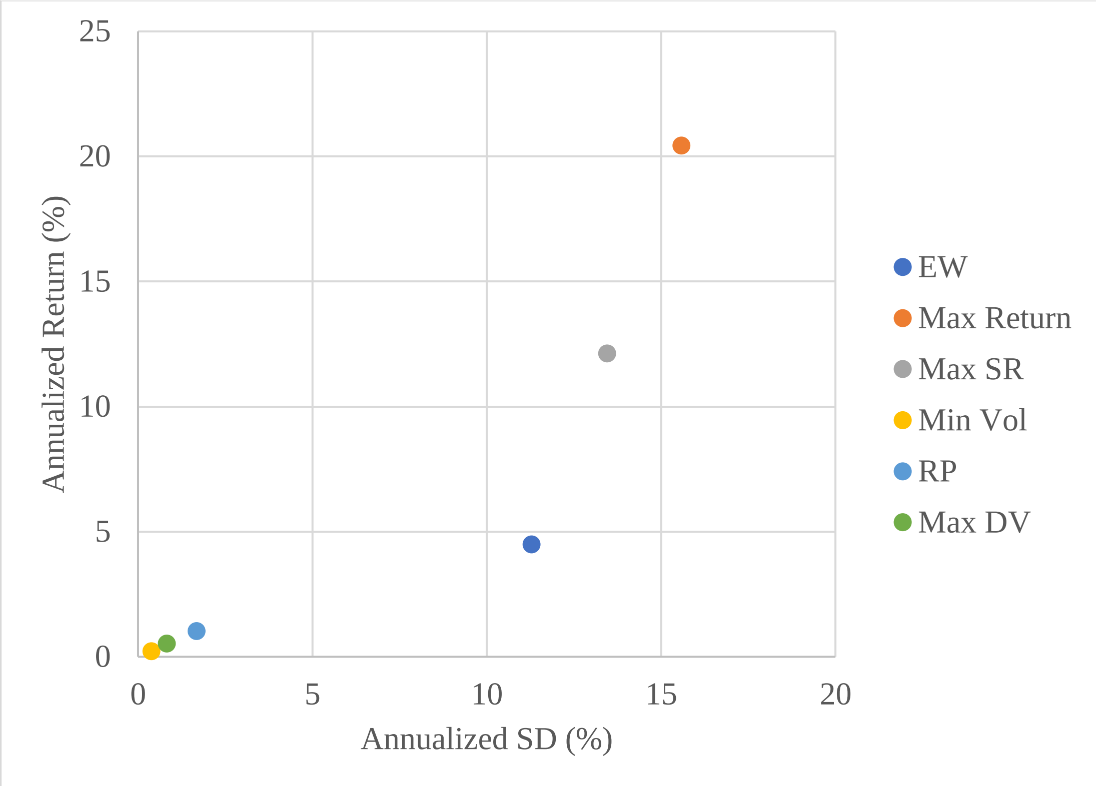


***Table 7**: Annualized returns, annualized standard deviations (SD), annualized Sharpe ratios, and maximum drawdowns of the portfolios from October 2008 to July 2019*

Strategy	Ann. Return (%)	Ann. SD (%)	Ann SR (%)	Max Drawdown (%)
EW	4.5008	11.2834	0.3989	-26.0941
Max Return	*20.4454	*15.5844	*1.3119	-14.1477
Max SR	12.1321	13.4559	0.9016	*-26.3453
Min Vol	0.2206	0.3802	0.5803	-0.6933
RP	1.0315	1.6771	0.6150	-4.1002
Max DV	0.5299	0.8210	0.6454	-2.0071

* denoted as the greatest value of each column

4.3 Asset allocations and ETF flows

Fixed-effect panel regression is utilized to investigate the relation between asset allocations and fund flows across asset classes. The empirical results are exhibited in table 8. Asset allocations with objectives of minimum volatility, risk parity, and maximum diversification significantly explain movements of ETF flows at 5% confidence interval. However, the coefficient of the asset allocation with minimum volatility approach unexpectedly expresses a negative relation. Excluding that, the magnitude of an impact of the maximum diversification portfolio is approximately two times greater than the risk parity portfolio. Whereas asset allocations of maximum return and maximum Sharpe ratio portfolios are not significant in explaining movements of fund flows. Noticeably, the significant portfolio strategies are risk-based optimizations. On the other hand, other independent variables – Bloomberg Economic Surprise Index of the US, Euro area, global, and emerging markets, and Bloomberg Financial Condition Index of the US, Euro area, UK, and Asia ex-Japan, as well as changes in implied Fed funds futures – are not significantly affect ETF flows.

Through a micro perspective, the study demonstrates that asset allocations across asset classes of risk-based optimization strategies significantly explain net fund flows. In other words, as ETF flows reflect actual transactions, changes in weights of the selected ETFs based on risk-based optimizations and their fund flows move correspondingly. It could be interpreted that ETF market participants widely adopt risk-based portfolio optimizations during the period of study. The result parallels the previous researches that risk-based optimization strategies are widely adopted particularly since the occurrence of global financial crisis as volatilities in financial markets were massively high at that time. Consequently, market participants attempt to stabilize portfolio risks and limit portfolio drawdowns rather than maximize expected returns or risk-adjusting returns. Moreover, the findings could magnify perspectives of fund flow determinants, emphasizing a crucial role of a micro landscape via asset allocations and portfolio rebalancing.

***Table 8**: The results of the fixed-effects panel regression investigating relations between asset allocations and fund flows of ETFs*

Optimization Strategy	**Max Return**	**Max SR**	**Min Vol**	**Risk Parity**	**Max DV**
Dep. V. / Indep. V.	$FLOW_{i,t}$	$FLOW_{i,t}$	$FLOW_{i,t}$	$FLOW_{i,t}$	$FLOW_{i,t}$
$AA_{i,t}$	-0.003064	0.011350	-0.789739**	0.345927**	0.640696**
	(0.3009)	(0.1656)	(0.0423)	(0.0119)	(0.0165)
ESI_t^{US}	-0.009645	-0.009167	-0.009849	-0.008262	-0.009044
	(0.1710)	(0.1930)	(0.1616)	(0.2406)	(0.1983)
ESI_t^{EU}	-0.006334	-0.005935	-0.006605	-0.005300	-0.005560
	(0.2710)	(0.3023)	(0.2506)	(0.3567)	(0.3333)
ESI_t^{GL}	0.033646	0.032095	0.035350	0.028262	0.030675
	(0.1969)	(0.2181)	(0.1749)	(0.2782)	(0.2385)
ESI_t^{EM}	-0.013945	-0.013420	-0.014540	-0.012119	-0.013131
	(0.2086)	(0.2259)	(0.1894)	(0.2739)	(0.2353)
FFF_t	0.425061	0.397470	0.355546	0.483071	0.419989
	(0.3762)	(0.4082)	(0.4597)	(0.3140)	(0.3809)
FCI_t^{US}	0.151671	0.183948	0.206459	0.112536	0.156365
	(0.4871)	(0.4013)	(0.3468)	(0.6063)	(0.4728)
FCI_t^{EU}	-0.071775	-0.079857	-0.077310	-0.091029	-0.088468
	(0.5964)	(0.5557)	(0.5679)	(0.5013)	(0.5134)
FCI_t^{UK}	-0.128340	-0.146310	-0.169579	-0.091795	-0.126044
	(0.5332)	(0.4780)	(0.4117)	(0.6559)	(0.5397)
FCI_t^{AXJ}	0.112355	0.122650	0.120355	0.126146	0.116093
	(0.2451)	(0.2055)	(0.2128)	(0.1915)	(0.2288)

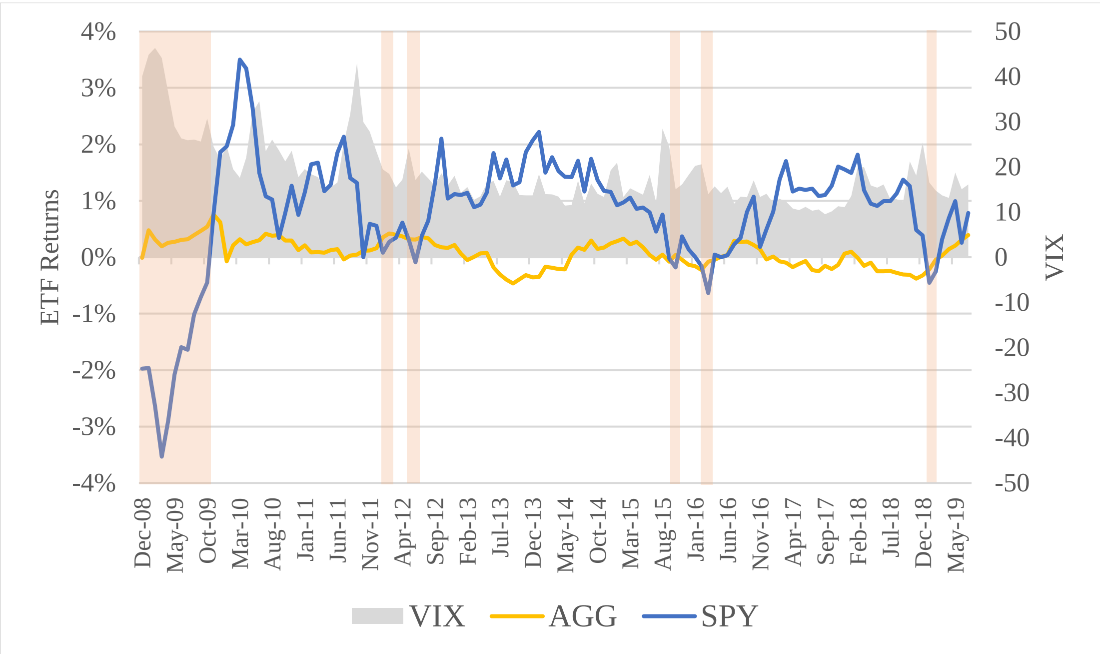
The table shows the coefficients of each independent variable. The values in the parentheses are p-values. ***, **, and * are denoted as significant levels at 1%, 5%, and 10% confidence interval, respectively.

4.4 Identification of flight-to-quality occurrences

4.4.1 Return movements of risky and less risk assets

As assets with high risks could be offset by high expected returns, relatively high-risk assets generally generate more returns than relatively low-risk assets. However, during economic downturns and financial turbulent times, willingness to take risks of market participants ebb. As a result, less risk assets could outperform risky assets in periods of market turmoil. These periods are called flight-to-quality times. This study selects SPY, or U.S. equities ETF, as a representative of risky assets and AGG, or U.S. aggregate bonds ETF, as a proxy for less risk assets. Their 12-month rolling returns are depicted in figure 13. The chart reiterates that SPY produces returns more than AGG most of the time. However, there are some periods when financial market volatility surges, proxying by the volatility index of S&P 500 (VIX): AGG outperforms SPY, representing as shaded orange areas in the diagram.

***Figure 13**: 12-month rolling returns of SPY and AGG from December 2008 to July 2019*



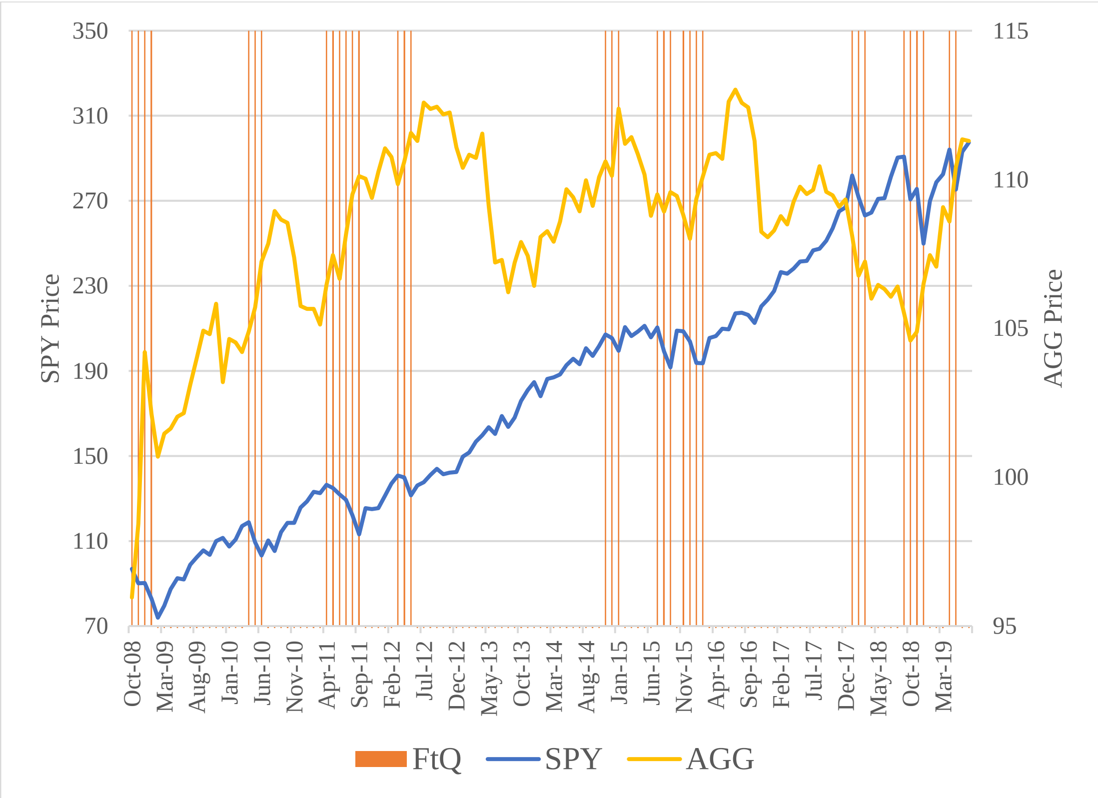
4.4.2 Flight-to-quality episodes

The flight-to-quality episode in this study is defined as months when returns of the less risk asset, or AGG, exceed returns of the risky asset, or SPY, by more than 5 percent. The method of identifying flight-to-quality months is presented in section 3.2.3. There are 10 flight-to-quality episodes during the period of study, demonstrating in table 9. During the flight-to-quality occurrences, returns of AGG exceed returns of SPY by an average of 11.31 percent, where SPY prices decline by an average of 10.18 percent and AGG prices slightly increase by an average of 1.42 percent. The maximum price difference between AGG and SPY is 20.49 percent, where SPY plunges by 17.06 percent and AGG rises by 3.43 percent. It is important to note that there are only 3 out of 10 episodes that net fund flows move accordingly to prices. Fund flows of SPY in episodes number 5, 8, and 10 are net outflows, related to decreases in SPY prices, and fund flows of AGG are net inflows, corresponding to increases in AGG prices. The further examination of these movements will be presented in the next section. Each episode occurs for 2- to 6-month long. Therefore, there are total 35 flight-to-quality months out of the total 129 months, or 27.13 percent of the whole period, representing as orange vertical lines in figure 14. Corresponding to the definition, prices of SPY decrease and prices of AGG increase during flight-to-quality months.

Table 9*: Flight-to-quality episodes during October 2008 – July 2019*

#	Month		Return (%)			Net Fund Flow	
	Initial	**End**	**SPY**	**AGG**	**AGG-SPY**	**SPY**	**AGG**
1	Nov 2008	Feb 2009	-17.94	2.28	20.21	3986.56	256.89
2	Apr 2010	Jun 2010	-13.12	2.25	15.37	700.36	518.08
3	Apr 2011	Sep 2011	-17.06	3.43	20.49	5144.33	1806.36
4	Mar 2012	May 2012	-6.63	1.56	8.19	3436.35	364.87
5	Nov 2014	Jan 2015	-3.74	1.60	5.34	-4352.80	2389.19
6	July 2015	Sep 2015	-8.96	0.07	9.04	9820.17	1533.84
7	Nov 2015	Feb 2016	-7.25	1.18	7.25	2424.80	5136.42
8	Jan 2018	Mar 2018	-6.65	-0.79	5.86	-14450.26	2761.50
9	Sep 2018	Dec 2018	-14.03	0.92	14.95	4378.10	891.53
10	Apr 2019	May 2019	-6.38	1.67	6.38	-11533.32	2207.16

***Figure 14**: Flight-to-quality months as well as price movements of SPY and AGG from October 2008 to July 2019*



4.5 ETF flows during flight-to-quality times

This study incorporates flight-to-quality episodes into the panel regression via dummy variables (D_t), where value 1 represents flight-to-quality months and the other months are replaced by 0. The empirical results are shown in table 10. The dummy variables of all 5 panel regressions are not significant. The results might be caused by an average-out effect: fund flows of some different asset classes move conversely during the flight-to-quality periods and they offset each other. As a result, the overall term of fund flow does not significantly respond to changes in returns during the phenomenon.

To prove whether movements of fund flows during flight-to-quality episodes average out, the study applies the fixed-effects panel regression with specific asset classes separately – the cross-sectional data of equities (EQ) and fixed incomes (FI). The equations are presented below, where the top one is the equation of equity and the bottom one is the equation of fixed income.

$$
\begin{aligned}
FLOW_{EQ,t} = \alpha_{EQ} &+ \beta_1 AA_{EQ,t} + \beta_2 ESI_t^{US} + \beta_3 ESI_t^{EU} \\
&+ \beta_4 ESI_t^{GL} + \beta_5 ESI_t^{EM} + \beta_6 FFF_t + \beta_7 FCI_t^{US} + \beta_8 FCI_t^{EU} + \beta_9 FCI_t^{UK} \\
&+ \beta_{10} FCI_t^{AXJ} + \beta_{11} D_t + \varepsilon_t
\end{aligned}
$$

$$
\begin{aligned}
FLOW_{FI,t} = \alpha_{FI} &+ \beta_1 AA_{FI,t} + \beta_2 ESI_t^{US} + \beta_3 ESI_t^{EU} + \beta_4 ESI_t^{GL} + \beta_5 ESI_t^{EM} + \beta_6 FFF_t \\
&+ \beta_7 FCI_t^{US} + \beta_8 FCI_t^{EU} + \beta_9 FCI_t^{UK} + \beta_{10} FCI_t^{AXJ} + \beta_{11} D_t + \varepsilon_t
\end{aligned}
$$

If a dummy variable in an equation of specific asset class significantly explains ETF flows, it implies that an average-out effect causes the non-significant relation of the overall term. The results demonstrate that dummy variables of ETF return during flight-to-quality episodes do not significantly explain ETF flows in a form of separated asset class.

The study further adjusts the regression by adding multiple terms between dummy variables of flight-to-quality episode and dummy variables of each ETF within an asset class (e.g. SPY, EFA, and VWO of equity ETFs), denoted as D_t*D_{ETF}, in order to examine whether there are an average-out effect within an asset class. The equation is shown below.

$$
\begin{aligned}
FLOW_{EQ,t} = \alpha_{EQ} &+ \beta_1 AA_{EQ,t} + \beta_2 ESI_t^{US} + \beta_3 ESI_t^{EU} \\
&+ \beta_4 ESI_t^{GL} + \beta_5 ESI_t^{EM} + \beta_6 FFF_t + \beta_7 FCI_t^{US} + \beta_8 FCI_t^{EU} + \beta_9 FCI_t^{UK} \\
&+ \beta_{10} FCI_t^{AXJ} + \beta_{11} D_t D_{SPY} + \beta_{12} D_t D_{EFA} + \beta_{13} D_t D_{VWO} + \varepsilon_t
\end{aligned}
$$

The results coincide with the earlier attempt; the additional multiple terms between dummy variables of flight-to-quality episode and dummy variables of each ETF within an asset class do not significantly explain ETF flows. In summary, it could be concluded that the non-significant relation between the flight-to-quality dummy variable and the overall term of ETF flows does not caused by an average-out effect.

Additionally, according to previous literatures, flow-return relations of ETFs remain vague. The relation could be classified into 3 types; (1) flows lead returns, (2) returns lead flows, and (3) flows and returns are co-move. Therefore, the above-mentioned conclusion indicates that movements of returns and fund flows during the flight-to-quality episodes are not corresponding – ETF flows and returns are not move responsively in the same period. Thus, flows and returns are not co-move.

This study then tweaks period *t* of the flight-to-quality dummy variables both backward and forward in order to search for the most significant period and find that the dummy variables at period t+2 (D_{t+2}) generate the minimum p-value for all 5 regressions, demonstrating in table 11. Among 5 regressions with different portfolio optimization strategies, D_{t+2} of the maximum return and maximum Sharpe ratio equations is significant at 10 percent confidence interval. The empirical results imply that flows lead returns.

***Table 10**: The results of the fixed-effects panel regression investigating relations between asset allocations and fund flows of ETFs with dummy variables representing flight-to-quality months*

Optimization Strategy	**Max Return**	**Max SR**	**Min Vol**	**Risk Parity**	**Max DV**
Dep. V. / Indep. V.	$FLOW_{i,t}$	$FLOW_{i,t}$	$FLOW_{i,t}$	$FLOW_{i,t}$	$FLOW_{i,t}$
$AA_{i,t}$	-0.003066	0.011349	-0.789721**	0.348715 **	0.640707**
	(0.3008)	(0.1658)	(0.0424)	(0.0116)	(0.0165)
D_t	-0.010017	-0.005706	-0.005857	-0.047863	-0.007019
	(0.9594)	(0.9768)	(0.9762)	(0.8079)	(0.9715)
ESI_t^{US}	-0.009626	-0.009156	-0.009837	-0.008158	-0.009030
	(0.1727)	(0.1944)	(0.1629)	(0.2477)	(0.1998)
ESI_t^{EU}	-0.006307	-0.005920	-0.006589	-0.005164	-0.005541
	(0.2753)	(0.3058)	(0.2539)	(0.3716)	(0.3372)
ESI_t^{GL}	0.033444	0.031979	0.035232	0.027257	0.030533
	(0.2050)	(0.2253)	(0.1816)	(0.3019)	(0.2463)
ESI_t^{EM}	-0.013842	-0.013361	-0.014479	-0.011611	-0.013059
	(0.2197)	(0.2359)	(0.1989)	(0.3031)	(0.2459)
FFF_t	0.430693	0.400681	0.358841	0.510437	0.423937
	(0.3824)	(0.4167)	(0.4673)	(0.3005)	(0.3890)
FCI_t^{US}	0.150198	0.183109	0.205598	0.105169	0.155335
	(0.4953)	(0.4078)	(0.3532)	(0.6335)	(0.4797)
FCI_t^{EU}	-0.072506	-0.080273	-0.077738	-0.094664	-0.088982
	(0.5949)	(0.5560)	(0.5680)	(0.4872)	(0.5135)
FCI_t^{UK}	-0.127035	-0.145567	-0.168816	-0.085258	-0.125131
	(0.5406)	(0.4838)	(0.4176)	(0.6817)	(0.5459)
FCI_t^{AXJ}	0.111807	0.122338	0.120035	0.123636	0.115709
	(0.2505)	(0.2096)	(0.2170)	(0.2032)	(0.2334)

The table shows the coefficients of each independent variable. The values in the parentheses are p-values. ***, **, and * are denoted as significant levels at 1%, 5%, and 10% confidence interval, respectively

***Table 11**: The results of the fixed-effects panel regression investigating relations between asset allocations and fund flows of ETFs with dummy variables representing flight-to-quality months at time t+2*

Optimization Strategy	**Max Return**	**Max SR**	**Min Vol**	**Risk Parity**	**Max DV**
Dep. V. / Indep. V.	$FLOW_{i,t}$	$FLOW_{i,t}$	$FLOW_{i,t}$	$FLOW_{i,t}$	$FLOW_{i,t}$
$AA_{i,t}$	-0.002842	0.010638	-0.765346*	0.344550**	0.660034**
	(0.3393)	(0.1959)	(0.0504)	(0.0131)	(0.0144)
D_{t+2}	0.304709*	0.301761*	0.289599	0.296253	0.299125
	(0.0947)	(0.0979)	(0.1122)	(0.1034)	(0.1001)
ESI_t^{US}	-0.007575	-0.007115	-0.007763	-0.006311	-0.006998
	(0.2933)	(0.3233)	(0.2808)	(0.3806)	(0.3303)
ESI_t^{EU}	-0.004962	-0.004579	-0.005229	-0.003977	-0.004201
	(0.3967)	(0.4340)	(0.3713)	(0.4965)	(0.4722)
ESI_t^{GL}	0.027763	0.026267	0.029383	0.022701	0.024854
	(0.2948)	(0.3213)	(0.2672)	(0.3912)	(0.3472)
ESI_t^{EM}	-0.011296	-0.010779	-0.011826	-0.009639	-0.010508
	(0.3182)	(0.3405)	(0.2955)	(0.3935)	(0.3519)
FFF_t	0.442066	0.416251	0.374515	0.499091	0.436351
	(0.3593)	(0.3884)	(0.4381)	(0.3001)	(0.3645)
FCI_t^{US}	0.058074	0.088568	0.113568	0.021996	0.064118
	(0.7962)	(0.6950)	(0.6157)	(0.9220)	(0.7750)
FCI_t^{EU}	-0.057761	-0.065563	-0.063896	-0.077571	-0.074875
	(0.6721)	(0.6310)	(0.6392)	(0.5694)	(0.5828)
FCI_t^{UK}	-0.066581	-0.083521	-0.108102	-0.031741	-0.065133
	(0.7507)	(0.6907)	(0.6073)	(0.8796)	(0.7554)
FCI_t^{AXJ}	0.089991	0.099564	0.097846	0.104587	0.094078
	(0.3581)	(0.3105)	(0.3175)	(0.2853)	(0.3357)

The table shows the coefficients of each independent variable. The values in the parentheses are p-values. ***, **, and * are denoted as significant levels at 1%, 5%, and 10% confidence interval, respectively

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