Geographical Diversification Using ETFs: Multinational Evidence from COVID-19 Pandemic

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Abstract

We examine the relations between dollar flows of U.S. listed ETFs with exposure to the U.S., Europe, Asia, and the rest of the world during the COVID-19 crisis, using a Markov Switching Model (MSVAR). We find evidence that investors use ETFs to gain exposure to foreign markets and swiftly adjust their portfolios in response to the change in the number of COVID-19 infected people in every location. We further extend our study to ETFs listed in the U.S., Europe, and Asia and investigate the change in foreign and domestic money flow, before and after the pandemic. Utilizing an OLS model, we show that investors around the world rebalance their portfolios by monitoring the countries' performance in controlling the pandemic. Our findings show that while investors in the U.S. and Asian countries direct their money to domestic funds and reduce their foreign investment following the pandemic, European investors increase foreign investment and reduce home bias. This is consistent with the flight-to-safety effect when investors shift their asset allocation away from riskier investments (here riskier location) and into safer ones during the adverse economic shock.

Keywords: COVID-19, Pandemic, Flight to safety, Markov Switching Model, Home bias, International Diversification

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1. Introduction

Since the beginning of 2020, the COVID-19 pandemic has turned into the most challenging and urgent task for almost all governments and communities across the world. The severity and high level of contagiousness of this disease have disrupted the supply chain and workforce of the world and resulted in an unprecedented impact on financial markets (Sharif, Aloui, & Yarovaya, 2020). While the adverse effect of the COVID-19 crisis has not been homogeneous across the countries, it has influenced the variance of the US and Europe's stock markets more than the 2008 financial crisis (Ali, Alam, & Rizvi, 2020). Governments try to hamper the adverse economic effect of social distancing and lockdowns by income support packages, quantitative easing, and lowering interest rates (Ashraf, 2020; Zhang, Hu, & Ji, 2020). Moreover, recent pandemic plummeted foreign investment by almost 50% across the globe for the first half of 2020, the largest decline on record, according to the Wall Street Journal.[2]

While the benefits of international portfolio diversification have been established in the literature (Grubel, 1968; Hodrick & Zhang, 2014; Lessard, 1973), the way investors can gain exposure to the other countries' capital market has not progressed at the same rate. Investors can either directly invest in the local market or indirectly through depository receipts (ADRs), closed-end country funds, or international mutual funds. As direct investing requires investors to obtain information about a foreign market, which is time-consuming, indirect investing is an easier option (Huang & Lin, 2011). A relatively new and very popular investment vehicle that can provide international exposure is the Exchange-Traded Fund (ETF). ETF popularity among investors has grown remarkably in the United States since the 2008 financial crisis to the extent that as of January 2020, ETFs hold more than $4.4 trillion assets under management. Features like intraday tradability, tax efficiency, low fees, buying on margin or short selling, and transparency have contributed to the ETFs' growth. While Pennathur, Delcoure, and Anderson (2002) and Zhong and Yang (2005) challenge the international diversification benefits of iShares closed-end funds, Tsai and Swanson (2009) find that ETFs provide U.S. investors greater diversification benefits than country funds. Huang and Lin (2011) and O'Hagan-Luff and Berrill (2015) also show that ETFs are effective instruments for investors to create an internationally diversified portfolio without the need to invest overseas.

In this study, we employ a novel approach to investigate investors' reactions to the pandemic by examining new money flows into U.S. ETFs with exposure to the U.S., Europe, and Asia. In other words, we employ *follow the money* approach to examine whether U.S. investors adjust the distribution of assets in their portfolio in response to the COVID-19 outbreak in a given geographic location. To this end, we set to find out the joint distribution and linkage between assets with different geographic exposure. A good understanding of the linkage between assets with different geographic exposure is a key element in portfolio management. This joint distribution, however, may not remain constant over time. As a result, investors would require

[2] https://www.wsj.com/articles/foreign-investment-plummets-during-pandemic-except-in-china-11603785873

information about the conditional joint distribution of assets to maintain dynamic portfolio rebalancing strategies (Chan, Treepongkaruna, Brooks, & Gray, 2011). For example, using a TVP-VAR connectedness approach Bouri, Cepni, Gabauer, and Gupta (2021) find evidence of a dramatic change in the structure and time-varying patterns of return across various assets classes around the COVID-19 outbreak. Similarly, Corbet, Larkin, and Lucey (2020) report evidence of changes in the distribution of assets and "flight to safety" following the COVID-19 pandemic. While these studies investigate the change in the linkage among different asset classes during the pandemic, our study is mainly focused on the geographical exposure of investors and highlights the importance of geographical risks for portfolio managers and policymakers.

Unlike previous studies that use asset's return as a proxy for asset allocation decisions (Guidolin & Timmermann, 2007), we use the money flow as the direct measure of asset allocation. We argue that studies that use the return to identify the joint distribution of assets have an implicit assumption that flow drives the return by affecting the supply and demand equilibrium. Correspondingly, return, which is easier to track, can proxy the investors' money flow. Studies like Lou (2012) and Yousefi, Najand, and Sun (2020) have documented the positive relationship between flow and subsequent return of funds. Using flow instead of return results in a cleaner measure of asset allocation and alleviates the endogeneity concerns regarding the reverse effect of return on flow (Clifford, Fulkerson, & Jordan, 2014).

To examine the money flow of different geographic regions, we classified all passively managed ETFs in the U.S. stock exchanges into four groups based on their geographic exposure: U.S., Europe, Asia, and others (Africa, Australia, Middle East, Canada, and unclassified). We seek to model the joint distribution of flows with exposure to these geographic regions, conditional on the level of COVID-19 spread in these areas. For this purpose, we use a Markov Regime Switching model to characterize the conditional joint distribution of these four series. Our model uses the lag of percentage change in the number of new COVID-19 cases in each area as an exogenous macro factor that identifies regimes.

To characterize the marginal flow distribution of each geographic location, we first carry out a univariate Markov switching model. This model allows us to monitor the dynamic of money flow for each geographic location during the period of the pandemic. We then extend our univariate procedure to the multivariate dynamic factor model. Using a Markov switching vector autoregressive (MSVAR) model, we measure the dynamic linkages between money flow into different geographic locations in response to the prevalence of COVID-19 around the world. Following Guidolin and Timmermann (2006), we adopt multivariate Markov switching intercept autoregressive heteroskedasticity (MSIAH) alongside simpler multivariate Markov switching intercept heteroskedasticity (MSIH) specification in our model selection process.

The results of our univariate analysis indicate that there exist two regimes for each of the U.S., Europe, and Asia flow time series. We label the first regime as "Normal" which is characterized by low volatility and new money inflow into funds with exposure to Asian and European countries. The second regime which we label as "Panic", denotes periods of high volatility and money outflow from ETFs with foreign countries' exposure.

Moreover, our univariate model reveals that investors make swift adjustments to their portfolios in response to rising COVID-19 risk around the world by moving their funds away from high-risk regions to lower-risk regions. For example, the panic regime and money outflows from Asian ETFs started in the last week of January 2020, when the number of infected people in China climbed from 200 to over 1300 in just a week. This is while the World Health Organization (WHO), declared the novel coronavirus (COVID-19) outbreak a global pandemic on March 11, 2020. As more information becomes available about the pandemic and the severity of COVID-19 disease, the learning period gets shorter, and investors show a faster response to the outbreak in a geographic area.

Consistent with the univariate results, our multivariate model also reveals a 2-state pattern. Specifically, our MSVAR model, which covers the money flow of all ETFs in the U.S. stock market under the umbrella of four geographic regions, clearly identifies the "normal" and "panic" regimes. In our defined normal regime, all four geographic regions experience money inflows characterized by low volatility across all regions. During the panic regime, however, ETFs with non-US exposure exhibit money outflows whereas U.S.-exposed ETFs show significant money inflows.

Our MSVAR model provides convincing evidence of contagion within the U.S. ETFs and *flight-to-safety*[3] effect. This, however, is different from the phenomenon in which investors shift their investment within asset classes from high-risk investments to safer assets like bonds, gold, and precious metal. Flight-to-safety in our study occurs when investors diversify their portfolios away from high-risk locations to safer places. In the normal regime, which is characterized by low volatility and positive money flow, ETFs with different geographic exposure enjoy new money inflows. By contrast, during the panic regime, which is characterized by higher volatility, ETFs with geographic exposure other than the U.S., experience negative flows while U.S.-exposed ETFs gain new money flows.

We further extend our study to a multinational level by investigating the ETF flow of Asian and European countries. We define a variable, Flow Share, which measures the daily distribution of fund flows in each geographic location with respect to the other locations. Using an OLS model, we show that the spread of the COVID-19 pandemic in each location affects the level of foreign investment. Investors of countries that were more successful in controlling the pandemic (East Asia) show signs of home bias and reduction in foreign investment during the pandemic. On the other hand, investors of European countries, which were hit harder by the COVID-19, seek to reduce their exposure to domestic funds by an increase in foreign investment. This finding is consistent with the flight to safety when investors shift their asset allocation away from riskier investments and into safer assets during adverse economic shocks.

[3] *Flight to safety* is also known as *flight to quality* in the literature.

This study contributes to the literature on passive investment, portfolio management, and flight to safety. Our study is among the first studies that use the flow of ETFs to study investors' sentiment during panic periods. The rise in contagious diseases and pandemics like SARS, Ebola, H5N1, H7N9 avian flu, and COVID-19 in recent decades is an alert for the global supply chain and financial markets that a new risk factor has emerged, and deserves more attention. A close study to ours is recent research by Navratil, Taylor, and Vecer (2021) that utilizes virus-related data to forecast future equity ETF returns during the COVID-19 pandemic.

The remainder of the paper is organized as follows. Section 2 presents the conditional univariate and multivariate Markov switching models that form the basis of our analysis. Section 3 describes the data description. Section 4 reports the empirical results and discusses their implications for portfolio managers and policymakers. Section 5 concludes the paper.

2. Markov Switching models of the conditional joint distribution of flows

Following Guidolin and Timmermann (2006), and Chan et al. (2011), we employ Markov Switching Intercept Autoregressive Heteroscedasticity (MSIAH) to estimate a general autoregressive Markov switching model as follows:

$$y_t = m_{S_t} + b_{S_t} y_{t-1} + e_t \qquad (1)$$

where y_t refers to a matrix of flows for four ETF groups we examine their interconnection, $m_{S_t} = (m_{1S_t}, m_{2S_t}, m_{3S_t}, m_{4S_t})$ is a vector of mean flows in the state S_t and b_{S_t} is a 4´4 matrix of autoregressive coefficients in state S_t. $S_t = 1, 2, .., k$ and e_t follows a Normal distribution with zero mean and s_1^2 variance.

$$e_t \sim (0, s_1^2) \qquad (2)$$

For a k-state Markov process, the transition of states is stochastic and assumed to follow an irreducible ergodic K-state Markov process with transition matrix

$$P = \begin{bmatrix} p_{11} & \cdots & p_{1k} \\ \vdots & \ddots & \vdots \\ p_{k1} & \cdots & p_{kk} \end{bmatrix} \qquad (3)$$

Where $p_{ij} = PR[S_t = j | S_{t-1} = i]; \quad i, j = 1, 2, .., k$.

While the transition probabilities in Eq. (3) are usually assumed constant, we use the time-varying transition probabilities (TVTP) introduced by (Ding, 2020), for each probability cell. As a result, for a k-state model, we have (k-1) k independent time-varying component as follows:

$$Q_t = \begin{bmatrix} q_{11,t} & q_{12,t} & \cdots & q_{1k,t} \\ q_{21,t} & q_{22,t} & & q_{2k,t} \\ \vdots & & \ddots & \vdots \\ q_{k-1,1,t} & q_{k-1,2,t} & \cdots & q_{k-1,k,t} \\ 1 & 1 & & 1 \end{bmatrix} \qquad (4)$$

For each probability cell of (4), we specify a probability generating function as follows:

$$q_{ij,t} = F\,(X_{ij,t} b_{ij}) \qquad (5)$$

Where F is the cumulative normal density function, $X_{ij,t}$ is the state variable vector for cell (i, j), and b_{ij} is the parameter to be estimated. In our model, we use lag of regional change in the number of new COVID-19 cases in the past one day as an exogenous variable that identifies the regimes. Next, using Q_t, we generate an auxiliary matrix R_t:

$$R_t = \begin{bmatrix} \frac{1}{1-q_{11,t}} & \frac{1}{1-q_{12,t}} & \cdots & \frac{1}{1-q_{1k,t}} \\ \vdots & & \ddots & \vdots \\ \prod_{i=1}^{k-2}(1-q_{i1,t}) & \prod_{i=1}^{k-2}(1-q_{i2,t}) & \cdots & \prod_{i=1}^{k-2}(1-q_{ik,t}) \\ \prod_{i=1}^{k-1}(1-q_{i1,t}) & \prod_{i=1}^{k-1}(1-q_{i2,t}) & & \prod_{i=1}^{k-1}(1-q_{ik,t}) \end{bmatrix} \qquad (6)$$

Finally, the time-varying transition probability matrix can be generated as follows:

$$P_t = Q_t \cdot R_t = \begin{bmatrix} p_{11,t} & p_{12,t} & \cdots & p_{1k,t} \\ p_{21,t} & p_{22,t} & & p_{2k,t} \\ \vdots & & \ddots & \vdots \\ p_{k1,t} & p_{k2,t} & \cdots & p_{kk,t} \\ 1 & 1 & & 1 \end{bmatrix} \qquad (7)$$

Where $\cdot$ is a sign for elementwise matrix production.

Consequently, the distribution of y_t conditional on state S_t and on a set of parameters Ψ is

$$f(y_t|S_t = j, Y) = \frac{1}{(2p)^{N/2}|S_{st}|^{1/2}} \exp\left[-\frac{1}{2} e_t' S_{st}^{-1} e_t\right] \qquad (8)$$

Where N is the number of vectors (4 ETF flow groups in our model) whose joint distribution is desired. Considering the k possible regimes, the full log-likelihood function of the model is:

$$\ln L = \sum_{t=1}^{T} ln \sum_{j=1}^{k} (f(y_t|S_t = j, Y)\Pr(S_t = j)) \qquad (9)$$

Where T is the number of observations. Eq. (9) is in fact, a weighted average of the likelihood function in each state. However, since the probabilities are not observable, Hamilton's filter is used to make inferences on the probabilities based on the available information (Hamilton, 1989). See Perlin (2015) for further details on this topic.

Eq. (1) represents a general form of the Markov switching model which can turn into simpler models by imposing some restrictions. For example, when y_t is restricted to a vector of aggregated ETF flows of one geographic area over period t, then Eq. (1) denotes a univariate MSIAH model. We also investigate the Markov Switching Intercept Heteroscedasticity (MSIH) model by restricting the autoregressive part of the model to zero ($b_{S_t} = 0$). Furthermore, we examine the 2-, 3-, and 4-state regimes to ensure the best model is fitted for each univariate case. To evaluate the trade-off between MSIH and MSIAH data fit and to determine the optimum number of states, we rely on the Akaike information criterion (AIC) and Bayesian information criterion (BIC) model fit statistics. We define the "best" Markov switching model as a model with the lowest average AIC and BIC values.

3. Data description

Our initial sample data consist of daily data of 2417 ETFs listed in US stock exchanges from January 2020 to the end of October 2020. We use two databases to collect the ETF data for this study: Bloomberg and ETF Global (ETFG). The ETFG data is sourced daily directly from the ETF issuers and their custodians and provides information like region and geographical exposure, active or passive status, and leverage level of the ETFs. Even though ETFG provides information about the daily flow of the ETFs, we choose to use Bloomberg as the first source of flow data. The main reason for taking this approach is the reporting agility of the data provider. Our cross-check analysis between the two databases (i.e. Bloomberg and ETFG) shows that Bloomberg is timelier in reporting the flow (generally with a 1-day lag) than ETFG. We also drop the leveraged and active ETFs from our sample. Leveraged ETFs do not use the "in-kind" mechanism in ETF share creation/redemption and similar to mutual funds, are settled in cash. Active ETFs are also removed from the sample because they may frequently change their geographic exposure during the period of the study. The final sample contains 1720 ETFs, comprising more than 336,600 fund-day observations. Needless to say, we keep ETFs from all asset classes (Equity, Fixed income, Currency, Commodities, and Real Estate) that exist in our sample since the focus of our study is on geographic exposure rather than asset type.

Next, ETFs are classified into four groups based on their region's exposure: Asia, Europe, U.S., and Others. Every region's exposure in the dataset is presented as a percentage of non-cash assets held by the fund. Exploiting a text analysis on the "geographical_exposure" variable, we could differentiate ETF exposure based on the country. We set 60% as a hurdle for geographic exposure. As a result, a fund is flagged as "Asia", if at least 60% of its holdings are exposed to Asian countries. For example, "IGOV" is the iShares International Treasury Bond ETF which provides exposure to bonds issued by the governments of countries around the world (excluding the U.S.). We classify IGOV as an ETF with exposure to Europe because our analysis shows more than 60% of its holdings have exposure to European countries. This is while IGOV holds treasury bills of countries like Japan, Canada, Singapore, and Israel in its portfolio as well. ETFs with exposure to the Middle East, Africa, and Global are also grouped as "Other". Variable "flow" is then aggregated based on geographical location and day. Finally, the aggregated flow data is merged with daily data on new and total confirmed COVID-19 cases in Asia, Europe, US., and the world. We use the European CDC published daily statistics on the COVID-19 pandemic as the source of our data[4]. ECDC reports harmonized daily data of COVID-19, not just for Europe, but for the entire world.

Fig. 1 plots the daily time-series of cumulative flows since Jan 2020 for each of the four geographic groups that we examine. Consistent with the "home bias" phenomenon, foreign assets on average account for 35% of the total value of assets owned by U.S. investors at the beginning of the pandemic. This number shrinks to 32% during the period of this study. The U.S. Flow generally exhibits an upward trend with a temporary drop on February 22, 2020, concurrent with the first spike in the number of confirmed cases. The Asian ETFs on the other hand started experiencing outflow beginning January 24, 2020 -- when China confirmed that COVID-19 cases reached 1000 in less than a week. This negative trend continued until the end of May when China records no new coronavirus cases for the first time since the pandemic began. What is interesting in Fig. 1 is the gain of the U.S. Flow index following the outflows from Asian ETFs. Similar to Asian ETFs, European funds also experienced outflows by the first signs of the outbreak in Spain and Italy.

Fig. 1.

Table 1 reports the descriptive statistics (Panel A) and a correlation matrix (Panel B) for the daily flow of the four geographic groups. The average flow is the lowest for Asia with $34 million daily outflows, and the highest for the U.S. with over $1 billion daily inflow. Daily changes of all the variables are demeaned and standardized prior to the analysis.

Table 1

Table 1 reports descriptive statistics for aggregated ETF flows with exposure to Asia, Europe, U.S., and the rest of the world. It is noteworthy that despite the financial crisis that was caused by the COVID-19 pandemic, ETF market on average grew larger during the first nine months of 2020 and attracted more than $270 billion in new funds. This is while, mutual funds experienced net new cash flow of -$420 billion for the same time period, according to the investment company institute (ICI) estimated long-term mutual fund flows.

4. Empirical Results

4.1. Univariate Markov Switching model of each geographical group

We begin our analysis by fitting a range of two and three-state MSIH and MSIAH models to each flow series. The goal of this step is to estimate the performance of different models in order to choose the best model for each individual series. We then use the AIC and BIC values to determine the most appropriate multi-regime model specification for each series of flows. Table 2 reports the AIC and BIC values for various models that fit the daily flow data of our sample. Judging from the AIC/BIC values, the two-state model is superior to the three-state, as evidenced by lower values. We further test a four-state model which its results are not reported since the

[4] https://ourworldindata.org/coronavirus-source-data

model could not converge in some cases due to the large dimensionality level. It is worthwhile to mention that the lag of daily percentage change in the number of new COVID-19 cases in each geographic group has been used as a macro factor determining the state.

Table 2

Table 2 presents our results for fitting a 2-state model. results for flow are comparable to prior literature which exploits a 2-state model in fitting asset return distribution (Alizadeh, Nomikos, & Pouliasis, 2008; Chan et al., 2011; Guidolin & Timmermann, 2006). Furthermore, the core of this study is to investigate the existence of a hidden regime at the time of crisis which makes our study closer to Wan and Kao (2015) who document a different relationship between oil and financial markets under "stressed" and "normal" regimes. Similarly, Al-Anaswah and Wilfling (2011) use a 2-state model in their study of the stock market to identify bubbles in stock price data.

Table 3 presents the estimates for the univariate 2-state Markov switching model. We, again, utilize AIC and BIC criteria to choose between MSIH and MSIAH models, based on the lowest average of AIC and BIC reported in Table 2. Focusing on ETFs with exposure to the Asian market, we find that the mean flows are positive in the normal regime and negative in the panic regime. Consistent with our expectations, the normal regime is recognized by lower volatility compared with the panic regime. Table 3 also reports the expected durations for each regime. The duration numbers indicate that the normal regime tends to last longer than the panic regime. Despite the simpler MSIH model fit to Europe flow series, the same conclusion can be inferred for the European ETFs. Negative flow along with higher volatility during the panic regime exhibits signs of flight to quality among ETFs with non-U.S. exposure.

Table 3

Analysis of U.S. ETF flows also capture periods of a normal regime with low volatility and a panic regime with high volatility. However, the direction of U.S. ETF flows is opposite to the Asian and European ETF flows. That is, U.S. ETFs exhibit counter-cyclical characteristics and have a negative flow during the normal regime and a positive flow during the panic regime. This is consistent with the "flight home effect" in which, following a shock, investors tend to rebalance their portfolio away from the international market to their domestic market where they have less information asymmetry. We further investigate this issue in the multivariate section.

To further investigate the effect of the COVID-19 pandemic on regime change across ETFs with different geographic exposure, we plot the smoothed probability (Eq. (8)) of the panic regime fitted to the individual flow series. We also overlap the graph of daily total COVID-19 cases in each geographic area as an indicator for when a regime switch has occurred. Panels A, B, and C in Fig. 2 illustrate the probability of panic regime during the study time, given total COVID-19 cases for Asia, Europe, and the U.S. flows series. For the sake of comparison, the first time that the number of infected people surpasses 100 individuals is annotated with an arrow for each geographic area.

Figure 2

From the data in Fig. 2, it is apparent that the number of new COVID-19 cases in each geographic location affects the regime-switching process. What is interesting about the data in this figure is the quick response of the market to the imminent risk of the pandemic. For example, Asian ETFs are among the first which exhibit signs of regime change and money outflows at the end of January 2020. This is while human-to-human transmission of COVID-19 was confirmed by the WHO and Chinese authorities on January 20, 2020; and on the same day, China reported the first outbreak by nearly 140 new cases in one day. We also reach a similar conclusion for the Europe flow series. Shortly following the regime change in the flow of Asian ETFs, the probability of the panic regime for ETFs with Europe exposure reached 100% on February 18. This coincides with the surge of new cases and the beginning of the lockdown policy in Europe. In the case of the U.S., however, the situation is different, and episodes of panic regimes depend on the other locations. The first signs of panic regime emerge in early February and following the outflow of money from Asian ETFs. Similarly, the second wave of panic regime started on February 24, soon after the regime change in the Europe flow series. This episode was then followed by the prevalence of the pandemic in the U.S. and the stock market crash. As the number of new cases decreased in the U.S., the panic regime gives its place to the normal episode. This normal situation, however, is tentative and turns to panic episodes with every raise in the number of new cases in the U.S.

Thus far, the univariate models broadly identify the relationship between COVID-19 cases and the flow of ETFs. There is also evidence of commonality between the flow of U.S. ETFs with Europe and Asia. For example, the U.S. flow series exhibit episodes of the panic regime around the time of the COVID-19 outbreak in China and Europe. One can attribute this trend to the flight to quality, in which capital migrates from where it perceives risky to where it finds a safe haven. However, this cannot fully explain the flow shift from international funds to U.S. ETFs, as the U.S. was hit equally hard or even harder by the pandemic than other parts of the globe. We further investigate this in a Markov switching vector autoregressive (MSVAR) model where interaction between flow series can be monitored.

These findings, while preliminary, have important implications for policymakers and portfolio managers. First, our results indicate that investors use ETFs as a tool to geographically diversify their portfolios in order to gain exposure to foreign markets. Exchange-tradability and high liquidity of ETFs enable investors to show a timely reaction to geographic threats. This outflow (inflow) of money can impose a negative (positive) price pressure on the underlying securities of ETFs and deviate their values from their market efficient price (Lou, 2012; Yousefi et al., 2020). We identify two states for each flow series during a global crisis where any asset allocation decision must follow a 2-state model. Moreover, we find that the panic regime corresponds with higher volatility and lower return across all series; a finding which challenges the efficiency of geographic diversification during a worldwide catastrophe. It is worthwhile to bear in mind that the regime process S_t in our univariate model is constrained by the changes in the number of new infected cases in each geographic area. The fact that the surge in the number of COVID-19 cases in each area is not common across series and thus, regime switches may be predictable up to an extent, suggests that asset allocation strategies may need to involve switching between geographic locations.

4.2. Markov Switching VAR model for the joint distribution of flows

To model the joint distribution of flow series in our sample, we need to consider the flow of all ETFs in the U.S. market. It means that the flow of ETFs with exposure to other geographic locations other than Asia, Europe, and the U.S., also needs to be considered. To do this, we aggregate the flow of funds with exposure to Africa, Australia, the Middle East, and the rest of unclassified ETFs, and label them as "Others. We also use the changes in the number of COVID-19 cases worldwide as a macro factor that can affect the regime-switching process. Next, we use AIC and BIC criteria to determine the appropriate model and number of regimes for our multivariate model, as we did in the univariate case. Eventually, a 2-state multivariate MSIAH model is selected to show the linkage between flow series across ETFs. Table 4 reports the parameter estimates for this model.

Table 4

Table 4 exhibits a homogenous pattern in the conditional flow estimates across four series. Judging from estimated values for duration and σ (volatility) in each regime, it can be noted that regime 1 is considerably more persistent and generally less volatile than regime 2. As a result, we label regime 1 as "normal" and regime 2 as "panic" states. Consistent with the growth of index investing, all ETFs aside from their geographic exposure exhibit positive mean flow in the normal regime. During the panic regime, however, ETFs with non-U.S. exposure experience a negative net flow, while new money flows into U.S. funds experience upswings.

During the panic period and episodes of economic decline, investors generally prefer safe-haven assets. A safe haven by definition is an asset with low volatility and high liquidity that investors are drawn to in uncertain times (Flavin, Morley, & Panopoulou, 2014; Kaul & Sapp, 2006). Baur and Lucey (2010) also add another condition where an asset needs to have a zero or negative correlation with the risky portfolio during a market crash to be considered as a safe haven. In our sample, the coefficient of variation (Std. Dev. /Mean) for the U.S. flows is lower than both Europe and Asia. It is also evident from the results in Table 4 that the correlation between the flow of U.S. ETFs and other geographic locations turns negative during the panic regime. Given this, one can conclude that the results of Table 4 show that U.S. ETFs represent the main characteristics of a safe asset during the panic regime. Specifically, the significance of $\mu_{2,Asia}$ and $\mu_{2,Others}$ coefficients show that U.S. investors retract their funds from emerging and developing markets which are perceived to be riskier and direct their investments toward U.S.

ETFs, in the presence of a crisis such as the COVID-19 pandemic. This shift in the new money flow away from international ETFs and toward domestic funds during the panic regime is comparable to findings of Giannetti and Laeven (2012) where they find that home bias in the international allocation of syndicate loans increases in the event of worldwide adverse economic shocks.

Another finding of this study is the autoregressive pattern of flow series in each regime. For the normal regime, there is a significant and positive relationship between the current and lagged flow of all four series. This sticky behavior of flow is consistent with the persistent flow hypothesis in mutual funds and ETFs (Jiang & Yuksel, 2017; Sialm, Starks, & Zhang, 2015). During the panic period, however, the persistent flow condition disrupts -- which considering the short duration of the panic period should come as no surprise. We do not provide an explanation for the effect that lagged flow on one geographic location has on the present flow of the other location, because this would be conditional on remaining in the same regime. While the coefficient of $\mu_{S,f}$ represents the average flow for one regime during the period of the study, the value of $\beta_{S,f}$ depends on the state of the regime in consecutive days.

Figure 3

Fig. 3 plots the smoothed probability of being in the panic regime. As can be seen from this figure, the market spends considerably more time in the normal regime. More specifically, the normal regime is interrupted by short periods of the panic regime which coincides with the beginning of the pandemic in Asia, Europe, and the U.S. up until April 2020. After that, there are only some periods of panic represented by spikes in Fig. 3 which are mainly contemporaneous with the second wave of the pandemic in the U.S. and Europe. In fact, panic regime constitutes only 20% of the total duration of the study which itself is distributed throughout multiple shorter periods. This means that one observation from the normal regime is highly likely to be followed by another observation from the same regime, whereas this is not the case for the panic regime. Once again, the heterogeneous distribution and short lifespan of the panic regime makes the interpretation of $\beta_{S,f}$ coefficients questionable.

4.3. International Evidence: Flight Home Vs. Flight to Safety

So far, our results show that ETFs with geographic exposure other than the U.S., experience a negative flow when hit by the pandemic, while U.S.-exposed ETFs gain new money flow. This is consistent with the flight to safety in which investors rebalance their portfolios towards higher quality and safer assets (in our case safer locations). One, however, may argue that since all countries are more or less affected by the same phenomenon at the same time, investors have a tendency to overinvest in their home country where they have less asymmetric information. This is similar to the findings of Giannetti and Laeven (2012) who document a flight home effect during the 2008 financial crisis. They find home bias in capital allocation tends to increase when adverse economic shocks reduce the wealth of international investors. To test this hypothesis, we expand our sample from only US ETFs to ETFs listed in European and Asian stock exchanges. We collect flow data for 8569 ETFs from the Bloomberg terminal. In order to record the variation in flow share, we extend our sample of the study, and extract data from January 2019 (almost a year before the pandemic), to June 2021. Similar to the approach in section 3, ETFs in each geographical location are classified into four groups based on their region's exposure: Asia, Europe, U.S., and Others. However, since data for the composition of non-US ETFs is not available, we use the "FUND_GEO_FOCUS" variable in Bloomberg to categorize ETFs geographically. Table 5 shows the descriptive statistics for ETFs from each geographical location to each destination.

Table 5

In this section, we study whether investors in each geographic location (Asia, Europe, and U.S.), when hit by COVID-19 shock, have a tendency to rebalance their portfolio away from international funds to their domestic funds. Since the beginning of the COVID-19 pandemic, financial markets around the world have experienced negative shocks following a rise in the number of infected people in each country. Our goal is to explore how negative shocks induced by the spread of the virus affect the flow of the ETFs and, in particular, whether a worldwide exogenous shock like COVID-19 affects flow to foreign and domestic ETFs. We build on the model of Giannetti and Laeven (2012) that investigates how negative shocks affect bank loans to foreign and domestic borrowers differently. In particular, we focus on the flow of ETFs listed in Asia, Europe, and U.S. and classify them based on the geographical exposure of their holdings. We model the flow share of ETFs in location i to location j at day t as follows:

$$\begin{aligned} Flow\ Share_{ijt} = {} & \propto_1 Foreign\ Flow_{ij} + \propto_2 Foreign\ Flow_{ij}\ ´\ COVID19\ Home\ Country_{it} \\ & + \propto_3 Foreign\ Flow_{ij}\ ´\ COVID19\ Host\ Country_{it} + b\,Y_{ijt} + e_{ijt} \end{aligned}$$

Where $Foreign\ Flow_{ij}$ is a dummy variable that takes the value of one if the geographical location that ETF i is listed is different from its geographical exposure, and zeroes otherwise. $COVID19\ Home\ Country_{it}$ measures the change in the number of new COVID-19 cases in the geographic location where ETF is listed; $COVID19\ Host\ Country_{it}$ measures the change in the number of new COVID-19 cases in the geographic location where ETF has exposure to; Y_{ijt} is a vector of control variables; and e_{ijt} is an error term.

The important feature of this model is that the dependent variable captures the geographical distribution of fund flow with respect to the total assets under management (AUM) of the home location, rather than the total flow. In other words, our dependent variable captures the allocation of fund flows within the whole ETFs in each geographic location. Since the daily flow is standardized by the total AUM at each day, our dependent variable is unaffected by market shocks changing the overall value of AUM and instead, captures the shift in the flow from one group to another. As a result, we do not analyze the effect of COVID-19 per se, but only differences in the effect of changes in the spread of the pandemic across funds using the interaction term.

$$Flow\ Share_{ijt} = \frac{\sum flow\ of\ ETFs\ listed\ in\ location\ i\ with\ exposure\ to\ location\ j\ at\ time\ t}{\sum AUM\ of\ ETFs\ in\ location\ i\ at\ time\ t-1}$$

In our model, a negative coefficient $\propto_1$ implies that investors systematically tend to invest more in domestic funds, indicating that there is a home bias in investors' portfolios. The coefficients of interaction terms, $\propto_2$ and $\propto_3$, allow us to capture any differential impact of COVID-19 spread in home and host countries on the share of foreign flow. The vector of control variables, Y_{ijt}, includes time fixed effect, and in some specifications, home and host fixed effects. Furthermore, we control for the supply shock in the home country by including the proportion of domestic flow to the total AUM of all funds in the home geographic location.

It can be seen from the data in Table 6 that there exists a home bias for investors in Asia, Europe, and the U.S. because investors across all these locations were found to systematically reduce new money flow to ETFs with foreign exposure. The share of money flow to an ETF with foreign exposure is lower by 0.01. This is consistent with a large body of literature that has documented home bias in international investment for investors from different countries. One pattern that emerges from the results, however, is that investors do not show a tendency toward home location when home is hit by the spread of the pandemic (column 1). This finding is more consistent with the flight to safety argument in which investors shift their portfolios toward safer assets and markets when exposed to a shock. One may argue that using OLS regression may not be the best choice when the dependent variable, Flow Share, fluctuates between zero and one. The main reason we use OLS in our model is the large number of dummy variables used in different specifications of the model. To alleviate this concern, we use a Tobit model assuming a truncated dependent variable in column 2 (Giannetti and Laeven (2012)). Using the same set of control variables, the results remain similar to the OLS estimation. The results also remain intact, even after controlling for the home and host country (column 3).

Interestingly, the results change after we control for the contemporaneous spread of COVID-19 in the host location. If anything, this indicates that the flight home effect depends on the situation at home relative to host location, and the ability of each location to control the situation and spread of the COVID-19 pandemic. Judging from the coefficients of interaction terms, the results suggest that the impact on the proportion of foreign flow is significantly higher when investors perceive the uncertainty in host location than when they experience a rise in the number of infected people at home.

If the direction of the flow depends on the geographical location and the ability of the countries in controlling the pandemic, then one can conclude that this effect is driven by a flight to safety. To further investigate this issue, we divide our sample into three subsamples based on the home geographic location. By differentiating the home geographic location, we seek to investigate the behavior of investors in each location in response to the spread of the COVID-19 pandemic in their home locations, and the rest of the world.

Table 6

Table 7 demonstrates the model estimation for each geographic location. The most surprising aspect of the data is the heterogeneous behavior of the investors across various locations. While the coefficient of Foreign Flow for Asian and U.S. funds signals a strong home bias, a positive and statistically significant coefficient for European investors shows a tendency for geographic diversification among European investors. This trend is most probably the byproduct of different sources of uncertainty including Brexit and the COVID-19 pandemic, considering the fact that our study dates back to January 2019, a year before the pandemic begins. Another interesting finding of Table 7 is the coefficient of the interaction term, $Foreign\ Flow_{ij} \times COVID19\ Home\ Country_{it}$. When hit by the COVID-19 pandemic, Asian countries significantly reduce investing in foreign countries and redirect money to home locations, where they believe that they have a better understanding of the pandemic situation. On the contrary, European investors increased their foreign investment following the spread of the pandemic. Once again, this finding rules out the flight home hypothesis at the time of a worldwide catastrophe and endorses the flight to safety hypothesis. The inability of European countries to a timely and agile response to the pandemic drove the European investors to rebalance their portfolio away from domestic funds to more international funds. Flow of the US funds also shows a similar, but less pronounced behavior to Asian funds. US investors also do not appear overly concerned about the shock in other locations. This can be observed by the statistically insignificant coefficient of the $Foreign\ Flow_{ij} \times COVID19\ Host\ Country_{it}$. A possible explanation for these results may be the fact that the US experienced the pandemic with a lag after Asia and Europe when investors did not have any other option to reallocate their portfolio. The result for the host interaction for Asia and Europe, however, remains negative and significant, showing the response of investors to the spread of the pandemic in other locations.

Table 7

5. Conclusion

The COVID-19 pandemic has given researchers a unique opportunity to study the effects of the pandemic on financial markets. Our study differs from previous studies in two major ways. First, as opposed to using returns, we *follow the money* by using actual dollars of fund flows where investors react to the pandemic by moving their funds between domestic and international focused funds. Our second contribution centers on the investigation of the existence of two distinct regimes during this pandemic: (1) a ‘‘normal” regime when all ETFs receive positive flows and (2) a ‘‘panic” regime which emerges when the number of infected people surges in a global location and investors shift their funds from non-U.S. ETFs to U.S.-exposed ETFs.

We employ the general Markov switching model to examine the relationship between the aggregated flow of four groups of U.S. ETFs with exposure to Asia, Europe, U.S., and the rest of the world during the COVID-19 pandemic crisis. We find mounting evidence that U.S. investors use international ETFs to geographically diversify their portfolios. We confirm the existence of two regimes during the first three quarters of 2020, concurrent with the prevalence of the COVID-19 pandemic across the world. The first regime (normal) is characterized by lower volatility and positive flow for all ETF groups. By contrast, the second regime is labeled “panic”, as it is characterized by higher volatility that emerges by the surge in the number of COVID-19 new cases in each geographic area. Furthermore, during the panic regime, we find evidence of an increase in home bias and flight to quality from international ETFs to U.S. ETFs.

In a different setting and using OLS regression, we develop a measure to distinguish the response of different investors across the world to COVID-19 spread in their home region. We find a very different asset allocation strategy among European and Asian investors. While Asian investors generally have a home bias and increase investment in domestic funds during the pandemic, European investors tend to diversify their portfolios and increase their foreign exposure during the same period. This finding is consistent with the flight to safety and shows the heterogeneous behavior of investors depending on their geographic location.

Another major finding of this study is the speed of the investor’s portfolio adjustment in response to the risk of the pandemic in a given geographic location. Liquidity provided by ETFs enables investors to react promptly to global news and causes investors to adjust their portfolio allocations accordingly. The first signs of the panic regime and new money outflow from Asian ETFs started less than a week after the number of infected people reached more than 100 in China. The investors' response time to the new information about the pandemic was reduced and became more instantaneous for money outflows from European ETFs toward U.S. ETFs, as investors learn more about the severity of the pandemic. This portfolio rebalancing away from international funds toward U.S. ETFs is consistent with the flight-to-safety effect and surge in “home bias” investing during the adverse economic shocks.

Our results have important implications for policymakers and portfolio managers. Despite all the progress in the world’s health improvements during the past century, human health is confronting new threats. As technology progresses, human communities become denser, and the entire world becomes more interconnected. The dark side of this internationalization is the growth of pandemic infections during the past few years. SARS, Ebola, H5N1, H7N9 avian flu, and recently COVID-19 are examples of health issues that can disrupt the global supply chain and trigger a financial crisis. As a result, governments and policymakers need to set new standards for effectively controlling contagion the spread of the virus. . From the viewpoint of portfolio management, using a measure of infection – similar to what is used in the present study, coupled with a dynamic asset allocation portfolio, can be used to rebalance the portfolio in a timely and efficient manner.

Even if the regime-switching process cannot be predicted by a factor, our findings are still relevant and useful for diversification. Our results also show that there is a contagion between geographic locations and investors can use ETFs to hedge against local uncertainties.

References:

Al-Anaswah, N., & Wilfling, B. (2011). Identification of speculative bubbles using state-space models with Markov-switching. *Journal of Banking & Finance, 35*(5), 1073-1086.

Ali, M., Alam, N., & Rizvi, S. A. R. (2020). Coronavirus (COVID-19)–An epidemic or pandemic for financial markets. *Journal of Behavioral and Experimental Finance*, 100341.

Alizadeh, A. H., Nomikos, N. K., & Pouliasis, P. K. (2008). A Markov regime switching approach for hedging energy commodities. *Journal of Banking & Finance, 32*(9), 1970-1983.

Ashraf, B. N. (2020). Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets. *Journal of Behavioral and Experimental Finance, 27*, 100371.

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review, 45*(2), 217-229.

Bouri, E., Cepni, O., Gabauer, D., & Gupta, R. (2021). Return connectedness across asset classes around the COVID-19 outbreak. *International Review of Financial Analysis, 73*, 101646.

Chan, K. F., Treepongkaruna, S., Brooks, R., & Gray, S. (2011). Asset market linkages: Evidence from financial, commodity and real estate assets. *Journal of Banking & Finance, 35*(6), 1415-1426.

Clifford, C. P., Fulkerson, J. A., & Jordan, B. D. (2014). What drives ETF flows? *Financial Review, 49*(3), 619-642.

Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the covid-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters*, 101554.

Ding, Z. (2020). Regime Switching Model with Time Varying Transition Probabilities. *MATLAB Central File Exchange. Retrieved October 24, 2020,* *https://www.mathworks.com/matlabcentral/fileexchange/37144-regime-switching-model-with-time-varying-transition-probabilities*.

Flavin, T. J., Morley, C. E., & Panopoulou, E. (2014). Identifying safe haven assets for equity investors through an analysis of the stability of shock transmission. *Journal of international financial markets, institutions and money, 33*, 137-154.

Giannetti, M., & Laeven, L. (2012). The flight home effect: Evidence from the syndicated loan market during financial crises. *Journal of Financial Economics, 104*(1), 23-43.

Grubel, H. G. (1968). Internationally diversified portfolios: welfare gains and capital flows. *The American Economic Review, 58*(5), 1299-1314.

Guidolin, M., & Timmermann, A. (2006). An econometric model of nonlinear dynamics in the joint distribution of stock and bond returns. *Journal of Applied Econometrics, 21*(1), 1-22.

Guidolin, M., & Timmermann, A. (2007). Asset allocation under multivariate regime switching. *Journal of Economic Dynamics and Control, 31*(11), 3503-3544.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the Econometric Society*, 357-384.

Hodrick, R. J., & Zhang, X. (2014). International diversification revisited. In *University of Columbia Working paper*.

Huang, M.-Y., & Lin, J.-B. (2011). Do ETFs provide effective international diversification? *Research in International Business and Finance, 25*(3), 335-344.

Jiang, G. J., & Yuksel, H. Z. (2017). What drives the “Smart-Money” effect? Evidence from investors’ money flow to mutual fund classes. *Journal of Empirical Finance, 40*, 39-58.

Kaul, A., & Sapp, S. (2006). Y2K fears and safe haven trading of the US dollar. *Journal of international money and finance, 25*(5), 760-779.

Lessard, D. R. (1973). International portfolio diversification: a multivariate analysis for a group of Latin American countries. *The Journal of Finance, 28*(3), 619-633.

Lou, D. (2012). A flow-based explanation for return predictability. *The Review of Financial Studies, 25*(12), 3457-3489.

Navratil, R., Taylor, S. M., & Vecer, J. (2021). On Equity Market Inefficiency During the COVID-19 Pandemic (preprint).

O'Hagan-Luff, M., & Berrill, J. (2015). Why stay-at-home investing makes sense. *International Review of Financial Analysis, 38*, 1-14.

Pennathur, A. K., Delcoure, N., & Anderson, D. (2002). Diversification benefits of iShares and closed-end country funds. *Journal of Financial Research, 25*(4), 541-557.

Perlin, M. (2015). MS_Regress-the Matlab package for markov regime switching models. *Available at SSRN 1714016*.

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, 101496.

Sialm, C., Starks, L. T., & Zhang, H. (2015). Defined contribution pension plans: Sticky or discerning money? *The Journal of Finance, 70*(2), 805-838.

Tsai, P.-J., & Swanson, P. E. (2009). The comparative role of iShares and country funds in internationally diversified portfolios. *Journal of Economics and Business, 61*(6), 472-494.

Wan, J.-Y., & Kao, C.-W. (2015). Interactions between oil and financial markets—Do conditions of financial stress matter? *Energy Economics, 52*, 160-175.

Yousefi, H., Najand, M., & Sun, L. (2020). Fund Flow and Managerial Skill: Evidence from Exchange-Traded Funds (Etfs). *Available at SSRN 3521664*.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 101528.

Zhong, M., & Yang, H. (2005). Risk exposures and international diversification: Evidence from iShares. *Journal of Business Finance & Accounting, 32*(3-4), 737-772.

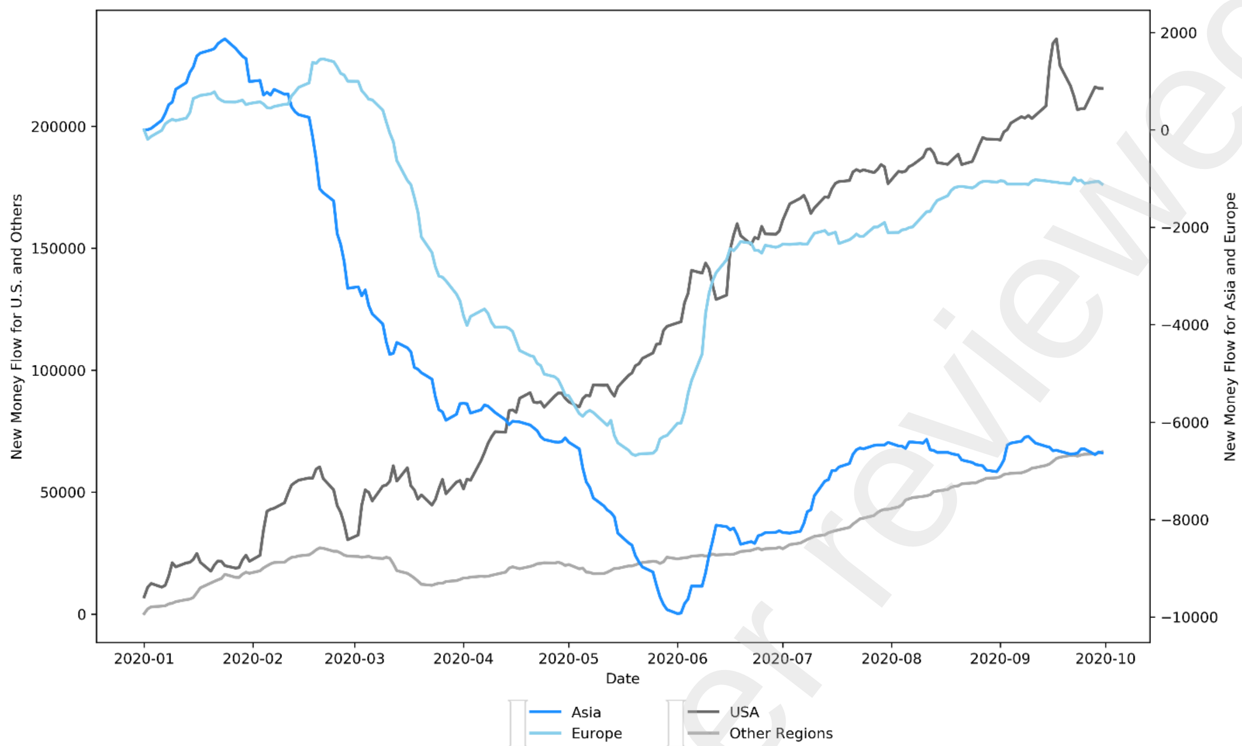

Figure 1. Cumulative new money flows ($million) into ETFs, by geographic exposure. This figure shows the daily flow into ETFs with exposure to Asia, Europe, U.S., and rest of the world since January 2020. To facilitate comparison across series, the left y-axis shows the dollar value of flows for U.S. and Others, while the right y-axis represents the dollar value of flow for Asia and Europe. The sample period is from January 2020 to October 2020.

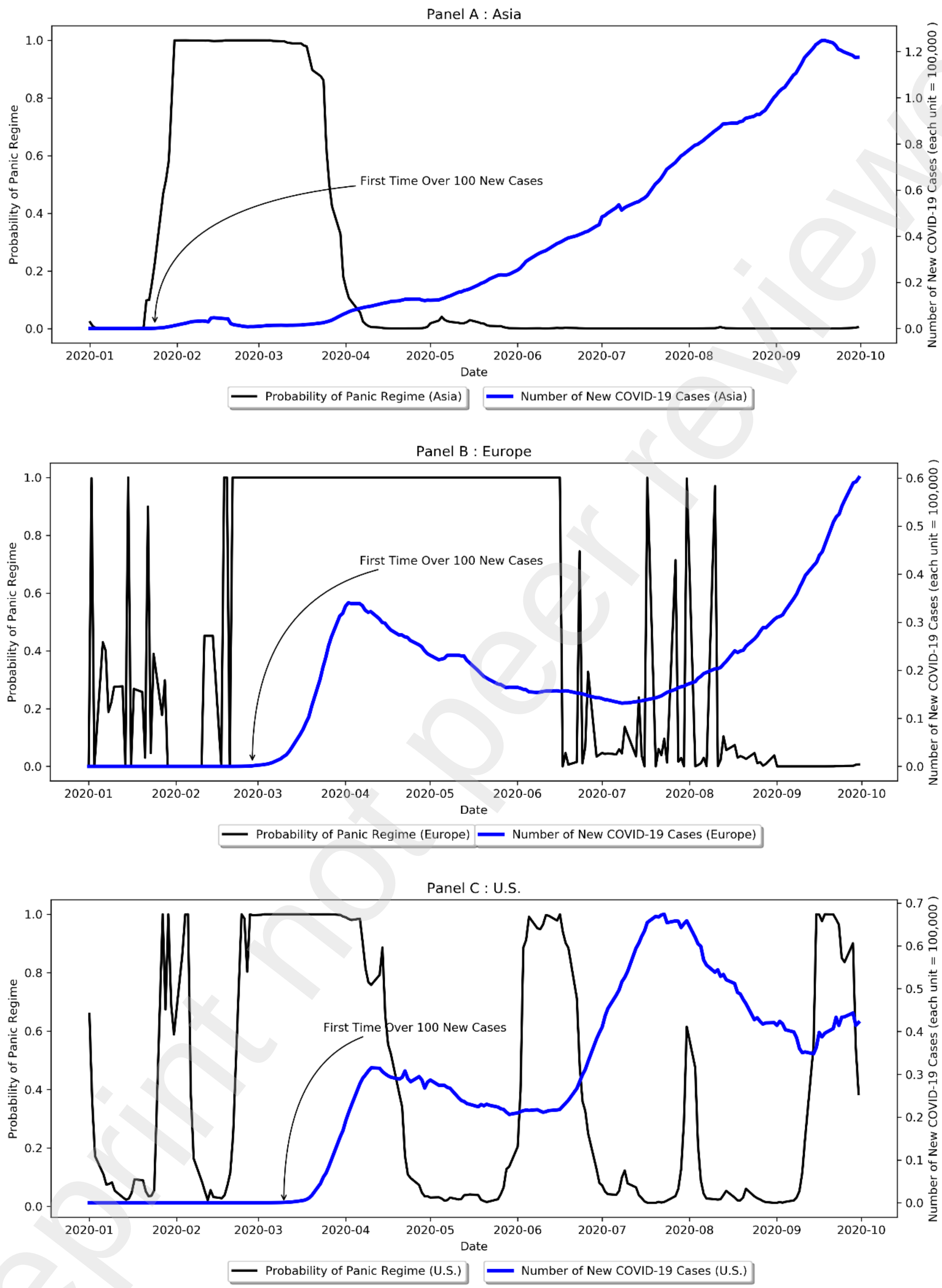

Figure 2. Smoothed probability of Panic Regime for univariate Markov switching models. The flow series considered are the aggregated flow of ETFs with exposure to Asia (panel A), Europe (panel B), and U.S. (panel C). The blue line represents the number of new COVID-19 cases in each geographic location during the period of study. The first time that the number of new infected people in each area surpassed 100 is indicated with an arrow. The sample period is from January 2020 to October 2020.

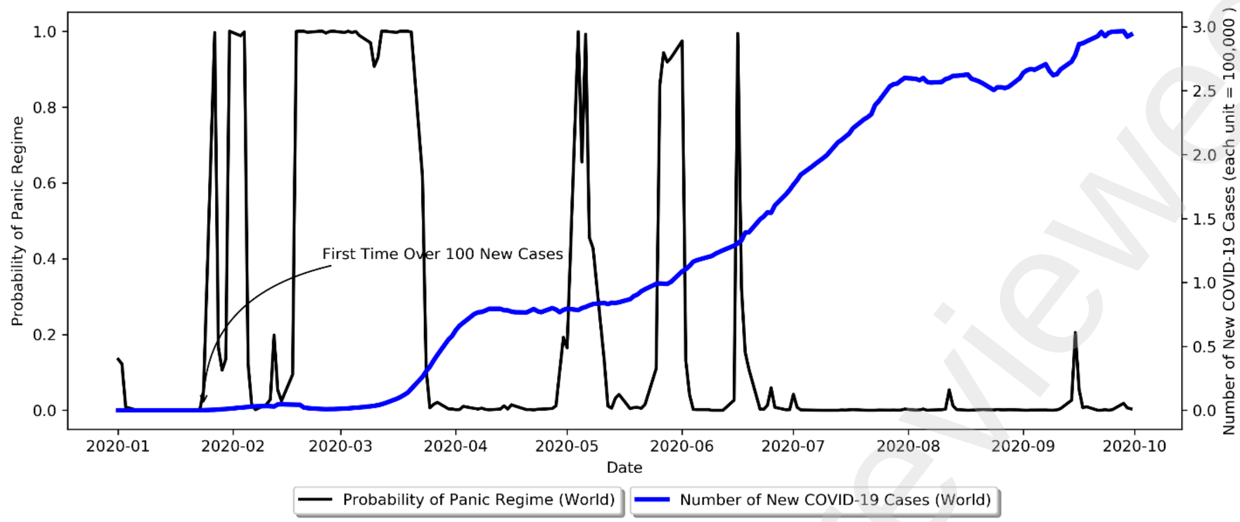

Figure 3. Smoothed probability of Panic Regime for multivariate MSIAH model. The blue line represents the number of new COVID-19 cases in each geographic location during the period of study. The first time that the number of new infected people in each area surpassed 100 is indicated with an arrow. The sample period is from January 2020 to October 2020.

Table 1. Descriptive Statistics. Panel A and B present summary statistics and correlation matrix for aggregated ETF flows with exposure to Asia, Europe, U.S., and rest of the world. The sample period is from January 2020 to October 2020 (196 days).

	Asia	**Europe**	**USA**	**Other**
Panel A: Daily Flow				
mean	-34	-6	1100	339
std	165	157	4000	713
min	-670	-514	-10982	-2745
25%	-102	-67	-955	86
50%	-16	2	1071	443
75%	52	52	3342	743
max	363	835	18719	2006
Panel B: Correlation Matrix				
Asia	1			
Europe	0.24	1		
USA	0.04	0.07	1	
Other	0.16	0.26	0.12	1

Table 2. Performance measures for univariate Markov switching models. For each geographic location, the first column shows the Akaike's Information Criteria (AIC), and the second column represents the Bayesian Information Criteria(BIC). The sample period is from January 2020 to October 2020.

	Asia		***Europe***		***USA***	
	AIC	BIC	AIC	BIC	AIC	BIC
2-State MSIAH	**464**	**497**	474	507	**522**	**555**
3-State MSIAH	486	555	**432**	502	528	598
2-State MSIH	501	528	457	**483**	**526**	**552**
3-State MSIH	518	577	433	492	540	599

Table 3. Parameter estimates for univariate models. This table reports the parameter estimates of the univariate 2-state Markov switching models for the daily flow of ETFs with exposure to Asia, Europe, and U.S. The model choice (MSIAH Vs. MSIH) is based on the lowest AIC and BIC score from Table 2. The general MSIAH model is specified as $y_t = m_{S_t} + b_{S_t} y_{t-1} + e_t$, where y_t refers to a vector of individual location flows, m_{S_t}represents the conditional mean in each state (1 and 2), and s_{S_t}shows the conditional volatility of each state. b_{S_t} denotes the first-order autoregressive term and e_t shows the residuals. The MSIH model is a special form of MSIAH where $b_{S_t} = 0$.Duration shows the respective duration of being in one regime during the period of the study. The sample period is from January 2020 to October 2020. The parentheses contain the standard error. *, **, and ***, respectively, denote significance at the 10%, 5%, and 1% levels.

	Asia	**Europe**	**USA**
Model	2S-MSIAH	2S-MSIH	2S-MSIAH
μ1	0.10* (0.06)	0.18*** (0.04)	-0.03 (0.06)
μ2	-0.72*** (0.26)	-0.17 (0.14)	0.03 (0.15)
β1	0.58*** (0.07)		0.10 (0.10)
β2	0.12 (0.16)		0.29*** (0.11)
σ1	0.40*** (0.04)	0.12*** (0.02)	0.35*** (0.06)
σ2	1.48*** (0.33)	1.80*** (0.26)	1.78*** (0.32)
Duration 1	143.38	9.11	10.33
Duration 2	32.69	2.72	7.68

Table Error! No text of specified style in document.**4.** Parameter estimates for multivariate MSIAH model. This table reports the parameter estimates of the multivariate 2-state Markov switching models for the daily flow of ETFs with exposure to Asia, Europe, U.S., and rest of the world. The model choice(MSIAH) is based on the lowest AIC and BIC score. The MSIAH model is specified as $y_t = m_{S_t} + b_{S_t} y_{t-1} + e_t$, where y_t refers to a matrix of four flow series, m_{S_t} represents a vector of mean flow in each state (1 and 2), and s_{S_t} shows the conditional volatility of each state. b_{S_t} is a 4´4 matrix of autoregressive term in each state and e_t shows the error term. Duration shows the respective duration of being in one regime during the period of the study. The sample period is from January 2020 to October 2020. The parentheses contain the standard error. *, **, and ***, respectively, denote significance at the 10%, 5%, and 1% levels.

	Asia	**Europe**	**USA**	**Other**
μ1	0.12** (0.06)	0.03 (0.06)	0.03 (0.08)	0.19*** (0.06)
μ2	-1.11*** (0.21)	-0.14 (0.21)	0.43* (0.24)	-0.73** (0.30)
β1_Asia	0.38*** (0.07)	0.13* (0.08)	-0.14 (0.09)	0.02 (0.07)
β2_Asia	-0.00 (0.01)	-0.09 (0.13)	0.29*** (0.01)	-0.09 (0.17)
β1_Europe	0.29*** (0.06)	0.57*** (0.07)	-0.04 (0.08)	-0.00 (0.02)
β2_Europe	-0.08 (0.19)	0.42*** (0.16)	0.40* (0.21)	0.42* (0.23)
β1_USA	-0.00 (0.06)	0.03 (0.06)	0.24*** (0.07)	0.07 (0.06)
β2_USA	0.31** (0.16)	0.13 (0.15)	0.14 (0.18)	0.21 (0.19)
β1_Others	0.13* (0.08)	-0.01 (0.08)	-0.04 (0.09)	0.28*** (0.08)
β2_Others	-0.19 (0.15)	0.27** (0.14)	0.03 (0.18)	0.13 (0.18)
σ1	0.35*** (0.04)			
σ2	1.16*** (0.27)			
Duration 1	20.90			
Duration 2	5.44			

Table 5. Relative ETF Flow Distribution Across the U.S., Europe, and Asia. This table represents the statistics of ETFs in each geographic location with exposure to itself and other two locations. *Number of ETFs* shows the number of funds in location i with exposure to location j. *Net Flow* shows the net of inflow and outflow of money in million dollars. *Average Flow Share* is a variable that captures the geographical distribution of fund flow with respect to the total assets under management (AUM) of the home location and is calculated by: $Flow\ Share_{ijt} = \frac{\sum flow\ of\ ETFs\ listed\ in\ location\ i\ with\ exposure\ to\ location\ j\ at\ time\ t}{\sum AUM\ of\ ETFs\ in\ location\ i\ at\ time\ t{-}1}$

	Number of ETFs	Net Flow ($M)	Avg. Flow Share (%)
Asia-Asia	1459	116,111	2.555
Asia-Europe	22	23	0.0018
Asia-U.S.	268	17,522	0.4007
Europe-Asia	214	21,038	0.1507
Europe-Europe	1117	-61,265	-0.0736
Europe- U.S.	503	58,943	0.4297
U.S. -Asia	129	5,422	0.0013
U.S.-Europe	99	667	-0.0151
U.S. - U.S.	1739	910,425	3.1092

Table 6. *Foreign Flow and Home Bias Effect.* This table shows the share of money flow to ETFs with foreign exposure. The dependent variable is $Flow\ Share_{ijt} = \frac{\sum flow\ of\ ETFs\ listed\ in\ location\ i\ with\ exposure\ to\ location\ j\ at\ time\ t}{\sum AUM\ of\ ETFs\ in\ location\ i\ at\ time\ t-1}$. Each column shows an OLS model, except for column 2, which represents a Tobit model.

	(1)	(2) Tobit	(3) Hom&Host FE	(4)
Foreign Flow	-0.017***	-0.005***	-0.017***	-0.016***
COVID-19 Home Country * Foreign Flow	-0.010	-0.012*	-0.011	-0.018**
COVID-19 Host Country * Foreign Flow				-0.044***
Domestic Flow	0.334***	0.343***	0.336***	0.335***
Time FE	Yes	Yes	Yes	Yes
Home and Host FE	No	No	Yes	No
Observations	5670	5670	5670	5670
R-squared	0.341		0.353	0.345
Adjusted R-squared	0.259		0.271	0.263

Table 7. Foreign Flow and Home Bias by Geographic Location. This table shows the share of money flow to ETFs with foreign exposure. The dependent variable is $Flow\ Share_{ijt} = \frac{\sum flow\ of\ ETFs\ listed\ in\ location\ i\ with\ exposure\ to\ location\ j\ at\ time\ t}{\sum AUM\ of\ ETFs\ in\ location\ i\ at\ time\ t-1}$. Each column shows the model for a subset of data, which the column name shows the home location.

	Asia	Europe	US
Foreign Flow	-0.019***	0.004***	-0.031***
COVID-19 Home Country * Foreign Flow	-0.491***	0.012**	-0.035*
COVID-19 Host Country * Foreign Flow	-0.098***	-0.012**	0.019
Domestic Flow			
Time FE	Yes	Yes	Yes
Home and Host FE	No	No	No
Observations	1890	1890	1890
R-squared	0.375	0.406	0.381
Adjusted R-squared	0.062	0.107	0.07