

International Portfolio Choice with Frictions: Evidence from Mutual Funds

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Abstract

Using data on international equity portfolio allocations of US mutual funds, we estimate a simple portfolio expression derived from a standard mean-variance portfolio model extended with portfolio frictions. The optimal portfolio depends on previous month and buy-and-hold portfolio shares, and a present discounted value of expected excess returns. We show that equity return differentials are predictable and use this prediction in the portfolio regressions. The estimates imply significant portfolio frictions and a modest rate of risk aversion. While portfolios respond significantly to expected returns, portfolio frictions lead to weaker and more gradual portfolio response. We also document heterogeneity across funds.

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, 2019) and Bacchetta, van Wincoop, and Young (2020) 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 aggregate US equity portfolios. Nonetheless none of the existing literature has provided direct evidence of portfolio frictions in

¹Some 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).

international portfolio allocation data. This paper aims to fill that gap.²

Our evidence is based on 15 years of monthly equity portfolio allocation data across 35 countries for 316 US mutual funds that report to EPFR (Emerging Portfolio Fund Research). Mutual funds are the most important players in external US equity holdings, accounting for 61 percent of all US foreign equity holdings at the end of 2018.³ 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

²Although our focus is on international portfolio choice, this ultimately has a significant effect on global capital flows, which in turn can have a significant effect on business cycles. 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, b, 2014).

³See Exhibit 19 in “Portfolio Holdings of Foreign Securities,” October 2019, Department of the Treasury.

(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 can think of the frictions as related to both trading costs and decision making costs, though we do not take a position on this. A parameter that captures the sum of the two portfolio frictions is referred to as the aggregate portfolio friction. For a given aggregate portfolio friction, an increase in the relative size of the first friction implies a higher relative weight on the lagged portfolio share and therefore more extensive rebalancing.

One difficulty with estimating portfolio expressions is endogeneity. Specifically, portfolio shocks that enter through the error term affect equity prices and through that expected excess returns. We exploit mutual fund heterogeneity to address this endogeneity problem. We consider the portfolio allocation of US mutual funds across different foreign countries. The share that a fund invests in a specific foreign country depends on the expected excess return in that country relative a (portfolio) weighted average of expected excess returns in other countries. This set of reference countries, and their importance, varies across funds. To control for the source of

endogeneity, i.e., country-level portfolio shifts, we introduce a country-month fixed effect. The heterogeneity in expected excess returns still allows us to estimate the portfolio response to expected excess returns.

We find that the funds respond to the discounted expected excess return with strong statistical significance. We also find that the 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 2.5. The aggregate portfolio friction is precisely estimated. We also find that the lagged portfolio share is more important than the buy-and-hold portfolio, which is consistent with extensive portfolio rebalancing by the mutual funds.

We also consider various types of fund heterogeneity: large versus small funds; active versus passive funds; global versus regional and emerging market funds. The results imply that large funds face bigger aggregate portfolio frictions than small funds, while small, active and emerging markets funds have larger relative friction of deviating from the previous portfolio share. The latter is consistent with very active rebalancing by these funds. Active funds are also found to have a higher risk parameter, reflecting either higher risk aversion or higher perceived uncertainty about excess returns.

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) is 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 Koiijen and Yogo (2019). 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 than we do as they do not have investor heterogeneity in expected excess returns. They 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. (2018) 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), Biliias 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. (2019), 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 ex-

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

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

planatory power for when investors trade, but help predict the direction and the 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 considers various types of fund heterogeneity. Section 6 concludes.

2 A Model of Portfolio Allocation with Financial Frictions

Our portfolio theory focuses on just two assets and therefore one portfolio share. There are several reasons for doing so. First, even though our mutual funds invest in many countries, one can always think of the optimal portfolio share invested in a particular country, conditional on the relative allocation to the other countries. Second, inverting a large variance matrix of portfolio returns can make results very sensitive to small measurement errors of numerous covariance terms.⁶ A related problem is that it is hard to introduce heterogeneity of perceived asset return risk across funds when the risk involves so many variance and covariance terms simultaneously. Finally, such an approach would involve a large matrix A of portfolio friction parameters in the portfolio cost $x'Ax$, where x is a vector of deviations from benchmark portfolios. Our approach has the advantage of leading to a simple optimal portfolio expression that can easily be brought to the data.

⁶A good example of this is Adler and Dumas (1983), who consider the optimal equity portfolio allocation across 9 countries and find quite extreme and implausible allocations that are inconsistent with equilibrium.

Consider a mutual fund allocating its portfolio to countries 1 and 2, with gross returns $R_{1,t+1}$ and $R_{2,t+1}$ from t to $t+1$. When applying this to the data below, the mutual fund is a US fund, country 1 is a specific foreign country, and country 2 a fund-specific aggregate of all other foreign countries that the fund invests in. $R_{2,t+s}$ therefore represents the overall return in relevant countries outside of country 1.

The share invested in country 1 is z_t and the excess return of that country is $er_{t+1} = R_{1,t+1} - R_{2,t+1}$. 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 passive benchmarks. There may be costs of transactions, information gathering or decision making. Mutual funds may also be evaluated against passive benchmarks by investors (e.g., see Berk and Green, 2004), making them reluctant to deviate from these benchmarks.

We assume a quadratic cost of deviating from two types of benchmarks. The first is the past portfolio share z_{t-1} , with a quadratic deviation cost $0.5\lambda_1(z_t - z_{t-1})^2$. The second benchmark is the buy-and-hold portfolio z_t^{bh} , with a deviation cost of $0.5\lambda_2(z_t - z_t^{bh})^2$. The only difference between the two benchmarks is the valuation effect between $t - 1$ and t . The buy-and-hold portfolio is equal to

$$z_t^{bh} = z_{t-1} \frac{1 + R_{1,t}}{1 + z_{t-1}R_{1,t} + (1 - z_{t-1})R_{2,t}}$$

The extent of financial frictions is given by λ_1 and λ_2 , which should be determined empirically. We will refer to the aggregate portfolio friction as $\theta = \lambda_1 + \lambda_2$.

The fund's objective function is:

$$\sum_{s=0}^{\infty} \beta^s E_t (z_{t+s}R_{1,t+s+1} + (1 - z_{t+s})R_{2,t+s+1})$$

$$\begin{aligned}
& -0.5\gamma \sum_{s=0}^{\infty} \beta^s \left(z_{t+s}^2 \sigma_1^2 + (1 - z_{t+s})^2 \sigma_2^2 + 2z_{t+s}(1 - z_{t+s})\sigma_{12} \right) \\
& -0.5 \sum_{s=0}^{\infty} \beta^s E_t \left(\lambda_1 (z_{t+s} - z_{t+s-1})^2 + \lambda_2 (z_{t+s} - z_{t+s}^{bh})^2 \right) \tag{1}
\end{aligned}$$

where γ measures risk aversion and for any $s \geq 0$: $\sigma_i^2 = \text{var}(R_{i,t+s+1})$ and $\sigma_{12} = \text{cov}(R_{1,t+s+1}, R_{2,t+s+1})$. The term in brackets in the second line is the variance of the portfolio return at $t + s + 1$. The fund therefore maximizes the present discounted value of the certainty equivalent of future portfolio returns minus the costs of deviating from the benchmarks.

Appendix A shows that the optimal portfolio is given by:

$$z_t = a_1 + a_2 \left(\frac{\lambda_1}{\lambda_1 + \lambda_2} z_{t-1} + \frac{\lambda_2}{\lambda_1 + \lambda_2} z_t^{bh} \right) + a_3 \sum_{s=1}^{\infty} \delta^{s-1} E_t er_{t+s} \tag{2}$$

Denoting the variance of the excess return er_{t+1} as $\sigma_{er}^2 = \sigma_1^2 + \sigma_2^2 - 2\sigma_{12}$, the Appendix shows that the parameters are⁷

$$\begin{aligned}
a_2 = \omega ; \quad a_3 = \frac{\omega}{\theta} ; \quad \delta = \beta\omega \\
\omega = \frac{2\theta}{\Gamma + (1 + \beta)\theta + \sqrt{\Gamma^2 + (1 - \beta)^2\theta^2 + 2(1 + \beta)\Gamma\theta}}
\end{aligned}$$

where

$$\Gamma = \gamma\sigma_{er}^2 \tag{3}$$

is what we refer to as a risk parameter that depends on both risk and risk-aversion.

It is easily checked that $\omega < 1$. In the simple case where $\beta = 0$ and agents are

⁷Here we abstract from an additional term in the expression for a_3 that numerically is very close to zero.

myopic, this becomes

$$z_t = a_1 + \frac{\theta}{\Gamma + \theta} \left(\frac{\lambda_1}{\lambda_1 + \lambda_2} z_{t-1} + \frac{\lambda_2}{\lambda_1 + \lambda_2} z_t^{bh} \right) + \frac{1}{\Gamma + \theta} E_t er_{t+1} \quad (4)$$

The optimal portfolio depends on a weighted average of the two benchmark portfolios and a present discounted value of future expected excess returns. The relative weight on the two benchmark portfolios depends on the relative size of the two portfolio frictions. In the absence of portfolio adjustment costs, the optimal portfolio is independent of β and is simply given by

$$z_t = a_1 + \frac{E_t er_{t+1}}{\Gamma} \quad (5)$$

It then does not depend on the benchmark portfolios and only depends on the expected excess return over the next period. Portfolio adjustment costs lead the portfolio today to depend on expected excess returns further into the future as investors wish to smooth portfolio changes in anticipation of changes in expected excess returns.⁸

The aggregate portfolio friction θ and risk parameter Γ critically drive the sensitivity to the benchmark portfolios and expected excess return in (2). Investors care about maximizing expected returns, minimizing portfolio risk and minimizing deviations from the benchmark portfolios. The relative weight of these three objectives depends on the parameters θ and Γ . An increase in the aggregate portfolio friction θ naturally gives more weight to the benchmark portfolios and less weight to expected excess returns, raising a_2 and lowering a_3 . An increase in the risk

⁸Bacchetta, van Wincoop, and Young (2020) obtain a similar dependence of the portfolio on the present value of expected future excess returns in a framework where instead of a cost of portfolio adjustment there is a given probability p of changing the portfolio each period, analogous to Calvo price setting.

parameter Γ naturally gives more weight to minimizing portfolio risk, lowering the weight a_2 on the benchmark portfolios and the sensitivity a_3 to expected excess returns. We can also see that investors give more weight to expected excess returns further into the future (higher δ) when the time discount rate β is higher, the aggregate portfolio friction θ is higher and the risk parameter Γ is lower.

In connecting reduced form parameter estimates from portfolio regressions more clearly to the structural parameters, it helps to write the portfolio share as a function of the average and the difference of the two benchmark portfolios. Specifically, in Section 4 we estimate portfolio expressions of the form

$$z_t = b_0 + b_1 \frac{z_{t-1} + z_t^{bh}}{2} + b_2 (z_{t-1} - z_t^{bh}) + b_3 \sum_{s=1}^{\infty} \delta^{s-1} E_t e r_{t+s} \quad (6)$$

An increase in the aggregate portfolio friction θ raises the overall weight b_1 on the benchmark portfolios and reduces the weight b_3 on the expected excess returns. An increase in the risk parameter Γ reduces both the overall weight b_1 on the benchmark portfolios and the weight b_3 on expected excess returns. Finally, a positive (negative) b_2 signifies that the portfolio friction λ_1 is larger (smaller) than the portfolio friction λ_2 . Mathematically, the structural parameters are linked to these reduced form parameters as follows:

$$\theta = \lambda_1 + \lambda_2 = \frac{b_1}{b_3} \quad (7)$$

$$\lambda_1 - \lambda_2 = \frac{2b_2}{b_3} \quad (8)$$

$$\Gamma = \frac{1}{b_3} (1 - b_1)(1 - \beta b_1) \quad (9)$$

We also have $\delta = \beta b_1$. To estimate (6), we first need estimates of expected return

differentials. We turn to this in the next section.

3 Predicting Cross-Country Equity Return Differentials

This section describes how we construct estimates for expected 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 previous section focused on the portfolio share allocated to country 1, with the remainder allocated to the aggregate of all other foreign countries. In the empirical analysis we focus on the portfolio share allocated by a US based fund to country n , with the remainder invested in other "relevant" foreign countries. The excess return is then fund specific. It is the equity return in country n minus a weighted average of the equity returns in other foreign countries, with the weights corresponding to the portfolio shares of the fund.

In this section, rather than considering excess return predictability 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 other foreign countries, using the portfolio shares of fund i for the 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 $er_{n,t,t+k} = er_{n,t+1} + \dots + er_{n,t+k}$ 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.⁹ Returns are computed from the MSCI total return index. We consider the following benchmark regression:

$$er_{n,t,t+k} = \alpha + \alpha_n + \beta' X_{n,t} + \varepsilon_{n,t} \quad (10)$$

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.¹⁰ Using pooled data and assuming a common coefficient β allows us to get more precise estimates.¹¹

⁹There are 18 countries in the sample in 1970, increasing to 35 in 1988, 44 in 1993, etc.

¹⁰Results 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.

¹¹Hjalmarsson (2010) shows that pooling across countries gives superior predictability.

The explanatory variables in the benchmark specification are standard in the literature on stock return predictability,¹² 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.¹³

Table 1 shows the results of regression (10) 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 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** (0.0167)			0.0426** (0.0177)	0.0439** (0.0173)	0.0441** (0.0178)
Dividend-Price		0.00695*** (0.00210)			0.00757*** (0.00208)	0.00595*** (0.00204)
Earning-Price			0.00660*** (0.00197)	0.00716*** (0.00196)		0.00459** (0.00196)
Constant	0.000846 (0.00146)	-0.00198 (0.00153)	-0.00177 (0.00149)	-0.00189 (0.00148)	-0.00218 (0.00152)	-0.00298* (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.

¹²See for example Kojien and Van Nieuwerburgh (2011) or Rapach and Zhou (2013) for surveys.

¹³Negative values are observed during the Asian and the Scandinavian financial crises.

The fit of equation (10) significantly improves when the horizon increases. Table 2 shows the results for one month (as in Table 1), 12 months, 24 months, and 60 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 18.5% at the 60-month horizon.

Table 2: REGRESSIONS RETURN DIFFERENTIAL - DIFFERENT HORIZONS

	(1)	(2)	(3)	(4)
	$er_{n,t,t+1}$	$er_{n,t,t+12}$	$er_{n,t,t+24}$	$er_{n,t,t+60}$
Momentum	0.0441** (0.0178)	0.332*** (0.0683)	0.493*** (0.113)	0.902*** (0.311)
Dividend-Price	0.00595*** (0.00204)	0.0994*** (0.00972)	0.229*** (0.0198)	0.759*** (0.0679)
Earning-Price	0.00459** (0.00196)	0.0372*** (0.00903)	0.0935*** (0.0161)	0.345*** (0.0564)
Constant	-0.00298* (0.00153)	-0.0265*** (0.00756)	-0.0563*** (0.0143)	-0.133*** (0.0359)
Observations	21908	21116	20254	17676
R^2	0.009	0.064	0.104	0.185

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 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 B 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.

4 International Equity Portfolios: Fund-Level Analysis

4.1 Basic Framework

In this section we analyze the allocations of portfolios across countries using the model developed in Section 2. We use panel data of US-based equity funds that report country allocations to EPFR and that have more than 5 million USD in assets under management (AUM) at the end of the sample. We restrict the sample to funds that are reporting at least 12 months. This leaves us with a total of 316 funds. We consider the main 35 investment countries.¹⁴ These countries represent on average 90% of international equity portfolios of our US mutual funds. At the fund level, we drop those countries in which the fund invests on average less than 2%. The sample runs from January 2002 to July 2016. We only consider observations where fund i positively invests in country n both at time t and $t-1$. This results in 316,732 observations.

For each fund i we compute $z_{i,n,t}$ as the share invested in country n out of the 35 non-US countries at time t . We construct the expected return differential relevant to fund i as

$$E_t er_{i,n,t,t+k}^\delta = \sum_{s=1}^k \delta^{s-1} E_t \left(R_{n,t+s} - \sum_{m \neq n} \bar{z}_{i,m,-n} R_{m,t+s} \right) \quad (11)$$

The term in brackets is the return in country n at $t+s$ minus the weighted average

¹⁴The 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, and U.K.. We dropped those countries in which less than 10 funds invest, as well as Argentina, the Russian Federation and the United Arab Emirates because of limited data coverage.

of the returns in the other countries, with the weights corresponding to the average portfolio weights of fund i . Specifically, $\bar{z}_{i,m,-n}$ is the average portfolio share of fund i in country m of its foreign equity holdings outside of country n .¹⁵ We then take a present discounted value of these excess returns with discount rate δ . While in the theory $k = \infty$, in the empirical applications k is necessarily finite. We consider $k = 24$ and $k = 60$. We assume a discount rate of $\delta = 0.89$. As we will see, this value is consistent with the theory. Other values for δ are considered in the Online Appendix.

Using the excess returns $er_{n,t+s} = R_{n,t+s} - R_{US,t+s}$ relative to the US, we can also write (11) as

$$E_t er_{i,n,t,t+k}^\delta = E_t \sum_{s=1}^k \delta^{s-1} er_{n,t+s} - \sum_{m \neq n} \bar{z}_{i,m,-n} E_t \sum_{s=1}^k \delta^{s-1} er_{m,t+s} \quad (12)$$

We obtain these expectations using panel regressions of $\sum_{s=1}^k \delta^{s-1} er_{n,t+s}$ 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 countries and using discounted returns. The three variables, momentum, dividend-price and earning-price, are all significant.

The valuation effect in the buy-and-hold portfolio is computed using fund-specific returns from EPFR. We have $z_{i,n,t}^{bh} = z_{i,n,t-1} \frac{1+R_{n,t}}{1+R_{i,p,t}}$, where $R_{n,t}$ is country n stock market return computed from MSCI and $R_{i,p,t}$ is the portfolio return of fund i obtained from EPFR.¹⁶

¹⁵The Online Appendix shows that results are virtually identical when we replace $\bar{z}_{i,m,-n}$ with the contemporaneous weights $z_{i,m,-n,t}$.

¹⁶One would prefer to use the country n return of fund i , but this data is not available. EPFR

Consistent with the theoretical portfolio expression (6), we consider the following regression:

$$z_{i,n,t} = b_0 + b_{i,n} + b_1 \frac{z_{i,n,t-1} + z_{i,n,t}^{bh}}{2} + b_2 (z_{i,n,t-1} - z_{i,n,t}^{bh}) + b_3 E_t er_{i,n,t,t+k}^\delta + \varepsilon_{i,n,t} \quad (13)$$

We assume a fund-country fixed effect $b_{i,n}$ because the mean portfolio share varies across fund-country combinations. For example, as shown in the Appendix, the intercept is higher when the perceived excess return risk σ_{er}^2 is lower, which is fund-country dependent. The other parameters are assumed to be the same across funds, but we examine various sources of heterogeneity in Section 5.

4.2 Endogeneity

Endogeneity is a concern in portfolio regressions. Portfolio shocks that enter through the error term can affect equity prices, which affect expected excess returns and the buy-and-hold portfolio (through valuation effects). Individual mutual funds are generally 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 of stock market capitalization of the country. However, there may be a common component to these portfolio shocks that is shared not just across US mutual funds, but also with other investors in the country. For example, changes in perceived risk of a country can lead to common portfolio shifts in and out of the country.

Such common portfolio shifts would bias downward the coefficient on the expected excess return and $z_{i,n,t-1} - z_{i,n,t}^{bh}$. A portfolio shift into country n , which only reports the overall return of each fund.

raises the error term, raises the country n equity price and therefore lowers its expected excess return and $z_{i,n,t-1} - z_{i,n,t}^{bh}$. This leads to a negative correlation between the error term and the expected excess return and between the error term and $z_{i,n,t-1} - z_{i,n,t}^{bh}$. It would bias upward the coefficient on $(z_{i,n,t-1} + z_{i,n,t}^{bh})/2$, which is positively correlated with the equity price of country n .

In order to account for such potential endogeneity through common portfolio shifts, we add a country-month fixed effect $b_{n,t}$ to the regression. This will sweep up portfolio shifts in and out of country n that are shared among funds (and likely other investors as well). If funds have the same expected excess returns in different countries, this would not allow us to estimate the coefficient on the expected excess return. Expected excess returns would only depend on country n and time t , and would be picked up by the country-month fixed effect $b_{n,t}$. However, expected excess returns in the same country differ across funds. This happens because the set of reference countries, and their portfolio weights $\bar{z}_{i,m,-n}$, vary across funds. This heterogeneity across funds of expected excess returns of country n allows us to estimate the coefficient b_3 .¹⁷

4.3 Benchmark Results

Table 3 presents the benchmark estimation of equation (13) with expected return differentials at different horizons. The last column is a bit different as it is based on a portfolio regression for aggregate EPFR data, which we will discuss at the

¹⁷Related, Giglio et al. (2019) are able to estimate the equity portfolio response to expected excess returns of US-based Vanguard investors through survey data of expected excess returns, which vary across investors. They control for common portfolio shocks through a time fixed effect. Since we consider portfolio shares in different countries, we include a country-time fixed effect. While their expected excess return heterogeneity originates from survey data, as opposed to reference country heterogeneity for our funds, in both cases cross-sectional heterogeneity of expected excess returns allows us to identify the portfolio response to expected excess returns.

end of this subsection. We will link the regression estimates in Table 3 to the structural parameters λ_1 , λ_2 and Γ from the theory. We will also explain why a discount rate of $\delta = 0.89$ is appropriate based on the theory. But before doing so, we first discuss the key takeaways from Table 3.

Table 3: PORTFOLIO REGRESSIONS, BENCHMARK

	Fund-Level			Aggregate
	(1)	(2)	(3)	(4)
$(z_{i,n,t-1} + z_{i,n,t}^{bh})/2$	0.928*** (0.004)	0.916*** (0.005)	0.918*** (0.007)	0.998*** (0.002)
$(z_{i,n,t-1} - z_{i,n,t}^{bh})$	0.173* (0.090)	0.313*** (0.069)	0.338*** (0.068)	-0.217*** (0.012)
$E_t er_{i,n,t,t+24}^{0.89}$	1.082*** (0.144)	2.324*** (0.291)		0.026** (0.012)
$E_t er_{i,n,t,t+60}^{0.89}$			5.054*** (0.825)	
Fund-Country FE	Yes	Yes	Yes	No ^a
Country-Month FE	No	Yes	Yes	No ^a
Observations	316732	316732	196828	5918
R^2	0.987	0.988	0.990	0.999

Standard errors clustered by month in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Table 3 estimates equation (13) with 35 countries over the horizon 2002:01-2016:07. The constant is included in all regressions but not shown. Columns (1)-(3) show the results at the fund level, while column (4) aggregates funds positions. ^aIn column (4), we use a country fixed effect.

The role of endogeneity can be seen by comparing columns (1) and (2). Both measure the expected excess return with a two-year horizon $k = 24$. The only difference between columns (1) and (2) is that column (1) does not include country-month fixed effects $b_{n,t}$, while column (2) does. The results in column (1) are therefore potentially subject to endogeneity. This does indeed appear to be the case. Consistent with the discussion above, not accounting for endogeneity leads to a downward bias of the coefficients on the expected excess return and $z_{i,n,t-1} - z_{i,n,t}^{bh}$,

and an upward bias of the coefficient on $(z_{i,n,t-1} + z_{i,n,t}^{bh})/2$. The coefficients on the expected excess return and $z_{i,n,t-1} - z_{i,n,t}^{bh}$ are roughly doubled once including the country-month fixed effect.

Even with the inclusion of country-month fixed effects, all coefficients remain highly significant in column (2). The coefficient on the expected excess return is positive as expected, with a t-value of about 8. We are able to identify the coefficient with such precision since there is significant variation of expected excess returns across funds due to different reference countries. The coefficient on the expected excess return is even higher in column (3), where we assume a 5-year horizon by setting $k = 60$. However, it has a larger standard error due to fewer observations. We lose about three years of portfolio data at the end of the sample, where there are most observations. We therefore treat column (2) as our benchmark result.¹⁸

The coefficients on the benchmark portfolios are also strongly significant, indicating that there are substantial costs to deviating from these benchmark portfolios. The weight on the average benchmark portfolio is 0.916, with a small standard error of only 0.005. We also find a positive and significant coefficient on $z_{i,n,t-1} - z_{i,n,t}^{bh}$, suggesting a higher cost of deviating from the lagged portfolio share than the buy-and-hold portfolio share.

Various robustness tests, presented in the Online Appendix, confirm these results. In particular, the results are similar when we focus on the latter part of the sample, starting in 2010 or 2012, where there is a larger number of funds. Similar results also apply when we focus on funds that report for the whole sample or for at least 24 months. We also examine regressions using different predictors for

¹⁸Since we use $\delta = 0.89$ (discussed below), almost all of the weight is on expected excess returns over the first 24 months, even if we use a 60-month horizon.

return differentials.

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. We consider alternative values of β in the Online Appendix. 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. We find $\delta = 0.89$ as follows. We re-estimate (13) for a wide range of δ . Then we use that the theory implies $\delta = \beta b_1$ and choose δ such that the assumed value in computing the present value of expected excess returns corresponds to βb_1 implied by the portfolio regression. It turns out that b_1 is not very sensitive to the assumed δ and always close to 0.916 as in column (2). This implies $\delta = 0.97 * 0.916 = 0.89$.

Next we use equations (7), (8) and (9) to determine the structural parameters from the estimates of b_1 , b_2 and b_3 . The results, together with standard errors and 95 percent confidence intervals, are reported in Table 4. It also reports a measure of the overall cost of portfolio adjustment that is discussed below. Several conclusions can be drawn regarding the portfolio friction parameters. First, there are costs of deviating from both benchmark portfolios: λ_1 and λ_2 are both positive and statistically significant and so is the aggregate portfolio friction $\theta = \lambda_1 + \lambda_2$. Second, the friction λ_1 of deviating from the lagged portfolio is substantially larger than the friction λ_2 of deviating from the buy-and-hold portfolio. This implies a strong desire by the mutual funds to rebalance portfolios after relative equity price changes.

A third conclusion relates to the overall cost of portfolio frictions from (1).

This is the cost in terms on an equivalent drop in the expected portfolio return.

This cost, when annualized and expressed in basis points, is

$$Cost = 60000 \left(\lambda_1 var(z_{i,n,t} - z_{i,n,t-1}) + \lambda_2 var(z_{i,n,t} - z_{i,n,t}^{bh}) \right) \quad (14)$$

Based on all observations, $var(z_{i,n,t} - z_{i,n,t-1})$ and $var(z_{i,n,t} - z_{i,n,t}^{bh})$ are respectively 0.0001258 and 0.0001437. The cost of portfolio frictions is reported at the bottom of Table 4. The overall cost is only 3 basis points, with a 95 percent confidence interval from 2.4 to 4 basis points. One should keep in mind though that this is the cost of changing just one portfolio share in one country. Funds face additional costs associated with changing the allocation across the remaining countries that they invest in.

Table 4: ESTIMATED STRUCTURAL PARAMETERS

	Estimate (s.e.)	95% confidence interval
λ_1	0.332 (0.049)	[0.255, 0.446]
λ_2	0.062 (0.033)	[0.004,0.135]
Γ	0.0040 (0.0006)	[0.0030,0.0055]
$\theta = \lambda_1 + \lambda_2$	0.394 (0.053)	[0.316,0.523]
$\lambda_1 - \lambda_2$	0.269 (0.064)	[0.154,0.407]
Cost	3.04 (0.42)	[2.43,4.05]

Notes: The table reports estimates, standard errors and 95 percent confidence intervals of the structural parameters implied by the regression reported in Table 3, column 2. It is based on 100,000 draws from the distribution of the reduced form parameters $[b_1, b_2, b_3]$. Cost is equal to the overall cost of portfolio frictions in terms of an equivalent drop in the expected portfolio return, annualized and in basis points.

Table 4 also reports $\Gamma = \gamma\sigma_{er}^2$. The point estimate is 0.0040, with a standard error of 0.0006. The mean variance of the excess return in the data is 0.0016. This implies a rate of risk aversion of γ of 2.5, which is reasonable. By contrast, if we just regress on the one-month expected excess return (plus the fund-country and the country-month fixed effects), as would be appropriate in the absence of

portfolio frictions, we obtain a coefficient of 3.1 (s.e.=0.35). Since the coefficient on the one-month expected excess return in the frictionless model is $1/\Gamma$, it would imply $\Gamma = 0.332$. With a variance of the excess return of 0.0016, this implies $\gamma = 208$, which is clearly excessive.¹⁹ 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.

Finally, consider the last column of Table 3. Here we run a portfolio regression based on portfolio shares in the 35 countries of the aggregate of all EPFR funds in our data. This is done for the same expected excess return variable as in column (2), but using aggregate positions to weigh reference countries. There remains a large and significant weight on the average of the benchmark portfolios and a statistically significant coefficient on the expected excess return. However, the coefficients have a very different magnitude than the comparable coefficients in column (2) based on fund-level regressions. With aggregate portfolio data we see that the coefficient on the average benchmark portfolio share is much higher (0.998 versus 0.916), the lagged portfolio share is less important than the buy-and-hold portfolio (opposite to fund-level data), while the expected excess return coefficient is tiny in comparison to fund-level data.

One explanation for this difference in results for aggregate and fund-level portfolio data is that we cannot control for endogeneity in aggregate data. We clearly cannot introduce a country-month fixed effect. This biases the coefficients in the same way as in column (1) of Table 3, where we did not include a country-month fixed effect for fund level data. But endogeneity is not the only reason for the

¹⁹Giglio et al. (2019) also make the point that excessive risk aversion is needed to account for the response of portfolios to expected returns in a frictionless model.

difference as there are large differences between columns (4) and (1) as well. The Online Appendix discusses additional explanations for the differences in coefficients, outside of endogeneity. Some have to do with the fact that aggregating the fund-level portfolio expressions (13) over all funds delivers a different portfolio expression than simply applying (13) directly to aggregate portfolio data, even if the coefficients are the same for all funds. For example, even if all funds are equally responsive to the expected excess return, the aggregate portfolio share is less responsive simply because only a limited fraction of funds invests in a particular country. Another set of explanations is associated with heterogeneity of the coefficients across funds, a topic that we address in the next section.

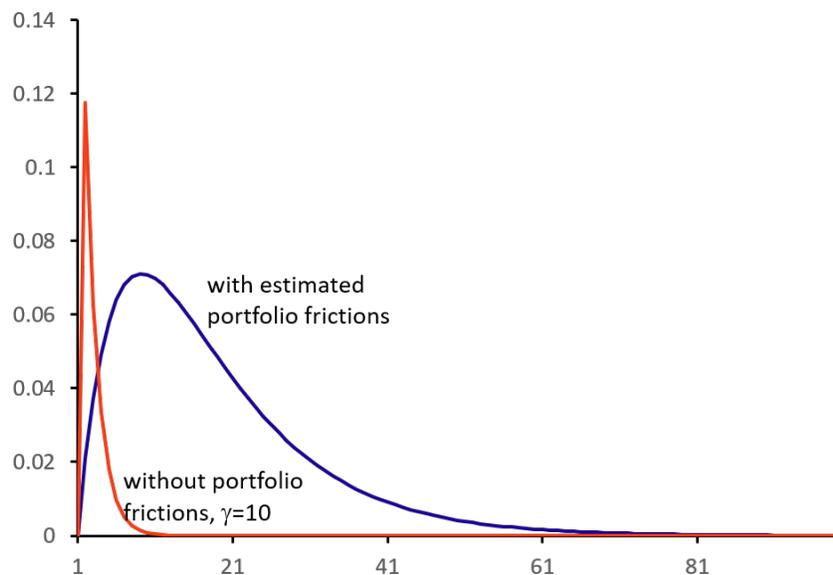
4.4 Portfolio Dynamics

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 $y_{i,n,t} = E_t er_{i,n,t,t+24}^{0.89}$. We estimate an AR(1) process for $y_{i,n,t}$ for each (i, n) , and then average the AR coefficient and standard deviation of the innovation across all (i, n) . The AR coefficient is 0.85 and the standard deviation of the expected excess return innovation is 0.0086. In the frictionless case the expected excess return is $E_t er_{i,n,t,t+1}$, which has an average AR coefficient of 0.535 and standard deviation 0.00188 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 0.916 and the coefficient on the expected excess return variable is 2.446. 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 $E_t er_{i,n,t,t+1}$ as that is based on data that provide strong evidence of portfolio frictions. As shown in (5), in the frictionless case the coefficient b_3 is equal to $1/(\gamma\sigma_{er}^2)$. We will use the average variance of the excess return in the data of 0.0016 and assume a rate of risk aversion of $\gamma = 10$. This simplifies a visual comparison of the portfolio response in the two cases. If instead $\gamma = 2.5$, the impulse response in the frictionless case is simply 4 times as high as shown.

Figure 1: IMPULSE RESPONSE PORTFOLIO SHARE TO EXPECTED EXCESS RETURN SHOCK



Notes: Impulse response to a one standard-deviation expected excess return innovation.

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 $\gamma = 2.5$ implied by estimates for the model with frictions, the initial response in the frictionless case would be even much higher. 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 (2019) 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.

5 Heterogeneity

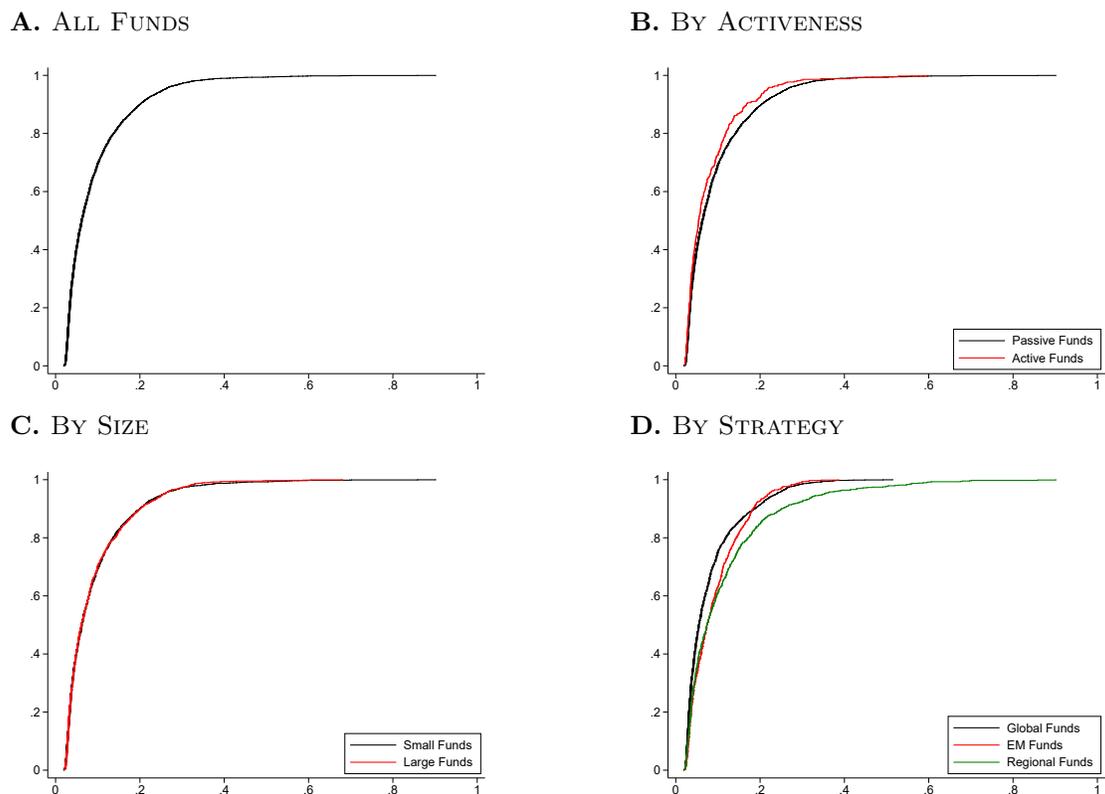
So far we have assumed that structural and reduced form parameters are the same for all funds and countries. In this section we consider two types of heterogeneity. The first is heterogeneity across fund-country pairs that leads to differences in the average portfolio shares \bar{z}_{in} . The second is heterogeneity across funds of various types. In both cases we investigate how differences in reduced form parameters are associated with differences in the structural parameters.

5.1 Frictions by Size of Portfolio Shares

The average portfolio share \bar{z}_{in} in the sample depends on the fund-country combination and varies considerably. Panel A of Figure 2 shows the cumulative distribution of all \bar{z}_{in} observations. In the lowest decile of \bar{z}_{in} , funds invest between 2 and 2.9 percent in a country, while in the largest decile funds invest more than 21

percent in a country. The regressions reported above, and the implied structural parameters, combine data on all portfolio shares, large and small. But the structural parameters may well vary with the size of the portfolio share. Specifically, a higher perceived risk σ_{er}^2 implies a smaller mean portfolio share. We can therefore expect a higher risk parameter Γ for smaller portfolio shares. Perceived risk may vary not just by country. Different funds may be more or less informed about individual countries and therefore perceive the risk to be different.

Figure 2: CUMULATIVE DISTRIBUTION $\bar{z}_{i,n}$



Notes: Cumulative distribution of $\bar{z}_{i,n}$ for all funds (Panel A); active and passive funds (Panel B); large and small funds (Panel C); global, emerging, and regional funds (Panel D).

It is also possible that the portfolio frictions λ_1 and λ_2 vary with \bar{z}_{in} . Gârleanu and Pedersen (2013) make an argument for a specification where the portfolio

frictions are proportional to σ_{er}^2 . In that case our portfolio friction parameters would be smaller for larger \bar{z}_{in} as a larger \bar{z}_{in} is associated with less perceived risk. It could also be that the portfolio cost depends on the percentage changes in portfolio shares rather than the absolute changes in portfolio shares. In that case our portfolio friction parameters would also be smaller for larger \bar{z}_{in} .

In order to consider the role of the size of portfolio shares, we add interactions of the dependent variables with \bar{z}_{in} . To deal with endogeneity, we include both a country-month fixed effect and a country-month fixed effect interacted with \bar{z}_{in} . The results are reported in the first column of Table 5. We do not include the interaction with the average of the two benchmark portfolios, which is not statistically significant. The main interaction is with the expected excess return. A higher \bar{z}_{in} implies a significantly higher coefficient on the expected excess return. The point estimate implies that the coefficient on the expected excess return varies from 1.27 when $\bar{z}_{in} = 0.02$ to 3.01 when $\bar{z}_{in} = 0.2$.

Figure 3 reports structural coefficients as a function of \bar{z}_{in} , and the associated 95 percent confidence bands. Rather than λ_1 and λ_2 , we only report their sum and difference. We also report Γ and the cost (14) of portfolio frictions. To compute the cost of portfolio frictions, we first regress $var(z_{i,n,t} - z_{i,n,t-1})$ and $var(z_{i,n,t} - z_{i,n,t}^{bh})$ on a constant, \bar{z}_{in} and \bar{z}_{in}^2 and then compute the cost in (14) given λ_1 and λ_2 and the fitted variances as functions of \bar{z}_{in} .

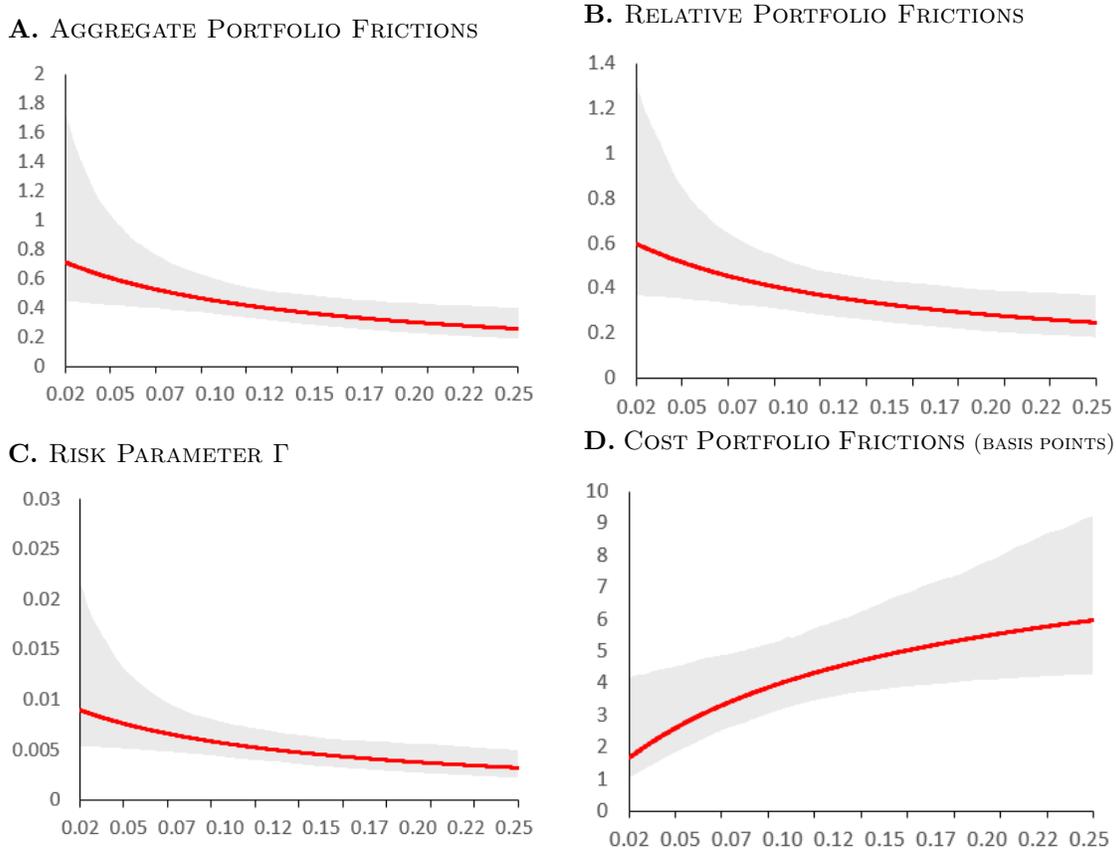
Panel A of Figure 3 shows that as conjectured above, the aggregate portfolio friction $\theta = \lambda_1 + \lambda_2$ is smaller for larger \bar{z}_{in} . Panel 3B shows that $\lambda_1 > \lambda_2$ independent of the level of \bar{z}_{in} . Panel 3C shows that the risk parameter Γ tends to be smaller when \bar{z}_{in} is larger. It is exactly this lower risk that is responsible for higher portfolio shares in the first place. Finally, Panel 3D shows that the cost of

Table 5: PORTFOLIO REGRESSIONS, INTERACTION WITH DUMMIES

	(1) Country Share $X1 = \bar{z}_{in}$	(2) Activeness $X1 = A$	(3) Size $X1 = L$	(4) Strategy $X1 = R, X2 = EM$
$(z_{i,n,t-1} + z_{i,n,t}^{bh})/2$	0.906*** (0.005)	0.929*** (0.004)	0.903*** (0.008)	0.893*** (0.007)
$(z_{i,n,t-1} - z_{i,n,t}^{bh})$	0.374*** (0.044)	0.148*** (0.024)	0.344*** (0.062)	0.267*** (0.028)
$E_t er_{i,n,t,t+24}^{0.89}$	1.073** (0.430)	2.172*** (0.230)	2.865*** (0.525)	2.044*** (0.337)
$X1 \times (z_{i,n,t-1} + z_{i,n,t}^{bh})/2$		-0.106*** (0.015)	0.032*** (0.009)	0.052*** (0.015)
$X1 \times (z_{i,n,t-1} - z_{i,n,t}^{bh})$	0.241* (0.142)	0.246*** (0.030)	-0.210*** (0.071)	
$X1 \times E_t er_{i,n,t,t+24}^{0.89}$	9.686*** (3.789)		-1.233*** (0.527)	
$X2 \times (z_{i,n,t-1} + z_{i,n,t}^{bh})/2$				0.020** (0.009)
$X2 \times (z_{i,n,t-1} - z_{i,n,t}^{bh})$				0.158*** (0.041)
Observations	316732	316732	316732	316732
R^2	0.990	0.990	0.989	0.989

Standard errors clustered by month in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Notes: Regressions for 35 countries over the interval 2002:01-2016:07. *A*, *L*, *R*, and *EM* stand for Active, Large, Regional and Emerging Market funds as described in the text. All regressions include fund-country and country-month fixed effects. The country-month effect is also interacted with *X1* and *X2*. The constant is included but not shown.

Figure 3: STRUCTURAL PARAMETERS AS A FUNCTION OF $\bar{z}_{i,n}$



Notes: The charts of Figure 3 show point estimates and 95 percent confidence bands for the structural parameters. Aggregate Portfolio Frictions (panel A) correspond to $\theta = \lambda_1 + \lambda_2$. Relative Portfolio Frictions (Panel B) correspond to $\lambda_1 - \lambda_2$. Panel D shows the cost of portfolio friction in basis points. This is based on 100,000 draws from the distribution of the estimated reduced form parameters.

portfolio frictions is higher for larger \bar{z}_{in} . While the aggregate portfolio friction θ is smaller for larger \bar{z}_{in} (Panel 3A), the deviations from the benchmark portfolios measured by the variance of $z_{i,n,t} - z_{i,n,t-1}$ and $z_{i,n,t} - z_{i,n,t}^{bh}$ are naturally larger for larger \bar{z}_{in} . The cost of portfolio adjustment varies from 1.7 basis points when $\bar{z}_{in} = 0.02$ to 5.5 basis points when $\bar{z}_{in} = 0.2$.

5.2 Fund Heterogeneity

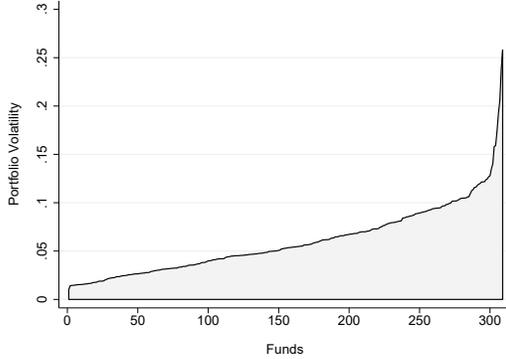
So far we have considered all funds in the sample. We now examine fund heterogeneity. We split the sample in three ways: active versus passive funds, small versus large funds and global versus regional and emerging markets funds. We investigate to what extent frictions are different for these different fund categories.

Panel A of Figure 4 shows a measure of how active funds are. We measure portfolio volatility of fund i as $V^i = \frac{1}{T} \sum_t \sum_{n=1}^{35} |z_{i,n,t} - z_{i,n,t}^{bh}|$, where T is the number of months over which we observe portfolio shares for the fund. The portfolio volatility measure V^i captures active trading. We see that volatility is particularly high for a small number of funds. We will refer to the top decile of funds in terms of V^i as active funds and the remainder as passive funds. Panel B of Figure 4 shows how funds differ in size, measured by average AUM over the period. The Figure uses a semi-log scale as the difference in fund size is substantial. We refer to the bottom 50 percent of funds in terms of size as small funds and the others as large funds. The final categorization of funds, as global, regional or EM funds, relates more to the geographic orientation of the funds.

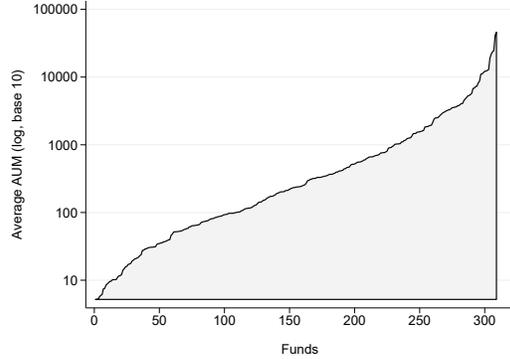
We first investigate if there is a systematic difference between the type of funds and the size of portfolio shares. For example, a fund that invests in more countries is likely to have smaller portfolio shares, which we found to be associated with

Figure 4: FUND HETEROGENEITY BY PORTFOLIO VOLATILITY AND SIZE

A. PORTFOLIO VOLATILITY



B. DISTRIBUTION OF FUND SIZE



Notes: Panel A shows V^i , defined in the text, as a measure of how active funds are. Panel B shows the average AUM over the period using a semi-log scale.

a higher risk parameter Γ and higher aggregate portfolio friction θ . Panels B to D of Figure 2 show the cumulative distribution of all \bar{z}_{in} by fund type. The differences are quite minor. There is virtually no difference between large and small funds. Active funds have slightly smaller portfolio shares than passive funds, but the difference is very small. Global funds have somewhat lower portfolio shares than the other funds. The difference relative to emerging market funds is again slight, only 0.01 on average. Regional funds tend to be a bit more specialized and have somewhat larger portfolio shares, on average 0.035 above that of global funds (0.116 versus 0.081). This would suggest slightly smaller Γ and θ for regional funds, although the difference is probably not statistically significant based on Figure 3. We conclude that any differences in structural parameters across fund types is not likely to be associated with differences in the size of portfolio shares.

Columns (2) to (4) in Table 5 show reduced form regressions, where we add interactions of the three variables with dummies for fund categories. In column (2) the dummy A is 1 when the fund is active and zero otherwise. In column (3) the

dummy L is 1 when the fund is large and 0 otherwise. In column (4) the dummy R is 1 when it is a regional fund and zero otherwise and the dummy EM is 1 when it is an emerging market fund and zero otherwise. We omit interaction terms that are not statistically significant. We include both a country-month fixed effect and country-month fixed effects interacted with the dummies as portfolio shocks may differ by fund type.

By considering the interaction with the dummies, we can immediately evaluate differences in the reduced form parameters across fund types. First, we see that active, small and emerging market funds give relatively more weight to the lagged portfolio share and less weight to the buy-and-hold portfolio. Second, we see that the weight on the average benchmark portfolio is lower for active, small and global funds. Finally, large funds are less responsive to expected excess returns.

The higher relative weight on the lagged portfolio share than the buy-and-hold portfolio share by active, small and emerging market funds suggests that these funds do more active rebalancing. In order to rebalance to keep the portfolio share unchanged, funds need to actively sell (buy) equity of countries whose relative price rises (falls). To investigate if these funds indeed rebalance more aggressively, Table 6 reports results for the following regression:

$$z_{i,n,t} - z_{i,n,t}^{bh} = \alpha_0 + \alpha_{in} + \alpha_1 \left(z_{i,n,t-1} - z_{i,n,t}^{bh} \right) \quad (15)$$

The variable $z_{i,n,t-1} - z_{i,n,t}^{bh}$ is associated with valuation effects. It is more negative the higher the increase in the relative price of country n equity. The dependent variable is the change in the portfolio share associated with active portfolio reallocation. If $\alpha_1 = 1$ there is perfect rebalancing. Funds rebalance completely to keep the portfolio share the same as one month ago. When $\alpha_1 = 0$ there is no rebal-

ancing. Table 6 confirms that indeed active, small and emerging market funds are more actively rebalancing. For active and emerging market funds there is almost perfect rebalancing, with α_1 very close to 1. We also see that the R^2 is 0.61 for active funds, considerably higher than for passive funds. We should emphasize though that the error term from the regression, which captures portfolio reallocation unrelated to rebalancing, is also significantly more volatile for active than for passive funds. Active funds engage in more active portfolio reallocation for reasons both related and unrelated to rebalancing. We should also point out that even funds that rebalance less than average, such as passive, large and regional funds, still rebalance between 65 and 80 percent. The high degree of rebalancing explains why we find in Table 4 that $\lambda_1 > \lambda_2$.

Table 6: REBALANCING DYNAMICS

Dep. Variable: $z_{i,n,t} - z_{i,n,t}^{bh}$							
	By Activeness		By Size		By Strategy		
	(1) 90% less active	(2) 10% more active	(3) Small	(4) Large	(5) Global	(6) EM	(7) Regional
$(z_{i,n,t-1} - z_{i,n,t}^{bh})$	0.671*** (0.026)	0.979*** (0.021)	0.887*** (0.066)	0.652*** (0.038)	0.800*** (0.053)	0.971*** (0.025)	0.790*** (0.043)
Observations	292802	23930	157954	158778	189470	85560	41206
R^2	0.193	0.607	0.317	0.202	0.132	0.439	0.610

Standard errors clustered by month in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

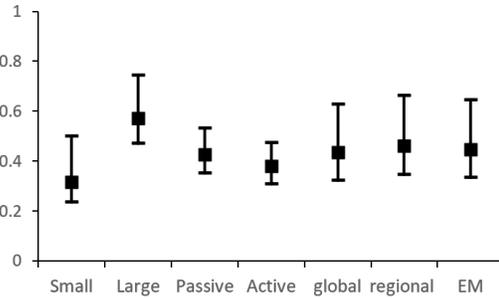
Notes: All regressions include a fund-country fixed effect and a country-month fixed effect. The constant is included but not shown.

Next we turn to the structural parameters. It is useful to recall some key insights discussed in Section 2 regarding the role of the aggregate portfolio friction θ and risk parameter Γ . A higher θ implies higher weight on the average benchmark portfolio and less responsiveness to expected excess returns. A higher Γ implies both less weight on the average benchmark portfolio and less responsiveness to expected excess returns. Figure 5 reports structural parameters and their 95 percent

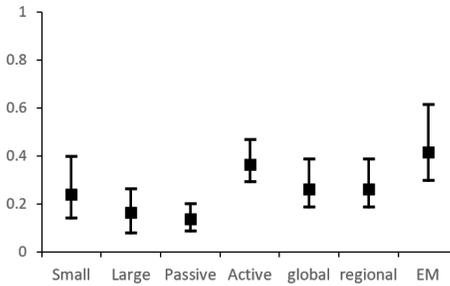
confidence intervals for all fund categories using the results from Table 5 and the associated variance of the vector of reduced form parameter estimates.

Figure 5: FUND HETEROGENEITY AND STRUCTURAL PARAMETERS

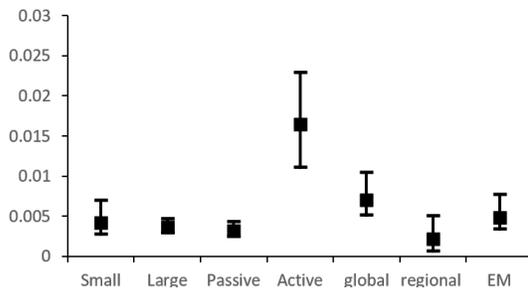
A. AGGREGATE PORTFOLIO FRICTIONS



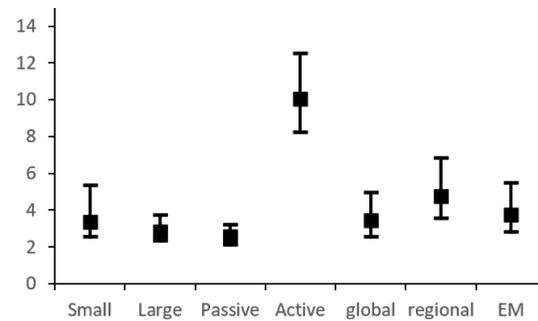
B. RELATIVE PORTFOLIO FRICTIONS



C. RISK PARAMETER Γ



D. COST PORTFOLIO FRICTIONS (BASIS POINTS)



Notes: Point estimates and 95 percent confidence bands for the structural parameters for different groups of funds. Aggregate Portfolio Frictions (panel A) correspond to $\theta = \lambda_1 + \lambda_2$. Relative Portfolio Frictions (Panel B) correspond to $\lambda_1 - \lambda_2$. Panel D shows the cost of portfolio friction in basis points. This is based on 100,000 draws from the distribution of the estimated reduced form parameters.

For the aggregate portfolio friction θ we see from panel A that large funds have a larger friction than small funds. This is inferred both from the weaker response of large funds to expected excess returns and the larger weight of large funds on the average benchmark portfolio. For the risk parameter Γ , we see in panel C that especially active funds stand out as having significantly higher risk-aversion or perceived risk. This is inferred from the lower weight on the benchmark portfolios. In panel B we see that $\lambda_1 - \lambda_2$ is larger for small, active and emerging market

funds. This is inferred from the higher coefficient on $z_{i,n,t-1} - z_{i,n,y}^{bh}$. As discussed, and confirmed in Table 6, these funds engage in more active rebalancing, which is consistent with a higher cost of deviating from the lagged portfolio share than the buy-and-hold portfolio share.

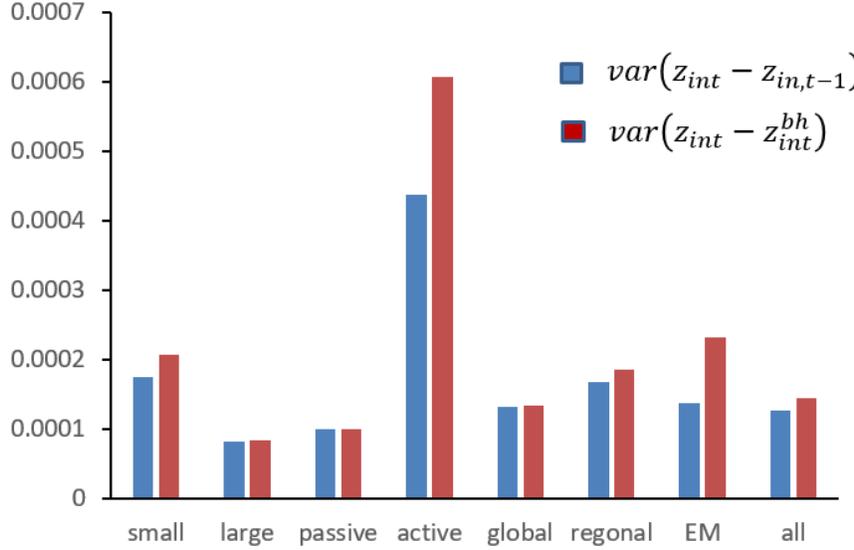
Finally, Panel D reports the cost of portfolio frictions. Here especially active funds stand out as having a high cost. To understand this, Figure 6 reports the variance of $z_{i,n,t} - z_{i,n,t-1}$ and $z_{i,n,t} - z_{i,n,t}^{bh}$ by fund type. Active funds naturally stand out as having the highest deviations from both benchmark portfolios. Even though the aggregate portfolio friction θ is virtually the same for active and passive funds (Panel A of Figure 5), active funds bear a much higher cost by being more active. Our estimates indicate that this cost is in the range of 8 to 12 basis points, versus 2 to 3 basis points for passive funds. We do not find evidence that this higher cost of active portfolio management is compensated by correspondingly higher expected portfolio returns.²⁰

6 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

²⁰To this end we consider the increase in the average portfolio return when replacing the mean portfolio share $\bar{z}_{i,n}$ with the actually observed portfolio share $z_{i,n,t}$, while holding the reference portfolio shares equal to their mean $\bar{z}_{i,m,-n}$. The average portfolio return gain is 5.7 annualized basis points for active funds versus 5.0 basis points for passive funds.

Figure 6: VARIANCE PORTFOLIO DEVIATIONS FROM BENCHMARKS



Notes: Variance of $z_{i,n,t} - z_{i,n,t-1}$ and $z_{i,n,t} - z_{i,n,t}^{bh}$ by fund type.

from US mutual funds, using heterogeneity in expected excess returns across funds to control for endogeneity. We find that portfolio shares of US mutual funds depend significantly on the average of the two benchmark portfolios, with a weight of 0.916 that is precisely estimated, with a standard error of only 0.005. Not surprisingly, we find a large and significant estimate of the aggregate portfolio friction (the sum of the two portfolio frictions).

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 2.5. 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.

We have also documented heterogeneities across funds and fund-country pairs. We find that when portfolio shares are larger, for example as a result of lower perceived risk, they are more sensitive to expected excess returns. This is found to be consistent with lower risk and a lower aggregate portfolio friction. Several types of fund heterogeneity are identified. Large funds have a larger aggregate portfolio friction. Small, active and emerging market funds have a higher relative friction of deviating from the lagged portfolio relative to the buy-and-hold portfolio, consistent with more active rebalancing. While the aggregate portfolio friction is about the same for active and passive funds, the cost of portfolio frictions is considerably higher for active funds due to their more aggressive deviations from the benchmark portfolios.

There is a clear need to introduce these portfolio frictions into open economy models. It has significant implications for exchange rates and other asset prices, as well as international capital flows. A portfolio response to expected returns that is weaker and more gradual implies excess return predictability in both the foreign exchange market and global equity markets. It also implies a much larger impact of exogenous portfolio shocks, such as foreign exchange intervention, 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 Muhkin (2019) and, as these papers emphasize, is consistent with a variety of evidence.

Appendix A: A Simple Model of Portfolio Allocation

Consider the portfolio model in Section 2. Agents maximize (1), where the buy and hold portfolio is

$$z_{t+s}^{bh} = z_{t+s-1} \frac{1 + R_{1,t+s}}{1 + z_{t+s-1}R_{1,t+s} + (1 - z_{t+s-1})R_{2,t+s}} \quad (\text{A.1})$$

Linearizing around returns of $\bar{R} = 0$ and an asset 1 portfolio share of \bar{z} (the mean portfolio share for the fund), this can be approximated as

$$z_{t+s}^{bh} = z_{t+s-1} + \bar{z}(1 - \bar{z})er_{t+s} \quad (\text{A.2})$$

where $er_{t+s} = R_{1,t+s} - R_{2,t+s}$ is the excess return.

Substituting (A.2) into (1), maximization with respect to z_t gives

$$\begin{aligned} & E_t er_{t+1} - \gamma z_t \sigma_{er}^2 + \gamma(\sigma_2^2 - \sigma_{12}) - \lambda_1(z_t - z_{t-1}) - \lambda_2(z_t - z_{t-1} - \bar{z}(1 - \bar{z})er_t) \\ & + \beta \lambda_1(E_t z_{t+1} - z_t) + \beta \lambda_2(E_t z_{t+1} - z_t - \bar{z}(1 - \bar{z})E_t er_{t+1}) = 0 \end{aligned}$$

Collecting terms, this is

$$Dz_t = E_t er_{t+1} + \gamma(\sigma_2^2 - \sigma_{12}) + \theta z_{t-1} + \beta \theta E_t z_{t+1} + \lambda_2 \bar{z}(1 - \bar{z})er_t - \beta \lambda_2 \bar{z}(1 - \bar{z})E_t er_{t+1} \quad (\text{A.3})$$

where

$$D = \Gamma + \theta(1 + \beta)$$

$$\theta = \lambda_1 + \lambda_2$$

$$\Gamma = \gamma\sigma_{er}^2$$

This can be written as

$$\begin{aligned} \left(L^{-2} - \frac{D}{\beta\theta}L^{-1} + \frac{1}{\beta}\right)z_{t-1} &= -\frac{1}{\beta\theta}E_t er_{t+1} - \frac{\gamma}{\beta\theta}(\sigma_2^2 - \sigma_{12}) \\ &\quad - \frac{1}{\beta\theta}\lambda_2\bar{z}(1 - \bar{z})er_t + \frac{1}{\theta}\lambda_2\bar{z}(1 - \bar{z})E_t er_{t+1} \end{aligned}$$

where $L^{-2}z_{t-1} = E_t z_{t+1}$ and $L^{-1}z_{t-1} = z_t$. Factoring gives

$$\begin{aligned} (L^{-1} - \omega_1)(L^{-1} - \omega_2)z_{t-1} &= -\frac{1}{\beta\theta}E_t er_{t+1} - \frac{\gamma}{\beta\theta}(\sigma_2^2 - \sigma_{12}) \\ &\quad - \frac{1}{\beta\theta}\lambda_2\bar{z}(1 - \bar{z})er_t + \frac{1}{\theta}\lambda_2\bar{z}(1 - \bar{z})E_t er_{t+1} \end{aligned}$$

where ω_1 and ω_2 are the roots of the characteristic equation

$$\omega^2 - \frac{D}{\beta\theta}\omega + \frac{1}{\beta} = 0 \tag{A.4}$$

These roots are

$$\omega = 0.5 \left(\frac{D}{\beta\theta} \pm \sqrt{\left(\frac{D}{\beta\theta}\right)^2 - (4/\beta)} \right) \tag{A.5}$$

It is easily checked that the larger root, ω_2 , is explosive (larger than 1), and the smaller root, ω_1 , is stable (less than 1).

Now write the solution as

$$\begin{aligned} (L^{-1} - \omega_1)z_{t-1} &= -\frac{1}{\beta\theta} \frac{E_t er_{t+1}}{L^{-1} - \omega_2} - \frac{\gamma}{\beta\theta}(\sigma_2^2 - \sigma_{12}) \frac{1}{L^{-1} - \omega_2} \\ &\quad - \frac{1}{\beta\theta}\lambda_2\bar{z}(1 - \bar{z}) \frac{er_t}{L^{-1} - \omega_2} + \frac{1}{\theta}\lambda_2\bar{z}(1 - \bar{z}) \frac{E_t er_{t+1}}{L^{-1} - \omega_2} \end{aligned}$$

This implies

$$z_t = \omega_1 z_{t-1} + \frac{1}{\beta\theta\omega_2} \sum_{s=1}^{\infty} \omega_2^{1-s} E_t er_{t+s} + \frac{\gamma}{\beta\theta(\omega_2 - 1)} (\sigma_2^2 - \sigma_{12})$$

$$+ \frac{\lambda_2 \bar{z}(1 - \bar{z})}{\beta\theta\omega_2} er_t + \frac{\lambda_2 \bar{z}(1 - \bar{z}) \left(\frac{1}{\omega_2} - \beta\right)}{\beta\theta\omega_2} \sum_{s=1}^{\infty} \omega_2^{1-s} E_t er_{t+s}$$

To summarize, we have

$$z_t = a_1 + a_2 z_{t-1} + a_3 \sum_{s=1}^{\infty} \omega_2^{1-s} E_t er_{t+s} + a_4 er_t \quad (\text{A.6})$$

where

$$a_1 = \frac{\gamma}{\beta\theta(\omega_2 - 1)} (\sigma_2^2 - \sigma_{12})$$

$$a_2 = \omega_1$$

$$a_3 = \frac{1}{\beta\theta\omega_2} + \frac{\lambda_2 \bar{z}(1 - \bar{z}) \left(\frac{1}{\omega_2} - \beta\right)}{\beta\theta\omega_2}$$

$$a_4 = \frac{\lambda_2 \bar{z}(1 - \bar{z})}{\beta\theta\omega_2}$$

We can also write the solution for z_t as a function of the lagged and buy and hold portfolio. For this, use that $z_t^{bh} = z_{t-1} + \bar{z}(1 - \bar{z})er_t$, so that

$$er_t = \frac{z_t^{bh} - z_{t-1}}{\bar{z}(1 - \bar{z})}$$

We then have

$$z_t = a_1 + \left(a_2 - \frac{a_4}{\bar{z}(1 - \bar{z})}\right) z_{t-1} + \frac{a_4}{\bar{z}(1 - \bar{z})} z_t^{bh} + a_3 \sum_{s=1}^{\infty} \omega_2^{1-s} E_t er_{t+s} \quad (\text{A.7})$$

Use that $\omega_2 = 1/(\beta\omega_1) = 1/(\beta a_2)$. This gives

$$z_t = a_1 + a_2 \left(\frac{\lambda_1}{\lambda_1 + \lambda_2} z_{t-1} + \frac{\lambda_2}{\lambda_1 + \lambda_2} z_t^{bh} \right) + a_3 \sum_{s=1}^{\infty} \omega_2^{1-s} E_t er_{t+s} \quad (\text{A.8})$$

It is easily checked that $a_2 = \omega_1$ can be written as the parameter ω in Section 2. The second term in the expression for a_3 is numerically very close to zero. As mentioned in footnote 5, we therefore abstract from it, so that $a_3 = 1/(\beta\theta\omega_2) = a_2/\theta$. Finally, the discount rate is $\delta = 1/\omega_2 = \beta a_2$. (A.8) therefore corresponds to (2) with the coefficients as shown below that.

Finally, we can also write it including the valuation effect er_t and the buy-and-hold portfolio. To this end, substitute $z_{t-1} = z_t^{bh} - \bar{z}(1 - \bar{z})er_t$ which gives

$$z_t = a_1 + a_2 z_t^{bh} - \tilde{a}_2 er_t + a_3 \sum_{s=1}^{\infty} \omega_2^{1-s} E_t er_{t+s} \quad (\text{A.9})$$

where $\tilde{a}_2 = a_2 \bar{z}(1 - \bar{z}) \left(\frac{\lambda_1}{\lambda_1 + \lambda_2} \right)$.

Appendix B: 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 B1 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 B1: 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.

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