Economic Analysis and Policy 57 (2018) 9–21

Contents lists available at ScienceDirect

Economic Analysis and Policy

journal homepage: www.elsevier.com/locate/eap

Full length article

Equity home bias—A global perspective from the shrunk frontier

Raja Mukherjee [a], Satya Paul [b], Sriram Shankar [c,*]

[a] Western Sydney University, Australia
[b] Amrita University, Kerala, India
[c] 2.21 Beryl Rawson Building, Australian National University, Australia

ARTICLE INFO

Article history:
Received 6 September 2017
Received in revised form 18 October 2017
Accepted 20 October 2017
Available online 10 November 2017

JEL classification:
G11
G12
G15

Keywords:
Equity home bias
Equity investment
Optimal investment weights
Bayes–Stein shrinkage
GMM estimation

ABSTRACT

Equity home bias research explicates the need for correct characterisation of benchmark (optimum) foreign equity investment weights required for the estimation of equity home bias. This paper improves upon the traditional mean–variance optimisation framework by utilising the Bayes–Stein shrinkage technique to obtain optimal equity weights and home bias estimates for 39 countries for the period, 2000–2009. A regression model estimated with system GMM identifies financial integration, trade openness (exposure), stock market capitalisation, idiosyncratic risk and Global Financial Crisis (GFC) as the significant determinants of equity home bias. Unlike earlier studies, the relationship between home bias and financial integration is found to be U-shaped.

1. Introduction

Despite well-theorised and documented gains from international diversification, investors in international financial markets display a strong preference for domestic equities. In their seminal paper, French and Poterba (1991) find that 98 percent of Japanese equity holdings are domestic; the UK and the US investors hold respectively 82 and 94 percent of domestic equities. A recent survey conducted by Schroder Investment Management Germany reveals that amongst the 112 respondents (consisting of insurers, banks, family offices and pension funds), 90% want to purchase German assets (Schroder, 2012). This skewing in equity portfolio holdings, seemingly contravening the postulated benefits of financial globalisation and integration, is referred to as (equity) "home bias".

A number of recent studies, e.g., Magi (2009), Barberis and Huang (2009), Barberis et al. (2006) and Barberis et al. (2001) have provided a plausible explanation for the observed home bias puzzle (aggregate portfolio behaviour) in a framework where economic agents have behavioural (narrow framing) preferences. A representative agent derives utility not only from consumption but also from risky financial wealth fluctuations. Individuals' cognitive skills, as argued in Christelis et al. (2010), may strongly affect investors' financial choices. These skills are closely related to the ability to process information, implying that cognitive skills act as an additional constraint that optimising individuals face when making their financial decisions. As a result of investor's limited capabilities of processing information, the foreign asset (equity) is perceived

* Corresponding author.
E-mail addresses: R.Mukherjee@westernsydney.edu.au (R. Mukherjee), satyapaul@outlook.com (S. Paul), Sriram.shankar@anu.edu.au (S. Shankar).

https://doi.org/10.1016/j.eap.2017.10.003
0313-5926/

less attractive than it would be if the investor had optimal information skills and were able to evaluate the domestic and foreign risky assets jointly. The investors with poor capabilities of processing information do not diversify their financial investments.

Despite this and other explanations, the equity home bias is still one of the most pervasive and unresolved empirical puzzles in financial economics. Needless to emphasise, the puzzle explicates the need for research on a correct characterisation of benchmark (optimum) foreign equity investment weights against which actual equity investment holdings can be compared. The existing approaches to estimating benchmark optimal weights can be classified into three analytical streams. The first is the International Capital Asset Pricing Model (ICAPM) driven approach which specifies benchmark weights as the proportion of each asset's (country's) share of the world equity market portfolio. The second is the data based mean–variance (MV) optimisation driven approach which uses sample estimates of the mean and covariance matrix of asset returns as inputs for estimating benchmark weights. The third is a mixed modelling approach which interfaces Bayesian inference with asset allocation models for benchmark weights estimation.

The ICAPM is often questioned on the basis of the restrictive assumptions like information symmetry and the absence of transaction costs that underlie capital asset pricing models (See, eg, Sendi and Bellalah, 2010). The data based approach of the MV optimisation framework is hindered by its reliance on the quality of the necessary inputs which are the sample moments of the returns data. Since the true values of these input parameters are seldom known, investors have to rely on estimates which are notoriously unreliable (Pungulescu, 2010). The mixed modelling Bayesian approach addresses the limitations of the ICAPM and mean–variance approaches through the portfolio allocation frameworks developed by Pastor (2000) and Garlappi et al. (2007). Pastor introduces varying degrees of mistrust in the ICAPM for investigating the extent of corresponding variance in optimal portfolio weights. As the degree of mistrust in the ICAPM increases, the resulting estimates of optimal weights move closer to the data based approach and away from that of the ICAPM. As compared to the purely data based approach of mean–variance framework, the optimal weights estimated through Pastor's approach are more stable over time, although extreme and volatile weights are still possible. Garlappi et al. adopt a multi-prior approach to address the optimal weights volatility problem. They utilise estimation risk by restricting expected asset returns in the standard mean–variance framework to lie within a specified confidence interval around its estimated value.

This paper contributes to the mixed modelling approach by introducing the Bayes–Stein shrinkage to the standard mean–variance (MV) framework. The Bayes–Stein shrinkage approach to MV optimisation focusses on yielding improved portfolio allocation weights by statistically lowering estimation uncertainty through the "shrinkage" of sample averages towards a common value.[1] This methodology is used to obtain optimal equity weights and thereby home bias estimates for 39 countries for the period 2000–2009. The estimates of equity home bias obtained through the shrinkage technique vary across countries and over the years. The estimates of home bias for some developed economies show a declining trend as opposed to an increasing trend observed for some emerging economies. The equity home bias averaged over the sample period is quite high (0.7475) for the emerging economies whereas for the developed economies it is low (0.4604).

The paper also makes an attempt to explain the observed home biases by relating them to a comprehensive set of explanatory variables in a regression model. The model is estimated with the System GMM. The model identifies financial integration, trade openness (exposure), stock market capitalisation, idiosyncratic risk and Global Financial Crisis (GFC) as the significant determinants of equity home bias. The relationship between home bias and financial integration is found to be U-shaped. Initially, when the correlation of returns across financially non-integrated geographical markets is low, financial integration provides opportunities for efficient international portfolio diversification and thereby reduces equity home bias. However, with increasing financial integration and higher covariance of domestic and global equity returns, the opportunities for efficient international equity investment diversification decline. This non-linear relationship between equity home bias and financial integration to our knowledge has not been explored in any of earlier empirical studies.

The paper is organised as follows. Section 2 formally defines equity home bias. Section 3 provides the analytical framework for implementing the Bayes–Stein shrinkage procedure for optimal equity investment weights estimation. Section 4 provides a brief description of data and discusses the estimates of optimal investment weights and equity home bias. Section 5 is devoted to estimation of a regression model to investigate the potential determinants of equity home bias. Section 6 brings together the conclusions.

2. Equity home bias—A definition

Equity Home Bias (EHB) is defined as the relative difference between the actual and optimal foreign equity portfolio weights, denoted by ACT_i and OPT_i respectively.

$$EHB_i = 1 - \frac{ACT_i}{OPT_i} \tag{1}$$

The share of foreign equity in the total equity portfolio of a country is the share of foreign equity holdings (FA_i) in the total (foreign and domestic) equity holdings. The domestic equity holdings are obtained as the difference between the market capitalisation of the country (MC_i) and the total domestic equity stocks held by foreign investors (FL_i). Thus,

$$ACT_i = \frac{FA_i}{FA_i + MC_i - FL_i} \tag{2}$$

[1] Zellner (2010) notes that "Bayesian shrinkage à la Stein and others can improve estimation of individual parameters and forecasts of individual future outcomes".

Typically, when actual foreign investment is lower than the optimal amount, a country's investment is home biased. $\mathrm{EHB_i}$ takes maximum value unity when the domestic investors hold only domestic assets and minimum value zero when the actual and optical weights are equal. Thus, $0 \leq \mathrm{EHB_i} \leq 1$.

However, there may be cases when the actual weights exceed optimal weights. In this case a country is not home-biased, but overinvests abroad. The previous measure of equity home bias would be misleading in such situations. The adjusted formula to account for cases of overinvestment abroad is expressed as (Baele et al., 2007):

$$EHB_i = \frac{\min(|OPT_i|, ACT_i)}{sign\,(OPT_i)\max(|OPT_i|, ACT_i)} - 1. \tag{3}$$

This formula has a lower bound of -1 for the cases where the optimal foreign stock holdings are zero. It can achieve values below -1 when short sales are allowed.

The actual portfolio holding weights are obtained using data from the IMF International Investment Position (IIP) dataset and optimal weights are calculated with the Bayes–Stein Shrinkage approach discussed below.

3. Optimal weights—A mixed modelling Bayes–Stein shrinkage approach

Growth and development in the global financial markets have been accompanied by a substantial increase in the variety and complexity of models and modelling techniques used in quantitative finance, particularly in portfolio allocation. The consequent and apparently excessive reliance on quantitative models for financial decision making draws scrutiny and criticism when financial market outcomes are extreme and deviant from investor expectations. It is therefore argued that greater emphasis may be placed on employing techniques that account for the likelihood of extreme events and the estimation uncertainty inherent in the decision-making environment. The Bayes–Stein shrinkage methodology is chosen from this perspective.

Given a global investment universe of N assets (over T time periods), we use the Bayes–Stein estimator[2] to shrink the historical mean returns vector ($\bar{r}$) and the historical variance–covariance matrix (Σ), utilising the return on the global minimum variance portfolio (gmvp)[3] as the "target" return ($r^* = \mu_{gmvp}$). Several studies including Jorion (1991) and Larsen and Resnick (2001) have documented that the use of shrinkage estimator in mean–variance portfolio selection leads to increased stability of optimal portfolio weights across time periods.

The Bayes–Stein estimate $E(r_{BS})$ of the expected return vector[4] and the variance–covariance matrix Σ_{BS}, are computed respectively as:

$$E\,(r_{BS}) = (1-\psi)\,\bar{r} + \psi r^* \iota' \tag{4}$$

and

$$\Sigma_{BS} = \Sigma + \Sigma \frac{1}{T+\lambda} + \frac{\lambda}{T(T+1+\lambda)} \frac{\iota'\iota}{\iota\Sigma^{-1}\iota'} \tag{5}$$

where $\iota = (1, \ldots, 1)$ is a $(1xN)$ row vector. The factor λ is computed as:

$$\lambda = \frac{(N+2)(T+1)}{\left[\left(\bar{r} - r^*\iota'\right)' \Sigma^{-1} \left(\bar{r} - r^*\iota'\right)\right]}$$

and the shrinkage factor ψ as:

$$\psi = {}^{\lambda}/_{(T+\lambda)}.$$

In Eq. (5), the first term represents variance–covariance matrix of excess returns, the second term arises due to the uncertainty in the measure of the sample average of excess returns, and the third term corresponds to uncertainty in the common factor. These shrunk parameters are then utilised towards constructing the optimal mean–variance equity investment portfolio of country assets with the maximum Sharpe ratio.

The optimal weights (vector w_{msr}) for the maximum Sharpe ratio (MSR) portfolio (Asgharian and Hansson, 2006) are obtained by solving the problem:

$$\max_{w} SR = \frac{w\mu}{(w\Sigma w')^{1/2}}$$

$$\text{st.} \quad \iota w' = 1$$

[2] For a more detailed explanation of the Bayes–Stein shrinkage estimator, see Stein (1956), Zellner and Chetty (1965) and Jorion (1986, 1991).

[3] A particularly important characteristic of the gmvp is that it is the only portfolio on the efficient portfolio that does not incorporate the expected asset returns in its computation.

[4] Stein (1956) showed that shrinkage estimators for the mean, although not unbiased, possess more desirable properties than the sample mean.

Table 1
Shrinkage parameters.

Parameters\ Period	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
λ	77.39	246.38	81.92	114.67	120.91	124.76	175.51	35.84	133.57	87.46
ψ	0.60	0.83	0.61	0.69	0.70	0.71	0.77	0.41	0.72	0.63
$1 + 1/(T + \lambda)$	1.0129	1.0041	1.0122	1.0087	1.0083	1.0080	1.0057	1.0279	1.0075	1.0114
Covariance—Last Term of Eq. (5) in the text	0.0010	0.0015	0.0008	0.0006	0.0005	0.0003	0.0007	0.0005	0.0005	0.0010

where μ is Nx1 vector of expected returns in excess of the risk free rate. The analytical solution of the problem in the equation above is given by:

$$w'_{msr} = (\iota \Sigma^{-1} \mu)^{-1} \Sigma^{-1} \mu \tag{6}$$

Note that MSR portfolios are constructed utilising μ and □; extracted from historical data for the purpose of comparison with MSR portfolios constructed with Bayes–Stein shrunk estimate E(r_{BS}) of the expected return vector and the variance–covariance matrix Σ_{BS}.

4. Estimates of Bayes–Stein shrunk equity investment optimal weights and home bias

The estimates of Bayes–Stein Shrunk equity investment optimal weights and Home Bias are obtained for 39 countries for the period 2000–2009 to obtain a global perspective on the phenomenon. Our sample consists of 25 developed and 14 emerging economies. Amongst the developed economies, 16 are the members of European Monetary Union (EMU).

The Weekly USD denominated returns[5] are first computed for the country asset set and the world market portfolio using MSCI country indices available in *Datastream*. The annualised 6-month US T-bills rates also available from *Datastream* are used as the risk-free rates. These datasets are utilised for obtaining the optimal portfolio weights.

The actual portfolio weights are obtained from the International Monetary Fund's International Investment Portfolio (IIP) dataset which is recorded on an annual basis in the IMF's International Financial Services (IFS) database. This dataset segregates direct investments, portfolio investments (holdings of less than 10% of the share capital of the company) and other investments which include financial derivatives.[6]

The annual estimates of equity home bias are obtained using two sets of optimal MSR country equity investment weights. The first set of optimal annual MSR country equity investment weights is obtained within the traditional MV optimisation framework using the historical vector of country excess returns and variance–covariance matrix of returns as inputs to the optimisation. The second set of optimal annual MSR country equity investment weights is obtained by plugging the Bayes–Stein shrinkage modified vector of excess returns E(r_{BS}) and the variance–covariance matrix Σ_{BS} of excess returns into Eq. (6). Short-selling is permitted within the estimation framework.

The shrinkage approach has reduced optimal weight sensitivity to estimation uncertainty. Table 1 reports the shrinkage parameters λ and ψ that are used to construct the shrunk vector of country excess returns and shrunk variance–covariance matrix of returns, which are utilised for creating the shrunk efficient frontier. In the instance of 2009, for $\lambda = 87.46$ and $\psi = 0.63$, shrinkage in the efficient frontier, as shown in Fig. 1, is quite substantial.

Further, the Bayes–Stein procedure with shrinkage parameters estimated directly from the sample data, achieved higher portfolio (equity investment) certainty equivalence[7] compared to the traditional mean–variance optimisation procedure based solely on parameters estimated from historical data (see Fig. 2). Thus, Bayes–Stein shrinkage better addresses the imperative financial-economic consideration of incorporating investor preferences in equity home bias estimation.

Table 2 presents the country-specific means and variances of the historical and Bayes–Stein shrunk portfolio weights. Two observations emerge from this table. First, the mean Bayes–Stein shrunk MSR weights do not seem to be much different from the corresponding historical MSR weights, though former are slightly lower than the latter for about half of the countries. Second, and more importantly the variances of Bayes–Stein Shrinkage MSR weights are consistently lower than the historical

---

[5] The weekly returns data have been extensively used in home bias literature, see e.g., Griffin et al. (2004), Barberis et al. (2006) and Acharya and Steffen (2013). Jagannathan and Ma (2003) note that the wide usage of higher frequency daily data in place of monthly data by both practitioners and researchers addresses the problem of a low degree of freedom when monthly returns are used. They also note in their main empirical findings that corrections suggested by Scholes and Williams (1977), Dimson (1979), and Cohen et al. (1983) for market microstructural effects in high frequency daily data do not alter performance.

[6] The IIP data is a highly acclaimed dataset for international portfolio holdings of relatively wide geographical and temporal coverage. However, as observed by Baele et al. (2007), there are however, possible biases associated with the data. The identified biases may manifest in several situations. First, when a foreign subsidiary located in a reference country invests in a third country for the ultimate benefit of its foreign owner, the reference country appears as the foreign investor and not the parent company (country). Second, the accuracy of data collection and the choice of price index for revaluating estimates of IIP holdings can be questioned (Griever et al., 2001; Tesar and Werner, 1995). However, given the increase in the frequency of surveys, the chances of significant ongoing biases are diminished.

[7] The certainty equivalent (CE), which measures the preference of a rational decision maker, is defined as "the amount of money that is equivalent in your mind to a given situation that involves uncertainty". Rationality entails that a rational decision maker should prefer the strategy with a greater CE. Based on an exponential utility function, the CE is approximated as: CE $\approx \mu - \sigma^2/2$R, where μ is the expected rate of return of an efficient portfolio; σ^2 is the corresponding variance; and *R* is the risk tolerance from a decision maker. For details, see Ding et al. (2009) and Nock et al. (2011).

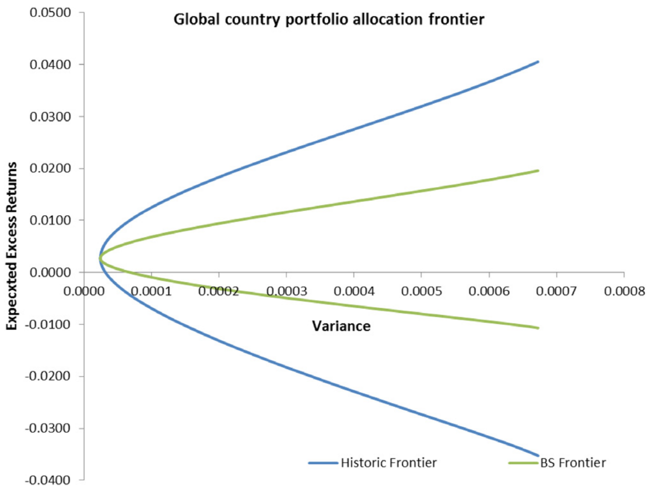

Fig. 1. Global allocation frontier comparative. Note: The allocation frontiers have been created using country stock index return's implications (first and second moments) as the target statistics for the global portfolios. The "BS Frontier" label in the figure indicates the frontier (green in colour) arising from the application of the Bayes–Stein shrinkage procedure. Both frontiers relate to the reporting period 2009.

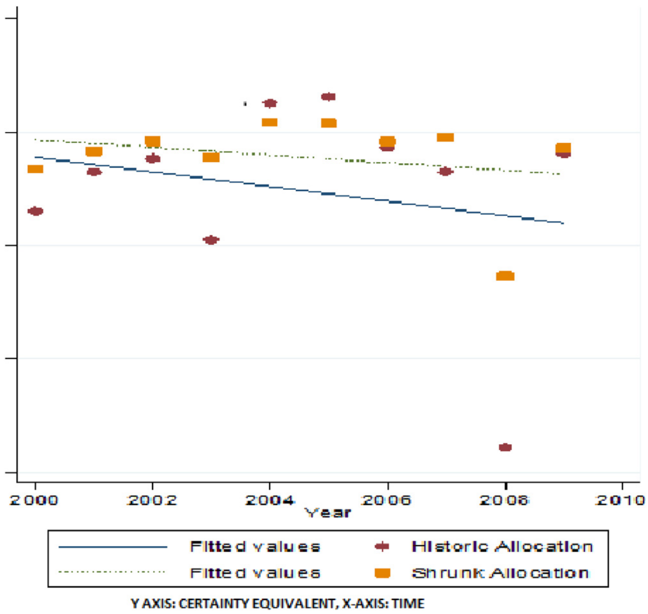

Fig. 2. Certainty equivalence comparison: historic MSR and Bayes–Stein shrunk MSR global equity allocation portfolios comprising country assets. Note: Certainty equivalent following the approach of Ding et al. (2009) is estimated as $CE = \mu - \sigma^2/2R$, where CE = Certainty Equivalent, μ = expected return from portfolio, σ^2 = variance of portfolio returns and R = investor risk tolerance. Following Ding et al. (2009), the value of R has been taken as 0.10 for the risk averse investor.

MSR weights for each country. We did not carry out any statistical test to see whether these differences in means and variances are statistically significant. This is because such tests would be highly unreliable due to lack of degrees of freedom.[8] However, we carried out tests to see whether the variance[9] of Bayes–Stein Shrinkage MSR weights (obtained from 39 across country observations) is statistically different from its historical counterpart in each year. The variance of Bayes–Stein MSR portfolio weights is consistently lower than that of historical MSR portfolio weights for each year (Table 3, Cols 2 and 3). The p-values presented in col 4 of this table re-enforce this conclusion for all, except two years, at 10% or higher levels of significance.

8 This is understandable as the weights are available for 10 years for calculating means and variance for each country.

9 Since the sum of weights adds up to one by construction in both approaches, there was no need for testing the equality of means.

Table 2
Optimal domestic weights comparison: Historic MSR and Bayes–Stein shrunk MSR portfolios.

Country	Historic MSR		Bayes Stein Shrunk MSR		Δ Var
	Mean	Var(a)	Mean	Var(b)	= a − b
Argentina	0.0317	0.027	0.0259	0.0166	0.0104
Australia	−0.5846	3.213	−0.4637	1.8563	1.3567
Austria	0.2568	1.0438	0.2587	0.5735	0.4703
Belgium	0.2887	0.3129	0.2411	0.1738	0.1391
Brazil	−0.2488	0.398	−0.2038	0.2059	0.1921
Canada	0.9682	11.1022	0.7783	6.3405	4.7617
Chile	−0.177	0.1446	−0.0869	0.0608	0.0838
Czech	−0.1839	0.0700	−0.1188	0.0406	0.0294
Denmark	0.0891	0.0543	0.0473	0.0326	0.0217
Finland	0.1194	0.7167	0.1059	0.3983	0.3184
France	−0.5388	5.1984	−0.419	3.1048	2.0936
Germany	−0.9825	4.2922	−0.7403	2.4274	1.8648
Greece	0.0369	0.1106	0.0287	0.0333	0.0773
Hong Kong	0.14	0.3739	0.0804	0.1663	0.2076
Hungary	0.1432	0.7646	0.1095	0.397	0.3676
India	0.0403	0.1655	−0.0072	0.0935	0.072
Indonesia	−0.2871	1.2576	−0.2257	0.7271	0.5305
Israel	−0.3417	1.6377	−0.2693	0.9376	0.7001
Italy	0.0004	0.5549	0.0197	0.2349	0.3200
Japan	−0.3498	1.7633	−0.1555	1.0134	0.7499
Korea	−0.084	0.0628	−0.0519	0.0164	0.0464
Malaysia	0.306	0.5486	0.2374	0.1852	0.3634
Netherlands	−0.9617	8.3284	−0.765	4.6647	3.6637
N Zealand	0.7201	4.4353	0.538	2.5646	1.8707
Norway	−0.6161	4.8403	−0.5119	2.6702	2.1701
Pakistan	−0.0882	0.2134	−0.0485	0.0899	0.1235
Peru	−0.0721	0.146	−0.0206	0.0876	0.0584
Philippines	0.446	0.9313	0.3357	0.462	0.4693
Poland	0.2448	0.5163	0.1755	0.2695	0.2468
Portugal	−0.4736	1.4453	−0.3008	0.8098	0.6355
Russia	0.3192	1.9263	0.2587	1.0848	0.8415
Singapore	0.1486	0.4598	0.0999	0.2645	0.1953
Spain	−0.2679	0.6679	−0.1882	0.344	0.3239
Sweden	0.3429	0.4682	0.2228	0.2579	0.2103
Swiss	2.5779	48.7846	1.89	27.8328	20.9518
Thailand	−0.0387	0.0311	−0.0493	0.0116	0.0195
Turkey	−0.0755	0.4712	−0.0918	0.2593	0.2119
UK	0.838	10.7699	0.7469	5.7897	4.9802
USA	−0.6861	15.3858	−0.4822	8.6641	6.7217

Note: Var() denotes the variance of weights for each country for the period 2000-2009.

The Bayes–Stein shrinkage approach has enabled improvements in equity home bias estimates (in terms of variability) compared to the traditional Markowitz mean–variance optimisation framework. For example, in the case of UK, the historical home bias variance estimates is 0.2173; whereas the home bias estimates obtained using Bayes–Stein approach is 0.0706 over the period under study. Similarly, for Peru the home bias variance estimates are 0.0333 and 0.0236 based on historic and Bayes–Stein approach respectively. Even though the mean home bias measures obtained from the two approaches are quite similar both in terms of magnitude and signs (columns 2 and 4 in Table 4), the estimates of their variance achieved through shrinkage are lower than those of the historical estimates for about two-third of the countries (columns 3 and 5 in Table 4).

Further, the year-wise mean and variance estimates of home bias are presented in columns. 5, 6, 8 and 9 of Table 3. We test two hypotheses: (i) the equality of home bias means and (ii) the equality of home bias variances from the two approaches. The p-values of these hypotheses tests shown in cols. 7 and 10 of this table reveals that: (a) for each year the mean home bias estimates obtained from the two approaches are not statistical different and (b) for 6 out of 10 years the home bias variance estimates from Bayes–Stein MSR approach are statistically lower than the historic MSR approach at 20% or higher levels of significance.

The following is observable from the mean values of the Bayes–Stein shrunk MSR country equity home bias estimates (Table 4, column 4): USA and Canada representing the developed North American economies display equity home bias of 0.8121 and 0.5804 respectively. Japan representing a developed Asian economy displays a mean equity home bias of 0.8487. Germany and the UK, representing developed economies from the Euro zone, display the lowest levels of equity home bias with mean estimates of 0.4867 and 0.5367 respectively. In contrast, Argentina and India representing emerging economies from South America and Asia, display highest equity home bias with mean estimates of 0.9967 and 0.9970 respectively.

Table 3
Historic MSR vs Bayes–Stein MSR: A statistical comparison.

Year	Variance of optimal weights		$H_0: \sigma_H^2 = \sigma_{BS}^2$ $H_1: \sigma_H^2 > \sigma_{BS}^2$	Mean of home bias		$H_0: \mu_H = \mu_{BS}$ $H_1: \mu_H \neq \mu_{BS}$	Variance of home bias		$H_0: \sigma_H^2 = \sigma_{BS}^2$ $H_1: \sigma_H^2 > \sigma_{BS}^2$
	Historical σ_H^2	Bayes–Stein σ_{BS}^2	p-value	Historical μ_H	Bayes–Stein μ_{BS}	p-value	Historical σ_H^2	Bayes–Stein σ_{BS}^2	p-value
2000	0.1025	0.0525	0.0225	0.6106	0.6302	0.8435	0.1710	0.1264	0.2075
2001	0.0795	0.0248	0.0003	0.5589	0.5994	0.7375	0.3284	0.1934	0.0609
2002	0.5694	0.1917	0.0007	0.4358	0.5689	0.3957	0.6136	0.2819	0.0110
2003	0.0664	0.0437	0.1042	0.5888	0.6001	0.9144	0.2106	0.2067	0.4774
2004	0.2619	0.0849	0.0005	0.4533	0.5445	0.5102	0.4428	0.2787	0.0819
2005	0.1067	0.0767	0.1597	0.5757	0.6024	0.7997	0.2317	0.1838	0.2426
2006	0.5319	0.1437	0.0001	0.4060	0.5111	0.4895	0.5172	0.3529	0.1248
2007	33.3103	19.1340	0.0458	0.1245	0.0435	0.7416	1.0897	1.1856	0.3994
2008	0.0505	0.0461	0.3908	0.6903	0.6939	0.9640	0.1202	0.1138	0.4336
2009	0.2333	0.0889	0.0021	0.5354	0.5325	0.9810	0.3270	0.2377	0.1682

Note: The tests in column 4 and 10 are upper-tail F-test and the test in column 7 is a two tail t-test.

Table 4
Equity home bias comparison: Historic MSR and Bayes–Stein shrunk MSR portfolios.

Country	Historic MSR		Bayes Stein Shrunk MSR		Δ Var
	Mean	Var(a)	Mean	Var(b)	$= a - b$
Argentina	0.9965	0.0000	0.9967	0.0000	0.0000
Australia	0.7803	0.0095	0.7972	0.0032	0.0063
Austria	0.2966	0.0782	0.2639	0.0714	0.0068
Belgium	0.0474	0.0441	0.0422	0.0266	0.0175
Brazil	0.9770	0.0004	0.9791	0.0003	0.0001
Canada	0.8113	0.0023	0.8121	0.0017	0.0006
Chile	0.7785	0.0067	0.7775	0.0049	0.0017
Czech	0.8111	0.0021	0.7998	0.0027	−0.0006
Denmark	0.5105	0.0172	0.5363	0.0094	0.0077
Finland	0.4817	0.0989	0.4829	0.0865	0.0124
France	0.2731	0.4605	0.4285	0.2558	0.2047
Germany	0.4762	0.1276	0.4867	0.0989	0.0287
Greece	0.8943	0.0029	0.9003	0.0029	0.0000
Hong Kong	−0.6648	0.0548	−0.6498	0.0270	0.0279
Hungary	0.8860	0.0147	0.8884	0.0158	−0.0011
India	0.9966	0.0000	0.9970	0.0000	0.0000
Indonesia	0.9971	0.0000	0.9972	0.0000	0.0000
Israel	0.8263	0.0024	0.8283	0.0032	−0.0008
Italy	0.3662	0.4423	0.4458	0.1413	0.3010
Japan	0.8560	0.0023	0.8487	0.0022	0.0000
Korea	0.9367	0.0044	0.9373	0.0034	0.0010
Malaysia	0.6761	0.5556	0.4217	0.8912	−0.3356
Netherlands	0.0787	1.3383	0.5389	0.0744	1.2639
N Zealand	0.1437	0.0853	0.2039	0.0591	0.0261
Norway	0.3618	0.0953	0.4351	0.0281	0.0673
Pakistan	0.9911	0.0000	0.9909	0.0000	0.0000
Peru	0.6383	0.0333	0.6449	0.0236	0.0097
Philippines	0.6386	0.8009	0.8501	0.1187	0.6822
Poland	0.9663	0.0010	0.9713	0.0009	0.0000
Portugal	0.2244	0.0943	0.2069	0.1151	−0.0208
Russia	0.9961	0.0000	0.9959	0.0000	0.0000
Singapore	0.5128	0.0132	0.5240	0.0103	0.0029
Spain	−0.4094	0.2047	−0.3597	0.2287	−0.0240
Sweden	0.2598	0.3532	0.4082	0.0782	0.2750
Swiss	0.1186	0.7461	0.2592	0.2201	0.5260
Thailand	0.9844	0.0002	0.9853	0.0001	0.0000
Turkey	0.9981	0.0000	0.9982	0.0000	0.0000
UK	0.4741	0.2173	0.5367	0.0706	0.1467
USA	0.3416	0.5902	0.5804	0.1558	0.4343

Note: Var() denotes the variance of weights for each country for the period 2000–2009.

Australian equity home bias with the mean estimate of 0.7972 is closer to that of Canada and Japan, but higher than that of the USA and the developed Euro zone economies.

The time series plots of equity home bias presented in Fig. 3 indicate a downward trend for Australia, Germany and UK (developed Euro-Zone economies), USA and Canada (developed American economies) and Japan (developed Asian economy). On the other hand, Argentina and India (emerging economies) display an upward trend in equity home bias.

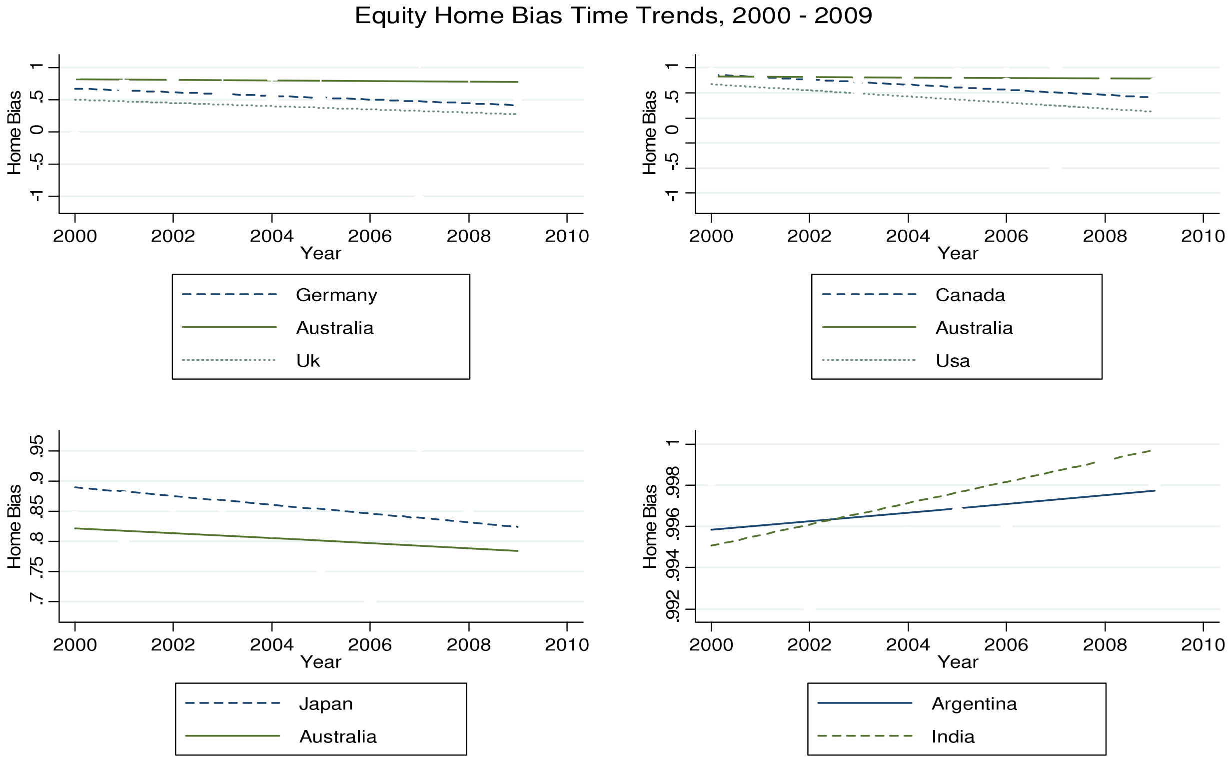

Fig. 3. Equity home bias time series (lines of best fit) plots—selected countries.

The estimate of equity home bias averaged over the sample period is quite high at 0.7475 for the emerging economies whereas for the developed economies it is only 0.4604. The average equity home bias estimate for the Eurozone countries is quite low at 0.4713 and for non-Eurozone countries it is 0.7822.

5. Determinants of equity home bias

The equity home bias estimates are found to be quite high for some countries and low for others. At the same time we also observed a declining trend in home bias for some countries and a downward trend for others. It is therefore worthwhile to explore the possible drivers of observed changes in home bias. To this end, the equity home bias estimates obtained from the shrinkage procedure are regressed on a number of variables drawn from the existing literature. We begin with a brief description of variables that enter into our base level regression.

Financial Integration: The financial integration of a country's equity market with global equity market indicates the responsiveness of a country's stock (equity) returns to factors affecting global equity returns. Following the single factor ICAPM, financial integration is captured by time-varying country βs which are measured as:

$$\beta_{iw,t} = \frac{Covar_{iw,t}}{Variance_{wt}}$$

where for the year t, $\beta_{iw,t}$ is the world market beta of country i, $Covar_{iw,t}$ is the covariance of country i excess returns with world market excess returns and $Variance_{wt}$ is variance of world market excess returns.

Premised on an initially low correlation of returns across financially non-integrated geographical markets, financial market integration is expected to provide opportunities for efficient international portfolio diversification and thereby reduce equity home bias. However, with increasing financial integration and higher covariance of domestic and global equity returns, the opportunities for efficient international equity investment diversification may decline. This may cause investors to seek alternative domestic investment opportunities, leading to an increase in equity home bias. Thus one can expect a U-shaped relationship between equity home bias and financial integration. To test this hypothesis, we include financial integration and its squared term in the regression model.

Trade Openness: Increasing trade openness reduces geographic information asymmetry exerting a diminishing effect on equity home bias. Trade openness for a country (economy) is expressed as the ratio of imports and exports to GDP.

Idiosyncratic risk: The country idiosyncratic risk refers to unsystematic risk or risk that is uncorrelated to the global financial market risk (Levine and Zervos, 1998; Baele and Inghelbrecht, 2006). An increase in country idiosyncratic risk results in a decrease[10] in the return–risk ratio at the firm (equity return source) level (Acemoglu et al., 2003). Consequently, domestic investors seek international diversification opportunities, leading to a decrease in home bias. However, at the same time foreign investors tend to decrease their exposure by investing at home, which leads to an increase in home bias. The net-effect of country idiosyncratic on home bias is determined based on whether the former effect dominates the latter or vice-versa. Country idiosyncratic risk is captured through the variances of the residuals from annual single-factor ICAPM regressions of country excess returns against world excess returns.

Bank Assets: As suggested in Baele et al. (2007), bank assets defined as the ratio of deposit money bank assets to GDP can be taken as a proxy for the importance of bank finance in a country. A country with a higher share of bank assets represents a less diversified financial system which is less attractive for foreign investors.

Stock Market Capitalisation: The state of stock market development in an economy can be proxied by the ratio of stock market capitalisation to GDP. Larger equity markets (relative to the real economy) tend to have lower costs of financial intermediation, higher liquidity, and better investment opportunities (Levine and Zervos, 1998). The increasing market development makes the local equity market more attractive to foreign investors, which may have a negative effect on home bias. On the other hand, domestic investors have less incentive to diversify their investment portfolios in the presence of developed market. Thus, the overall effect of financial market development on equity home bias will depend on which effect dominates.

Global Financial Crisis: In order to see the effect of global financial crisis on equity home bias, GFC is specified as a dummy variable taking value 1 for the period 2007–2009 and 0 for the earlier years.

The summary statistics and the data sources for the explanatory variables are provided in Appendix Tables A.1 and A.2. The mean and standard deviations of variables reveal substantial variations across countries.

5.1. The model specification

A base level model incorporating the above variables is specified as

$$EHB_{it} = \alpha + \mu_i + \lambda t + \beta_1 X_{it} + \varepsilon_{it} \tag{7}$$

where EHB_{it} is equity home bias for country i during the year t, μ_{i} represents the country specific unobserved effects, X is a vector of explanatory variables, t is time trend capturing the effects of all those variables (not included in X) that may vary with time and ε_{it} is a well-behaved random error term.

In the absence of unobserved effect (μ_i), ordinary least squares (OLS) estimator of the parameters would be consistent and efficient. In the presence of unobserved country specific heterogeneity, the pooled OLS regression estimates are inconsistent and inefficient. This problem may be overcome by fixed effects or random effects estimators. However, these estimators do not account for the potential endogeneity in the explanatory variables. To address the endogeneity problem we employ the System Generalised Method of Moments (SGMM) to estimate the parameters in (7) using panel data for 38 countries over 10 years (2000–2009).[11]

GMM has gained immense popularity in the field of economics and finance over the last two decades. The GMM estimation methodology starts from a set of over-identified population of moment conditions and seeks to find an estimator that minimises a quadratic norm of the sample moment vector. The resulting estimation has been shown to be consistent and asymptotically normal, under different conditions. For example, GMM approach proposed by Arellano and Bond (1991) utilises first differenced transformed series to adjust for unobserved individual specific heterogeneity in the series. However, the first difference GMM estimator suffers from a major shortcoming. Blundell and Bond (1998) have shown that when the explanatory variables are persistent over time, lagged levels of these variables are weak instruments for the regression equation expressed in first differences. This is likely to lead to biased coefficients, and the problem is generally worsened in small samples. To avoid this bias, Blundell and Bond (1998) proposed a system GMM (SGMM) estimator, which combines in a system the first-differenced equation with the same equation expressed in levels. The instruments for the regression in differences are the lagged levels of the explanatory variables, while the instruments[12] for the equation in levels are lagged differences of the corresponding variables. On the basis of Monte-Carlo simulation, Arellano and Bover (1995) show that this additional information results in a substantial gain in the precision of the estimates.

The parameter estimates of System GMM panel regression presented in col 1 of Table 5 seem to be quite reasonable in terms of sign and statistical significance at conventional levels. The coefficient of financial integration is negative (−0.48) and that of its squared term is positive (0.26). Both these coefficients are also statistically significant. This supports the hypothesis

10 For example, Castagneto-Gissey and Nivorozhkin (2016) find that rest of the world substantially decoupled itself from the Russian market in order to avoid financial contagion from the Russian stock market.

11 From the original set of 39 countries, Hong Kong has been excluded from the panel analysis for determinants of EHB, as it is a financial centre.

12 The usage of excessive instruments can result in biased estimates. Hence we use a sub-sample of the whole history of the series as instruments in the later cross-section. To determine the optimal lag length of the instruments we use the procedure discussed in Tamazian and Rao (2010). We started by using the full set of moment conditions and reduced them step-by step. For each set of regression moment conditions, we compared the Sargan test statistic of the current set with that of the previous set. Once the Sargan test started decreasing in significance, the procedure was stopped and the specification with the highest p-value taken.

Table 5
System GMM panel regression results (Blundell–Bond procedure).

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Trend	0.0673	0.0305	0.0348	0.0188	0.0312
	(3.10)***	(0.93)	(1.33)	(0.56)	(0.95)
Financial integration	−0.4841	−0.4613	−0.3002	−0.2962	−0.4470
	(−2.10)**	(−1.94)**	(−1.2)	(−1.14)	(−1.86)*
(Financial integration)^2	0.2646	0.2781	0.1898	0.2159	0.2728
	(2.28)**	(2.30)**	(1.5)	(1.78)*	(2.24)**
ln (Trade openness)	−0.2343	−0.2371	−0.2219	−0.2321	−0.2306
	(−2.61)***	(−2.53)**	(−2.36)**	(−2.45)**	(−2.42)**
ln (Idiosyncratic risk)	0.2455	0.2421	0.2581	0.2663	0.2410
	(5.62)***	(5.28)***	(5.71)***	(5.52)***	(5.24)***
ln (Bank assets)	−0.1123	−0.0423	0.0629		−0.0293
	(−1.30)	(−0.31)	(0.43)		(−0.21)
ln (Stock market capitalisation)	0.1325	0.1381	0.1966	0.1475	0.1254
	(1.62)*	(1.65)*	(2.26)**	(1.69)**	(1.4)
GFC dummy	−0.4363	−0.3767	−0.3966	−0.3734	−0.3702
	(−4.45)***	(−3.60)***	(−3.87)***	(−3.59)***	(−3.49)***
Institutional quality		−0.1486	−0.0913	−0.2173	−0.1271
		(−1.00)	(−0.86)	(−1.61)*	(−0.80)
Broadband penetration		0.0043		0.0043	0.0038
		(0.53)		(0.51)	(0.45)
Telephone lines			−0.0039		
			(−0.86)		
ln (Bank liquid liabilities)				0.0970	
				(0.64)	
EMU dummy					−0.0489
					(−0.39)
No of observations	318	318	334	318	318
No of instruments	63	76	79	76	76
No of groups	38	38	38	38	38
Sargan over-id test (p-values)	0.561	0.831	0.480	0.621	0.808
AR(1) test for serial correlation	0.000	0.000	0.000	0.000	0.000
AR (2) test for serial correlation	0.405	0.664	0.814	0.774	0.678
GMM estimation method	System	System	System	System	System
Endogenous variables used as Instruments	Integration, (Integration)^2, ln(Trade Openness), ln(Idiosyncratic risk), ln(Bank Assets), ln(Stock market capitalisation), Institutional Quality and Broadband Penetration				
Exogenous variables used as instruments	Trend, GFC Dummy, EU Dummy				

The numbers reported in parentheses are t-values. The institutional quality and broadband penetration could not be taken in log values as the former takes negative values and the latter zero values. The Sargan tests for over-identifying restrictions do not reject the orthogonality conditions at the 95% significance level for all estimations. The AR (2) tests do not reject the null hypothesis of no second-order serial correlation in all estimations.

*** 1% levels of significance.

** 5% levels of significance.

* 10% levels of significance.

of U-shaped relationship between financial integration and equity home bias. The existing studies have reported a negative relationship between financial integration and equity home bias (see Baele et al., 2007; Coeurdacier and Rey, 2011). To the best of our knowledge, this is the first study to propose and test the U-shaped hypothesis empirically.

Trade openness is found to exert a negative and significant effect on equity home bias. This is sensible in view of the fact that trade openness reduces geographic information asymmetry and exposes investors to the world investment opportunities.

The coefficient of country idiosyncratic risk is positive and statistically significant which implies that foreign equity investors undertake fewer globally diversifiable investment opportunities (risks) in higher idiosyncratic risk countries, thereby leading to a concentration of equity investment in domestic economies and a consequent increase in equity investment home bias. The coefficient of stock market capitalisation is also positive and significant. This suggest that increasing domestic stock market capitalisation increases domestic investment opportunities and reduces the incentives for investors to diversify globally, thereby increasing equity home bias. The coefficient of trend is positive and significant.[13]

The coefficient of GFC[14] dummy is negative and significant. This may be taken to imply that during GFC investors sought foreign investment opportunities for the purpose of risk reduction/ diversification. This result is contrary to the emerging

13 The readers will notice that in the subsequent versions of our model, trend becomes statistically insignificant.

14 The signs and statistical significance of the coefficients on idiosyncratic risk and GFC in this paper is consistent (see Table 6 on page 307 in Mishra, 2015) with those found in Mishra (2015).

literature in portfolio choice which suggests that investors retrench from countries with a greater increase in uncertainty and from countries they are less familiar with. There are a number of studies which report that investors left foreign markets for home in 2008 (see e.g. Giannetti and Laeven, 2012; Milesi-Ferretti and Tille, 2011; Forbes and Warnock, 2011; Fratzscher, 2011). However, there is only one study by Wynter (2012) that supports our result. Wynter's research, which is based on data for drawn from the International Monetary Fund's Coordinated Portfolio Investment survey (CPIS) for multilateral equity holdings of 45 countries, reveals that across countries, the foreign portfolio share rose by an average of 3.62%.

5.2. Robustness of results

The existing literature on equity home bias also discusses a few other determinants not included in our basic model. One of them is the quality of institutions prevailing in a country. Investors are likely to allocate their equity holding towards markets with relatively strong institutional qualities. An empirical study by Fidora et al. (2007) reports that bilateral home bias decreases with the quality of institutions in the investment destination country. Another variable which is worth considering in the regression model is the information technology. Information technology enhances the cognitive and information skills/ abilities of individuals. The low cognitive and information skills adversely affect investors' financial choices/ decisions. As a result of investor's limited capabilities of processing information, the foreign asset (equity) is perceived less attractive. The information technology not only enhances the informational skills but also reduces the trading cost which may affect global investment diversification (Portes and Rey, 2005).

We re-estimated the model with these two additional variables. Each country's Kaufman et al. (2010) score of institutional quality are calculated as the average of the following six indices: government effectiveness, regulatory quality, adherence to the rule of law, control of corruption, political stability and degree to which people participate in selecting a government. The information technology is measured by the broadband penetration (broadband subscription per 100 persons in the country). The results presented in col 2 of Table 5 reveal that the coefficients on both broadband[15] penetration and institutional quality are statistically insignificant. We then experimented by including each component of Kaufman score in the model separately. We did not find a statistically significant association between changes in home bias and each one individually. These results are not tabulated to save space. All other variables (except trend) have retained their signs and levels of significance.

We also checked whether the results are sensitive to the choice of alternative proxies for some of the variables. We re-estimated the model by replacing broadband penetration with the telephone line penetration. The coefficient of the latter variable has the expected sign but is statistically insignificant. Some studies have used bank liquid liabilities as a percentage of GDP as an alternative to bank assets. A higher value of this ratio can be interpreted as a sign of lower financial investment and diversification opportunity, and thereby lower investment attractiveness for foreign investors (Garcia and Liu, 1999). The coefficient of this alternative variable has also turned statistically insignificant.

Finally, we checked whether common currency used in the Euro Zone has helped reducing home bias in member countries of European Monetary Union (EMU). A benefit of common currency that may affect home bias is the elimination of exchange rate risk and related transaction costs. We introduced a dummy for members of EMU in model. The results of estimated model are presented in the last column of Table 5. While the coefficient of EMU has the correct sign (−0.0489), it is statistically not different from zero. The inclusion of EMU dummy in the regression has not affected the sign and levels of significance of other coefficients.

6. Concluding remarks

This paper contributes to the mixed modelling approach by introducing the Bayes–Stein shrinkage to the standard mean–variance (MV) framework. The Bayes–Stein shrinkage yields improved portfolio allocation weights by statistically lowering estimation uncertainty through the "shrinkage" of sample averages towards a common value. This methodology is used to obtain optimal equity weights and thereby home bias estimates for 39 countries for the period 2000–2009.

The estimates of equity home bias obtained through the shrinkage methodology vary across countries and over time. The home bias puzzle continues to persist as the estimates for some developed economies show a declining trend as opposed to an increasing trend in some emerging economies during the study period. The equity home bias averaged over the sample period is quite high (0.7475) for the emerging economies whereas for the developed economies it is only 0.4604. The average equity home bias estimate for the Eurozone countries is quite low (0.4713) and for non-Eurozone countries it is 0.7822.

A regression model estimated with System GMM identifies financial integration, trade openness (exposure), stock market capitalisation, idiosyncratic risk and GFC as the significant determinants of equity home bias. The relationship between home bias and financial integration is found to be U-shaped.

Trade openness exerts a negative effect on equity home bias. This is quite sensible in that trade reduces geographic information asymmetry and exposes investors to the world investment opportunities. The stock market capitalisation and country idiosyncratic risk are found to have a positive effect on equity home bias. Contrary to emerging literature in portfolio choice which suggests that during periods of financial crises investors retrench from foreign countries they are less familiar with, the GFC is found to have a negative and significant effect on equity home bias. The results are quite robust not only to the choice of alternative proxies for some variables but also to the inclusion of additional variable in the regression model.

15 Harb (2017) finds that internet penetration has a positive impact on economics growth in Arab and Middle Eastern countries.

Table A.1
Panel data summary statistics.

Variable	Mean	Std. Dev.	Min.	Max.
Equity home bias	0.5953	0.4840	−0.8048	0.9982
Financial integration (Time varying country betas)	0.7968	0.5639	−0.9669	2.4538
Trade openness (Exposure)	84.1455	65.6508	20.2579	460.4711
Bank assets (Deposit bank assets As a % of GDP)	0.9504	0.4774	0.1846	2.4237
Bank liquid liabilities (Bank liquid liabilities as a percentage of GDP)	0.7803	0.3763	0.1736	2.4220
Idiosyncratic risk (Variances of the residuals from the annual ICAPM regressions)	0.0011	0.0014	0.0000	0.0143
Stock market capitalisation (as % of GDP)	0.8376	0.5905	0.0809	3.4029
Institutional quality (Weighted Kaufman index)	0.7500	0.7714	−0.7707	1.9834
Broadband penetration (Number of subscribers per 100 people)	10.1051	10.5873	0.0000	37.0185
Telephone line penetration (Number of subscribers per 100 people)	39.4905	18.5137	2.0665	74.6877

Note: The Maximum value of trade openness shown in this table is for Singapore, which is quite well known in the literature.

Table A.2
Data sources for explanatory variables.

Variable	Source
Financial integration (Time varying country betas)	Estimated from weekly country and world excess returns data derived from Datastream MSCI Country and World Equity Indices.
Trade openness (Exposure)	World Development Indicators and Global Development Finance (World Bank).
Bank assets (% of GDP)	Financial Structure Dataset, Thornstern Beck, Tilburg University, Netherlands and The World Bank, Washington D.C.; www.center.nl/staff/beck
Bank liquid liabilities (% of GDP)	Financial Structure Dataset, Thornstern Beck, Tilburg University, Netherlands and The World Bank, Washington D.C.; www.center.nl/staff/beck
Stock market capitalisation (as % of GDP)	Financial Structure Dataset, Thornstern Beck, Tilburg University, Netherlands and The World Bank, Washington D.C.; www.center.nl/staff/beck
Idiosyncratic risk (Variances of the residuals from the annual ICAPM regressions of country excess returns and world excess returns)	Country excess returns, world excess returns data derived from Datastream MSCI Country and World Equity Indices; world risk free rate (6 month US Treasury Bills rate) obtained from Datastream.
Stock market capitalisation (as % of GDP)	Financial Structure Dataset, Thornstern Beck, Tilburg University, Netherlands and The World Bank, Washington D.C.; www.center.nl/staff/beck.
Institutional quality (Weighted Kaufman index)	Obtained from the Kaufman Indices available in Kaufman et al. (2010) and presented through the "Worldwide Governance Indicators", 2011 update.
Broadband penetration (subscribers per 100 people)	World Development Indicators and Global Development Finance (World Bank).
Telephone line penetration (subscribers per 100 people)	World Development Indicators and Global Development Finance (World Bank).

Appendix

See Tables A.1 and A.2.

References

Acemoglu, D., Johnson, S., Robinson, J.A., Thaicharoen, Y., 2003. Institutional causes, macroeconomic symptoms: Volatility, crises and growth. J. Monet. Econ. 50, 49–123.
Acharya, V., Steffen, S., 2013. The "greatest" carry trade ever? Understanding Eurozone Bank Risks, CEPR Discussion Paper No. 9432.
Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and application to employment equations. Rev. Econom. Stud. 58, 227–297.
Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. J. Econometrics 68, 29–51.

Asgharian, H., Hansson, B., 2006. Home bias among European investors from a Bayesian perspective. Int. Financ. Markets Inst. Money 16, 397–410.
Baele, L., Inghelbrecht, K., 2006. Structural versus temporary drivers of country and industry risk. J. Int. Money Finance 16 (3), A1.
Baele, L., Pungulescu, C., Horst, J.T., 2007. Model uncertainty, financial market integration and the home bias puzzle. J. Int. Money Finance 26, 606–630.
Barberis, N., Huang, M., 2009. Preferences with frames: a new utility specification that allows for the framing of risks. J. Econ. Dyn. Control 33, 1555–1576.
Barberis, N., Huang, M., Santos, T., 2001. Prospect theory and asset prices. Q. J. Econ. 116, 1–53.
Barberis, N., Huang, M., Thaler, R., 2006. Individual preferences, monetary gambles, and stock market participation: a case for narrow framing. Am. Econ. Rev. 96, 1069–1090.
Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econometrics 87, 11–143.
Castagneto-Gissey, G., Nivorozhkin, 2016. No contagion from Russia toward global equity markets after the 2014 international sanctions. Econ. Anal. Policy 52, 79–98.
Christelis, D., Jappelli, T., Padula, M., 2010. Cognitive abilities and portfolio choice. Eur. Econ. Rev. 54 (1), 18–38.
Coeurdacier, N., Rey, H., 2011. Home Bias in Open Economy. Financial Macroeconomics. NBER Working Paper No. 17691.
Cohen, K., Hawawini, C.G., Maier, S., Schwartz, R., Whitcome, D., 1983. Friction in the trading process and the estimation of systematic risk. J. Financ. Econ. 12, 263–278.
Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading. J. Financ. Econ. 7, 197–226.
Ding, X.-S., Chen, X., Zhang, J.-H., 2009. Certainty equivalent in portfolio management. In: The Eighth International Symposium on Operations Research and Its Applications, ORSC & APORC, pp. 115-123.
Fidora, M., Fratzscher, M., Thimann, C., 2007. Home bias in global bond and equity markets: The role of real exchange volatility. J. Int. Money Finance 26, 631–655.
Forbes, K., Warnock, F., 2011. Capital Flow Waves: Surges, Stops, Flight, and Retrenchment. NBER Working Paper No 17351.
Fratzscher, M., 2011. Capital Flows, Push Versus Pull Factors and the Global Financial Crisis. NBER Working Paper No 17357.
French, K.R., Poterba, J.M., 1991. Investor Diversification and International Equity Markets. NBER Working Paper No. 3609.
Garcia, V.F., Liu, L., 1999. Macroeconomic determinants of stock market development. J. Appl. Econ. II (1), 29–59.
Garlappi, L., Uppal, R., Wang, T., 2007. Portfolio selection with parameter and model uncertainty: A multi-prior approach. Rev. Financ. Stud. 20, 41–81.
Giannetti, M., Laeven, L., 2012. The flight home effect: Evidence from the syndicated loan market during financial crises. J. Financ. Econ. 104, 23–43.
Griever, W., Lee, G., Warnock, F., 2001. The US System for Measuring Cross-Border Investment in Securities: A Primer with a Discussion of Recent Developments. Federal Reserve Bulletin.
Griffin, J.M., Nardari, F., Stulz, R.M., 2004. Are daily cross-border equity flows pushed or pulled? Rev. Econ. Stat. 86, 641–657.
Harb, G., 2017. The economic impact of the internet penetration rate and telecom investments in Arab and Middle Eastern countries. Econ. Anal. Policy 56, 148–162.
Jagannathan, R., Ma, T., 2003. Risk reduction in large portfolios: Why imposing the wrong constraints. J. Finance 58 (4), 1651–1683.
Jorion, P., 1986. Bayes-Stein estimation for portfolio analysis. J. Financ. Quant. Anal. 21 (3), 279–292.
Jorion, P., 1991. Bayesian and CAPM estimators of the means: Implications for portfolio selection. J. Bank. Finance 15 (6), 717–727.
Kaufman, D., Kraay, A., Mastruzzi, M., 2010. The Worldwide Governance Indicators: A Summary of Methodology, Data and Analytical Issues. World Bank Policy Research Working Paper No. 5430.
Larsen, G.A., Resnick, B., 2001. Parameter estimation techniques, optimization frequency, and equity portfolio return enhancement. J. Portfolio Manage. 27, 27–34.
Levine, R., Zervos, S., 1998. Stock markets, banks, and economic growth. Am. Econ. Rev. 88 (3), 537–558.
Magi, A., 2009. Portfolio choice, behavioral preferences and equity home bias. Q. Rev. Econ. Finance 49, 501–520.
Milesi-Ferretti, G.-M., Tille, C., 2011. The great retrenchment: international capital flows during the global crisis. Econ. Policy 26, 295–342.
Mishra, A., 2015. Measures of equity home bias puzzle. J. Empir. Finance 34, 293–312.
Nock, R., Magdalou, B., Briys, E., 2011. On tracking portfolios with certainty equivalents on a generalisation of Markowitz model: The fool, the wise and the adaptive. In: Proceedings of the 28th International Conference on Machine Learning, Bellevue, WA, USA.
Pastor, L., 2000. Portfolio selection and asset pricing models. J. Finance 55, 179–223.
Portes, R., Rey, H., 2005. The determinants of cross-border equity flows. J. Int. Econ. 65 (2), 269–296.
Pungulescu, C., 2010. Does Lower Home Bias Lead to Welfare Benefits? Toulouse Business School, Barcelona Campus (ESEC), Department of Economics, Finance and Law.
Scholes, M., Williams, J., 1977. Estimating betas from nonsynchronous data. J. Financ. Econ. 5, 309–328.
Schroder, 2012. German investor focus on domestic, western Europe –. Available from: http://www.pie-mag.com/articles/2621/german-investor-focus-on-domestic-western-europe-schroder/, [12th February, 2012].
Sendi, I., Bellalah, M., 2010. The equity home bias: Explanations and financial anomalies. Int. J. Econ. Finance 2 (2), 78–96.
Stein, C., 1956. Inadmissibility of the usual estimator for the mean of a multivariate normal distribution. In: Proc. Third Berkeley Symposium. On Mathematics, Statistics and Probability, Vol. 1. Univ. of Calif. Press, pp. 197–206.
Tamazian, A., Rao, B.B., 2010. Do economic, financial and institutional developments matter for environmental degradation? Evidence from transitional economies. Energy Econ. 32 (1), 137–145.
Tesar, L.L., Werner, I.M., 1995. Home bias and turnover. J. Int. Money Finance 14, 467–492.
Wynter, M.M., 2012. Why did equity home bias fall during the financial panic of 2008? Unpublished paper.
Zellner, A., 2010. Bayesian shrinkage estimates and forecasts of individual and total or aggregate outcomes. Econ. Model. 27, 1392–1397.
Zellner, A., Chetty, V.K., 1965. Prediction and decision problems in regression models from the Bayesian point of view. J. Amer. Statist. Assoc. 60, 608–615.