Bilateral Home Bias and Country Performance: A Gravity Model

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First Draft

Abstract

This paper uses gravity models to bring new evidence that informational and cultural variables are key elements in explaining the bilateral home bias. Using both the traditional home bias measure as well as an alternative Bayesian measurement shows that country performance (expressed by the evolution of asset returns) plays a role in determining cross-border equity holdings. As expected, distance acts as a barrier to optimal cross-border investment (less for Bayesian home bias, suggesting that the perspective of financial gains helps overcoming various informational and cultural barriers). Having a common border appears to be one of the strongest drivers to foreign investment and also one favouring better investment policies, while having a common language appears to be investment inducing to the point of overinvestment (a so-called 'partner bias'). Participation to international agreements leads to lower home bias (most notably in the case of the European Monetary Union).

JEL classification: F36, G11, G15

Keywords: Home Bias, Country Performance, Gravity Models, International Portfolio Choice, Model Uncertainty

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1 Introduction

While it is generally agreed that international diversification improves portfolio performance, many countries hold puzzling low levels of foreign assets. The difference between optimal and observed (far too low) foreign holdings is known as the home bias puzzle (see French and Poterba, 1991). The academic literature has proposed several possible explanations for the home bias puzzle.

The prime targets were transaction costs such as fees, commissions and higher spreads (see Tesar and Werner, 1995; Glassman and Riddick, 2001; Warnock, 2001) and direct barriers to international investment (see Black, 1974; Stulz, 1981; Errunza and Losq, 1985). Evidence in Tesar and Werner (1995) and more recently Glassman and Riddick (2001) and Warnock (2001), however, rules out transaction cost as an important driver of the equity home bias. Moreover, the home bias puzzle persists even in times when most direct obstacles to foreign investment have disappeared.

While home bias remains one of the important "puzzles in international finance, while searching for the possible causes, important contributions focus on differences in the amount and quality of information between domestic and foreign stocks (see Gehrig, 1993; Brennan and Cao, 1997; Veldkamp and Van Nieuwerburgh, 2006), on hedging of non-traded goods consumption as a motive for holding domestic securities (see Adler and Dumas, 1983; Stockman and Dellas, 1989; Cooper and Kaplanis, 1994), and more recently on psychological or behavioral factors (see Huberman, 2001; Coval and Moskowitz, 1999; Grinblatt and Keloharju, 2000).

Okawa and van Wincoop (2012) witness that the gravity models that have been the realm of the international trade literature, since the important contribution of Portes and Rey (2005), they have recently enjoyed a substantial attention in international finance. They answer important questions such as as the impact of various phenomena and policy (i.e. globalization, trade agreements etc.) on cross-border trade in financial assets. While in the gravity models of international trade, distance is a measure of transportation costs, financial assets are 'weightless - distance cannot proxy transportation cost. Portes and Rey (2005) note however that "a gravity model explains international transactions in financial assets at least as well as goods trade transactions interpreting distance as indicative of "barriers to interaction and, more broadly, to cultural exchange.

The availability of the Coordinated Portfolio Survey (CPIS) on bilateral equity holdings database collected by the IMF data, makes it possible to use gravity models to investigate the home bias "puzzle in a novel way.

The comparison of the results for the two measures of home bias (computed in the framework of the I-CAPM and the Bayesian framework - which takes into account data on asset returns in deriving optimal portfolio weights) shows that country performance plays a role in the decisions of cross-border investments.

Section 2 details the procedure of computing optimal portfolio weights, Section 3 discusses the particularities of computing bilateral home bias and data issues, the results are presented in Section 4 and Section 5 concludes.

2 Optimal Portfolio Weights

This section presents alternative ways to calculate theoretically optimal portfolio weights with which observed weights can be compared. Section 2.1 reviews the standard mean-variance model of portfolio choice. Section 2.2 discusses the International CAPM. Sections 2.3 and 2.4 present the Bayesian modeling approaches of Pástor (2000) and Garlappi et al. (2007), respectively.

2.1 Classical Mean-Variance Portfolio Model

The common starting point is the mean-variance framework of Markowitz (1952) and Sharpe (1963) where the investor makes his portfolio choice in order to maximize his expected utility,

$$\max_{\omega} \omega'\mu - \frac{\gamma}{2}\omega'\Sigma\omega, \tag{1}$$

where ω is the N-vector of portfolio weights allocated to N assets, i.e. domestic and foreign equity holdings ($N = 2$), μ is the N-vector of expected returns, Σ is the $N \times N$ variance-covariance matrix and γ is the coefficient of relative risk aversion. Under the assumption that $\omega'\iota = 1$ (the budget constraint), the solution of the portfolio problem becomes

$$\omega^* = \frac{1}{\gamma}\Sigma^{-1}(\mu - \eta\iota), \tag{2}$$

where η denotes the expected return on the zero-beta portfolio corresponding to the optimal portfolio and ι is a N-vector of ones. The budget constraint effectively fixes γ for a known value of the zero-beta expected return through $\gamma = \iota'\Sigma^{-1}(\mu - \eta\iota)$ and determines uniquely the optimal portfolio weights (De Roon and Nijman, 2001). If a risk-free rate is available and chosen as the zero-beta portfolio, the coefficient of risk aversion becomes $\gamma = \iota'\Sigma^{-1}\mu_e$, where μ_e is the vector of the expected excess returns (over the risk-free rate). The analytical portfolio choice solution in the mean-variance framework, when short sales are allowed is:

$$\omega^* = \frac{\Sigma^{-1}\mu_e}{\iota'\Sigma^{-1}\mu_e}. \tag{3}$$

The solution of the optimization problem involves the true (unobserved) expected returns and variance-covariance matrix of the returns. Available returns data enables us to use the sample moments as estimates of the true parameters. However, Merton (1980) shows that the sample variance-covariance matrix gives an accurate estimate of the true parameter but the estimation of the expected returns based on historical data is very unreliable due to the high volatility of returns. The impact of the mean estimated imprecisely, is amplified in the context of international portfolio choice, as the inverse of the variance-covariance matrix tends to be a large number when the correlations between the countries are high (Jenske, 2001). Therefore, the "data-based" approach (i.e. substituting the sample mean and variance in equation 3) directs investors to take extreme and volatile positions.

2.2 International CAPM

An asset pricing model, such as the International Capital Asset Pricing Model (I-CAPM), provides an alternative to the "data-based" approach. The I-CAPM is valid in a perfectly integrated world, where the law of one price holds universally and markets clear (total wealth is equal to total value of securities). The world market portfolio can then be defined as the sum of all individual portfolios weighted by the positions held by mean-variance investors. The portfolio implication of the CAPM is that the average mean-variance investor holds the market portfolio (Lintner, 1965). In an international setting, the optimal investment weights of a country according to this so-called "model-based" approach, are given by the relative shares of domestic and foreign equities in the world market capitalization. For a US investor, this implies that domestic equity holdings should have been about 40% in 2004. The actual domestic allocations figures for the US were as high as 80%. The resulting "model-based" home bias has been traditionally used in the literature and gives the first measure of home bias in the present study.

The I-CAPM results in the well-known linear beta relationship between risk premium on the domestic portfolio and the expected excess return on the world market benchmark[1]:

$$E(r_d) - r_f = \beta \left[E(r_w) - r_f \right], \tag{4}$$

where r_d is the return on the domestic market portfolio, r_f is the risk free rate, $\beta \equiv \frac{cov(r_w, r_d)}{var(r_w)}$ is the world beta of the domestic market and r_w is the return on the world market portfolio. The empirical counterpart of equation 4 is given by

$$r_d - r_f = \alpha + \beta \left(r_w - r_f \right) + \varepsilon, \tag{5}$$

where α and ε are respectively the intercept and the disturbance term. The I-CAPM is considered valid if estimates of the intercept, $\hat{\alpha}$ are zero. However, an intercept different than zero, even if insignificant, can be used by a Bayesian investor to question the optimality of the portfolio prediction of the I-CAPM, and therefore the reliability of the traditional "model-based" measure of home bias.

[1] This model makes the additional assumption that currency risk is not priced. See De Santis and Gérard (2006) and Fidora et al. (2007) for an analysis of exchange rate risk on home bias measures.

2.3 Bayesian Mean-Variance Portfolio Weights

Considering the stringency of the assumptions of the I-CAPM, it is reasonable to expect that some investors do not accept the model unconditionally.

When the I-CAPM holds, the world benchmark fully describes the asset returns and captures all sources of priced risk. In terms of the beta pricing relationship (5), a valid model results in a zero value for the intercept $\hat{\alpha}$. In the Bayesian framework developed by Pástor (2000), when there is mistrust in the I-CAPM, the data becomes informative and is involved in the portfolio allocation decision. The degree of trust (i.e. the belief that the intercept $\hat{\alpha}$ is zero) is expressed in values of the standard errors of the intercept σ_α. A small value indicates a strong belief that the theoretical model is valid and results in optimal portfolio weights that closely correspond to the "model-based" approach. A higher value involves data to a larger extent in the computation of optimal weights leading thus to a different set of optimal weights and brings us closer to the results of the "data-based" approach. Full mistrust in the model (i.e. $\sigma_\alpha \to \infty$) coincides with the "data-based" optimal weights. This Bayesian interpretation is an insightful reconciliation of the "model" and "data-based" approaches. For instance, a nonzero value for $\hat{\alpha}$, even if insignificant according to a standard t-test (and therefore failing to reject the I-CAPM), could become instrumental in explaining why observed allocations deviate from the model prescriptions.

The starting point of the Bayesian analysis is a *prior* (non-data) belief in the the model, in this case, the belief in a zero intercept and no mispricing. The prior is updated using returns data to a certain extent depending on the chosen degree of mistrust in the model. The sample mispricing, α is "shrunk" accordingly towards the prior mean of α to obtain the posterior mean of α.

Using the data in combination with the model prediction ultimately results in different estimates for the mean and variance covariance matrix of returns, since now the moments of the predictive distribution are used to compute the portfolio weights. These Bayesian mean-variance optimal weights are computed as:

$$\omega^* = \frac{\Sigma^{*-1}\mu_e^*}{\iota'\Sigma^{*-1}\mu_e^*} \tag{6}$$

where μ_e^* and Σ^* are the predictive mean and variance that replace in this approach the sample moments of the distribution of returns.

The predictive density of returns (entering the utility function of the investor that maximizes next period wealth) is defined as:

$$p\left(r_{t+1}|\Phi\right) = \int_\theta p\left(r_{t+1}|\theta, \Phi\right) p\left(\theta|\Phi\right) d\theta \tag{7}$$

where $p\left(r_{t+1}|\Phi\right)$ is the probability density function of excess returns conditional on Φ (the sample data) and θ is the set of parameters of the statistical model that describes the stochastic behavior of asset returns. To treat the estimates of the parameters $\hat{\theta}$ as the true values, is to ignore estimation risk. An alternative is to use Bayesian analysis to account for estimation risk. The predictive density (equation 7) involves $p(\theta|\Phi)$, the conditional probability of the parameters of the model given the data available. According to Bayes' Rule, the *posterior density*, $p(\theta|\Phi)$, is proportional to the product of the *likelihood function*, or probability distribution function for the data given the parameters of the model, $p(\Phi|\theta)$, and the *prior density*, $p(\theta)$, that reflects the non-data information available about θ (see Koop, 2003):

$$p(\theta|\Phi) \propto p(\Phi|\theta)\, p(\theta)\,. \tag{8}$$

In the present setting, the prior of a zero intercept follows from assuming a valid I-CAPM and is subsequently updated through incorporation of the information revealed by the data. The methodology and the analytical solutions for the mean and variance of the predictive density are presented in further detail in the Appendix.

A degree of mistrust in the I-CAPM depending on the empirical performance of the model on specific country data, may result in optimal weights that are closer to the observed allocations and thereby imply for certain countries, a lower home bias than the deviation from the market capitalization share.

2.4 Bayesian Multi-Prior Framework

The alternative, "data-based" approach, using historical return data for estimating the optimal allocations, results in volatile and extreme investment predictions (see Baele et al., 2007, for an example). Garlappi et al. (2007) tackle the problem of volatile data by extending the mean-variance framework to incorporate the investors' aversion to uncertainty around the estimate of the mean returns. This changes the standard mean-variance problem in two ways: (1) it binds the expected returns to a confidence interval around their estimate, thus taking into account the eventual estimation error and (2) it allows the investor to minimize over the choice of expected returns, thus manifesting its aversion to uncertainty. The Multi-Prior framework of Garlappi et al. (2007) is defined by the following problem:

$$\max_{\omega} \min_{\mu} \omega'\mu - \frac{\gamma}{2}\omega'\Sigma\omega, \tag{9}$$

subject to

$$f(\mu, \hat{\mu}, \Sigma) \leq \epsilon \tag{10}$$

$$\omega'\iota = 1 \tag{11}$$

where $\hat{\mu}$ is the sample mean of asset returns. If the confidence intervals are defined jointly for all assets, f can be taken as $\frac{T(T-N)}{(T-1)N}(\hat{\mu}-\mu)'\,\Sigma^{-1}(\hat{\mu}-\mu)$ and ϵ as a quantile for the F-distribution[2], where N is

[2]If asset returns are normally distributed and Σ is known, f has a χ^2 distribution with N d.f. If Σ is not known, it follows a F-distribution with N,$T-N$ d.f. (Garlappi et al., 2007)

the number of assets and T, the number of observations. The constraint translates into $P(f \leq \epsilon) = 1-p$ for a corresponding probability level. This framework can also be extended to include uncertainty over a chosen return-generating model, such as the I-CAPM. The solution to the Multi-Prior max-min problem is a set of optimal weights with considerably smoother behavior compared to the ones obtained through the direct influence of the data.

This methodology is applied to obtain the second measure of home bias, the volatility corrected Bayeasian home bias.

3 Home Bias Measures and Data Issues

The previous section presented alternative ways of defining optimal portfolio allocations. This section introduces our measure of home bias in terms of actual and optimal portfolio weights, as well as the main characteristics of the dataset used.

3.1 Home Bias Measures

Bilateral home bias of source country i with respect to destination country j is quantified as the relative difference between actual (ACT_{ij}) and optimal (OPT_{ij}) foreign portfolio weights:

$$BHB_{ij} = 1 - \frac{ACT_{ij}}{OPT_{ij}}. \tag{12}$$

Optimal portfolio weights are calculated using the alternative methodologies described in Section 2. The actual portfolio holdings of source country i in the equity of destination country j (ACT_{ij}) are determined using data Coordinated Portfolio Survey conducted by the IMF. The domestic equity holdings are calculated as the difference between the market capitalization of the country (MC_i) and the total domestic equity stocks held by foreign investors (FL_i):

$$ACT_{ij} = \frac{FA_{ij}}{FA_i + MC_i - FL_i}. \tag{13}$$

In the typical case, when actual foreign involvement is lower than the optimal share of international assets, and the country is subject to home bias, the measure takes values between 1 (when the investors hold only domestic assets) and 0 (when actual and optimal portfolio weights are equal).However, bilateral data offers frequent cases when the actual weights exceed optimal weights, for instance when negative or very low weights are assigned to the world market index in the optimization framework. This can be the case when the world market index has a high variance and covariance with the domestic index and a lower mean. In such instances the country appears not home biased, but on the contrary, overinvesting abroad and the former measure of home bias would be misleading. Therefore, the formula is extended to take into account the case of overinvestment abroad (negative ‘home bias’) and obtain comparable results, as follows:

$$BHB_{ij} = \frac{(OPT_j - ACT_{ij})}{max(\mid OPT_j \mid, \mid ACT_{ij} \mid)}. \tag{14}$$

This formula is used to compute a negative measure of ‘home bias’ when optimal allocations are lower than the observed foreign investment.In this perspective, both actual and optimal weights can be negative (short sales being allowed) and countries may be overinvested in some of their investment destinations. If equation 12 were applied here, the (much lower) optimal weights in the denominator might result in extreme values for home bias that are practically irrelevant for subsequent analysis. Equation 14 redefines the formula for computing home bias in such cases, maintaining therefore the scale of the resulting home bias. In their paper linking home bias to exchange rate volatility, Fidora et al. (2007) make the same choice when computing bilateral home bias.

3.2 Data

The current exercise on bilateral home bias is made possible by the initiative of the International Monetary Fund (IMF) to conduct the Coordinated Portfolio Investment Survey (CPIS) in which 113 economies volunteer information about the geographical distribution of their foreign assets. The first trial was successfully conducted in 1997 and starting with 2001, the CPIS takes place every year. This paper uses the 11 years of data on cross-border stocks and bilateral foreign trade (imports) available since 2001.

While the value-added in information brought about by such detailed statistics is substantial, it has to be noticed that several possible bias are in-built in this database. If for instance, country A uses a broker company in country B in order to ultimately invest in a third country C, the database will not allow us to uncover country A’s holdings of country C’s equity. Also, participating economies may (and do) on occasion choose to withhold information on the amounts of their holdings.

Data on weekly market index prices and their respective market capitalization is obtained from Datastream. Weekly US$-denominated total returns have been computed for 54 of the 113 economies covered by the CPIS. Where available (34 cases) Datastream’s total market indices have been used. The coverage starts in January 1973 for the more established markets and as late as 2006 for Uruguay and Luxembourg. The world market index has been computed as a weighted average of the available market indices at each point in time. In order to compute Bayesian optimal weights every period, only the countries with 520 weekly observations of returns data available prior to the year-end observation, have been taken into consideration.

Annual market capitalization figures for the full sample are obtained from the World Development Indicators database.

The risk-free rate is the one-month Treasury Bill rate from Ibbotson and Associates Inc., available on Kenneth French's website[3].

Finally, the gravity variables (distance between capital cities, common border and common language) are obtained from the *GeoDist* database developed in Mayer and Zignago (2005) and explained in Mayer and Zignago (2006).

4 Results

4.1 Descriptive Statistics

Table 1 presents descriptive statistics for the full sample for the two measures of bilateral home bias obtained under the the I-CAPM framework (HB I) and under the Bayesian framework (HB B). As data availability constrains the Bayesian home bias to a smaller sample, the measure of I-CAPM home bias is also restrained for comparative purposes to the same data points, giving an alternative measure of I-CAPM home bias (HB IC).

Several patterns capture attention. Firstly, home bias across the full sample is high, with averages of over 0.64 to 0.83 across the three measures. Secondly, the phenomenon overinvestment is considerable (i.e. a so-called 'partner bias' is consistently identified in bilateral equity holdings). 17% of the bilateral home bias observations for the I-CAPM home bias, representing more than 7000 country pair yearly positions, are negative. Interestingly, the instances of negative bilateral home bias are halved (relative to the comparative sample) for Bayesian home bias, which indicates that the financial market performance of the destination country justifies higher holdings of that country.

Reducing the sample to the OECD member states (Table 2) decreases the average home by approximatively 0.30, which suggests that developed countries are better placed to take advantage of the benefits of international diversification. At the same time the percentage of negative instances of bilateral home bias is increased to 36%. The pattern of less overinvestment for the measure of Bayesian home bias is maintained.

These patterns are maintained for samples reduced to EU member states (Table 3) and EMU member states (Table 4) with the notable impact of the common currency, which reduces the average bilateral home bias to virtually 0 for the I-CAPM home bias (full sample). Also the Euro Area bilateral home bias exhibits the highest percentage of negative instances (half of the number of observations for the I-CAPM measures and a quarter for the Bayesian measure). Consistent with the view that the common currency fosters increased cross-border financial activity (even to the point of overinvestment), the average Bayesian bilateral home bias is lowest for the EMU.

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Tables 5 to 7 show the time variation of the three measures of bilateral home bias over four subperiods: (1) 2001-2003; (2) 2004-2006; (3) 2007-2009; (4) 2010-2011. Across all three measures, over time, bilateral home bias appears to be decreasing and the percentage of overinvestment increases.

4.2 Econometric Specification

This section presents the results of panel data estimation allowing for fixed effects both for source and destination countries, using the estimation procedure proposed by Guimarães and Portugal (2009):

$$BHB_{ij} = \alpha_i + \alpha_j + \beta InitialBHB_{ij} + \gamma ln(Distance_{ij}) +$$
$$\delta ln(Imports_{ij}) + \zeta CommonLanguage_{ij} + \eta CommonBorder_{ij} +$$
$$\theta EU + \tau EMU + \lambda OECD + \mu NAFTA + \pi ASEAN, \quad (15)$$

where EU, EMU, OECD, NAFTA, ASEAN are dummies that take the value 1 when both the source and the destination countries are part of the respective international organizations.

Table 8 reports the results of fitting a gravity model to explain the dynamics of the bilateral home bias, where the dependent variables represent in turn: (1) the I-CAPM bilateral home bias for the the full sample (HB I), the I-CAPM bilateral home bias for the comparative sample (HB IC) and the Bayesian home bias (HB B). The empirical analysis shows that bilateral home bias exhibits persistence (a high initial value leads to higher values of home bias in the future). The hypothesis of distance proxying barriers to cross-border financial flows is confirmed, as higher distance results in higher values of home bias. Trade links (proxied by bilateral imports) appear to matter little in economic terms, but home bias appears lower for countries sharing a common language and more importantly a common border. Consistent to the descriptive statistics, sharing EMU membership lowers bilateral home bias most significantly.

The impact of gravity variables in determining the dynamics of deviations from optimality (bilateral home bias in absolute terms) is presented in Table 9. The results show that the deviations from optimality are persistent and increase with distance. A relevant pattern is given by the fact that having a common border increases the optimality of bilateral investment, which suggests that the possibly higher transparency allows for a better allocation of resources.

Table 10 restricts the investigation only to the instances of positive home bias and shows that home bias increases with initial value and distance. Among the factors that matter most in overcoming the barriers to trade, having a common border and membership in EU/EMU/OECD matter most.

Table 11 presents the results of the same model fitted to the instances of overinvestment (or 'partner bias), which appear not dependent on either initial values or distance. Negative home bias seems to be driven by common language and membership to international organizations (EMU/OECD).

Fitting graviy models to the subperiods samples, gives a time evolution of the impact of the gravity variables on bilateral home bias. The results [4] show that persistence (i.e. impact of initial home bias level) is decreasing, while the impact of distance is (slightly) increasing (both being consistently lower for Bayesian home bias). The impact of bilateral trade is small and decreases to insignificance for the Bayesian home bias. While the impact of common language is (slightly) decreasing, the impact of common border is (strongly) increasing. Also, the importance of EU/OECD memberships declines to insignificance and that of the common currency is strongest in the second period after which it declines (slightly).

Overall, the results show that gravity models describe well the phenomenon of bilateral home (and partner) bias, singling out the common border as one of the strongest factors lowering the biases.

5 Concluding Remarks

This paper used gravity models to bring new evidence that informational and cultural variables are key elements in explaining the bilateral home bias. Using an alternative Bayesian measurement of home bias (that takes into account country performance expressed in the evolution of asset returns) shows that while there is evidence that investment decisions are taking into account country performance, bilateral home bias remains substantial and is persistent. As expected, distance acts as a barrier to optimal cross-border investment (less for Bayesian home bias, suggesting that the perspective of financial gains helps overcoming various informational and cultural barriers). Having a common border appears to be one of the strongest drivers to foreign investment and also one favouring better investment policies, while having a common language appears to be investment inducing to the point of overinvestment. Participation to international agreements leads to lower home bias (most notably in the case of EMU).

[4] Available upon request.

Appendix

A The Bayesian Framework

This appendix outlines the steps of deriving the moments of the predictive distribution of excess returns, r_{t+1}, conditional on the set of sample data, Φ in terms of the prior and the likelihood function.

The Prior

The way in which the prior distribution incorporates the information given by the estimated intercept reflects the degree of belief in the model. Complete belief in the model assumes that the eventual nonzero intercepts are merely a result of sampling or estimation error and ignores them when computing the expectations of excess returns (the fitted value of the dependent variable) while complete disbelief in the model uses the sample mean as the estimate of expected returns. As our main interest lies in the intercept it sufficient to construct a prior which is informative only with respect to α and diffuse (highly volatile, non-informative) for the other parameters. Pástor (2000) chose a normal inverted Wishart prior for the intercept:

$$\alpha|\Sigma \sim N\left(0, \sigma_\alpha^2\left(\frac{1}{s^2}\right)\right), \tag{A-1}$$

with Σ following a inverted Wishart distribution: $\Sigma^{-1} \sim W\left(H^{-1}, \upsilon\right)$, H^{-1} the parameter matrix of the Wishart distribution and υ, the degrees of freedom. The expectation of the inverted Wishart distribution is given by $E\left(\Sigma\right) = \frac{H}{(\upsilon-N-1)}$, where N is the number of asset returns in our time series. We can rewrite the expectation for the prior residual covariance matrix, as $E\left(\Sigma\right) = s^2 I_N$, for $H = s^2\left(\upsilon - N - 1\right)$ The prior involves a diagonal and homoskedastic covariance matrix for the residuals, which is set to be non-informative by choosing υ=15, the equivalent of the sample of 15 observations. The prior of homoskedasticity can easily be reversed under the pressure of data that enters the computation of the posterior density. At this point, taking expectation of the conditional prior distribution of α, leads to an unconditional distribution in the from:

$$\alpha \sim N\left(0, \sigma_\alpha^2 I_N\right), \tag{A-2}$$

where σ_α^2 incorporates the degree of disbelief in the model. Based on the interpretation that the intercepts that are different than zero reflect omitted sources of risk from the model, the size of this mispricing is directly linked to the size of the residual covariance matrix. If the variance of the intercepts has been large, the model is consequently less trusted. The asset pricing model is linear in the benchmark risk factor, the world returns under the I-CAPM [5]: $R_t = \alpha + \beta F_t + \varepsilon_t$, assuming $E\left(\varepsilon_t\right) = 0$, $E\left(\varepsilon_t \varepsilon_t'\right) = \Sigma$,

[5] Pástor (2000) derives the results for the general case of N assets and K benchmarks. In the case of International CAPM, the only benchmark is given by the world returns. Notation follows closely Asgharian and Hansson (2006).

$E(F_t) = \mu_t$, $E\left[(F_t - \mu_t)(F_t - \mu_t)'\right] = \Omega_F$, $cov(F_t, \varepsilon_{i,t}) = 0$, $\forall i = \overline{1, N}$. The prior joint distribution is:

$$p(\theta) = p(\alpha|\Sigma)\, p(\Sigma)\, p(\beta)\, p(\mu_F)\, p(\Omega_F), \tag{A-3}$$

where only the priors on the last three distributions are diffuse as derived by Pástor and Stambaugh (2000):

$$p(\alpha|\Sigma) \propto |\Sigma|^{-\frac{1}{2}} exp\left\{-\frac{1}{2}\alpha'\left(\frac{\sigma_\alpha^2}{s^2}\Sigma\right)^{-1}\alpha\right\}, \tag{A-4}$$

$$p(\Sigma) \propto |\Sigma|^{-\frac{(v+N+1)}{2}} exp\left\{-\frac{1}{2}trH\Sigma^{-1}\right\}, \tag{A-5}$$

$$p(\beta) \propto 1, \tag{A-6}$$

$$p(\mu_F) \propto 1, \tag{A-7}$$

$$p(\Omega_F) = \Omega_F^{-1}. \tag{A-8}$$

The Likelihood

In the linear model for asset returns, the disturbances are assumed uncorrelated and homoskedastic. The benchmark returns are assumed i.i.d., normal, independent over time and independent of the error terms. Under these independence assumptions, the likelihood function can be written as a product of two normal likelihood functions, for the returns on the assets and respectively for the returns on the benchmark factor:

$$p(\Phi|\theta) = p(R|\theta, F)\, p(F|\theta). \tag{A-9}$$

The product terms are further expanded using computational results of Pástor and Stambaugh (2000) into:

$$p(R|\theta, F) \propto |\Sigma|^{-\frac{T}{2}} exp\left(-\frac{T}{2}tr\hat{\Sigma}\Sigma^{-1} - \frac{1}{2}\left(b - \hat{b}\right)\left(\Sigma^{-1} \otimes F'F\right)\left(b - \hat{b}\right)\right), \tag{A-10}$$

$$p(F|\theta) \propto |\Omega_F|^{-\frac{T}{2}} exp\left(-\frac{T}{2}tr\hat{\Omega}_F\Omega_F^{-1} - \frac{1}{2}(\mu_F - \hat{\mu}_F)(\mu_F - \hat{\mu}_F)'\,\Omega_F^{-1}\right), \tag{A-11}$$

where $b = vec(B)$ [6] and $B = (\alpha \quad \beta)'$.

The Posterior Density

We return to the key relation of Bayesian analysis, that defines the posterior distribution via proportionality with the product of prior density and likelihood functions. Pástor and Stambaugh (2000) combine the results for the priors with the ones for the likelihood functions separately for the regression parameters and for the benchmark returns.

[6] The transformation *vec* applied to a matrix, stacks its columns resulting into a vector.

The posterior means of the model parameters result from:

$$b \equiv E(b|\Phi) = \left(I_N \otimes P^{-1}X'X\right)\hat{b}, \tag{A-12}$$

where $\hat{b}$ the vector of OLS estimates of the model on the dataset, $X = (\iota_T F)$, $P = S + X'X$, $D_{[2\times 2]}$ is a matrix with the first element $d_{(1,1)} = \frac{s^2}{\sigma_\alpha^2}$ and the rest of the elements $d_{(m,n)} = 0$, with $m,n \neq 1$.

The posterior variance of the model parameters is given by:

$$var(b|\Phi) = \tilde{\Sigma} \otimes P^{-1}, \tag{A-13}$$

where $\tilde{\Sigma} = E(\Sigma|\Phi) = \frac{\left(H + T\hat{\Sigma} + \hat{B}'Q\hat{B}\right)}{T-\upsilon-N-K-1}$, $Q = X'\left(I_T - XP^{-1}X'\right)X$ and $\hat{\Sigma}$ and $\hat{B}$ result from estimating the model on the available sample.

Finally, the predictive means and variance of asset returns are defined using the posterior moments.

The predictive means can be computed as:

$$\mu^* \equiv E\left[R_{T+1}|\Phi\right] = \tilde{\mu} = \tilde{\alpha} + \tilde{\beta}\tilde{\mu}_F, \tag{A-14}$$

where $\tilde{\mu}$, $\tilde{\alpha}$, $\tilde{\beta}$, $\tilde{\mu}_F$ are posterior means and parameters.

The predictive variance-covariance matrix of asset returns is given by:

$$cov\left(R_{i,T+1}R_{j,T+1}|\Phi\right) \equiv \tilde{\beta}_i'\Omega_F^*\tilde{\beta}_j + tr\left[\Omega cov\left(\beta_i, \beta_j|\Phi\right)\right] + \tilde{\sigma}_{i,j} + \left[1 \quad \tilde{\mu}_F'\right] cov\left(b_i, b_j'|\Phi\right)\left[1 \quad \tilde{\mu}_F'\right]', \tag{A-15}$$

where $\tilde{\sigma}_{i,j}$ is the respective (i,j) element of the posterior variance covariance matrix, $\tilde{\Sigma}$ and Ω_F^* is the predictive covariance matrix factor employed by the model explaining the returns: $\Omega_F^* = \tilde{\Omega}_F + var(\mu_F|\Phi)$, where $\tilde{\Omega}_F = \frac{T\hat{\Omega}_F}{T-3}$, $var(\mu_F|\Phi) = \frac{\hat{\Omega}_F}{T-3}$.

The analytical result for the predictive variance-covariance matrix for the asset returns is:

$$cov(R, F|\Phi) = \tilde{\beta}\tilde{\Omega}_F + \tilde{\beta}var(\mu_F|\Phi). \tag{A-16}$$

B The Multi-Prior Framework

Garlappi et al. (2007) prove that the Multi-Prior optimization problem in the case when uncertainty about the estimation of expected returns is expressed jointly for all assets, is equivalent to the maximization problem:

$$\max_\omega \omega'\mu - \frac{\gamma}{2}\omega'\Sigma\omega - \sqrt{\varepsilon}\omega'\Sigma\omega, \tag{B-1}$$

subject to

$$\omega'\iota = 1, \tag{B-2}$$

where

$$\varepsilon = \epsilon \frac{(T-1)\,N}{T\,(T-N)}. \tag{B-3}$$

Without imposing short sales constrains, the problem can be solved analytically and the optimal weights are given by:

$$\omega^* = \frac{\sigma_P^*}{\sqrt{\varepsilon} + \gamma \sigma_P^*} \Sigma^{-1} \left(\hat{\mu} - \frac{1}{A} \left(B - \frac{\sqrt{\varepsilon} + \gamma \sigma_P^*}{\sigma_P^*} \right) \iota \right), \tag{B-4}$$

where σ_P^* is the variance of the optimal portfolio and the (unique) positive real solution to the polynomial equation:

$$A\gamma^2 \sigma_P^4 + 2A\gamma \sigma_P^3 + \left(A\varepsilon - AC + B^2 - \gamma^2 \right) \sigma_P^2 - 2\gamma \sqrt{\varepsilon} \sigma_P - \varepsilon = 0, \tag{B-5}$$

and $A = \iota' \Sigma^{-1} \iota$, $B = \hat{\mu}' \Sigma^{-1} \iota$ and $C = \hat{\mu}' \Sigma^{-1} \hat{\mu}$.

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Table 1: **Descriptive Statistics: Bilateral Home Bias**

This table presents some descriptive statistics (total number of observations (No. Obs.), number of negative observations (% Negative), mean of the sample (Mean), standard deviation (Std. Deviation), minimum (Min) and maximum (Max) for three measures of home bias: Home Bias I-CAPM Full Sample (HB I), Home Bias I-CAPM Comparative Sample (HB IC) and Bayesian Home Bias (HB B).

	HB I	HB IC	HB B
No. Obs.	41975	31824	31824
% Negative	**0.1726**	**0.1420**	**0.0733**
Mean	0.6451	0.7030	0.8324
Std. Deviation	0.6614	0.6033	0.4291
Min	-1.0000	-0.9999	-0.9945
Max	1	1	1

Table 2: **Descriptive Statistics: Bilateral Home Bias: OECD Member States**

This table presents some descriptive statistics (total number of observations (No. Obs.), number of negative observations (% Negative), mean of the sample (Mean), standard deviation (Std. Deviation), minimum (Min) and maximum (Max) for three measures of home bias: Home Bias I-CAPM Full Sample (HB I), Home Bias I-CAPM Comparative Sample (HB IC) and Bayesian Home Bias (HB B). The data covers the OECD Member States.

	HB I	HB IC	HB B
No. Obs.	7807	7011	7011
% Negative	**0.3613**	**0.3128**	**0.1901**
Mean	0.2663	0.3562	0.5769
Std. Deviation	0.7880	0.7491	0.6053
Min	-1.0000	-0.9998	-0.9916
Max	1	1	1

Table 3: **Descriptive Statistics Bilateral Home Bias: EU Member States**

This table presents some descriptive statistics (total number of observations (No. Obs.), number of negative observations (% Negative), mean of the sample (Mean), standard deviation (Std. Deviation), minimum (Min) and maximum (Max) for three measures of home bias: Home Bias I-CAPM Full Sample (HB I), Home Bias I-CAPM Comparative Sample (HB IC) and Bayesian Home Bias (HB B). The data covers the EU Member States.

	HB I	HB IC	HB B
No. Obs.	10575	4027	4027
% Negative	**0.4476**	**0.4107**	**0.1895**
Mean	0.3502	0.1702	0.5684
Std. Deviation	0.7930	0.8072	0.6186
Min	-1.0000	-0.9999	-0.9836
Max	1	1	1

Table 4: **Descriptive Statistics Bilateral Home Bias: EMU Member States**

This table presents some descriptive statistics (total number of observations (No. Obs.), number of negative observations (% Negative), mean of the sample (Mean), standard deviation (Std. Deviation), minimum (Min) and maximum (Max) for three measures of home bias: Home Bias I-CAPM Full Sample (HB I), Home Bias I-CAPM Comparative Sample (HB IC) and Bayesian Home Bias (HB B). The data covers the EMU Member States.

	HB I	HB IC	HB B
No. Obs.	1888	1663	1663
% Negative	**0.5164**	**0.4726**	**0.2532**
Mean	-0.0316	0.0472	0.4230
Std. Deviation	0.8125	0.8002	0.6685
Min	-0.9998	-0.9998	-0.9836
Max	1	1	1

Table 5: **Time Variation of Bilateral Home Bias I-CAPM (Full Sample)**

This table presents some descriptive statistics (total number of observations (No. Obs.), number of negative observations (% Negative), mean of the sample (Mean), standard deviation (Std. Deviation), minimum (Min) and maximum (Max) for the full sample of bilateral home bias I-CAPM (HB I). The sample is divided in fours subperiods: (1) 2001-2003; (2) 2004-2006; (3) 2007-2009; (4) 2010-2011.

	HB I	HB I	HB I	HB I
	2001-2003	2004-2006	2007-2009	2010-2011
No. Obs.	9600	11033	12294	9048
% Negative	**0.159896**	**0.162694**	**0.17716**	**0.191866**
Mean	0.670943	0.664123	0.634514	0.608896
Std. Deviation	0.640017	0.643096	0.667623	0.694371
Min	-0.99995	-0.99993	-0.9999	-0.99998
Max	1	1	1	1

Table 6: **Time Variation of Bilateral Home Bias I-ICAPM (Comparative Sample)**

This table presents some descriptive statistics (total number of observations (No. Obs.), number of negative observations (% Negative), mean of the sample (Mean), standard deviation (Std. Deviation), minimum (Min) and maximum (Max) for the comparative sample of bilateral home bias I-CAPM (HB IC). The sample is divided in fours subperiods: (1) 2001-2003; (2) 2004-2006; (3) 2007-2009; (4) 2010-2011.

	HB IC	HB IC	HB IC	HB IC
	2001-2003	2004-2006	2007-2009	2010-2011
No. Obs.	6580	8071	9957	7216
% Negative	**0.125532**	**0.126502**	**0.14643**	**0.168099**
Mean	0.735547	0.733785	0.692069	0.654189
Std. Deviation	0.565721	0.565726	0.615158	0.654754
Min	-0.99789	-0.99992	-0.99989	-0.99991
Max	1	1	1	1

Table 7: **Time Variation Bayesian Home Bias**

This table presents some descriptive statistics (total number of observations (No. Obs.), number of negative observations (% Negative), mean of the sample (Mean), standard deviation (Std. Deviation), minimum (Min) and maximum (Max) for the bilateral home bias Bayesian (HB B). The sample is divided in fours subperiods: (1) 2001-2003; (2) 2004-2006; (3) 2007-2009; (4) 2010-2011.

	HB B 2001-2003	HB B 2004-2006	HB B 2007-2009	HB B 2010-2011
No. Obs.	6580	8071	9957	7216
% Negative	**0.059726**	**0.067897**	**0.079743**	**0.082871**
Mean	0.85194	0.841027	0.822163	0.819191
Std. Deviation	0.395572	0.412883	0.444524	0.453009
Min	-0.98362	-0.99454	-0.98552	-0.99367
Max	1	1	1	1

Table 8: **Gravity Model Results Full Sample**

This table reports the results of (fixed effects) panel regressions of bilateral home bias computed in the I-CAPM framework for the full sample (HB I) and comparative sample (HB IC) and the Bayesian framework (HB B) on: the initial level of bilateral home bias (Initial), distance between capital cities (Distance), bilateral imports (Trade), common language (Language), common border (Contiguous), as well as dummy variables for both source and destination countries belonging to EU, EMU, OECD, NAFTA or ASEAN. Fixed effects are included both for source and destination countries. Values of the coefficients, T-statistics and adjusted R^2, are reported. Significance of the coefficients is denoted by *** (at 1%), ** (at 5%) and * (at 10%).

Full Sample	(-1-)	(-2-)	(-3-)	(-4-)	(-5-)	(-6-)
	HB I	HB IC	HB B	HB I	HB IC	HB B
No. Obs.	28000	19058	19058	28000	19058	19058
Initial	0,14567***	0,17575***	0,14248***	0,141128***	0,17055***	0,13891***
	(39,70)	(43,97)	(33,32)	(38,48)	(42,96)	(32,58)
Distance	0,12273***	0,11800***	0,08177***	0,08224***	0,09100***	0,06263***
	(25,72)	(24,74)	(19,99)	(16,12)	(17,45)	(13,96)
Trade	-0,02628***	-0,01672***	-0,00399**	-0,02549***	-0,01605***	-0,00501***
	(-15,69)	(-8,95)	(-2,50)	(-15,28)	(-8,61)	(-3,13)
Language	-0,07677***	-0,04243***	-0,06827***	-0,08690***	-0,04858***	-0,07088***
	(-7,68)	(-4,42)	(-8,35)	(-8,74)	(-5,08)	(-8,66)
Contiguous	-0,08450***	-0,14661***	-0,20246***	-0,09018***	-0,15700***	-0,19556***
	(-5,64)	(-9,42)	(-15,25)	(-6,02)	(-10,03)	(-14,58)
EU				-0,17194***	-0,09770***	-0,02924***
				(-14,24)	(-7,53)	(-2,63)
EMU				-0,15058***	-0,16640***	-0,10617***
				(-10,17)	(-11,37)	(-8,45)
OECD				-0,07801***	-0,00285	-0,09509***
				(-6,74)	(-0,21)	(-7,99)
NAFTA				0,18972**	0,18999**	-0,02137
				(2,55)	(3,06)	(-0,40)
ASEAN				-0,33827***	-0,40128***	-0,20377***
				(-6,74)	(-5,80)	(-3,44)
Adj-R^2	0.62	0.66	0.59	0.63	0.67	0.59

Table 9: **Dependent Variable: Bilateral Home Bias in Absolute Terms (i.e. Deviations from Optimality)**

This table reports the results of (fixed effects) panel regressions of the absolute value of bilateral home bias computed in the I-CAPM framework for the full sample (HB I) and comparative sample (HB IC) and the Bayesian framework (HB B) on: the initial level of bilateral home bias (Initial), distance between capital cities (Distance), bilateral imports (Trade), common language (Language), common border (Contiguous), as well as dummy variables for both source and destination countries belonging to EU, EMU, OECD, NAFTA or ASEAN. Fixed effects are included both for source and destination countries. Values of the coefficients, T-statistics and adjusted R^2, are reported. Significance of the coefficients is denoted by *** (at 1%), ** (at 5%) and * (at 10%).

	Absolute		
	HB I	HB C	HB B
No. Obs.	28000	19058	19058
Initial	0,02437***	0,04832***	0,04476***
	(14,97)	(24,43)	(20,14)
Distance	0,02034***	0,02271***	0,02498***
	(8,98)	(8,74)	(10,68)
Trade	0,00134*	-0,00104	-0,00334***
	(1,81)	(-1,12)	(-4,00)
Language	-0,00080	0,00849*	0,01125***
	(-0,18)	(1,78)	(2,64)
Contiguous	-0,03223***	-0,04799***	-0,07873***
	(-4,86)	(-6,15)	(-11,26)
EU	-0,02737***	-0,02541***	-0,01135*
	(-5,11)	(-3,93)	(-1,96)
EMU	0,02091***	0,01251*	-0,02082***
	(3,18)	(1,72)	(-3,18)
OECD	-0,06496***	-0,06182***	-0,05601***
	(-12,65)	(-8,94)	(-9,03)
NAFTA	0,10190***	0,14570***	0,05524**
	(3,09)	(4,71)	(1,99)
ASEAN	-0,11899***	-0,14591***	-0,22767***
	(-3,21)	(-4,23)	(-7,37)
Adj-R^2	0.28	0.39	0.50

Table 10: **Dependent Variable: Positive Instances of Bilateral Home Bias**

This table reports the results of (fixed effects) panel regressions of the positive instances of bilateral home bias computed in the I-CAPM framework for the full sample (HB I) and comparative sample (HB IC) and the Bayesian framework (HB B) on: the initial level of bilateral home bias (Initial), distance between capital cities (Distance), bilateral imports (Trade), common language (Language), common border (Contiguous), as well as dummy variables for both source and destination countries belonging to EU, EMU, OECD, NAFTA or ASEAN. Fixed effects are included both for source and destination countries. Values of the coefficients, T-statistics and adjusted R^2, are reported. Significance of the coefficients is denoted by *** (at 1%), ** (at 5%) and * (at 10%).

	Positive		
	HB I	HB IC	HB B
No. Obs.	23009	16481	17476
Initial	0,02959***	0,05768***	0,06480***
	(16,70)	(26,74)	(24,07)
Distance	0,026169***	0,02582***	0,02927***
	(13,00)	(11,43)	(14,49)
Trade	-0,02368***	-0,00280***	-0,00050
	(-3,83)	(-3,70)	(-0,73)
Language	-0,00969**	-0,00411	-0,00321
	(-2,42)	(-0,99)	(-0,86)
Contiguous	-0,04187***	-0,08209***	-0,09379***
	(-6,30)	(-10,17)	(-13,86)
EU	-0,05807***	-0,04715***	-0,02146***
	(-11,71)	(-8,39)	(-4,32)
EMU	-0,05798***	-0,05948***	-0,04282***
	(-8,60)	(-8,51)	(-7,26)
OECD	-0,05341***	-0,03112***	-0,052161***
	(-11,32)	(-5,03)	(-9,77)
NAFTA	0,11894***	0,14501***	-0,12468***
	(3,77)	(4,91)	(-4,55)
ASEAN	-0,06815*	-0,12019***	-0,19986***
	(-1,87)	(-3,67)	(-7,93)
Adj-R^2	0.38	0.46	0.50

Table 11: **Dependent Variable: Negative Instances of Bilateral Home Bias**

This table reports the results of (fixed effects) panel regressions of the negative instances of bilateral home bias computed in the I-CAPM framework for the full sample (HB I) and comparative sample (HB IC) and the Bayesian framework (HB B) on: the initial level of bilateral home bias (Initial), distance between capital cities (Distance), bilateral imports (Trade), common language (Language), common border (Contiguous), as well as dummy variables for both source and destination countries belonging to EU, EMU, OECD, NAFTA or ASEAN. Fixed effects are included both for source and destination countries. Values of the coefficients, T-statistics and adjusted R^2, are reported. Significance of the coefficients is denoted by *** (at 1%), ** (at 5%) and * (at 10%).

		Negative	
	HB I	HB IC	HB B
No. Obs.	4991	2577	1582
Initial	0,00631**	-0,00040	-0,00696
	(1,97)	(-0,09)	(-1,26)
Distance	0.01175	0.01051	0.00032
	(1,64)	(1,04)	(-0,02)
Trade	-0,02325***	-0,01504***	-0,02848***
	(-7,02)	(-2,84)	(-3,39)
Language	-0,06680***	-0,05967*	-0,14300***
	(-5,36)	(-3,51)	(-6,09)
Contiguous	-0,01718	-0,03322*	0,04044
	(-1,14)	(-1,71)	(1,49)
EU	-0,01951	0,02927	-0,07490**
	(-1,40)	(1,23)	(-2,15)
EMU	-0,08356***	-0,15680***	-0,13705***
	(-5,72)	(-7,72)	(-4,74)
OECD	-0,04285***	-0,09281***	-0,21116***
	(-2,85)	(-3,42)	(-5,07)
NAFTA	0,25900***	0,31199***	0,26612***
	(3,44)	(4,08)	(3,19)
ASEAN	0,24606***	0,03094	
	(2,73)	(0,23)	
Adj-R^2	0.37	0.43	0.36