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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 following an emergency like 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 portfolio's allocation 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. 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 locations) and into safer ones during the adverse economic shock.

1. Introduction

U.S. market experienced massive new money inflows into ETFs during the COVID-19 pandemic. Dollar flow into U.S. ETFs surpassed $600 billion in 2020 and set a record in 2021 as it breached the $1 trillion inflow. This huge flow of money increased the U.S. ETFs' total assets under management (AUM) by more than 60% from 2019 ($4.4 trillion) to 2021 ($7.2 trillion). The share of ETFs with different geographic exposure from the new money flow, however, has not been the same. While ETFs with exposure to the U.S. were the biggest recipients of money flow during the COVID-19 pandemic, ETFs with exposure to Europe and Asia experienced a negative daily flow of about $14 million and $22 million, respectively from March to October 2020. That U.S. ETF new money flow increased is clear; however, the distribution mechanism is unclear.

The severity and high level of contagiousness of the COVID-19 pandemic 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 homogenous across the countries, it influenced the variance of the US and Europe's stock markets more than the 2008 financial crisis (Ali, Alam, & Rizvi, 2020). Moreover, the 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.1

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 other countries' capital markets 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). Features like intraday tradability, tax efficiency, low fees, buying on margin or short selling, and transparency have contributed to the ETFs' growth. While Pennathur, Delcour, 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.

If ETFs indeed provide an efficient diversification instrument for investors, then the flow of ETFs should comprise information about the behavior of investors during different episodes of the market. More specifically, during periods of market stress and high volatility, investors behave like fund managers and reduce holding of less liquid assets (Vayanos, 2004), and shed risky assets in favor of safer claims (Caballero & Krishnamurthy, 2008). This phenomenon, which is referred to in the literature as flight to safety or flight to quality, can explain the heterogeneity in asset allocation between ETFs during high-uncertainty periods.

In this study, we seek to test if investors use ETFs as a medium of geographic diversification to rebalance their portfolio exposure in response to concerns about the financial fragility of a specific location. The spread of the COVID-19 pandemic across the world provides an opportunity to conduct such an analysis and investigate investors’ behavior in a major stress event. We employ follow the money 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. 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 information about the conditional joint distribution of assets to maintain dynamic portfolio rebalancing strategies (Chan, Treppongkaruna, 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 an 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. Moreover, ETF flows are reflecting primary market trades that are different from secondary market trades. While return data in the secondary market might be contaminated by the noise induced by residual investors, primary market flows occur only by new money flow or violation of the law of one price. ETF investors may trade based on fundamental reasons and create positive/negative returns, but as long as no new ETF unit is created/redeemed in the primary market it does not necessarily mean a shift in asset allocation has occurred.2 Hence, using flow instead of return results in a cleaner measure of asset allocation and alleviates the emergent concerns regarding the reverse effect of return on flow (Clifford, Fullerton, & Jordan, 2014). Information embedded in the flow of mutual funds (Boney, 2012; Ferriani, 2021), Cross-Border banking flows (Choi & Furerki, 2019), or even individual depositors (Levine, Lin, Tai, & Xie, 2021) following a major event like financial or health crisis has proven to be a robust measure of sentiment. Choi and Furerki (2019) show that country-specific uncertainty shocks alter cross-border banking flows. More recently and consistent with the finding of the present study, Ferriani (2021) documents larger-than-expected negative abnormal flows to mutual funds investing in emerging markets in the aftermath of events like COVID-19. Similarly, Falato, Goldstein, and Hortaçsu (2021) document major outflows in corporate-bond funds during the COVID-19 crisis. For the sake of robustness, we further calculate the average value-weighted return for each location using the return and assets under management (AUM) data. Results in Appendix 1 show that our main findings hold when using return.

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 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.

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 “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. 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 the flight-to-safety 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

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2 For more information about the creation/redemption mechanism and the role of Authorized Participant (AP) in ETF primary market refer to Ben-David, Franzoni, and Moussawi (2018)
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.

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. Moreover, our findings have important implications for policymakers and portfolio managers. Our results indicate that investors use ETFs as a medium of geographic diversification to gain exposure to foreign markets. Exchange-tradability and high liquidity of ETFs enable investors to respond swiftly to geographic threats and switch asset allocations between locations. The fact that the surge in the number of COVID-19 cases in each country is not common across the world suggests that regime switches may be predictable up to an extent and hence, asset allocation strategies may need to involve switching between geographic locations.

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

The behavior of financial markets may change abruptly over time. These changes often persist for many periods, until the market enters another phase. For example, the mean, volatility, and correlation characteris (i.e., mean and variance) for time series, regime-switching models can capture the sudden changes in the behavior of time series and also specify the length of the period that this new price dynamic persists.

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:

\[ y_t = m_{k_t} + b_{k_t} y_{t-1} + e_t \]  

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

For a k-state Markov process, we assume that the state parameter, \( S_t \), is unobservable and follows an irreducible ergodic k-state Markov process with transition matrix

\[ P = \begin{bmatrix} p_{11} & \cdots & p_{1k} \\ \vdots & \ddots & \vdots \\ p_{k1} & \cdots & p_{kk} \end{bmatrix} \]  

(3)

Where \( p_{ij} = \Pr(S_t = j | S_{t-1} = i) \); \( i, j = 1, 2, \ldots, k \).

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

\[ Q_t = \begin{bmatrix} q_{11,t} & q_{12,t} & \cdots & q_{1k,t} \\ q_{21,t} & q_{22,t} & \cdots & q_{2k,t} \\ \vdots & \vdots & \ddots & \vdots \\ q_{k-1,1,t} & q_{k-1,2,t} & \cdots & q_{k-1,k,t} \end{bmatrix} \]  

(4)

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

\[ q_{ij,t} = F(X_{yi,t}, b_{ij}) \]  

(5)

Where \( F \) is the cumulative normal density function, \( X_{yi,t} \) is the state variable vector for cell \((i, j)\), and \( b_{ij} \) is the parameter to be estimated. In our model, we use the 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 \( R_t \):

\[ R_t = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ 1 - q_{11,t} & 1 - q_{12,t} & \cdots & 1 - q_{1k,t} \\ \vdots & \vdots & \ddots & \vdots \\ 1 - q_{k-1,1,t} & 1 - q_{k-1,2,t} & \cdots & 1 - q_{k-1,k,t} \end{bmatrix} \]  

(6)

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

\[ P_t = Q_t R_t \]  

(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 \( \Psi \) is

\[ f(y_t | S_t = j, Y) = \frac{1}{(2\pi)^{\frac{n}{2}} |S_t|} \exp \left( -\frac{1}{2} y_t^T S_t^{-1} e_t \right) \]  

(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:

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

(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 about the probabilities based on the available information.
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 ($b_k = 0$). 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 the U.S. 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 that 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, U.S., and the world. We use the European CDC published daily statistics on the COVID-19 pandemic as the source of our data. 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 on 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 recorded 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.

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. The correlations between pairs of flows are statistically significant for half of the pairwise combinations. In particular, the correlation between non-US flows is more pronounced and significant, while US flow has almost no significant correlation with other regions. Positive correlation between non-US ETFs during the period of this study can be explained by investors’ perception of a higher level of risk in other countries compared with the US.

| Panel A: Descriptive Statistics (USD million) | 2020-01-02 | 2020-12-31 | Yearly Average | Yearly Percentage |
|---------------------------------------------|------------|------------|----------------|------------------|
| Asia                                        | 1,200,000  | 1,300,000  | 1,250,000      | 0.5%             |
| Europe                                      | 1,500,000  | 1,600,000  | 1,550,000      | 1.2%             |
| U.S.                                        | 2,000,000  | 2,100,000  | 2,050,000      | 2.5%             |
| Others                                      | 500,000    | 600,000    | 550,000        | 0.5%             |

Table 1 reports descriptive statistics for aggregated ETF flows with exposure to Asia, Europe, the 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 a net new cash outflow 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. A lower level of AIC/BIC denotes a model with a better fit. 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 (highlighted numbers in Table 2). We further test a four-state model which its results are not reported since the 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. The results of Table 2 are comparable to prior literature that exploit 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 documented a different relationship between oil and financial markets under “stressed” and “normal” regimes. Similarly, Al-Anaswah and Willingham (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 MSIH or 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 one regime and negative in another regime. The positive-flow state (Regime 1) coincides with relatively low volatility, and the negative-flow state (Regime 2) corresponds to

https://ourworldindata.org/coronavirus-source-data
relatively high volatility. We tag the first regime as the normal state when ETF market is growing by receiving dollar inflow and a relatively low daily volatility. Conversely, regime 2 captures panic periods that are characterized by money outflow and relatively higher volatility. Table 3 also reports the expected durations for each regime. Duration represents the relative time period of lingering in one regime. The duration numbers indicate that the normal regime tends to last longer than the panic regime. Despite the simpler MSIH model fit to the 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 safety among ETFs with non-U.S. exposure.

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. Duration represents the relative time period of lingering in one regime. The duration numbers indicate that the normal regime tends to last longer than the panic regime. Despite the simpler MSIH model fit to the 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 safety among ETFs with non-U.S. exposure.

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 later test this hypothesis in the multivariate section.

To 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. Duration represents the relative time period of lingering in one regime. The duration numbers indicate that the normal regime tends to last longer than the panic regime. Despite the simpler MSIH model fit to the 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 safety among ETFs with non-U.S. exposure.

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Table 3
Parameter estimates for univariate models.

|  | Asia | Europe | USA |
|---|------|--------|-----|
| Model | 2S-MSIAH | 2S-MSIAH | 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) |
| ε1 | 0.40*** (0.04) | 0.12*** (0.02) | 0.35*** (0.06) |
| ε2 | 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 |

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 the 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 $y_t = m + b_0 y_{t-1} + e_t$, where $y_t$ refers to a vector of individual location flows, $m_0$ represents the conditional mean in each state (1 and 2), and $e_t$ shows the conditional volatility of each state. $b_0$ denotes the first-order autoregressive term and $e_t$ shows the residuals. The MSIH model is a special form of MSIAH where $b_0 = 0$. 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.

3.2. Financial crisis: a human-to-human transmission of COVID-19 was confirmed by the WHO for the first time that the number of infected people surpasses 100 individuals is in the number of new cases in the U.S. The model choice (MSIAH vs. MSIH) is based on the lowest AIC and BIC score from COVID-19 cases and the flow of ETFs. There is also evidence of panic in the number of new cases in the U.S.

3.2.1. Multivariate model: we 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 the 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 exhibits a homogenous pattern in the conditional flow estimates across four series. Judging from estimated values for duration and $\sigma$ 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. 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; Kauf & 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 a safe haven.

In our sample and evident from the results in Table 4, the relationship between the flow of U.S. ETFs and other geographic locations changes during the panic regime. 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. 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 $p_{2, Asia}$ and $p_{2, Others}$ coefficients show that U.S. investors retransit 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 the findings of Giannetti and Laeven (2012) who 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 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 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.
Fig. 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Parameter estimates for multivariate MSIAH model.

|                | Asia       | Europe     | USA         | Other       |
|----------------|------------|------------|-------------|-------------|
| $\mu_1$        | 0.12** (0.06) | 0.03 (0.06) | 0.03 (0.08) | 0.19*** (0.06) |
| $\mu_2$        | -1.11*** (0.21) | -0.14 (0.21) | 0.43* (0.24) | -0.73** (0.30) |
| $\beta_{1,\text{Asia}}$ | 0.38*** (0.07) | 0.13* (0.08) | -0.14 (0.09) | 0.02 (0.07) |
| $\beta_{2,\text{Asia}}$ | -0.00 (0.01) | -0.09 (0.13) | 0.29*** (0.01) | -0.09 (0.17) |
| $\beta_{1,\text{Europe}}$ | 0.29*** (0.06) | 0.57*** (0.07) | -0.04 (0.08) | -0.00 (0.02) |
| $\beta_{2,\text{Europe}}$ | -0.08 (0.19) | 0.42*** (0.16) | 0.40* (0.21) | 0.42* (0.23) |
| $\beta_{1,\text{USA}}$ | -0.00 (0.06) | 0.03 (0.06) | 0.24*** (0.07) | 0.07 (0.06) |
| $\beta_{2,\text{USA}}$ | 0.31*** (0.16) | 0.13 (0.15) | 0.14 (0.18) | 0.21 (0.19) |
| $\beta_{1,\text{Others}}$ | 0.13* (0.08) | -0.01 (0.08) | -0.04 (0.09) | 0.28*** (0.08) |
| $\beta_{2,\text{Others}}$ | -0.19 (0.15) | 0.27** (0.14) | 0.03 (0.18) | 0.13 (0.18) |
| $\sigma_1$     | 0.35*** (0.04) |                 |              |              |
| $\sigma_2$     | 1.16*** (0.27) |                 |              |              |
| Duration 1      | 20.90      |             |              |              |
| Duration 2      | 5.44       |             |              |              |

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 $y_t = m_0 + b_s y_{t-1} + \epsilon_t$, where $y_t$ refers to a matrix of four flow series, $m_0$ represents a vector of mean flow in each state (1 and 2), and $s_t$ shows the conditional volatility of each state. $b_s$ is a $4 \times 4$ matrix of autoregressive term in each state and $\epsilon_t$ 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 *** denote significance at the 10%, 5%, and 1% levels.

Fig. 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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 toward 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 that 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, and the 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.

In this section, we study whether investors in each geographic location (Asia, Europe, and the 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 the 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 the 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:

\[
Flow_{ij} = \alpha F + \beta F_{t-1} + \gamma X + \epsilon_{ijt}
\]

Where \( F \) 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. \( Y \) is a home bias in investors’ portfolios. The coefficients of interaction terms, \( \beta \) and \( \gamma \), 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, \( X \), 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 a variable that measures the change in the number of new COVID-19 cases in the geographic location where ETF is listed. COVID19 Host Location captures the change in the number of new COVID-19 cases in the geographic location where ETF has exposure to; \( Y_{it} \) is a vector of control variables; and \( \epsilon_{ijt} \) 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 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.

\[
Flow_{ij} = \frac{\sum \text{flow of ETFs listed in location } i \text{ with exposure to location } j \text{ at time } t}{\sum \text{AUM of ETFs in location } i \text{ at time } t - 1}
\]
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 the 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 the 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 the 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 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_{it} * 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 portfolios away from domestic funds to more international funds. The 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_{it} * COVID19 Home 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 portfolios. 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.

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 is using the information embedded in the flow of ETFs to gauge the investors' sentiment during various market conditions.

We employ the general Markov switching model to examine the relationship between the aggregated flow of four groups of US ETFs with exposure to Asia, Europe, the 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 safety 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 quite different asset allocation strategies 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

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**Table 7**

| 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 | | | |

**Flow Share** = \( \sum_{i} \frac{\text{Flow of ETFs listed in location } i \text{ with exposure to location } j \text{ at time } t}{\sum_{i} \text{AUM of ETFs in location } i \text{ at time } t - 1} \)

. Each column shows the model for a subset of data, and the column name shows the home location.
surge in “home bias” investing during 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.

CRediT authorship contribution statement

Hamed Yousefi: Conceptualization, Methodology, Writing – original draft, Investigation, Software, Validation, Data curation. Mohammadm Najand: Conceptualization, Supervision.

Data availability

Data will be made available on request.

Appendix A. Appendix

Table A1

Parameter estimates for univariate and multivariate models using return data

Panel A: Parameter estimates for univariate models using return data

| Parameter estimates for univariate models using return data |
|--------------------------------------------------------|
| Model                                   | Asia  | Europe | USA  |
| 2S-MSIAH                                 | 0.12  | 0.016  | 0.18 |
| μ1                                      | -0.73 | -1.05  | -0.46 |
| μ2                                      | -0.11 | -0.15  | -0.11 |
| μ3                                      | -0.49 | -0.36  | -0.86 |
| σ1                                      | 1.38  | 1.26   | 0.73  |
| σ2                                      | 15.91 | 17.42  | 10.75 |
| Duration 1                              | 66.86 | 44.37  | 65.61 |
| Duration 2                              | 7.49  | 1.95   | 14.48 |

Panel B: Parameter estimates for multivariate models using return data

| Parameter estimates for multivariate models using return data |
|-------------------------------------------------------------|
| Model                                              | Asia  | Europe | USA  | Other |
| 2S-MSIAH                                           | 0.32  | 0.29   | 0.36  | 0.26  |
| μ1                                                  | -1.31 | -0.83  | -0.68 | -0.62 |
| μ2                                                  | 0.20  | 0.21   | 0.26  | 0.09  |
| μ3                                                  | 0.29  | 0.34   | 0.22  | 0.31  |
| μ4                                                  | -0.67 | -0.85  | -0.77 | -0.66 |
| μ5                                                  | -0.89 | -0.97  | -0.90 | -0.78 |
| μ6                                                  | 0.10  | 0.30   | 0.44  | 0.11  |
| μ7                                                  | 0.87  | 0.91   | 0.89  | 0.69  |
| μ8                                                  | 1.62  | 1.81   | 1.15  | 1.61  |
| σ1                                                  | 1.45  | 1.48   | 0.44  | 0.11  |
| σ2                                                  | 3.48  | 0.54   | 0.44  | 0.11  |
| Duration 1                                          | 4.68  |        |       |       |
| Duration 2                                          | 1.25  |        |       |       |

This table reports the parameter estimates of the univariate and multivariate 2-state Markov switching models for the daily return of ETFs with exposure to Asia, Europe, and the U.S. The return is calculated based on the value(AUM) weighted average return of all ETFs in each group. The model choice (MSIAH) is based on the lowest AIC and BIC score. 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 return, $m_{S_t}$ represents the conditional mean in each state (1 and 2), and $b_{S_t}$ shows the conditional volatility of each state. $b_{S_t}$ denotes the first-order autoregressive term and $e_t$ shows the residuals. 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.

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