Essays in Equity Portfolio Management

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Abstract

Active mutual funds, passive ETFs and index funds, as well as single stocks account for the large majority of assets within investors' equity allocations. The challenge for investors, however, is not limited to choosing the product type that suits their needs best, but rather extends to the much more complex question of which product to choose within a given category. Covering the question of how to fill the equity asset allocation from various angles, the overall results of my thesis therefore provide important guidance on equity portfolio management for both academics and practitioners. While profitable mutual fund selection is shown to be more difficult than previously assumed, adequately dealing with one's home bias seems to offer significant benefits for both private and institutional investors. In particular, while institutional investors can gain from either international diversification or deviating from capitalization weighted investments under home bias, private investors are likely to lose less on their home bias than they would otherwise pay in terms of various additional costs that are associated with international diversification.

Abstract in German

Aktive Fonds, passive ETFs und Index Fonds, sowie Einzeltitel machen den Großteil der Aktienallokation der meisten Investoren aus. Die Herausforderung für die Investoren beschränkt sich dabei jedoch nicht nur auf die Wahl des für sie passenden Produkttyps, sondern schließt auch die komplexere Frage ein, welches Produkt innerhalb einer Kategorie zu wählen ist. Indem die Frage des optimalen Aktieninvestments aus verschiedenen Perspektiven beleuchtet wird, liefert meine Dissertation eine wichtige Hilfestellung zur Umsetzung des gewünschten Aktienexposures aus akademischer und praktischer Sicht. Während die Wahl der richtigen aktiven Fonds sich als schwerer herausstellt als in bisherigen Untersuchungen angenommen, scheint der richtige Umgang mit dem Home Bias (der Übergewichtung des Heimatmarktes) erheblichen Nutzen für private und institutionelle Investoren zu bieten. Institutionelle Investoren können dabei entweder durch internationale Diversifikation oder durch ein Abweichen von der Marktgewichtung profitieren. Private Investoren hingegen verlieren oftmals weniger durch ihr Home Bias, als sie andernfalls an Zusatzkosten für eine internationale Diversifikation zahlen würden.

Introduction

While long-term investors' split between risky and safe assets is often easily inferred from their risk profile, filling the resulting equity allocation remains one of the most challenging tasks in both private and institutional investors' asset allocation. Despite the availability of a broad range of derivative products that are supposed to suit individual needs, three types of more traditional and/or transparent investment vehicles still account for the large majority of assets within the investors' equity allocations. In particular, while both active mutual funds and single stocks have been around for decades, passive ETFs and index funds have gained most of their momentum within the last five to ten years. The challenge for investors, however, is not limited to choosing the product type that suits their needs best, but rather extends to the much more complex question of which product to choose within a given category.

Today's equity mutual fund industry leaves investors, academics, as well as asset management companies overwhelmed by the plentiful opportunities. In consequence, they frequently rely on various fund characteristics to assist their investment processes, performance evaluations or strategic decision making. Identifying skilled fund managers or deciding upon a fund's response to growth in assets under management are just some of the numerous challenges that are tackled by means of academic research on how fund characteristics relate to performance. In consequence, virtually all observable characteristics of equity mutual funds have been evaluated extensively with respect to their relations to risk-adjusted performance. However, existing decompositions of risk-adjusted mutual fund performance might deliver biased results. In my first paper, I therefore provide new reliable insights on the drivers of mutual fund performance by decomposing risk-adjusted performance of U.S. equity mutual funds using the Generalized Calendar Time regression model. In addition, the importance of the addressed methodological issues is illustrated by performing the very same analysis by means of the previously used methodologies. According to my results, out of all previously considered fund characteristics, only the negative effect of lagged fund size and the positive effects of lagged performance and lagged family size remain highly significant. A methodological hybrid further allows isolating the bias of ignoring cross-sectional dependence from those of ignoring first-stage estimation errors and using historical estimates of factor loadings to compute risk-adjusted performance. By means of this analysis, a large part of the variation in previous empirical results can be explained by methodological issues.

With mutual fund selection shown to be much more difficult than indicated by prior research, my second paper puts more emphasis on the growing use of passive ETFs and index funds in investors' equity allocation. More specifically, this papers deals with the combination of passive, capitalization weighted (Cap Weight) investments and home bias, the most prominent behavioral bias in asset allocation that describes investors' heavy overweighting of domestic assets as compared to a supposed efficient international diversification. While it is often argued that Cap Weight investments – representing the portfolio of the average investor – must be efficient in an efficient global capital market, I provide evidence that, due to investors' home bias, Cap Weight investments are inefficient even in a globally efficient market. Based on a 1987 to 2012 dataset of global equities, I analyze the link between Cap Weight efficiency and home bias by decomposing total home bias costs into contributions of a pure home bias component and a Cap Weight component. The Cap Weight component constitutes the marginal costs of filling a home-biased between-market allocation with Cap Weight investments and appears to be statistically and economically significant across several home countries and parameter specifications.

While the potential gains of deviating from Cap Weight investments can help alleviating the costs of home bias for some investors, many investors with smaller portfolios, lack of financial expertise or high transaction costs have no choice other than relying on passive investments even if their home bias makes this choice costly. With ever changing financial markets and a globalizing world, this raises the natural question of how the costs of home bias have developed over time. In this context, my third paper shows these costs to have halved throughout the 1990 to 2012 period, thereby supporting the hypothesis that international diversification has lost importance over the past decades. Further analysis suggests a home-biased portfolio allocation to have even become rational rather than puzzling for a large number of investors. I find decreasing idiosyncratic risk of individual stocks to be the main driver of this development. With international diversification easily achieved within individual companies in today's globalized world, investors can therefore save the effort of carrying out this diversification themselves.

Covering the question of how to fill the equity asset allocation from various angles, the overall results of my thesis therefore provide important guidance on equity portfolio management for both academics and practitioners. While profitable mutual fund selection has shown to be more difficult than previously assumed, adequately dealing with one's home bias seems to offer significant benefits for both private and institutional investors. In particular, while institutional investors can gain from either international diversification or deviating from Cap Weight investments under home bias, private investors are likely to lose less on their home bias than they would otherwise pay in terms of various additional costs that are associated with international diversification.

I. A statistically robust decomposition of mutual fund performance

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Abstract Previous decompositions of risk-adjusted mutual fund performance might deliver biased results. In this paper, we provide new reliable insights on the drivers of mutual fund performance by decomposing risk-adjusted performance of U.S. equity mutual funds using the Generalized Calendar Time regression model. According to our results, out of all previously considered fund characteristics, only the negative effect of lagged fund size and the positive effects of lagged performance and lagged family size remain highly significant. Our analysis further suggests that much of the variation in previous empirical results can be attributed to methodological issues.

Keywords Mutual fund performance · Cross-sectional dependence · GCT-regression model

JEL Classification G23 C21

1. Introduction

Today's equity mutual fund industry leaves investors, academics, as well as asset management companies overwhelmed by the plentiful opportunities. In consequence, they frequently rely on various fund characteristics to assist their investment processes, performance evaluations or strategic decision making. Identifying skilled fund managers or deciding upon a fund's response to growth in assets under management are just some of the numerous challenges that are tackled by means of academic research on how fund characteristics relate to performance. In consequence, virtually all observable characteristics of equity mutual funds have been evaluated extensively with respect to their relations to risk-adjusted performance. Among others, the list of evaluated characteristics includes expenses, load fees, past performance, fund size, fund family size, fund age, inflows, diversification, and turnover.

Despite the large body of literature, the relations between fund characteristics and risk-adjusted performance remain a controversial topic, as existing research offers diverse results on the relations' signs or significances for all of the above-mentioned fund characteristics.[1] Naturally, some of these differences might be driven by deviations in the sampling period, the sampling universe, the measures of risk-adjusted performance, the measures of fund characteristics, or the choice of control variables. However, statistically insignificant differences might have easily been exacerbated to being significant by several methodological issues neglected in existing literature.

In particular, relying mainly on various two-step regression frameworks, previous decompositions of risk-adjusted performance might provide biased results. More specifically, by implicitly assuming cross-sectional independence and by ignoring first stage estimation errors, these analyses are likely to severely overstate the significance of their results (Hoechle et al. 2012; Driscoll & Kraay, 1998). Moreover, when risk-adjusted returns are computed using historical factor loadings, coefficient estimates on fund characteristics are biased as well if the resulting measurement error in factor loadings is correlated with variations in fund characteristics.

The relevance of these methodological issues is strengthened by prior literature's repeated indication of the existence of cross-sectional dependencies in risk-adjusted mutual fund returns (e.g. Wermers, 1999; Barras et al., 2010; Seasholes & Zhu, 2010) and

[1] Table A.I provides an overview of the existing literature.

correlations between changes in portfolio risk and fund characteristics (e.g. Huang et al., 2011).

To allow for an unbiased decomposition of risk-adjusted performance, Hoechle et al. (2012) suggest the Generalized Calendar Time portfolio approach (GCT-regression model). Generalizing a regression based replication of the calendar time portfolio approach, the GCT-regression model allows for robust statistical inference in the presence of temporal and cross-sectional dependence, while controlling for multiple time-varying fund characteristics that may also be continuous in nature.

This paper provides new reliable insights on the drivers of mutual fund performance by decomposing risk-adjusted performance of U.S. equity mutual funds using the GCT-regression model. We contribute to existing literature by performing the first statistically robust decomposition of mutual fund performance as judged by the methodological standards of Hoechle et al. (2012) and Driscoll & Kraay (1998). In addition, the importance of the addressed methodological issues is illustrated by performing the very same analysis by means of the previously used methodologies. A methodological hybrid further allows isolating the bias of ignoring cross-sectional dependence from those of ignoring first-stage estimation errors and using historical estimates of factor loadings to compute risk-adjusted performance. By means of this analysis, a large part of the variation in previous empirical results can be explained by methodological issues. Using a 2002-2012 dataset of more than 2,100 U.S. equity mutual funds, this study takes into account the recent developments on global financial markets by including the global financial crisis and the sovereign debt crisis.

When relying on the previously used methodologies, our dataset yields results largely consistent with prior research. However, once the above mentioned issues are resolved by using the GCT-regression model, our results indicate that only the negative effect of lagged fund size and the positive effects of lagged performance and lagged fund family size on risk-adjusted mutual fund performance remain significant at the 5% level. In particular, we provide evidence that previous findings of significantly negative relations of expenses (e.g. Sharpe, 1966; Carhart, 1997; Dahlquist et al., 2000; Prather et al., 2004; Kacperczyk et al., 2005; Pollet & Wilson, 2008; Cremers & Petajisto, 2009; Huang et al., 2011) to risk-adjusted performance, significantly positive relations of fund age (e.g. Cremers & Petajisto, 2009; Massa & Patgiri, 2009) and turnover (Grinblatt and Titman, 1994; Dahlquist et al., 2000) to risk-adjusted performance, as well as the findings of no significant performance-persistence (e.g. Jensen, 1969; Carhart, 1997; Dahlquist et al., 2000), could easily be driven by the above mentioned methodological issues. The larger part of these deviations in statistical inference is caused by the downwards bias on standard errors due to ignoring cross-sectional dependence and by the changes in coefficient estimates due to using historical estimates of factor loadings in computing risk-adjusted performance. These results are consistent with Hoechle et al.'s (2012) findings for the investment performance of private investors, that is, decomposing risk-adjusted performance in a statistically robust manner renders some of the most popular results on the determinants of risk-adjusted performance insignificant.

Our results support the popular hypothesis of past performance being an indication of future performance, as well as the hypothesis that mutual funds belonging to large fund families can profit from economies of scale. Furthermore, we provide evidence in favor of Berk and Green's (2004) hypothesis that allows reconciling fund manager skill with the lack of average mutual fund outperformance by suggesting that mutual funds receive money until they can no longer outperform passive benchmarks.

However, the findings of no highly significant relationships between expenses, loads, fund age, inflows, diversification, and turnover to risk-adjusted performance contrast with some of the prominent hypotheses on the drivers of mutual fund performance. In particular, we provide evidence that funds with higher expenses might actually recover those expenses in terms of higher performance.

The remainder of this paper is organized as follows. Section 2 describes the dataset used throughout this paper. Section 3 explains the methodology and outlines important aspects of how previous research might have generated biased results. The empirical results of our analysis are provided in section 4. Section 5 discussed implications for future research. Section 6 concludes.

2. Data

Our empirical analysis employs a survivorship-bias free sample of U.S. equity mutual funds from the Center for Research in Security Prices (CRSP) database. The sample covers the period from January 2002 to March 2012 and contains monthly data on fund net returns as well as quarterly data on several fund characteristics, including expense ratios, load fees, total net assets (TNA), fund family, fund age, portfolio weights and holdings, turnover ratio, and funds' investment objectives.[2]

We follow among others Carhart (1997) and Wermers (2000) in limiting the dataset to active U.S. diversified equity funds as stated by their Lipper classification,[3] thereby excluding all international funds, bond funds, money market funds, sector funds, commodity funds, real estate funds, balanced funds, funds that are on average investing less than 50% of their assets in equities, as well as all passive and index funds. For funds with different share classes we merge returns and fund characteristics into a single portfolio based on a TNA-weighted measure for each variable (e.g. Wermers, 2000; Chen et al., 2004).

To compute risk-adjusted returns, we obtain monthly data on several risk factors from the website of Kenneth French.[4] In particular, this data includes the market return defined as the value weighted return on all NYSE, AMEX, and NASDAQ stocks, the risk-free rate measured by the 1-month Treasury bill rate, the small minus big (SMB) factor measured as the difference in returns between small and large stocks, the high minus low (HML) factor measured as the difference in returns between high and low book-to-market ratio stocks, and the momentum factor (MOM) measured as the difference in returns between past winners and past losers.[5]

Our final dataset consists of 2,111 mutual funds and 27,665 fund quarters for each of which the required (lagged) variables are available. Table I shows a description of the included variables, as well as the summary statistics for our dataset. The median U.S. diversified equity mutual fund in our dataset manages 294 million U.S.-Dollars and belongs to a fund family managing a further 4.7 billion U.S.-Dollars in U.S. diversified equities. It allocates these assets with a sum of squared portfolio weights of 0.0174, which implies about 59 stocks for an equally weighted portfolio. The annual turnover of the median fund amounts to 0.71. For its service and expenses, it charges a total expense ratio of 1.21% with 5.5% total loads in its most expensive share class. Each quarter, the median fund experiences an outflow of 1.74% of its asset, while still managing to have slightly

[2] A detailed documentation of the database is available from CRSP.

[3] The Lipper classifications included in our sample are LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE, CE, GE, and VE.

[4] We would like to thank Kenneth French for making his data publicly available.

[5] For a detailed description of the factor specifications please visit the website of Kenneth French.

growing TNA due to a quarterly excess return of 1.41% with a risk-free rate of 0.43%. The median fund is 11.2 years old. Lagged risk-adjusted returns (alphas) for the median fund are between -0.31% and -0.25% dependent on the specification of the risk factors, thereby indicating that the median fund does not outperform the market on a risk-adjusted basis and net of fees.

3. Methodology

3.1. Variables

For our main results, we employ the Fama-French (1993) and Carhart (1997) four-factor alpha as a measure of risk-adjusted performance, thereby controlling for style differences with respect to the market risk, value vs. growth, small vs. large caps, and momentum. To ensure comparability with prior research, we further employ alphas computed using a one-factor model (Jensen, 1969) and a three-factor model (Fama & French, 1993), where only the first one or the first three of the above mentioned style differences are controlled for.

To decompose risk-adjusted returns, we choose fund characteristics consistent with prior research, thereby including expenses, load fees, past performance, size, family size, fund age, inflows, diversification, and turnover. To mitigate potential endogeneity problems, we use one quarter lagged variables for size, family size, inflows, and diversification. Details on how the respective fund characteristics are computed can be found in Table I.

3.2. The CrossReg approach

A frequently used approach to evaluate the relation between risk-adjusted performance and some fund characteristic is the Calendar Time (*CalTime*) approach of Jaffe (1974) and Mandelker (1974), which essentially comes down to evaluating alpha for groups sorted on the fund characteristic of interest (e.g. Carhart, 1997; Dahlquist et al., 2000; Wermers, 2000; Kacperczyk et al., 2005; Cremers & Petajisto, 2009; Massa & Patgiri, 2009). While this approach is very parsimonious and ensures robustness in the presence of cross-sectional dependence, it is likely to suffer from an omitted variable bias, as fund characteristics which are known to affect performance cannot be controlled for. In consequence, academic research heavily relies on a two-step multivariate regression framework which we will refer to as the *CrossReg* approach (e.g. Grinblatt & Titman, 1994; Carhart, 1997; Dahlquist et al., 2000; Prather et al., 2004; Chen et al., 2004; Kacperczyk et al., 2005; Pollet & Wilson, 2008, Cremers & Petajisto, 2009; Massa & Patgiri, 2009).[6]

Generally, in the CrossReg approach the first step involves estimating for each subject h a time-series regression of the subjects' time τ excess returns $y_{h,\tau}$ on k factors $x_{s,\tau}$ ($s = 1, \dots, k$) as follows:

$$y_{h,\tau} = \alpha_h + \beta_{1,h}x_{1,\tau} + \cdots + \beta_{k,h}x_{k,\tau} + e_{h,\tau} \tag{1}$$

where, as in our case, Eq. (1) is often specified as a Fama-French (1993) and Carhart (1997) type regression with the factors $x_{s,\tau}$ being the market excess return, the small minus big factor, the high minus low factor, and the momentum factor. This yields for each subject h an estimate of the subject's alpha α_h. In the second step, these alphas are then decomposed by performing a cross-sectional regression of the coefficient estimates for α_h from (1) on a set of m subject specific explanatory variables $z_{q,h}$ ($q = 1, \dots, m$):

$$\hat{\alpha}_h = c_0 + c_1 z_{1,h} + \cdots + c_m z_{m,h} + w_h \tag{2}$$

To allow for time varying explanatory variables, studies of mutual fund performance usually adjust this procedure to create time varying estimates of α_h, i.e. $\hat{\alpha}_{h,\tau}$. In particular, in the first step the fitted Carhart four-factor alphas $\hat{\alpha}_{h,\tau}$ are computed as (e.g. Carhart, 1997, Pollet & Wilson, 2008):

$$\hat{\alpha}_{h,\tau} = y_{h,\tau} - \hat{\beta}_{1,[\tau-1,\tau-36]}x_{1,\tau} + \cdots + \hat{\beta}_{k,[\tau-1,\tau-36]}x_{k,\tau} \tag{3}$$

where $\hat{\beta}_{s,[\tau-1,\tau-36]}$ ($s = 1, \dots, k$) are the factor loadings for the four Fama-French (1993) and Carhart (1997) factors estimated according to (1) over the previous 36 months and $y_{h,\tau}$ and $x_{k,\tau}$ are defined as in (1). This yields for each fund h a time series of fitted values of the monthly intercept $\hat{\alpha}_{h,\tau}$, which are subsequently converted to quarterly values $\hat{\alpha}_{h,t}$ to fit the frequency of the other variables in the dataset. The second step then involves decomposing the risk-adjusted performance by estimating a pooled regression of the fitted quarterly alphas on a set of m possibly continuous and time-varying fund characteristics $z_{q,h,t}$ ($q = 1, \dots, m$):

$$\hat{\alpha}_{h,t} = c_0 + c_1 z_{1,h,t} + \cdots + c_m z_{m,h,t} + w_{h,t} \tag{4}$$

---

[6] The description of the CrossReg approach follows Hoechle et al. (2012).

Whether or not a particular fund characteristic has a significant effect on funds' risk-adjusted performance is then judged based on the coefficient estimates and their respective *t*-statistics from estimating Eq. (4).

The CrossReg approach has the obvious advantage of allowing to control for multiple time-varying fund characteristics that may also be continuous in nature. However, while this advantage is a crucial one, the CrossReg approach also has some serious drawbacks. Driscoll and Kraay (1998) argue that estimating cross-sectional dependence consistent standard errors is impossible for a model of a single cross section as is (2). Hoechle et al. (2012) conclude that therefore the second-step regression of the CrossReg approach will always make the implicit assumption of having cross-sectionally uncorrelated excess returns of the individual funds. If this assumption fails, by ignoring cross-sectional dependence, one is at risk of producing severely biased statistical results (Driscoll & Kraay, 1998).

In particular, by considering the investment performance of private investors, Hoechle et al. (2012) show that ignoring cross-correlation can lead to *t*-statistics that are three and more times higher than the cross-sectional dependence consistent *t*-statistics. Although Driscoll and Kraay (1998) argue that the sign of the bias in standard errors and hence in *t*-statistics is not a general result, they suggest that in many empirical applications it is a priori reasonable to assume that standard errors are too low when not taking cross-sectional dependence into account. Hoechle et al. (2012) note that the CrossReg approach further fails to adjust the second-stage *t*-statistics for the fact that the dependent variables of Eq. (4) are estimated. This naturally exacerbates the downward bias in the standard errors. Hence, using the CrossReg approach in the presence of cross-sectional dependence is likely to severely overestimate the significance of the results.

Next to providing biased standard errors, the CrossReg approach may also yield biased coefficient estimates. In particular, to allow controlling for time-varying fund characteristics, the CrossReg approach requires estimating fitted values of alphas by means of historical factor loadings. Since time variations in factor loadings and hence the measurement errors in alphas are likely to be correlated with variations in fund characteristics (e.g. Huang et al., 2011), the coefficient estimates of Eq. (4) might be biased, too.

To illustrate these points, our first set of results employs the CrossReg approach to provide a benchmark case against which to compare our main results. Additionally, this set of results will serve as a validation for our dataset's consistency with prior research. Hence, for this benchmark case we will estimate Eqs. (1), (3), and (4) with the m fund characteristics $z_{q,h,t}$ being expenses, load fees, past performance, size, family size, fund age, inflows, diversification, and turnover. To ensure consistency with a large body of existing literature, we employ cluster-robust standard errors of Rogers (1993) clustered by fund.[7]

3.3. The GCT-regression model

Hoechle et al. (2012) conclude that the above described drawbacks of the CrossReg approach are mainly due to its two-step procedure, since it abandons valuable information which can be used to ensure robust statistical inference in the presence of cross-sectional dependence. To remedy the drawbacks of the CrossReg approach, they suggest a new regression-based methodology, the *GCT-regression model*, for decomposing the risk-adjusted performance of private investors, firms or mutual funds into investor- or fund-specific characteristics. They prove that the GCT-regression model allows for the inclusion of multiple time-varying fund characteristics that may also be continuous in nature in the analysis, while at the same time ensuring that its results are robust to very general forms of cross-sectional and temporal dependence. Accordingly, we will decompose the risk-adjusted performance of the mutual funds in our dataset using the GCT-regression model to ensure robust statistical inference in the presence of cross-sectional dependence.[8]

Hoechle et al. (2012) build their GCT-regression model based on a regression-based replication of the traditional CalTime approach.[9] They first prove that the results of the CalTime approach, e.g. with groups $j = m, w$, can be completely replicated estimating a pooled linear regression model with Driscoll and Kraay (1998) standard errors as follows:[10]

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[7] Further explanation on these type of standard errors, why they were frequently used in prior research, as well as their properties versus other choices, can be found in Appendix B.

[8] The discussion in this paper is mainly based on Hoechle et al. (2012).

[9] A more extensive discussion of the CalTime approach is provided by Hoechle et al. (2012).

[10] As the original covariance matrix estimator of Driscoll and Kraay (1998) only works for balanced panels, Hoechle (2007) adjusts this estimator for use with unbalanced panels.

$$
\begin{aligned}
y_{h,t} \;=\;& d_{0,0} + d_{0,1}x_{1,t} + \dots + d_{0,k}x_{k,t} \\
&+ d_{1,0}z_{h,t}^{(w)} + d_{1,1}x_{1,t}z_{h,t}^{(w)} + \dots + d_{1,k}x_{k,t}z_{h,t}^{(w)} + v_{h,t}
\end{aligned}
\tag{5}
$$

where $y_{h,t}$ is the funds quarter t excess return and the factors $x_{s,t}$ $(s = 1, \dots, k)$ are the quarter t Fama-French (1993) and Carhart (1997) factor returns. Furthermore, regression (5) includes a dummy variable $z_{h,t}^{(w)}$ which is one if fund h belongs to group w and zero otherwise. Finally, the regression contains a set of interaction variables between the factors $x_{s,t}$ $(s = 1, \dots, k)$ and the dummy variable $z_{h,t}^{(w)}$.

Hoechle et al. (2012) show that the regression-based replication of the CalTime approach can be generalized to include continuous and multivariate fund characteristics while preserving its desirable statistical properties. In particular, they argue that the dichotomous variable $z_{h,t}^{(w)}$ from regression (5) can be replaced by a continuous variable $z_{h,t}$, thereby making it no longer necessary to segregate funds into clear cut groups and hence allowing for continuous fund characteristics. Moreover, regression (5) can be augmented by including additional fund characteristics $z_{q,h,t}$, as well as all interaction terms $d_{q,s}$ $(q = 0, 1, \dots, m;\ s = 0, 1, \dots, k)$ between the additional fund characteristics $z_{qh,t}$ and the factors $x_{s,t}$, thus allowing to add control variables and to perform robustness checks. Hoechle et al. (2012) therefore suggest generalizing the regression-based replication of the CalTime approach by estimating with OLS the following linear regression model with Driscoll and Kraay (1998) standard errors:[11]

$$
\begin{aligned}
y_{h,t} &= \left(\left[1\ z_{1h,t} \dots z_{mh,t}\right] \otimes \left[1\ x_{1,t} \dots x_{k,t}\right]\right)\mathbf{d} + v_{h,t} \\
&= d_{0,0} + d_{0,1}x_{1,t} + \dots + d_{0,k}x_{k,t} \\
&+ d_{1,0}z_{1,h,t} + d_{1,1}x_{1,t}z_{1,h,t} + \dots + d_{1,k}x_{k,t}\, z_{1,h,t} \\
&+ \dots \\
&+ d_{m,0}z_{m,h,t} + d_{m,1}x_{1,t}z_{m,h,t} + \dots + d_{m,k}x_{k,t}\, z_{m,h,t} + v_{h,t}
\end{aligned}
\tag{6}
$$

As a consequence of its derivation, regression (6) is referred to as the Generalized Calendar Time (GCT)-regression model. They note that while the structure of the GCT-regression model is closely related to Ferson and Schadt's (1996) conditional performance measurement model, the conditional coefficients of the GCT-regression model are

[11] Hoechle et al. (2012) note that the GCT-regression model can also be estimated with standard errors that do not account for cross-sectional dependence.

allowed to vary over both time and the cross-section, while Ferson and Schadt (1996) allow them to be time-varying only.

Hoechle et al. (2012) prove that if the panel is balanced and if fund characteristics $z_{q,h,t}$ are constant over time (i.e. $z_{q,h,t} = z_{q,h}$), the OLS coefficient estimates for $d_{q,0}$ in (6) are identical to the OLS coefficient estimates for c_q in (2), i.e. $\hat{c}_q \equiv \hat{d}_{q,0}$ for $q = 0,1,\ldots,m$. That is, the GCT-regression model can replicate the coefficient estimates of the CrossReg approach. However, in contrast to the CrossReg approach, any time-series information inherent in the data is preserved in the GCT-regression model, which allows carrying out a performance evaluation of mutual funds with standard error estimates that are robust to very general forms of both temporal and cross-sectional dependence. Moreover, while the coefficient estimates of (2) and (6) coincide for a balanced panel and time-constant fund characteristics, this is not the case if these assumptions are relaxed. In particular, the possible bias in the CrossReg coefficient estimates in case of time-varying fund characteristics is resolved in the GCT-regression model, as is does not estimate risk-adjusted performance based on historical factor loadings.[12]

For our main results, we therefore estimate the GCT-regression model, i.e. Eq. (6) with Driscoll and Kraay (1998) standard errors, with the factors $x_{s,t}$ being the quarterly market excess return, small minus big factor, high minus low factor, and momentum factor, respectively, and with the m fund characteristics $z_{q,h,t}$ being expenses, load fees, past performance, size, family size, fund age, inflows, diversification, and turnover. The corresponding results correct for all of the aforementioned biases, thereby providing a statistically robust decomposition of risk-adjusted mutual fund performance.[13]

3.4. Methodological hybrid

To provide a more detailed analysis of how prior results were affected by the aforementioned biases, we isolate the bias of ignoring cross-sectional dependence from those of ignoring first-stage estimation errors and using historical estimates of factor

[12] By not requiring historical factor loadings, depending on the specifications of other included variables, the GCT-regression model offers the additional advantage of allowing to include funds with less data points. This not only increases the sample size but also reduces the multi-period sampling bias. To allow for a comparison of the different methodologies, we keep the sample constant in this paper.

[13] Further explanation on these type of standard errors, as well as their properties vs. other choices, can be found in Appendix B.

loadings to compute risk-adjusted performance. This can be done by estimating Eq. (6) with Rogers (1993) standard errors rather than the cross-sectionally robust Driscoll and Kraay (1998) standard errors. While both of these standard errors are heteroskedasticity-consistent and cluster-robust, only the latter are robust to cross-sectional dependence. As the overall structure of the model remains unchanged, none of the other biases is introduced in this step. Hence, the resulting difference in t-statistics can be fully attributed to ignoring cross-sectional dependence, while the coefficient estimates will be identical to those of the standard GCT-regression model.

Moving from the methodological hybrid to the CrossReg approach introduces the two further biases caused by ignoring first-stage estimation errors and by using historical estimates of factor loadings to compute risk-adjusted performance. While the two biases cannot be completely disentangled, ignoring first-stage estimation errors can merely drive standard errors downwards. In consequence, changes in coefficient estimates as well as increases in standard errors can be fully attributed to the usage of historical factor loadings.

4. Results

4.1. Results using the CrossReg approach

Previous research on mutual fund performance decomposition has been heavily relying on the CrossReg approach (e.g. Carhart, 1997; Dahlquist et al., 2000; Wermers, 2000; Kacperczyk et al., 2005; Cremers & Petajisto, 2009; Massa & Patgiri, 2009). Hence, despite possible differences in the sampling period, the sampling universe, the measures of risk-adjusted performance, the measures of fund characteristics, or the choice of control variables, our dataset's results when using the CrossReg approach should be similar to those of prior literature.

Table II presents the results of an estimation using the CrossReg approach, i.e. estimating Eqs. (1), (3), and (4), with the m fund characteristics $z_{q,h,t}$ being expenses, load fees, past performance, size, family size, fund age, inflows, diversification, and turnover. Note that these results are likely to be biased and hence are reported merely to provide a benchmark case against which to compare our main results, as well as to validate our dataset's consistency with prior research.

Table II shows that the results obtained using the CrossReg approach are largely consistent with existing literature. Expenses are found to have a significantly negative effect on risk-adjusted mutual fund performance, which corresponds to the findings of Sharpe (1966), Carhart (1997), Dahlquist et al. (2000), Prather et al. (2004), Kacperczyk et al. (2005), Pollet and Wilson (2008), Cremers and Petajisto (2009), and Huang et al. (2011). The results further indicate a significantly negative effect of lagged fund size on risk-adjusted performance, which is consistent with the findings of Chen et al. (2004), Pollet and Wilson (2008), Cremers and Petajisto (2009), Massa and Patgiri (2009), and Huang et al. (2011). Lagged fund family size is found to have a significantly positive effect, which is in accordance with the results of Chen et al. (2004), Massa and Patgiri (2009), and Huang et al. (2011). Fund age is also indicated to have a significantly positive effect on risk-adjusted performance, which corresponds to the findings of Cremers and Petajisto (2009) and Massa and Patgiri (2009). While contradicting existing findings, the significantly negative effect of lagged diversification on risk-adjusted mutual fund performance seems reasonable, as mutual fund managers frequently face a trade-off between diversification and alpha-potential. Total load fees are found to have no significant effect on risk-adjusted performance. These findings are consistent with the findings of Grinblatt and Titman (1994), Chen et al. (2004), and Prather et al. (2004).

While all of the above results are robust to the choice of the performance measurement model, the findings for past performance, lagged inflows, and turnover vary depending on the chosen model. For the most relevant case of the four-factor model, past performance and lagged inflows are both found to have no significant effect on risk-adjusted performance. These findings correspond to those of Jensen (1969), Carhart (1997), and Dahlquist et al. (2000) for past performance, and Dahlquist et al. (2000), Chen et al. (2004), Sapp and Tiwari (2004), and Cremers and Petajisto (2009) for inflows. A significantly positive relation is found between turnover and risk-adjusted performance in the four-factor model, which corresponds to the findings of Grinblatt and Titman (1994) and Dahlquist et al. (2000).

4.2. Results using the GCT-regression model

The results for the CrossReg approach show that, despite possible differences in the sampling period, the sampling universe, the measures of risk-adjusted performance, the measures of fund characteristics, or the choice of control variables, our dataset is roughly consistent with those of prior literature. However, methodological biases in the CrossReg approach suggest that those results, as well as those found in prior literature, should be reassessed using a statistically robust methodological framework. Such a framework is provided by the GCT-regression model, where the results are robust to very general forms of cross-sectional and temporal dependence. Table III shows the results of estimating the GCT-regression model, i.e. Eq. (6) with Driscoll and Kraay (1998) standard errors, with the m fund characteristics $z_{q,h,t}$ being expenses, load fees, past performance, size, family size, fund age, inflows, diversification, and turnover.

The results obtained using the GCT-regression model suggest that the results of the CrossReg approach are likely to be biased. In particular, only the negative effect of lagged fund size and the positive effects of lagged performance and lagged fund family size on risk-adjusted mutual fund performance remain significant at the 5% level. In contrast, previous findings of significantly negative relations of expenses (e.g. Sharpe, 1966; Carhart, 1997; Dahlquist et al., 2000; Prather et al., 2004; Kacperczyk et al., 2005; Pollet & Wilson, 2008; Cremers & Petajisto, 2009; Huang et al., 2011) to risk-adjusted performance, as well as significantly positive relations of turnover (Grinblatt and Titman, 1994; Dahlquist et al., 2000) and highly significant positive relations of fund age (e.g. Cremers & Petajisto, 2009; Massa & Patgiri, 2009) to risk-adjusted performance, are not confirmed in the GCT-regression model. This indicates that these results could be driven by the above mentioned methodological issues. The same holds for previous findings of no significant performance-persistence (e.g. Jensen, 1969; Carhart, 1997; Dahlquist et al., 2000).

More specifically, for fund age the GCT-regression model finds a positive relation that is merely significant at the 10% level, which is roughly consistent with the findings of no significance by Chen et al. (2004), Prather et al. (2004), and Huang et al. (2011). Hence, the hypothesis of older funds not earning higher risk-adjusted performance can only be rejected at the 10% but not at the 5% significance level.

For expenses, the finding of no significance corresponds to those of Ippolito (1989), Grinblatt and Titman (1994), and Chen et al. (2004). This implies that the hypothesis of funds with higher expenses earning corresponding higher risk-adjusted gross returns cannot be rejected at the 10% significance level.

While contradicting the results of the CrossReg approach, the finding of a significant persistence in risk-adjusted mutual fund performance is in line with the findings of Grinblatt and Titman (1992), Elton et al. (1993, 1996), Hendricks et al. (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Wermers (1997), Davis (2001), Dutta (2002), and Ibbotson and Patel (2002). A 10 bps higher past quarterly risk-adjusted performance is associated with 1.8 and 7.3 bps higher quarterly and annual risk-adjusted performance, respectively. This result is consistent with some fund managers being more skilled and hence persistently performing better than others. Alternatively, different restrictions with respect to funds' tracking errors – possibly in combination with different benchmarks –, as well as differences in the permitted investment universes, might allow some funds to persistently outperform others. All of these explanations are consistent with the hypothesis that past performance might be an indication of future performance after all. However, persistence in mutual fund performance could as well be driven by hidden risk factors which some funds are continuously more exposed to.

Further differences to the results of the CrossReg approach are implied by the finding of no significant relation between diversification and risk-adjusted performance, which corresponds to the findings of Prather et al. (2004) and Pollet and Wilson (2008). The hypothesis of funds that are taking higher idiosyncratic risks not generating additional risk-adjusted performance can therefore not be rejected at reasonable significance levels. This suggests that those fund managers holding badly diversified portfolios might be overconfident about their abilities to generate additional risk-adjusted performance.

The finding of no significant effect of turnover constitutes a difference to the results of the CrossReg approach as well. It is consistent with the results of Ippolito (1989), Wermers (2000), Chen et al. (2004), Prather et al. (2004), Kacperczyk et al. (2005), Cremers and Petajisto (2009), and Huang et al. (2011). This provides evidence against the hypothesis that better managers trade more to exploit their superior information.

Despite the discussed methodological issues of the CrossReg approach, some of its results are confirmed in the statistically robust framework of the GCT-regression model. In particular, the results in Table III suggest a significantly negative relation of lagged fund size on risk-adjusted performance, which is again corresponding to the findings of Chen et al. (2004), Pollet and Wilson (2008), Cremers and Petajisto (2009), Massa and Patgiri (2009), and Huang et al. (2011). While the *t*-statistics are somewhat smaller than those of the CrossReg approach, the coefficient estimates are almost identical. For the four-factor model, a 100% higher fund size is associated with 4.6 and 18.6 bps smaller quarterly and annual risk-adjusted performance, respectively. This result provides evidence in favor of Berk and Green's (2004) hypothesis that allows reconciling fund manager skill with the lack of average mutual fund outperformance by suggesting that mutual funds receive money until they can no longer outperform passive benchmarks.

The findings for lagged fund family size also correspond to those of the CrossReg approach. That is, the relationship is found to be significantly positive, which is in accordance with the results of Chen et al. (2004), Massa and Patgiri (2009), and Huang et al. (2011). Again, the *t*-statistics are somewhat smaller than those of the CrossReg approach, while the coefficients estimates are almost identical. Dependent on the chosen performance measurement model, a 100% higher fund family size implies at least 1.8 and 7.2 bps higher quarterly and annual risk-adjusted performance, respectively. This result suggests that mutual funds belonging to large fund families can profit from economies of scale in various categories, e.g. administration, research etc.

Further consistency with the results of the CrossReg approach is found for total load fees, and lagged inflows, as the GCT-regression model suggests no significant relation to risk-adjusted returns for these variables. This corresponds to the findings of Grinblatt and Titman (1994), Chen et al. (2004), and Prather et al. (2004) for load fees and Dahlquist et al. (2000), Chen et al. (2004), Sapp & Tiwari (2004), and Cremers and Petajisto (2009) for inflows.

All results except for those on performance persistence are robust to the choice of the performance measurement model. Generally, the results of Table III are consistent with Hoechle et al.'s (2012) findings for the investment performance of private investors, that is, decomposing risk-adjusted performance in a statistically robust manner renders some of the most popular results on the determinants of risk-adjusted performance insignificant.

4.3. Decomposition of the overall bias

The comparison between the results of the biased CrossReg approach in Table II and those of the robust GCT-regression model in Table III illustrates the difference in statistical inference caused by the overall bias of the CrossReg approach. To provide further insights, we isolate the bias of ignoring cross-sectional dependence from those of ignoring first-stage estimation errors and using historical estimates of factor loadings to compute risk-adjusted performance. Table IV shows the results of decomposing the overall bias by comparing the GCT-regression model and the CrossReg approach to the methodological hybrid of estimating Eq. (6) with Rogers (1993) standard errors.

As indicated by the differences between the GCT-regression model and methodological hybrid in Table IV, ignoring cross-sectional dependence causes biased statistical inference for expenses and fund age, where in both cases the significance is overstated in the methodological hybrid. While standard errors are also biased downwards for load fees, past performance, fund size, fund family size, and turnover, statistical inference at relevant significance levels is not influenced by these differences. Note that the bias caused by ignoring cross-sectional dependence affects standard errors only, while coefficient estimates are identical to those of the statistically robust GCT-regression model.

The differences between the methodological hybrid and the CrossReg approach indicate that ignoring first-stage estimation errors and using historical estimates of factor loadings to compute risk-adjusted performance causes further biases in statistical inference. In particular, standard errors are biased further downwards for all variables. Coefficient estimates become more extreme for expenses and diversification, while the coefficient estimate on past performance is drastically reduced towards zero. The coefficient estimates for total load and turnover are even subject to a change in sign. The combination of these two forces causes biased statistical inference for expenses, past performance, diversification, and turnover, where the significance of expenses and diversification is overstated, while the significance of past performance is understated. For turnover, the combination of a change in the sign and magnitude of the coefficient and a decrease in standard errors even implies a highly significant result in the opposite direction. While the two biases cannot be completely disentangled, ignoring first-stage estimation errors can merely drive standard errors downwards. In consequence, all changes in coefficient estimates can be fully attributed to the usage of historical factor loadings.

Overall, the results indicate that the larger part of the biases in statistical inference is caused by the downward bias on standard errors due to ignoring cross-sectional dependence and the changes in coefficient estimates due to using historical estimates of factor loadings in computing risk-adjusted performance. In contrast, the changes in standard errors caused by ignoring first stage estimation errors and using historical factor loadings seem to have a smaller influence and might have averaged out somewhat between the two forces.

5. Implications for future research

Our results' importance for future research transcends the field of mutual fund performance evaluation. Cross-sectional dependencies are likely to appear in many relationships on today's complex financial markets. In two-stage regression frameworks, inflated *t*-statistics due to ignoring first-stage estimation errors, as well as biased coefficient estimates due to overlooked relations of measurement errors in first-stage to second-stage independent variables, cause additional problems that are often addressed incorrectly in existing studies.

In particular, studies on panel data inference in the presence of cross-sectional and temporal dependence (e.g. Skoulakis, 2008; Petersen, 2009; Vogelsang, 2012) typically focus on panels where the dependent variable is not estimated.[14] When this assumption is violated, however, the discussed methods merely constitute different means of performing the second step of the CrossReg approach. While these studies rightfully find some of the evaluated methods to be robust within their analyzed framework, the ultimate source of the biases discussed in this paper lies in the information loss associated with the two-step procedure of the CrossReg approach. Hence, although robustness might be ensured when applying these methods under certain assumptions, our results indicate that they are likely to yield biased results within a two-stage regression framework of the type discussed in this paper.[15]

More generally, our findings cause doubts on the robustness of results in all analyses where a variation of either the CalTime or the CrossReg approach is applied. This explicitly includes not only decompositions of the intercept, but also of any other

[14] The methods discussed in these studies include among others the Fama-MacBeth procedure (Fama & MacBeth, 1973), fixed effects estimation, OLS with adjustment for within cluster correlation, the Newey-West procedure, clustered standard errors (e.g. Rogers, 1993), GLS of a random effects model, adjusted Fama-MacBeth and Driscoll & Kraay (1998) standard errors.

[15] While Fama-MacBeth standard errors (Fama & MacBeth, 1973) are computed in a two-step framework as well, this type of two-step analysis nevertheless only covers the second step of the CrossReg approach. Hence, when applied in the case of an estimated dependent variable, the Fama-MacBeth standard errors are essentially obtained by means of a three-step procedure. The first step, i.e. the estimation of the dependent variable, is usually not taken into account in analyses of the approach's robustness.

coefficient from the first-stage regression of the CrossReg approach. In consequence, decompositions of alphas, as well as factor exposures (e.g. market, size, value, momentum, skewness, kurtosis), for all types of subjects (e.g. investors, funds, stocks, firms) should be reassessed in the statistically robust framework of the GCT-regression model.[16]

6. Conclusions

Investors, academics, as well as asset management companies frequently rely on various fund characteristics to assist their investment processes, performance evaluations or strategic decision making, where the list of evaluated characteristics includes expenses, load fees, past performance, size, family size, fund age, inflows, diversification, and turnover. However, by implicitly assuming cross-sectional independence, ignoring first stage estimation errors, using historical estimates of factor loadings to compute risk-adjusted performance, previous decompositions of risk-adjusted performance might provide biased results.

The GCT-regression model of Hoechle et al. (2012) allows for an unbiased decomposition of risk-adjusted performance in the presence of temporal and cross-sectional dependence, while controlling for multiple time-varying fund characteristics that may also be continuous in nature.

In this paper, we provide new reliable insights on the drivers of mutual fund performance and the importance of using the appropriate methodology by decomposing risk-adjusted performance of U.S. equity mutual funds using the GCT-regression model

[16] To give just one example, parts of Sapp and Tiwari's (2004) analysis of the relation between fund net cash flows and momentum can be performed using the GCT-regression model. A standard case is the analysis in Table III, where alphas for positive and negative cash-flow portfolios are compared. Decomposing alphas in the GCT-regression model with cash-flows being only one of the fund characteristics (as is done in section 4 of this paper) will remove the apparent omitted variable bias and at the same time allow for inference based on a continuous rather than a discrete variable. A less straight-forward case concerns the results in Table V, where positive cash-flow percentages are reported for mutual fund deciles sorted by momentum. The GCT-regression model allows decomposing funds' momentum exposure into the contributions of cash-flows and other fund characteristics. This will not only allow any statistical inference in the first place, but will additionally remove the omitted variable bias, the discrete nature of the analysis, as well as the reliance on past 36-months momentum data. The latter will furthermore allow for an increased sample size while eliminating the multi-period sampling bias.

on a 2002-2012 dataset of more than 2,100 U.S. equity mutual funds, thereby including the global financial crisis and the sovereign debt crisis.

When relying on the previously used methodologies, our dataset yields results largely consistent with existing research. However, once the above mentioned issues are resolved by using the GCT-regression model, our results indicate that only the negative effect of lagged fund size and the positive effects of lagged performance and lagged fund family size on risk-adjusted mutual fund performance remain significant at the 5% level. In particular, we provide evidence that previous findings of significantly negative relations of expenses to risk-adjusted performance, significantly positive relations of turnover and fund age to risk-adjusted performance, as well as the findings of no significant persistence in risk-adjusted mutual fund performance, could easily be driven by the above mentioned methodological issues.

Our results support Berk and Green’s (2004) hypothesis that allows reconciling fund manager skill with the lack of average mutual fund outperformance by suggesting that mutual funds receive money until they can no longer outperform passive benchmarks. We further provide evidence in favor of the popular hypothesis of past performance being an indication of future performance, as well as the hypothesis that mutual funds belonging to large fund families can profit from economies of scale.

In contrast, the findings of no highly significant relationships between expenses, loads, fund age, inflows, diversification, and turnover to risk-adjusted performance contrast with some of the prominent hypothesis on the drivers of mutual fund performance. In particular, we provide evidence that funds with higher expenses might actually recover those expenses in terms of higher performance.

Our analysis reveals that much of the variation in previous empirical results can be attributed to various methodological issues. In particular, statistically insignificant differences might easily have been exacerbated to being significant by the several methodological issues neglected in existing literature. The larger part of the biases in statistical inference is caused by the downward bias on standard errors due to ignoring cross-sectional dependence and the changes in coefficient estimates due to using historical estimates of factor loadings in computing risk-adjusted performance.

Our findings further imply that decompositions of alphas, as well as factor exposures (e.g. market, size, value, momentum, skewness, kurtosis), for all types of subjects (e.g.

investors, funds, stocks, firms) should be reassessed in the statistically robust framework of the GCT-regression model.

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Tables

Table I: Variables and summary statistics

This table reports the variables included in our dataset, details on their computation, as well as their corresponding summary statistics for the period from Q1/2004 to Q1/2012. The sample includes a total of 2'111 funds and 27'665 fund quarters.

Variable name	Description	Minimum	25th pctl.	Median	75th pctl.	Maximum
Q_NET_EXC_RET	TNA-weighted quarterly fund excess return (net of fees)	-50.71%	-5.56%	1.41%	6.30%	53.17%
MARKET_EXC_RET	Quarterly market excess return	-24.02%	-3.83%	1.33%	5.72%	18.18%
RF	Quarterly risk-free rate	0.00%	0.03%	0.43%	0.93%	1.26%
SMB	Small minus big factor	-8.04%	-1.52%	1.07%	3.33%	8.73%
HML	High minus low factor	-13.85%	-2.97%	0.65%	3.56%	14.53%
MOM	Momentum factor	-39.83%	-1.82%	1.40%	5.80%	15.88%
EXP_RATIO	expense ratio p.a. TNA-weighted over all share classes	0.08%	1.00%	1.21%	1.48%	11.2%
TOTAL_LOAD	Sum of front and rear load of the share class with the highest load	0.00%	0.00%	5.50%	9.75%	13.50%
LAG_ALPHA_4F	1 quarter lagged quarterly alpha of 36-months 4-factor regression	-6.77%	-0.81%	-0.31%	0.21%	6.18%
LAG_ALPHA_3F	1 quarter lagged quarterly alpha of 36-months 3-factor regression	-7.29%	-0.83%	-0.31%	0.24%	7.51%
LAG_ALPHA_1F	1 quarter lagged quarterly alpha of 36-months 1-factor regression	-6.91%	-0.86%	-0.25%	0.41%	8.10%
lag_tna	1 quarter lagged total net assets (TNA) in million US$	0.1	87.6	294.1	970.1	195,806.9
LN_LAG_TNA	ln[lag_tna]	-2.30	4.47	5.68	6.88	12.18
lag_fam_tna	1 quarter lagged TNA of all other funds in the same fund family in million US$	0.0	675.2	4,709.0	17,131.0	478,670.1
LN_LAG_FAM_TNA	ln[1+lag_fam_tna]	0	6.62	8.46	9.75	13.08
age	Time since the first share class of the fund was first offered in years	0.25	7.42	11.17	17.17	86.33
LN_AGE	ln[1+age]	0.22	2.13	2.50	2.90	4.47
lag_inflows	1 quarter lagged flows into the portfolio as a share of lagged TNA	-99.91%	-4.91%	-1.74%	2.21%	5,532.9%
LN_LAG_INFLOWS	ln[1+lag_inflows]	-7.11	-0.05	-0.02	0.22	8.62
LAG_SUM_SQ_WEIGHTS	3 months lagged sum of squared portfolio weights	0.0007	0.0120	0.0175	0.0250	0.4287
TURN_RATIO	Funds turnover ratio over the last 12 months	0.00	0.41	0.71	1.15	22.20

Table II: Results using the CrossReg approach

This table reports the coefficient estimates and *t*-statistics (in parentheses) for decomposing risk-adjusted mutual fund performance using the CrossReg approach, i.e. estimating Eqs. (1), (3), and (4), for different models of performance measurement. The CrossReg approach is likely to yield biased standard errors and coefficient estimates as it ignores cross-sectional dependence and first-stage estimation errors and uses historical estimates of factor loadings to compute risk-adjusted performance. The table only reports the coefficients of the second stage regression, i.e. (4), where the dependent variable is the fitted alpha obtained with historical factor loadings of the respective performance measurement model. The fund characteristics employed are expenses, load fees, past performance, size, family size, fund age, inflows, diversification, and turnover, where the variables are computed as described in Table I. All results are based on a Q1/2004 to Q1/2012 sample of 2'111 funds and 27'665 fund quarters, where all lagged observations might be based on observations preceding this time period. The columns labeled 4-factor model, 3-factor model, and 1-factor model contain the coefficient estimates for the cases where risk-adjusted performance is measured using the Fama-French (1993) and Carhart (1997) four-factor model, the Fama-French (1993) three-factor model, and the Jensen (1969) one-factor model, respectively. The reported standard errors are cluster-robust standard errors of Rogers (1993) clustered by fund, denoted R93. Coefficients are multiplied with 100. ***, **, and * indicate significance at the 1, 5, and 10 percent significance levels.

Method	CrossReg	CrossReg	CrossReg
Factor model	4-factor model	3-factor model	1-factor model
SE type	R93	R93	R93
EXP_RATIO	-16.177 **	-15.633 **	-16.279 **
	(-2.20)	(-2.12)	(-2.19)
TOTAL_LOAD	-0.411	-0.413	-0.169
	(-0.80)	(-0.80)	(-0.33)
LAG_ALPHA_4F	2.868		
	(1.17)		
LAG_ALPHA_3F		-6.981 **	
		(-2.40)	
LAG_ALPHA_1F			22.524 ***
			(9.98)
LN_LAG_TNA	-0.066 ***	-0.052 ***	-0.123 ***
	(-4.79)	(-3.52)	(-7.73)
LN_LAG_FAM_TNA	0.025 ***	0.036 ***	0.044 ***
	(3.22)	(4.24)	(5.26)
LN_AGE	0.140 ***	0.081 **	0.153 ***
	(4.34)	(2.46)	(4.49)
LN_LAG_INFLOWS	-0.074	0.039	-0.278 ***
	(-1.14)	(0.58)	(-2.82)
LAG_SUM_SQ_WEIGHTS	4.991 ***	7.319 ***	3.727 *
	(2.83)	(3.81)	(2.01)
TURN_RATIO	0.099 ***	0.035	0.047
	(3.13)	(-1.29)	(1.80)

Table III: Results using the GCT-regression model

This table reports the coefficient estimates and *t*-statistics (in parentheses) for decomposing risk-adjusted mutual fund performance using the statistically robust GCT-regression model of Hoechle et al. (2012), i.e. estimating Eq. (6) with Driscoll and Kraay (1998) standard errors for different models of performance measurement. The GCT-regression model yields results that are robust to very general forms of cross-sectional and temporal dependence, while allowing to control for multiple time-varying fund characteristics that may also be continuous in nature. The table only reports the coefficients on the relations between fund characteristics and risk-adjusted performance. The fund characteristics employed are expenses, load fees, past performance, size, family size, fund age, inflows, diversification, and turnover, where the variables are computed as described in Table I. All results are based on a Q1/2004 to Q1/2012 sample of 2'111 funds and 27'665 fund quarters, where all lagged observations might be based on observations preceding this time period. The columns labeled 4-factor model, 3-factor model, and 1-factor model contain the coefficient estimates for the cases where risk-adjusted performance is measured using the Fama-French (1993) and Carhart (1997) four-factor model, the Fama-French (1993) three-factor model, and the Jensen (1969) one-factor model, respectively. The reported standard errors of Driscoll and Kraay (1998), denoted DK98, are heteroskedasticity-consistent and robust in the presence of cross-sectional dependence. All coefficients are multiplied with 100. ***, **, and * indicate significance at the 1, 5, and 10 percent significance levels.

Method Factor model SE type	GCT-regression model 4-factor model DK98	GCT-regression model 3-factor model DK98	GCT-regression model 1-factor model DK98
EXP_RATIO	-13.052 (-1.53)	-9.485 (-1.01)	-11.022 (-0.61)
TOTAL_LOAD	0.472 (0.65)	0.279 (0.44)	-0.696 (-0.78)
LAG_ALPHA_4F	18.217 *** (2.87)		
LAG_ALPHA_3F		24.322 ** (2.30)	
LAG_ALPHA_1F			14.546 (0.93)
LN_LAG_TNA	-0.067 *** (-3.65)	-0.064 *** (-4.27)	-0.120 *** (-6.57)
LN_LAG_FAM_TNA	0.026 *** (2.74)	0.027 ** (2.47)	0.040 *** (2.89)
LN_AGE	0.131 * (1.84)	0.124 * (1.79)	0.126 * (1.73)
LN_LAG_INFLOWS	-0.105 (-0.87)	0.063 (0.41)	-0.228 (-1.18)
LAG_SUM_SQ_WEIGHTS	2.311 (0.94)	2.850 (0.59)	0.796 (0.15)
TURN_RATIO	-0.039 (-0.30)	-0.034 (-0.26)	-0.085 (-0.57)

Table IV: Decomposition of the overall bias

This table reports the coefficient estimates, *t*-statistics (in parentheses), and standard errors (in square brackets) for decomposing risk-adjusted mutual fund performance using several methodologies. Column 1 shows the results of the statistically robust GCT-regression model of Hoechle et al. (2012), i.e. estimating Eq. (6) with Driscoll and Kraay (1998) standard errors. The GCT-regression model yields results that are robust to very general forms of cross-sectional and temporal dependence, while allowing to control for multiple time-varying fund characteristics that may also be continuous in nature. Column 2 shows the results for the methodological hybrid, i.e. estimating Eq. (6) with Rogers (1993) standard errors, which yields biased standard errors in the presence of cross-sectional dependence. Column 3 shows the results of the biased CrossReg approach, i.e. estimating Eq. (1), (3), and (4) with Rogers (1993) standard errors. The CrossReg approach is likely to yield biased standard errors and coefficient estimates as it ignores cross-sectional dependence and first-stage estimation errors and uses historical estimates of factor loadings to compute risk-adjusted performance. The table only reports the coefficients on the relations between fund characteristics and risk-adjusted performance. The fund characteristics employed are expenses, load fees, past performance, size, family size, fund age, inflows, diversification, and turnover, where the variables are computed as described in Table I. All results are based on a Q1/2004 to Q1/2012 sample of 2’111 funds and 27’665 fund quarters, where all lagged observations might be based on observations preceding this time period. The risk-adjusted performance is measured using the Fama-French (1993) and Carhart (1997) four-factor model. The reported standard errors of Driscoll and Kraay (1998) and Rogers (1993) are denoted DK98 and R93, respectively. All coefficients and standard errors are multiplied with 100. ***, **, and * indicate significance at the 1, 5, and 10 percent significance levels.

Method	GCT-regression model	Methodological hybrid	CrossReg
Factor model	4-factor model	4-factor model	4-factor model
SE type	DK98	R93	R93
	-13.052	-13.052 *	-16.177 **
EXP_RATIO	(-1.53)	(-1.77)	(-2.20)
	[8.524]	[7.398]	[7.362]
	0.472	0.472	-0.411
TOTAL_LOAD	(0.65)	(0.93)	(-0.80)
	[0.725]	[0.510]	[0.511]
	18.217 ***	18.217 ***	2.868
LAG_ALPHA_4F	(2.87)	(6.87)	(1.17)
	[6.342]	[2.653]	[2.454]
	-0.067 ***	-0.067 ***	-0.066 ***
LN_LAG_TNA	(-3.65)	(-4.56)	(-4.79)
	[0.018]	[0.015]	[0.014]
	0.026 ***	0.026 ***	0.025 ***
LN_LAG_FAM_TNA	(2.74)	(3.20)	(3.22)
	[0.010]	[0.008]	[0.008]
	0.131 *	0.131 ***	0.140 ***
LN_AGE	(1.84)	(4.03)	(4.34)
	[0.071]	[0.033]	[0.032]
	-0.105	-0.105	-0.074
LN_LAG_INFLOWS	(-0.87)	(-0.79)	(-1.14)
	[0.120]	[0.132]	[0.065]
	2.311	2.311	4.991 ***
LAG_SUM_SQ_WEIGHTS	(0.94)	(0.96)	(2.83)
	[2.446]	[2.406]	[1.762]
	-0.039	-0.039	0.099 ***
TURN_RATIO	(-0.30)	(-0.94)	(3.13)
	[0.130]	[0.041]	[0.032]

Appendix A

Table A.I: Overview of existing literature

This table reports results of prior research on decomposing risk-adjusted mutual fund performance. Columns 1-3 show which papers found the various fund characteristics to have a significantly positive, no significant or a significantly negative relation to risk-adjusted mutual fund performance, respectively. Results printed in bold correspond to those we obtain in the statistically robust framework of the GCT-regression model. Results printed in italics correspond to those we obtain when applying the CrossReg approach to our dataset. The CrossReg approach is likely to yield biased standard errors and coefficient estimates as it ignores cross-sectional dependence and first-stage estimation errors and uses historical estimates of factor loadings to compute risk-adjusted performance. While the referenced papers might provide further results using various other methodological specifications, this table only provides those results relevant for our analysis.

Fund Characteristic	Significantly Positive	Not Significant	Significantly Negative
Expenses		**Ippolito (1989), Grinblatt & Titman (1994), Chen et al. (2004)**	*Sharpe (1966), Carhart (1997), Dahlquist et al. (2000), Prather et al. (2004), Kacperczyk et al. (2005), Pollet & Wilson (2008), Cremers & Petajisto (2009), Huang et al. (2011)*
Load Fees		***Grinblatt & Titman (1994), Chen et al. (2004), Prather et al. (2004)***	Carhart (1997), Pollet & Wilson (2008)
Past Performance	**Grinblatt & Titman (1992), Elton et al. (1993), Hendricks et al. (1993), Goetzmann & Ibbotson (1994), Brown & Goetzmann (1995), Elton et al. (1996), Wermers (1997), Davis (2001), Dutta (2002), Ibbotson & Patel (2002)**	*Jensen (1969), Carhart (1997), Dahlquist et al. (2000)*	Prather et al. (2004)
Fund Size		Grinblatt & Titman (1994), Carhart (1997), Dahlquist et al. (2000), Prather et al. (2004), Kacperczyk et al. (2005)	***Chen et al. (2004), Pollet & Wilson (2008), Cremers & Petajisto (2009), Massa & Patgiri (2009), Huang et al. (2011)***
Fund Family Size	***Chen et al. (2004), Massa & Patgiri (2009), Huang et al. (2011)***		Prather et al. (2004)
Fund Age	*Cremers & Petajisto (2009), Massa & Patgiri (2009)*	**Chen et al. (2004), Prather et al. (2004), Huang et al. (2011)**	
Inflows	Gruber (1996), Zheng (1999)	***Dahlquist et al. (2000), Chen et al. (2004), Sapp & Tiwari (2004), Cremers & Petajisto (2009)***	
Diversification	Cremers & Petajisto (2009)	**Prather et al. (2004), Pollet & Wilson (2008)**	
Turnover	*Grinblatt & Titman (1994), Dahlquist et al. (2000)*	**Ippolito (1989), Wermers (2000), Chen et al. (2004), Prather et al. (2004), Kacperczyk et al. (2005), Cremers & Petajisto (2009), Huang et al. (2011)**	Carhart (1997), Massa & Patgiri (2009)

Appendix B

To see why prior research has been frequently relying on Rogers (1993) standard errors, we discuss their differences as compared to White (1980) and Driscoll and Kraay (1998) standard errors based on an example in Dahlquist et al. (2012). They consider the simple regression model

$$y_{it} = x_{it}' b + \varepsilon_{it} \tag{A.1}$$

with x_{it} being a $K \times 1$ vector of regressors. In standard GMM, the probability limit of the variance-covariance matrix of the estimator approaches

$$Cov(\hat{b}) = \Sigma_{xx}^{-1} S \Sigma_{xx}^{-1} \tag{A.2}$$

Dahlquist et al. (2012) show that the methods of White (1980), Rogers (1993) and Driscoll and Kraay (1998) differ only in terms of how the matrix S is estimated, that is:

$$S_{W80} = \frac{1}{T^2 N^2} \sum_{t=1}^{T} \sum_{i=1}^{N} h_{it} h_{it}' \tag{A.3}$$

$$S_{R93} = \frac{1}{T^2 N^2} \sum_{t=1}^{T} \sum_{j=1}^{M} h_t^j \left(h_t^j\right)', \qquad where\ h_t^j = \sum_{i \epsilon j} h_{it} \tag{A.4}$$

$$S_{DK98} = \frac{1}{T^2 N^2} \sum_{t=1}^{T} h_t h_t', \qquad where\ h_t = \sum_{i=1}^{N} h_{it} \tag{A.5}$$

where $h_{it} = x_{it} \varepsilon_{it}$. These formulas imply that while the standard errors of Driscoll and Kraay (1998) take into account correlations both within and among clusters, Rogers (1993) standard errors assume that correlations exist only within clusters. Finally, White (1980) standard errors completely neglect correlations between individuals, both within and among clusters.

While this makes it intuitive that only Driscoll and Kraay (1998) standard errors are robust in the presence of cross-sectional dependence, the question remains why prior research has been relying on White (1980) or Rogers (1993) standard errors in decomposing risk-adjusted mutual fund performance. To answer this question, consider again the two-step procedure of the CrossReg approach. By generating either only a single cross-section of alpha estimates or a time-series of fitted alpha estimates for each fund based on 36-month historical factor loadings, most of the information on cross-sectional dependencies is already lost in the first step of the procedure. In consequence, the robustness of Driscoll and Kraay (1998) standard errors cannot be exploited in the second step of the regression. The GCT-regression model resolves this issue by aggregating the two steps, thereby preserving valuable information about the cross-sectional dependencies in the data. This information is critical for a statistically robust decomposition of mutual fund performance in the presence of cross-sectional dependence.

II. Inefficiency of capitalization weighted investments under home bias

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Abstract This paper provides evidence that, due to investors' home bias, capitalization weighted (Cap Weight) investments are inefficient even in a globally efficient market. Based on a 1987 to 2012 dataset of global equities, we analyze the link between Cap Weight efficiency and home bias by decomposing total home bias costs into contributions of a pure home bias component and a Cap Weight component. The Cap Weight component constitutes the marginal costs of filling a home-biased between-market allocation with Cap Weight investments and appears to be statistically and economically significant across several home countries and parameter specifications.

Keywords Home bias · Cost decomposition · Capitalization weighted · Implied expected returns

JEL Classification G11

1. Introduction

Passive, capitalization weighted (*Cap Weight*) equity investments are frequently advocated by both academics and practitioners. Prominent arguments in favor of Cap Weight investing include their low management fees and turnover, as well as the supposed mean-variance efficiency of the underlying indices. In particular, based on the seminal paper of Sharpe (1964), it is often argued that Cap Weight investments – representing the portfolio of the average investor – must be efficient in an efficient global capital market. In consequence, more and more private as well as institutional investors build up their equity exposure via the continuously increasing number of Cap Weight index funds that are available for a large variety of global and local indices.

At the same time, with a whole industry of active fund managers existing based on the conjecture of market inefficiency, naturally some convincing arguments against Cap Weight investing prevail. More specifically, all of these arguments challenge the supposed Cap Weight efficiency. The so called 'noise effect' (e.g. Arnott, 2005; Treynor, 2005; Hsu, 2006; Arnott et al., 2010) is based on the assumption that asset prices deviate from equilibrium by a mean-reverting error. In this scenario, by weighting each asset according to its market capitalization, Cap Weight indices automatically overweight overvalued and underweight undervalued assets, respectively. The apparent impossibility to forecast expected returns constitutes another frequently mentioned argument, since the assumption of Cap Weight efficiency implies certain expected return differences between assets that might not be justified (e.g. Haugen & Baker, 1991; Chopra & Ziemba, 1993; Clarke et al., 2006; DeMiguel et al., 2009; Arnott et al., 2010; Chow et al., 2011). An analogous point can be made for the covariance matrix, as Cap Weight efficiency also implies a concrete risk structure between individual assets (e.g. DeMiguel et al., 2009; Arnott et al., 2010; Chow et al., 2011).[1]

A hitherto overlooked argument in the debate about Cap Weight efficiency is investors' home-biased between-market allocation (*home bias*). This extreme overweighting of the home market as compared to a supposed efficient international diversification (e.g. the

[1] Fund managers frequently try to benefit from these issues by disentangling portfolio weights from market values (e.g. fundamental indexing), or by additionally assuming expected returns (e.g. minimum variance, risk-cluster equal weighting) or even the covariance matrix (e.g. equal weighting, diversity weighting) to be fully or partly unknown. See Arnott et al. (2010) or Chow et al. (2011) for an overview of these alternative indexing strategies.

global Cap Weight portfolio) has been observed for the large majority of both private and institutional investors in the U.S. and in international markets, where home market weights mostly range between 70% and 100% (e.g. French & Poterba, 1991; Britten-Jones, 1994; Cooper & Kaplanis, 1994; Tesar & Werner, 1995; Lewis, 1999; Ahearne et al., 2004; Kho et al., 2009). With home-biased investors typically suffering efficiency losses due to foregone gains of diversification (*home bias costs*), the academic and practical relevance of home bias largely stems from this avoidable inefficiency.

The existing home bias literature focuses mainly on explaining the bias, where suggested explanations include among others transaction costs (e.g. Tesar & Werner, 1995; Glassmann & Riddick, 2001; Warnock, 2002), direct barriers to international investments (e.g. Black, 1974; Stulz, 1981; Errunza & Losq, 1981), information quality differences (e.g. Gehrig, 1993; Brennan & Cao, 1997; Van Nieuwerburgh & Veldkamp, 2009), hedging of non-traded goods consumption (e.g. Adler & Dumas, 1983; Stockmann & Dellas, 1989; Cooper & Kaplanis, 1994) or psychological and behavioral factors (e.g. Coval & Moskowitz, 1999; Grinblatt & Keloharju, 2000; Huberman, 2001). Rationalized by globalization-driven decreases in the former of these factors, some more recent evidence also suggests slight decreases in home bias over time (e.g. Ahearne et al., 2004; Kho et al., 2009).

Independent of its ultimate drivers, the substantial observed home bias in investors' between-market allocation might have important implications for their within-market allocation. While practitioners and academics nowadays frequently advocate a Cap Weight within-market allocation, their theoretical and practical reasoning neglects the dependence of within-market efficiency on the between-market allocation in general and on home bias in particular. More specifically, even under the strong assumption of global Cap Weight efficiency, the constrained investment opportunity set resulting from a home-biased between-market allocation is likely to contain more efficient portfolios than the home-biased combination of regional Cap Weight investments. Conceptually, this renders global Cap Weight efficiency largely irrelevant for the efficiency of regional Cap Weight investments and hence for the home-biased investor. Nevertheless, the efficiency argument employed by Cap Weight advocates frequently also convinces home-biased private and institutional investors, who in turn rely on a home-biased between-market allocation filled with regional Cap Weight investments. This common extrapolation of the supposed global Cap Weight efficiency to a constrained investment universe raises the hitherto unanswered question of how inefficient Cap Weight investing becomes in the presence of home bias. Put differently, while home bias generally implies some forgone gains of diversification, parts of these home bias costs might be recovered by abandoning the status quo of a Cap Weight within-market allocation towards a more efficient allocation that is tailored to investors' home bias.

Our paper contributes to existing research in the areas of home bias and Cap Weight efficiency by answering this key question of how Cap Weight investments contribute to home bias costs. In particular, based on a 1990 to 2012 survivorship bias free dataset of global equities, we analyze the link between Cap Weight efficiency and home bias by decomposing total home bias costs into the contributions of a pure home bias component and a Cap Weight component. In that context, while the pure home bias component refers to the foregone gains of a home-biased between-market allocation, the Cap Weight component constitutes the marginal foregone gains caused by filling this allocation with Cap Weight investments. It is this latter component that answers our research question by quantifying what part of home bias costs might be recovered when tailoring the within-market allocation to the investors' home bias rather than relying on Cap Weight investments.

Forming portfolios with different restrictions based on the expected excess returns implied by global Cap Weight efficiency, our methodological approach isolates home bias costs from other potential sources of portfolio inefficiency in general and Cap Weight inefficiency in particular. Within this framework, we measure home bias costs in terms of expected performance, realized idiosyncratic risk, and realized performance, thereby covering forward-looking, expected home bias costs, as well as backward-looking, realized home bias costs. To allow for comparisons among a wide range of regions, home market sizes, globalization levels and types of investors, we perform this analysis for 15 different home countries and several parameter specifications.

Our results suggest the Cap Weight component within total home bias costs to be statistically and economically significant for several home countries and parameter specifications, thereby providing evidence of Cap Weight inefficiency under home bias. In terms of expected performance, we find almost half of the annual 1.58% total home bias costs to be caused by Cap Weight inefficiency for the average non-U.S. home country. Practical restrictions in investors' ability to reach the home-biased tangency portfolio reduce this share to about one fifth out-of-sample. In particular, we find a significant share of 6.4% of investors' realized total portfolio risk to be idiosyncratic risk caused by Cap Weight inefficiency. While comparably low market excess returns during our sample period result in average realized total home bias costs and Cap Weight inefficiency of only 1.22% p.a. and 0.24% p.a., respectively, merging the 1.58% p.a. expected total home bias costs with the 19.7% out-of-sample share of the Cap Weight component suggests an expected out-of-sample Cap Weight component of 0.31% p.a. A comparison of our results across countries and parameter specifications shows the finding of Cap Weight inefficiency under home bias to be robust across various regions, home market sizes, globalization levels, and across different types of investors.

The rest of this paper is structured as follows. Section 2 and 3 describe the dataset and methodology used throughout this paper. The empirical results of our analysis are provided in section 4. Section 5 concludes.

2. Data

Our empirical analysis is based on a January 1987 to December 2012 dataset of all constituents of the Standard & Poor's (S&P) Global 1200 index, a composite of the seven regional equity indices S&P 500, S&P Europe 350, S&P Topix 150, S&P/TSX 60, S&P/ASX All Australian 50, S&P Asia 50, and S&P Latin America 40. Covering 1'200 stocks with approximately 70% of the world's equity market capitalization, the S&P Global 1200 constitutes a reasonable proxy for the global equity market portfolio.

Data on all historical index constituents is provided by Compustat, a leading financial database owned by S&P. This data includes the dates of all historical index additions and deletions, as well as the constituent-countries.[2] Weekly historical data on constituent market values and both currency-hedged and unhedged U.S.-Dollar constituent total return indices, the 1-year T-bill rate, as well as on spot and 1-year forward exchange (*FX*) rates from U.S.-Dollar to all relevant currencies, is provided by Thomson Reuters Datastream for the time period from January 1987 to December 2012.[3]

[2] As Compustat does not provide data on the S&P/TSX 60 constituents before January 1999, we approximate its holdings by the 60 largest constituents of the S&P TSX Composite Index in terms of market value at each point of the preceding time period.

[3] We use weekly rather than daily data to alleviate the effect of differences in opening hours between international exchanges.

At each point in time t ($t = 1, 2, \dots, T$), we form our universe of n_t risky assets by including the respective time t historical index constituents of the S&P Global 1200, thereby ensuring that the universe of risky assets is free of survivorship bias. Furthermore, for a stock to be included at a given point in time, our methodology requires it to have at least 156 weeks of prior return data.[4] For each desired home currency, we convert the U.S.-Dollar constituent total return indices to the respective currency based on spot exchange rates.[5] We implement different levels of currency hedging by blending the weekly hedged and unhedged excess returns for each constituent at the required hedging ratio, thereby creating partially hedged excess return series with weekly rebalancing of the FX-hedge.

We generate a risk-free asset for each home currency by adjusting the 1-year T-bill rate based on the 1-year forward-implied interest rate difference.[6] Assuming that the 1-year T-bill constitutes a truly risk-free asset, this provides us with synthetic risk-free assets for all home currencies including those where no truly risk-free asset is available.

3. Methodology

3.1 Implied expected returns

We perform our analysis in the standard mean-variance framework, thereby assuming investors to only care about the mean and variance of their overall portfolio. The investment universe at time t consists of a risk-free asset in the investors' respective domestic currency and all n_t risky assets with currency exposure hedged at the desired hedging ratio. While we assume short-selling of all risky assets to be prohibited, the both lending and borrowing is assumed to be possible at the risk-free rate. Following the two fund separation theorem (Tobin, 1958), rational investors will divide their wealth between the tangency portfolio of risky assets, i.e. the combination of risky assets that maximizes the expected Sharpe ratio, and the risk-free asset. At each point in time t, the $n_t \times 1$

[4] Since this prior return data is used for covariance estimation only, the resulting multi-period sampling bias should be negligible.

[5] We use the (synthetic) Euro as the home currency for all Eurozone countries throughout the whole sampling period.

[6] In those cases where the forward rate is not available for the full sampling period, we write the T-bill adjustment backwards based on the earliest available observation of the respective adjustment.

vector of weights of the tangency portfolio w_t^{TP} is a function of the $n_t \times 1$ vector of expected excess returns $E[r_t^e]$ and the $n_t \times n_t$ expected covariance matrix $E[\Sigma_t]$, i.e.:

$$w_t^{TP} = f(E[r_t^e], E[\Sigma_t]). \quad (1)$$

Global market efficiency would imply the tangency portfolio to equal the Cap Weight portfolio of all n_t risky assets (Sharpe, 1964). In contrast, the aforementioned arguments against Cap Weight investing all imply that w_t^{TP} differs from the vector of global Cap Weight portfolio weights w_t^{GCW}. While we do not take sides in this discussion, our methodology nevertheless assumes $w_t^{TP} = w_t^{GCW}$ to isolate the implications of home bias on portfolio efficiency in general and Cap Weight efficiency in particular from other potential sources of Cap Weight inefficiency. [7] More specifically, inserting $w_t^{TP} = w_t^{GCW}$ into Eq. (1) and rearranging allows us to extract $E[r_t^e]_{impl}$, the $n_t \times 1$ vector of expected excess returns implied by the assumption of global Cap Weight efficiency, thereby explicitly assuming no home bias, no pricing errors in individual stocks and full inclusion of the expected covariance structure between stocks in the portfolio allocation:

$$E[r_t^e]_{impl} = g(w_t^{GCW}, E[\Sigma_t]). \quad (2)$$

Following among others Black and Litterman (1991) and Da Silva et al. (2009), this functional relationship can be concretized as:

$$\widehat{E[r_t^e]}_{impl} = \lambda * \widehat{E[\Sigma_t]} * w_t^{GCW}, \quad (3)$$

where λ is a risk aversion coefficient that scales the implied expected excess returns to reflect investors' required Sharpe Ratio and where $\widehat{E[\Sigma_t]}$ is an estimate of $E[\Sigma_t]$.

To minimize estimation error, we estimate $E[\Sigma_t]$ with a shrinkage approach suggested by Ledoit and Wolf (2003) for estimating the covariance matrix of stock returns when the number of stocks is larger than the number of observations per stock. More specifically, this estimator constitutes the optimally weighted average of the unbiased but very variable sample covariance matrix and the biased but less variable single-index covariance matrix, thereby providing the most efficient trade-off between bias and variance for our type of data. We further alleviate the estimation error by using weekly rather than the commonly

[7] The very same reasoning holds for our restrictive assumption of risk-free borrowing. In particular, while several papers discuss potential inefficiencies of the global Cap Weight portfolio in the absence of a risk-free borrowing facility (e.g. Black, 1972; Ross, 1977; Sharpe, 1991; De Giorgio et al., 2012), we intentionally make this simplistic assumption to isolate the implications of home bias on Cap Weight inefficiency.

employed monthly return data, where we base each estimation on the past 156 weeks of return data.

Whereas the proportions within the covariance matrix are typically found to be fairly persistent over time, this is not necessarily the case for the overall magnitude of the covariance matrix. For the commonly used case of the risk aversion coefficient λ being time-invariant, estimating $E[\Sigma_t]$ based on historical data therefore typically causes large fluctuations in the overall magnitude of $\widehat{E[r_t^e]}_{impl}$. Being mainly caused by realized past covariance magnitudes, these fluctuations are usually inconsistent with actual expectations. We remove this inconsistency by adjusting λ to be time-variant, thereby allowing for the expected global Cap Weight excess return $E[r^e]^{GCW}$ to be constant over time, i.e.:

$$\widehat{E[r_t^e]}_{impl} = \lambda_t * \widehat{E[\Sigma_t]} * w_t^{GCW} \tag{4}$$

$$with \quad \lambda_t = \frac{E[r^e]^{GCW}}{w_t^{GCW^T} * \widehat{E[\Sigma_t]} * w_t^{GCW}}. \tag{5}$$

While we report results based on assuming $E[r^e]^{GCW}$ to equal 6% p.a., note that the relevance of this value is limited to the absolute level of the implied expected home bias costs. In particular, our various out-of-sample home bias cost measures, as well as all statistical significances and relative sizes of home bias cost across home countries and components are fully independent of this choice.

3.2 Home bias cost measures

With home bias costs defined as the efficiency loss due to foregone gains of diversification in home-biased portfolios, these costs can be quantified in terms of several expectation-based and out-of-sample measures. In particular, we report results based on forward-looking implied expected performance (section 4.1), as well as backward-looking realized idiosyncratic risk (section 4.2) and realized performance (section 4.3).

Being the least noisy and most stable home bias cost measure across time, countries, and components, a reasonable starting point for analyzing the link between Cap Weight efficiency and home bias is provided by implied expected performance home bias costs (*expected home bias costs*). Given the time-series of implied expected returns for portfolio j and the global Cap Weight (*GCW*) portfolio, obtained following Eqs. (4) and (5) and (de-)leveraged to a certain target volatility as described in section 3.3, we compute our measure of expected home bias costs for portfolio j, $E[hbcost]^j$, as the average expected return difference between portfolios GCW and j, that is:

$$E[hbcost]^j = \frac{1}{k}\sum_{\tau=\tau_1}^{\tau_k}\left(\widehat{E[r_t^e]}_{impl,\tau}^{GCW} - \widehat{E[r_t^e]}_{impl,\tau}^{j}\right), \tag{6}$$

where $\widehat{E[r_t^e]}_{impl,\tau}^{GCW}$ and $\widehat{E[r_t^e]}_{impl,\tau}^{j}$ are (de-)leveraged time τ implied expected returns for portfolios GCW and j, respectively, and $\tau_1, \dots, \tau_k$ are the k points of rebalancing. Per definition, $E[hbcost]^j$ can only deviate from the true, efficient expectation due to market inefficiency at times τ, differences between $\widehat{E[\Sigma_\tau]}$ and $E[\Sigma_\tau]$, and wrong specification of λ_τ. Hence, while the impossibility of quantifying market inefficiencies implies that we cannot calculate the resulting standard errors, the aforementioned sources of disturbance all suggest the standard errors to be comparably low, thereby allowing for comparisons across countries, components, and over time in this expectation-based framework.[8]

With noise and a dynamic covariance structure adding complexity to the analysis out-of-sample, further measures are required to test whether the expectation-based findings also materialize in terms of realized, out-of-sample home bias costs. Recalling that home bias costs are nothing more than foregone gains of diversification, the most natural out-of-sample measure is the realized idiosyncratic, uncompensated risk that investors have taken in the presence of home bias. In particular, we define idiosyncratic risk home bias costs for portfolio j, $irisk\_hbcost^j$, as one minus the R^2 from regressing portfolio j's (de-)leveraged excess returns on those of the GCW portfolio and a constant over the full sample period, that is:

$$irisk\_hbcost^j = 1 - R^2 = \frac{SS_{res}^j}{SS_{tot}^j}, \tag{7}$$

where SS_{tot}^j and SS_{res}^j are the total sum of squares and residual sum of squares from estimating

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[8] In particular, Chopra and Ziemba (1993) find estimation errors in covariances to result in cash equivalent losses that are only about 1/57th to 1/5th of those resulting from estimation errors in expected returns. Furthermore, while both expected and out-of-sample measures are exposed to variation caused by market inefficiencies, the effect is much lower for the implied expected home bias costs. For example, while an overvaluation of 5% causes the annual realized return to be biased upwards by about 0.5% p.a. for a ten year sample period, the increased market weight resulting from this overvaluation will make annual implied expected returns increase by only about 0-3 bps (cf. Eqs. (4) and (5)).

$$r_t^{e,j} = \alpha^j + \beta^j r_t^{e,GCW} + \varepsilon_t^j, \tag{8}$$

and where $r_t^{e,j}$ and $r_t^{e,GCW}$ are the (de-)leveraged excess returns of portfolios j and GCW. Given two portfolios j_1 and j_2 with equal volatility in excess returns and hence equal total sum of squares, we can then test whether portfolio j_1 has a significantly larger share of idiosyncratic risk and hence significantly larger idiosyncratic risk home bias costs than portfolio j_2 by performing a Diebold-Mariano (1995) test of the error terms $\varepsilon_t^{j_1}$ against $\varepsilon_t^{j_2}$.

Finally, we are interested in how idiosyncratic risk home bias costs translate into realized performance home bias costs. Notably, while taking idiosyncratic risk is inefficient in general, taking more systematic risk instead only results in better performance when market excess returns are positive. In consequence, given the generally volatile stock markets and low excess returns during our sample period, we do not expect to find realized performance home bias costs that are statistically or economically significant.[9] Despite these drawbacks, we can use this measure to gain insights on the performance home bias costs actually suffered by investors during our 23-year sample period. For this purpose, consistent with our general setup of evaluating home bias costs and Cap Weight inefficiency in an efficient market, we are only interested in the performance difference caused by the lower amount of systematic risk (beta) that can be taken at a given amount of total risk (volatility) due to underdiversification in the presence of home bias. That is, any alpha in realized returns must be caused by market inefficiencies and is therefore not part of what we want to measure. Given the equal volatilities of the time series of (de-)leveraged excess returns $r_t^{e,j}$ and $r_t^{e,GCW}$ of portfolios j and GCW, our measure of realized performance home bias costs for portfolio j, $perf\_hbcost^j$, therefore corresponds to the beta-driven average return difference between portfolios GCW and j, i.e.:

$$perf\_hbcost^j = \left(1 - \hat{\beta}^j\right)\bar{r}^{e,GCW}, \tag{9}$$

where $\hat{\beta}^j$ is the beta estimate from Eq. (8) and $\bar{r}^{e,GCW}$ is the time-series average return of the GCW portfolio. To assess the statistical significance of this measure, we use p-values

[9] That is, just as realized returns are not considered good proxies for expected or future realized returns, realized performance home bias costs should not be used as a proxy for expected or future realized home bias costs.

based on Newey-West (1987) standard errors that are robust to autocorrelation and heteroskedasticity.

3.3 Decomposition of home bias costs

Based on the aforementioned home bias cost measures, we can decompose total home bias costs into the contributions of a pure home bias component and a Cap Weight component by constructing portfolios under different allocation constraints. In particular, our analysis evaluates three types of portfolios that are formed using the expected excess returns implied by global Cap Weight efficiency $\widehat{E[r_t^e]}_{impl}$ and our estimate of the covariance matrix $\widehat{E[\Sigma_t]}$. To achieve the equal level of volatility required for our home bias cost measures, each portfolio is rebalanced and (de-)leveraged to an annualized volatility of 20% at points in time $\tau = \tau_1, \tau_2, \ldots \in t$.[10]

Global Cap Weight portfolio (GCW)

The GCW portfolio has weights w_t^{GCW} and is efficient and thereby free of idiosyncratic risk per definition in our theoretical framework. In practical terms, this portfolio corresponds to buying a Cap Weight index fund replicating the global stock market index. Representing the ideal setting of investors not exhibiting home bias and thereby taking full advantage of both between- and within-market diversification, it serves as the natural benchmark case for our analysis with home bias costs being zero per definition for all measures.

Home-biased Cap Weight portfolio (HBCW)

The $HBCW$ portfolio with weights w_t^{HBCW} represents the frequently observed setting where investors only deviate from the GCW portfolio by overweighting the domestic stock market. Put differently, while the split between domestic and foreign stocks is given by a home market weight $w_{home} \leq 1$ that substantially exceeds the home market weight

[10] First, at each point of rebalancing τ, we (de-)leverage all portfolios to the time τ volatility of the Global Cap Weight portfolio based on each portfolio's time varying expected volatility, thereby corresponding to the investors' actual (de-)leveraging accuracy. Second, to remove volatility differences between various home markets (e.g. due to currency risk), we (de-)leverage all portfolios to an expected portfolio volatility of 20% based on the average expected portfolio volatility over our sample period. Finally, we remove the small remaining volatility differences by further adjusting the (de-)leveraged empirical return time series based on the realized volatility over the full sample period, thereby ensuring accurate risk-adjusted evaluation of the portfolios.

of the GCW portfolio $w_{t,home}^{CW}$, the within-market allocation is completely determined by the Cap Weight portfolio weights within home and foreign stock market. That is, let d_τ^{home} be a $n_\tau \times 1$ vector of home market dummies indicating whether stock i ($i = 1, 2, \ldots, n_\tau$) is a home ($d_{i,\tau}^{home} = 1$) or foreign ($d_{i,\tau}^{home} = 0$) market stock, and let d_τ^{fgn} be the accordingly defined $n_\tau \times 1$ vector of foreign market dummies. Then at each point of rebalancing τ:

$$w_\tau^{HBCW} = \frac{w_{home}}{w_{\tau,home}^{CW}} * w_\tau^{GCW} \circ d_\tau^{home} + \frac{1 - w_{home}}{1 - w_{\tau,home}^{CW}} * w_\tau^{GCW} \circ d_\tau^{fgn}. \tag{10}$$

In practical terms, this portfolio corresponds to investing shares w_{home} and $(1 - w_{home})$ of the portfolio in Cap Weight index funds replicating the domestic and foreign stock market indices, respectively.

Optimized home bias portfolio (OHB)

While for the OHB portfolio we assume the home market weight to be the same as for the $HBCW$ portfolio, we allow for full flexibility in choosing the within-market allocation. In particular, its portfolio weights w_t^{OHB} are determined based on optimizing the within-market weights of all assets under the restriction of a home market weight w_{home} and no short-selling at each point of rebalancing τ, i.e.:

$$w_\tau^{OHB} = \underset{w_\tau^{OHB}}{\arg\max} \frac{{w_\tau^{OHB}}^T * \widehat{E[r_\tau^e]}_{impl}}{{w_\tau^{OHB}}^T * \widehat{E[\Sigma_t]} * w_\tau^{OHB}} \tag{11}$$

$$s.t. \quad {w_\tau^{OHB}}^T * d_\tau^{home} = w_{home}, \quad \sum_{i=1}^{n_\tau} w_{i,\tau}^{OHB} = 1, \quad and \quad w_{i,\tau}^{OHB} \geq 0. \tag{12}$$

Using $\widehat{E[r_\tau^e]}_{impl}$ and $\widehat{E[\Sigma_t]}$, the mean-variance optimization is based on the assumption of global Cap Weight efficiency at times τ. In practical terms, this portfolio corresponds to the tangency portfolio of the home-biased efficient frontier.

Based on the (de-)leveraged versions of theses portfolios, we can then analyze the link between Cap Weight efficiency and home bias by decomposing total home bias costs into the contributions of a pure home bias component and a Cap Weight component. In this framework, total home bias costs for the typical investor constitute the foregone gains of diversification caused by moving from the global Cap Weight portfolio to a home-biased between-market allocation filled with regional Cap Weight investments, thereby corresponding to the home bias costs of the $HBCW$ portfolio. Following Eqs. (6) to (9), we hence obtain the following measures of total home bias costs:

$$E[hbcost]^{total} = E[hbcost]^{HBCW} \tag{13}$$

$$irisk\_hbcost^{total} = irisk\_hbcost^{HBCW} \tag{14}$$

$$perf\_hbcost^{total} = perf\_hbcost^{HBCW} \tag{15}$$

Notably, these total home bias costs contain not only the foregone gains of a home-biased between-market allocation, but also the marginal foregone gains caused by filling this allocation with Cap Weight investments. To disentangle these two components, the less constrained OHB portfolio isolates the foregone gains of a home-biased between-market allocation, thereby defining the pure home bias component of total home bias costs:

$$E[hbcost]^{pureHB} = E[hbcost]^{OHB} \tag{16}$$

$$irisk\_hbcost^{pureHB} = irisk\_hbcost^{OHB} \tag{17}$$

$$perf\_hbcost^{pureHB} = perf\_hbcost^{OHB} \tag{18}$$

The marginal foregone gains caused by filling this between-market allocation with Cap Weight investments constitute the Cap Weight component of home bias costs and is consequentially defined as:

$$E[hbcost]^{CapWeight} = E[hbcost]^{HBCW} - E[hbcost]^{OHB} \tag{19}$$

$$irisk\_hbcost^{CapWeight} = irisk\_hbcost^{HBCW} - irisk\_hbcost^{OHB} \tag{20}$$

$$perf\_hbcost^{CapWeight} = perf\_hbcost^{HBCW} - perf\_hbcost^{OHB} \tag{21}$$

It is this latter component that answers our research question by quantifying what part of home bias costs might be recovered when tailoring the within-market allocation to the investors' home bias rather than relying on Cap Weight investments.

We perform this decomposition of home bias costs for 15 different home countries, where we use those 15 countries that have the largest number of stocks within our universe of n_t risky assets on December 28, 1989. The resulting list of home countries contains Australia, Belgium, Canada, Denmark, France, Germany, Great Britain, Hong Kong, Italy, Japan, the Netherlands, Singapore, Sweden, Switzerland, and the USA, thereby allowing for comparisons among a wide range of regions, home market sizes, and globalization levels. Our standard parameter specification assumes a home market weight of 80%,[11] a rebalancing frequency of 52 weeks[12] with $t = 1 = \tau_1$ corresponding to December 28, 1989 (i.e. annual rebalancing with $\tau = 1, 53, 105, \ldots$), and currency risk being 80% hedged.[13] To reflect different degrees of home bias and currency hedging that might apply to different types of investors and regions, as well as to check our results robustness towards changes in these parameter specifications, we also report results for home market weights of 70% and 100% and for currency hedging levels of 0% and 100%.

4. Results

4.1. Expected home bias costs

Following Eqs. (13), (16), and (19), the results from decomposing total expected home bias costs $E[hbcost]^{total}$ into a pure home bias and a Cap Weight component are shown in Table I. Panel A reports the results for all 15 choices of home countries using our standard parameter specifications with a home market weight of 80% and currency risk 80% hedged. For the home-biased U.S. investor, we find total home bias costs to be at 0.18% p.a. While most of these costs stem from the Cap Weight component, the low absolute size suggests both home bias costs and the corresponding Cap Weight component to be a rather negligible issue for U.S. investors. Not surprisingly, with decreasing capitalization and increasing idiosyncratic risk of the home market, total home bias costs increase and are within an economically significant range of 0.71% p.a. (Great Britain) to 2.70% p.a. (Singapore) for all other home countries, with average total home bias costs being 1.58% p.a. across non-U.S. home countries.

More interestingly, we can decompose these total home bias costs into a pure home bias component $E[hbcost]^{pureHB}$ of 0.85% p.a. (54.1%), and a Cap Weight component $E[hbcost]^{CapWeight}$ of 0.72% p.a. (45.9%). Indicating that - within this idealized, expectation-based framework - almost half of the total home bias costs might be

[11] The choice of this value is based on the average findings within the existing literature (e.g. French & Poterba, 1991; Britten-Jones, 1994; Cooper & Kaplanis, 1994; Tesar & Werner, 1995; Lewis, 1999; Ahearne et al., 2004; Kho et al., 2009).

[12] Unreported robustness checks suggest that our results are not sensitive to changes in the rebalancing frequency to e.g. 26 or 13 weeks.

[13] The assumption of 80% currency risk hedging is based on the equivalent assumption in Black (1989) and Black and Litterman (1992), following their reasoning that in a global equilibrium all investors want to take a small amount of currency risk.

recovered by deviating from Cap Weight investments, this finding provides first evidence for an economically significant Cap Weight inefficiency under home bias. A comparison of results across countries shows the relative importance of the Cap Weight component to increase for decreasing total home bias costs. While the pure home bias component therefore varies widely across countries between 0.28% p.a. (Great Britain) and 1.62% p.a. (Singapore), the Cap Weight component is much more stable with a range of 0.42% p.a. (Netherlands) to 1.08% p.a. (Denmark). In consequence, unlike the relevance of pure home bias costs that seems to depend on the particular home market, the finding of Cap Weight inefficiency under home bias is robust across various regions, home market sizes, and globalization levels.

The robustness of Cap Weight inefficiency under home bias is further supported when considering alternative parameter specifications that correspond to different types of investors. Panel B reports the mean results over all 14 non-U.S. home countries for home market weights of 70% and 100% and currency hedging levels of 0% and 100%. While total home bias costs naturally decrease with a decreasing home market weight, the relative importance of the Cap Weight component again increases. In consequence, similar to our results across countries, the Cap Weight component is within a stable range of 0.42% p.a. to 0.72% p.a. for varying home market weights, whereas the pure home bias component varies between 0.60% p.a. and 1.76% p.a. In contrast to variation in home market weights, changing the level of currency hedging in either direction only has a minor effect on our results. In particular, while both cost components increase slightly with a more extreme currency hedging level, the relative importance of the Cap Weight component is not sensitive to the level of currency hedging.

4.2. Idiosyncratic risk home bias costs

The evidence of an economically significant Cap Weight inefficiency under home bias in the expectation-based framework raises the question whether this theoretical inefficiency also materializes out-of-sample, where noise and a dynamic covariance structure are present. On this front, Table II shows the realized idiosyncratic risk home bias costs $irisk\_hbcost^{total}$ and their split up into a pure home bias and Cap Weight component following Eqs. (14), (17), and (20). Panel A reports the home bias costs, as well as the p-values from the corresponding Diebold-Mariano (1995) tests, for all 15 choices of home countries using our standard parameter specifications with a home market weight of 80% and currency risk 80% hedged. The total idiosyncratic risk home bias costs are both economically and statistically highly significant for all home countries. With a range of 6.3% (United States) to 60.5% (Singapore) and an average of 38.7% among non-U.S. home countries, our results indicate that the uncompensated risk taken by the average home-biased investor accounts for more than one third of his total portfolio risk. Consistent with our findings for expected home bias costs, the total idiosyncratic risk home bias costs are as well increasing with decreasing capitalization and increasing idiosyncratic risk of the home market.

Our expectation-based key result of an economically significant Cap Weight inefficiency under home bias also finds further support in the idiosyncratic risk framework. In particular, the decomposition of total home bias costs into a pure home bias component $irisk\_hbcost^{pureHB}$ and a Cap Weight component $irisk\_hbcost^{CapWeight}$ suggests Cap Weight inefficiency to cause statistically and economically significant amounts of idiosyncratic risk in portfolios of home-biased investors for all considered non- U.S. home countries. For the average country, this risk makes up 6.4% of investors' total portfolio risk, corresponding to roughly 1.3 percentage points of volatility in our setting with 20% portfolio volatility. However, while our expectation-based decomposition suggested this component to account for almost half of total home bias costs, this share shrinks to less than one fifth in the out-of-sample decomposition due to practical restrictions. More specifically, the likely cause of this reduction are deviations of realized covariances Σ_t from investors' ex-ante estimate $\widehat{E[\Sigma_t]}$. While these do not affect total home bias costs, they prevent investors from optimizing to the true tangency portfolio of the home-biased efficient frontier, thereby reducing the within-market optimization potential that drives the Cap Weight components and leaving a larger share of total home bias costs in the pure home bias component. Despite these practical restrictions, the dynamics of the Cap Weight component across countries remains consistent with our findings for expected home bias costs. In particular, our results confirm the previously found increase in relative importance of the Cap Weight component for decreasing total home bias costs. In consequence, while the pure home bias component varies between 17.0% (Great Britain) and 54.1% (Singapore) for non-U.S. home countries, the Cap Weight component is again more stable across countries with a range of 3.3% (Germany) to 9.7% (Belgium), thereby documenting the out-of-sample robustness of Cap Weight inefficiency under home bias across various regions, home market sizes, and globalization levels.

To check robustness across different types of investors, Panel B again reports the mean results over all 14 non-U.S. home countries for home market weights of 70% and 100% and currency risk hedging levels of 0% and 100%. The dynamics of our findings on idiosyncratic risk home bias costs over varying parameter specifications are fully consistent with the corresponding dynamics for expected home bias costs. In particular, we again find total home bias costs to decrease and the relative importance of the Cap Weight component to increase with a decreasing home market weight. In consequence, the Cap Weight component is again more stable across home country weights (1.6% to 6.8%) than the pure home bias component (23.7% to 45.9%), with total home bias costs ranging between 30.5% and 47.5%. The level of currency hedging only influences results when going towards the non-hedged end of the scale. However, while this increases total home bias costs to some extent, the Cap Weight component is again not very sensitive to this parameter.

4.3. Realized performance home bias costs

With realized idiosyncratic risk home bias costs shown to be both economically and statistically significant, we are interested in how these translate into realized performance. Table III shows the realized performance home bias costs $perf\_hbcost^{total}$ and their split up into a pure home bias and Cap Weight component following Eqs. (15), (18), and (21). Panel A reports the home bias costs, as well as their p-values based on Newey-West (1987) standard errors that are robust to autocorrelation and heteroskedasticity, for all 15 choices of home countries using our standard parameter specifications with a home market weight of 80% and currency risk 80% hedged. With a non-U.S. home country average of 1.22% p.a., the total realized performance home bias costs are about 0.36% p.a. lower than the previously reported total expected home bias costs. This 30% difference between investors' realized home bias costs within our 23-year sample period and the expected home bias costs is likely to stem from the comparably low market excess returns during our sample period. While the highly volatile stock market returns prohibit total home bias costs to be significant, we get some indication of robustness by finding the same dynamics across home markets as for expected home bias costs and idiosyncratic risk home bias costs. In particular, total home bias costs are 0.18% p.a. for the U.S. investor and increase with decreasing capitalization and increasing idiosyncratic risk of the home market to a range of 0.60% p.a. (Great Britain) to 2.00% p.a. (Singapore) for all other home countries.

Decomposing these realized costs into a pure home bias component $perf\_hbcost^{pureHB}$ of 0.98% p.a. (80.3%) and a Cap Weight component $perf\_hbcost^{CapWeight}$ of 0.24% p.a. (19.7%) naturally shows a similar split as for idiosyncratic risk home bias costs, thereby again indicating that about one fifth of realized home bias costs is caused by Cap Weight inefficiency. As for our previous findings, the relative importance of this Cap Weight component increases for decreasing total home bias costs, thereby causing the Cap Weight component to be robust across regions, home market sizes, and globalization levels. However, with a range of 0.11% p.a. (Germany) to 0.35% p.a. (Belgium) for non-U.S. home countries and an average annual portfolio turnover of roughly 15% to 45%, whether or not this realized Cap Weight component is actually economically inefficient depends on the home country and the transaction costs faced by the investor.

Despite the aforementioned practical restrictions, the consistency with our previous findings also holds for the robustness checks shown in Panel B. As before, we report mean results over all 14 non-U.S. home countries for home market weights of 70% and 100% and currency risk hedging levels of 0% and 100%. During our 23-year sample period, investors have realized decreasing total home bias costs for decreasing home market weights while seeing the importance of the Cap Weight component increase. In consequence, while both not statistically significant, the Cap Weight component was more stable across home country weights (0.07% to 0.24%) than the pure home bias component (0.75% to 1.58%), with total home bias costs ranging between 1.00% and 1.65%. Consistency with previous results is also established for the level of currency hedging, as we again find the Cap Weight inefficiency to be insensitive to this parameter.

5. Conclusions

Cap Weight equity investments are frequently advocated by both academics and practitioners. In particular, it is often argued that in an efficient global capital market, Cap Weight investments must be efficient as well. A hitherto overlooked argument in the debate about Cap Weight efficiency is investors' home-biased between-market allocation.

While the existing home bias literature focuses on explaining the bias, independent of its drivers, the substantial observed home bias in investors' between-market allocation might have important implications for their within-market allocation. More specifically, even under the strong assumption of global Cap Weight efficiency, the constrained investment opportunity set resulting from a home-biased between-market allocation contains more efficient portfolios than the home-biased combination of Cap Weight within-market investments. Nevertheless, the efficiency argument employed by Cap Weight advocates frequently also convinces home-biased private and institutional investors, who in turn rely on a home-biased between-market allocation filled with Cap Weight investments. This raises the hitherto unanswered question of how inefficient Cap Weight investing becomes in the presence of home bias.

Based on a 1987 to 2012 survivorship bias free dataset of global equities, we analyze the link between Cap Weight efficiency and home bias by decomposing total home bias costs into the contributions of a pure home bias component and a Cap Weight component. In that context, while the pure home bias component refers to the foregone gains of diversification resulting from a home-biased between-market allocation, the Cap Weight component constitutes the marginal foregone gains caused by filling this allocation with Cap Weight investments. Forming portfolios with different restrictions based on the expected excess returns implied by global Cap Weight efficiency, our methodological approach isolates home bias costs from other potential sources of portfolio inefficiency in general and Cap Weight inefficiency in particular.

Our results suggest the Cap Weight component within total home bias costs to be statistically and economically significant for several home countries, thereby providing evidence of Cap Weight inefficiency under home bias. In an expectation-based framework, we find almost half of the annual 1.58% total home bias costs to be caused by Cap Weight inefficiency for the average non-U.S. home country. Practical restrictions in investors' ability to reach the home-biased tangency portfolio reduce this share to about one fifth out-of-sample. In particular, we find a significant 6.4% of investors' realized total portfolio risk to be idiosyncratic risk caused by Cap Weight inefficiency. While comparably low market excess returns during our sample period result in average realized total home bias costs and Cap Weight inefficiency of only 1.22% p.a. and 0.24% p.a., respectively, merging the 1.58% p.a. expected total home bias costs with the 19.7% realized share of the Cap Weight component suggests an expected out-of-sample Cap

Weight component of 0.31% p.a. A comparison of our results across countries and parameter specifications shows the finding of Cap Weight inefficiency under home bias to be robust across various regions, home market sizes, globalization levels, and across different types of investors.

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Tables

Table I: Expected home bias costs and their components

This table reports the annualized total expected home bias costs, $E[hbcost]^{total}$, as well as their decomposition into a pure home bias and a Cap Weight component, for our list of 15 home countries. The calculations are based on the expected excess returns implied by the assumption of global Cap Weight efficiency using Eqs. (4) and (5) for a 01/1990 to 12/2012 dataset of S&P Global 1200 index constituents. The decomposition follows Eqs. (13), (16), and (19), where the pure home bias component, $E[hbcost]^{pureHB}$, refers to the foregone gains of a home-biased between-market allocation, and the Cap Weight component $E[hbcost]^{CapWeight}$, constitutes the marginal foregone gains caused by filling this between-market allocation with Cap Weight investments. Panel A reports the results for our standard parameter specifications with a home market weight of 80% and currencies 80% hedged. Panel B reports the mean results over all 14 non-U.S. home countries for home market weights of 70% and 100% and currency hedging levels of 0% and 100%. Total home bias costs are reported in absolute terms only, while their components are also reported as a share of these total home bias costs.

Panel A: Detailed results for 80% home market weight and currencies 80% hedged

Variable / Country	Total home bias costs	Pure home bias component		Cap Weight component	
	Absolute	Absolute	Relative	Absolute	Relative
Australia	1.91%	0.96%	50.5%	0.95%	49.5%
Belgium	1.67%	0.86%	51.5%	0.82%	48.5%
Canada	1.27%	0.49%	38.8%	0.78%	61.2%
Denmark	2.62%	1.54%	59.0%	1.08%	41.0%
France	0.92%	0.48%	52.3%	0.44%	47.7%
Germany	1.01%	0.54%	53.7%	0.47%	46.3%
Great Britain	0.71%	0.28%	39.5%	0.43%	60.5%
Hong Kong	2.44%	1.45%	59.4%	0.99%	40.6%
Italy	1.86%	1.18%	63.7%	0.67%	36.3%
Japan	1.29%	0.52%	40.1%	0.77%	59.9%
Netherlands	0.97%	0.55%	56.6%	0.42%	43.4%
Singapore	2.70%	1.62%	60.2%	1.07%	39.8%
Sweden	1.65%	0.99%	60.1%	0.66%	39.9%
Switzerland	1.08%	0.49%	45.1%	0.59%	54.9%
United States	0.18%	0.04%	20.0%	0.14%	80.0%
Mean ex U.S.	1.58%	0.85%	54.1%	0.72%	45.9%

Panel B: Means (ex U.S.) for different parameter specifications

Variable / Parameter	Total home bias costs	Pure home bias component		Cap Weight component	
	Absolute	Absolute	Relative	Absolute	Relative
70% w_{home}	1.28%	0.60%	47.0%	0.68%	53.0%
100% w_{home}	2.18%	1.76%	80.7%	0.42%	19.3%
0% hedged	1.66%	0.93%	56.0%	0.73%	44.0%
100% hedged	1.60%	0.87%	54.2%	0.73%	45.8%

Table II: Idiosyncratic risk home bias costs and their components

This table reports the total idiosyncratic risk home bias costs for the full sample period, $irisk\_hbcost^{total}$, as well as their decomposition into a pure home bias and a Cap Weight component, for our list of 15 home countries. The results are based on portfolios implied by the assumption of global Cap Weight efficiency for a 01/1990 to 12/2012 dataset of S&P Global 1200 index constituents. The decomposition follows Eqs. (14), (17), and (20), where the pure home bias component, $irisk\_hbcost^{pureHB}$, refers to the idiosyncratic risk of a home-biased between-market allocation, and the Cap Weight component $irisk\_hbcost^{CapWeight}$ constitutes the marginal idiosyncratic risk caused by filling this between-market allocation with Cap Weight investments. Panel A reports the results for our standard parameter specifications with a home market weight of 80% and currencies 80% hedged. Panel B reports the mean results over all 14 non-U.S. home countries for home market weights of 70% and 100% and currency hedging levels of 0% and 100%. Total home bias costs are reported in absolute terms only, while their components are also reported as a share of these total home bias costs. p-values from the Diebold-Mariano (1995) test are reported in parentheses, with *, **, and *** indicating significance at the 10%-, 5%-, and 1%- level.

Panel A: Detailed results for 80% home market weight and currencies 80% hedged

Variable / Country	Total home bias costs	Pure home bias component		Cap Weight component	
	Absolute	Absolute	Relative	Absolute	Relative
Australia	49.2% *** (0.000)	40.9% *** (0.000)	83.2%	8.3% *** (0.000)	16.8%
Belgium	40.3% *** (0.000)	30.6% *** (0.000)	75.9%	9.7% *** (0.000)	24.1%
Canada	35.0% *** (0.000)	25.6% *** (0.000)	73.1%	9.4% *** (0.000)	26.9%
Denmark	51.8% *** (0.000)	43.0% *** (0.000)	83.1%	8.8% *** (0.000)	16.9%
France	23.9% *** (0.000)	20.3% *** (0.000)	84.8%	3.6% *** (0.000)	15.2%
Germany	24.5% *** (0.000)	21.2% *** (0.000)	86.7%	3.3% *** (0.000)	13.3%
Great Britain	21.7% *** (0.000)	17.0% *** (0.000)	78.3%	4.7% *** (0.000)	21.7%
Hong Kong	58.3% *** (0.000)	50.1% *** (0.000)	86.1%	8.1% *** (0.000)	13.9%
Italy	40.6% *** (0.000)	37.0% *** (0.000)	91.1%	3.6% *** (0.002)	8.9%
Japan	42.7% *** (0.000)	33.6% *** (0.000)	78.6%	9.1% *** (0.000)	21.4%
Netherlands	25.0% *** (0.000)	20.0% *** (0.000)	80.1%	5.0% *** (0.000)	19.9%
Singapore	60.5% *** (0.000)	54.1% *** (0.000)	89.3%	6.5% * (0.064)	10.7%
Sweden	39.6% *** (0.000)	33.6% *** (0.000)	84.9%	6.0% *** (0.000)	15.1%
Switzerland	28.1% *** (0.000)	20.5% *** (0.000)	72.9%	7.6% *** (0.000)	27.1%
United States	6.3% *** (0.000)	4.5% *** (0.000)	71.7%	1.8% *** (0.000)	28.3%
Mean ex U.S.	36.5%	30.1%	82.6%	6.4%	17.4%

Panel B: Mean results (ex U.S.) for different parameter specifications

Variable / Parameter	Total home bias costs	Pure home bias component		Cap Weight component	
	Absolute	Absolute	Relative	Absolute	Relative
70% w_{home}	30.5%	23.7%	77.7%	6.8%	22.3%
100% w_{home}	47.5%	45.9%	96.7%	1.6%	3.3%
0% hedged	41.6%	35.8%	86.1%	5.8%	13.9%
100% hedged	36.5%	30.1%	82.4%	6.4%	17.6%

Table III: Realized performance home bias costs and their components

This table reports the total realized performance home bias costs, $perf\_hbcost^{total}$, as well as their decomposition into a pure home bias and a Cap Weight component, for our list of 15 home countries. The results are based on portfolios implied by the assumption of global Cap Weight efficiency for a 01/1990 to 12/2012 dataset of S&P Global 1200 index constituents. The decomposition follows Eqs. (15), (18), and (21), where the pure home bias component, $perf\_hbcost^{pureHB}$, refers to the performance loss of a home-biased between-market allocation, and the Cap Weight component $perf\_hbcost^{CapWeight}$ constitutes the marginal performance loss caused by filling this between-market allocation with Cap Weight investments. Panel A reports the results for our standard parameter specifications with a home market weight of 80% and currencies 80% hedged. Panel B reports the mean results over all 14 non-U.S. home countries for home market weights of 70% and 100% and currency hedging levels of 0% and 100%. Total home bias costs are reported in absolute terms only, while their components are also reported as a share of these total home bias costs. p-values based on Newey-West (1987) standard errors that are robust to autocorrelation and heteroskedasticity are reported in parentheses, with *, **, and *** indicating significance at the 10%-, 5%-, and 1%- level.

Panel A: Detailed results for 80% home market weight and currencies 80% hedged

Variable / Country	Total home bias costs	Pure home bias component		Cap Weight component	
	Absolute	Absolute	Relative	Absolute	Relative
Australia	1.41% (0.596)	1.13% (0.630)	80.5%	0.27% (0.842)	19.5%
Belgium	1.33% (0.591)	0.97% (0.633)	73.4%	0.35% (0.801)	26.6%
Canada	1.04% (0.646)	0.74% (0.706)	70.8%	0.30% (0.871)	29.2%
Denmark	1.62% (0.554)	1.30% (0.614)	80.3%	0.32% (0.835)	19.7%
France	0.75% (0.672)	0.62% (0.699)	83.8%	0.12% (0.886)	16.2%
Germany	0.77% (0.711)	0.66% (0.723)	85.8%	0.11% (0.914)	14.2%
Great Britain	0.60% (0.699)	0.47% (0.761)	77.1%	0.14% (0.903)	22.9%
Hong Kong	1.95% (0.572)	1.62% (0.609)	83.0%	0.33% (0.821)	17.0%
Italy	1.34% (0.580)	1.20% (0.608)	89.9%	0.13% (0.898)	10.1%
Japan	1.38% (0.584)	1.05% (0.641)	76.1%	0.33% (0.773)	23.9%
Netherlands	0.78% (0.665)	0.62% (0.698)	78.9%	0.17% (0.852)	21.1%
Singapore	2.00% (0.540)	1.74% (0.583)	86.6%	0.27% (0.906)	13.4%
Sweden	1.22% (0.611)	1.01% (0.625)	83.1%	0.21% (0.886)	16.9%
Switzerland	0.82% (0.675)	0.58% (0.722)	71.2%	0.23% (0.860)	28.8%
United States	0.18% (0.839)	0.13% (0.862)	71.0%	0.05% (0.923)	29.0%
Mean ex U.S.	1.22% (0.300)	0.98% (0.384)	80.3%	0.24% (0.733)	19.7%

Panel B: Mean results (ex U.S.) for different parameter specifications

Variable / Parameter	Total home bias costs	Pure home bias component		Cap Weight component	
	Absolute	Absolute	Relative	Absolute	Relative
70% w_{home}	1.00% (0.331)	0.75% (0.446)	75.0%	0.24% (0.737)	25.0%
100% w_{home}	1.65% (0.260)	1.58% (0.294)	95.8%	0.07% (0.899)	4.2%
0% hedged	0.99% (0.404)	0.78% (0.511)	78.8%	0.21% (0.759)	21.2%
100% hedged	1.21% (0.314)	0.97% (0.391)	80.2%	0.24% (0.737)	19.8%

III. Rational home bias in globalizing markets

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Abstract Both the practical and the academic relevance of home bias largely depend on the extent of the corresponding home bias costs. This paper shows these costs to have halved throughout the 1990 to 2012 period, thereby supporting the hypothesis that international diversification has lost importance over the past decades. Further analysis suggests a home-biased portfolio allocation to have even become rational rather than puzzling for a large number of investors. We find decreasing idiosyncratic risk of individual stocks to be the main driver of this development. With international diversification easily achieved within individual companies in today's globalized world, investors can save the effort of carrying out this diversification themselves.

Keywords Home bias · Time-series trend · Globalization · Cost decomposition · International diversification

JEL Classification G11

1. Introduction

While theory suggests an efficient international diversification to be given by the global, capitalization weighted market portfolio (e.g. Sharpe, 1964), empirical research finds the large majority of both private and institutional investors to heavily overweight their home market (*home bias*). More specifically, these studies typically observe home market weights ranging between 70% and 100% for both the U.S. and international home markets, thereby finding investors' portfolios to be far from efficiently allocated (e.g. French & Poterba, 1991; Britten-Jones, 1994; Cooper & Kaplanis, 1994; Tesar & Werner, 1995; Lewis, 1999; Ahearne et al., 2004; Kho et al., 2009).

The existing home bias literature focuses mainly on explaining the bias, where suggested explanations include among others transaction costs (e.g. Tesar & Werner, 1995; Glassmann & Riddick, 2001; Warnock, 2002), direct barriers to international investments (e.g. Black, 1974; Stulz, 1981; Errunza & Losq, 1981), information quality differences (e.g. Gehrig, 1993; Brennan & Cao, 1997; Van Nieuwerburgh & Veldkamp, 2009), hedging of non-traded goods consumption (e.g. Adler & Dumas, 1983; Stockmann & Dellas, 1989; Cooper & Kaplanis, 1994) or psychological and behavioral factors (e.g. Coval & Moskowitz, 1999; Grinblatt & Keloharju, 2000; Huberman, 2001). Rationalized by globalization-driven decreases in the former of these factors, some more recent evidence also suggests home bias to have decreased slightly over time (e.g. Ahearne et al., 2004; Kho et al., 2009).

What makes home bias puzzling in the first place is the corresponding home bias costs, caused by efficiency losses due to foregone gains of diversification. Naturally, both the practical and the academic relevance of home bias therefore largely depend on the extent of these costs. In this context, intuition suggests that globalization might have eased international diversification not only for investors, thereby reducing home bias over time, but for companies as well. In consequence, investing heavily in domestic companies today might be associated with a much higher international diversification than investing in the very same companies one or two decades ago. With idiosyncratic risk of individual companies thereby potentially decreasing in globalizing markets, the question arises whether, analogous to the home bias itself, home bias costs have decreased over time as well. Given the high marginal costs faced by many investors for investing in foreign rather than domestic assets, decreasing home bias costs in the course of a country's globalization would imply a heavy overweighting of the home market to become rational rather than puzzling for a growing number of investors, thereby having important theoretical and practical implications for investors' portfolio allocation.

Our paper contributes to the existing home bias literature by analyzing the time-series development of home bias costs and its implications for investors' portfolio allocation based on a 1990 to 2012 survivorship bias free dataset of global equities. In particular, we evaluate the trend in benefits of international diversification measuring home bias costs in terms of implied expected performance and realized idiosyncratic risk, thereby covering forward-looking, expected home bias costs, as well as backward-looking, realized home bias costs. Defining a measure of break-even marginal foreign investment costs for each home market, we also analyze the time-series development of the marginal costs for investing in foreign rather than domestic assets that are sufficient for making a home-biased portfolio allocation rational rather than puzzling. Finally, we provide insights on the drivers of these time-series developments by disentangling the dynamics caused by changing idiosyncratic risk of the home market and its individual constituents from those caused by changing correlation and hence changing diversification potential across these stocks and markets under home bias. To allow for comparisons among a wide range of regions, home market sizes, globalization levels, and types of investors, we perform this analysis for 15 different home countries and several parameter specifications.

Our results suggest mean home bias costs to have decreased by a significant 4.93% p.a. to about half of their initial value throughout our 23 year sample period, thereby supporting the hypothesis that international diversification has lost importance over the past decades. The practical implications of this decrease are illustrated by a contemporaneous significant decrease of 4.80% p.a. in mean annual break-even marginal foreign investment costs to a 2010 to 2012 average of 73 basis points. While this result suggests international diversification to remain relevant among investors facing low marginal foreign investment costs (e.g. large institutional investors), a home-biased portfolio allocation seems to have become rational rather than puzzling for an increasingly large number of investors with medium to high marginal foreign investment costs (e.g. private and small institutional investors). Finally, our analysis shows decreasing idiosyncratic risk of individual stocks to be the main driver of this development. A likely explanation of this result is that in today's globalized world, international diversification is easily achieved within individual companies, thereby saving investors the effort of carrying out this diversification themselves.

The rest of this paper is structured as follows. Section 2 and 3 describe the dataset and methodology used throughout the paper. The empirical results of our analysis are provided in section 4. Section 5 concludes.

2. Data

Our empirical analysis is based on a January 1987 to December 2012 dataset of all constituents of the Standard & Poor's (S&P) Global 1200 index, a composite of the seven regional equity indices S&P 500, S&P Europe 350, S&P Topix 150, S&P/TSX 60, S&P/ASX All Australian 50, S&P Asia 50, and S&P Latin America 40. Covering 1'200 stocks with approximately 70% of the world's equity market capitalization, the S&P Global 1200 constitutes a reasonable proxy for the global equity market portfolio.

Data on all historical index constituents is provided by Compustat, a leading financial database owned by S&P. This data includes the dates of all historical index additions and deletions, as well as the constituent-countries.[1] Weekly historical data on constituent market values and both currency-hedged and unhedged U.S.-Dollar constituent total return indices, the 1-year T-bill rate, as well as on spot and 1-year forward exchange (FX) rates from U.S.-Dollar to all relevant currencies, is provided by Thomson Reuters Datastream for the time period from January 1987 to December 2012.[2]

At each point in time t ($t = 1, 2, \dots, T$), we form our universe of n_t risky assets by including the respective time t historical index constituents of the S&P Global 1200, thereby ensuring that the universe of risky assets is free of survivorship bias. Furthermore, for a stock to be included at a given point in time, our methodology requires it to have at least 156 weeks of prior return data.[3] For each desired home currency, we convert the U.S.-Dollar constituent total return indices to the respective currency based on spot

[1] As Compustat does not provide data on the S&P/TSX 60 constituents before January 1999, we approximate its holdings by the 60 largest constituents of the S&P TSX Composite Index in terms of market value at each point of the preceding time period.

[2] We use weekly rather than daily data to alleviate the effect of differences in opening hours between international exchanges.

[3] Since this prior return data is used for covariance estimation only, the resulting multi-period sampling bias should be negligible.

exchange rates.[4] We implement different levels of currency hedging by blending the weekly hedged and unhedged excess returns for each constituent at the required hedging ratio, thereby creating partially hedged excess return series with weekly rebalancing of the FX-hedge.

To generate a risk-free asset for each home currency, we adjust the 1-year T-bill rate based on the 1-year forward-implied interest rate difference.[5] Assuming that the 1-year T-bill constitutes a truly risk-free asset, this provides us with synthetic risk-free assets for all home currencies, including those where no truly risk-free asset is available.

3. Methodology

3.1 Investor portfolios under home bias

We perform our analysis in the standard mean-variance framework, thereby assuming investors to only care about the mean and variance of their overall portfolio. The investment universe at time t consists of a risk-free asset in the investors' respective domestic currency and all n_t risky assets with currency exposure hedged at the desired hedging ratio. Both lending and borrowing is assumed to be possible at the risk-free rate. Following the two fund separation theorem (Tobin, 1958), rational investors will divide their wealth between the tangency portfolio of risky assets, i.e. the combination of risky assets that maximizes the expected Sharpe ratio, and the risk-free asset. At each point in time t, the $n_t \times 1$ vector of weights of the tangency portfolio w_t^{TP} is a function of the $n_t \times 1$ vector of expected excess returns $E_t[r^e]$ and the $n_t \times n_t$ expected covariance matrix $E_t[\Sigma]$, i.e.:

$$w_t^{TP} = f(E_t[r^e], E_t[\Sigma]). \tag{1}$$

Global market efficiency would imply the weights of the tangency portfolio w_t^{TP} to equal those of the global market portfolio of all n_t risky assets, $w_t^{GlobMkt}$ (Sharpe, 1964). While we do not take sides in the debate about market efficiency, our methodology nevertheless assumes $w_t^{TP} = w_t^{GlobMkt}$ to isolate the implications of home bias on portfolio efficiency from other potential sources of inefficiency. Given these assumptions, the rational investor will always hold the efficient global market portfolio, thereby taking

[4] We use the (synthetic) Euro as the home currency for all Eurozone countries throughout the whole sampling period.

[5] In those cases where the forward rate is not available for the full sampling period, we write the T-bill adjustment backwards based on the earliest available observation of the respective adjustment.

full advantage of both between- and within-market diversification and hence not having any home bias costs.

In contrast, the home-biased investor will deviate from the global market portfolio weights by overweighting the domestic stock market. For simplicity, our analysis assumes this investor to be represented by the frequently observed setting where at each point of rebalancing τ the split between domestic and foreign stocks is given by a home market weight w_{home} that substantially exceeds the home market weight of the global market portfolio: $0 \leq w_{t,home}^{GlobMkt} < w_{home} \leq 1$. The within-market allocations for the home and foreign market are completely determined by the respective capitalization-weighted portfolio weights within these markets. That is, let d_{τ}^{home} be a $n_{\tau} \times 1$ vector of home market dummies indicating whether stock $i = 1, 2, \dots, n_{\tau}$ is a home ($d_{\tau,i}^{home} = 1$) or foreign ($d_{\tau,i}^{home} = 0$) market stock, and let d_{τ}^{fgn} be the accordingly defined $n_{\tau} \times 1$ vector of foreign market dummies. Then at each point of rebalancing $\tau = \tau_1, \tau_2, \dots \in t$, the portfolio weights of the home-biased portfolio, w_{τ}^{HB}, are given by:

$$w_{\tau}^{HB} = \frac{w_{home}}{w_{\tau,home}^{GlobMkt}} * w_{\tau}^{GlobMkt} \circ d_{\tau}^{home} + \frac{1 - w_{home}}{1 - w_{\tau,home}^{GlobMkt}} * w_{\tau}^{GlobMkt} \circ d_{\tau}^{fgn}. \qquad (2)$$

In practical terms, this portfolio corresponds to investing shares w_{home} and $(1 - w_{home})$ of the portfolio in index funds replicating the capitalization weighted domestic and foreign stock market indices, respectively.

To allow comparing the costs suffered by the home-biased investor, both the global market portfolio and the home-biased portfolio are rebalanced and (de-)leveraged to an annualized volatility of 20% at points in time $\tau = \tau_1, \tau_2, \dots \in t$ in our analysis.[6] With home bias costs defined as the efficiency loss due to foregone gains of diversification in home-biased portfolios, these costs can then be quantified in terms of several expectation-based and out-of-sample measures based on our two portfolios. In particular, we report

[6] First, at each point of rebalancing τ, we (de-)leverage all portfolios to the time τ volatility of the Global Cap Weight portfolio based on each portfolio's time varying expected volatility, thereby corresponding to the investors' actual (de-)leveraging accuracy. Second, to remove volatility differences between various home markets (e.g. due to currency risk), we (de-)leverage all portfolios to an expected portfolio volatility of 20% based on the average expected portfolio volatility over our sample period. Finally, we remove the small remaining volatility differences by further adjusting the (de-)leveraged empirical return time series based on the realized volatility over the full sample period, thereby ensuring accurate risk-adjusted evaluation of the portfolios.

results based on forward-looking implied expected performance (section 4.1 to 4.3), as well as backward-looking realized idiosyncratic risk (section 4.4).

3.2 Expected home bias costs

Being the least noisy and most stable home bias cost measure over time and across countries, and providing flexibility for computing break-even marginal foreign investment costs and disentangling components of home bias costs, implied expected performance home bias costs (*expected home bias costs*) is the key measure for our analysis. To obtain this measure, inserting our assumption of global market efficiency, $w_t^{TP} = w_t^{GlobMkt}$, into Eq. (1) and rearranging allows us to extract $E_t[r^e]_{impl}$, the $n_t \times 1$ vector of expected excess returns implied by this efficiency assumption, thereby explicitly assuming no home bias, no pricing errors in individual stocks and full inclusion of the expected covariance structure in the portfolio allocation:

$$E_t[r^e]_{impl} = g(w_t^{GlobMkt}, E_t[\Sigma]). \tag{3}$$

Following among others Black and Litterman (1991) and Da Silva et al. (2009), this functional relationship can be concretized as:

$$\widehat{E_t[r^e]}_{impl} = \lambda * \widehat{E_t[\Sigma]} * w_t^{GlobMkt}, \tag{4}$$

where λ is a risk aversion coefficient that scales the implied expected excess returns to reflect investors' required Sharpe Ratio and where $\widehat{E_t[\Sigma]}$ is an estimate of $E_t[\Sigma]$.

To minimize estimation error, we estimate $E_t[\Sigma]$ with a shrinkage approach suggested by Ledoit and Wolf (2003) for the covariance matrix of stock returns when the number of stocks is larger than the number of observations per stock. More specifically, this estimator constitutes the optimally weighted average of the unbiased but very variable sample covariance matrix and the biased but less variable single-index covariance matrix, thereby providing the most efficient trade-off between bias and variance for our type of data. We further alleviate the estimation error by using weekly rather than the commonly employed monthly return data, where we base each estimation on the past 156 weeks of return data.

Whereas the proportions within the covariance matrix are typically found to be fairly persistent over time, this is not necessarily the case for its overall magnitude. For the commonly used case of a time-invariant risk aversion coefficient λ, estimating $E_t[\Sigma]$ based on historical data therefore typically causes large fluctuations in the overall magnitude of $\widehat{E_t[r^e]}_{impl}$. Being mainly caused by realized past covariance magnitudes, these fluctuations are usually inconsistent with actual expectations. We remove this inconsistency by adjusting λ to be time-variant, thereby allowing for the expected global market excess return $E[r^e]^{GlobMkt}$ to be constant over time, i.e.:

$$\widehat{E_t[r^e]}_{impl} = \lambda_t * \widehat{E[\Sigma_t]} * w_t^{GlobMkt} \tag{5}$$

$$with \quad \hat{\lambda}_t = \frac{E[r^e]^{GlobMkt}}{w_t^{GlobMkt^T} * \widehat{E_t[\Sigma]} * w_t^{GlobMkt}}. \tag{6}$$

While we report results based on assuming $E[r^e]^{GlobMkt}$ to equal 6% p.a., note that the relevance of this value is limited to the absolute level of expected home bias costs. In particular, all statistical tests and relative sizes of home bias cost across home countries, components and over time are fully independent of this choice.

The time-series of implied expected returns for an arbitrary portfolio j at points of rebalancing $\tau = \tau_1, \tau_2, \ldots \in t$, $\widehat{E_\tau[r^e]}_{impl}^{j}$, are then obtained based on its respective portfolio weights w_τ^j and the implied expected returns for the n_τ individual stocks from Eqs. (5) and (6), with (de-)leveraging to a certain target volatility performed as described in section 3.1.[7] Given this time-series, we compute our measure of time τ expected home bias costs for the home-biased portfolio, $\widehat{E_\tau[hbc]}^{HB}$, as the difference in implied expected excess returns between the global market portfolio and the home-biased portfolio, that is:

$$\widehat{E_\tau[hbc]}^{HB} = \widehat{E_\tau[r^e]}_{impl}^{GlobMkt} - \widehat{E_\tau[r^e]}_{impl}^{HB}, \tag{7}$$

where $\widehat{E_\tau[r^e]}_{impl}^{GlobMkt}$ and $\widehat{E_\tau[r^e]}_{impl}^{HB}$ are (de-)leveraged time τ implied expected excess returns for the global market portfolio and home-biased portfolio, respectively. Per definition, $\widehat{E_\tau[hbc]}^{HB}$ can only deviate from the true, efficient expectation due to market inefficiency at time τ, differences between $\widehat{E_\tau[\Sigma]}$ and $E_\tau[\Sigma]$, and wrong specification of $E[r^e]^{GlobMkt}$ in Eq. (6). Hence, while the impossibility of quantifying market inefficiencies implies that we cannot calculate the resulting standard errors, the aforementioned sources of disturbance all suggest these standard errors to be comparably

[7] Note that while the absolute of home bias costs depends on the chosen target volatility, all relative comparisons across time and cross-section are independent of this choice.

low, thereby allowing for comparisons across countries, components, and over time in this expectation-based framework.[8]

Given the expected home bias costs at each point of rebalancing τ, $E_\tau\widehat{[hbc]}^{HB}$, we can answer our research question of how home bias costs changed over time by analyzing the time-series trend in this cost measure. A natural starting point for this analysis is testing for a linear trend in expected home bias costs by regressing $E_\tau\widehat{[hbc]}^{HB}$ on the corresponding points in time $\tau = \tau_1, \dots, \tau_k$ and a constant $a_{E[hbc]}^{HB}$:

$$E_\tau\widehat{[hbc]}^{HB} = a_{E[hbc]}^{HB} + \theta_{E[hbc]}^{HB} * \tau + \varepsilon_{\tau,E[hbc]}^{HB}. \tag{8}$$

While easily interpretable, the linear trend merely constitutes a first order approximation of the true underlying relation. Hence, in an alternative specification, we test for a linear trend in the log of expected home bias costs, thereby evaluating the relative change of expected home bias costs, by regressing the natural logarithm of expected home bias costs, $log\left(E\widehat{[hbc_\tau]}^{HB}\right)$, on the corresponding points in time $\tau = \tau_1, \dots, \tau_k$ and a constant $a_{LOG\_E[hbcost]}^{HB}$:

$$log\left(E_\tau\widehat{[hbc]}^{HB}\right) = a_{log(E[hbc])}^{HB} + \theta_{log(E[hbc])}^{HB} * \tau + \varepsilon_{\tau,log(E[hbc])}^{HB}. \tag{9}$$

Based on estimating Eqs. (8) and (9) with OLS, we then obtain our measures of time-series trends in expected home bias costs, $\hat{\theta}_{E[hbc]}^{HB}$ and $\hat{\theta}_{log(E[hbc])}^{HB}$, where we use p-values based on Newey-West (1987) standard errors that are robust to autocorrelation and heteroskedasticity for statistical inference.

3.3 Expected break-even costs

Given our measure of time τ expected home bias costs, $E_\tau\widehat{[hbc]}^{HB}$, we can compute the annual implied expected marginal costs for investing in foreign rather than domestic assets that would make suffering these home bias costs rational (*expected break-even*

[8] In particular, Chopra and Ziemba (1993) find estimation errors in covariances to result in cash equivalent losses that are only about 1/57th to 1/5th of those resulting from estimation errors in expected returns. Furthermore, while both expected and out-of-sample measures are exposed to variation caused by market inefficiencies, the effect is much lower for the implied expected home bias costs. For example, while an overvaluation of 5% causes the annual realized return to be biased upwards by about 0.5% p.a. for a ten year sample period, the increased market weight resulting from this overvaluation will make annual implied expected returns increase by only about 0-3 bps (cf. Eqs. (4) and (5)).

costs).[9] This measure, $E_\tau\widehat{[bec]}^{HB}$, is constructed by spreading the expected home bias costs $E_\tau\widehat{[hbc]}^{HB}$ on the difference in the scaled foreign market weights of the global market portfolio and the home-biased portfolio, respectively, that is:

$$E_\tau\widehat{[bec]}^{HB} = \frac{E_\tau\widehat{[hbc]}^{HB}}{SF_\tau^{GlobMkt} * (1 - w_{\tau,home}^{GlobMkt}) - SF_\tau^{HB} * (1 - w_{home})}, \tag{10}$$

where $SF_\tau^{GlobMkt}$ and SF_τ^{HB} are the time τ scaling factors for adjusting the volatility of the global market portfolio and the home-biased portfolio, respectively, as described in section 3.1. Note that in contrast to home bias costs, break-even costs are measured per unit of foreign investment. Hence, while the level of home bias costs increases with the chosen target volatility, the level of break-even costs is independent of this choice. Depending on the chosen target volatility, break-even costs can therefore be substantially lower than home bias costs.

As for expected home bias costs, we can analyze the question of how expected break-even costs changed over time by testing for a linear trend in both expected break-even costs and their natural logarithm, $log\left(E_\tau\widehat{[bec]}^{HB}\right)$, by regressing each of them on the corresponding points in time $\tau = \tau_1, \ldots, \tau_k$ and a constant $a_{E[bec]}^{HB}$ and $a_{log(E[bec])}^{HB}$, respectively:

$$E_\tau\widehat{[bec]}^{HB} = a_{E[bec]}^{HB} + \theta_{E[bec]}^{HB} * \tau + \varepsilon_{\tau,E[bec]}^{HB}, \tag{11}$$

$$log\left(E_\tau\widehat{[bec]}^{HB}\right) = a_{log(E[bec])}^{HB} + \theta_{log(E[bec])}^{HB} * \tau + \varepsilon_{\tau,log(E[bec])}^{HB}, \tag{12}$$

Based on estimating Eqs. (11) and (12) with OLS, we then obtain our measures of time-series trends in expected break-even costs, $\hat{\theta}_{E[bec]}^{HB}$ and $\hat{\theta}_{log(E[bec])}^{HB}$, where we again use p-values based on Newey-West (1987) standard errors that are robust to autocorrelation and heteroskedasticity for statistical inference.

3.4 Decomposition of expected home bias costs

A trend in expected home bias costs could potentially stem from multiple sources, each of which comes with a different economic interpretation. To provide insights on its main drivers, we decompose this trend into several components.

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[9] Note that this measure neglects several aforementioned potential other sources of home bias and thereby provides and upper bound for investors' actual break-even costs.

In a first step, this involves distinguishing between change caused by dynamics in home market idiosyncratic risk on the one hand and by dynamics in the between-market correlation of home and foreign market on the other hand. To isolate the dynamics in home market idiosyncratic risk, we compute the (de-)leveraged time-series of implied expected excess returns, $\widehat{E_\tau[r^e]}_{impl}^{HFcorr1}$, for a portfolio with home-biased portfolio weights w_τ^{HB} under a modified covariance matrix. In particular, this covariance matrix eliminates all dynamics in between-market correlation by synthetically fixing the between-market correlation at one, that is:

$$\rho_{ij,\tau}^{HFcorr1} = 1 \quad when \quad d_{\tau,i}^{home} \neq d_{\tau,j}^{home} \quad for \quad i,j = 1,2,\dots,n_\tau, \tag{13}$$

where $\rho_{ij,\tau}^{HFcorr1}$ is the synthetic time τ correlation between assets i and j and where $d_{\tau,i}^{home}$ is defined as in Eq. (2). Given this return time-series, we can then define the corresponding contributions of home market idiosyncratic risk and between-market correlation to expected home bias costs, $\widehat{E_\tau[hbc]}^{Hidiorisk}$ and $\widehat{E_\tau[hbc]}^{BetweenCorr}$, respectively, as:[10]

$$\widehat{E_\tau[hbc]}^{Hidiorisk} = \widehat{E[r_t^e]}_{\tau,impl}^{GlobMkt} - \widehat{E[r_t^e]}_{\tau,impl}^{HFcorr1}, \tag{14}$$

and $$\widehat{E_\tau[hbc]}^{BetweenCorr} = \widehat{E_\tau[hbc]}^{HB} - \widehat{E_\tau[hbc]}^{Hidiorisk}. \tag{15}$$

As for overall expected home bias costs, we then test for a trend in each of these contributions by estimating regressions of the respective cost measures and their natural logarithm on a constant and the corresponding points in time analogous to Eqs. (8) and (9).

In a second step, we further decompose the change caused by dynamics in home market idiosyncratic risk into change caused by dynamics in individual home market stock idiosyncratic risk and in the corresponding correlations within the home market. To do this, we extend the modification of correlations in Eq. (13) to correlations between home market stocks as well, thereby synthetically also eliminating all dynamics in within-market correlations in the home market, that is:

$$\rho_{ij,\tau}^{HMScorr1} = 1 \quad when \quad d_{\tau,i}^{home} = 1 \quad or \quad for \quad i,j = 1,2,\dots,n_\tau, \tag{16}$$

where $\rho_{ij,\tau}^{HMScorr1}$ is the synthetic time τ correlation between assets i and j and where $d_{\tau,i}^{home}$ is defined as in Eq. (2). Given the (de-)leveraged implied excess return series under

[10] Note that the contribution of between-market correlation, $E[hbcost]_\tau^{BetweenCorr}$, will always be ≤0 by definition.

this assumption, $\widehat{E[r_t^e]}_{\tau,impl}^{HMScorr1}$, we can then define the corresponding contributions of individual home market stock idiosyncratic risk and within-market correlations, $\widehat{E_\tau[hbc]}^{HMSidiorisk}$ and $\widehat{E_\tau[hbc]}^{WithinCorr}$, as:

$$\widehat{E_\tau[hbc]}^{HMSidiorisk} = \widehat{E[r_t^e]}_{\tau,impl}^{GlobMkt} - \widehat{E[r_t^e]}_{\tau,impl}^{HMScorr1}, \tag{17}$$

and
$$\widehat{E_\tau[hbc]}^{WithinCorr} = \widehat{E_\tau[hbc]}^{Hidiorisk} - \widehat{E_\tau[hbc]}^{HMSidiorisk}. \tag{18}$$

We again test for a trend in each of these contributions by estimating regressions of the respective cost measures on a constant and the corresponding points in time analogous to Eq. (8).

3.5 Idiosyncratic risk home bias costs

With noise and a dynamic covariance structure adding complexity to the analysis out-of-sample, further measures are required to test whether the expectation-based findings also materialize in terms of realized, out-of-sample home bias costs. Recalling that home bias costs are nothing more than foregone gains of diversification, the most natural out-of-sample measure is the realized idiosyncratic, uncompensated risk that investors have taken in the presence of home bias.[11] In particular, we define idiosyncratic risk home bias costs between two points in time τ_i and τ_{i+1}, $irisk_{[\tau_i,\tau_{i+1}]}^{HB}$, as one minus the R^2 from regressing the (de-)leveraged excess returns of the home-biased portfolio on those of the global market portfolio and a constant over the time period $[\tau_i, \tau_{i+1}]$, that is:

$$irisk_{[\tau_i,\tau_{i+1}]}^{HB} = 1 - R_{[\tau_i,\tau_{i+1}]}^2 = \frac{SS_{res,[\tau_i,\tau_{i+1}]}^{HB}}{SS_{tot,[\tau_i,\tau_{i+1}]}^{HB}}, \tag{19}$$

where $SS_{tot,[\tau_i,\tau_{i+1}]}^{j}$ and $SS_{res,[\tau_i,\tau_{i+1}]}^{j}$ are the total sum of squares and residual sum of squares from estimating

$$r_t^{e,HB} = \alpha_{[\tau_i,\tau_{i+1}]}^{HB} + \beta_{[\tau_i,\tau_{i+1}]}^{HB} r_t^{e,GlobMkt} + \varepsilon_t^{HB} \tag{20}$$

[11] While we would also be interested in how idiosyncratic risk home bias costs translate into realized performance differences, although taking idiosyncratic risk is inefficient in general, taking more systematic risk instead only results in better performance when market excess returns are positive. In consequence, given the generally volatile stock markets and low excess returns during our sample period, we would not expect any economically or statistically sensible or robust findings from analyzing the time-series trend in short-time realized performance home bias costs.

over the time period $[\tau_i, \tau_{i+1}]$, and where $r_t^{e,HB}$ and $r_t^{e,GlobMkt}$ are the time t (de-)leveraged excess returns of the home-biased portfolio and the global market portfolio, respectively. Consistent with our annual rebalancing frequency, we estimate idiosyncratic risk home bias costs over 52 weeks periods, thereby having each idiosyncratic risk home bias cost observation cover the period between two subsequent points of rebalancing.

As for expected home bias costs, we analyze the time-series trend in idiosyncratic risk home bias costs by regressing the time-series of idiosyncratic risk home bias costs, $irisk_{[\tau_1,\tau_2]}^{HB}$, …, $irisk_{[\tau_{k-1},\tau_k]}^{HB}$, on the respective starting points $\tau_i = \tau_1, \dots, \tau_{k-1}$ of the time periods and a constant a_{irisk}^{HB}:

$$irisk_{[\tau_i,\tau_{i+1}]}^{HB} = a_{irisk}^{HB} + \theta_{irisk}^{HB} * \tau_i + \varepsilon_{\tau_i,irisk}^{HB}, \tag{21}$$

In an alternative specification, we again test for a linear trend in the log of home bias costs, thereby evaluating a linear trend in the relative change of home bias costs, by regressing the natural logarithm of idiosyncratic risk home bias costs, $log\left(irisk_{[\tau_i,\tau_{i+1}]}^{HB}\right)$, on the corresponding points in time $\tau = \tau_1, \dots, \tau_{k-1}$ and a constant $a_{LOG\_irisk}^{HB}$:

$$log\left(irisk_{[\tau_i,\tau_{i+1}]}^{HB}\right) = a_{log(irisk)}^{HB} + \theta_{log(irisk)}^{HB} * \tau_i + e_{\tau_i,log(irisk)}^{HB}, \tag{22}$$

Based on estimating Eqs. (21) and (22) with OLS, we then obtain our measures of time-series trends in expected home bias costs, $\hat{\theta}_{irisk}^{HB}$ and $\theta_{log(irisk)}^{HB}$, where we use p-values based on Newey-West (1987) standard errors that are robust to autocorrelation and heteroskedasticity for statistical inference.

3.6 Parameter specifications

We perform our analysis for 15 different home countries, where we use those 15 countries that have the largest number of stocks within our universe of n_t risky assets on December 28, 1989. The resulting list of home countries contains Australia, Belgium, Canada, Denmark, France, Germany, Great Britain, Hong Kong, Italy, Japan, the Netherlands, Singapore, Sweden, Switzerland, and the USA, thereby allowing for comparisons among a wide range of regions, home market sizes, and globalization levels.[12] Our standard parameter specification assumes a home market weight of 80%,[13] a

[12] Note that we drop the country indices in all of our variables for clarity.

rebalancing frequency of 52 weeks[14] with $t = 1 = \tau_1$ corresponding to December 28, 1989 (i.e. annual rebalancing with $\tau = 1, 53, 105, \ldots$), and currency risk being 80% hedged.[15] To reflect different degrees of home bias and currency hedging that might apply to different types of investors and regions, as well as to check our results robustness towards changes in these parameter specifications, we also report results for home market weights of 70% and 100% and for currency hedging levels of 0% and 100%.

4. Results

4.1. Expected home bias costs

The results for annualized expected home bias costs computed following Eq. (7) are shown in Table I. Panel A reports the results for all 15 choices of home countries using our standard parameter specifications with a home market weight of 80% and currency risk 80% hedged. For the home-biased U.S. investor, we find annual home bias costs to be at 18 basis points (*bps*) on average over our 23 year sample period. Not surprisingly, with decreasing capitalization and increasing idiosyncratic risk of the home market, these costs increase and are within an economically significant range of 71 bps (Great Britain) to 270 bps (Singapore) for all other home countries, with mean annual home bias costs being 148 bps across all 15 home countries.

More interestingly, when analyzing linear trends in annual home bias costs and in their natural logarithm following Eqs. (8) and (9), we find these costs to have decreased significantly over time for almost all home countries. In particular, while home bias costs have stayed roughly flat with temporary increase and decrease in Japan, we find annual decreases in the range of 1.4 bps (United States) to 10.2 bps (Sweden) in absolute terms and 2.56% (Singapore) to 8.86% (Italy) in relative terms for the remaining home countries, where the mean annual decrease is at 6.9 bps or 4.93%, respectively. Not only

[13] The choice of this value is based on the average findings within the existing literature (e.g. French & Poterba, 1991; Britten-Jones, 1994; Cooper & Kaplanis, 1994; Tesar & Werner, 1995; Lewis, 1999; Ahearne et al., 2004; Kho et al., 2009).

[14] Unreported robustness checks suggest that our results are not sensitive to changes in the rebalancing frequency to e.g. 26 or 13 weeks.

[15] The assumption of 80% currency risk hedging is based on the equivalent assumption in Black (1989) and Black and Litterman (1992), following their reasoning that in a global equilibrium all investors want to take a small amount of currency risk.

are these decreases statistically significant for all home countries except Singapore and hence robust across countries, but they are also economically significant. That is, with the 2010 to 2012 average of annual home bias costs being only 77 bps for the mean home country, these costs have come down to less than half of their 1990 to 1992 average of 177 bps. Figure I shows this development in terms of individual observations and the two regression lines for the mean home country. Despite their approximate nature, both regression lines seem to fit the individual observations quite well. While our first set of results do not yet reveal the ultimate drivers and consequences of this decrease, they strongly support the hypothesis that international diversification has lost importance over the past decades.

The robustness of a negative trend in home bias costs is further supported when considering alternative parameter specifications that correspond to different types of investors. Panel B of Table I reports the mean results over all 15 home countries for home market weights of 70% and 100% and currency hedging levels of 0% and 100%. Average annual home bias costs over the first three years naturally increase with increasing home market weight with a range of 142 bps to 248 bps throughout specifications and are roughly stable over different currency hedging levels. More importantly, the highly significant decreases in home bias costs over time are robust across all parameter specifications, thereby lending further support to the hypothesis of decreasing importance of international diversification.

4.2. Expected break-even costs

Having found strong evidence for decreasing importance of international diversification, we are interested in how this decrease affects investors' portfolio allocation. To see this, our measure of break-even marginal foreign investment costs, computed following Eq. (10), illustrates what marginal annual costs for investing in a unit of foreign rather than domestic stocks would make investors indifferent between holding a home-biased and a globally diversified portfolio. Table II shows our findings for expected break-even costs, where Panel A again reports the results for all 15 choices of home countries using our standard parameter specifications with a home market weight of 80% and currency risk 80% hedged. While the cross country variations in break-even costs can differ from those in expected home bias costs in both magnitude and trend due to differences in the magnitude and trend of the home market capitalization, break-even costs generally show a similar picture as home bias costs. That is, whereas the average break-even costs are a relatively small 39 bps p.a. for the home-biased U.S. investor, they are again increasing with decreasing capitalization and increasing idiosyncratic risk of the home market and lie in an economically significant range of 74 bps p.a. (Great Britain) to 236 bps p.a. (Denmark) for all non-U.S. home countries. For the mean home country, we find average annual break-even costs of 137 bps.

While these figures suggest international diversification to have provided benefits to many investors in the average year in our 23 year sample period, the linear trends in expected break-even costs and in their natural logarithm estimated following Eqs. (11) and (12) are significantly negative for all 15 home countries in economic terms and for all home countries except Japan and Singapore in statistical terms. Specifically, we find annual decreases in the range of 1.2 bps (Japan) to 13.1 bps (Italy) in absolute and 1.04% (Japan) to 8.62% (Germany, Italy) in relative terms, where the mean annual decrease is at 6.2 bps or 4.82%, respectively. Figure II shows this development in terms of individual observations and the two regression lines for the mean home country. Despite their approximate nature, both regression lines seem to fit the individual observations quite well and correspond closely to those for expected home bias costs in relative terms. While this is not particularly surprising given the strong connection between expected home bias costs and expected break-even costs, the range of only 14 bps (United States) to 149 bps (Belgium) for the 2010 to 2012 average of annual break-even costs with a 73 bps mean across countries nicely illustrates the economic implications of decreasing home bias and break-even costs. That is, although our findings suggest international diversification to remain relevant among investors facing low marginal foreign investment costs (e.g. large institutional investors), a home-biased portfolio allocation seems to have become rational rather than puzzling for an increasingly large number of investors with medium to high marginal foreign investment costs (e.g. private and small institutional investors) throughout the past decades.

Reporting the mean results over all 15 home countries for home market weights of 70% and 100% and currency hedging levels of 0% and 100%, Panel B of Table II shows these results to be robust across alternative parameter specifications that correspond to different types of investors. In particular, average annual break-even costs naturally increase with increasing home market weight with a range of 125 bps to 157 bps throughout specifications and are somewhat higher for the fully unhedged variation. More importantly, the highly significant decreases in break-even costs over time are robust across all parameter specifications, thereby lending further support to the hypothesis that home bias might have become rational for an increasing number of investors over the past decades.

4.3. Decomposition of expected home bias costs

Given the strong evidence on home bias having become rational for an increasing number of investors, we would like to provide insights on the main drivers of this development. Table III shows the absolute trend in expected home bias costs as obtained in section 4.1 (column 1), as well as its decomposition (columns 2-5). In a first step, we decompose the trend into contributions of dynamics in between-market correlation of home and foreign market on the one hand (column 2) and dynamics in home market idiosyncratic risk on the other hand (column 3) following Eqs. (14) to (15). In a second step, we further decompose the change caused by dynamics in home market idiosyncratic risk into the contributions of dynamics in within-market correlation (column 4) and dynamics in individual home market stock idiosyncratic risk (column 5) following Eqs. (17) to (18).

Panel A reports the results for all 15 choices of home countries using our standard parameter specifications with a home market weight of 80% and currency risk 80% hedged. For 12 out of our 15 home countries, the dynamics in between-market correlation (column 2) have a positive effect on annual home bias costs, with a statistically highly significant but economically rather negligible mean trend of 0.5 bps p.a. Given the significantly negative trend in annual home bias costs (column 1), this indicates that this overall trend is more than fully driven by dynamics in home market idiosyncratic risk for the large majority of home countries. More specifically, while the mean trend in annual home bias costs amounts to -6.9 bps p.a., dynamics in home market inefficiency contribute -7.3 bps p.a. to this decrease. Consistent with our findings on the overall trend in home bias costs, we find Japan to deviate from all other home countries. For the remaining home countries, we find the contribution of dynamics in home market inefficiency to be in the economically significant range of -2.3 bps p.a. (United States) to -16.2 bps p.a. (Italy), where except for Singapore all results are statistically highly significant. A further decomposition of this component shows within-market correlation (column 4) to have a statistically and economically minor contribution that heavily depends on the chosen home country, whereas most of the negative trend in home bias costs is driven by dynamics in individual stock idiosyncratic risk. In particular, these dynamics contribute a statistically and economically significant -6.3 bps p.a. to the -6.9 bps p.a. decrease in annual home bias costs over our 23 year sample period. The range of -4.7 bps p.a. (Singapore, United States) to -12.5 bps p.a. (Italy) among the 14 home countries, with statistical significance for all except Singapore, shows these findings to be robust across home countries. Hence, while changing correlations between stocks and markets have contributed slightly to vanishing home bias costs in some countries, our findings support the hypothesis that decreasing idiosyncratic risk of individual home market stocks is the main driver of home bias having become rational for a large number of investors. A likely explanation of this decrease in individual stock idiosyncratic risk is that globalization has eased international diversification not only for investors (e.g. Ahearne et al., 2004; Kho et al., 2009), but for companies as well. With international diversification therefore heavily implemented on a company level, private investors can avoid the effort of carrying out this diversification heavily themselves.

Reporting the mean results over all 15 home countries for home market weights of 70% and 100% and currency hedging levels of 0% and 100%, Panel B again shows these findings to be robust across alternative parameter specifications that correspond to different types of investors. In particular, while the contribution of dynamics in between-market correlation is only significant statistically but not economically, dynamics in within-market correlation again lack statistical significance. In consequence, as for our standard specification, the statistically and economically highly significant dynamics in individual stock idiosyncratic risk are the main driver of decreasing home bias cost across all alternative parameter specifications. The robustness of our results lends further support to the hypothesis of globalization having caused home bias to become rational for a large number of investors.

4.4. Idiosyncratic risk home bias costs

The evidence of a statistically and economically highly significant decrease in home bias costs over time in the expectation-based framework raises the question whether this trend also materializes out-of-sample, where noise and a dynamic covariance structure are present. Computed following Eqs. (19) and (20), Table IV therefore shows the results based on realized idiosyncratic risk home bias costs, the most natural out-of-sample measure of investors' foregone gains of diversification under home bias. Panel A reports the results for all 15 choices of home countries using our standard parameter specifications with a home market weight of 80% and currency risk 80% hedged. Average annual idiosyncratic risk home bias costs over the full sample period are economically highly significant for most home countries. With a range of 7.2% (United States) to 60.8% (Singapore) and a mean of 38.8% across all home countries, our results indicate that the uncompensated risk taken by the average home-biased investor accounts for more than one third of his total portfolio risk throughout our 23 year sample period.

More interestingly, when analyzing linear trends in annual idiosyncratic risk home bias costs and in their natural logarithm following Eqs. (21) and (22), consistent with expected home bias costs we find these costs to have decreased significantly over time for almost all home countries. In particular, while home bias costs have again stayed roughly flat in Japan, we find annual decreases in the range of 0.63 percentage points (United States) to 3.26 percentage points (Italy) in absolute terms and 2.76% (Singapore) to 8.41% (France) in relative terms for the remaining home countries, where the mean annual decrease is at 1.69 percentage points or 4.34%, respectively. Not only are these decreases statistically significant for all home countries and hence robust across countries, but they are also economically significant. That is, with the 2010 to 2012 average of annual home bias costs being only 24.1% for the mean home country, these costs have come down to roughly 60% of what we found on average over the full 23 year sample period. Figure III shows this development in terms of individual observations and the two regression lines for the mean home country. Again, both regression lines seem to fit the individual observations quite well. Overall, these results suggest our expectation-based findings to be robust out-of-sample, thereby further supporting the hypothesis that international diversification has lost importance over the past decades.

The robustness of our results is further supported when considering alternative parameter specifications that correspond to different types of investors. Panel B of Table IV reports the mean results over all 15 home countries for home market weights of 70% and 100% and currency hedging levels of 0% and 100%. Average annual home bias costs naturally increase with increasing home market weight with a range of 32.9% to 49.3% throughout specifications and are roughly stable over different currency hedging levels. More importantly, the highly significant decreases in home bias costs over time are robust across all parameter specifications, thereby lending further support to the hypothesis of decreasing importance of international diversification.

5. Conclusions

While theory suggests an efficient international diversification to be given by the global, capitalization weighted market portfolio, empirical research finds a home bias in the large majority of both private and institutional investors' portfolios. Both the practical and the academic relevance of this bias largely depend on the extent of the corresponding home bias costs. In this context, intuition suggests that globalization might have eased international diversification not only for investors, but for companies as well. With idiosyncratic risk of individual companies thereby potentially decreasing in globalizing markets, the question arises whether home bias costs have decreased over time.

Our paper contributes to the existing home bias literature by analyzing the time-series development of home bias costs and its implications for investors' portfolio allocation based on a 1990 to 2012 survivorship bias free dataset of global equities. Our results suggest home bias costs to have decreased significantly to about half of their initial value throughout our 23 year sample period, thereby supporting the hypothesis that international diversification has lost importance over the past decades. The practical implications of this decrease are illustrated by our findings of a contemporaneous significant decrease in annual break-even marginal foreign investment costs to a 2010 to 2012 mean of 73 basis points. While this result suggests international diversification to remain relevant among investors facing low marginal foreign investment costs (e.g. large institutional investors), a home-biased portfolio allocation seems to have become rational rather than puzzling for an increasingly large number of investors with medium to high marginal foreign investment costs (e.g. private and small institutional investors). Finally, our analysis shows decreasing idiosyncratic risk of individual stocks to be the main driver of this development. A likely explanation of this result is that in today's globalized world, international diversification is easily achieved within individual companies, thereby saving private investors the effort of carrying out this diversification themselves.

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Tables

Table I: Expected home bias costs over time

This table reports the average of annualized expected home bias costs as defined in Eq. (7) over the first three observations (1990-1992), the full sample period, and the last three observations (2010-2012), as well as their absolute and relative annual trend computed following Eqs. (8) and (9), for our list of 15 home countries. The calculations are based on the expected excess returns implied by the assumption of global market efficiency using Eqs. (5) and (6) for a 01/1990 to 12/2012 dataset of S&P Global 1200 index constituents. Panel A reports the results for our standard parameter specifications with a home market weight of 80%, currencies 80% hedged, and annual observations. Panel B reports the mean results over all 15 home countries for home market weights of 70% and 100% and currency hedging levels of 0% and 100%. p-values based on Newey-West (1987) standard errors that are robust to autocorrelation and heteroskedasticity are reported in parentheses, with *, **, and *** indicating significance at the 10%-, 5%-, and 1%- level.

Panel A: Detailed results for 80% home market weight and currencies 80% hedged

Country \ Variable	Average 1990-1992	Average	Average 2010-2012	Absolute Trend (p.a.) $100 * coeff.$	Absolute Trend (p.a.) Adjusted R^2	Relative Trend (p.a.) $exp(coeff.) - 1$	Relative Trend (p.a.) Adjusted R^2
Australia	262 bps	191 bps	83 bps	-0.093*** (0.000)	0.771	-5.41%*** (0.000)	0.768
Belgium	194 bps	167 bps	162 bps	-0.046** (0.010)	0.346	-2.65%** (0.014)	0.322
Canada	144 bps	127 bps	63 bps	-0.058*** (0.001)	0.454	-4.95%*** (0.000)	0.509
Denmark	280 bps	262 bps	149 bps	-0.092*** (0.003)	0.471	-4.07%*** (0.002)	0.504
France	167 bps	93 bps	29 bps	-0.077*** (0.000)	0.811	-8.75%*** (0.000)	0.907
Germany	167 bps	101 bps	32 bps	-0.081*** (0.000)	0.755	-8.58%*** (0.000)	0.847
Great Britain	103 bps	71 bps	27 bps	-0.044*** (0.000)	0.776	-6.83%*** (0.000)	0.812
Hong Kong	293 bps	244 bps	142 bps	-0.087*** (0.000)	0.599	-3.84%*** (0.000)	0.606
Italy	239 bps	186 bps	58 bps	-0.153*** (0.001)	0.552	-8.86%*** (0.000)	0.740
Japan	70 bps	129 bps	91 bps	0.000 (0.983)	-0.045	0.19% (0.920)	-0.044
Netherlands	131 bps	97 bps	52 bps	-0.052*** (0.000)	0.587	-5.33%*** (0.000)	0.614
Singapore	168 bps	270 bps	140 bps	-0.069 (0.245)	0.102	-2.56% (0.245)	0.120
Sweden	253 bps	165 bps	70 bps	-0.102*** (0.000)	0.834	-6.54%*** (0.000)	0.875
Switzerland	154 bps	108 bps	52 bps	-0.059*** (0.000)	0.674	-5.59%*** (0.000)	0.752
United States	29 bps	18 bps	7 bps	-0.014*** (0.001)	0.357	-6.95%*** (0.001)	0.385
Mean	177 bps	148 bps	77 bps	-0.069%*** (0.000)	0.667	-4.93%*** (0.000)	0.732

Panel B: Mean results for different parameter specifications

Parameter \ Variable	Average 1990-1992	Average	Average 2010-2012	Absolute Trend (p.a.) $100 * coeff.$	Absolute Trend (p.a.) Adjusted R^2	Relative Trend (p.a.) $exp(coeff.) - 1$	Relative Trend (p.a.) Adjusted R^2
70% w_{home}	142 bps	120 bps	60 bps	-0.058*** (0.000)	0.640	-5.15%*** (0.000)	0.716
100% w_{home}	248 bps	206 bps	116 bps	-0.088*** (0.000)	0.713	-4.49%*** (0.000)	0.761
0% hedged	190 bps	156 bps	100 bps	-0.061*** (0.000)	0.654	-4.01%*** (0.000)	0.686
100% hedged	176 bps	150 bps	78 bps	-0.070*** (0.000)	0.639	-4.95%*** (0.000)	0.714

Table II: Break-even marginal foreign investment costs over time

This table reports the average of annualized expected break-even foreign investment costs as defined in Eq. (10) over the first three observations (1990-1992), the full sample period, and the last three observations (2010-2012), as well as their absolute and relative annual trend computed following Eqs. (11) and (12), for our list of 15 home countries. The calculations are based on the expected excess returns implied by the assumption of global market efficiency using Eqs. (5) and (6) for a 01/1990 to 12/2012 dataset of S&P Global 1200 index constituents. Panel A reports the results for our standard parameter specifications with a home market weight of 80%, currencies 80% hedged, and annual observations. Panel B reports the mean results over all 15 home countries for home market weights of 70% and 100% and currency hedging levels of 0% and 100%. p-values based on Newey-West (1987) standard errors that are robust to autocorrelation and heteroskedasticity are reported in parentheses, with *, **, and *** indicating significance at the 10%-, 5%-, and 1%- level.

Panel A: Detailed results for 80% home market weight and currencies 80% hedged

Country \ Variable	Average 1990-1992	Average	Average 2010-2012	Absolute Trend (p.a.)		Relative Trend (p.a.)	
				$100 * coeff.$	Adjusted R^2	$exp(coeff.) - 1$	Adjusted R^2
Australia	237 bps	178 bps	78 bps	-0.081*** (0.000)	0.746	-5.09%*** (0.000)	0.746
Belgium	175 bps	151 bps	149 bps	-0.042** (0.014)	0.330	-2.65%** (0.020)	0.304
Canada	136 bps	115 bps	59 bps	-0.052*** (0.001)	0.489	-4.87%*** (0.000)	0.523
Denmark	261 bps	236 bps	135 bps	-0.085*** (0.002)	0.498	-4.14%*** (0.001)	0.527
France	155 bps	86 bps	28 bps	-0.071*** (0.000)	0.818	-8.53%*** (0.000)	0.904
Germany	156 bps	94 bps	30 bps	-0.077*** (0.000)	0.744	-8.62%*** (0.000)	0.839
Great Britain	109 bps	74 bps	28 bps	-0.046*** (0.000)	0.805	-6.87%*** (0.000)	0.818
Hong Kong	252 bps	211 bps	134 bps	-0.070*** (0.000)	0.583	-3.47%*** (0.000)	0.593
Italy	218 bps	163 bps	52 bps	-0.131*** (0.000)	0.589	-8.62%*** (0.000)	0.756
Japan	104 bps	143 bps	97 bps	-0.012 (0.570)	-0.16	-1.04% (0.494)	0.002
Netherlands	119 bps	88 bps	48 bps	-0.048*** (0.000)	0.578	-5.39%*** (0.000)	0.598
Singapore	140 bps	233 bps	130 bps	-0.051 (0.307)	0.073	-2.05% (0.343)	0.070
Sweden	211 bps	138 bps	62 bps	-0.082*** (0.000)	0.844	-6.23%*** (0.000)	0.875
Switzerland	144 bps	104 bps	52 bps	-0.054*** (0.000)	0.661	-5.27%*** (0.000)	0.733
United States	57 bps	39 bps	14 bps	-0.030*** (0.002)	0.384	-7.25%*** (0.000)	0.525
Mean	165 bps	137 bps	73 bps	-0.062*** (0.000)	0.691	-4.80%*** (0.000)	0.749

Panel B: Mean results for different parameter specifications

Parameter \ Variable	Average 1990-1992	Average	Average 2010-2012	Absolute Trend (p.a.)		Relative Trend (p.a.)	
				$100 * coeff.$	Adjusted R^2	$exp(coeff.) - 1$	Adjusted R^2
70% w_{home}	150 bps	125 bps	65 bps	-0.058*** (0.000)	0.677	-4.96%*** (0.000)	0.741
100% w_{home}	190 bps	157 bps	88 bps	-0.067*** (0.000)	0.610	-4.52%*** (0.000)	0.633
0% hedged	199 bps	160 bps	101 bps	-0.064*** (0.000)	0.697	-4.11%*** (0.000)	0.725
100% hedged	163 bps	138 bps	74 bps	-0.063*** (0.000)	0.659	-4.80%*** (0.000)	0.727

Table III: Decomposition of expected home bias costs

This table reports the absolute trend in expected home bias costs as well as its components for our list of 15 home countries. The calculations are based on the expected excess returns implied by the assumption of global market efficiency using Eqs. (5) and (6) for a 01/1990 to 12/2012 dataset of S&P Global 1200 index constituents. The decomposition follows section 3.4, where each column show the trend in home bias costs caused by the respective component. Panel A reports the results for our standard parameter specifications with a home market weight of 80%, currencies 80% hedged, and annual observations. Panel B reports the mean results over all 15 home countries for home market weights of 70% and 100% and currency hedging levels of 0% and 100%. p-values based on Newey-West (1987) standard errors that are robust to autocorrelation and heteroskedasticity are reported in parentheses, with *, **, and *** indicating significance at the 10%-, 5%-, and 1%- level.

Panel A: Detailed results for 80% home market weight and currencies 80% hedged

Variable / Country	Trend in home bias costs (p.a.)		Components of trend in home bias costs				Components of change caused by dynamics in home market idiosyncratic risk			
			Between-market correlation		Home market idiosyncratic risk		Within-market correlation		Individual stock idiosyncratic risk	
	$100 * coeff.$	Adj. R^2	$100 * coeff.$	Adj. R^2	$100 * coeff.$	Adj. R^2	$100 * coeff.$	Adj. R^2	$100 * coeff.$	Adj. R^2
Australia	-0.093***	0.768	0.007	0.163	-0.101***	0.758	-0.049***	0.581	-0.052**	0.352
	(0.000)		(0.125)		(0.000)		(0.001)		(0.034)	
Belgium	-0.046**	0.322	0.005*	0.178	-0.051**	0.308	0.007	0.017	-0.058***	0.340
	(0.010)		(0.077)		(0.013)		(0.332)		(0.003)	
Canada	-0.058***	0.509	0.010***	0.484	-0.069***	0.539	0.000	-0.045	-0.069**	0.335
	(0.001)		(0.000)		(0.001)		(0.999)		(0.015)	
Denmark	-0.092***	0.504	0.008***	0.497	-0.100***	0.522	-0.024**	0.271	-0.077***	0.449
	(0.003)		(0.000)		(0.002)		(0.027)		(0.006)	
France	-0.077***	0.907	0.011***	0.312	-0.088***	0.888	0.008	-0.004	-0.096***	0.752
	(0.000)		(0.000)		(0.000)		(0.638)		(0.000)	
Germany	-0.081***	0.847	0.013***	0.333	-0.094***	0.821	-0.014	0.060	-0.080***	0.601
	(0.000)		(0.000)		(0.000)		(0.344)		(0.000)	
Great Britain	-0.044***	0.812	0.008***	0.308	-0.052***	0.796	0.009	-0.014	-0.061**	0.457
	(0.000)		(0.000)		(0.000)		(0.641)		(0.012)	
Hong Kong	-0.087***	0.606	-0.000	-0.044	-0.087***	0.610	-0.006	0.012	-0.081***	0.577
	(0.000)		(0.895)		(0.000)		(0.304)		(0.000)	
Italy	-0.153***	0.740	0.010***	0.634	-0.162***	0.751	-0.037	0.238	-0.125***	0.623
	(0.001)		(0.000)		(0.000)		(0.101)		(0.002)	
Japan	0.000	-0.044	-0.025*	0.306	0.026	0.133	-0.001	-0.044	0.027	0.033
	(0.983)		(0.010)		(0.349)		(0.884)		(0.452)	
Netherlands	-0.052***	0.614	0.009***	0.169	-0.061***	0.569	-0.016	0.136	-0.045**	0.258
	(0.000)		(0.002)		(0.000)		(0.211)		(0.040)	
Singapore	-0.069	0.120	-0.005**	0.363	-0.064	0.082	-0.017*	0.064	-0.047	0.033
	(0.245)		(0.029)		(0.291)		(0.073)		(0.399)	
Sweden	-0.102***	0.875	0.006***	0.658	-0.107***	0.877	-0.030**	0.284	-0.077***	0.610
	(0.000)		(0.000)		(0.000)		(0.044)		(0.000)	
Switzerland	-0.059***	0.752	0.006***	0.420	-0.065***	0.735	-0.011*	0.158	-0.053***	0.446
	(0.000)		(0.000)		(0.000)		(0.083)		(0.001)	
United States	-0.014***	0.385	0.010	-0.001	-0.023**	0.100	0.024	0.121	-0.047*	0.228
	(0.001)		(0.181)		(0.026)		(0.220)		(0.082)	
Mean	-0.069***	0.732	0.005***	0.809	-0.073***	0.746	-0.011	0.097	-0.063***	0.525
	(0.000)		(0.000)		(0.000)		(0.291)		(0.006)	

Panel B: Mean results for different parameter specifications

Variable / Parameter	Trend in home bias costs (p.a.)		Components of trend in home bias costs				Components of change caused by dynamics in home market inefficiency			
			Between-market correlation		Home market idiosyncratic risk		Within-market correlation		Individual stock idiosyncratic risk	
	$100 * coeff.$	Adj. R^2	$100 * coeff.$	Adj. R^2	$100 * coeff.$	Adj. R^2	$100 * coeff.$	Adj. R^2	$100 * coeff.$	Adj. R^2
70% w_{home}	-0.058***	0.716	0.009***	0.829	-0.066***	0.738	-0.007	0.013	-0.060***	0.511
	(0.000)		(0.000		(0.000)		(0.507)		(0.007)	
100% w_{home}	-0.088***	0.761	-0.002***	0.560	-0.086***	0.761	-0.019*	0.331	-0.067***	0.553
	(0.000)		(0.000)		(0.000)		(0.054)		(0.004)	
0% hedged	-0.061***	0.686	0.006***	0.738	-0.067***	0.703	-0.015	0.246	-0.052***	0.509
	(0.000)		(0.000)		(0.000)		(0.103)		(0.004)	
100% hedged	-0.070***	0.714	0.004***	0.784	-0.074***	0.724	-0.010	0.090	-0.064***	0.515
	(0.000)		(0.000)		(0.000)		(0.302)		(0.007)	

Table IV: Idiosyncratic risk home bias costs over time

This table reports the average of annual idiosyncratic risk home bias costs as defined in Eq. (19) over the first three observations (1990-1992), the full sample period, and the last three observations (2010-2012), as well as their absolute and relative annual trend computed following Eqs. (21) and (22), for our list of 15 home countries. Panel A reports the results for our standard parameter specifications with a home market weight of 80%, currencies 80% hedged, and annual observations. Panel B reports the mean results over all 15 home countries for home market weights of 70% and 100% and currency hedging levels of 0% and 100%. p-values based on Newey-West (1987) standard errors that are robust to autocorrelation and heteroskedasticity are reported in parentheses, with *, **, and *** indicating significance at the 10%-, 5%-, and 1%- level.

Panel A: Detailed results for 80% home market weight and currencies 80% hedged

Variable / Country	Average 1990-1992	Average	Average 2010-2012	Absolute Trend (p.a.) $100 * coeff.$	Absolute Trend (p.a.) Adjusted R^2	Relative Trend (p.a.) $exp(coeff.) - 1$	Relative Trend (p.a.) Adjusted R^2
Australia	64.7%	51.2%	29.8%	-1.84*** (0.000)	0.499	-4.03%*** (0.000)	0.488
Belgium	50.7%	42.9%	33.7%	-1.48*** (0.002)	0.342	-3.53%*** (0.001)	0.350
Canada	47.6%	37.4%	25.2%	-1.58*** (0.001)	0.366	-4.05%*** (0.000)	0.326
Denmark	55.8%	54.9%	38.9%	-1.52** (0.025)	0.236	-3.02%** (0.028)	0.227
France	47.9%	27.4%	11.1%	-2.24*** (0.000)	0.666	-8.41%*** (0.000)	0.728
Germany	53.5%	29.7%	12.0%	-2.46*** (0.000)	0.653	-8.24%*** (0.000)	0.740
Great Britain	34.5%	24.7%	7.2%	-1.73*** (0.000)	0.576	-7.84%*** (0.000)	0.658
Hong Kong	69.4%	57.3%	47.3%	-1.71*** (0.001)	0.372	-2.80%*** (0.001)	0.346
Italy	66.2%	43.9%	21.8%	-3.26*** (0.000)	0.615	-7.78%*** (0.000)	0.620
Japan	23.5%	42.4%	37.1%	0.21 (0.706)	-0.037	1.13% (0.493)	-0.007
Netherlands	39.7%	28.5%	18.8%	-1.50*** (0.000)	0.428	-5.29%*** (0.000)	0.443
Singapore	54.3%	60.8%	35.5%	-1.72** (0.037)	0.292	-2.76%* (0.081)	0.210
Sweden	62.2%	41.4%	21.7%	-2.26*** (0.000)	0.592	-5.36%*** (0.000)	0.600
Switzerland	38.7%	32.2%	18.6%	-1.58*** (0.001)	0.399	-5.00%*** (0.000)	0.484
United States	12.7%	7.2%	2.9%	-0.63*** (0.003)	0.385	-7.33%*** (0.002)	0.377
Mean	48.1%	38.8%	24.1%	-1.69*** (0.000)	0.578	-4.34%*** (0.000)	0.616

Panel B: Mean results for different parameter specifications

Variable / Parameter	Average 1990-1992	Average	Average 2010-2012	Absolute Trend (p.a.) $100 * coeff.$	Absolute Trend (p.a.) Adjusted R^2	Relative Trend (p.a.) $exp(coeff.) - 1$	Relative Trend (p.a.) Adjusted R^2
70% w_{home}	40.9%	32.9%	19.4%	-1.55*** (0.000)	0.556	-4.71%*** (0.000)	0.604
100% w_{home}	60.7%	49.3%	33.4%	-1.83*** (0.000)	0.610	-3.71%*** (0.000)	0.633
0% hedged	49.4%	42.6%	32.9%	-1.32*** (0.001)	0.475	-2.97%*** (0.001)	0.491
100% hedged	49.3%	39.4%	24.2%	-1.74*** (0.000)	0.572	-4.41%*** (0.000)	0.605

Figures

Figure I: Expected home bias costs over time

This figure shows the individual observations of annualized expected home bias costs as defined in Eq. (7), as well as the regression lines for their absolute and relative annual trend computed following Eqs. (8) and (9), for the mean across our 15 home countries. The calculations are based on the expected excess returns implied by the assumption of global market efficiency using Eqs. (5) and (6) for a 01/1990 to 12/2012 dataset of S&P Global 1200 index constituents. The results in this figure are computed for our standard parameter specifications with a home market weight of 80%, currencies 80% hedged, and annual observations.

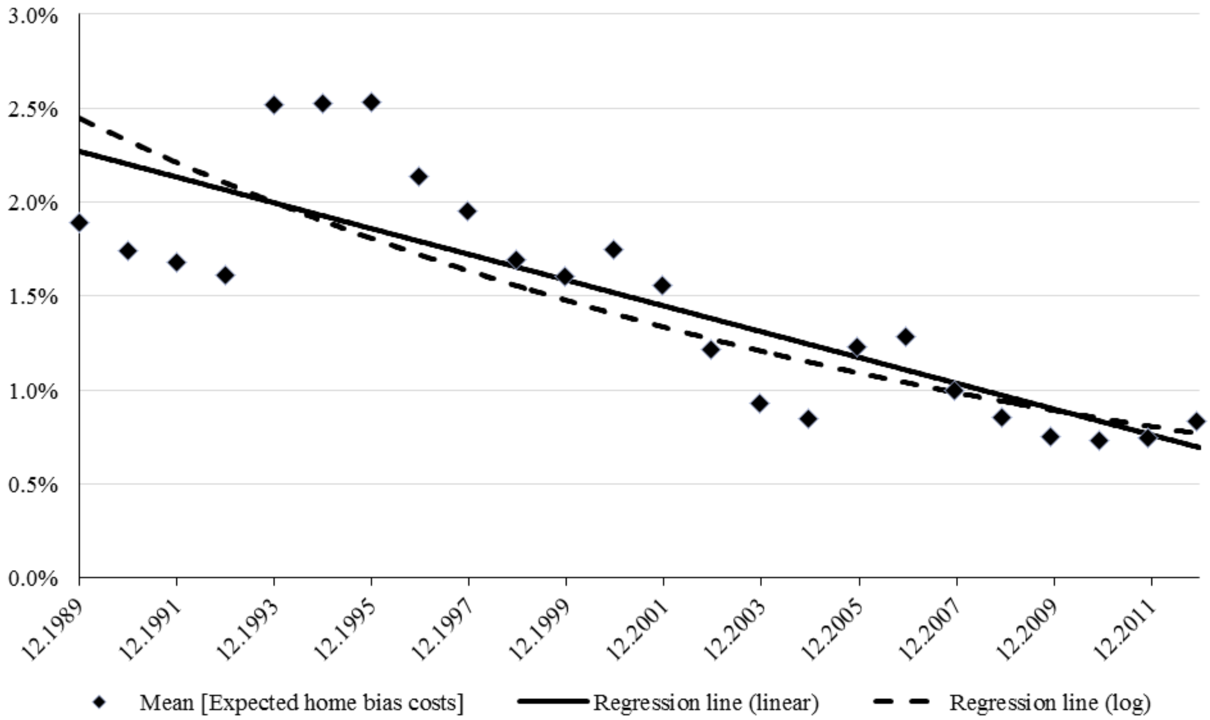


Figure II: Expected break-even costs over time

This figure shows the individual observations of annualized expected break-even foreign investment costs as defined in Eq. (10), as well as the regression lines for their absolute and relative annual trend computed following Eqs. (11) and (12), for the mean across our 15 home countries. The calculations are based on the expected excess returns implied by the assumption of global market efficiency using Eqs. (5) and (6) for a 01/1990 to 12/2012 dataset of S&P Global 1200 index constituents. The results in this figure are computed for our standard parameter specifications with a home market weight of 80%, currencies 80% hedged, and annual observations.

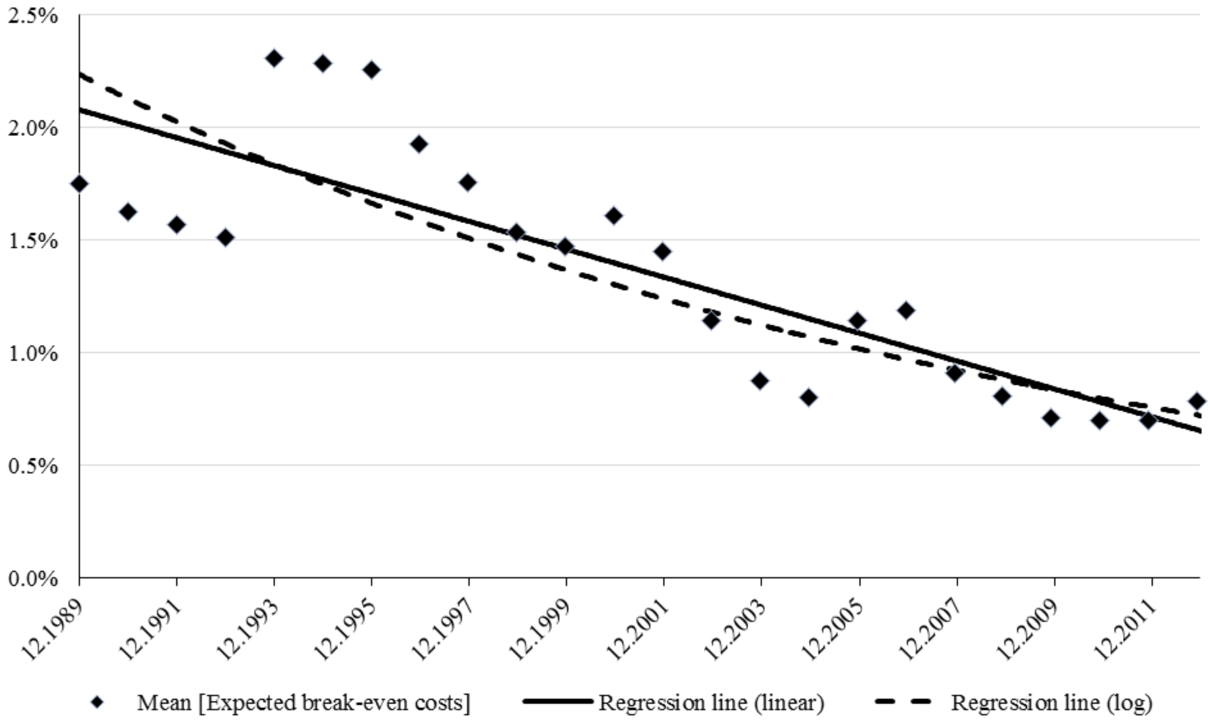
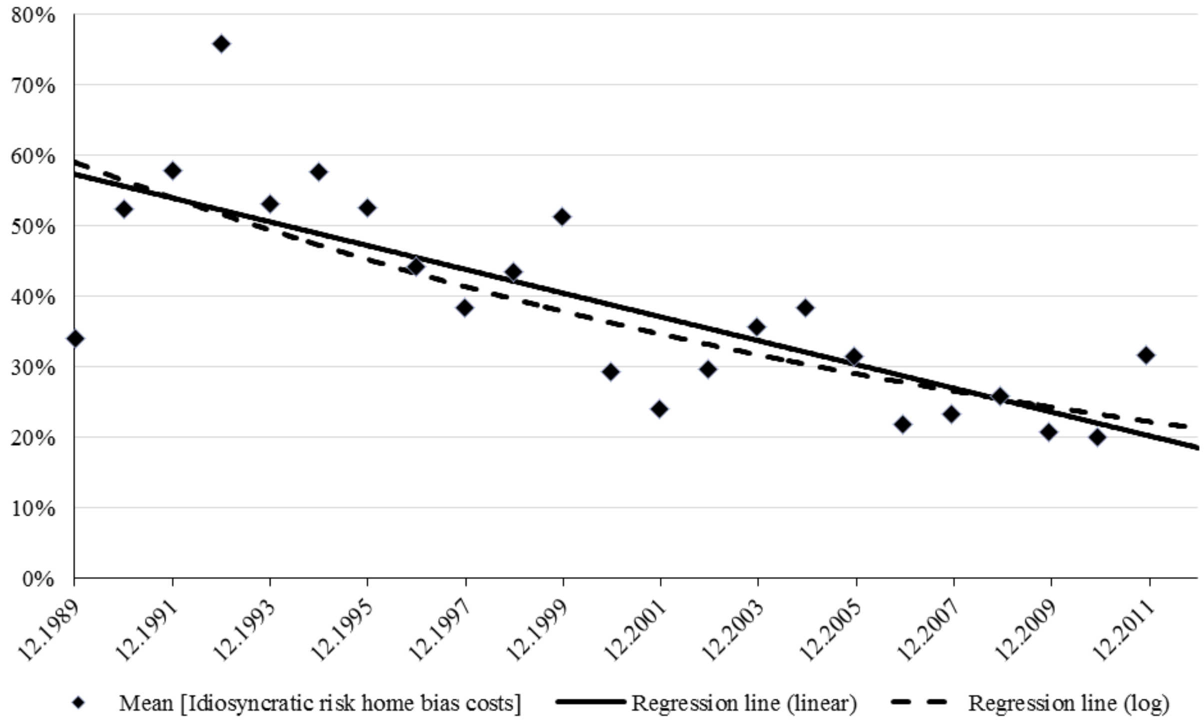


Figure III: Idiosyncratic risk home bias costs over time

This figure shows the individual observations of annual idiosyncratic risk home bias costs as defined in Eq. (19), as well as the regression lines for their absolute and relative annual trend computed following Eqs. (21) and (22), for the mean across our 15 home countries. The calculations are based on the expected excess returns implied by the assumption of global market efficiency using Eqs. (5) and (6) for a 01/1990 to 12/2012 dataset of S&P Global 1200 index constituents. The results in this figure are computed for our standard parameter specifications with a home market weight of 80%, currencies 80% hedged, and annual observations.



Curriculum Vitae

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11/2013 – today	**Finreon AG** Zurich, Switzerland
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