International Portfolio Choice with Frictions: Evidence from Mutual Funds[1]

Philippe Bacchetta
University of Lausanne
Swiss Finance Institute
CEPR

Simon Tièche
University of Lausanne

Eric van Wincoop
University of Virginia
NBER

October 31, 2021

[1]We would like to thank Margaret Davenport, Amit Goyal, and two referees for useful discussions. We gratefully acknowledge financial support from the Swiss National Science Foundation and the Bankard Fund for Political Economy.

Abstract

Using data on international equity portfolio allocations by US mutual funds, we estimate a simple portfolio expression derived from a standard Markowitz mean-variance portfolio model extended with portfolio frictions. The optimal portfolio depends on two benchmark portfolios, the previous month and the buy-and-hold portfolio shares, and a present discounted value of expected future excess returns. We show that equity return differentials are predictable and use the expected return differentials in the mutual fund portfolio regressions. The estimated reduced form parameters are related to the structural model parameters. The estimates imply significant portfolio frictions and a modest rate of risk aversion. While mutual fund portfolios respond significantly to expected returns, portfolio frictions lead to a weaker and more gradual portfolio response to changes in expected returns.

1 Introduction

An extensive literature has introduced frictions into models of portfolio choice that lead to deviations from the standard Markowitz mean-variance portfolio.[1] This is supported by micro evidence of sluggish portfolio decisions by households and helps explain various asset pricing facts. In this paper we focus on international portfolio decisions. The objective is to provide evidence on how US mutual funds allocate their equity portfolios across countries, and specifically to what extent this is affected by portfolio frictions that lead to a weaker and more gradual response to changes in expected returns. It has frequently been suggested that global investors are slow to adjust their portfolios in response to new information. In the context of US external equity investments, Bohn and Tesar (1996) comment that "we suspect that investors may adjust their portfolios to new information gradually over time, resulting in both autocorrelated net purchases and a positive linkage with lagged returns." Froot et al. (2001) provide similar evidence. Froot and Thaler (1990), in attempting to explain the forward discount puzzle of excess return predictability in the foreign exchange market, hypothesize that "...at least some investors are slow in responding to changes in the interest differential." More formally, Bacchetta and van Wincoop (2010, 2021) and Bacchetta et al. (2021a, 2021b) show that open economy models with portfolio frictions can explain a variety of evidence related to excess return predictability in foreign exchange and equity markets as well as various data moments involving capital flows, saving, investment, or aggregate US equity portfolios.[2] Nonetheless none of the existing literature has provided direct evidence of portfolio frictions in international portfolio allocation data. This paper aims to fill that gap.

Our evidence is based on 15 years of monthly equity portfolio allocation data across 36 countries for 316 US mutual funds that report to EPFR (Emerging Port-

[1]Some recent contributions include Abel et al. (2007), Bogousslavsky (2016), Chien et al. (2012), Duffie (2010), Greenwood et al. (2018), Hendershott et al. (2018) and Vayanos and Woolley (2012).

[2]While there are many models of international capital flows driven by portfolio choice, these tend to abstract from portfolio frictions considered here. Examples of recent DSGE models of capital flows based on portfolio choice include Benhima and Cordonier (2020), Davis and van Wincoop (2018), Devereux and Sutherland (2007, 2010), Didier and Lowenkron (2012), Evans and Hnatkovska (2012, 2014), Gabaix and Maggiori (2015), Hnatkovska (2010) and Tille and van Wincoop (2010a, 2010b, 2014).

folio Fund Research). Mutual funds are the most important players in external US equity holdings, accounting for 53 percent of all US foreign equity holdings at the end of 2020.[3] To structure the analysis, we present a portfolio choice model that enables us to derive a simple and testable portfolio equation. While the standard Markowitz mean-variance portfolio is embedded as a special case, the model allows for deviations from the Markowitz portfolio as a result of portfolio frictions that involve costs of deviating from two benchmark portfolios. The optimal portfolio share then depends on both of these benchmark portfolios and a present discounted value of expected future excess returns. We first document that international differences in stock returns are predictable and that predictability improves over longer horizons. We then use estimates of these expected excess returns in our portfolio regressions. We find that portfolios respond to expected return differentials, but deviate gradually from benchmark portfolios. The results from the portfolio regressions are used to obtain estimates of the structural parameters of the model, such as the two portfolio frictions and risk aversion.

The simple theoretical portfolio choice model that structures the empirical analysis is analogous to Gârleanu and Pedersen (2013). It assumes that funds (investors) maximize the present discounted value of risk-adjusted portfolio returns minus quadratic costs of deviating from two benchmark portfolios. The first portfolio friction is a cost of deviating from the portfolio share during the previous month, which is the portfolio under complete rebalancing (like an index fund). The second is a cost of deviating from a buy-and-hold portfolio. The more important these portfolio frictions are, the more the optimal portfolio share depends on the two benchmark portfolios and the less it depends on expected excess returns. In addition, the portfolio frictions imply that the optimal portfolio depends not just on expected excess returns over the next period (as in the Markowitz portfolio), but on a present discounted value of future excess returns. The frictions lead to a more gradual response of portfolio shares to changes in expected returns.

One difficulty with estimating portfolio expressions is endogeneity. The error term of the portfolio expression, which for example captures latent time-varying risk, can lead to portfolio shifts that affect equity prices. While individual mutual funds are too small to impact equity prices, there may be common components across investors of such portfolio shifts. This leads to endogeneity of our explana-

[3]See Exhibit 19 in "Portfolio Holdings of Foreign Securities," October 2021, Department of the Treasury.

tory variables (the lagged portfolio share, buy-and-hold portfolio share and measure of expected excess returns). We address this issue by using Two-Stage Least Squares (2SLS), using instruments that are unlikely to be associated with equity portfolio shifts. We find that point estimates do not differ significantly from those under OLS.

We find that the funds respond to the discounted expected excess return with strong statistical significance. We also find that both benchmark portfolios are very important, so that portfolio frictions matter. Our estimates imply a humped shaped portfolio response to an expected excess return innovation. The initial portfolio response is weaker than in the absence of portfolio frictions, while the portfolio response builds gradually as a result of the frictions. The regression estimates imply a plausible rate of risk aversion of 2.8. We also find that the lagged portfolio share is at least as important as the the buy-and-hold portfolio, which is consistent with extensive portfolio rebalancing by the mutual funds.

The paper is related to various strands of literature. The first is the literature on excess return predictability. While the evidence we report on the predictability of international stock return differentials is new, the evidence on the predictability of international short term bond return differentials (UIP deviations) has been known since Fama (1984). Predictability has also been widely documented in the context of country or individual stock returns or the excess of stock returns over bond returns (for a textbook discussion, see Campbell, Lo and MacKinlay, 1997). While the latter literature focuses mainly on the US, some papers document stock return predictability in other countries or show, by pooling the data, that there is global predictability (Hjalmarsson, 2010). Cenedese et al. (2016) consider the profitability of trading strategies that exploit international equity return differentials. They sort countries into various "bins" based on the realization of variables like the dividend yield that are likely to predict future equity returns. They do not estimate portfolio expressions or excess returns, but find substantial Sharpe ratios from trading strategies that exploit in which bin countries are located.

In terms of estimation of portfolio regressions, the open economy literature is very limited, which is the motivation for doing this project. Frankel and Engel (1984) invert the portfolio expression obtained from a simple frictionless mean variance portfolio model, relating expected returns on various currencies to asset supplies. They strongly reject the model. Also relevant is recent work by Koijen and Yogo (2020). As we do, they adopt a two-step approach, first estimating expected excess returns and then estimating portfolio expressions. They differ in that they do not allow for portfolio frictions and use aggregate bilateral portfolio shares in three asset classes. They also handle the endogeneity issue differently as they can use their global demand system to instrument asset prices with macroeconomic variables. Some papers have investigated the link between international capital flows (as opposed to portfolio shares) and past returns as well as expected future returns (e.g. Bohn and Tesar (1996), Froot et al. (2001), Didier and Lowenkron (2012)).

There is also a literature that has investigated portfolio allocation using mutual fund data. For example, Raddatz and Schmukler (2012) and Raddatz et al. (2017) use EPFR data to regress portfolio allocation of funds across countries on variables such as lagged portfolio shares, buy-and-hold portfolio shares and valuation effects.[4] The impact of valuation effects and portfolio rebalancing is analyzed by Camanho et al. (2020) using another source of mutual fund data. However, the regressions in this literature do not have a clear theoretical foundation. In particular, there is no forward-looking dimension of portfolios. Expected excess returns are not included.[5]

Outside the open economy literature, there is a literature on individual portfolio choice that has documented significant portfolio inertia. This literature (e.g. Ameriks and Zeldes (2004), Bilias et al. (2010), Brunnermeier and Nagel (2008), Mitchell et al. (2006)) uses data on portfolio allocation by individual households. It is consistent with gradual portfolio adjustment, although (like the other literatures discussed above) it does not relate portfolio allocation to expected excess returns as in standard portfolio theory. An exception is the recent paper by Giglio et al. (2021), which relates equity portfolio shares to expected returns based on survey data of US-based Vanguard investors. They find that portfolio shares depend positively on reported equity return expectations, but that responsiveness to expected equity returns is too weak to make sense in the context of the frictionless mean-variance portfolio choice model (implied risk aversion is excessive). They further provide evidence that changes in expected returns have limited explanatory power for when investors trade, but help predict the direction and the

[4]Disyatat and Gelos (2001) compare EPFR portfolio weights to the predictions of a simple mean-variance portfolio model.

[5]Curcuru et al. (2014) stress the role of future returns, but use *ex post* realized returns in their regressions.

magnitude of trading conditional on its occurrence. They argue that the evidence is consistent with infrequent trading.

The remainder of the paper is organized as follows. Section 2 presents the model. Section 3 analyzes the predictability of international equity return differentials. Section 4 presents results from estimating the fund-level portfolio regressions. Section 5 concludes.

2 A Model of Portfolio Allocation with Financial Frictions

2.1 Portfolio Objective

Consider a fund i that allocates its equity portfolio to N countries. We will focus the analysis here on a specific fund i, although one should keep in mind that the investment universe varies across funds. We take the set of countries that a fund invests in as given and consider the portfolio allocation across these countries. One should therefore keep in mind that the number of countries N in the investment universe will vary across funds.

The vectors of portfolio shares and country equity returns are

$$\mathbf{z}_{i,t} = \begin{pmatrix} z_{i,1,t} \\ ... \\ z_{i,N,t} \end{pmatrix} \qquad \mathbf{R}_{t+1} = \begin{pmatrix} R_{1,t+1} \\ ... \\ R_{N,t+1} \end{pmatrix} \tag{1}$$

where $z_{i,n,t}$ is the share that fund i allocates to country n at time t and $R_{n,t+1}$ is the country n equity return from t to $t+1$.

Define the buy-and-hold portfolio as

$$z_{i,n,t}^{bh} = z_{i,n,t-1} \frac{1 + R_{n,t}}{1 + \mathbf{z}'_{i,t-1}\mathbf{R}_t} \tag{2}$$

This is the portfolio held at time t in the absence of asset trade at time t. The buy-and-hold portfolio share only differs from the lagged portfolio share $z_{i,n,t-1}$ due to valuation effects associated with equity returns.

We consider a structure similar to Gârleanu and Pedersen (2013), where funds maximize the present discounted value of risk-adjusted portfolio returns, but face costs of deviating from benchmark portfolios. The objective of the fund is to maximize

$$\sum_{s=0}^{\infty} \beta^s E_{i,t} \mathbf{z}'_{i,t+s} \mathbf{R}_{t+s+1} - 0.5\gamma_i \sum_{s=0}^{\infty} \beta^s \mathbf{z}'_{i,t+s} \mathbf{\Omega}_{i,t} \mathbf{z}_{i,t+s}$$
$$-0.5\mu_{1,i} \sum_{s=0}^{\infty} \beta^s E_{i,t} \left(\mathbf{z}_{i,t+s} - \mathbf{z}_{i,t+s-1}\right)' \mathbf{A}_{i,t} \left(\mathbf{z}_{i,t+s} - \mathbf{z}_{i,t+s-1}\right)$$
$$-0.5\mu_{2,i} \sum_{s=0}^{\infty} \beta^s E_{i,t} \left(\mathbf{z}_{i,t+s} - \mathbf{z}^{bh}_{i,t+s}\right)' \mathbf{A}_{i,t} \left(\mathbf{z}_{i,t+s} - \mathbf{z}^{bh}_{i,t+s}\right) \quad (3)$$

where $E_{i,t}$ is the expectation of fund i at time t. The variance at time t of $\mathbf{R}_{t+s+1}$ is denoted $\mathbf{\Omega}_{i,t}$.

The first line of (3) is a present-value version of a standard mean-variance objective. The discount rate is β and the rate of risk aversion is γ_i. The last two lines capture the cost of deviating from the benchmark portfolios, respectively the lagged portfolios and the buy-and-hold portfolios. The parameters $\mu_{1,i}$ and $\mu_{2,i}$ determine the cost of deviating from respectively the lagged portfolios and the buy-and-hold portfolios. We follow Gârleanu and Pedersen (2013) by assuming $A_{i,t} = \mathbf{\Omega}_{i,t}$, for which they provide micro foundations.

There can be multiple underlying frictions that generate the gradual portfolio adjustment implied by (3). Gârleanu and Pedersen (2013) think of it as transaction costs. This is particularly relevant when deviating from the buy-and-hold portfolio, which involves asset trade. There may also be costs to acquiring information or costs to portfolio reoptimization that make fund managers more conservative and stick closer to prior benchmarks. In addition, it is possible that fund managers are penalized more for bad performance if this happens after they make significant portfolio changes relative to benchmark portfolios. This can take the form of fund outflows that affect manager compensation or lead to replacement of managers.

2.2 Optimal Portfolio

For a given optimal portfolio share $z_{i,n,t}$, consider the allocation of the remaining portfolio share $1 - z_{i,n,t}$ among countries other than n. Specifically, define

$$z_{i,m,-n,t} = \frac{z_{i,m,t}}{\sum_{k \neq n} z_{i,k,t}} = \frac{z_{i,m,t}}{1 - z_{i,n,t}} \quad (4)$$

This is the share allocated to country m of the equity portfolio outside country n. We can define a vector $\mathbf{z}_{i,-n,t}$, where element m is equal to $z_{i,m,-n,t}$ if $m \neq n$

and element n is zero. Choosing the optimal $\mathbf{z}_{i,t}$ is equivalent to choosing $z_{i,n,t}$ and $\mathbf{z}_{i,-n,t}$. The first-order condition with respect to $z_{i,n,t}$ therefore takes the optimal $\mathbf{z}_{i,-n,t}$ as given.

We define a reference portfolio return for fund i and country n as the return on the portfolio of countries other than country n, with portfolio weights $z_{i,m,-n,t}$:

$$R_{ref(i,n),t+1} = \sum_{m \neq n} z_{i,m,-n,t} R_{m,t+1} = \mathbf{z}'_{i,-n,t} \mathbf{R}_{t+1} \tag{5}$$

The excess return of country n relative to the reference portfolio is

$$er_{i,n,t+1} = R_{n,t+1} - R_{ref(i,n),t+1} = \left(\mathbf{e}_n - \mathbf{z}_{i,-n,t}\right)' \mathbf{R}_{t+1} \tag{6}$$

where $\mathbf{e}_n$ is a vector of size N with element n equal to 1 and zeros otherwise.

We maximize (3) with respect to $z_{i,n,t}$ after substituting the identity

$$\mathbf{z}_{i,t} = \mathbf{z}_{i,-n,t} + \left(\mathbf{e}_n - \mathbf{z}_{i,-n,t}\right) z_{i,n,t} \tag{7}$$

Appendix A derives the first-order condition with respect to $z_{i,n,t}$. After some rewriting, it becomes:

$$\begin{aligned} & E_{i,t} er_{i,n,t+1} + u_{i,n,t} - \gamma_i \sigma^2_{i,n} \hat{z}_{i,n,t} \\ & + (\mu_{1,i} + \mu_{2,i}) \sigma^2_{i,n} (\beta E_{i,t} \hat{z}_{i,n,t+1} - (1+\beta) \hat{z}_{i,n,t} + \hat{z}_{i,n,t-1}) \\ & + \mu_{2,i} \sigma^2_{i,n} \bar{z}_{i,n} (1 - \bar{z}_{i,n}) \left(er_{i,n,t} - \beta E_{i,t} er_{i,n,t+1}\right) = 0 \end{aligned} \tag{8}$$

Here $\hat{z}_{i,n,t} = z_{i,n,t} - \bar{z}_{i,n}$, where

$$\bar{z}_{i,n} = -\frac{\sigma_{n,ref(i,n)}}{\sigma^2_{i,n}} \tag{9}$$

is the mean (over time) of the portfolio share allocated to country n by fund i, where $\sigma_{n,ref(i,n)}$ is the mean value of $cov_{i,t}(er_{i,n,t+1}, R_{ref(i,n),t+1})$ and $\sigma^2_{i,n}$ is the mean value of $var_{i,t}(er_{i,n,t+1})$. While $\bar{z}_{i,n}$ depends on the mean level of risk, the term $u_{i,n,t}$ in (8) captures time-varying risk in deviation from its mean:

$$u_{i,n,t} = -\gamma_i \left(cov_{i,t}(er_{i,n,t+1}, R_{ref(i,n),t+1}) - \sigma_{n,ref(i,n)}\right) - \gamma_i \bar{z}_{i,n} \left(var_{i,t}(er_{i,n,t+1}) - \sigma^2_{i,n}\right) \tag{10}$$

Appendix B derives the following solution to the second-order difference equation (8) in $\hat{z}_{i,n,t}$:

$$\hat{z}_{i,n,t} = \omega_i \left(\frac{\mu_{1,i}}{\mu_{1,i} + \mu_{2,i}} \hat{z}_{i,n,t-1} + \frac{\mu_{2,i}}{\mu_{1,i} + \mu_{2,i}} \hat{z}^{bh}_{i,n,t} \right) + \frac{\omega_i}{\theta_i \sigma^2_{i,n}} \sum_{s=1}^{\infty} \left(\beta \omega_i\right)^{s-1} E_t er_{i,n,t+s} + \epsilon_{i,n,t} \tag{11}$$

where $\theta_i = \mu_{1,i} + \mu_{2,i}$,

$$\epsilon_{i,n,t} = \frac{\omega_i}{\theta_i \sigma^2_{i,n}} \sum_{s=1}^{\infty} (\beta\omega_i)^{s-1} E_{i,t} u_{i,n,t+s-1} + \frac{\omega_i}{\theta_i \sigma^2_{i,n}} \sum_{s=1}^{\infty} (\beta\omega_i)^{s-1} \left(E_{i,t} er_{i,n,t+s} - E_t er_{i,n,t+s} \right) \tag{12}$$

and

$$\omega_i = \frac{2\theta_i}{\gamma_i + (1+\beta)\theta_i + \sqrt{\gamma_i^2 + (1-\beta)^2\theta_i^2 + 2(1+\beta)\gamma_i\theta_i}} \tag{13}$$

In (12) the term $E_{i,t} er_{i,n,t+s} - E_t er_{i,n,t+s}$ captures the expected excess return by fund i minus the expected excess return by the econometrician. The expectation operator for the latter is denoted E_t.

In general there is heterogeneity across funds in γ_i, $\mu_{1,i}$ and $\mu_{2,i}$, as well as heterogeneity across (i,n) pairs with respect to $\sigma^2_{i,n}$ and risk that determines $\bar{z}_{i,n}$. The same parameters without the i and n subscripts will refer to their mean across funds and countries. Since we will not be able to precisely characterize the heterogeneity across funds in the data, we focus on the mean of these parameters. To do so, we linearize the optimal portfolio expression (11) with respect to these parameters equal to their mean and all $\hat{z}$ variables and excess returns equal to zero.[6]

Defining $\delta = \beta\omega$, this gives

$$z_{i,n,t} = b_{i,n} + b_1 z_{i,n,t-1} + b_2 z^{bh}_{i,n,t} + b_3 ER_{i,n,t} + \epsilon_{i,n,t} \tag{14}$$

where

$$b_{i,n} = (1-\omega)\bar{z}_{i,n};\ b_1 = \omega\frac{\mu_1}{\mu_1+\mu_2};\ b_2 = \omega\frac{\mu_2}{\mu_1+\mu_2};\ b_3 = \frac{\omega}{\theta\sigma^2(1-\delta)}$$

$$\omega = \frac{2\theta}{\gamma + (1+\beta)\theta + \sqrt{\gamma^2 + (1-\beta)^2\theta^2 + 2(1+\beta)\gamma\theta}}$$

Here ω, θ, γ, μ_1 and μ_2 refer to the mean across funds of ω_i, θ_i, γ_i, $\mu_{1,i}$ and $\mu_{2,i}$, while σ^2 is the mean across all (i,n) of $\sigma^2_{i,n}$. The present discounted value of future expected excess returns is defined as

$$ER_{i,n,t} = \sum_{s=1}^{\infty} (1-\delta)\delta^{s-1} E_t er_{i,n,t+s} \tag{15}$$

[6] We therefore omit second and higher order terms such as $(\omega_i - \omega)\hat{z}_{i,n,t-1}$, where ω is the mean of ω_i. This involves the product of two variables that both have a mean of zero. In Section 4.8 we will consider heterogeneity associated with $\sigma^2_{i,n}$ that leads to heterogeneity in the coefficient on the present discounted value of the expected excess return.

Note that it is defined such that the weights on all future expected excess returns sum to 1.

2.3 Intuition

Equation (14) writes the optimal portfolio as a linear function of the two benchmark portfolios, $z_{i,n,t-1}$ and $z^{bh}_{i,n,t}$, the expected present discounted value of the excess return on country n equity relative to the reference portfolio, and a time-varying error term.

First consider the role of risk aversion. In general, investors face a trade-off between risk, expected returns and the cost of deviating from the benchmark portfolios. A rise in risk aversion implies that investors are more concerned with risk, and therefore relatively less concerned with deviating from the benchmark portfolios and expected excess returns. This therefore reduces b_1, b_2 and b_3 (through ω).

Next consider the role of the portfolio frictions. A higher relative cost of deviating from the lagged portfolio compared to the buy-and-hold portfolio leads to a higher relative weight on the lagged portfolio in the portfolio expression: $b_1/b_2 = \mu_1/\mu_2$. An increase in the aggregate portfolio friction θ implies that investors are relatively more concerned with deviating from the benchmark portfolios and therefore relatively less concerned with risk and expected returns. It therefore raises the weight on both benchmark portfolios (b_1 and b_2), while it lowers the weight on the present discounted value of expected future excess returns (b_3).

Portfolio frictions also have the implication that the optimal portfolio gives relatively more weight to expected excess returns further into the future. The weight on the expected excess return s periods into the future is $(1-\delta)\delta^{s-1}$ with $\delta = \beta\omega$. A higher average portfolio friction θ raises δ, which implies more weight on expected returns further into the future. Without portfolio frictions all the weight is on the expected excess return in the immediate future:

$$z_{i,n,t} = b_{i,n} + \frac{E_t er_{i,n,t+1}}{\gamma\sigma^2_{i,n}} + \epsilon_{i,n,t} \tag{16}$$

The reason that portfolio frictions shift the weight to expected returns further into the future is that investors wish to smooth portfolio changes in anticipation of changes in expected future excess returns.[7] We can also see that investors give

[7]Bacchetta, van Wincoop, and Young (2021) obtain a similar dependence of the portfolio

more weight to expected excess returns further into the future (higher δ) when the time discount rate β is higher and the risk aversion γ is lower.

Finally some comments are in order regarding the error term $\epsilon_{i,n,t}$ defined in (12). The first term is the expected present discounted value of risk in deviation from its mean. Risk is defined by $u_{i,n,t}$ in (10) and depends on both the variance of the excess return and the covariance of the excess return with the reference portfolio. The second term captures differences between expected excess returns by fund i and that by the econometrician (denoted with the expectation operator E_t). This may include deviations from rational expectations of excess returns that lead to noise trade. It may also capture changes in expected excess returns associated with information that is not easily available to an econometrician. Waves of optimism or pessimism about a country that we cannot easily measure therefore go into the error term as well.

It should finally be pointed out that there is an alternative way of writing the optimal portfolio expression. Define a valuation effect variable as the difference between the buy-and-hold portfolio and the lagged portfolio:

$$val_{i,n,t} = z^{bh}_{i,n,t} - z_{i,n,t-1} \tag{17}$$

Linearizing, we have $val_{i,n,t} = \bar{z}_{i,n}(1 - \bar{z}_{i,n})er_{i,n,t}$. It tells us how much the portfolio share increases due to an increase in the excess return in the absence of any asset trade.

The portfolio can then be written as

$$z_{i,n,t} = b_{i,n} + a_1 z_{i,n,t-1} + a_2 val_{i,n,t} + a_3 ER_{i,n,t} + \epsilon_{i,n,t} \tag{18}$$

where $a_1 = b_1 + b_2$, $a_2 = b_2$, $a_3 = b_3$. The coefficient on the valuation effect therefore corresponds to the coefficient on the buy-and-hold portfolio in (14), while the coefficient on the lagged portfolio is now the sum of the coefficients on the lagged and buy-and-hold portfolios in (11). Raddatz and Schmukler (2012) estimate a portfolio expression for mutual funds that includes the lagged portfolio and valuation effect, but not the expected excess returns.

Given estimates of the reduced form parameters a_1, a_2 and a_3 from the portfolio regression, we can then extract the structural parameters. We will used scaled

on the present value of expected future excess returns in a framework where there is a given probability p of changing the portfolio each period, analogous to Calvo price setting.

structural parameters for the portfolio frictions, defined as $\lambda_1 = \mu_1\sigma^2$ and $\lambda_2 = \mu_2\sigma^2$. Then

$$\lambda_1 = \frac{a_1 - a_2}{a_3 (1 - \delta)} \tag{19}$$

$$\lambda_2 = \frac{a_2}{a_3 (1 - \delta)} \tag{20}$$

$$\gamma = \frac{1 - a_1}{a_3\sigma^2} \tag{21}$$

We also have $\delta = \beta a_1$.

3 Predicting Cross-Country Equity Return Differentials

A key variable in the portfolio expression derived above is the expected excess return variable $ER_{i,n,t}$. This section describes how we construct estimates for expected excess return differentials. After reviewing the empirical strategy, we show that return differentials can be predicted by standard variables: dividend-price, earnings-price and momentum. We present results for pooled linear regressions.

3.1 Outline

The excess return in a specific country is fund-specific as it depends on equity returns in the reference countries and the portfolio weights of the fund in these countries. In this section, rather than considering expected excess returns for individual funds, we consider return differentials relative to the US. Specifically, the excess return for country n at $t + s$ is $er_{n,t+s} = R_{n,t+s} - R_{US,t+s}$, where $R_{n,t+s}$ and $R_{US,t+s}$ are the equity returns of country n and the US at $t + s$. As discussed further in the next section, the expected excess return for a specific fund can easily be computed once we know the expected excess returns relative to the US for individual countries. For a fund i it is simply the expected excess return $E_t er_{n,t+s}$ for country n minus the weighted average of expected excess returns $E_t er_{m,t+s}$ of the reference countries, using the portfolio shares for the reference portfolio of fund i as weights.

In the theory, portfolio shares depend on a present discounted value of expected excess returns at all future dates. We will indeed use such present values when applying the theory to US mutual fund portfolio shares in the next section. But in this section we consider either the predictability of excess returns $er_{n,t+1}$ over the next month or cumulative excess returns $er_{n,t,t+k} = er_{n,t+1} + ... + er_{n,t+k}$ over the next k months. We use panel regressions to report predictability at different horizons.

3.2 Panel Regressions

We use pooled regressions over 73 countries with monthly data from January 1970 to March 2019. All data in the baseline regressions come from MSCI, using the last trading day of the month. Since data availability starts later for many countries, this gives us an unbalanced panel with more than 22,000 observations.[8] Returns are computed from the MSCI total return index. We consider the following benchmark regression:

$$er_{n,t,t+k} = \alpha_n + \beta' X_{n,t} + \varepsilon_{n,t} \tag{22}$$

where $X_{n,t}$ is a set of explanatory variables known at time t. Following Petersen (2009), we include a country fixed effect and cluster standard errors by month.[9] Using pooled data and assuming a common coefficient β allows us to get more precise estimates.[10]

The explanatory variables in the benchmark specification are standard in the literature on stock return predictability,[11] but here we consider the differential with the US. These variables are the differential in the log earning-price ratio $dep_{n,t} = ln(E/P)_{n,t} - ln(E/P)_{US,t}$; the differential in the log dividend-price ratio $ddp_{n,t} = ln(D/P)_{n,t} - ln(D/P)_{US,t}$; and momentum, measured by the current return differential $er_{n,t-1,t}$. Since we take the log of the earning-price ratio, we omit the periods where it takes a negative value.[12]

Table 1 shows the results of regression (22) for one-period ahead returns $er_{n,t,t+1}$. We see that the three variables are strongly significant and have the expected sign. From the first column, it is interesting to notice that the small coefficient of 0.0426 on momentum implies that excess returns are not very persistent. In line with

[8] There are 18 countries in the sample in 1970, increasing to 35 in 1988, 44 in 1993, etc.

[9] Results do not change much if we include time fixed effects. We notice, however, that since we consider return differentials, global stock market shocks should not matter much.

[10] Hjalmarsson (2010) shows that pooling across countries gives superior predictability.

[11] See for example Koijen and Van Nieuwerburgh (2011) or Rapach and Zhou (2013) for surveys.

[12] Negative values are observed during the Asian and the Scandinavian financial crises.

the literature on return predictability, the R^2 is extremely low for short-horizon predictions.

Table 1: Regressions One-Month Return Differential $er_{n,t,t+1}$

	(1)	(2)	(3)	(4)	(5)	(6)
Momentum	0.0426**			0.0426**	0.0439**	0.0441**
	(0.0167)			(0.0177)	(0.0173)	(0.0178)
Dividend-Price		0.00695***			0.00757***	0.00595***
		(0.00210)			(0.00208)	(0.00204)
Earning-Price			0.00660***	0.00716***		0.00459**
			(0.00197)	(0.00196)		(0.00196)
Constant	0.000846	-0.00198	-0.00177	-0.00189	-0.00218	-0.00298*
	(0.00146)	(0.00153)	(0.00149)	(0.00148)	(0.00152)	(0.00153)
Observations	24675	22873	22033	22021	22856	21908
R^2	0.006	0.006	0.006	0.007	0.008	0.009

Standard errors clustered by month in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Notes: Regressions with 73 countries over the interval 1970:01-2019:02. All regressions include a country fixed effect.

The fit of equation (22) significantly improves when the horizon increases. Table 2 shows the results for one month (as in Table 1), 12 months, 24 months, and 36 months excess returns, using the three variables in the regression. We see that coefficient values increase with the horizon. Moreover, the R^2 increases significantly, reaching 13.7% at the 36-month horizon.

The results in Tables 1 and 2 show that there is indeed predictability of stock market return differentials and that it is particularly strong at longer horizons. In Appendix C we show that the predictability is also economically significant, following an approach similar to Cenedese et al. (2016). When sorting countries each month into quintiles based on their values of momentum, dividend-price differential, or earning-price differential, we show that returns are substantially higher for higher quintiles, i.e., higher values of momentum, dividend-price, or earning-price are associated with higher returns.

Table 2: Regressions Return Differential - Different Horizons

	(1) $er_{n,t,t+1}$	(2) $er_{n,t,t+12}$	(3) $er_{n,t,t+24}$	(4) $er_{n,t,t+36}$
Momentum	0.0441**	0.3318***	0.4930***	0.8175***
	(0.0178)	(0.0683)	(0.1130)	(0.1621)
Dividend-Price	0.0060***	0.0994***	0.2289***	0.3866***
	(0.0020)	(0.0097)	(0.0198)	(0.0336)
Earning-Price	0.0046**	0.0372***	0.0935***	0.1537***
	(0.0020)	(0.0090)	(0.0161)	(0.0255)
Constant	-0.0030*	-0.0265***	-0.0563***	-0.0969***
	(0.0015)	(0.0076)	(0.0143)	(0.0212)
Observations	21908	21116	20254	19392
R^2	0.009	0.064	0.104	0.137

Standard errors clustered by month in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Notes: Regressions with 73 countries over the interval 1970:01-2019:02. All regressions include a country fixed effect.

4 Results for Mutual Fund Portfolios

In this section we use panel data of US-based equity funds that report country portfolio allocations to EPFR. These data are used to estimate portfolio equations implied by the model developed in Section 2. The sample runs from January 2002 to July 2016.

4.1 Sample Selection and Portfolio Shares

The US mutual funds that report their country allocation to EPFR are mostly globally or regionally oriented, with a relative small average share allocated to US equity. The funds report their equity holdings in 135 countries (including the US) and cash holdings. Cash holdings are relatively small, on average 2.8 percent of total AUM (assets under management). In what follows we focus on the non-cash component of AUM, the equity holdings in the 135 countries. Aggregating across all funds, during an average month 7.5 percent of equity holdings are allocated to the United States. This shows the strong global bias of our funds. As discussed further below, the far majority of the funds have no US equity holdings at all.

It is useful to put the foreign equity holdings of these funds into broader perspective. At the end of the sample, July 2016, total US foreign equity holdings was $7,045 billion.[13] Of that, $3,394 billion (47 percent) was held by US mutual funds.[14] US equity mutual funds that report their country allocation to EPFR report a $436 billion allocation to foreign equity, which is 13 percent of all foreign equity held by US mutual funds. The remaining 87 percent is held by US funds that do not report to EPFR and funds that do report to EPFR, but do not report their country allocation.

We clean the original sample. We focus on a subset of 316 funds investing in 36 countries and remove very small portfolio shares.[15] The sample selection is described below. In July 2016, this cleaned sample has a $395 billion foreign equity allocation. This is 91 percent of the full sample AUM, so not much AUM is lost by cleaning the sample.

In the Online Appendix, we report some evidence of how representative this sample is in terms of the allocation across foreign countries. For July 2016, we report the portfolio shares allocated to the 35 foreign countries. We do this both for our sample of 316 mutual funds and for total US foreign equity holdings. The correlation is 0.88. Our mutual fund sample invests a higher share in emerging markets, particularly in Asian and Latin American countries. We also report time series of portfolio shares allocated to 3 regions (Europe, Asia and Latin America) from January 2002 to July 2016. These portfolio shares look quite similar to those based on total foreign equity holdings, with correlations of respectively 0.67, 0.56 and 0.79 for the three regions.[16]

Regarding the selection of funds, we only include US equity funds with more than $5 million in AUM at the end of the sample. In addition, we impose that the fund must report its global equity allocations for at least 12 consecutive months

[13]Monthly US foreign equity holdings are reported by Bertaut and Tryon (2007), later extended by Bertaut and Judson (2014), who have since further updated it through December 2018.

[14]See Exhibit 18A of the 2016 report "U.S. Portfolio Holdings of Foreign Securities" from the US department of Treasury.

[15]The countries are: Australia, Belgium, Brazil, Canada, Chile, China, Colombia, Denmark, Finland, France, Germany, Hong-Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Malaysia, Mexico, Netherlands, Norway, Peru, Philippines, Poland, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom and United States.

[16]Related, Miao and Pant (2012) find that EPFR capital flows and balance of payments capital flows behave similarly for different regions of the world for both equity and bonds.

during the sample. This leaves us with a total of 316 funds. We then drop very small portfolio shares and countries in which very few funds invest or for which we have insufficient MSCI data. There are two problems with small portfolio shares. First, valuation effects are very close to zero. As discussed, after linearizing we can write the valuation effect as $val_{i,n,t} = \bar{z}_{i,n}(1 - \bar{z}_{i,n})er_{i,n,t}$. When $\bar{z}_{i,n}$ is very close to zero, the valuation effect is essentially zero. This makes it difficult to determine the coefficient on the valuation effect, which is needed to determine the relative importance of the two portfolio costs (deviation from the lagged portfolio and the buy-and-hold portfolio). Second, as discussed below, we assume that the return of a fund in country n is the MSCI return of country n. If a fund invests very little in country n, its country n portfolio is much less likely to be well represented by the MSCI return in that country.[17]

To be more precise with our selection, consider the allocation of each fund to the aggregate of the 135 countries. Write the corresponding portfolio share as $k_{i,n,t}$, which is the investment by fund i in country n in month t as a share of the total allocation by fund i to the 135 countries in month t. Let $\bar{k}_{i,n}$ be the sample average, with the average taken over the months for which the fund reports the country allocation. Here we use the letter k instead of z to be clear that these are not the shares that will be used in the regression analysis.

For portfolio shares, we only consider (i, n) pairs for which $\bar{k}_{i,n}$ is at least 2 percent. Regarding countries, only 74 of the 135 have complete MSCI equity return data that are needed to compute excess returns and valuation effects. Many of these countries have very few funds that invest in them. We only include countries n in which at least 10 of the 316 funds invest during some month of the sample, not including the (i, n) pairs we removed. This reduces the sample to 36 countries. The Online Appendix extends our main analysis by including smaller portfolio shares.

Funds enter and exit the sample. The 316 funds are never all reporting simultaneously. The number of funds reporting rises over time. During the first 12 months of the sample an average of 46 funds report each month, while during the last 12 months of the sample an average of 222 funds report each month. For an average country and an average month, 29 percent of reporting funds report

[17]A final problem is that when the average portfolio share in a country by a fund is very small, the number of months for which the fund reports portfolio data in that country tends to be smaller.

a portfolio allocation to that country. For an average month, only 21 percent of reporting funds report a portfolio allocation to the United States. Therefore 79 percent of the funds only invest in foreign equity.

For our sample of 316 funds and 36 countries we compute $z_{i,n,t}$ as the equity that fund i holds in country n during month t, divided by the total equity allocation of fund i to the 36 countries in the sample during month t. In addition, as necessary for the regressions, we only use observations $z_{i,n,t}$ when data are available for both $z_{i,n,t}$ and $z_{i,n,t-1}$. This results in a total of 154,407 observations.

4.2 Equity Returns

We need data on equity returns both to compute an estimate of expected excess returns and to compute the buy-and-hold portfolio. We would preferably use equity returns of individual funds in each country. Unfortunately EPFR does not provide the return of funds in individual countries. We therefore follow Raddatz and Schmukler (2012) and use MSCI returns in each country. They argue that this provides a reasonable approximation. In what follows it is therefore assumed that $R_{n,t}$ is the equity return of country n for all funds.

We construct the expected excess return variable $ER_{i,n,t}$ as follows. We use the average sample weights $\bar{z}_{i,m,-n}$ to compute the reference portfolio. In the Online Appendix we show that results are similar when we use the contemporaneous weights $z_{i,m,-n,t}$. The excess return relative to the reference portfolio can then be written as

$$er_{i,n,t+s} = R_{n,t+s} - \sum_{m \neq n} \bar{z}_{i,m,-n} R_{m,t+s} = er_{n,t+s} - \sum_{m \neq n} \bar{z}_{i,m,-n} er_{m,t+s}$$

where $er_{n,t+s}$ is the excess return at $t+s$ of country n relative to the United States. It then follows that

$$ER_{i,n,t} = (1-\delta) \sum_{s=1}^{k} \delta^{s-1} E_t \left(er_{n,t+s} - \sum_{m \neq n} \bar{z}_{i,m,-n} er_{m,t+s} \right) \tag{23}$$

First some comments are in order regarding k and δ. While in the theory $k = \infty$, in the empirical applications k is necessarily finite. We assume $k = 24$. We consider lower and higher values in the Online Appendix. The estimation of δ is discussed in Section 4.5. It is consistent with its theoretical value of βa_1, where a_1 is the coefficient on the lagged portfolio share in (18).

We compute the expectation in (23) by estimating a panel regression of

$$(1-\delta)\sum_{s=1}^{k}\delta^{s-1}er_{n,t+s}$$

on the same variables that we regressed $er_{n,t,t+k}$ on in Section 3. However, in contrast to the previous section, here we create true forecasts using recursive regressions up to the time of the forecast rather than using the entire sample. The sample starts in January 1970. As shown in the Online Appendix, we still find predictability when restricting the sample to the 35 foreign countries and using discounted returns. The three variables, momentum, dividend-price and earning-price, are all significant.

The buy-and-hold portfolio is computed as follows. We have $z^{bh}_{i,n,t} = z_{i,n,t-1}\frac{1+R_{n,t}}{1+R_{i,p,t}}$. For $R_{i,p,t}$ we use the portfolio return of fund i obtained from EPFR. Since EPFR does not provide the return of funds in individual countries, we again use the country n equity return from MSCI for $R_{n,t}$. We compute the valuation effect as $val_{i,n,t} = z^{bh}_{i,n,t} - z_{i,n,t-1}$.

4.3 Portfolio Regression

We will report results for the portfolio equations (14) and (18). As discussed, these are identical equations, just written slightly differently. Consider (18). We will estimate

$$z_{i,n,t} = b_{i,n} + a_1 z_{i,n,t-1} + a_2 val_{i,n,t} + a_3 ER_{i,n,t} + a_4' X_{i,n,t} + \varepsilon_{i,n,t} \tag{24}$$

Here we have written the error term in (18) as $\epsilon_{i,n,t} = a_4' X_{i,n,t} + \varepsilon_{i,n,t}$. The variables $X_{i,n,t}$ include additional controls that are observable and may be related to risk. The remaining error term $\varepsilon_{i,n,t}$ captures latent portfolio demand shocks, both related to risk and time-varying differences between expected excess returns of the funds and the ones we have computed above (e.g. waves of optimism and pessimism that we do not capture, whether rational or not).

The regression includes a country-fund dummy $b_{i,n}$. As we have seen in the theory, this is related to differences in mean portfolio shares $\bar{z}_{i,n}$. We get the same results when we simply subtract the mean of all variables for each country-fund pair. Not including the country-fund dummy is highly problematic. Since portfolio shares differ significantly across funds, it will bias the coefficient a_1 on the lagged portfolio share to be very close to 1. The same will happen when including imperfect controls related to $\bar{z}_{i,n}$.

The controls $X_{i,n,t}$ we can include are limited by data availability on a monthly basis for all 36 countries. We include three controls. Using daily data of equity returns from MSCI, we compute a measure of stock return volatility over the last month in country n, subtracting the portfolio-weighted average of the same risk measure for countries in the reference portfolio. We also include the inflation rate and industrial production growth over the past 12 months, again subtracting the portfolio-weighted average for countries in the reference portfolio.[18] Appendix D describes details regarding the data.

4.4 Endogeneity

The error term $\varepsilon_{i,n,t}$ in equation (24) is likely to have a component that is common across both US mutual funds and other investors. This may for example be driven by time variation in perceived risk that is common across investors, or bouts of optimism and pessimism about the expected excess returns of a country that we do not capture with $ER_{i,n,t}$. This common component will lead to portfolio shifts that affect asset demand and requires changes in equity prices and expected excess returns to generate equilibrium. Bacchetta, van Wincoop and Young (2021) and Bacchetta, Davenport and van Wincoop (2021) discuss the impact of portfolio shocks on equilibrium asset prices and expected excess returns in the context of general equilibrium models with gradual portfolio adjustment.

This naturally leads to a correlation between the error term and the explanatory variables. This is immediate for the expected excess return variable $ER_{i,n,t}$ and the valuation effect (or buy-and-hold portfolio), which depend on equity prices. To the extent that the portfolio shocks are persistent and have a persistent effect on the equity price, it also leads to a correlation of the error term with the lagged portfolio share.[19]

[18]Koijen and Yogo (2020) also include bilateral variables like distance. Bilateral distance cannot be included in our context as it is a country-specific variable since all funds are located in the US. It would then be absorbed by the country-fund dummy.

[19]Portfolio shifts in the error term that are not common across investors are unlikely to generate endogeneity problems. Individual US mutual funds are much too small to have a significant effect on equity prices of other countries. On average individual funds represent 0.02 percent of US equity investment in a country, and US equity investment in a country is only a small fraction

To address this potential endogeneity problem, we use Two-Stage Least Squares (2SLS). We consider a benchmark specification with 5 instruments. We make the following identifying assumption:

$$E_t\left[\varepsilon_{i,n,t}|e_{i,n,t}, \Delta d_{i,n,t}, i_{i,n,t}, y_{i,n,t}, val_{i,n,t-1}\right] = 0 \tag{25}$$

$e_{i,n,t}$ is log earnings for country n equity, minus the portfolio-weighted average of log earnings for the reference countries with portfolio weights $\bar{z}_{i,m,-n}$. Earnings is obtained by multiplying the earnings price ratio with the price index. $d_{i,n,t}$ is defined analogously for dividends. $\Delta d_{i,n,t}$ is $d_{i,n,t} - d_{i,n,t-1}$. We use the change over time as regulatory changes often lead to persistent shifts between dividend payouts and equity repurchases. $i_{i,n,t}$ is the 3-month Euro Libor interest rate for country n minus the portfolio weighted average interest rates of the reference countries. $y_{i,n,t}$ is the monthly log industrial production index for country n, minus the portfolio weighted average for reference countries. $val_{i,n,t-1}$ is simply the lagged valuation effect.

Earnings and dividends are natural instruments. They should affect equity prices, but are associated with equity payoffs and not equity risk that enters the error term. The interest rate is also a good instrument. A higher interest rate leads to a shift from equity to bonds that lowers the equity price. It is again not associated with equity price risk that enters the error term. The industrial production variable can affect equity prices both as a proxy of equity payoffs and wealth that affects equity demand.

Finally, the lagged valuation effect is associated with relative equity price changes from $t-2$ to $t-1$. It has predictive power for the current valuation effect and therefore also for expected excess returns. It is not likely to be much correlated with the error term. Gabaix and Koijen (2021) find that financial shocks, which are analogous to common portfolio shocks, have a very persistent effect on equity prices. While the error term can then be expected to be correlated with the level of the equity price, it will not be much correlated with the lagged price change.

While these are good instruments, in robustness analysis below we will discuss a variety of additional instruments.

of stock market capitalization of the country.

4.5 Benchmark Results

Table 3 presents the benchmark estimation of equations (14), (18), and (24), both with OLS and IV. The first stage Sanderson-Windmeijer F statistics are reported at the bottom of the table. They are all well above 10, suggesting strong instruments. The first four columns do not include controls $X_{i,n,t}$, while the last two columns do.

The role of endogeneity can be seen by comparing columns (1) and (2) or (3) and (4). While the differences are not large, we see that the coefficient on the valuation effect is a bit higher under OLS, while the coefficient on the expected excess return variable is a bit lower. This is intuitive. The error term is positively correlated with the valuation effect as an exogenous financial flow towards country n raises the country n equity price. This leads to upward bias of the coefficient on $val_{i,n,t}$. At the same time the higher price lowers the dividend-price and earnings-price ratios, which lowers the expected excess return. The negative correlation between the expected excess return and the error term therefore leads to a downward bias of the coefficient on the expected excess return variable under OLS.

Nonetheless, both the OLS and IV results yield a similar message. The weight on the lagged portfolio in (24) is highly significant and large, respectively 0.93 under OLS and 0.955 under IV. The coefficient on the valuation effect is positive and also highly significant. For the regression (14) in columns (3) and (4) this means a substantial weight on both the lagged portfolio and the buy-and-hold portfolio. It appears therefore that both portfolio frictions are important. The coefficient on the buy-and-hold portfolio is biased upwards under OLS. The IV result suggests that the weight on the lagged portfolio is more than 3 times as big as on the buy-and-hold portfolio.

The coefficient on the expected excess return is also highly significant, 8.2 under OLS and 9.5 under IV. The standard error is substantially larger under IV, but the t-value is still a respectable 3.2 (versus 10 under OLS). The IV coefficient on the expected excess return variable is similar to findings by Giglio et al. (2021), even though their data are completely different. They regress the equity share of Vanguard investors on one-year expected excess returns on equity. The cross-sectional variation of expected excess returns, obtained from survey data, is key to their results. They implicitly assume that the portfolio depends on expected excess returns over the next 12 months, with equal weight on each month. In our

Table 3: Portfolio Regressions, Benchmark

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
$z_{i,n,t-1}$	0.930***	0.955***	0.507***	0.727***	0.930***	0.953***
	(0.004)	(0.012)	(0.027)	(0.069)	(0.004)	(0.012)
$val_{i,n,t}$	0.423***	0.228***			0.421***	0.222***
	(0.027)	(0.072)			(0.028)	(0.074)
$ER_{i,n,t}$	8.243***	9.451***	8.243***	9.451***	8.458***	10.338***
	(0.817)	(2.972)	(0.817)	(2.972)	(0.826)	(3.233)
$z^{bh}_{i,n,t}$			0.423***	0.228***		
			(0.027)	(0.072)		
Volatility					-0.040**	-0.061***
					(0.019)	(0.021)
Industrial production growth					0.004***	0.004***
					(0.001)	(0.001)
Inflation					-0.003	0.002
					(0.004)	(0.004)
Observations	154,407	150,179	154,407	150,179	154,404	150,176
R^2	0.99	0.87	0.99	0.87	0.99	0.87
SW F-test $z_{i,n,t-1}$		117.82		48.96		92.83
SW F-test $val_{i,n,t}$		54.6				49.33
SW F-test $ER_{i,n,t}$		115.42		115.42		86.12
SW F-test $z^{bh}_{i,n,t}$				54.6		

Clustered standard errors by months in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Notes: Regressions for 36 countries over the interval 2002:01-2016:07. The regressions include a fund-country fixed effect. In columns (2), (4) and (6), the instruments are $val_{i,n,t-1}$, the log of earnings, the first difference in the log of dividends, the 3-month Euro Libor interest rate and log industrial production. SW F-test stands for the Sanderson-Windmeijer F-test of excluded instruments from the first stage regressions.

expected excess return variable, most of the weight is also on the first 12 months (71 percent under OLS and 60 percent under IV).

For comparability, we multiply the coefficient on the expected excess return in Giglio et al. (2021) by 12 to translate to monthly expected excess returns. Their coefficient is then 8.3. It is 13.9 when they remove some outliers from their data. These numbers are broadly consistent with our estimates. They emphasize that this weight on the expected excess return is substantially lower than what one might expect in a frictionless model.

Finally, in the last two columns we add the three controls: stock return volatility, inflation and industrial production growth. Under both OLS and IV the coefficients on stock return volatility and industrial production growth are statistically significant and have the expected sign. Higher stock return volatility raises risk, which lowers the portfolio share in a country. Higher output growth can be expected to happen in a reduced risk environment, which raises the portfolio share. The inflation coefficient is insignificant. Importantly, introducing these controls has very little effect on the coefficients on the lagged portfolio share, valuation effect and expected excess return.

4.6 Retrieving the Structural Parameters

In connecting the estimates in Table 3 to the structural parameters from the theory, we will assume a time discount rate of $\beta = 0.97$. The time discount rate is not identified by the reduced form parameter estimates. While $\beta = 0.97$ may seem low with monthly data, it is important to keep in mind that the average turnover of portfolio managers is 2 percent per month (see Kostovetsky and Warner, 2015). An even lower β may need to be assumed if we take into account that many funds have short lives. In the Online Appendix we consider alternative values for β.

In the theory δ is equal to βa_1, where a_1 is the coefficient on $z_{i,n,t-1}$ in (24). It turns out that the estimate of a_1 is virtually unaffected by the assumed δ. In the regression, we first set $\delta = 0.9$, then estimate (24) to obtain an estimate of a_1 and therefore δ. We then estimate (24) again when $ER_{i,n,t}$ is computed with this estimate of δ.

Next we use equations (19), (20) and (21) to obtain point estimates and confidence intervals for the structural parameters λ_1, λ_2 and γ from the point estimates and variance matrix of a_1, a_2 and a_3. We set $\sigma^2 = 0.00172$, which is the mean variance of the excess return across (i, n). Table 4 reports results based on the OLS and IV estimates of Table 3 (columns (1) and (2)). It reports both point estimates of the structural parameters and 95 percent confidence intervals.

A first point to note is that the confidence intervals for λ_1, λ_2, as well as $\lambda_1 - \lambda_2$, are much tighter based on the OLS than IV estimates. This is because in (19)-(20) the parameters λ_1 and λ_2 depend inversely on a_3, the coefficient on the expected excess return. We can see from Table 3 that while the magnitudes of the expected excess return coefficients for OLS and IV do not differ dramatically, the standard error is much smaller for OLS, leading to substantially tighter estimates of the structural parameters.

Several points are immediate from Table 4. First, for both OLS and IV we see that λ_1 and λ_2 are positive and significant. There is therefore strong evidence that both portfolio frictions are important. Second, $\lambda_1 - \lambda_2$ is positive. It is significant under IV, which means that there is a larger cost of deviating from the lagged portfolio than the buy-and-hold portfolio. This relates to the substantially higher coefficient on the lagged portfolio than the buy-and-hold portfolio in column (4) of Table 3.

Finally, the point estimate of γ is 2.8 under IV, with a 95 percent confidence interval of [1.8,4.9]. This is quite reasonable. By contrast, if we just regress on the one-month expected excess return (plus the fund-country fixed effect), as would be appropriate in the absence of portfolio frictions, we obtain a IV coefficient of 3.8 (s.e.=0.27). Since the coefficient on the one-month expected excess return in the frictionless model is $1/(\gamma\sigma^2)$, it would imply $\gamma = 153$, which is clearly excessive.[20] For a more reasonable, lower, level of risk aversion, the coefficient on the expected excess return would be far higher in the frictionless model. Therefore the estimates of λ_1, λ_2 and γ all provide evidence of the importance of portfolio frictions.

4.7 Portfolio Dynamics

It is useful to consider the implication of the results above for the dynamic response of portfolios to an expected excess return innovation and compare the case with the estimated portfolio frictions to the frictionless case. For the case with frictions, the expected excess return variable is $ER_{i,n,t}$. Using the pooled data, we estimate

[20] Giglio et al. (2021) also make the point that excessive risk aversion is needed to account for the response of portfolios to expected returns in a frictionless model.

Table 4: Estimated Structural Parameters

	OLS		IV	
	Estimate	95% confidence interval	Estimate (s.e.)	95% confidence interval
λ_1	0.628	[0.520, 0.782]	1.044	[0.645, 2.602]
λ_2	0.524	[0.409,0.687]	0.328	[0.095,1.081]
γ	4.94	[4.12,6.07]	2.76	[1.84,4.85]
$\lambda_1 - \lambda_2$	0.104	[-0.028,0.233]	0.717	[0.328,1.739]

Notes: The table reports point estimates and 95 percent confidence intervals of the structural parameters implied by the regression results reported in Table 3, columns 1 and 2. It is based on 100,000 draws from the distribution of the reduced form parameters $[a_1, a_2, a_3]$.

an AR(1) process $ER_{i,n,t} = a_{i,n} + \rho ER_{i,n,t-1} + \nu_{i,n,t}$, where $a_{i,n}$ is a fund-country dummy. We obtain an AR coefficient $\rho = 0.87$ and an average standard deviation of $\nu_{i,n,t}$ across (i,n) pairs of 0.00076. In the frictionless case the expected excess return is $E_t er_{i,n,t+1}$, for which we analogously obtain an AR coefficient of 0.51 and average standard deviation 0.0017 of the expected excess return innovation.

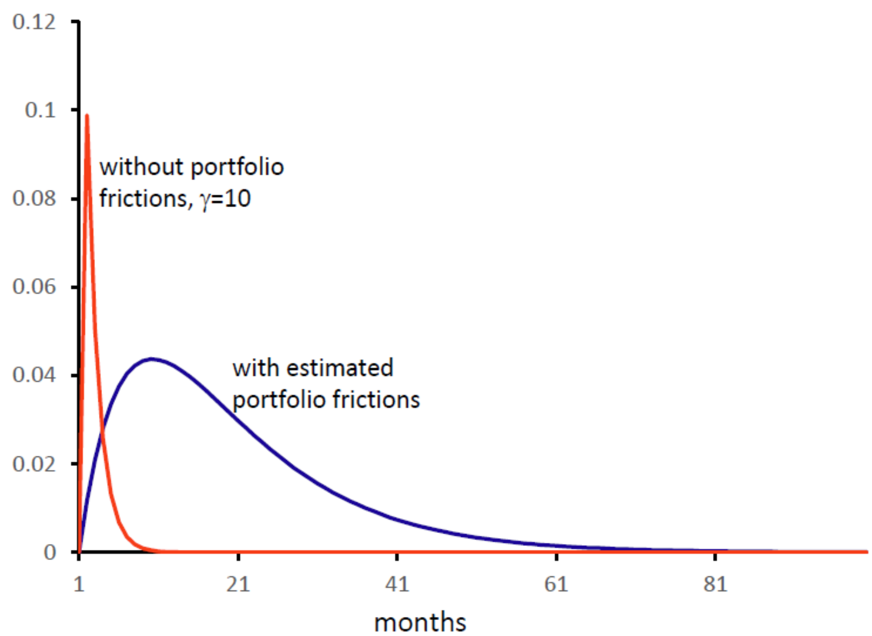
We make two additional assumptions. First, for the purpose of this exercise we only include the lagged portfolio share in the regression in order to abstract from valuation effects in the buy-and-hold portfolio. This regression is shown in the Online Appendix. The coefficient on the lagged portfolio share is 0.918 and the coefficient on the expected excess return variable is 15.4. Second, we need to make an assumption about the portfolio response in the frictionless case. We cannot use the estimated response when regressing $z_{i,n,t}$ on $E_t er_{i,n,t+1}$ as that is based on data that provide strong evidence of portfolio frictions.

As shown in (16), in the frictionless case the coefficient on the expected excess return is equal to $1/(\gamma\sigma^2)$. We again set $\sigma^2 = 0.00172$ and assume a rate of risk aversion of $\gamma = 10$. We can scale the portfolio response in the frictionless case up or down by respectively lowering or raising the rate of relative risk aversion.

Figure 1 shows the results. The initial portfolio response to a one standard deviation expected excess return innovation is much larger in the frictionless case. If we set the risk aversion equal to the $\gamma = 2.8$ implied by estimates for the model with frictions, the initial response in the frictionless case would be even much higher by a factor 4. Apart from the initial portfolio inertia with the estimated frictions, we also see significant portfolio persistence. The portfolio response peaks after 9 months, while in the frictionless case it peaks at the time of the shock and dies out quickly.

Bacchetta and van Wincoop (2021) refer to the initial portfolio response as return sensitivity and the gradual portfolio response as portfolio persistence. They show in a model for the foreign exchange market with portfolio frictions that both diminished return sensitivity and increased portfolio persistence are key to accounting for a variety of currency excess return predictability puzzles.

Figure 1: Impulse Response Portfolio Share to Expected Return Shock



4.8 Heterogeneous Country Shares

So far we have focused on the average coefficients a_1, a_2 and a_3 that describe the relationship between $z_{i,n,t}$ and respectively $z_{i,n,t-1}$, $val_{i,n,t}$ and $ER_{i,n,t}$. We will now consider, both theoretically and empirically, how these coefficients vary with the mean portfolio share in a country, $\bar{z}_{i,n}$. These mean portfolio shares vary substantially, as shown in the Online Appendix. The 10th, 50th and 90th percentiles are 2.7%, 6% and 20.4%.

The theory in Section 2 implies that both $\bar{z}_{i,n}$ and the coefficient on $ER_{i,n,t}$ will be higher when a fund i perceives risk associated with country n to be relatively low. This is idiosyncratic risk of the country n return, uncorrelated with the reference portfolio. Equation (9) implies that lower perceived idiosyncratic risk of the country n equity return raises the mean portfolio share $\bar{z}_{i,n}$. It also lowers $\sigma^2_{i,n}$, the variance of the excess return, which from (11) raises the portfolio weight on the expected excess return $ER_{i,n,t}$. It is also immediate from (11) that the theoretical weights on the lagged portfolio and the buy-and-hold portfolio (or the lagged portfolio and the valuation effect) are unaffected.

Intuitively, the higher weight on the expected excess return can be understood as follows. Investors care about expected returns, risk and portfolio costs. Risk and portfolio costs go down when $\sigma^2_{i,n}$ is lower, leading investors to respond more to expected excess returns. The theoretical results imply that the weight on $ER_{i,n,t}$ will be higher when $\bar{z}_{i,n}$ is higher, which we now explore empirically.

Table 5 shows three columns. The first column is the benchmark IV result corresponding to column (2) of Table 3. The second column adds an interaction term between the expected excess return $ER_{i,n,t}$ and $\bar{z}_{i,n}$.[21] In column (3) we add the valuation effect $val_{i,n,t}$ interacted with $\bar{z}_{i,n}$. We find that when we interact the lagged portfolio share $z_{i,n,t-1}$ with $\bar{z}_{i,n}$, the coefficient is insignificant, consistent with the theory. In the second and third columns we include both the benchmark instruments and the benchmark instruments interacted with $\bar{z}_{i,n}$.

We see that the response to changes in $ER_{i,n,t}$ is substantially larger when $\bar{z}_{i,n}$ is larger, consistent with the theory. Specifically, the coefficient on $ER_{i,n,t}$ varies from 6.3 for small $\bar{z}_{i,n}$ (10th percentile) to 9.5 for the median $\bar{z}_{i,n}$ and 23.5 for large $\bar{z}_{i,n}$ (90th percentile). The benchmark regression result in column (1) is consistent with the median fund.

Column 3 shows that the weight on the valuation effect is smaller for larger $\bar{z}_{i,n}$, even though the theory implies no clear relationship. However, the differences are not large. The difference in the weight on the valuation effect for the 90th and 10th percentiles of $\bar{z}_{i,n}$ is only 0.095 (s.e.=0.046).[22]

[21]Note that while we empirically observe $\bar{z}_{i,n}$, we do not observe $\sigma^2_{i,n}$, whose variation we believe is responsible for different values of $\bar{z}_{i,n}$. $\sigma^2_{i,n}$ measures the perceived risk of country n equity by fund i, which depends on the information set of fund i that we do not observe.

[22]We have also considered heterogeneity of the portfolio response parameters by large versus small funds, active versus passive funds and whether they are global, regional or emerging market funds. However, the instruments are not strong enough to distinguish the portfolio response to $z_{i,n,t-1}$, $val_{i,n,t}$ and $ER_{i,n,t}$ across these fund types.

Table 5: Portfolio Regressions, Heterogeneous Country Shares

	(1)	(2)	(3)
$z_{i,n,t-1}$	0.955***	0.924***	0.933***
	(0.012)	(0.023)	(0.023)
$val_{i,n,t}$	0.228***	0.202**	0.423***
	(0.072)	(0.093)	(0.116)
$ER_{i,n,t}$	9.451***	3.617	1.213
	(2.972)	(2.264)	(2.342)
$\bar{z}_{i,n} \times ER_{i,n,t}$		97.717**	98.077**
		(47.776)	(48.416)
$\bar{z}_{i,n} \times val_{i,n,t}$			-0.538**
			(0.261)
Observations	150,179	150,179	150,179
R^2	0.87	0.87	0.88
SW F-test $z_{i,n,t-1}$	117.82	46.04	38.77
SW F-test $val_{i,n,t}$	54.6	18.61	26.75
SW F-test $ER_{i,n,t}$	115.42	330.36	274.58
SW F-test $\bar{z}_{i,n} \times val_{i,n,t}$			25.14
SW F-test $\bar{z}_{i,n} \times ER_{i,n,t}$		36.43	42.87

Clustered standard errors by months in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Notes: Regressions for 36 countries over the interval 2002:01-2016:07. The regressions include a fund-country fixed effect. The set of instruments in column (1) corresponds to $val_{i,n,t-1}$, the log earnings, the first difference in the log of dividends, the 3-months Euro Libor interest rates and the log of industrial production. The instruments in columns (2) and (3) include the instruments in column (1) and the instruments in column (1) interacted with $\bar{z}_{i,n}$. SW F-test stands for the Sanderson-Windmeijer F-test of excluded instruments from the first stage regressions.

4.9 Robustness Analysis

We consider various types of robustness analysis. In Table 6 we consider additional instruments. In the Online Appendix we consider alternative regression specifications and samples, which we will briefly discuss as well.

Table 6: Portfolio Regressions, Instruments Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
$z_{i,n,t-1}$	0.960***	0.957***	0.948***	0.935***	0.922***	0.945***
	(0.012)	(0.012)	(0.011)	(0.014)	(0.013)	(0.013)
$val_{i,n,t}$	0.262***	0.248***	0.193**	0.171**	0.120	0.221***
	(0.068)	(0.069)	(0.074)	(0.076)	(0.087)	(0.068)
$ER_{i,n,t}$	7.723***	9.142***	10.028***	12.036***	13.591***	10.307***
	(2.831)	(2.839)	(2.958)	(3.201)	(2.851)	(2.933)
Observations	150,115	149,949	146,756	142,103	117,121	141,824
R^2	0.87	0.87	0.88	0.87	0.87	0.87
SW F-test $z_{i,n,t-1}$	95.12	89.39	68.55	69.46	167.23	35.69
SW F-test $val_{i,n,t}$	47.08	41.79	39.87	38.02	35.6	24.96
SW F-test $ER_{i,n,t}$	94.3	89.36	81.06	63.2	297.8	40.91

Clustered standard errors by months in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Notes: Regressions for 36 countries over the interval 2002:01-2016:07. The regressions include a fund-country fixed effect. In addition to the set of benchmark instruments, we include in columns (1)-(5) the log earning in first difference, the 3-month Euro Libor interest rate in first difference, the log book value, the log bond index and the 12-months lagged country share $z_{i,n,t-12}$, respectively. In column (6), we include the benchmark instruments and the additional instruments from columns (1)-(4). SW F-test stands for the Sanderson-Windmeijer F-test of excluded instruments from the first stage regressions.

Columns (1) to (5) of Table 6 report results when we add one additional instrument at a time to the instruments used for the benchmark IV regression (24) reported in column (2) of Table 3. In column (6) we add the 4 additional instruments from columns (1)-(4) to the instruments from the benchmark regression. Recall that the benchmark instruments are log earnings $e_{i,n,t}$, the change in log dividends $\Delta d_{i,n,t}$, the 3-month Euro Libor interest rate $i_{i,n,t}$, the log industrial production index $y_{i,n,t}$ and the lagged valuation effect $val_{i,n,t-1}$. In each case we subtract the corresponding portfolio weighted average for reference countries.

In columns (1) to (5) of Table 6 we add to these benchmark instruments respectively the first difference of log earnings $\Delta e_{i,n,t}$, the first difference of the 3-month Euro Libor interest rate $\Delta i_{i,n,t}$, the log book value, the log bond price index and the 12-month lagged portfolio share $z_{i,n,t-12}$. As before, in all cases we subtract the portfolio-weighted average for the reference countries. The variables and data sources are described in Appendix D.

The log book value is a measure of equity supply, equal to market value divided by the price. It naturally affects equity prices, but should be exogenous to the portfolio error term, which is associated with portfolio demand shocks. The log bond price index is a price index for 10-year government bonds. It can effect the relative demand of equity versus bonds. This affects equity prices, but is likely unrelated to portfolio shifts between equity of different countries (our error term). Lagged portfolio shares should generally be avoided as instruments because shocks to the error term can be persistent and have a persistent price effect, which leads the error term to be correlated with lagged portfolio shares. We only consider a 12-month lagged portfolio share in the robustness analysis.

The results are broadly in line with those reported in Table 3. The estimated coefficients in columns (1)-(4) and (6) are very close to those reported in column (2) of Table 3. In column (5), which adds the lagged portfolio share $z_{i,n,t-12}$ as an instrument, the results start to diverge a bit. In this case the valuation effect becomes insignificant and the coefficient on the expected excess return is a bit higher. As pointed out above, lagged portfolio shares are not the most desirable instruments.

Additional robustness analysis is described in the Online Appendix, which we briefly summarize here. We again report IV results for regression (18), comparable to column (2) of Table 3, both for alternative regression specifications and alternative samples.

We consider 7 alternative regression specifications. The first assumes that the only friction is associated with the portfolio share change, so that we regress on just the lagged portfolio share and $ER_{i,n,t}$. The next two consider respectively $k = 12$ and $k = 36$ to compute $ER_{i,n,t}$ in (23). The next two consider alternative values of β of respectively 0.96 and 0.98. Next we consider weights $z_{i,m,-n,t-1}$ to compute the reference portfolio instead of sample average weights $\bar{z}_{i,m,-n}$. We finally report a non-recursive regression, which uses data over the entire sample to compute expected excess returns as opposed to forecasts using recursive regressions up to the time of the forecast.

We also consider 4 alternative samples. The first two samples have a start date of respectively January 2010 and January 2012 as fewer funds report country allocations at the beginning of our sample. We also consider restricting the sample to funds that report their global equity allocation for at least 24 consecutive months (as opposed to 12). Finally, we consider a sample where $\bar{k}_{i,n}$ is at least 1 percent, as opposed to 2 percent, which leads to the inclusion of smaller portfolio shares.

Setting aside the case where we do not regress on the valuation effect, the results are broadly consistent with the benchmark results. All of the coefficients are always highly significant. Across all of these regressions, the coefficient on the lagged portfolio varies from 0.948 to 0.972. The coefficient on the valuation effect varies from 0.181 to 0.274. The coefficients on the expected excess return vary a bit more, from 6.923 to 11.390, but all remain within one standard error of our benchmark result.

5 Conclusion

The objective of the paper was to provide empirical evidence on international portfolio choice and specifically the role of portfolio frictions. We developed a simple optimal portfolio expression that relates portfolio choice to the present discounted value of expected excess returns and two benchmark portfolios, the lagged portfolio share and the buy-and-hold portfolio. We estimated the reduced form parameters of the portfolio expression with international equity portfolio data from US mutual funds, using instrumental variables to address endogeneity. We find that portfolio shares of US mutual funds depend significantly on both benchmark portfolios, with coefficients that are quite precise.

We also find that international equity return differentials are predictable and that mutual fund portfolios respond to expected excess returns. The results are consistent with a reasonable rate of risk aversion of 2.8. While the responsiveness to the present value of expected excess returns is strongly statistically significant, we also find that quantitatively the portfolio response to expected returns is much smaller than it would be in a frictionless portfolio model. Portfolio frictions make the response to changes in expected returns smaller initially and more gradual.

There is a clear need to introduce these portfolio frictions into open economy models, as recently done by Bacchetta and van Wincoop (2021), Bacchetta et al. (2021a,2021b) for respectively the foreign currency market, global financial markets broadly and the global equity market. It has significant implications for the response of asset prices, capital flows, saving and investment to shocks. A weaker and more gradual portfolio response to expected returns implies more excess return predictability in both the foreign exchange market and global equity markets. It also implies a much larger impact of exogenous portfolio shocks, including also central bank asset purchases, on asset prices and capital flows. The importance of such financial shocks for exchange rates and capital flows has recently been emphasized by Gabaix and Maggiori (2015) and Itskhoki and Mukhin (2021) and, as these papers emphasize, is consistent with a variety of evidence.

Appendix A: First-Order Condition Optimal Portfolio

After substituting (7) into (3) we maximize with respect to $z_{i,n,t}$. To do so, use that for a function $f(\mathbf{z}_{i,t})$ we have

$$\frac{\partial f(\mathbf{z}_{i,t})}{\partial z_{i,n,t}} = (\mathbf{e}_n - \mathbf{z}_{i,-n,t})' \frac{\partial f(\mathbf{z}_{i,t})}{\partial \mathbf{z}_{i,t}} \tag{A.1}$$

The first-order condition with respect to $z_{i,n,t}$ is then

$$\begin{aligned} &(\mathbf{e}_n - \mathbf{z}_{i,-n,t})' E_{i,t}\mathbf{R}_{t+1} - \gamma_i (\mathbf{e}_n - \mathbf{z}_{i,-n,t})' \mathbf{\Omega}_{i,t}\mathbf{z}_{i,t} \\ &-\mu_{1,i} (\mathbf{e}_n - \mathbf{z}_{i,-n,t})' \mathbf{\Omega}_{i,t} (\mathbf{z}_{i,t} - \mathbf{z}_{i,t-1}) + \mu_{1,i}\beta (\mathbf{e}_n - \mathbf{z}_{i,-n,t})' \mathbf{\Omega}_{i,t} E_{i,t} (\mathbf{z}_{i,t+1} - \mathbf{z}_{i,t}) \\ &-\mu_{2,i} (\mathbf{e}_n - \mathbf{z}_{i,-n,t})' \mathbf{\Omega}_{i,t} \left(\mathbf{z}_{i,t} - \mathbf{z}_{i,t}^{bh}\right) + \mu_{2,i}\beta (\mathbf{e}_n - \mathbf{z}_{i,-n,t})' \mathbf{\Omega}_{i,t} E_{i,t} \left(\mathbf{z}_{i,t+1} - \mathbf{z}_{i,t+1}^{bh}\right) = 0 \end{aligned} \tag{A.2}$$

The last line uses that $z_{i,n,t+1}^{bh}$ can be written as $z_{i,n,t}$ plus a time $t+1$ valuation effect (see (17)).

Using that $\mathbf{z}_{i,t} = \mathbf{z}_{i,-n,t} + (\mathbf{e}_n - \mathbf{z}_{i,-n,t}) z_{i,n,t}$, the first line can be written as

$$E_{i,t}er_{i,n,t+1} - \gamma_i cov_{i,t}(er_{i,n,t+1}, R_{ref(i,n),t+1}) - \gamma_i z_{i,n,t} var_{i,t}(er_{i,n,t+1}) \tag{A.3}$$

In what follows we will think of moments involving the reference portfolio as evaluated at mean portfolios $\bar{z}_{i,m,-n}$ as in the data such covariances are virtually identical whether evaluated at portfolios $z_{i,m,-n,s}$ for $s = t-1, t, t+1$ or $\bar{z}_{i,m,-n}$. The same applies to moments with the excess return, which depend on the reference portfolio.

Next take the first term of the second line of (A.2), substituting $\mathbf{z}_{i,t} = \mathbf{z}_{i,-n,t} + (\mathbf{e}_n - \mathbf{z}_{i,-n,t}) z_{i,n,t}$ and $\mathbf{z}_{i,t-1} = \mathbf{z}_{i,-n,t-1} + (\mathbf{e}_n - \mathbf{z}_{i,-n,t-1}) z_{i,n,t-1}$. We can then write it as

$$-\mu_{1,i} var_{i,t}(er_{i,n,t+1})(z_{i,n,t} - z_{i,n,t-1}) \tag{A.4}$$

In analogy, the second term of the second line of (A.2) can be written as

$$\mu_{1,i}\beta var_{i,t}(er_{i,n,t+1})(E_t z_{i,n,t+1} - z_{i,n,t}) \tag{A.5}$$

The second line of (A.2) then becomes

$$\mu_{1,i} var_{i,t}(er_{i,n,t+1})(\beta E_t z_{i,n,t+1} - (1+\beta) z_{i,n,t} + z_{i,n,t-1}) \tag{A.6}$$

Approximating the buy-and-hold portfolio as $z^{bh}_{i,n,t} - z_{i,n,t-1} = z_{i,n,t-1}\left(R_{n,t} - R^{i,p}_t\right)$, with $R^{i,p}_t = \sum_{m=1}^N z_{i,m,t-1} R_{m,t}$, we can write the last line of (A.2) as

$$
\begin{aligned}
&-\mu_{2,i}\left(\mathbf{e}_n - \mathbf{z}_{i,-n,t}\right)' \Omega_{i,t}\left(\mathbf{z}_{i,t} - \mathbf{z}_{i,t-1}\right) + \mu_{2,i}\beta\left(\mathbf{e}_n - \mathbf{z}_{i,-n,t}\right)' \Omega_{i,t} E_{i,t}\left(\mathbf{z}_{i,t+1} - \mathbf{z}_{i,t}\right) \\
&+\mu_{2,i}\left(\mathbf{e}_n - \mathbf{z}_{i,-n,t}\right)' \Omega_{i,t}\begin{pmatrix} z_{i,1,t-1}\left(R_{1,t} - R^{i,p}_t\right) \\ \dots \\ z_{i,N,t-1}\left(R_{N,t} - R^{i,p}_t\right)\end{pmatrix} \\
&-\mu_{2,i}\beta\left(\mathbf{e}_n - \mathbf{z}_{i,-n,t}\right)' \Omega_{i,t} E_{i,t}\begin{pmatrix} z_{i,1,t}\left(R_{1,t+1} - R^{i,p}_{t+1}\right) \\ \dots \\ z_{i,N,t}\left(R_{N,t+1} - R^{i,p}_{t+1}\right)\end{pmatrix} = 0
\end{aligned}
\tag{A.7}
$$

The first line is the same as the second line of (A.2), with $\mu_{1,i}$ replaced by $\mu_{2,i}$. It can therefore be written as

$$
\mu_{2,i} var_{i,t}(er_{i,n,t+1})(\beta E_t z_{i,n,t+1} - (1+\beta) z_{i,n,t} + z_{i,n,t-1}) \tag{A.8}
$$

Take the second line of (A.7). This can be written as

$$
\begin{aligned}
&\mu_{2,i}\sum_{m=1}^{N} cov_{i,t}(er_{i,n,t+1}, R_{m,t+1}) z_{i,m,t-1}(R_{m,t} - R^{i,p}_t) = \\
&\mu_{2,i} cov_{i,t}(er_{i,n,t+1}, R_{n,t+1}) z_{i,n,t-1}(R_{n,t} - R^{i,p}_t) \\
&+\mu_{2,i}(1 - z_{i,n,t-1})\sum_{m \neq n} cov_{i,t}(er_{i,n,t+1}, R_{m,t+1}) z_{i,m,-n,t-1}(R_{m,t} - R^{i,p}_t)
\end{aligned}
\tag{A.9}
$$

One can think of the summation in the last line as a cross-sectional covariance $E(xy)$, with $x = cov_{i,t}(er_{i,n,t+1}, R_{m,t+1})$ and $y = (R_{m,t} - R^{i,p}_t)$ and $z_{i,m,-n,t-1}$ the probability. Since there is no reason why the x and y would be correlated, when the number of countries is large enough, we can write this as $E(x)E(y)$. (A.9) then becomes

$$
\begin{aligned}
&\mu_{2,i} cov_{i,t}(er_{i,n,t+1}, R_{n,t+1}) z_{i,n,t-1}(R_{n,t} - R^{i,p}_t) \\
&+\mu_{2,i}(1 - z_{i,n,t-1}) cov_{i,t}(er_{i,n,t+1}, R_{ref(i,n),t+1})(R_{ref(i,n),t} - R^{i,p}_t)
\end{aligned}
\tag{A.10}
$$

Using that $(1 - z_{i,n,t-1})(R_{ref(i,n),t} - R^{i,p}_t) = z_{i,n,t-1}(R^{i,p}_t - R_{n,t})$, and that $cov_{i,t}(er_{i,n,t+1}, R_{n,t+1}) = var_{i,t}(er_{i,n,t+1}) + cov_{i,t}(er_{i,n,t+1}, R_{ref(i,n),t+1})$, this becomes

$$
\mu_{2,i} var_{i,t}(er_{i,n,t+1}) z_{i,n,t-1}(R_{n,t} - R^{i,p}_t) = \mu_{2,i} var_{i,t}(er_{i,n,t+1})(z^{bh}_{i,n,t} - z_{i,n,t-1}) \tag{A.11}
$$

Analogously, the last line of (A.7) is

$$-\mu_{2,i}\beta var_{i,t}(er_{i,n,t+1})(E_t z^{bh}_{i,n,t+1} - z_{i,n,t}) \tag{A.12}$$

We can write the difference between the buy-and-hold portfolio and lagged portfolio as

$$z^{bh}_{i,n,t} - z_{i,n,t-1} = z_{i,n,t-1}\left(R_{n,t} - R^{i,p}_t\right) = z_{i,n,t-1}(1 - z_{i,n,t-1})er_{i,n,t} \tag{A.13}$$

Combining (A.11) and (A.12), we then have

$$\begin{aligned}&\mu_{2,i}var_{i,t}(er_{i,n,t+1})z_{i,n,t-1}(1 - z_{i,n,t-1})er_{i,n,t}\\ &-\beta\mu_{2,i}var_{i,t}(er_{i,n,t+1})z_{i,n,t}(1 - z_{i,n,t})E_{i,t}er_{i,n,t+1}\end{aligned} \tag{A.14}$$

We can now combine all terms of (A.2), which gives

$$\begin{aligned}&E_{i,t}er_{i,n,t+1} - \gamma_i cov_{i,t}(er_{i,n,t+1}, R_{ref(i,n),t+1}) - \gamma_i z_{i,n,t} var_{i,t}(er_{i,n,t+1})\\ &+(\mu_{1,i} + \mu_{2,i})var_{i,t}(er_{i,n,t+1})(\beta E_{i,t}z_{i,n,t+1} - (1 + \beta)z_{i,n,t} + z_{i,n,t-1})\\ &+\mu_{2,i}var_{i,t}(er_{i,n,t+1})z_{i,n,t-1}(1 - z_{i,n,t-1})er_{i,n,t}\\ &-\beta\mu_{2,i}var_{i,t}(er_{i,n,t+1})z_{i,n,t}(1 - z_{i,n,t})E_{i,t}er_{i,n,t+1} = 0\end{aligned} \tag{A.15}$$

Define $\sigma^2_{i,n}$ as the mean of $var_{i,t}(er_{i,n,t+1})$ and $\sigma_{n,ref(i,n)}$ as the mean value of $cov_{i,t}(er_{i,n,t+1}, R_{ref(i,n),t+1})$. The mean of the excess return is zero. From (A.15) the steady state portfolio is then

$$\bar{z}_{i,n} = -\frac{\sigma_{n,ref(i,n)}}{\sigma^2_{i,n}} \tag{A.16}$$

Linearizing (A.15) around the second moments equal to their mean, the portfolio shares equal to $\bar{z}_{i,n}$ and the excess returns equal to zero, we have

$$\begin{aligned}&E_{i,t}er_{i,n,t+1} + u_{i,n,t} - \gamma_i\sigma^2_{i,n}\hat{z}_{i,n,t}\\ &+(\mu_{1,i} + \mu_{2,i})\sigma^2_{i,n}(\beta E_{i,t}\hat{z}_{i,n,t+1} - (1 + \beta)\hat{z}_{i,n,t} + \hat{z}_{i,n,t-1})\\ &+\mu_{2,i}\sigma^2_{i,n}\bar{z}_{i,n}(1 - \bar{z}_{i,n})\left(er_{i,n,t} - \beta E_{i,t}er_{i,n,t+1}\right) = 0\end{aligned} \tag{A.17}$$

where $\hat{z}_{i,n,t} = z_{i,n,t} - \bar{z}_{i,n}$ and

$$u_{i,n,t} = -\gamma_i\left(cov_{i,t}(er_{i,n,t+1}, R_{ref(i,n),t+1}) - \sigma_{n,ref(i,n)}\right) - \gamma_i\bar{z}_{i,n}\left(var_{i,t}(er_{i,n,t+1}) - \sigma^2_{i,n}\right) \tag{A.18}$$

Appendix B: Solution Optimal Portfolio

We now solve the second-order difference equation (A.17) in the portfolio share $\hat{z}_{i,n,t}$. Collecting terms, we can write (A.17) as

$$\begin{aligned}\sigma_{i,n}^2 D_i \hat{z}_{i,n,t} &= E_{i,t} er_{i,n,t+1} + \theta_i \sigma_{i,n}^2 \hat{z}_{i,n,t-1} + \beta\theta_i \sigma_{i,n}^2 E_{i,t} \hat{z}_{i,n,t+1} \\ &+ \mu_{2,i} \sigma_{i,n}^2 \bar{z}_{i,n}(1-\bar{z}_{i,n}) \left(er_{i,n,t} - \beta E_{i,t} er_{i,n,t+1}\right) + u_{i,n,t}\end{aligned} \tag{A.19}$$

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

This can be written as

$$\begin{aligned}\left(L^{-2} - \frac{D_i}{\beta\theta_i} L^{-1} + \frac{1}{\beta}\right) \hat{z}_{i,n,t-1} &= -\frac{1}{\beta\theta_i \sigma_{i,n}^2} E_{i,t}\left(er_{i,n,t+1} + u_{i,n,t}\right) \\ -\frac{1}{\beta\theta_i} \mu_{2,i} \bar{z}_{i,n}(1-\bar{z}_{i,n}) er_{i,n,t} &+ \frac{1}{\theta_i} \mu_{2,i} \bar{z}_{i,n}(1-\bar{z}_{i,n}) E_{i,t} er_{i,n,t+1}\end{aligned}$$

where $L^{-2} z_{i,n,t-1} = E_{i,t} z_{i,n,t+1}$ and $L^{-1} z_{i,n,t-1} = z_{i,n,t}$. Factoring gives

$$\begin{aligned}(L^{-1} - \omega_{1,i})(L^{-1} - \omega_{2,i}) \hat{z}_{i,n,t-1} &= -\frac{1}{\beta\theta_i \sigma_{i,n}^2} E_{i,t}\left(er_{i,n,t+1} + u_{i,n,t}\right) \\ -\frac{1}{\beta\theta_i} \mu_{2,i} \bar{z}_{i,n}(1-\bar{z}_{i,n}) er_{i,n,t} &+ \frac{1}{\theta_i} \mu_{2,i} \bar{z}_{i,n}(1-\bar{z}_{i,n}) E_{i,t} er_{i,n,t+1}\end{aligned}$$

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

$$\omega_i^2 - \frac{D_i}{\beta\theta_i}\omega_i + \frac{1}{\beta} = 0 \tag{A.20}$$

These roots are

$$\omega_i = 0.5\left(\frac{D_i}{\beta\theta_i} \pm \sqrt{\left(\frac{D_i}{\beta\theta_i}\right)^2 - (4/\beta)}\right) \tag{A.21}$$

For convenience, we 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

$$\begin{aligned}(L^{-1} - \omega_i) \hat{z}_{i,n,t-1} &= -\frac{1}{\beta\theta_i \sigma_{i,n}^2} \frac{E_{i,t}\left(er_{i,n,t+1} + u_{i,n,t}\right)}{L^{-1} - \omega_{2,i}} \\ -\frac{1}{\beta\theta_i} \mu_{2,i} \bar{z}_{i,n}(1-\bar{z}_{i,n}) \frac{er_{i,n,t}}{L^{-1} - \omega_{2,i}} &+ \frac{1}{\theta_i} \mu_{2,i} \bar{z}_{i,n}(1-\bar{z}_{i,n}) \frac{E_{i,t} er_{i,n,t+1}}{L^{-1} - \omega_{2,i}}\end{aligned}$$

This implies

$$\hat{z}_{i,n,t} = \omega_i \hat{z}_{i,n,t-1} + \frac{1}{\beta\theta_i\sigma^2_{i,n}\omega_{2,i}} \sum_{s=1}^{\infty} \omega_{2,i}^{1-s} E_{i,t}\left(er_{i,n,t+s} + u_{i,n,t+s-1}\right)$$
$$+ \frac{\mu_{2,i}\bar{z}_{i,n}(1-\bar{z}_{i,n})}{\beta\theta_i\omega_{2,i}} er_{i,n,t} + \frac{\mu_{2,i}\bar{z}_{i,n}(1-\bar{z}_{i,n})\left(\frac{1}{\omega_{2,i}} - \beta\right)}{\beta\theta_i\omega_{2,i}} \sum_{s=1}^{\infty} \omega_{2,i}^{1-s} E_{i,t} er_{i,n,t+s}$$

To summarize, we have

$$\hat{z}_{i,n,t} = a_{2,i}\hat{z}_{i,n,t-1} + a_{3,i,n} \sum_{s=1}^{\infty} \omega_{2,i}^{1-s} E_t er_{i,n,t+s} + a_{4,i,n} er_{i,n,t} + \epsilon_{i,n,t} \tag{A.22}$$

where E_t is the expectation operator of the econometrician based on public information and

$$a_{2,i} = \omega_i$$
$$a_{3,i,n} = \frac{1}{\beta\theta_i\sigma^2_{i,n}\omega_{2,i}} + \frac{\mu_{2,i}\bar{z}_{i,n}(1-\bar{z}_{i,n})\left(\frac{1}{\omega_{2,i}} - \beta\right)}{\beta\theta_i\omega_{2,i}}$$
$$a_{4,i,n} = \frac{\mu_{2,i}\bar{z}_{i,n}(1-\bar{z}_{i,n})}{\beta\theta_i\omega_{2,i}}$$

and

$$\epsilon_{i,n,t} = \frac{1}{\beta\theta_i\sigma^2_{i,n}\omega_{2,i}} \sum_{s=1}^{\infty} \omega_{2,i}^{1-s} E_{i,t} u_{i,n,t+s-1} + a_{3,i,n} \sum_{s=1}^{\infty} \omega_{2,i}^{1-s}\left(E_{i,t} er_{i,n,t+s} - E_t er_{i,n,t+s}\right) \tag{A.23}$$

Numerically the second term in $a_{3,i,n}$ is very close to zero. We therefore abstract from it in what follows.

We can also write the solution for $z_{i,n,t}$ as a function of the lagged portfolio and the buy-and-hold portfolio. For this, use that from linearizing (A.13) $z^{bh}_{i,n,t} = z_{i,n,t-1} + \bar{z}_{i,n}(1-\bar{z}_{i,n})er_{i,n,t}$, so that

$$er_{i,n,t} = \frac{z^{bh}_{i,n,t} - z_{i,n,t-1}}{\bar{z}_{i,n}(1-\bar{z}_{i,n})}$$

We then have

$$\hat{z}_{i,n,t} = \left(a_{2,i} - \frac{a_{4,i,n}}{\bar{z}_{i,n}(1-\bar{z}_{i,n})}\right)\hat{z}_{i,n,t-1} + \frac{a_{4,i,n}}{\bar{z}_{i,n}(1-\bar{z}_{i,n})}\hat{z}^{bh}_{i,n,t} + a_{3,i,n}\sum_{s=1}^{\infty}\omega_{2,i}^{1-s}E_t er_{i,n,t+s} + \epsilon_{i,n,t} \tag{A.24}$$

where $\hat{z}^{bh}_{i,n,t} = z^{bh}_{i,n,t} - \bar{z}_{i,n}$. Use that $\omega_{2,i} = 1/(\beta\omega_i) = 1/(\beta a_{2,i})$. This gives

$$\hat{z}_{i,n,t} = \omega_i \left(\frac{\mu_{1,i}}{\mu_{1,i} + \mu_{2,i}} \hat{z}_{i,n,t-1} + \frac{\mu_{2,i}}{\mu_{1,i} + \mu_{2,i}} \hat{z}^{bh}_{i,n,t} \right) + \frac{\omega_i}{\theta_i \sigma^2_{i,n}} \sum_{s=1}^{\infty} (\beta\omega_i)^{s-1} E_t er_{i,n,t+s} + \epsilon_{i,n,t} \tag{A.25}$$

with

$$\epsilon_{i,n,t} = \frac{\omega_i}{\theta_i \sigma^2_{i,n}} \sum_{s=1}^{\infty} (\beta\omega_i)^{s-1} E_t u_{i,n,t+s-1} + \frac{\omega_i}{\theta_i \sigma^2_{i,n}} \sum_{s=1}^{\infty} (\beta\omega_i)^{s-1} (E_{i,t} er_{i,n,t+s} - E_t er_{i,n,t+s}) \tag{A.26}$$

Using the expression for D_i, we can also write the stable root (A.21) as

$$\omega_i = \frac{2\theta_i}{\gamma_i + (1+\beta)\theta_i + \sqrt{\gamma_i^2 + (1-\beta)^2\theta_i^2 + 2(1+\beta)\gamma_i\theta_i}} \tag{A.27}$$

Appendix C: Trading Strategies

To evaluate the prediction performance and estimate the economic significance of predictability reported in Section 3, we follow the literature in building trading strategies based on the three predictors used in the regressions. The analysis is close to Cenedese et al. (2016). For each month, we sort countries into quintiles based on their values of momentum, dividend-price differential, or earning-price differential. 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 pair month-quintile, we take the equally weighted average equity return differential with the US. Then, for each predictor variable we form a long-short HML portfolio, obtained by going long on Q5 and short on Q1. The sample is January 1970 to February 2019.

Table C1 reports the average annualized equity return by quintile and the portfolio return when the predictor is momentum, the dividend-price ratio, or the earning-price ratio (it is also possible to build strategies based on a combination of the three variables). The table shows that returns tend to be higher for higher quintiles, i.e., higher values of momentum, dividend-price, or earning-price are associated with higher returns. This is confirmed by the results in the last column that show large returns from HML portfolios. These results are in line with

Cenedese et al. (2016), who use a more restricted sample. 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 C1: Equity Excess Returns

	Q1	Q2	Q3	Q4	Q5	HML
Momentum	.69	1.01	-.28	2.33	9.56	8.87
Dividend-Price	-2.02	2.62	.86	1.2	4.42	6.44
Earning-Price	.06	-1.1	.11	3.31	5.49	5.43

Notes: Mean annualized equity excess returns relative to the US by sorting countries-months in quintiles based on their values for momentum, dividend-price and earning-price. HML shows the return from borrowing in Q1 and investing in Q5. Sample: 73 countries over the horizon 1970:01-2019:02.

Appendix D: Data Appendix

We describe here the data used other than the portfolio data from EPFR that are described in detail in Section 4.1.

We obtain the following monthly MSCI data: 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 we also compute

- **Equity Return**: relative change of the total return index from the prior month.
- **Earnings**: earning-price ratio multiplied by the price index.
- **Dividend**: dividend-price ratio multiplied by the price index.
- **Book value**: market value divided by the price index.
- **Volatility**: for each country and each month, we compute the standard deviation of the daily returns, using the *daily* total return index from MSCI.

In addition to these MSCI data, we obtain the following variables from other sources:

- **Industrial Production**. The main source is the industrial production index from IFS. If not available, we use the manufacturing or the retail index from the IFS. When countries do not report the industrial production, the manufacturing nor the retail index, we use the monthly gross domestic product index obtained from the Leading Indicators of the OECD. Finally, for Hong-Kong and Thailand, we use quarterly real GDP data from OECD, interpolated to a monthly series. We transform the final series for each country into an index equal to 100 in July 2016.

- **Inflation**. Monthly consumer price index series are from the IFS compiled by the IMF. If the consumer price index is not available, we use the producer price index or the wholesale price index from the IFS. For Taiwan, we obtain the consumer price index from the Statistical Bureau of Taiwan. For Australia, monthly data are not available and we interpolate the monthly series from the quarterly series. We transform the final series for each country into an index equal to 100 in July 2016.

- **Nominal Interest Rate**. We use the 3-month Eurorates obtained from Datastream. The data are midpoint of the offer and bid rates. Original data are expressed at annual rates in percent. We transform the data into a monthly rate by dividing by 1200.

- **Bond Price Index**. We obtain the data on bond price index from J.P. Morgan and Merrill Lynch obtained through Datastream. We use the price index of a 10-year government bond provided by JPM. For emerging economies, when the price index of the 10-year government bond is not available, we use the Emerging Market Bond Index provided by JPM. For Taiwan and Thailand, we use the Government Bond Index provided by Merrill Lynch. When the bond price index is in local currency, we convert to dollars.

References

[1] Abel, Andrew B., Janice C. Eberly and Stavros Panageas (2007), "Optimal Inattention in the Stock Market," *American Economic Review Papers and Proceedings*, May 2007, 244-249.

[2] Ameriks, John and Stephen Zeldes (2004), "How do Household Portfolio Shares vary with Age," working paper.

[3] Bacchetta, Philippe and Eric van Wincoop (2021) "Puzzling Exchange Rate Dynamics and Delayed Portfolio Adjustment," *Journal of International Economics* 131.

[4] Bacchetta, Philippe and Eric van Wincoop (2010), "Infrequent Portfolio Decisions: A Solution to the Forward Discount Puzzle," *American Economic Review* 100, 837-869.

[5] Bacchetta, Philippe, Margaret Davenport, and Eric van Wincoop (2021a) "Can Sticky Portfolios Explain International Capital Flows and Asset Prices?" mimeo.

[6] Bacchetta, Philippe, Eric van Wincoop, and Eric Young (2021b), "Gradual Portfolio Adjustment: Implications for Global Equity Portfolios and Returns," working paper, University of Virginia.

[7] Benhima, Kenza and Rachel Cordonier (2020), "News, Sentiment and Capital Flows," working paper, University of Lausanne.

[8] Bertaut, Carol C. and Ruth Judson (2014), "Estimating U.S. Cross-Border Securities Positions: New Data and New Methods," Board of Governors of the Federal Reserve System (U.S.), International Finance Discussion Paper 1113.

[9] Bertaut, Carol C. and Ralph W. Tryon (2007), "Monthly Estimates of U.S. Cross-Border Securities Positions, " Board of Governors of the Federal Reserve System (U.S.), International Finance Discussion Paper 910.

[10] Bilias, Yannis, Dimitris Georgarakos and Michael Haliassos (2010), "Portfolio Inertia and Stock Market Fluctuations," *Journal of Money, Credit and Banking* 42: 715-742.

[11] Bogousslavsky, Vincent (2016), "Infrequent Rebalancing, Return Autocorrelation, and Seasonality," *Journal of Finance* LXXI (6), 2967-3006.

[12] Bohn, Henning and Linda L. Tesar (1996), "U.S. Equity Investment in Foreign Markets: Portfolio Rebalancing or Return Chasing?" *American Economic Review* 86, 77-81.

[13] Brunnermeier, Markus and Stefan Nagel (2008), "Do Wealth Fluctuations Generate Time-Varying Risk-Aversion? Micro-Evidence on Individuals' Asset Allocation," *American Economic Review* 98, 713-736.

[14] Camanho, Nelson, Harald Hau, and Hélène Rey (2020),"Global Portfolio Rebalancing and Exchange Rates," mimeo.

[15] Campbell, John Y., Andrew W. Lo and Archie C. MacKinlay (1997), *The Econometrics of Financial Markets*, Princeton University Press, New York.

[16] Cenedese, Gino, Richard Payne, Lucio Sarno, and Giorgio Valente (2016), "What Do Stock Markets Tell Us about Exchange Rates?" *Review of Finance* 20, 1045-1080.

[17] Chien, Yili, Harold Cole, and Hanno Lustig (2012), "Is the Volatility of the Market Price of Risk Due to Intermittent Portfolio Rebalancing," *American Economic Review* 102, 2859-2896.

[18] Curcuru, Stephanie E., Charles P. Thomas, Francis Warnock, and Jon Wongswan (2014), "Uncovered Equity Parity and Rebalancing in International Portfolios," *Journal of International Money and Finance* 47, 86-99.

[19] Davis, J. Scott and Eric van Wincoop (2018),"Globalization and the Increasing Correlation between Capital Inflows and Outflows," *Journal of Monetary Economics* 100, 83-100.

[20] Devereux, Michael B. and Alan Sutherland (2007), "Monetary Policy and Portfolio Choice in an Open Economy Macro Model," *Journal of the European Economic Association* 5, 491-499.

[21] Devereux, Michael B. and Alan Sutherland (2010), "Country Portfolio Dynamics," *Journal of Economic Dynamics and Control*, 34, 1325-1342.

[22] Didier, Tatiana and Alexandre Lowenkron (2012), "The Current Account as a Dynamic Portfolio Choice Problem," *Journal of The Japanese and International Economies* 26, 518-541.

[23] Disyatat, Piti and R. Gaston Gelos (2001), "The Asset Allocation of Emerging Market Mutual Funds," IMF Working Paper 01/111.

[24] Duffie, Darrell (2010), "Asset Price Dynamics with Slow-Moving Capital," *Journal of Finance* LXV, 1237-1267.

[25] Evans, Martin D.D. and Viktoria V. Hnatkovska (2012), "A Method for Solving General Equilibrium Models with Incomplete Markets and Many Financial Assets," *Journal of Economic Dynamics and Control* 36(12), 1909–1930.

[26] Evans, Martin D.D. and Viktoria V. Hnatkovska (2014), "International Capital Flows, Returns and World Financial Integration," *Journal of International Economics* 92(1), 14-33.

[27] Fama, Eugene F. (1984), "Forward and Spot Exchange Rates," *Journal of Monetary Economics* 14, 319-338.

[28] Frankel, Jeffrey and Charles M. Engel (1984), "Do asset-demand functions optimize over the mean and variance of real returns? A six-currency test," *Journal of International Economics* 17(3-4), 309-323.

[29] Froot, Kenneth A. and Richard H. Thaler (1990) "Anomalies: Foreign Exchange," *Journal of Economic Perspectives* 4, 179-192.

[30] Froot, Kenneth A., Paul G.J. O'Connell and Mark S Seasholes (2001), "The Portfolio Flows of International Investors," *Journal of Financial Economics* 59, 151-193.

[31] Gabaix, Xavier and Ralph S.J. Koijen (2020), "In Search of the Origins of Financial Fluctuations: The Inelastic Markets Hypothesis," mimeo.

[32] Gabaix, Xavier and Matteo Maggiori (2015), "International Liquidity and Exchange Rate Dynamics," *Quarterly Journal of Economics* 130(3), 1369-1420.

[33] Gârleanu, Nicolae, and Lasse Heje Pedersen (2013), "Dynamic Portfolio Choice with Frictions," *Journal of Finance* LXVIII, No. 6, 2309-2340.

[34] Giglio, Stefano, Matteo Maggiori, Johannes Stroebel and Stephen Utkus (2021), "Five Facts about Beliefs and Portfolios," *American Economic Review* 111(5), 1481-1522.

[35] Greenwood, Robin, Samuel G. Hanson, and Gordon Y. Liao (2018), "Asset Price Dynamics in Partially Segmented Markets," *The Review of Financial Studies* 31(9), 3307-3343.

[36] Hendershott, Terrence, Sunny X. Li, Albert J. Mankfeld, Mark S. Seasholes (2018), "Asset Price Dynamics with Limited Attention," mimeo.

[37] Hjalmarsson, Erik (2010), "Predicting Global Stock Returns," *Journal of Financial and Quantitative Analysis* 45, 49-80.

[38] Hnatkovska, Viktoria V. (2010), "Home Bias and High Turnover: Dynamic Portfolio Choice with Incomplete Markets," *Journal of International Economics* 80(1), 113-128.

[39] Itskhoki, Oleg and Dmitry Mukhin, 2021, "Exchange Rate Disconnect in General Equilibrium," *Journal of Political Economy*, forthcoming.

[40] Koijen, Ralph S.J. and Stijn Van Nieuwerburgh (2011), "Predictability of Returns and Cash Flows," *Annual Review of Financial Economics* 3, 467–91.

[41] Koijen, Ralph S.J and Motohiro Yogo (2020), "Exchange Rates and Asset Prices in a Global Demand System," mimeo.

[42] Kostovetsky, Leonard and Jerold B. Warner (2015), "You're Fired! New Evidence on Portfolio Manager Turnover and Performance," *Journal of Financial and Quantitative Analysis* 50(4), 729-755.

[43] Miao,Yanliang and Malika Pant (2012), "Coincident Indicators of Capital Flows, " IMF Working Paper 12/55.

[44] Mitchell, Olivia S., Gary R. Mottola, Stephen P. Utkus and Takeshi Yamaguchi (2006), "The Inattentive Participant: Portfolio Trading Behavior in 401(k) plans," working paper.

[45] Petersen, Mitchell A. (2009), "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches " *Review of Financial Studies* 22, 435-480.

[46] Raddatz, Claudio and Sergio L. Schmukler (2012), "On the International Transmission of Shocks: Micro-Evidence from Mutual Fund Portfolios," *Journal of International Economics* 88, 357-374.

[47] Raddatz, Claudio, Sergio L. Schmukler and Tomás Williams (2017), "International Asset Allocations and Capital Flows: The Benchmark Effect," *Journal of International Economics* 108, 413-430.

[48] Rapach, David E. and Guofu Zhou (2013), "Forecasting stock returns," in: G. Elliott and A. Timmermann (eds.), *Handbook of Economic Forecasting*, Elsevier, North-Holland, Amsterdam, 328–383.

[49] Tille, Cédric and Eric van Wincoop (2010a), "International Capital Flows," *Journal of International Economics* 80(2), 157-175.

[50] Tille, Cédric and Eric van Wincoop (2010b), "A New Perspective on the "New Rule" for the Current Account," *Journal of International Economics* 80(1), 89-99.

[51] Tille, Cédric and Eric van Wincoop (2014), "International Capital Flows under Dispersed Private Information," *Journal of International Economics* 93(1), 31-49.

[52] Vayanos, Dimitri and Paul Woolley (2012), "An Institutional Theory of Momentum and Reversal," *Review of Financial Studies* 26, 1087-1145.