Zeros in International Portfolio Choice

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Abstract

This article examines country shares of zero in international portfolio choice using data from 1592 equity mutual funds. The study presents stylized facts about these zeros, such as their prevalence, persistence, and factors influencing their occurrence. Then, I present a general equilibrium model of international portfolio, which incorporates those new facts. The model solves an optimal portfolio equation that I estimate using the data. To do so, I estimate a present discount value of expected equity returns that are exogenous to global changes in equity demand. The estimated model provides realistic estimates of risk aversion (4.8) and matches 94% of zeros in the data. Omitting the zeros underestimates the magnitude and the persistence of country shares to shocks in the expected excess return innovation.

JEL Codes: F30, F40, G11, C24

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Introduction

Over the last 20 years, world external assets as a ratio of world GDP went from 60% to more than 200%, (Lane and Milesi-Ferretti, 2018). In the same time, the importance of mutual funds in foreign equity holdings has sharply increased. In the United States, equity mutual funds account for more than 50% of all US foreign equity holdings in 2021.[2] The growing importance of equity mutual funds and the recent availability of data on mutual funds' portfolio choice have sparkled a growing literature on international portfolio choice.[3] Equity inflows and outflows, which are a result of reallocation of international equity portfolios, are volatile and could lead to distortions for the real economy, specially for emerging economies in the face of sudden stops (Mendoza, 2010; Bianchi and Mendoza, 2020; Eichengreen and Gupta, 2016). Moreover, given the growing magnitude of world external assets, misestimation of capital flows, triggered by movements in portfolios, can produce large differences with actual flows. As a result, understanding international portfolio choice is particularly determinant for emerging economies trying to stabilize their equity funding.

A particular feature present in data on international portfolio choice is the substantial share of country shares of zero. The literature has studied zeros in domestic portfolio choice (Koijen and Yogo, 2019; Falkenstein, 1996), but not in international portfolio choice. An exception is Giglio et al. (2021), which considers the zeros in an international portfolio regression, but does not describe the zeros nor what we can learn from them. There is a need in the literature for a guide about those zeros. For instance, Raddatz and Schmukler (2012) p. 368 writes "It is not obvious if these zeroes should be included or not because some cases may correspond to countries that are out of the scope of investment of a fund for reasons we do not observe."

The ambition of this paper is to document country shares of zero in international portfolio choice and discuss their economic importance with a general equilibrium model and regression analysis. We will see that ignoring the zeros leads to an underestimation of the magnitude and the persistence of the portfolio response to a shock in the expected excess return innovation.

[2]See exhibit 19 in "U.S. Portfolio Holdings of Foreign Securities," October 2022, Department of the Treasury. https://ticdata.treasury.gov/resource-center/data-chart-center/tic/Documents/shc2021_fullreport.pdf.

[3]See for instance, Bacchetta et al. (2023), Camanho et al. (2022), Raddatz and Schmukler (2012).

I start by providing stylized facts about country shares of zero using 20 years of Emerging Portfolio Fund Research (EPFR) data recording the portfolio allocation of 1592 international equity mutual funds across 113 developed and developing countries. I identify country shares of zero by defining the investment universe of a fund (Koijen and Yogo, 2019). I use four different time-varying investment universes and one fixed investment universe. The investment universe is fund specific and consists of the countries a fund considers in its investment strategy. When I identify the investment universe based on all countries in which the fund has invested a strictly positive share in the last 24-months, I find the following five stylized facts. *Stylized fact 1*: Country shares of zero represent 20% of all observations. *Stylized fact 2*: On average, zeros persist for 12 months. *Stylized fact 3*: 95% (80%) [55%] of the strictly positive shares that drop to zero are lower than 4% (2%) [1%]. *Stylized fact 4*: Controlling for the funds' type, the number of periods and the size of the investment universe, the only fund characteristic that increases the fraction of reported country shares of zero is the fund activeness. The more active a fund is, the higher the reported fraction of country shares of zero. *Stylized fact 5*: The market value, the volatility of the equity market and the liquidity of the equity market explain more than 90% of the variation in the fraction of zeros at the country level. Funds are more likely to report country shares of zero in countries that are financially small, have an illiquid equity market and have volatile equity returns.

Then, I incorporate those stylized facts in a general equilibrium macroeconomic model with an international portfolio choice block. A natural starting point is the model of Bacchetta et al. (2022a) which solves a macroeconomic model with frictions in international portfolios. I extend their model by adding a non-negativity constraint and the role of a transaction cost. The model has two countries: Home and Foreign. There is a representative firm in each country that produces a final good using capital and labor. Each country is populated with a representative consumer and heterogeneous investors. Consumers provide labor to the firms, receive a fraction of the final good which they consume. Investors differ in their level of risk aversion, cost to adjust their portfolio from the past portfolio and the variance of their portfolio return. Investors choose consumption and portfolio shares to maximize Rince preference. With Rince preference, consumption is a constant fraction of financial wealth and the investors maximize their wealth by maximizing portfolio return. The investors invest in the firms' capital. The optimal portfolio share depends on the average country share, the past share and the present discounted value of expected excess returns. The average country share depends on the average variance-covariance of equity returns and on the transaction cost. The higher the volatility in the foreign country, the higher the share allocated in the home country. The higher the transaction cost in the home country, the lower the share in the home country. The present discounted value of expected future excess return corresponds to the expected return an investor makes in the Home country in excess of the return made in the Foreign country. The non-negativity constraint starts binding when investors expect negative excess return. The non-negativity constraint binds for several periods because of the gradual portfolio adjustment. Gabaix and Maggiori (2015) also provides a model of imperfect asset intermediation which generates frictions in international finance. In the Handbook of International Economics (chapter 5), Maggiori (2022) reviews the recent literature on international macroeconomic with imperfect financial markets.[4]

Finally, I show the best model to explain the zeros features gradual portfolio adjustment and the present discounted value of expected excess returns. To estimate the portfolio regression, I predict equity returns using variables that are exogenous to a global shift in portfolios. The standard explanatory variables to predict future equity returns are the dividend-price ratio, earning-price ratio and the current equity return.[5] Even though each mutual fund in my sample is small, the average fund is representative of financial intermediaries. Following a negative country-month financial shock, all financial intermediaries would reduce the portfolio shares allocated to this country. Following this common reallocation, the equity price of this

[4]Gradual portfolio adjustment can also explain various puzzles and facts. See for instance the works of Philippe Bacchetta and Eric van Wincoop: (Bacchetta et al., 2022a; Bacchetta and van Wincoop, 2021; Bacchetta and van Wincoop, 2010; Bacchetta et al., 2022b). Costly deviations from the past shares are micro-founded. Bilias et al. (2010), Brunnermeier and Nagel (2008), Mitchell et al. (2006)), among others, use data on portfolio allocation by individual households and find strong evidence of inertia. In the same spirit, Giglio et al. (2021) use survey data. In this micro literature, past portfolio is a key determinant of portfolio shares.

[5]See for instance Campbell et al. (1997); Hjalmarsson (2010).

country drops. When equity price is used to predict the expected excess returns, the error term of the portfolio regression is negatively correlated with the portfolio, which bias downwards the coefficient of the expected excess return. Gabaix and Koijen (2021) shows that financial shocks are very persistent. Hence, contemporaneous portfolio respond to past equity return and equity prices. Therefore, I use variables that are exogenous to shift in portfolio demand to predict the equity returns. Then, I regress the discounted sum of expected excess return on the difference in the log dividends and log earnings. Because current equity demand shocks do not impact the dividends or the earnings, my measure of expected excess return is exogenous to portfolio shocks. I find predictability at various horizons. The longer the horizon, the more the predictability. I show this predictability is profitable by building a trading strategy. Then, I estimate the portfolio equation with the two-limit random effect Tobit of Loudermilk (2007). For the investment universe consisting of all countries in which the fund has invested a strictly positive shares over the last 24-months, only the portfolio regression featuring gradual portfolio adjustment estimated with Tobit gives a realistic value of risk aversion, 4.8, matches 94% of the country shares of zero present in the data and has the lowest root mean squared errors compared to various models including OLS. OLS underestimates the persistence and the response to expected excess return. I obtain the structural parameters (risk aversion and cost to deviate from the past shares) using the regression coefficients. OLS underestimates the impulse response of portfolio shares to a one standard deviation in the expected excess return by 0.3 percentage points. This impulse response varies across the different characteristics of the mutual funds. Active, regional and more exposed funds react more to the financial shock. Only the model including the non-negative constraint and the gradual portfolio adjustment estimates a reasonable risk aversion, matches the zeros in the data and has the lowest root mean squared errors.

Contribution This paper contributes to our understanding of international portfolio choice by (i) providing stylized facts about zeros in international portfolio choice, (ii) incorporating those facts in a general equilibrium, (iii) predicting a measure of expected excess return exogenous to shifts in portfolios, (iv) estimating the bias from using OLS in a portfolio regression, (v) showing portfolio regressions by funds' heterogeneity and (vi) discussing what model is best to explain the zeroes in the data.

Structure Section 1 provides descriptive statistics and stylized facts about the country shares of zero. Section 2 presents the general equilibrium model of international portfolio choice incorporating the stylized facts with gradual portfolio adjustment. This model solves an optimal portfolio equation. Section 3 estimates the portfolio equation and uses the portfolio regression results to explain country shares of zero present in the data. Section 4 provides broader implications of the results for policy making and future research. Finally, section 5 concludes. The remaining introduction contains the literature review.

Closest Literature

To my knowledge the closest papers to this article are Bacchetta et al. (2023), Bacchetta et al. (2022a), Giglio et al. (2021), Koijen and Yogo (2019), Falkenstein (1996), and Raddatz and Schmukler (2012).

Using EPFR data on equity mutual funds, Bacchetta et al. (2023) establishes the importance of frictions in international portfolio choice and lays down the foundation of a general equilibrium model that reconciles predictions from models of portfolio choice with asset pricing puzzles. Bacchetta et al. (2023) motivates their empirical analysis with a partial equilibrium model in which funds face costly deviation from two benchmark portfolios: the past portfolio and from the buy-and-hold. This buy-and-hold portfolio represents the passive portfolio, which changes with market valuation. Their optimal country share is a linear expression featuring the past share, the valuation effect (return of a county minus the portfolio return) and the expected excess return. Because their valuation effect term approaches zeros with small shares and would have had a zero coefficient in their regressions when small shares had been kept, the authors drop the observations in which the average country shares is lower than 2% and country shares of zero. Bacchetta et al. (2022a) builds on their result and solves a general equilibrium model of international portfolio with portfolio frictions to show those frictions can reconcile predictions from models of portfolio choice with asset pricing facts. This paper adds the non-negativity constraint and the transaction cost to their model. Stylized fact 3 reveals 80% of the strictly positive shares that drop to zero in the next month are lower than 2%.

Using data on the portfolio choice of Vanguard investors, Giglio et al. (2021) regresses the portfolio choice on a measure of expected returns they obtained with survey data. Giglio et al. (2021) only mentions country shares of zero once at page 1493 "Since most Vanguard investors find it hard to short-sell or obtain leverage, the equity share is essentially censored at both 0 percent and 100 percent. We thus estimate [our] regression using Tobit models." The authors find a significant role of expected excess returns for portfolio choice. While Giglio et al. (2021) takes the zeros into account, it does not provide descriptive statistics about the zeros and does not discuss the role of portfolio frictions to explain the zeros, which I do.

Koijen and Yogo (2019) builds a global asset demand for domestic portfolio choice with a short-selling constraint. However, Koijen and Yogo (2019) does not model portfolio frictions and does not provide descriptive statistics about the zeros. I build on the authors discussion on how to identify country shares of zero with the investment universe.

Using Morningstar data on portfolio choice, Falkenstein (1996) regresses the portfolio shares on various stock characteristics with censored least absolute deviations and Tobit. While Falkenstein (1996) provides descriptive statistics on the country shares of zero, it studies domestic portfolio choice and not international portfolio choice. The study finds zero holdings represents 17 percent of the observations. Moreover, Falkenstein (1996) does not link the portfolio to past portfolio and expected excess return but on current stock characteristics.

Using EPFR data, Raddatz and Schmukler (2012) regresses the (log) portfolio shares on the (log) past shares and the contemporaneous excess return. The authors write at page 368 "The log transformation [...] discards the information contained in the zero weight countries. It is not obvious if these zeroes should be included or not because some cases may correspond to countries that are out of the scope of investment of a fund for reasons we do not observe (prospectus or underlying unobserved benchmark)." Raddatz and Schmukler (2012) then regresses the portfolio shares in level on the buy-and-hold portfolio and contemporaneous excess returns to include the zeros. The authors do not provide descriptive statistics about the zeros and do not discuss the implications of those zeros. Recent articles also use EPFR data and focus on the strictly positive shares (Cenedese and Elard, 2021; Raddatz et al., 2017).

1 Data on International Portfolio Choice

I start this paper by providing stylized facts about the zeros in international portfolio choice using a detailed monthly panel data on international equity mutual funds reporting to EPFR (Emerging Portfolio Fund Research). Each month the funds report non-negative country allocations for a total of 135 developed and developing countries and cash. Funds also report their assets under management and their type (Global, Latin America, Asia, etc). The EPFR data covers a large amount of mutual funds and is representative of all mutual funds.[6] I focus on EPFR mutual funds for two additional reasons. First, mutual funds hold well diversified international portfolios. Second, the countries in which they invest is given by the fund manager, which means funds do not simultaneously choose the portfolio shares and the composition of the investment universe.

1.1 Reporting of Country Shares

Each month, funds report to EPFR the share of their assets under management allocated across the countries in which the fund invests. For a specific country-month pair, a fund can either report a strictly positive share, a country share of zero or leave the cell empty. Eventually, EPFR compiles the country allocation data for all funds. The data contains strictly positive shares, zeros and missing observations.

Imagine a fund invests only in Thailand and in India. This fund could report strictly

[6]Bacchetta et al. (2023) show that the correlation between the aggregate country allocation of US mutual funds reporting in EPFR and the aggregate country allocation of all US investors is equal to 88%.(Jotikasthira et al., 2012) and Miao and Pant show that country flows vary closely with aggregate measures. Fratzscher (2012) writes "EPFR data [...] is the most comprehensive one of international capital flows, in particular at high frequencies and in terms of its geographic coverage at the fund level."

positive shares and country shares of zero for Thailand and strictly positive shares and missing observations for India. Moreover, this fund could also report shares of zero in Peru but do not report for Colombia (leaving the cells empty). In the data, the shares reported to Colombia are missing. In this particular example, the country shares of zero reported for Thailand are chosen by the fund. They are optimal. Can we consider the missing observations in India to be country shares of zero optimally chosen by the funds but reported as missing observations? Are the zeros reported to Peru relevant? The general question is the following: Which reported country shares of zero or reported missing observations should be treated as an optimal investment chosen by the fund? The identification of the investment universe is key to answer this question.

1.2 Investment Universe

The investment universe corresponds to the countries the funds consider in its investment strategy. In theory, mutual funds could optimize the investment universe and the optimal portfolio choice simultaneously. However, the mutual funds I observe take the investment universe as given. Their type is decided by the fund manager who may own several funds differing in their investment universe to segment the asset intermediation market.[7] Hence, the investment universe is exogenous at the fund level. Given the investment universe, the funds choose the optimal portfolio. The resulting portfolio consists of strictly positive country shares summing to one (across countries) and country shares of zero.

I build my results around 5 distinct investment universes: 4 different time-varying investment universes and one fixed investment universe. The fixed investment universe considers all countries in which the fund has invested over its lifetime. The 4 time-varying investment

[7] Lease et al. (1976) find strong evidence of market fragmentation. It suggests that mutual funds' managers have much to gain by segment the market with funds appealing to various classes of customers. Massa (1998) models the endogeneity between the market segmentation and the fund proliferation in the mutual fund industry. He argues that these phenomena can be seen as marketing strategies used by the managing companies to exploit investors' heterogeneity. For instance, a manager may own a fund specialized in Latin America and a fund specialized in Asia.

universe consider the countries the fund has invested in the last 3-months, 12-months, 24-months and 36-months. I emphasize that all country shares of zero reported in one those different investment universes are considered optimal. While most mutual funds, insurance companies, pension funds and hedge funds have a fixed investment universe (Sharpe, 1981; Van Binsbergen et al., 2008; Blake et al., 2013), Koijen and Yogo (2019) uses a time-varying investment universe consisting of all the stocks in which a fund has invested in over the last 11 quarters. Using a time-varying investment universe is robust to fixed investment universe. Mutual funds also report their investment universe in their factsheet. Factsheets are public and contain information about the fund. For instance, the Barings Asia Growth Fund writes in their factsheet at page 1 "The benchmark is MSCI All Country Asia ex Japan (Total Net Return) Index. Previously MSCI All Country Far East ex Japan (Total Gross Return) Index until August 1, 2010, followed by MSCI All Country Asia ex Japan (Total Gross Return) Index until December 31, 2019."

1.3 Data Cleaning

I keep as many observations as possible for the descriptive statistics. My sample consists of 1592 international equity mutual funds, reporting their country shares across 113 countries from January 1996 to July 2016. I only drop those funds which have less than 5 millions USD in assets under management at the end of the sample and those funds which were reporting for less than 12 months to avoid backfill bias (Elton and Gruber, 2013).

In Section 3, I combine the EPFR data with the total return index provided by MSCI. The sample used in Section 3 is based on 72 countries (out of the 113). Those 72 countries represent more than 95% of equity holdings. Table F.1 in the Appendix lists the 113 countries and provides descriptive statistics for each country. It also reports in bold the 72 countries for which I have both EPFR and MSCI data.

1.4 Predicting Exogenous Excess Equity Return

In the next sections, I link the portfolio share to various factors amid a measure of expected equity return. The measure of expected equity return is determinant to explain country shares of zero in the model of Section 2 and in the regression results in Section 3. Negative expected equity return is the driving force that leads funds to disinvest in a country. A negative enough expected return pushes the optimal country share to zero. Bacchetta et al. (2023) shows frictions in international portfolio leads funds to consider the present discounted value of expected excess returns instead of the next period expected equity return as they cannot freely update their portfolio each period. In the data, we do not observe the fund specific country return or the fund expected excess return. Nevertheless, we can build an expected excess return for each fund combining public information and the funds' portfolio shares.

1.4.1 Methodology

The econometrician can first predict the discounted sum of excess return of country n relative to the return of a reference country (e.g. the US or the world return), where the equity return comes from the total return index compiled by MSCI. Equation (1) represents the discounted sum of excess return of country n.

$$er^{\delta}_{n,t,t+K} = \sum_{s=1}^{K} \delta^{s-1} \left[E_t(R_{n,t+s} - R^B_{t+s}) \right] \tag{1}$$

with δ is the time discount rate, E_t is the expectation operator, $R_{n,t+s}$ is the return in country n in period $t+s$, R^B_{t+s} is the return in the reference country. While in theory the sum goes to infinity, in practice the sum is necessarily finite. Here the econometrician considers an horizon of K periods.

Then, the econometrician can regress the discounted sum of excess return on some predictors to obtain the fitted values, i.e., the expected discounted sum of excess return. The econometrician runs a recursive regression using only the information available up to t to predict the excess return from t to $t+K$.

$$er^{\delta}_{n,t,t+K} = \alpha(t)_n + \beta(t)' X_{n,t} + \eta_{n,t} \tag{2}$$

where $\alpha(t)_n$ is a country fixed effect, $X_{n,t}$ is a set of explanatory variables and $\eta_{n,t}$ is the residual. $\beta(t)$ is the time-dependent vector of coefficients. Let $\hat{er}^{\delta}_{n,t,t+K}$ denote the fitted value obtained with (2).

Finally, the econometrician can construct the fund expected excess return for each fund using the funds' country shares $z_{i,n,t}$, where i denotes the fund. Equation (3) represents the discounted sum of the expected excess return made in country n by fund i.

$$E_t er^{\delta}_{i,n,t,t+K} \equiv \sum_{s=1}^{\infty}(\delta)^{s-1}\Big[E_t er_{i,n,t+s}\Big] = \hat{er}^{\delta}_{n,t,t+K} - \sum_{m\neq n} z_{i,m,-n,t-1}\hat{er}^{\delta}_{m,t,t+K} \tag{3}$$

Heterogeneity in the fund expected excess return comes from the portfolio shares. The portfolio share $z_{i,m,-n,t-1}$ represents the lag share invested in country m out of country n with $\sum_{m\neq n} z_{i,m,-n,t-1} = 1$. If there were two countries the present discounted value of expected return would be $E_t er^{\delta}_{i,1,t,t+K} = \hat{er}^{\delta}_{1,t,t+K} - \hat{er}^{\delta}_{2,t,t+K}$.

1.4.2 Predictors

Campbell et al. (1997) and Hjalmarsson (2010) regress future equity return in level on current equity return (momentum), dividend-price and earning-price. Bacchetta et al. (2023) predict future equity equity return in excess of the US on current equity return differential, dividend-price differential and equity-price differential. Those authors find profitable predictability using those explanatory variables.

However, anticipating the regression of portfolio shares on expected excess returns, I cannot use the aforementioned predictors as the resulting expected excess return is endogenous with portfolio. That is, there is endogeneity between equity demand, $z_{i,n,t}$ and the equity price present in the predictors of country returns. Even though investors are small, common reallocation following a global demand shock can affect equity prices and thus affect the predictors: current equity return, dividend-price and earning-price.

Therefore, I predict the expected excess returns with variables that are exogenous to demand shocks. I use a parsimonious set of exogenous data provided by MSCI to keep as many countries as possible: the growth rate in dividends from $t-24$ to t, $\Delta d_{i,n,t}$, and in earnings, $\Delta e_{i,n,t}$. I take those variables in differential of the US. Appendix B describes the source of the data. Contemporaneous global shifts in equity demand have no impact on those quantities. Therefore, the predicted equity return is exogenous. This results in a sample of 72 countries in which MSCI provides data and in which the EPFR funds invest. Equivalently, Bacchetta et al. (2023) uses 2SLS to instrument their expected excess return based on momentum, dividend-price and earning price with macroeconomic variables. They show their instruments are exogenous and relevant. Because I want to include all 72 countries for which MSCI provides data and because monthly macroeconomics data are not available for all those 72 countries, I do not use an instrument variable approach.

Table 1 shows the pooled predictability regression for the horizon t+1, t+12, t+24 and t+60. I include a country fixed effect as in (2). In the portfolio regression, I use the expected excess return based on recursive regressions. I cluster standard errors by month following Petersen (2008).

Table 1: *Expected Equity Return*

	(1) $er_{n,t,t+1}$	(2) $er^{0.9}_{n,t,t+12}$	(3) $er^{0.9}_{n,t,t+24}$	(4) $er^{0.9}_{n,t,t+60}$
$\Delta e_{n,t}$	0.002	0.010**	0.014***	0.016***
	(0.002)	(0.004)	(0.004)	(0.005)
$\Delta d_{n,t}$	0.003	0.022***	0.025***	0.016***
	(0.002)	(0.005)	(0.005)	(0.006)
Observations	18117	18117	18117	16121
Adjusted R^2	0.003	0.054	0.073	0.082

Clustered standard errors by months in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions with 72 countries over the interval 1970:01-2019:02. All regressions include a country fixed effect.

Table 1 shows those exogenous financial variables are statistically significant predictors of equity excess returns. The adjusted R^2 increases with the horizon. It is equal to 0.3% in column (1) and is equal to 7% in column (3) and goes to 8% in column (4). However the horizon of 60 months reduces the sample size. I use as benchmark an horizon of 24 months.

In Appendix G, I build a trading strategy for the 1-month ahead equity return based on those predictors to estimate whether this predictability is profitable by following the literature (Cenedese et al., 2015). For each month, I sort the 72 countries based on their values $\Delta_1 d_{n,t}$ and $\Delta_1 e_{n,t}$. The one fifth of countries whose predictors have the lowest value are allocated to the first quintile Q1, the next fifth to the second quintile Q2, and so on. Thus, Q1 should contain low excess returns and Q5 high excess returns. For each month, the trading strategy consists of going long on those countries in which their $\Delta_1 d_{n,t}$ and $\Delta_1 e_{n,t}$ are at the same time in the fifth quintile. I refer to this trading strategy as "top". I compare this trading strategy to the one of going long on those countries in which their $\Delta_1 d_{n,t}$ and $\Delta_1 e_{n,t}$ are at the same time in the first quintile. I refer to this trading strategy as "bottom". I also compare to the average value of the 1-month ahead equity return. The sample is January 1996 to February 2019 for the 72 countries. Table G.1 reports the average annualized equity return one could obtain by following the top, bottom or mean trading strategy. The table shows that the return obtained by following the top strategy is higher by 4 p.p. and 1.2 p.p. in comparison to the bottom and the mean strategy, respectively. These results therefore demonstrate the economic significance of equity return predictability, which justifies that time-varying expected excess returns are taken into account in actual portfolio allocations.

1.5 Data Description

I now describe the data and offer new facts for international portfolio choice. What is the distribution of country shares of zero? Are they persistent? What is the level of a strictly positive country share, whose past or future country share is zero? What fund characteristics increase the likelihood of not investing in a country? What country characteristics are associated with funds investing a zero? I answer those questions for each investment universe. But first, I provide descriptive statistics about the EPFR funds.

1.5.1 Mutual Funds

Table 2 shows some characteristics of those EPFR equity mutual funds. Panel A considers the whole sample. Panel B splits the characteristics by the fund's type. Column (1) counts the number of funds for each funds' type. Column (2) reports the average size of the investment universe. Column (3) reports the average number of months in which the funds report. Columns (4) and (5) show respectively the average assets under management (USD millions) and the average level of activeness. I measure activeness by a measure of portfolio volatility defined as $V_i = \frac{100}{T_i} \sum_t \sum_n |z_{i,n,t} - z_{i,n,t-1}|$, where $z_{i,n,t}$ is the portfolio share invested by fund i, in country n at month t. The numbers in parenthesis represent standard errors.

Table 2 shows that most of the fund are global. The remaining funds mostly specialize in Europe, Asia (excluding Japan) and in Latin America. The average non-global fund invests in less than 12 countries while the average global fund invests in more than 19 countries. Funds with a type "Emerging Europe" reports to EPFR for a longer period. The funds reporting the least are the "frontier" and "Europe" funds. The global funds are the largest in terms of assets under management and the "Emerging Europe, Middle East and Africa" are the smallest. Funds investing in Asia, Middle East, Africa and Emerging Europe and in Frontier countries have the highest level of activeness.

1.5.2 Distribution of zeros

For each investment universe u, let $N0_i^u$ count the total number of country shares of zero the fund i reports across countries and months. Let N_i^u count the total number of country shares of fund i across countries countries and month. Then, the fraction (in percent) of country shares of zero at the fund level is denoted by

$$S0_i^u = 100 \times \frac{N0_i^u}{N_i^u}. \tag{4}$$

Figure 1a shows the average distribution of $S0_i$ for all investment universes. It shows that the fraction of country shares of zero varies with the investment universe. For instance, the average fund reports a bit less than 5% of country shares of zero with the 3-months investment

Table 2: *Statistics*

	(1) Number of Funds	(2) Number of Countries	(3) Number of Months	(4) Assets Under Management	(5) Activeness
A. Whole Sample					
	1592	13.7	67.3	913.1	7.0
		(0.2)	(1.4)	(108.7)	(0.1)
B. By Type					
Asia Ex-Japan	253	9.1	81.0	396.9	8.2
		(0.1)	(4.2)	(58.4)	(0.2)
BRIC	24	4.7	69.1	548.9	5.0
		(0.1)	(6.7)	(149.8)	(0.3)
Emerging Europe,	55	7.5	57.5	108.2	8.4
Middle East and Africa		(0.2)	(5.5)	(22.4)	(0.4)
Emerging Europe	98	6.6	101.9	197.1	7.4
		(0.2)	(6.6)	(26.9)	(0.3)
Europe	375	11.5	48.1	740.4	6.0
		(0.2)	(1.7)	(66.6)	(0.2)
Frontier	14	18.1	18.2	330.1	8.8
		(1.8)	(0.7)	(102.2)	(0.9)
Global Emerging	253	19.2	84.4	956.5	8.6
		(0.3)	(4.2)	(221.6)	(0.2)
Global	380	21.1	51.8	1969.1	6.3
		(0.5)	(2.1)	(418.3)	(0.2)
Latin America	95	5.7	87.5	237.6	5.9
		(0.1)	(6.4)	(41.3)	(0.2)
Pacific	49	9.0	84.1	413.4	6.1
		(0.4)	(7.9)	(120.5)	(0.4)

Table 2 shows some characteristics of the EPFR equity mutual funds. Panel A considers the whole sample. Panel B splits the characteristics by the fund's type. Column (1) counts the number of funds for each funds' type. Column (2) reports the average size of the investment universe. Column (3) reports the average number of months in which the funds report. Columns (4) and (5) show the average assets under management (USD millions) and the average level of activeness, respectively. I measure activeness by a measure of portfolio volatility defined as $V_i = \frac{100}{T_i}\sum_t \sum_n |z_{i,n,t} - z_{i,n,t-1}|$, where $z_{i,n,t}$ is the portfolio share invested by fund i, in country n at month t. Standard errors are in parenthesis.

Figure 1: *Fraction Country Shares of Zero*

(a) *Average distribution* (b) *Persistence*

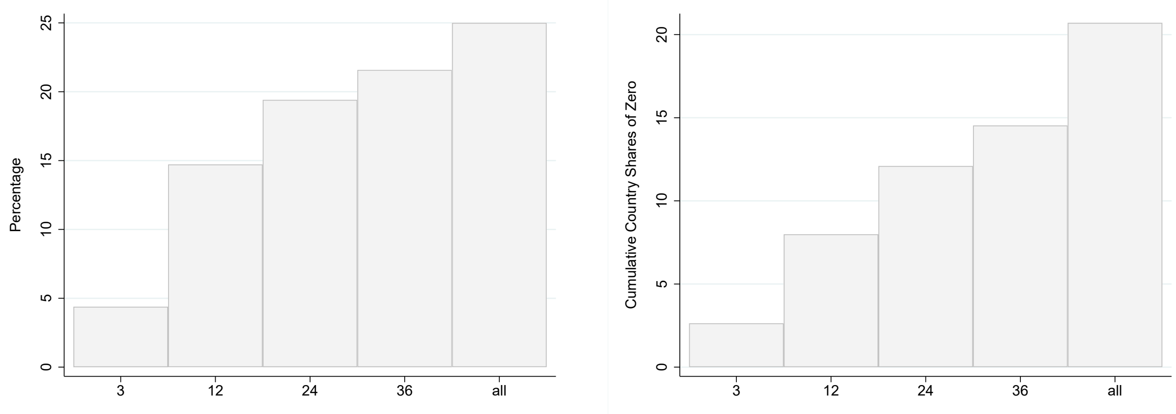


Figure 1a shows the average distribution of $S0_i$ for all investment universes. Figure 1b shows the average length of consecutive country shares of zero for the different investment universes.

universe, while this fraction goes to 21% with the 36-months investment universe. Loosening the investment universe increases the fraction of country shares of zero. For the investment universe consisting of all countries in which the fund has invested in the last 24-months, the average fraction of country shares of zero is 20%.

Stylized Fact 1 *For the investment universe consisting of all countries in which the fund has invested in the last 24-months, country shares of zero represent 20% of the data.*

1.5.3 Persistence of zeros

Figure 1b shows the average length of consecutive country shares of zero for the different investment universes. It measures how persistent are the zeros.

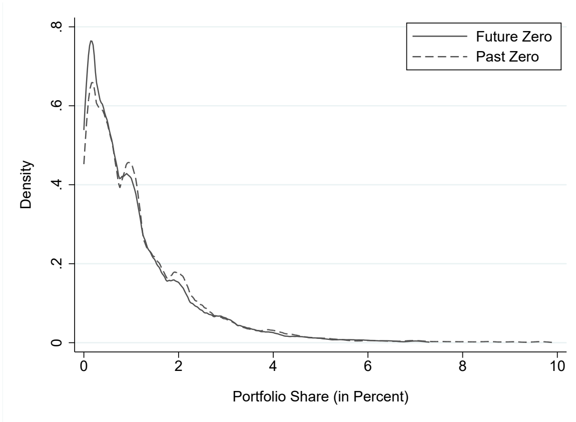
Stylized Fact 2 *For the investment universe consisting of all countries in which the fund has invested in the last 24-months, country shares of zero persist for 12 months, on average.*

Figure 1b shows that the looser the investment universes, the more country shares of zero persist. An average fund reports an average of 2.5 consecutive country shares of zero with the 3-months investment universe, while the average consecutive country shares of zero goes to 15 with the 36-months investment universe.

1.5.4 Country shares of zero before and after strictly positive shares

Figure 2 shows the distribution of those strictly positive country shares when the past country share equals zero or when the future country share equals zero. 95% of the strictly positive country shares that drop to zero are lower than 4%. 80% of the strictly positive country shares that drop to zero are lower than 2%. 55% of the strictly positive country shares that drop to zero are lower than 1%.

Figure 2: *Distribution of* $z_{i,n,t} > 0 | z_{i,n,t+1} = 0$ *or* $z_{i,n,t} > 0 | z_{i,n,t-1} = 0$



Distribution of the current country share when the past country share is equal to zero or when the future country share is equal to zero. I truncate the sample to the bottom 99% of the distribution for both lines.

Stylized Fact 3 *95% of the strictly positive country shares that drop to zero are lower than 4%. 80% of the strictly positive country shares that drop to zero are lower than 2%. 55% of the strictly positive country shares that drop to zero are lower than 1%.*

1.5.5 Country shares of zero and funds' characteristics

What funds' characteristic is associated with a higher fraction of reported country shares of zero. To answer this question, I regress the fraction of country shares of zero each fund reports on the funds' characteristics. The funds' characteristics are the level of activeness V_i, the (log) average assets under management, number of months it reports, number of countries in the investment universe and its type. I estimate equation (5) with Tobit because 52 funds out of the 1592 only report strictly positive country shares, i.e. $S0_i^u = 0$

$$S0_i^u = \max(0, \vartheta_0 + X\vartheta + \epsilon_i), \tag{5}$$

where ϵ is the regression residual and where X is the vector of fund's characteristics described above. ϑ is the vector of coefficients.

Table 3 shows the regression for the different investment universes. Columns (1)-(5) show the results based on the 3-, 12-, 24-, 36- and the all-months investment universe, respectively.

Table 3: *Fraction Zeros and Funds Characteristics*

	(1)	(2)	(3)	(4)	(5)
	3	12	24	36	all
Activeness	70.924***	154.371***	177.457***	184.685***	182.812***
	(2.406)	(6.335)	(7.991)	(8.635)	(8.904)
log AUM	-0.011	-0.009	0.133	0.186	0.141
	(0.045)	(0.122)	(0.156)	(0.171)	(0.180)
Control fund type	Yes	Yes	Yes	Yes	Yes
Control size inv. universe	Yes	Yes	Yes	Yes	Yes
Observations	1592	1592	1592	1592	1592
Pseudo R^2	0.121	0.079	0.072	0.075	0.105

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The constant is included but not shown.

Activeness is statistically significant for all investment universes. The size of the investment universe and the number of months the funds report are significant for most of the investment universes. The benchmark fund has a "Asia excluding-Japan" type. Compared to this benchmark fund, all funds report more country shares of zero. Larger funds do not report more country shares of zero than lower funds. Controls for the size of the investment universe consist of the number of countries and the number of months the funds report.

Stylized Fact 4 *Controlling for the funds' type and the size of the investment universe, funds that are more active report a higher fraction of country shares of zero.*

1.5.6 Country shares of zero and countries' characteristics

Finally, I provide evidence on what country characteristics explain the variation in the fraction of zeros at the country level. In this exercise, I focus on the investment universe consisting of all the countries in which the fund has invested a strictly positive share in the last 24 months. Moreover, I only consider global funds and countries in which more than 30 global funds have ever invested in it. This result in a sample of 39 countries. I focus on global funds as regional funds sometimes invest in countries outside their specific area of specialization.

Let $N0_n$ count the total number of country shares of zero that were reported to country n. Let N_n count the total number of observations that were reported to country n. Then, the fraction (in percent) of country shares of zero at the country level is denoted by

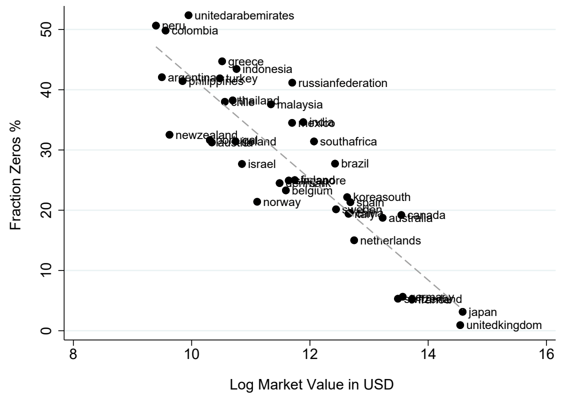
$$S0_n = 100 \times \frac{N0_n}{N_n}. \tag{6}$$

In the first evidence, Figure 3a plots $S0_n$ as a function of the log market value compiled by MSCI. For those 39 countries, MSCI provides each month the market value in USD. I report in the figure the log average market value across months. The market value measures how important is a country financially. Figure 3a shows a strong negative correlation between the fraction of zeros at the country level and the financial importance of the country. The more important is a country financially, the less the funds report country shares of zero across this country.

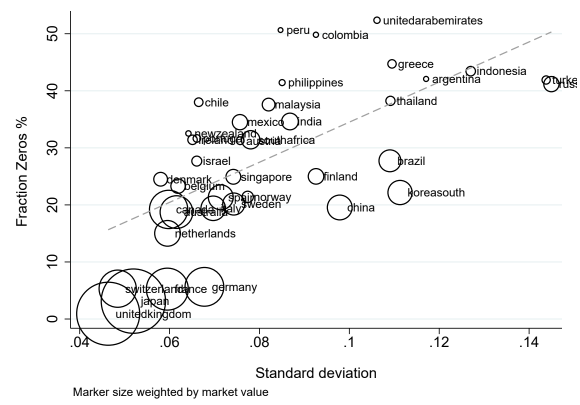
In the second evidence, Figure 3b plots $S0_n$ as a function of the volatility of the equity returns measured by the standard deviation of monthly equity returns. The equity return is calculated from the total return index compiled by MSCI. Figure 3b shows a strong positive correlation between the fraction of zeros at the country level and volatility. The higher the

Figure 3: *Fraction of Zeros at the Country Level*

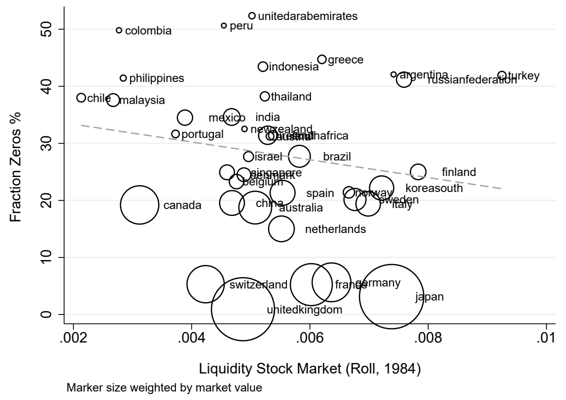
(a) *Market Value*



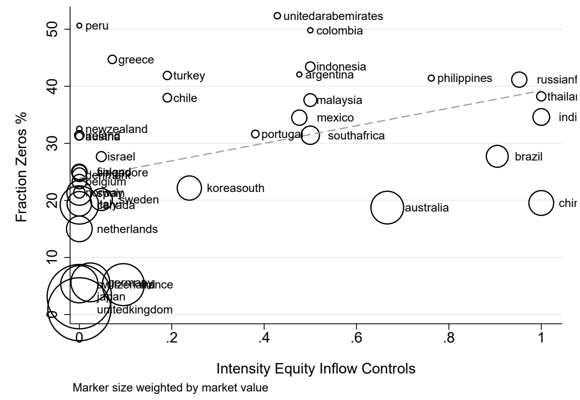
(b) *Volatility*



(c) *Liquidity*



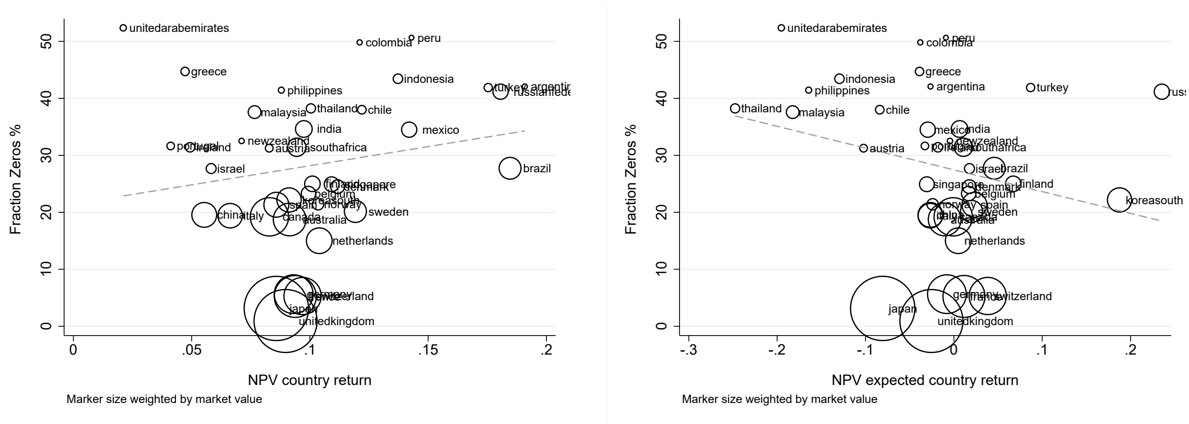
(d) *Equity Inflow Controls*



Notes: Figure 3a plots $S0_n$ as a function of the log market value compiled by MSCI. Figure 3b plots $S0_n$ as a function of the standard deviation of monthly equity returns. Figure 3c plots $S0_n$ as a function of the liquidity of the equity market. Figure 3d plots $S0_n$ as a function of the intensity of equity inflow controls. The marker size is weighted by market value. The grey dashed line is a regression line.

Figure 4: *Fraction of Zeros at the Country Level and Present discounted values of returns*

(a) *NPV return* (b) *NPV expected return*



Notes: Figures 4a and 4b plot $S0_n$ as a function of the NPV of country returns and the NPV of expected returns, respectively. The marker size is weighted by market value. The grey dashed line is a regression line.

volatility of the equity returns, the more the funds report country shares of zero across this country.

In the third evidence, Figure 3c plots $S0_n$ as a function of the liquidity of the equity market. I calculate the liquidity of the equity market of each country using Roll (1984). Roll defines the liquidity as follows:

$$\text{Roll}_n = \frac{1}{T}\sum_{t=1}^{T}\sqrt{\max\Big(-cov_n(\Delta p_{n,d+1\in t}, \Delta p_{n,d\in t}), 0\Big)} \tag{7}$$

where $p_{n,d}$ represents the log of the equity price at day d. The monthly measure of the covariance is based on the daily equity price inside this month. Roll (1984) justifies this approach as "Trading costs induce negative serial dependence in successive observed market price changes". If the equity market were liquid, the liquidity measure would equal zero. Figure 3c shows a weak negative correlation between the fraction of zeros at the country level and liquidity. The higher the liquidity of the equity market, the less the funds report country shares of zero across this country.

In the fourth evidence, Figure 3d plots $S0_n$ as a function of the intensity of equity inflow controls as measured by Fernández et al. (2015). Fernández et al. (2015) provides a panel data on the intensity of capital flow controls amid equity inflow controls. The authors use IMF country reports to calibrate their intensity measure. In Figure 3d, I use the average measure of equity inflow controls across years. Figure 3d shows a weak positive correlation between the fraction of zeros at the country level and how intense are equity inflow controls. The more intense the equity inflow controls, the more the funds report country shares of zero across this country.

In the fifth evidence, Figure 4a plots $S0_n$ as a function of the average present discounted value of actual equity return. The figure shows a positive relationship between the fraction of country shares of zero and the present discounted actual return, which is counterintuitive. This positive relationship is more likely to come from the fact that mutual funds are unskilled. Unskilled funds could not invest in those countries that have positive expected returns. One could also argue that funds could not invest in those countries that have high actual return if those countries also have high transaction cost. However, Figure 4b plots $S0_n$ as a function of the average present discounted value of expected equity returns. The relationship is negative, which indicates that funds report more zeros in those countries in which they expect the expected return to be low. If transaction costs were higher in countries that have positive actual returns and if funds were skilled in predicting equity returns, the relationship in Figure 4b would have been negative. Finally, Elton and Gruber (2013) reviews the literature on mutual funds performance. Their conclusion indicates that mutual funds are unskilled.

Finally, I regress $S0_n$ on the variables used in Figures 3a-3d controlling for the average monthly equity return. Table 4 shows the results. Column (1) uses the log market value. Column (2) adds the volatility measure. Column (3) adds the liquidity, the intensity of the equity inflow controls and the average present discounted value of expected equity return.

Table 4 shows the market value, the volatility and the liquidity measures explain more than 90% of the variation in the fraction of zeros at the country level. Funds are more likely to report country shares of zero in countries that are financially small, have an illiquid equity market and have volatile equity returns. The coefficient on the expected excess return has the right sign but is not statistically significant. The statistical significance improves when we omit Russia but remains insignificant. This non-significant result is a limitation that is

Table 4: *Country Characteristics and Zeros*

Dep. variable: Fraction zeros	(1)	(2)	(3)
Log market value	-8.410***	-7.069***	-5.892***
	(0.693)	(0.663)	(0.718)
Volatility		174.4***	266.87***
		(33.22)	(57.97)
Liquidity			-2319.3***
			(686.8)
Equity Inflow Controls			-0.329
			(3.745)
$\hat{er}^{\delta}_{n,t,t+K}$			-0.457
			(10.964)
Observations	39	39	39
R^2	0.785	0.869	0.915

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Notes:* Regressions with 39 countries over the interval 1996-2016. Constant included but not shown.

discussed in the discussion section. Those results give stylized fact 5.

Stylized Fact 5 *The market value, the volatility of the equity market and the liquidity of the equity market explain more than 90% of the variation in the fraction of zeros at the country level. Funds are more likely to report country shares of zero in countries that are financially small, have an illiquid equity market and have volatile equity returns.*

Next, I present a macroeconomic model featuring those stylized facts.

2 Model

To explain the stylized facts, the macroeconomic model should feature an international portfolio block in which the shares are subject to a non-negativity constraint. Moreover, the portfolio block should feature frictions to explain the persistence in portfolio,[8] and hetero-

[8] The gradual portfolio adjustment, also called portfolio frictions, is micro-founded. e.g. Giglio et al. (2021), Camanho et al. (2022), Bilias et al. (2010), Brunnermeier and Nagel (2008) among others.

geneity to match the distribution of shares in the data. Furthermore, the portfolio shares should be a function of return volatility and a transaction cost. The transaction cost should increase with the portfolio shares (as it implies a higher trade volume all things being equal) but decrease with the market capitalization of a country. Countries with a higher capitalization are more liquid and have lower transaction costs. The macroeconomics block should contain countries differing in their stock of capital (market capitalization). Market capitalization could also be linked to return volatility as in the data countries that are financially more developed also have more stable returns. However, I take the volatility of return to be exogenous to simplify the model. Finally, I emphasize the model does not feature a risk-free option such as a bond. Investors can only invest equities. Workers do not invest as they are hand-to-mouth.

2.1 Model environment

The natural starting point is the model of Bacchetta et al. (2022a), which solves international portfolio choice in a one-good, two-country model of saving and investment with costly portfolio adjustment. I modify their model by adding a non-negativity constraint and modeling transaction cost as a function of shares and market capitalization. Gradual portfolio adjustment is key to explain the persistence of the country shares of zero present in the data. The two countries are Home (H) and Foreign (F) and there are two assets. Each country is populated with $\mathcal{I}_n$ investors and a representative worker. Investors hold the assets, make savings and portfolio decisions. Investors differ in their level or risk-aversion, cost of portfolio adjustment and the volatility of their asset returns. Motivated by the stylized facts, risk aversion and cost to deviate from the past shares are linked to activeness. More active fund are less risk averse and rebalance less towards the past portfolio. Workers earn labor income and are hand to mouth. Workers do not have access to the financial market.

2.2 Portfolio Problem

The assets are claims on capital of both countries with returns $R_{n,t+1}$, $n = \{H, F\}$. Investors allocate their wealth across those two assets. The share invested in the home and foreign assets by investor i is $z_{i,t}$ and $1 - z_{i,t}$, respectively. For simplicity, I assume all investors start with the same amount of financial wealth.

The portfolio adjustment cost is a quadratic adjustment cost $0.5\psi_i(z_{i,t} - z_{i,t-1})$ following Bacchetta et al. (2023), Bacchetta et al. (2022a) and Gârleanu and Pedersen (2013). The parameter ψ determines the size of the portfolio friction. It represents costly information gathering and decision making. Moreover, when the portfolio decisions are made by mutual fund managers, gradual portfolio adjustment can be related to various frictions that lead fund managers stick close to various benchmarks. For instance, they may be penalized if bad fund performance occurs after significant portfolio changes relative to benchmark portfolios.[9] This also leads to more gradual portfolio adjustment as noted by Bacchetta et al. (2022a). Bacchetta et al. (2022b) models portfolio frictions through a Calvo type portfolio frictions, where investors can update their portfolio with a certain probability. The resulting portfolio equation takes the form of a portfolio equation one could obtain by solving a mean-variance Markowitz portfolio optimization such as in Bacchetta et al. (2023).

The transaction cost is positively influenced by the transaction volume and negatively by the market capitalization of the country in which the investment is made. The literature has already discussed that transaction increases with investment volume (Markeprand, 2008; Préchac, 1996). More recently, da Rocha and Vailakis (2010) argues that providing a financial market is more labor intensive than capital intensive, which is why wages are high in finance compared to manufacture. da Rocha and Vailakis (2010) links transaction cost to the size of the labor that is used in finance. The more people are employed in finance, the less the transaction cost as intermediate have more competition. Because I fix the labor supply to one, I link the transaction cost to capital in the spirit that economies which are better capitalized have lower transaction cost.

[9] A vast literature on mutual funds investigates performance based on holdings data (see, Grinblatt and Titman (1993), Cornell (1979), Grinblatt and Titman (1989a,b), Elton et al. (2011b,a), Daniel et al. (1997)). Their measures of performance corresponds to the value added by profitable portfolio reallocations. If the manager increases the weight on securities that perform well in the future and decreases weights on securities that perform poorly, the manager is adding value.

While in theory the country share might be equal to one, in practice international investors do not put all their eggs in a single country. There are benefits from international diversification.[10] Therefore, I only model the non-negativity constraint.

2.3 Investors

Investors have Rince preferences (Bacchetta et al., 2022a; Davis and Van Wincoop, 2018). Rince preference implies the intertemporal elasticity of substitution equals 1, so that the optimal consumption-wealth ratio solely depends on the time discount rate, while the rate of risk-aversion γ_i is a separate parameter that is important for portfolio choice. With Rince preferences investors maximize consumption by maximizing their wealth, which translates to choosing the portfolio shares to maximizing portfolio return given risk, gradual portfolio adjustment, transaction cost and the non-negativity constraint.[11] The Bellman equation for investor i is represented in equation (8)

$$\begin{aligned}\ln(V_{i,t}) = \max_{C^I_{i,t}, z_{i,t}} \Bigg\{ (1-\beta)\ln(C^I_{i,t}) + \beta \Bigg[\ln\left([E_{i,t}(V_{i,t+1})^{1-\gamma_i}]^{\frac{1}{1-\gamma_i}} \right) \\ - 0.5\sigma^2_{er,i}\psi_i(z_{i,t} - z_{i,t-1})^2 - \xi_{i,t}(0 - z_{i,t}) - \tau(z_{i,t}, K_{H,t}) \Bigg] \Bigg\},\end{aligned} \tag{8}$$

where $\sigma^2_{er,i}$ is the volatility of the excess return $\sigma^2_{er,i} = Var_i(R_{H,t+1} - R_{F,t+1})$ with $er_{t+1} = R_{H,t+1} - R_{F,t+1}$.

The investor maximizes the portfolio share $z_{i,t}$ and her consumption $C^I_{i,t}$. β measures the time discount factor and $E_{i,t}$ is the expectation of investor i at time t. The firs term in

[10] A large literature in international finance shows the benefit of international diversification (Coeurdacier and Rey (2013), Coeurdacier and Guibaud (2011),Agmon and Lessard (1977), Kroencke et al. (2013), Levy and Sarnat (1970), Brewer (1981), Hitt et al. (1997), among many others).

[11] I omit costly deviation from a buy-and-hold, also called passive, portfolio. The buy-and-hold portfolio depends on the market realization of country returns, which is called valuation effect. With small portfolio shares, valuation effects are very close to zero. Moreover, when the average country share is very close to zero, the valuation effect is essentially zero. This makes it difficult to determine the coefficient on the valuation effect (Bacchetta et al., 2023). Nevertheless, Bacchetta et al. (2023) finds that the frictions associated with the past share is more important than the friction associated with the buy-and-hold portfolio.

the second line represents the gradual portfolio adjustment. Gârleanu and Pedersen (2013) provides micro-foundations for using the variance of excess returns in the gradual portfolio cost. The investor weights costly deviation from the past shares with the variance of the excess return to account for the volatility of future deviations from the benchmark portfolio. If the returns is volatile, the magnitude of the rebalancing is higher and so is the gradual portfolio adjustment cost. The second term in the second line $\xi_{i,t}(0 - z_t)$ represents the non-negativity constraint for investor i at time t. ξ is the shadow-price of relaxing the non-negativity constraint. $\xi_{i,t}$ represents the utility gain from relaxing the constraint by one unit. The complementary slackness conditions of Karush-Kuhn-Tucker (KKT) imply $\xi > 0$, when the non-negativity constraint binds ($z_{i,n,t} = 0$) and $\xi = 0$ when $z > 0$. Finally, the last term in the second line is the transaction cost, $\tau(z_{i,t}, K_{n,t})$, which increases with share z and decreases with the stock of capital in the home country. To ease algebra, it is assumed the partial effect of the function τ with respect to z, τ_z is positive but negligible. Moreover, τ_z lowers with the stock of capital.

The financial wealth of investor i, $W_{i,t+1}$, evolves according to

$$W_{i,t+1} = (W_{i,t} - C^I_{i,t})R^p_{i,t+1}, \tag{9}$$

where $R^p_{i,t+1}$ is the portfolio return given by

$$R^p_{i,t+1} = z_{i,t}R_{H,t+1} + (1 - z_{i,t})R_{F,t+1}. \tag{10}$$

2.4 Optimal Portfolios and Consumption

The optimal consumption of investor i is a constant fraction of her wealth

$$C^I_{i,t} = (1 - \beta)W_{i,t}. \tag{11}$$

Appendix A shows the optimal portfolio is

$$z_{i,t} = \max\left\{0, \quad (1 - a_{1,i})\bar{z}_i + a_{1,i}z_{i,t-1} + a_{2,i}\sum_{s=1}^{\infty}(\beta a_{1,i})^{s-1}E_{i,t}(er_{t+s})\right\}, \tag{12}$$

where

$$\bar{z}_i = \frac{\left(\sigma^2_{F,i} - \sigma_{H,F,i}\right) - \tau_{\bar{z}_i}(K)}{\sigma^2_{er,i}} \tag{13}$$

$$a_{1,i} = \frac{2\psi_i}{\gamma_i + (1+\beta)\psi_i + \sqrt{\gamma_i^2 + (1-\beta)^2\psi_i^2 + 2(1+\beta)\gamma_i\psi_i}} < 1, \tag{14}$$

$$a_{2,i} = \frac{a_{1,i}}{\psi_i \sigma^2_{er,i}}. \tag{15}$$

The average country share $\bar{z}_i$ depends on the volatility of returns as well as on the transaction cost. The volatility depends on the mean over time of the portfolio share allocated to the Home country by fund i where $\sigma^2_{H,i}$ and $\sigma^2_{F,i}$ are the variance of the home and foreign equity return, respectively. $\sigma_{H,F,i}$ is the covariance of the home and foreign equity return. Funds invest a lower share, on average, in those countries in which they receive a volatile return. The average country share also depends on the partial derivative of the transaction cost with respect to the average country share, which is a negative function of capital. The higher the stock of capital, the lower is $\tau_{\bar{z}_i}$. Hence, investors invest a larger share in countries that have low volatility or more capital. Remember that the magnitude of the average portfolio share is determinant as the lower is the portfolio share, the higher the probability that a given negative expected excess return push the optimal country share to zero.

The optimal country share depends on the average country share, the past country share, and the expected excess return. The persistence parameter a_1 represents the gradual portfolio adjustment. *Ceteris paribus*, the higher the portfolio friction ψ, the higher the persistence and the lower the coefficient on the expected excess return. The higher the risk aversion, the lower the persistence and the coefficient on the expected excess return. The higher the variance of the excess return, the lower the average country share and the lower the coefficient on the expected excess return. In contrast to a frictionless model in which the investor reoptimizes her portfolio each period and cares only about the 1-period ahead excess return, here the investor considers the present discounted value of future excess returns. The investor discounts the future with the time discount factor β times the persistence coefficient a_1. A high persistence means a high cost to deviate from the past share which makes the investor more patient.

2.5 Firm

The production side of the model features two representative firms: one foreign (F) and one home (H). The firms produce a final good using capital and labor. Producing firms own the installment firms which transform investment in capital. The investors allocate their financial wealth across those two firms. They claim the capital of both firms, with $Q_{H,t}$ and $Q_{F,t}$, respectively. The gross return in country n from t to $t+1$ is

$$R_{n,t+1} = \frac{D_{n,t+1} + (1-\delta)Q_{n,t+1}}{Q_{n,t}}, \tag{16}$$

where $D_{n,t+1}$ is the dividend payed by the firm to the shareholders. Capital accumulates according to

$$K_{n,t+1} = (1-\delta)K_{n,t} + I_{n,t}, \tag{17}$$

where δ is the depreciation rate of capital and $I_{n,t}$ denotes investment.

The firm produces the output with capital and labor

$$Y_{n,t} = K_{n,t}^{\theta} N_{n,t}^{1-\theta}, \tag{18}$$

Following Bacchetta et al. (2022a), labor supply is fixed at 1 for all periods. Workers receive a fraction $(1-\theta)$ of output, which they consume. The rest goes to profits of the shareholders

$$D_{n,t+1} = \frac{\Pi_{n,t+1}}{K_{n,t+1}} = \theta K_{n,t+1}^{\theta-1} + \frac{\pi_{n,t+1}}{K_{n,t+1}}, \tag{19}$$

where $\Pi_{n,t}$ is the profit of the producing firms and $\pi_{n,t}$ is the profit of the installment firms producing capital.

Installment firms sell new capital at given price Q but need units of consumption goods to produce the new capital. The installment firms maximize profits

$$\max_{I_{n,t}} \pi_{n,t} = Q_{n,t}I_{n,t} - \left[I_{n,t} + 0.5\zeta\frac{1}{K_{n,t}}(I_{n,t} - \delta K_{n,t})^2\right]. \tag{20}$$

Optimal investment per unit of capital is a Tobin's Q

$$\frac{I_{n,t}}{K_{n,t}} = \delta + \frac{1}{\zeta}(Q_{n,t} - 1). \tag{21}$$

2.6 Market Clearing

The market clearing condition for the good is

$$C_{i,t}^{I} = (1-\beta)W_{i,t}.$$

Therefore, they invest $\beta W_{i,t}$ in the two assets. The two assets market clearing conditions are then

$$\beta\left[\sum_{i=1}^{\mathcal{I}} z_{i,t}\Big[W_{i,t}^{H} + W_{i,t}^{F}\Big]\right] = Q_{H,t}K_{H,t+1}, \tag{22}$$

$$\beta\left[\sum_{i=1}^{\mathcal{I}} (1-z_{i,t})\Big[W_{i,t}^{H} + W_{i,t}^{F}\Big]\right] = Q_{F,t}K_{F,t+1}, \tag{23}$$

where $W_{i,t}^{H}$ emphasizes the financial wealth of investors in the home country and $W_{i,t}^{F}$ emphasizes the financial wealth of investors in the foreign country. At market clearing, the financial wealth invested in country n equals the asset supply, which corresponds to the capital multiplied by the asset price.

In the next section, I regress the portfolio equation derived in this model by taking the equation to the data described in Section 2. Moreover, I discuss what portfolio equation and what ingredients do we need to explain the country shares of zero present in the data.

3 Explaining Country Shares of Zero

Can equation (12) explain the country shares of zero present in the EPFR data? In other words, is this portfolio equation a good representation of how international equity mutual funds allocate their portfolio in the real world? To answer those questions, I first transform the two countries equation in a N-country portfolio equation. Second, I estimate a measure of expected excess return for each fund that I can use in the portfolio equations. Third, I estimate the portfolio equation by pooling the data and using a two-limit random effect Tobit. Finally, I use the estimated coefficient to evaluate whether the model is able to explain the country shares of zero by simulating the data with a dynamic prediction. The model explains

94% of country shares of zero when we have two ingredients: the gradual portfolio adjustment and the present discounted value of future expected excess returns.

In theory, there is heterogeneity in the structural parameters across funds. Since I won't be able to precisely estimate the parameters for each fund, I show two sets of results. First, I follow Bacchetta et al. (2023) and focus on the mean of those parameters. The mean of those parameters take no subscripts.[12] Second, I consider near-heterogeneity by focusing on the mean of those parameters by groups of funds. I look at active versus passive funds, small versus large funds and global versus regional funds. I report those results in Table E.1 and Figure E.1 in the Appendix.

3.1 N-Countries

Imagine there were only two countries as in the general equilibrium model: Home and Foreign. The excess return of country H for investor i at time t corresponds to the return of country H minus the return in country F. Denote the expected return by $er_{i,n,t}$. In a N-countries model, the excess return of country n for investor i at time t is the return of country n minus the weighted average of the return made in the other countries in which the investor invests. Equation (24) shows the excess return from t to t+1.

$$er_{i,n,t+1} = R_{n,t+1} - \boldsymbol{z}'_{i,-n,t}\boldsymbol{R}_{t+1} \tag{24}$$

where the vector $\boldsymbol{z}_{i,-n,t}$ has element $m \neq n$ equal to $z_{i,m,-n,t}$ and zero if $m = n$. $z_{i,m,-n,t}$ is the share allocated to country m of the equity portfolio outside country n with $\sum_{m \neq n} z_{i,m,-n,t} = 1$. $\boldsymbol{R}_{t+1}$ is the vector of country returns. It must be noted that the investment universe varies for each fund i. To lighten the notation, I do not explicitly write the investor's specific investment universe.

[12]Using panel data, Blomquist and Westerlund (2013) build on Pesaran and Yamagata (2008) and give a function form to the heterogeneity. Namely, $\beta_{in} = \beta + N^{-1/4}T^{-1/2}\theta_{in}$, where N represents the number of countries, T the number of periods and θ_{in} is an idiosyncratic term with mean 0. As the panel gets large, the idiosyncratic term goes to zero.

The fund expected excess return is the return the fund expects in country n minus the weighted average of the expected return in the other countries in the investment universe

$$E_{i,t}er_{i,n,t+1} = E_{i,t}R_{n,t+1} - \boldsymbol{z}'_{i,-n,t}E_{i,t}\boldsymbol{R}_{t+1}. \tag{25}$$

3.2 Decompose Expected Excess Return

Following Giglio et al. (2021), I decompose the expected excess return in three components: (i) fixed individual characteristics, (ii) idiosyncratic components, and (iii) by common variation in expectations. Therefore, I rewrite the excess return of country n as

$$E_{i,t}er_{i,n,t+s} = f_{i,n} + x_{i,n,t+s} + E_t er_{i,n,t+s} \tag{26}$$

where $f_{i,n}$ denotes the fixed fund-country characteristics, $x_{i,n,t+s}$ denotes the fund idiosyncratic expectation of excess returns and $E_t er_{i,n,t+s}$ the common expectation. The common expectation is based on public information and is obtained by *the* econometrician. As in Giglio et al. (2021), assumption 1 about the idiosyncratic expected excess return holds.

Assumption 1 *The idiosyncratic fund expected excess return follows an iid normal distribution with zero mean and variance σ_u^2, where*

$$x_{i,n,t} \sim iid\mathcal{N}(0, \sigma_x^2). \tag{27}$$

3.3 Econometric Estimator

Appendix B shows equation (28) depicts the portfolio equation I will estimate using the data

$$z_{i,n,t} = \max\left\{0, a_{i,n} + a_1 z_{i,n,t-1} + a_2 \sum_{s=1}^{\infty} (\beta a_1)^{s-1} E_t er_{i,n,t+s} + \varepsilon_{i,n,t}\right\}, \tag{28}$$

where a_1 and a_2 are the mean parameters of $a_{1,i}$ and $a_{2,i}$, respectively, with

$$a_1 = \frac{2\psi}{\gamma + (1+\beta)\psi + \sqrt{\gamma^2 + (1-\beta)^2\psi^2 + 2(1+\beta)\gamma\psi}} < 1, \tag{29}$$

$$a_2 = \frac{a_1}{\psi\sigma_{er}^2}, \tag{30}$$

$$a_{i,n} = (1-a_1)\bar{z}_{i,n} + \frac{a_2}{1-\beta a_1} f_{i,n}, \tag{31}$$

$$\varepsilon_{i,n,t} = a_2 \sum_{s=1}^{24} (\beta a_1)^{s-1} x_{i,n,t+s}. \tag{32}$$

Under assumptions 1, the residual of the portfolio regression follows a normal distribution with mean zero and variance σ_ε^2.

$$\varepsilon_{i,n,t} \sim iid\mathcal{N}(0, \sigma_\varepsilon^2), \qquad \sigma_\varepsilon^2 = \frac{a_2^2}{1-(\beta a_1)^2}\sigma_x^2. \tag{33}$$

Given the dynamic fractional nature of the data, the assumptions about the distribution of the error term and the exogenous expected excess return, the best econometric estimator for equation (28) is the two-limit random effect Tobit of Loudermilk (2007). This estimator produces consistent estimates of a_1 and a_2 when the dependent variable is a fraction with a massive number of corner solutions, when the regressors are exogenous and when the error term is normally distributed. In the next section, I discuss how an econometrician can predict an exogenous excess return. Loudermilk (2007) uses this estimator in an application to dividends payout. Wooldridge (2005) and Papke and Wooldridge (2008) recommend the use of the two-limit random effect Tobit in dynamic applications with a fractional dependent variable. Giglio et al. (2021) also use Tobit in an application to portfolio shares.

I compare the results obtained with Tobit with the results obtained with OLS on the strictly positive shares. OLS would estimate biased coefficients because it does not take into account the corner solutions. Using the distributional assumptions of the residuals, we can formally describe the OLS bias for a representative fund[13] by computing

[13] Because the error term follows a normal distribution with mean zero and variance σ_ε^2,

$$E[\varepsilon_{i,n,t} | \varepsilon_{i,n,t} > -z_{i,n,t}^*] = \sigma_\varepsilon \left[\frac{\phi(z_{i,n,t}^*/\sigma_\varepsilon)}{\Phi(z_{i,n,t}^*/\sigma_\varepsilon)} \right] \tag{34}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denotes the probability density function and the cumulative density function of the

$E[z_{i,n,t}|z^*_{i,n,t}]$ and $E[z_{i,n,t}|z^*_{i,n,t}, z_{i,n,t} > 0]$, where

$$z^*_{i,n,t} = a_{i,n} + a_1 z_{i,n,t-1} + a_2 \sum_{s=1}^{\infty} (\beta a_1)^{s-1} E_t er_{i,n,t+s}. \tag{37}$$

Therefore, we can rewrite the optimal country share as

$$z_{i,n,t} = \max \left\{ 0, z^*_{i,n,t} + \varepsilon_{i,n,t} \right\}. \tag{38}$$

3.4 Data and Sample

Combining the EPFR with with the MSCI data results in a sample of 72 countries. Those countries represent more than 95% of the country allocations in terms of capital investment. Figure F.1 in the Appendix shows the average fraction of country shares of zero in panel (a) and the average episode of persistence country shares of zero in panel (b). Compared to Figure 1, the distribution of the country shares of zero is not affected by this smaller sample. Table F.1 in the Appendix lists the 72 countries (in bold).

When combining the EPFR data with the MSCI data, the number of countries shrinks. As a result, the sum of country shares across countries for each fund-month pair does not necessarily equal one. Hence, I normalize the country shares reported in the 72 countries such that the normalized shares sum to 1.

standard normal distribution, respectively. Therefore,

$$E[z_{i,n,t}|z^*_{i,n,t}, z_{i,n,t} > 0] = z^*_{i,n,t} + \sigma_\varepsilon \left[\frac{\phi(z^*_{i,n,t}/\sigma_\varepsilon)}{\Phi(z^*_{i,n,t}/\sigma_\varepsilon)} \right] \tag{35}$$

If we were to estimate (12) with OLS using only the country shares that are strictly higher than zero, we would omit the last term which is correlated with the dependent and the explanatory variables. Estimating equation (12) on the strictly positive country shares with OLS gives an inconsistent coefficient for a_j

$$a_j^{OLS+} = \theta(z^*_{i,n,t}/\sigma_\varepsilon) a_j \tag{36}$$

with $\theta(z^*_{i,n,t}/\sigma_\varepsilon) = \left[1 - \frac{\phi(z^*_{i,n,t}/\sigma_\varepsilon)}{\Phi(z^*_{i,n,t}/\sigma_\varepsilon)} \left[\frac{z^*_{i,n,t}}{\sigma_\varepsilon} + \frac{\phi(z^*_{i,n,t}/\sigma_\varepsilon)}{\Phi(z^*_{i,n,t}/\sigma_\varepsilon)} \right] \right]$

3.5 Portfolio Regression

Remember the portfolio equation (28), depicted here for an horizon of 24-months

$$z_{i,n,t} = \max\left\{0, a_{i,n} + a_1 z_{i,n,t-1} + a_2 \sum_{s=1}^{24} (\beta a_1)^{s-1} E_t er_{i,n,t+s} + \varepsilon_{i,n,t}\right\}. \tag{28}$$

By estimating the coefficients associated with the portfolio equations, I can recover the average values of the structural parameters given in equations (39) and (40). I use scaled structural parameters for the portfolio frictions, defined as $\lambda = \psi\sigma_{er}^2$.

$$\lambda = \frac{a_1}{a_2} \tag{39}$$

$$\gamma = \frac{(1-a_1)(1-\beta a_1)}{a_2 \sigma_{er}^2} \tag{40}$$

The portfolio risk σ_{er}^2 corresponds to the average of $\sigma_{er,i,n}^2$ across i and n. It is equal to 0.00328. I use $\beta = 0.97$. While this estimate of β might seem low for monthly data, it reflects the turnover of managers (Kostovetsky and Warner, 2015).

Table 5 reports the estimates of equation (28). I report the coefficients on the past share, the expected excess returns and the estimated average structural parameters. I also report the coefficient on the expected excess return scaled by $1/(1-\beta a_1)$ to compare coefficients between columns. Columns (1)-(5) estimate the portfolio regression with the two-limit random effect Tobit. Columns (1), (2), (3), (4) and (5) use the 3-, 12-, 24-, 36-, all-months investment universe, respectively. Column (6) estimates the portfolio regression with OLS on the strictly positive shares ($z_{i,n,t} > 0$ and $z_{i,n,t-1} > 0$). The regression contains a fund-country fixed effect. I cluster standard errors by months following Raddatz and Schmukler (2012).

The different Tobit regressions estimate a higher persistence and a lower expected excess return than OLS+. The looser the investment universe, the more the persistence and the less the coefficient on the expected excess return. The average risk aversion is estimated at 7.7 with OLS+, while is estimated between 3.5 and 6.5 with Tobit. The investment universe of 24 months leads to a reasonable estimation of the risk aversion of 4.8. The cost to deviate from the past share, λ, is lower with OLS+ than with the Tobit regressions. Loosening the investment universe leads to a greater cost to deviate from the past shares. The last line

Table 5: *Portfolio Regressions*

$$z_{i,n,t} = \max\left\{0, a_{i,n} + a_1 z_{i,n,t-1} + a_2 \sum_{s=1}^{24} (\beta a_1)^{s-1} E_t er_{i,n,t+s} + \varepsilon_{i,n,t}\right\}$$

	Tobit					OLS+
	(1)	(2)	(3)	(4)	(5)	(6)
	3	12	24	36	all	
$z_{i,n,t-1}$	0.943***	0.952***	0.957***	0.960***	0.965***	0.937***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$E_t er^{\beta a_1}_{i,n,t,t+24}$	0.229***	0.214***	0.195***	0.191***	0.193***	0.235***
	(0.033)	(0.032)	(0.031)	(0.031)	(0.031)	(0.035)
γ	6.5	5.2	4.8	4.4	3.5	7.7
$\lambda = \psi\sigma^2$	4.1	4.4	4.9	5.0	5.0	4.0
βa_1	0.91	0.92	0.93	0.93	0.93	0.91
$(1 - \beta a_1) E_t er^{\delta}_{i,n,t,t+24}$	2.685	2.795	2.719	2.776	3.018	2.568
Observations $z_{i,n,t} > 0$	1,361,826	1,361,826	1,361,826	1,361,826	1,361,826	1,361,826
Observations $z_{i,n,t} = 0$	60,715	228,572	353,675	434,999	666,650	

Clustered standard errors by month and domicile in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions for 72 countries over the interval 1996:01-2016:07. OLS regressions include a fund-country fixed effect. Tobit regressions include the first country share, the mean of the country shares and the mean of the expected excess return.

of Table 5 shows the scaled coefficient on the expected excess return. All Tobit regressions estimate a higher value of those scaled expected excess returns compared to OLS$+$. That's because OLS$+$ underestimates the persistence of the past shares.

Table C.1 in the Appendix shows the predictability regressions using different combinations of MSCI data. Table D.1 in the Appendix shows portfolio regressions associated with an investment universe of 24-months using the different specifications of Table C.1. Results are robust to a variety of specifications. In column (2), I use the 24-months lagged equity return, dividend-price and earning-price. The portfolio coefficient a_2 is smaller compared to the one in Table 5, which reflects the endogeneity problem. Because the financial shocks are very persistent, portfolio shares today might still be affected by the 24-months lagged prices. Hence, the negative correlation between the error term and the equity price leads to an underestimation of a_2.

3.6 Impulse Response

Using the coefficients obtained in Table 5 and by specifying an AR(1) structure for the expected excess return, I obtain the impulse response of the portfolio to a one standard deviation shock in the expected excess return innovation.

First, let the expected excess return follow an AR(1).

$$E_t er^{\beta a_1}_{i,n,t,t+24} = \rho E_{t-1} er^{\beta a_1}_{i,n,t-1,t+24-1} + \eta_{i,n,t} \tag{41}$$

where ρ represents the AR coefficient and η the innovation. I pooled my data to obtain ρ and the AR residuals η. I obtain the average standard deviation of the residual by first taking the standard deviation of η across (i,n) pairs. Then, I take the average of those standard deviations. For all Tobit and OLS$+$, $\rho = 0.953$. For Tobit, the standard deviation of η equals 0.0095. For OLS$+$, the standard deviation of η equals 0.0080. The difference comes from βa_1, which equals 0.93 and 0.91 for Tobit and OLS$+$, respectively.

Figure 5 shows the impulse response of the portfolio shares to a one standard deviation shock to the expected excess return innovation for all investment universe and OLS$+$. The y-axis corresponds to the percentage points deviation from the steady state.

Compared to OLS+, portfolio shares respond more and longer to a financial shock. OLS+ underestimates the magnitude and the persistence of the portfolio response. Loosening the investment universe does not affect the magnitude of the impulse response but its persistence. A looser investment universe increases the persistence of the financial shock.

Figure 5: *Impulse Response Portfolio Share to Expected Return Shock*

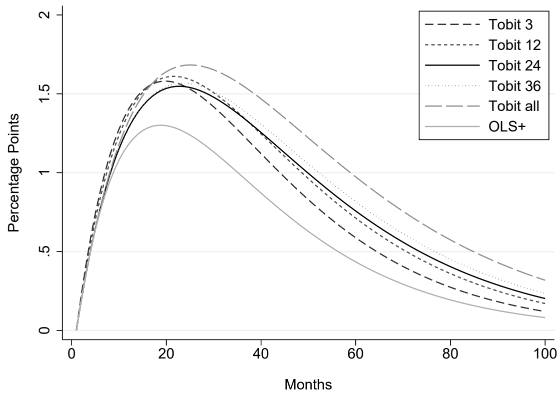


Figure 5 shows the impulse response of the portfolio shares to a one standard deviation shock to the expected excess return innovation. The y-axis correspond to the percentage points deviation from the steady state.

Funds differ in their level of activity, size, type and in their exposition to country shocks. Figure E.1 in the Appendix shows the portfolio response to a one standard deviation of the expected excess return innovation for those different characteristics. The financial shock increases the magnitude and the persistence of the portfolio response of active funds, regional funds, small funds and more exposed funds more than their respective counterpart. The funds that respond less to the financial shock are passive, large and global.

3.7 Explaining country shares of zero

Now that we have worked our way through regressing the portfolio equation (28), we can evaluate what ingredients we need to explain the corner solutions that are observed in the data? In other words, what model is better at predicting the zeros?

To answer those questions, I run a horserace between four different models: frictionless Tobit, myopic Tobit, friction Tobit and OLS+. For this exercise, I consider the benchmark investment universe of 24-months. In the frictionless case ($\beta = 0$ and $\psi = 0$), all the weight is on the average country share and on the next period expected excess return. Because there is no friction, the investor can reoptimize its portfolio each period without incurring any cost. Therefore, the investor only looks at the next period ahead. Equation (42) shows the frictionless portfolio

$$z_{i,n,t} = \max\left\{0, b_{i,n} + b_1 E_t er_{i,n,t+1} + \varepsilon_{i,n,t}\right\}. \tag{42}$$

In the myopic Tobit, $\beta = 0$. The investor only takes into account the 1-month ahead expected equity return. Equation (43) shows the myopic portfolio.

$$z_{i,n,t} = \max\left\{0, c_{i,n} + c_1 z_{i,n,t-1} + c_2 E_t er_{i,n,t+1} + \varepsilon_{i,n,t}\right\} \tag{43}$$

I do not include the frictionless portfolio in the main analysis as the data clearly rejects the frictionless case (see Giglio et al. (2021) for instance). I do not include the myopic case as it is not validated by the theory. Table D.2 in the Appendix shows the frictionless and myopic portfolio coefficients.

The horserace starts from $z_{i,n,0}$, the initial country share. From this initial share at month 0, I predict the share for month 1, $\hat{z}^j_{i,n,1}$ using model j. For this step, I use the pooled coefficients, reported in Tables 5 and D.2 in the Appendix. The predicted share at month 2, $\hat{z}_{i,n,2}$ uses the past predicted share $\hat{z}^j_{i,n,1}$. Hence, the prediction is dynamic. I keep iterating until I have predicted all country shares up to $\hat{z}_{i,n,T_i}$.

Table 6 shows two sets of results. Panel A shows the fraction of matched observations for the country shares of zero $z_{i,n,t} = 0$ and Panel B shows the fraction of matched observations for the strictly positive shares and $z_{i,n,t} > 0$. In Panel C, I report the root mean squared error using the simulated shares for each model defined as

$$RMSE^{(j)} = \sqrt{\frac{1}{NFT} \sum_{i=1}^{F} \sum_{n}^{N} \sum_{t}^{T} \left(z_{i,n,t} - \hat{z}^{(j)}_{i,n,t}\right)^2}. \tag{44}$$

Comparing the RMSE indicates which regression is better at predicting the overall country shares. Even though this measure is not optimal for panel data, it sheds some light on the best model.

Table 6: *Prediction of Corner Solutions: Different Models*

	(1) Frictionless	(2) Myopic	(3) Benchmark	(4) OLS+
Panel A: $z_{i,n,t} = 0$				
$\hat{z}_{i,n,t} = 0$	67.2%	93%	93.4%	33.4%
$\hat{z}_{i,n,t} > 0$	32.8%	7%	6.6%	66.6%
Panel B: $z_{i,n,t} > 0$				
$\hat{z}_{i,n,t} = 0$	19.1%	11.5%	11.4%	6%
$\hat{z}_{i,n,t} > 0$	80.9%	88.5%	88.6%	94%
Panel C: Performance				
RMSE	0.2416	0.2500	0.2395	0.2397

The benchmark Tobit has the lowest RMSE, predicts the highest fraction of country shares of zero and the highest fraction of strictly positive shares compared to the other models. Only OLS+ is able to predict a higher fraction of strictly positive shares (panel B). The myopic regression includes the past share to the frictionless portfolio. From column (2) to column (1), the fraction of predicted country shares of zero sharply increases and the fraction of predicted strictly positive shares also increases. when we add gradual portfolio adjustment to the model. However, the RMSE decreases. Compared to the myopic case, the benchmark Tobit uses the present discounted value of expected excess return. The benchmark Tobit has a lower RMSE indicating the simulated shares are closer to the data than those of the myopic case even though the predicted fraction of country shares of zero and strictly positive shares only increase by a small amount. The portfolio persistence helps predicting what shares are zero and what shares are strictly positive. The expected excess return helps obtaining shares closer to their true values. OLS+ underestimates the persistence and the expected excess return. Hence, OLS+ is the worst at estimating country shares of zero. Remarkably, simulating country shares based on OLS+ leads to a RMSE close to the benchmark Tobit.

The benchmark Tobit gives a fraction of false negative (data is positive while prediction is negative) of 11%. The median values of those shares which are strictly positive in the data but predicted to be zero by Tobit equals 0.2%. The values at the 1th and 99th percentile indicate that 98% of the unmatched shares are between 0.004% and 3.4%. Those results indicate that the mutual funds tend to invest a substantial number of negligible shares when the model suggests to invest zero.[14]

In the next section, I discuss the results obtained in the previous sections for policymakers, put the results in a broader perspective and provide insights for future work.

4 Discussion of Results

Using 20 years of data on the international portfolio choice of equity mutual funds, this paper reveals some stylized facts about zeros in portfolio choice. While the literature has discussed zeros in domestic portfolio choice (Falkenstein, 1996; Koijen and Yogo, 2019), the zeros have not been discussed in the international context. Exposing those new facts matter for the international economy as international portfolio choice is the root of capital flows. Having a deep understanding of portfolio choice to understand changes in capital flows is even more crucial as over the last 20 years, world external assets as a ratio of world GDP went from 60% to more than 200%, (Lane and Milesi-Ferretti, 2018). Therefore, misestimation of capital flows induced by movements in portfolios can produce large differences with actual flows.[15] Moreover, zeros could be linked to the literature on sudden stops for which abrupt

[14]There might cost to exit a country. For instance, the fund might lose intelligence on the country if none of its specialists investigate its investment opportunities.

[15]Examples of recent DSGE models of capital flows based on portfolio choice include Benhima and Arulraj-Cordonier (2022), Davis and Van Wincoop (2018), Devereux and Sutherland (2007, 2010), Didier and

changes in flows (and hence portfolios) lead to major disruptions in the receiving countries (Mendoza, 2010; Bianchi and Mendoza, 2020; Eichengreen and Gupta, 2016). This study also proposes a macroeconomic model with international portfolio choice that incorporates the new facts. The model solves an optimal portfolio equation which relates the portfolio share to the average share, the past portfolio and the present discounted value of expected excess returns. The model fits in a new literature that shows the importance of frictions for the international economy (Bacchetta et al., 2023, 2022a; Maggiori, 2022; Gabaix and Maggiori, 2015). Estimating this equation has led me to predict equity returns for an horizon of several periods. This exercise is in the same vein as Campbell et al. (1997); Hjalmarsson (2010); Cenedese et al. (2015). Using predictors that are exogenous to shift in global portfolio change, I show that my measure of expected excess returns is profitable and exogenous. When we take into account the zeros, the impulse response function of portfolio shares to a shock in expected excess returns innovation is higher and more gradual than when we omit the zeros in the regression. Hence, omitting the zeros leads to an underestimation of the magnitude and persistence of shocks in the economy. This study is, however, limited by the fact that funds do not report the specific country-month return. This study approximates those returns by looking at MSCI country returns. We cannot exclude that those returns might be different and hence change how zeros are related to country returns. This limitation might explain why the link between the fraction of zeros at the country level and my measure of the present discounted value of expected excess return is not statistically significant when we control for other financial variables such as market value, volatility and liquidity. While I believe this limitation does not change the results, future work could seek to approximate fund-country-month specific return, provide better methodology to forecast equity returns or seek to compile more precise data with mutual funds consent.

Lowenkron (2012), Evans and Hnatkovska (2012, 2014), Gabaix and Maggiori (2015), Hnatkovska (2010) and Tille and van Wincoop (2010); Tille and van Wincoop (2010); Tille and van Wincoop (2014).

5 Conclusion

Using a data on the international portfolio choice of equity mutual funds, the main result of this paper is to reveal the following stylized facts about zeros in international portfolio choice: (i) zeros represent 20% of the observations, (ii) country shares of zero persist for 12-month on average, (iii) 95% of the strictly positive shares that drop to zeros are lower than 4%, (iv) controlling for various funds' charactersistics, more active (as opposed to passive) funds invest more often a country share of zero, (v) variation in the market value, volatility of return, liquidity of the equity market, controls on equity inflow and the present discounted value of expected excess returns explain 92% of the variation in the fraction of zeros at the country level. Moreover, estimating a portfolio regression, derived from a general equilibrium model presented in this paper, reveals that omitting the zeros leads to an underestimation of the magnitude and persistence of the portfolio response to financial shocks.

From a country's point of view, the country shares of zero imply that countries with an already weak financial market are more likely to receive country shares of zero, which reduces further the possibility to obtain stable funding via the equity market.

Appendix A Solving the portfolio problem

Remember the Bellman equation for investor i is represented in equation (A.1)

$$\ln(V_{i,t}) = \max_{C^I_{i,t}, z_{i,t}} \Bigg\{ (1-\beta)\ln(C^I_{i,t}) + \beta \Bigg[\ln\Big([E_{i,t}(V_{i,t+1})^{1-\gamma_i}]^{\frac{1}{1-\gamma_i}} \Big) \\ - 0.5\sigma^2_{er,i}\psi_i(z_{i,t} - z_{i,t-1})^2 - \xi_{i,t}(0 - z_{i,t}) - \tau(z_{i,t}, K_{H,t}) \Bigg] \Bigg\}, \tag{A.1}$$

The financial wealth of investor i, $W_{i,t+1}$, evolves according to

$$W_{i,t+1} = (W_{i,t} - C^I_{i,t})R^p_{i,t+1}, \tag{A.2}$$

where $R^p_{i,t+1}$ is the portfolio return given by

$$R^p_{i,t+1} = z_{i,t}R_{H,t+1} + (1 - z_{i,t})R_{F,t+1}. \tag{A.3}$$

Conjecture that the value function takes the form

$$V_{i,t} = \alpha_i W_{i,t} \tag{A.4}$$

Plugging (A.4) and (A.2) in (A.1) yields the portfolio problem

$$\max_{z_{i,t}} \Bigg\{ \frac{1}{1-\gamma_i} \ln\Big(E_{i,t}(R^p_{i,t+1})^{1-\gamma_i} \Big) - 0.5\sigma^2_{er,i}\psi_i(z_{i,t} - z_{i,t-1})^2 \\ - \xi_{i,t}(0 - z_{i,t}) - \tau(z_{i,t}, K_{H,t}) \Bigg] \Bigg\} \tag{A.5}$$

The first order condition is

$$E_{i,t}e^{er_{i,t+1}} + E_{i,t}e^{(1-\gamma_i)r^p_{i,t+1}}\xi_{i,t} + E_{i,t}e^{(1-\gamma_i)r^p_{i,t+1}}\psi_i\sigma^2_{er,i}\beta(z_{i,t+1} - z_{i,t}) = \\ E_{i,t}e^{(1-\gamma_i)r^p_{i,t+1}}\psi_i\sigma^2_{er,i}(z_{i,t} - z_{i,t-1}) + E_{i,t}e^{(1-\gamma_i)r^p_{i,t+1}}\tau_{z_{i,t}}(K) \tag{A.6}$$

Here the lower case r refers to log asset returns and portfolio returns. $er_{i,t+1} = r^H_{i,t+1} - r^F_{i,t+1}$.

I approximate each term by taking the expectation of the exponential terms, assuming normality, and then linearizing around expectation and variance terms in the exponential being zero.

For the first, second and last terms of the first order condition, I compute the expectation of the exponential and then linearize with respect to a zero variance and expectation and positive country share

$$E_{i,t}[er_{i,t+1} + \xi_{i,t}] + \gamma_i z_{i,t}\sigma^2_{er,i} + \gamma_i[\sigma_{H,F,i} - \sigma^2_{F,}] + \gamma_i \tau_{z_{i,t}}(K). \tag{A.7}$$

For the third and last term of the first order condition, first compute the expectation of the exponential, then linearize, including with respect to portfolio shares

$$\psi_i \sigma^2_{er,i}(z_{i,t} - z_{i,t-1}), \tag{A.8}$$

$$\psi_i \sigma^2_{er,i}\beta(E_{i,t}z_{i,t+1} - z_{i,t}). \tag{A.9}$$

Combining the terms yields

$$\begin{aligned} &E_{i,t}[er_{i,t+1} + \xi_{i,t}] + \gamma_i z_{i,t}\sigma^2_{er,i} + \gamma_i[\sigma_{H,F,i} - \sigma^2_{F,i}] - \psi_i\sigma^2_{er,i}(z_{i,t} - z_{i,t-1}) \\ &+ \psi_i\sigma^2_{er,i}\beta(E_{i,t}z_{i,t+1} - z_{i,t}) + \gamma_i\tau_{z_{i,t}}(K) = 0. \end{aligned} \tag{A.10}$$

To solve for the average country share, linearize the above equation around $E_{i,t}[er_{i,t+1}+\xi_{i,t}] = 0$ and $z_{i,t} = \bar{z}_i > 0\,\forall t$, which yield

$$\bar{z}_i = \frac{\sigma^2_{F,i} - \sigma_{H,F,i} - \tau_{\bar{z}_i}(K)}{\sigma^2_{er,i}} \tag{A.11}$$

Denote by $\hat{z}_{i,t}$ the share in t minus the average share $\hat{z}_{i,t} = z_{i,t} - \bar{z}_i$ and using the assumption that the change in transaction cost is negligible for changes in z. We can rewrite the first order condition as

$$E_{i,t}[er_{i,t+1} + \xi_{i,t}] - \gamma_i\hat{z}_{i,t}\sigma^2_{er,i} - \psi_i\sigma^2_{er,i}(\hat{z}_{i,t} - \hat{z}_{i,t-1}) + \psi_i\sigma^2_{er,i}\beta(E_{i,t}\hat{z}_{i,t+1} - \hat{z}_{i,t}) = 0. \tag{A.12}$$

I now solve the second-order difference equation in the portfolio share $\hat{z}_{i,n,t}$. Collecting terms, I can write as

$$\sigma^2_{er,i}D_i\hat{z}_{i,t} = E_{i,t}er_{i,t+1} + \xi_{i,t} + \psi_i\sigma^2_{er,i}\hat{z}_{i,t-1} + \beta\psi_i\sigma^2_{er,i}E_{i,t}\hat{z}_{i,t+1} \tag{A.13}$$

where $D_i = \gamma_i + \psi_i(1+\beta)$.

This can be written as

$$\left(L^{-2}-\frac{D_i}{\beta\psi_i}L^{-1}+\frac{1}{\beta}\right)\hat{z}_{i,t-1}=-\frac{1}{\beta\psi_i\sigma^2_{er,i}}E_{i,t}\left(er_{i,t+1}+\xi_{i,t}\right) \tag{A.14}$$

where $L^{-2}\hat{z}_{i,t-1}=E_{i,t}\hat{z}_{i,t+1}$ and $L^{-1}\hat{z}_{i,t-1}=\hat{z}_{i,t}$. Factoring gives

$$(L^{-1}-\omega_{1,i})(L^{-1}-\omega_{2,i})\hat{z}_{i,t-1}=-\frac{1}{\beta\psi_i\sigma^2_{er,i}}E_{i,t}\left(er_{i,t+1}+\xi_{i,t}\right) \tag{A.15}$$

where $\omega_{1,i}$ and $\omega_{2,i}$ are the roots of the characteristic equation

$$\omega_i^2-\frac{D_i}{\beta\psi_i}\omega_i+\frac{1}{\beta}=0 \tag{A.16}$$

These roots are

$$\omega_i=0.5\left(\frac{D_i}{\beta\psi_i}\pm\sqrt{\left(\frac{D_i}{\beta\psi_i}\right)^2-(4/\beta)}\right) \tag{A.17}$$

For convenience, I will refer to the stable root (with the minus sign) simply as ω_i and the unstable root (with the positive sign) as $\omega_{2,i}$.

Now write the solution as

$$(L^{-1}-\omega_i)\hat{z}_{i,t-1}=-\frac{1}{\beta\psi_i\sigma^2_{er,i}}\frac{E_{i,t}\left(er_{i,t+1}+\xi_{i,t}\right)}{L^{-1}-\omega_{2,i}} \tag{A.18}$$

This implies

$$z_{i,t}=(1-a_{1,i})\bar{z}_i+a_{1,i}z_{i,t-1}+a_{2,i}\sum_{s=1}^{\infty}\beta a_{1,i}^{s-1}E_{i,t}\left(er_{i,t+s}+\xi_{i,t+s-1}\right) \tag{A.19}$$

where $w_2=1/(\beta w)$ and $w=a_1$.

The term ξ compensates negative expected excess returns such that $z_{i,t}\geq 0$. Equivalently,

$$z_{i,t}=\max\left\{0,(1-a_{1,i})\bar{z}_i+a_{1,i}z_{i,t-1}+a_{2,i}\sum_{s=1}^{\infty}\beta a_{1,i}^{s-1}E_{i,t}\left(er_{i,t+s}\right)\right\} \tag{A.20}$$

Appendix B Data Appendix

I obtain the following monthly MSCI data from DataStream for the 72 countries in my sample: monthly total return index, price index, earning-price ratio, dividend-price ratio and market value (market capitalization). The total return index includes both the capital gains and dividend component of the return. All data are denominated in dollars. From these MSCI data I also compute the equity return as the relative change of the total return index from the prior month, the earnings as the earning-price ratio multiplied by the price index, and the dividend as the dividend-price ratio multiplied by the price index.

Appendix C Predicting Equity Return Differentials

I predict three other measures of expected excess returns, that I use in the portfolio regressions. Table C.1 shows the predictability regressions. Column (1) regresses the expected excess return at an horizon of 24-month on the first difference (Δ_1) in the log dividends, the level and the first difference in log earnings. Column (2) uses the 24-months lagged excess return, dividend-price (dp) and earning-price (ep). Column (3) uses the the first difference in the log dividends, the level and the first difference in log earnings and the difference from $t-24$ to t of the log dividends and log earnings. There is predictability in all regressions.

Table C.1: **Expected Equity Return $er^{0.9}_{n,t,t+24}$, Robustness**

	(1)	(2)	(3)
$\Delta_1 d_{n,t}$	0.045**		-0.009
	(0.023)		(0.023)
$\Delta_1 e_{n,t}$	0.041***		0.024*
	(0.013)		(0.013)
$e_{n,t}$	-0.055***		-0.113***
	(0.006)		(0.006)
$er_{n,t-24}$		0.081**	
		(0.039)	
$dy_{n,t-24}$		0.064***	
		(0.008)	
$ep_{n,t-24}$		0.015***	
		(0.005)	
$\Delta d_{n,t}$			0.041***
			(0.005)
$\Delta e_{n,t}$			0.064***
			(0.004)
Observations	20128	19079	18072
Adjusted R^2	0.070	0.093	0.154

Clustered standard errors by months in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Regressions with 72 countries over the interval 1970:01-2019:02. All regressions include a country fixed effect.

Appendix D Portfolio Regressions

I use the predicted expected excess returns obtained with the predictors in Table C.1 to estimate the portfolio equation with the two-limit random effect Tobit. I report the results in Table D.1.

Table D.1: **Portfolio Regressions, Tobit, 24-months Investment Universe, Robustness**

$z_{i,n,t} = \max\{0, a_{i,n} + a_1 z_{i,n,t-1} + a_2 E_t er^{\delta}_{i,n,t,t+K} + \varepsilon_{i,n,t}\}$				
	(1)	(2)	(3)	(4)
$z_{i,n,t-1}$	0.957***	0.960***	0.958***	0.958***
	(0.003)	(0.003)	(0.003)	(0.003)
$E_t er^{\beta a_1}_{i,n,t,t+24}$	0.195***	0.259***	0.087***	0.091***
	(0.032)	(0.047)	(0.021)	(0.029)
Observations $z_{i,n,t} > 0$	1,361,826	1,361,826	1,361,826	1,361,826
Observations $z_{i,n,t} = 0$	353,675	353,675	353,675	353,675

Clustered standard errors by months in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions for 72 countries over the interval 1996:01-2016:07.

Table D.2 shows the coefficients associated with the frictionless and the myopic Tobit regressions.

Table D.2: **Portfolio Regressions: Tobit**

$z_{i,n,t} = \max\{0, a_{i,n} + a_1 z_{i,n,t-1} + a_2 er_{i,n,t+1} + \varepsilon_{i,n,t}\}$		
	(1) Frictionless	(2) Myopic
$z_{i,n,t-1}$		0.956***
		(0.003)
$er_{i,n,t,t+1}$	0.816***	0.093***
	(0.059)	(0.030)
Observations $z_{i,n,t} > 0$	1,361,826	1,361,826
Observations $z_{i,n,t} = 0$	353,675	353,675

Clustered standard errors by month in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions for 72 countries over the interval 1996:01-2016:07.

Appendix E Heterogeneous Impulse Response

Funds differ in their level of activity, size, type and in their exposition to country shocks. Figure 6 shows the portfolio response to a one standard deviation of the expected excess return innovation for those different characteristics. The benchmark is the Tobit regression with an investment universe of 24 months. Active funds are the ones in the top 25% of the distribution of the measure of portfolio volatility discussed in section 2. Large funds are the ones with an average asset under management higher than the median value of the assets under management. Type refer to the geographical exposition of the funds. I split the funds in two categories: (i) global funds and (ii) regional funds. Global funds invest in developed and developing countries worldwide. Regional funds invest in certain continents (e.g. Asia, Latin America, Europe, BRIC). I also consider funds' heterogeneity by their level of exposition towards a country. The higher is the average portfolio share, the more the funds would respond to a financial shock. Table E.1 shows the portfolio regression coefficients associated with the heterogeneity and Figure 6.

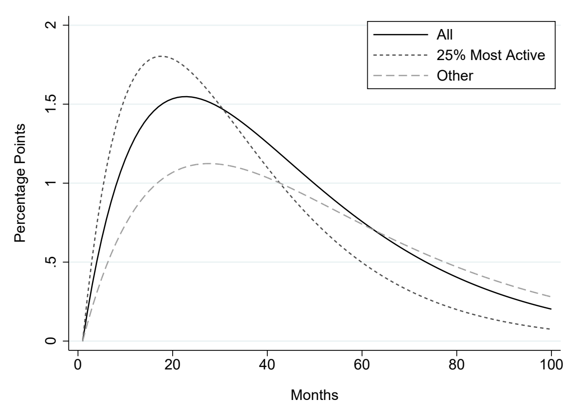
Table E.1: **Portfolio Regressions, Heterogeneity**

$z_{i,n,t} = \max\left\{0, a_{i,n} + a_1 z_{i,n,t-1} + a_2 \sum_{s=1}^{\infty}(\beta a_1)^{s-1}\left[E_t er_{i,n,t+s}\right] + a_3 X_i z_{i,n,t-1} + a_4 X_i \sum_{s=1}^{\infty}(\beta a_1)^{s-1}\left[E_t er_{i,n,t+s}\right] + \varepsilon_{i,n,t}\right\}$				
	(1) Size	(2) Activeness	(3) Type	(4) Exposure
$z_{i,n,t-1}$	0.948***	0.967***	0.968***	0.971***
	(0.003)	(0.003)	(0.003)	(0.005)
$E_t er^{\beta a_1}_{i,n,t,t+24}$	0.246***	0.173***	0.157***	0.146***
	(0.045)	(0.030)	(0.022)	(0.029)
$X_i z_{i,n,t-1}$	0.017*	-0.026***	-0.018**	-0.088
	(0.010)	(0.004)	(0.008)	(0.054)
$X_i E_t er^{\beta a_1}_{i,n,t,t+24}$	-0.083***	0.057**	0.080**	0.497**
	(0.029)	(0.028)	(0.031)	(0.226)
Observations $z_{i,n,t} > 0$	1,269,952	1,269,952	1,269,952	1,269,952
Observations $z_{i,n,t} > 0$	316,654	316,654	316,654	316,654

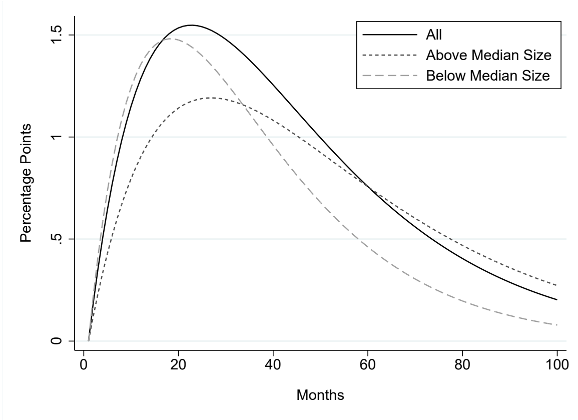
Clustered standard errors by month in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Regressions for 72 countries over the interval 1996:01-2016:07. Tobit regressions include the first country share, the mean of the country shares and the mean of the expected excess return and those variables interacted with X_i.

Figure 6: **Heterogeneous Impulse Response Portfolio Share to Expected Return Shock**

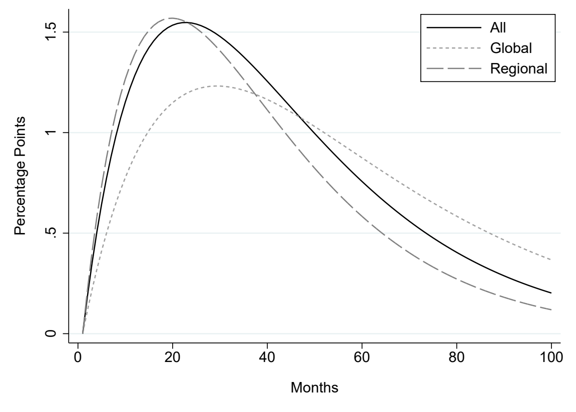
(a) **Activeness**



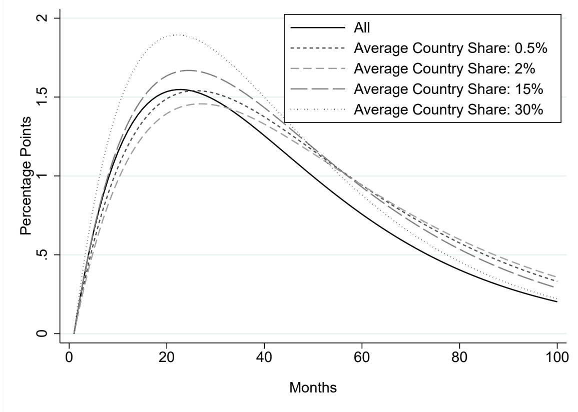
(b) **Size**



(c) **Type**



(d) **Exposure**

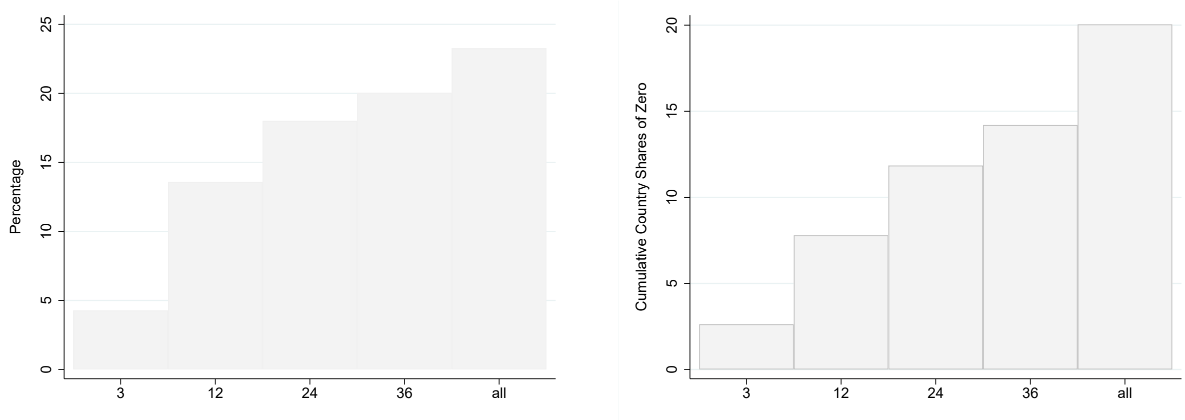


Notes: Figure 6 shows the impulse response of the portfolio shares to a one standard deviation shock to the expected excess return innovation by funds' characteristics. The y-axis is the percentage points deviation from the steady state. The x-axis represents the months.

The financial shock increases the magnitude and the persistence of the portfolio response of active funds, regional funds, small funds and more exposed funds more than their respective counterpart. The funds that respond less to the financial shock are passive, large and global.

Appendix F Descriptives

Figure F.1: **Fraction Country Shares of Zero**



(a) **Average Fraction Country Shares of Zero** (b) **Persistence**

Notes: Figure F.1 shows the average fraction of country shares of zero in panel (a) and the average episode of persistence country shares of zero in panel (b) for the investment universes.

Table F.1 shows the average fraction of country shares of zero that are invested in the countries by the funds. The last column counts the number of funds that report for the countries. When only a few funds invest in a country, loosening the investment universe sharply increases the fraction of zeros.

Table F.1: **Countries and Reported zeros**

	3	12	24	36	all	Number Funds
Algeria	15.0	65.0	95.0	95.0	95.0	1
Angola	2.5	17.7	28.7	38.6	91.7	3
Argentina	4.2	18.1	26.8	31.4	39.3	483
Australia	3.5	14.7	20.7	24.2	30.3	549
Austria	4.7	20.0	29.6	34.8	44.8	581
Bahrain	6.7	26.7	39.6	46.5	67.1	30
Baltic Republics	4.3	23.6	37.9	47.4	83.7	46
Bangladesh	3.2	14.5	21.8	26.8	50.1	40
Belgium	3.4	12.6	17.1	19.1	21.7	671

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Table F.1: – continued from previous page

	3	12	24	36	all	Number Funds
Bolivia	4.0	18.7	32.4	43.2	89.4	20
Botswana	4.2	16.3	26.3	34.0	64.0	39
Brazil	2.5	8.0	10.7	12.0	13.5	646
Bulgaria	5.7	26.8	41.6	50.3	70.5	43
Cambodia	1.3	10.1	20.3	30.4	98.7	1
Canada	3.4	13.2	18.7	21.6	25.3	366
Chile	3.3	13.3	19.5	22.8	27.1	498
China	2.2	8.6	11.4	12.6	13.9	906
Colombia	5.0	21.7	32.8	38.7	50.2	360
Costa-Rica	2.5	19.7	38.5	48.4	99.2	1
Croatia	4.5	19.6	30.1	38.0	68.7	151
Cyprus	4.4	27.9	45.6	55.9	83.6	91
Czech Republic	4.2	17.0	25.3	29.6	37.3	399
Denmark	3.5	14.1	19.7	22.3	26.1	570
Dominican Republic	2.0	44.8	67.1	75.3	77.3	2
Ecuador	4.1	20.3	36.8	49.0	80.6	35
Egypt	4.1	20.0	29.7	35.3	43.9	334
El Salvador	4.1	32.4	64.9	86.5	90.5	1
Estonia	4.1	19.8	33.6	44.3	73.2	98
Finland	4.3	15.5	21.3	23.7	26.6	608
France	1.0	2.9	3.7	4.1	4.8	774
Georgia	7.2	30.9	45.4	53.7	66.7	39
Germany	0.7	3.1	4.1	4.4	4.9	765
Ghana	3.1	17.5	27.7	34.9	58.6	63
Greece	4.8	22.3	33.5	39.8	54.1	566
Guatemala	4.8	28.1	46.1	60.0	93.1	2
Hong-Kong	3.4	11.2	14.7	16.5	18.8	899
Hungary	3.4	13.1	19.3	22.6	27.5	397
Iceland	7.7	36.8	66.0	74.7	97.4	3
India	2.7	11.0	15.7	18.1	21.2	764
Indonesia	3.6	13.2	17.9	20.4	23.5	707
Iran	5.6	19.7	31.7	43.6	74.4	2
Iraq	4.6	33.7	52.2	61.0	71.5	17
Ireland	5.3	19.9	27.3	30.3	33.6	571
Israel	3.6	16.3	23.9	28.4	36.2	492
Italy	2.8	9.4	12.3	13.5	15.4	731
Ivory Coast	2.4	15.6	25.4	27.7	41.7	4
Japan	0.8	3.7	5.0	5.7	7.3	437
Jordan	10.1	34.5	49.2	56.5	76.6	116

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Table F.1: – continued from previous page

	3	12	24	36	all	Number Funds
Kazakhstan	4.7	23.0	36.6	45.9	63.5	239
Kenya	2.1	13.2	21.0	27.2	43.5	76
Korea North	8.3	34.8	55.5	75.4	94.9	9
Korea South	1.6	5.9	7.9	8.8	9.7	794
Kuwait	2.3	10.1	15.4	19.3	30.7	54
Latvia	4.0	18.7	32.3	44.1	77.3	10
Lebanon	5.3	21.5	35.3	45.2	70.3	48
Liberia	7.5	35.0	35.0	35.0	35.0	1
Lithuania	4.6	18.2	30.0	39.7	69.9	29
Madagascar	10.0	32.5	42.5	42.5	42.5	1
Malawi	4.0	16.7	27.8	31.9	56.6	9
Malaysia	3.3	11.0	15.0	17.1	20.4	616
Mauritius	4.2	14.5	21.8	26.6	52.5	36
Mexico	2.0	9.0	12.4	14.3	16.6	592
Mongolia	5.8	37.5	58.8	67.2	84.5	24
Morocco	4.3	21.6	32.6	40.3	60.8	135
Mozambique	4.5	14.4	19.3	22.1	58.5	2
Myanmar	0.0	11.4	22.9	34.3	87.6	1
Namibia	4.1	17.7	29.6	40.1	69.9	12
Netherlands	2.0	7.4	9.5	10.5	12.1	747
New Zealand	3.5	17.7	25.8	30.4	41.9	241
Nigeria	3.6	17.0	24.9	29.9	46.6	105
Norway	4.9	16.5	21.9	24.1	26.8	551
Oman	3.4	12.9	18.4	22.9	37.9	64
Pakistan	4.2	19.0	30.8	38.9	64.6	188
Panama	5.6	26.8	41.7	50.1	68.0	175
Papua New Guinea	1.7	13.8	27.6	40.5	97.1	2
Peru	4.7	18.3	27.0	31.7	39.5	374
Philippines	4.7	17.0	24.6	28.5	35.2	572
Poland	3.0	12.6	18.6	21.8	26.8	430
Portugal	4.7	18.9	27.6	32.3	44.8	527
Qatar	3.5	19.0	28.0	33.5	49.5	137
Romania	3.1	21.6	34.4	42.4	60.3	138
Russian Federation	3.0	12.6	17.4	19.6	23.0	651
Rwanda	0.0	5.5	9.7	12.2	12.2	3
Saudi Arabia	2.0	11.6	18.9	24.5	44.6	73
Serbia	8.7	25.5	38.0	46.6	58.0	7
sierra Leone	1.6	13.2	25.8	32.4	98.4	1
Singapore	3.4	14.0	19.6	22.8	27.5	742

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Table F.1: – continued from previous page

	3	12	24	36	all	Number Funds
Slovakia	3.9	16.7	27.5	35.9	80.3	66
Slovenia	4.0	18.7	31.5	40.4	67.7	70
South Africa	2.4	10.7	15.1	17.8	22.4	640
Spain	3.0	10.3	13.9	15.3	17.3	723
Sri Lanka	3.2	15.5	25.5	32.0	55.3	115
Swaziland	10.6	44.1	65.7	79.8	94.8	5
Sweden	3.7	12.8	17.4	19.3	22.4	645
Switzerland	1.4	4.9	7.0	8.0	10.0	710
Taiwan	1.5	6.2	8.6	9.7	10.8	738
Tajikistan	3.2	18.2	33.4	48.6	98.3	2
Tanzania	2.5	27.6	40.1	48.3	66.2	12
Thailand	2.9	9.7	13.0	14.4	17.3	681
Tunisia	5.2	22.7	33.7	40.7	59.5	27
Turkey	2.8	10.4	15.8	18.9	23.1	477
Turkmenistan	3.4	22.2	37.4	50.1	92.6	9
Uganda	3.8	29.1	46.0	58.4	75.7	5
Ukraine	5.3	24.8	38.9	48.1	68.4	157
United Arab Emirates	2.4	22.4	33.9	40.7	55.5	266
United Kingdom	1.2	6.7	10.3	12.5	17.9	784
United States	3.0	13.9	19.8	23.2	32.7	516
Uruguay	3.1	26.6	36.7	42.9	71.1	8
Venezuela	5.8	23.1	33.5	39.3	63.7	167
Vietnam	3.4	17.0	26.7	34.0	58.2	93
Yemen	6.3	47.9	72.9	97.9	97.9	1
Zambia	3.7	14.6	22.2	29.1	54.4	23
Zimbabwe	3.6	14.0	23.1	31.1	64.5	57

Appendix G Profitability

Is the predictability profitable? In this section, I construct a trading strategy to estimate the economic significance of predictability by following the literature (Cenedese et al., 2016). For each month, I sort the 72 countries based on their values $\Delta_1 d_{n,t}$ and $\Delta_1 e_{n,t}$. The one fifth of countries whose predictors have the lowest value are allocated to the first quintile Q1, the next fifth to the second quintile Q2, and so on. Thus, Q1 should contain low excess returns and Q5 high excess returns. For each month, the trading strategy consists of going long on those countries in which their $\Delta_1 d_{n,t}$ and $\Delta_1 e_{n,t}$ are at the same time in the fifth quintile. I refer to this trading strategy as "top". I compare this trading strategy to the one of going long on those countries in which their $\Delta_1 d_{n,t}$ and $\Delta_1 e_{n,t}$ are at the same time in the first quintile. I refer to this trading strategy as "bottom". I also compare to the average value of the 1-month ahead equity return. The sample is January 1996 to February 2019 for the 72 countries.

Table G.1 reports the average annualized equity return one could obtain by following the top, bottom or mean trading strategy. The table shows that the return obtained by following the top strategy is higher by 4pp and 1.2pp in comparison to the bottom and the mean strategy. These results therefore demonstrate the economic significance of equity return predictability, which justifies that time-varying expected excess returns are taken into account in actual portfolio allocations.

Table G.1: **Trading Strategies**

	Top	Bottom	Mean
Annual equity return (%)	9.889	5.846	8.654

The sample is January 1996 to February 2019 for the 72 countries.

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