Information and Cross-Border Equity Holdings

Vicentiu M. Covrig          Patrice Fontaine
Sonia Jimenez-Garcès        Mark S. Seasholes

This Version 04-Apr-2008*

Abstract

This paper studies, both theoretically and empirically, dispersion in cross-border equity holdings. We propose a rational expectations equilibrium model in which agents have information about asset specific and/or common components of stocks’ payoffs. The model produces closed-form solutions for asset prices and investor holdings (positions). A numerical analysis can generate home bias levels similar to those found in existing studies as well as reverse home bias (i.e., investors from one country overweigh stocks from another country). The last section of the paper analyzes cross-border mutual fund holdings of 5,781 stocks from 21 developed countries. We create a proxy variable for the degree of asset specific information about a stock and another proxy for the degree of common component information. Double sorting stocks using our information proxies produces ownership dispersion similar to that implied by the model. In regression analysis, our information proxies explain holding levels even after including variables that have previously been linked to home bias.

JEL Classification: D82, G11, G12, G15

Keywords: Information Economics, REE Models, Home Bias

*We thank Magnus Dahlquist, Harald Hau, Soeren Hvidkjaer for helpful comments and suggestions as well as seminar participants at the 2007 AFFI Conference (Paris), 2007 ASAP Conference (London), 2008 Cerag-Ensimmag-Isfa joint seminar, ESSEC Paris, Tilburg University, and University of Rotterdam. Covrig is at California State University, Northridge. Fontaine is at the University Pierre Mendès–France and Eurofidai-Cerag(CNRS). Jimenez-Garcès is at the Grenoble Institute of Technology and Eurofidai-Cerag. Seasholes is visiting INSEAD for the 2007-2008 academic year. Questions and comments can be emailed to “Sonia.Jimenez@grenoble-inp.fr” or to “Mark.S.Seasholes@emailias.com”.
Information and Cross-Border Equity Holdings

This paper studies, both theoretically and empirically, dispersion in cross-border equity holdings. We propose a rational expectations equilibrium model in which agents have information about asset specific and/or common components of stocks’ payoffs. The model produces closed-form solutions for asset prices and investor holdings (positions). A numerical analysis can generate home bias levels similar to those found in existing studies as well as reverse home bias (i.e., investors from one country overweight stocks from another country). The last section of the paper analyzes cross-border mutual fund holdings of 5,781 stocks from 21 developed countries. We create a proxy variable for the degree of asset specific information about a stock and another proxy for the degree of common component information. Double sorting stocks using our information proxies produces ownership dispersion similar to that implied by the model. In regression analysis, our information proxies explain holding levels even after including variables that have previously been linked to home bias.

JEL Classification: D82, G11, G12, G15

Keywords: Information Economics, REE Models, Home Bias
1 Introduction

Why do institutional investors from North America hold large fractions of some foreign equities while eschewing others? Consider a quick study of aggregate mutual fund positions in 467 German stocks. From the perspective of the average German stock, foreign funds own 3.66% of the shares outstanding. For 25% of the stocks, the same funds hold less than 0.01% of the equity in aggregate. For the upper 25% of stocks, funds hold at least 4.35% of the equity. Foreign ownership dispersion of this magnitude is typical when we look at non-French mutual fund positions in French stocks, non-UK fund positions in UK stocks, and so on. Cross-border ownership of equities is low, but varies considerably across assets.\(^1\) The goal of this paper is to understand the dispersion in ownership and we ask: which stocks do mutual fund managers choose when they invest overseas? In particular, we are interested in how well information structures can explain the large dispersion in cross-border equity holdings.

We begin our investigation by proposing a two-period, rational expectations equilibrium model with multiple assets, common factors, and investors.\(^2\) Economists have long been interested in how markets aggregate and transmit disperse pieces of information. We contribute to understanding the role of information in determining asset prices by considering three different components of each asset’s payoffs (dividends). The first component is asset specific and investors may be differentially informed about this component. The second component is a function of common (global) factors and investors may also be differentially informed about these common components. The third component is called “residual uncertainty” and no investor has information about this part of an asset’s payoff. We envisage a generalized information structure that allows an agent to have information about all, some, or none of the asset specific components. The same agent may also have information about all, some, or none of the common components.

The model produces closed-form solutions for both asset prices and the holdings of individual agents. The solutions, in turn, allow for a straightforward analysis of equilibrium prices. When all agents have full information about asset payoffs we obtain a form of the capital asset pricing model (CAPM) adjusted for the supply uncertainty present in our model. Suppose an asset’s residual uncertainty is positively correlated with the residual

\(^1\)Low average levels of cross-border ownership, known as the “home bias puzzle”, have been extensively studied in the literature. A search for the term “Home Bias” in the title or abstract yields 222 papers from EconLit and 177 papers from SSRN. Classic articles on home bias include French and Poterba (1991), Cooper and Kaplanis (1994), Teser and Werner (1995), and many others. Section 4 provides details about the mutual fund data and reports results of our empirical tests.

uncertainty of other assets in the market. The CAPM tells us the asset’s price today equals its expected future payoff discounted by the riskfree rate and the CAPM risk premium. The CAPM price discount (risk premium) is a function of the covariance of the asset’s payoffs with payoffs of other assets in the market.

When not all agents have full information, an asset’s price today equals its expected future payoff minus the CAPM (full information) discount and minus an additional discount called the “information price discount”. In our model, an asset’s information price discount can be related to both the asset specific component of its payoffs and to the common components. The extra discount results from two sources: i) a non-zero covariance between the asset’s payoff and the market’s payoff; ii) the fact that the market clearing price reflects the premium that uninformed investors charge for holding an asset they know little about. Thus, the information price discount is a function of how many agents have information about the asset’s future payoffs, how important common components are to the payoffs, which agents have information about the common components, and whether these agents have information about other assets’ payoffs.

The foremost contribution of this paper is to introduce information asymmetries about the common components of assets’ payoffs—see Admati (1985) for a note about the difficulty in extending her model to one with a factor structure. In fact, our model is able to link a rich variety of information structures with asset prices and investor portfolios. Consider three groups of investors with asset specific information about three, different and non-overlapping set of stocks. The first group may have information about a common component that only affects a small subset of stocks. The second group may have no information about common components. The third group may have information about two common components that affect the payoffs of all stocks. While stylized, such a situation reflects how information is distributed globally. No one group of investors is better informed about all stocks nor do common components affect all stocks in the same manner. Our paper is the first to allow agents to have asset specific information or information about common components or both or neither.

We present a numerical analysis of our model in order to understand the effect of different information structures on asset prices and investor portfolios. To make the numerical example more concrete, we focus on international portfolio choice, cross-border holdings, and the home bias puzzle. Investors and assets in the model are partitioned into groups (nationalities and national stock markets). We follow existing papers and assume agents receive superior information about the asset specific component of their home country’s assets. In this way, investors are said to have an information advantage about their home
country’s assets. We next assume that a few investors have superior information about the common components of payoffs (e.g., some investors have an information advantage about the common components). One can think of this group of investors as being located in a major financial center such as New York City. Analysts working for large investment banking houses or mutual funds synthesize and produce information about economic variables such as short-term interest rates, commodity prices, and global shipping costs. Information about these economic variables plays an important role when estimating the future payoffs of many different assets. Fund managers with access to this research use the information when choosing their portfolios.

A simple two-country, two-asset, single-factor numerical analysis confirms that high levels of information about the asset specific components of payoffs lead residents of one country to overweight assets from their own country. We calculate the fraction (dollar weight) of each investor’s portfolio that is invested in domestic and foreign assets. We also calculate the weight of a given country’s asset in the world market portfolio. In this way, we are able to calculate whether a particular investor over- or underweighs a given asset relative to the asset’s weight in the world market portfolio. Our numerical results regarding portfolio choice parallel existing studies of home bias as investors place up to 30% more of their wealth in the domestic asset than world market capitalizations indicate.

A second contribution of this paper is to show that low levels of information advantages about asset specific information, high levels of information advantages about common (cross-border) components, and different factor loadings lead to a large dispersion in home bias measures. Our model is capable of producing situations where investors in one country overweigh assets from other countries—a phenomenon we call “reverse home bias” in the spirit of Bravo-Ortega (2003). Consider a high-tech computer company located in France. French investors may speak the same language as the CEO, know people who work at the company, and have immediate access to information released by the company. However, the company’s future dividends are likely to be sensitive to the world-wide demand for high-tech equipment. Sophisticated investment funds (say in the United States) with skills in analyzing world hardware prices may have superior information about the French company's prospects—even if the funds are located far

---

Gehrig (1993) presents a related two-country model of home bias. Brennan and Cao (1997) study investment flows (changes in holdings) and information asymmetries. In their model, investors with less information (foreigners) update priors about future payoffs more heavily than investors with more information (locals). Van Nieuwerburgh and Veldkamp (2006a) use a rational expectations model to justify the persistence of the home bias when investors initially have a small information advantage.

French and Poterba (1991) document that American investors allocate about 84% of their wealth in domestic stocks although the weight of the American stocks in the world market portfolio is only about 50% (an overweighing of 34% or 1.68 × ). Using 1997 data, Ahearne, Griever, and Warnock (2004) show that 89.9% of US portfolio holdings are allocated to US stocks even though these stocks comprise 48.3% of the world market portfolio (overweight by 41.6% or 1.86 × ). Chan, Covrig and Ng (2005) show that the degree of home bias in other countries is generally greater than 30%.
from Europe. In such cases, U.S. investment funds may require a smaller risk premium for holding the stock than French investors require for holding the same stock. A smaller risk premium implies a higher willingness to pay, which translates into increased ownership by U.S. investment funds.

The numerical example helps to shed light on general properties of equilibrium prices in our model. For example, an asset is less risky from the perspective of a single agent if he has precise information about its future payoffs. The asset is more risky if he must glean information from equilibrium prices. When common components of payoffs are considered, a single asset may no longer be viewed as low-risk even if the agent has information about the asset specific component of payoffs. As the common components become more prominent in payoffs, asset specific information becomes less valuable. Thus, the price of a given asset is sensitive to how many agents have information about the asset specific component of payoffs, how many agents have information about common components, how sensitive the asset’s payoffs are to the common components, and what other information the agents have.

Our paper extends existing theoretical work on information structures and risk premia. For example, Easley and O’Hara (2004) present a multi-asset model that focuses on the role of public and private signals in determining a firm’s cost of capital. Private signals in their model are received only by a group of informed investors as in Grossman and Stiglitz (1980). In our model, it is possible for different groups of investors to have information about different groups of the securities. In this way, investors can be asymmetrically informed without introducing a strict information hierarchy. Bacchetta and van Wincoop (2006) argue in favor of structures with a “[broad] dispersion of information.” Finally, and in a paper similar in spirit to ours, Hughes, Liu, and Liu (2007) model two groups of investors. All informed investors effectively observe a global signal “$s$” which is different from the Admati (1985) model where the signals are uncorrelated. One innovation is that the signal is the sum of information about the systematic component of payoffs and information about the idiosyncratic component. Unlike our paper, investors cannot separate the two components nor is information about the components differentially dispersed across investors.

---

Our approach incorporates an aspect of models which endow all agents with small pieces of information about risky assets payoffs—see Grossman (1976), Hellwig (1980), and Admati (1985). Coval (1997) use of diffuse information is similar to ours. Easley and O’Hara (2004) contains an excellent review of information structures and existing papers. Two recent working papers also address information and home bias. Van Nieuwerburgh and Veldkamp (2006a) study information acquisition and dynamic learning. The authors show that small home-country information advantages can persist as investors may choose to specialize in obtaining information about home-country assets. Like our paper, Albuquerque, Bauer, and Schneider (2006) model local and global information (the papers were developed independently.) Investors in their model receive signals about future payoffs. There is a single global signal which conveys information about the sum of all payoffs.

---
Our model is also related to a working paper by Biais, Bossaerts, and Spatt (2007). The authors analyze a partially revealing dynamic rational expectations model. Like our paper, “equilibrium prices are set as in a representative agent economy where the market would include the aggregate risky endowment shock and the beliefs of the representative agent would average those of the informed and uninformed.” Their paper contains an overlapping generations (multi-period) framework, while our paper has a static, two-period model. All agents in their paper observe the same signal (receive the same information) while agents in our paper can be differentially informed about both the asset-specific component of payoffs or the common component.

We end the paper with an empirical, cross-sectional analysis of international portfolio holdings that complements our numerical analysis. The data represent primarily the holdings of North American mutual funds and come from the Thomson Financial International Mutual Fund Holdings dataset. The data consist of US$720 billion of cross-border holdings (positions) in 5,781 stocks from 21 developed countries. As mentioned at the start of this paper, we measure the fraction of a non-North American stock’s equity that is owned by the mutual funds in our dataset. The average cross border holding of individual stocks is 2.76% of shares outstanding. The interquartile range is 0.14% to 3.22%. Our goal is to explain this dispersion.

We create two proxy variables: one for the degree of asset specific information about a stock and the other for the degree of common component information. Cross-border holdings increase as asset specific information advantages decrease and the holdings increase as common components information increases. Our results continue to hold after controlling for variables that have, in the past, been used as proxies for familiarity (the size of the company and the number of equity analysts following the company). Our results also hold after controlling for a firm’s leverage—another variable that has been found to explain cross-border holdings.6 A number of robustness checks give consistent results.

The third contribution of our paper is to show that our information proxy variables help explain a large fraction of the observed dispersion in cross-border holdings. We sort stocks into quartiles based on both our proxy variables. When the proxy for common component information is high (top 25%), stocks with a low value of the asset specific proxy have average holdings of 4.90% while stocks with a high value of the asset specific proxy have average holdings of 2.23%. The dispersion in holdings is 2.67%. Likewise, when the asset specific component is low (bottom 25%), stocks with a low value of the common

---

component proxy have average holdings of 2.93%. The dispersion of holdings is 1.97% (equal to 4.90% - 2.93%). The sort results and additional empirical tests are motivated by implications of our model. Our results highlight the fact that both common and asset specific information are important for understanding cross border holdings.

The paper proceeds as follows. Section 2 presents our model, notation, and assumptions. We provide closed-form solutions for equilibrium prices, holdings, and information price discounts. Section 3 numerically analyzes prices and holdings as functions of parameters in the model. Section 4 empirically studies cross-border mutual fund holdings. The final section concludes.

2 Model

The model has $I$ investors indexed $i = 1, \ldots, I$ who trade at date 0 and consume at date 1. Each agent $i$ can invest his initial wealth, $w_0^i$, in a riskless asset and $J$ risky assets indexed $j = 1, \ldots, J$. The riskless interest rate is denoted $r_f$ and we define $R \equiv (1 + r_f)$. For simplicity, we normalize the price of the riskless asset to one. Each risky asset $j$ pays a liquidating dividend $\tilde{P}_j^1$ at date 1. The vector of final payoffs $\tilde{P}^1 = (\tilde{P}_1^1, \ldots, \tilde{P}_J^1)'$ is generated by a $K$-factor linear process:

$$\tilde{P}^1 = \tilde{\theta} + B\tilde{f} + \tilde{\varepsilon}$$

(1)

The vector $\tilde{\theta} = (\tilde{\theta}_1, \ldots, \tilde{\theta}_J)'$ is the asset specific component of payoffs, the vector $\tilde{f} = (\tilde{f}_1, \ldots, \tilde{f}_K)'$ contains the $K$ common factors, and $B$ is a $J \times K$ matrix of factor loadings. The remaining part of each asset’s final payoff, $\tilde{\varepsilon} = (\tilde{\varepsilon}_1, \ldots, \tilde{\varepsilon}_J)'$, is unknown to all investors and referred to as residual uncertainty. We assume that $\tilde{\theta}$, $B\tilde{f}$, and $\tilde{\varepsilon}$ are jointly multivariate normal and independent. We further assume that $\tilde{f}$ and $\tilde{\varepsilon}$ have mean zero. Since $\tilde{\theta}$ is the asset specific component, we assume its covariance matrix is diagonal and denoted $T$.

For tractability, we assume that the covariance matrix of $\tilde{f}$ is the identity matrix. The covariance matrix of $B\tilde{f}$ is $L$, with $L = BB'$. Finally, the covariance matrix of $\tilde{\varepsilon}$ is denoted $\Sigma$.

The per-capita supply of risky assets is defined as the realization of a random vector $\tilde{z}$. The vector $\tilde{z}$ is independent and jointly normally distributed along with the other variables in the model and has a covariance matrix denoted $Z$. The assumption of random net supply is standard in rational expectations models. As Easley and O’Hara (2004) write

---

7This assumption is not necessary to solve the model. However, it enables us to distinguish information that affects a single asset from common factors that affect two or more assets.
“one theoretical interpretation is that this approximates noise trading in the market. A more practical example of this concept is portfolio managers current switch toward using float-based indices from shares-outstanding indices.” In order to insure the existence and uniqueness of the date 0 equilibrium price vector, $\tilde{P}^0$, we assume that $\Sigma$, $T$, and $Z$ are regular matrices.

We assume all agents have an exponential utility function: $U(\tilde{w}_i^1) = -e^{-a\tilde{w}_i^1}$, where $\tilde{w}_i^1$ is the wealth of investor $i$ on date 1. The utility function has a constant absolute risk aversion with coefficient $a > 0$ which is the same for all agents. The choice of utility functions is also common in rational expectations equilibrium models and ensures that an investor’s demand for the risky asset is independent of his initial wealth. Let $X_i$ be investor $i$’s vector of holdings of the risky assets. Investor $i$’s final wealth is:

$$\tilde{w}_i^1 = w_i^0 R + X_i'(\tilde{P}^1 - R\tilde{P}^0)$$ (2)

### 2.1 Information Structure and Notation

To facilitate linking our model to international holdings data, we partition investors, assets, and common factors into groups. A group of investors can be thought of as a nationality (French investors, Japanese investors, etc.) The $I$ investors in our model are partitioned into $N$ non-overlapping groups labeled $n = 1, \ldots, N$. Each group of investors represents a fraction, $\lambda_n$, of the total number of investors ($I$) in the market such that $\sum_{n=1}^{N} \lambda_n = 1$.

**Asset Specific Information** The $J$ securities are partitioned into $N$ non-overlapping groups. A group of securities can be thought of as comprising a country’s equities (French stocks, Japanese stocks, etc.) We define the set of all assets as $S$. The set of assets in group $n$ contains $J_n$ risky assets and is denoted $S_n$. Thus, $\bigcup_{n=1}^{N} S_n = S$ and $\forall(n_1, n_2), n_1 \neq n_2, S_{n_1} \cap S_{n_2} = \emptyset$. We assume there are an equal number ($N$) of securities groups and investors groups to ensure that each security has at least one investor with specific information about that security. A single investor $i$ in group $n$ knows the realization of the asset specific component, $\tilde{\theta}_j$, of each asset $j$ in the set $S_n$. For any asset $j$ not in $S_n$, investor $i$ only knows the distribution of $\tilde{\theta}_j$ but he does not know its realization.

**Common Component Information** We assign the $K$ common factors into $N$ groups denoted $F_n$, with $n = 1, \ldots, N$. The set $F_n$ contains $K_n$ common factors. A single investor $i$ in group $n$ knows the realization of each common factor $\tilde{f}_k$ in the set $F_n$. For any factor not in $F_n$, the investor only knows the distribution of $\tilde{f}_k$ but not its realization. For tractability purposes of the model, we assume that two groups of investors do not
have information about the same common factor.

Chen et al. (1986) document nine macroeconomic risk factors affecting stock returns. We therefore envisage the number of common factors to be much less than the number of assets, $K \ll J$. If the number of common factors is less than the number of investor groups, then $K < N$, some $F_n$ sets will not contain any common factors ($K_n = 0$), and the corresponding investor group will not be informed about any of the common factors.

**Notation** The information structure of our model implies that investors belonging to the same group $n$ possess the same private information (for asset specific components and for factors), they face the same optimization problem, and they optimally choose identical portfolios. In this sense they can be said to be identical. We use the following terms interchangeably (and a bit loosely): “investor $i$ from group $n$”, “investor group $n$”, and “investor $n$”. Furthermore, to simplify the notation, we write the payoffs of the risky assets as:

$$
\tilde{P}^1 = C\tilde{\eta} + \tilde{\varepsilon}
$$

Where, $\tilde{\eta} = \left( \tilde{\eta}' \quad \tilde{f}' \right)'$ is a $J + K$ column vector and $C$ is a $J \times (J + K)$ block-diagonal matrix consisting of a $J \times J$ identity matrix, $I_J$, and the matrix $B$. The variance-covariance matrix of $\tilde{\eta}$ is $Q = \begin{pmatrix} T & 0 \\ 0 & I_K \end{pmatrix}$ where $I_K$ is the identity matrix of order $K$.

**Definition 2.1.** For each investor $n$, we define the diagonal matrix $D_n$ of order $J + K$ with $D_n(j, j) = 1$ if investor $n$ knows the realization of the $j^{th}$ random variable in $\tilde{\eta}$ and $D_n(j, j) = 0$ otherwise. The $j^{th}$ random variable represents an asset specific component of stock $j$’s payoffs if $j \leq J$, and a common factor otherwise.

**Definition 2.2.** We define $D \equiv \sum_{n=1}^{N} \lambda_n D_n$. The matrix $D$ plays an important role in our model as each element on the main diagonal represents the proportion of investors who know the realization of the corresponding random variable in the vector $\tilde{\eta}$.

**Definition 2.3.** For each investor group $n$, the matrix $M_n$ is obtained by eliminating all the null rows of $D_n$. Consequently, the number of rows of $M_n$ is equal to $J_n + K_n$, which represents the number of asset specific and common factors about which investor $n$ is informed. If investor $n$ does not receive any private information, $D_n$ becomes the null matrix and $M_n$ cannot be defined. It is straightforward that $M_n' M_n = D_n$ and $M_n M_n' = I_{J_n + K_n}$, where $I_{J_n + K_n}$ is the identity matrix of order $J_n + K_n$. 
Under these definitions, the private information received by investor \( n \) consists of the realization of the random vector \( \mathbf{M}_n \tilde{\eta} \). As in Admati (1985), equilibrium prices also reveal some information to investors beyond their own private information. Consequently, each investor \( n \) maximizes his expected utility of consumption conditional on the realization of his private information and on the observation of the public information in the form of prices at date 0.

2.2 Equilibrium Prices

We seek a closed-form solution for prices at date 0 within the class functions that are linear in our information variable \( \tilde{\eta} \) and supply variable \( \tilde{z} \). The form of the solution implies investors assume prices are a linear function of private signals and noise. In equilibrium, this hypothesis is verified. The date 0 price vector is:

\[
\tilde{P}^0 = \mathbf{A}_0 + \mathbf{A}_1 \tilde{\eta} - \mathbf{A}_2 \tilde{z}
\]

where the dimensions of the matrix \( \mathbf{A}_0 \) is \( J \times 1 \), the matrix \( \mathbf{A}_1 \) is \( J \times (J + K) \), and the matrix \( \mathbf{A}_2 \) is \( J \times J \). We suppose that \( \mathbf{A}_2 \) is regular. Under these assumptions, investor \( n \)'s demand is:

\[
\tilde{X}_n = a^{-1} V^{-1}_n \left( E_n [\tilde{P}^1] - R \tilde{P}^0 \right)
\]

Equation (5) gives an expression for agent \( n \)'s holdings at date 0—please see Appendix A for additional details. The expression \( E_n [\tilde{P}^1] = E[\tilde{P}^1 | \mathbf{M}_n \tilde{\eta}, \tilde{P}^0] \) gives the expected prices of the risky assets at date 1 from investor \( n \)'s point of view (i.e. conditional on his information set). \( V_n = Var[\tilde{P}^1 | \mathbf{M}_n \tilde{\eta}, \tilde{P}^0] \) represents the conditional return variance of \( \tilde{P}^1 \) from investors \( n \)'s point of view. By equating the supply and the aggregate demand of the \( N \) groups of investors, \( \left( \sum_{n=1}^{N} \lambda_n \tilde{X}_n = \tilde{z} \right) \), it follows:

\[
\sum_{n=1}^{N} \lambda_n V_n^{-1} \left( E_n [\tilde{P}^1] - R \tilde{P}^0 \right) - a \tilde{z} = 0
\]

Joint normality implies that the distribution of prices, conditional on investor \( n \)'s private and public information, is also multi-variate normal with the following expectation:

\[
E_n [\tilde{P}^1] = E [\tilde{P}^1 | \mathbf{M}_n \tilde{\eta}, \tilde{P}^0] = \mathbf{B}_0 + \mathbf{B}_1 \mathbf{M}_n \tilde{\eta} + \mathbf{B}_2 \tilde{P}^0
\]
where the dimension of the matrix $B_{0n}$ is $J \times 1$, $B_{1n}$ is $J \times (J_n + K_n)$, and $B_{2n}$ is $J \times J$ respectively. Equations (4), (6), and (7) imply the system to be solved has the following form (please see Appendix B):

$$aA_2^{-1}A_0 = \sum_{n=1}^{N} \lambda_n V^{-1}_n B_{0n}$$

$$aA_2^{-1}A_1 = \sum_{n=1}^{N} \lambda_n V^{-1}_n B_{1n} M_n$$

$$aA_2^{-1} = \sum_{n=1}^{N} \lambda_n V^{-1}_n (RI_J - B_{2n})$$

(8)

As shown in Appendix C, the matrices $B_{1n}$, $B_{2n}$ and $V_n$ can be written as functions of the matrices $A_1$ and $A_2$. The system of equations in (8) represents a fixed point problem in a $2J^2 + JK + J$ Euclidian space. To obtain a solution for $\tilde{P}^0$, we define the matrix $U \equiv A_2^{-1}A_1$. We also introduce the function $g(G) = \sum_{n=1}^{N} D_n GD_n$, where $G$ is a matrix of order $J + K$. The function $g(\cdot)$ transforms a matrix $G$ into a $N$-block diagonal matrix whose block elements are the same as the elements of the matrix $G$.

**Definition 2.4.** We define a “$g$-matrix” to be any square matrix $G$ of order $J + K$ which satisfies $g(G) = G$. This means that $G$ is an $N$-block diagonal matrix, the size of block $n$ is equal to the number of specific and common factors known by investor $n$.

Define $\Psi \equiv Var[\tilde{\eta}|\tilde{P}^0]$ i.e., the variance-covariance matrix of $\tilde{\eta}$ conditional on observing the equilibrium price vector at date 0. The matrix $\Psi$ is endogenously defined and represents the variance of $\tilde{\eta}$ from the point of view of an investor who does not possess any private information but only observes the equilibrium price vector. The following lemma gives an analytical solution for $U$.

**Lemma 2.1.** If $(\Psi^{-1} + C^\prime \Sigma^{-1} C)$ is a $g$-matrix, then the closed-form solution for $U$ is:

$$U = a^{-1} \Sigma^{-1} CD$$

(9)

**Proof:** See Appendix D.

For the particular case of Lemma (2.1), $U$ is not a function of the coefficients $B_{0n}$, $B_{1n}$, and $B_{2n}$. Therefore, to determine $A_0$, $A_1$, and $A_2$, we must first compute the matrix $\Psi$.
as a function of $\mathbf{U}$. In this way, the variance-covariance matrix of any investor group, $\mathbf{V}_n$, can be written as a function of $\Psi$:

$$\mathbf{V}_n = \mathbf{\Sigma} + \mathbf{C}\Psi\mathbf{C}' - \mathbf{C}\mathbf{M}_n\Psi^{-1}\mathbf{M}_n\mathbf{C}'$$

(10)

Where $\Psi_n = \mathbf{M}_n\Psi\mathbf{M}_n'$. Also, $\Psi = \mathbf{Q} - \mathbf{Q}\mathbf{U}'\mathbf{M}^{-1}\mathbf{U}\mathbf{Q}$ and $\mathbf{M} = \mathbf{U}\mathbf{Q}\mathbf{U}' + \mathbf{Z}$. The following theorem gives a closed-form solution for the equilibrium price vector at date 0.

**Theorem 2.1.** Under the conditions of Lemma (2.1), there exists a closed form solution for Equation (6) within the class of linear functions of $\mathbf{\tilde{\eta}}$ and $\mathbf{\tilde{z}}$. The solution can be written as, $\mathbf{\tilde{P}}^0 = \mathbf{A}_0 + \mathbf{A}_1\mathbf{\tilde{\eta}} - \mathbf{A}_2\mathbf{\tilde{z}}$, where $\mathbf{A}_2$ is a regular matrix and:

$$\mathbf{A}_0 = \frac{1}{R} \left( \left( \mathbf{C} - R\mathbf{A}_1 \right)\mathbf{E}[\mathbf{\tilde{\eta}}] + \left( R\mathbf{A}_2 - a\mathbf{V}_N \right)\mathbf{E}[\mathbf{\tilde{z}}] \right)$$

(11)

$$\mathbf{A}_1 = \frac{1}{R} \left( \mathbf{C}\mathbf{Q}\mathbf{C}' + \mathbf{\Sigma} - \mathbf{V}_N \right) \left( \mathbf{C}\mathbf{D}\mathbf{Q}\mathbf{C}' \right)^{-1} \mathbf{C} \mathbf{D}$$

(12)

$$\mathbf{A}_2 = \frac{1}{R} a \left( \mathbf{C}\mathbf{Q}\mathbf{C}' + \mathbf{\Sigma} - \mathbf{V}_N \right) \left( \mathbf{C}\mathbf{D}\mathbf{Q}\mathbf{C}' \right)^{-1} \mathbf{\Sigma}$$

(13)

**Proof:** See Appendix E.

The matrix $\mathbf{V}_N = (\sum_{n=1}^{N} \lambda_n\mathbf{V}_n^{-1})^{-1}$ represents the variance-covariance matrix of $\mathbf{\tilde{P}}^1$ for the “average” investor in the market. The precision matrix $\mathbf{V}_N^{-1}$ equals the weighted mean of each group’s precisions where the weights are proportional to the number of agents in each group. From Equation (10), it is straightforward to show that $\mathbf{V}_N$ can be written as:

$$\mathbf{V}_N = (\mathbf{\Sigma} + \mathbf{C}\Psi\mathbf{C}'(\mathbf{I}_J + \mathbf{\Sigma}^{-1}\mathbf{C}\mathbf{D}\mathbf{C}')^{-1})$$

(14)

Thus we have provided a closed-form solution for prices at date 0. The solution takes the form shown in (4) with constant values shown in (11), (12), and (13). Holdings of investors in group $n$ are given in Equation (5).

### 2.3 Price Discounts (Risk Premia)

We analyze the relationship between information structures and asset prices. Our analysis produces a closed-form expression for the information price discount (the difference between asset prices when all agents are fully informed and asset prices when not all agents are fully informed.) Rearranging Equation (6) gives a general expression for prices
at date 0:  
\[ E\left[\hat{P}^0\right] = \frac{1}{R} \left( E\left[\hat{P}^1\right] - aV_{N}E\left[\hat{z}\right]\right) \]  (15)

Equation (15) shows that asset prices at date 0 are less than the value of expected future payoffs. The total price discount (risk premium) is given by the expression \( aV_{N}E\left[\hat{z}\right] \). The price discount depends on risk aversion (\( a \)) and the market’s “average” uncertainty about future payoffs (\( V_{N} \)).

**Full Information:** We consider the case where all investors in the market are informed about all asset specific components and all factors. In this case, all investors belong to the same group (\( \lambda = 1 \)), \( D \) is the identity matrix, and \( V_{N} = \Sigma \). It can be shown that our asset pricing equation reduces to a form of the capital asset pricing model (CAPM):

\[ E\left[\hat{P}^0\right] = \frac{1}{R} \left( E\left[\hat{P}^1\right] - a\Sigma E\left[\hat{z}\right]\right) \]  (16)

For a given stock \( j \), we can express the CAPM in terms of prices. Please see Appendix G for details.

\[ E\left[\hat{P}^0_{j}\right] = \frac{1}{R} \left( E\left[\hat{P}^1_{j}\right] - a\text{Cov}\left[\hat{P}^1_{j}, \hat{P}^1_{m}\right]\right) \]

**Information Price Discount:** We define the “information price discount” (or “IPD”) as the difference between the price discounts shown in Equations (15) and (16). The IPD represents the amount an asset’s price at date 0 is below its expected future value solely due to agents not having full information about future payoffs.

\[ IPD \equiv aV_{N}E\left[\hat{z}\right] - a\Sigma E\left[\hat{z}\right] \]  (17)

\[ = a(V_{N} - \Sigma)E\left[\hat{z}\right] \]

In a single-asset model with no factor structure, the information price discount is pro-
portional to the difference between the market’s average uncertainty about future payoffs ($V_N$) and residual uncertainty about the same payoffs ($\Sigma$). This difference is a signal-to-noise measure. When the difference is small, investors have a lot of information about future payoffs, the IPD is low, and prices are high. Note that $IPD \geq 0$ as the market is always bounded in its assessment of future payoffs by $\Sigma$.

In a multi-asset model with uncorrelated residual uncertainties and no factor structure, the single-asset intuition discussed in the paragraph above continues to hold. The diagonal matrix ($V_N - \Sigma$) represents a series of signal-to-noise differences.

In a multi-asset model with correlated residual uncertainties and/or a factor structure, the information price discount can be driven by both the asset specific component of payoffs and common factors. The matrix ($V_N - \Sigma$) can still be roughly interpreted as signal-to-noise differences. However, the matrix is no longer diagonal which means that covariance terms affect the IPD. Section 3 now turns to numerically investigating the effects of the covariance terms.

### 3 Numerical Analysis of Prices and Holdings

In this section we numerically analyze equilibrium prices and holdings. One goal is to understand the role of covariance terms in the information price discount—see Equation (17).\footnote{Covariance terms also play a role in the equilibrium holdings of individual investors. An explicit expression for these holdings, as well as an economic interpretation, is given in Appendix F. For notes on the ex-ante analysis, please see Footnote 8.} We focus on international portfolio choice, cross-border holdings, and the home bias puzzle.

The numerical analysis considers a simple setting with two assets (an American stock and a French stock), a single factor, and two groups of investors in equal numbers (American people and French people). Each investor group has specific information about their home country’s stock. All investors have a risk aversion coefficient of $a = 1.00$. Payoffs of the American (A) and French (F) assets follow from Equation (1):

$$
\tilde{P}_A^1 = \tilde{\theta}_A + B_A \tilde{f} + \tilde{\varepsilon}_A \\
\tilde{P}_F^1 = \tilde{\theta}_F + B_F \tilde{f} + \tilde{\varepsilon}_F
$$

The expected asset specific component of both payoffs is $E[\tilde{\theta}_A] = E[\tilde{\theta}_F] = 1.00$ and the expected supply of both assets is $E[\tilde{z}_A] = E[\tilde{z}_B] = 0.01$. We assume that the variance-covariance matrices $Z$ and $\Sigma$ are both equal to the identity matrix. The variance-covariance matrices $Z$ and $\Sigma$ are both equal to the identity matrix.
covariance matrix $\mathbf{T}$ is proportional to the identity matrix. We measure the degree of information advantage about $\theta$ (the asset specific component of payoffs) by the matrix $\mathbf{T}$ (i.e. by the diagonal elements of $\mathbf{T}$).\footnote{Fundamentally, the information asymmetry/advantage about an asset should be measured by the corresponding element of the matrix $\Psi$. However, as seen in the model section, $\Psi$ is an endogenous matrix. All else being equal, an increase in the matrix $\mathbf{T}$ corresponds to an increase in the matrix $\Psi$, and vice-versa. This is due to the fact that an increase in the variance of asset specific information corresponds to an increase in the asymmetric information surrounding this asset. We note that in this section the matrix $\mathbf{U}$ is obtained numerically and not by using the expression in Equation (9).} We vary the degree of information advantage about the asset specific components of payoffs from 0 to 10 for both groups of assets/investors.

The realization of the common component is known by only one of the two investor groups (assume the Americans have information about the common component). In the calibration, the expected factor realization is $E\left[\tilde{f}\right] = 0$ and the variance is $Var\left[\tilde{f}\right] = 1$. The degree of information advantage about the common component is proportional to the variance of $\mathbf{B}\tilde{f}$ and we vary the loading for the French asset ($\mathbf{B}_F$) from 0 to 4. In this analysis, the factor loading for the American asset ($\mathbf{B}_A$) is half than that of the French asset.

### 3.1 Asset Prices

We calculate asset prices at date 0. The value of the world market portfolio is equal to the value of the American asset plus the value of the French asset. In Figure 1, the x-axis shows different degrees of information advantage about the asset specific components of payoffs. For x-axis values greater than zero, the American investors have increasingly valuable information about the American asset and the French investors have increasingly valuable information about the French asset.

![Insert Figure 1 About Here](image)

The top graph line (thick red) assumes the common component plays no role in determining asset payoffs. The line starts at $19.80$ when there is no asset-specific information advantage and drifts down very slightly to $19.68$ where there are high levels of information advantages. The “flatness” of this line comes from the fact that the American investors have information about the American asset and the French investors have information about their asset. As information advantages increase, each group of investors increases the value they place on their own country’s assets and decreases the value they place on the other country’s asset. There is little change in overall asset prices.

Figure 1 also depicts the role of the common component. In this analysis, the American investors have information about the common component. As the price of the French
asset becomes more sensitive to the common factor, the information advantage of the American investors about the French asset due to the common component increases, and the French investors’ asset specific information becomes less valuable. The bottom graph line (thin, purple, with “O” markings) represents the highest degree of the American investor’s information advantage about the common component. The right-hand side of Figure 1 represents situations when asset specific information is normally valuable. However, as the common component becomes more important, the French asset becomes less valuable, and its information price discount increases. The net result is that the price of the world market portfolio falls.

[ Insert Figure 2 About Here ]

Figure 1 shows the value of the world market portfolio decreases when there is high asset specific information advantages and high information advantages about the common component. The same information structure causes the weight of the American asset in the world market portfolio to increase. Figure 2 shows changes in the composition of the world market portfolio. As can be seen, the relative value of the American asset increases (and the relative value of the French asset falls) as we move from left to right across Figure 2. In this figure, the top graph line (thin, purple, with “O” markings) represents the highest levels of information advantage about the common component.

### 3.2 Home Bias and Portfolio Holdings

We calculate the weight of the French asset in the American investors’ portfolios ($W_{Amer}^F$) and the weight of the French asset in the world portfolio ($W_{World}^F$). Weights are calculated using market values. To measure the relative weight investors put on cross-border holdings, we define a variable “$\text{Diff}_{Wgt}^F$” such that a value of $\text{Diff}_{Wgt}^F < 0$ indicates the existence of home bias.

$$\text{Diff}_{Wgt}^F \equiv W_{Amer}^F - W_{World}^F$$ (18)

Figure 3 plots the level of foreign holdings in the American investors’ portfolio ($\text{Diff}_{Wgt}^F$) for different levels of asset specific information advantages about the home country assets. When there is no information advantages about the common component (bottom line), results are symmetric and we obtain the same graph when we measure foreign holdings in the French investors’ portfolio.

[ Insert Figure 3 About Here ]
Graph lines slope downward indicating that higher levels of asset specific information advantages lead investors to decrease the weight of the other country’s asset (i.e., higher home bias). In other words, an increase in the degree of information advantage about the American asset encourages the American investors to allocate a higher part of their wealth to the American asset and to deviate from the world market portfolio. For high levels of information advantage, $Diff^Wgt_F$ approaches -30%, in accordance with existing empirical results for U.S. investors. Note that the empirical degree of home bias for investors from other parts of the world (Japan, etc.) has been found to be even greater in magnitude than 30%.

We also calculate the fraction of the French company owned by the American investor. The fraction equals the number of French asset shares in the American investor’s portfolio divided by the total number of French shares outstanding. A larger fraction indicates reduced home bias.

$$\Omega_F \equiv \frac{Shrs^Amer_F}{Shrs^World_F}$$

Figure 4 shows when there are no information advantages, the measure $\Omega_F=0.50$ as the numerical analysis has equal number of French and American investors and equal number of French and American shares. As asset specific information advantages increase, the American investor holds fewer and fewer shares of the French stock—the lines in Figure 4 slope downward.

### 3.3 Reverse Home Bias

We consider the role of the common components and again examine portfolio holdings. Figure 3 depicts three additional graph lines for three different levels of information advantage about the common component. The figure illustrates home bias, no bias, and reverse home bias. For low levels of information advantage about the common component, the American investors always have a preference for the American asset ($Diff^Wgt_F < 0$). The bottom graph line (thick and red) shows the lowest level of information advantage about the common component. For high values of information advantage about the common component, the American investors may choose to overweight the French asset ($Diff^Wgt_F > 0$) in their portfolio. When $Diff^Wgt_F > 0$ one can say there is “reverse home bias”. The top graph line (thin, purple, with “O” markings) represents the highest level
of advantage about the common component. The finding of reverse home bias is due to the relative informational advantage of the American investors when considering the French asset compared to the American asset.

Figure 4 shows a similar pattern of home bias being reduced. As the American information advantage about the common component increases, American investors hold a greater fraction of French shares outstanding.

The economic intuition behind reverse home bias is: i) the French asset’s payoff is sensitive to the common component and its price is affected by large information asymmetries, ii) the American investors are informed about the common component. The informational advantage of the American investors about the French asset factor may overwhelm their informational disadvantage vis-a-vis the asset specific component of the French asset’s payoff. In such cases, the information price discount required by the American investors for holding the French asset can be lower than the information price discount required by the French investors for holding the French asset. This implies that the American investors overweight the French asset and, in this example, the French investors overweight the American asset.

4 Data and Empirical Analysis

We empirically analyze a cross-section of international mutual fund holdings. Our goal is to explore broad implications of the model presented in Section 2. The unit of analysis is a publicly listed company and we measure the fraction of shares outstanding held by cross-border investors (sometimes referred to as “foreign holdings”). Comparisons with Figure 4 are highlighted. Our approach complements many existing studies that measure the fraction of investors’ portfolios allocated to home-country versus foreign assets.

We start with the hypothesis that sophisticated money managers may generate and/or possess information about economy-wide factors. If this hypothesis is true, our model predicts that cross-border holdings should increase (home bias should decrease) as factors become more prominent in a stock’s payoffs. Under the assumption that investors have an information advantage about stocks from their own countries, we predict that cross-border holdings decrease as the asset specific component of payoffs becomes more prominent in a stock’s returns.

The empirical tests in this section parallel the numerical analysis from Section 3 and Figure 4 in particular. We create a proxy variable for different levels of information advantage that may exist about the asset specific components of payoffs. We also create
a proxy variable for different levels of information advantage that may exist about the common (economy-wide) components of payoffs.

**Holdings Data:** We obtain international mutual fund holdings on December 31, 2002 from the same source used by Chan, Covrig, and Ng (2005). For a single security, the data consist of the number of shares held by domestic mutual funds and the number of shares held by cross-border (foreign) mutual funds. We consider listed stocks from all 21 developed countries except Canada and the United States. The main dataset contains 10,292 different securities which are identified by Sedol number.

Table 1, Panel A provides a list of the 21 countries along with the number of stocks from each country. More stocks are Japanese (2,676) than from any other country. There are 1,973 stocks from the U.K., 744 from Germany, down to 56 stocks from Portugal. For each stock in our sample, we calculate the fraction of total shares held by foreign mutual funds in our dataset. The measure below is analogous to the measure shown in Equation (19).

\[
\Omega_j = \frac{\# \text{ Shares of Stock } j \text{ Held by Foreign Funds}}{\# \text{ of Shares of Stock } j \text{ Outstanding}}
\]  

(20)

**Return Data:** We obtain up to 60 months of individual stock return data from Datastream (dividends included) starting July 1997 and ending June 2002. Returns are lagged by at least six months (from the Dec-2002 holdings date) in order to separate the holdings measure from information proxy variables (described in Section 4.1 below). The return series may be denominated in a currency other than US dollars (USD). Therefore, we also obtain monthly exchanges rates in order to convert to a base currency (USD). Datastream has available Sedol numbers and sufficient return data for 7,553 stocks as shown in the second column of Table 1, Panel A. For each stock, Datastream includes an associated sector code. There are 38 sectors which are listed in Table 1, Panel B. For each sector, we obtain the monthly return of a US dollar index. We also obtain the monthly returns

---

12 The data we obtain are aggregated at the stock level and do not include holdings of US and Canadian stocks. Note that approximately 71% of the mutual funds are located in Canada and the United States. Since we are interested in cross-border holdings, excluding stocks from these two countries is not likely to affect results.

13 If North American funds hold the world market portfolio, the measures \( \Omega_j \) should be equal across stocks. A fund that wants to hold 1% of the world market portfolio at market capitalization weights can simply buy 1% of each company’s shares outstanding. As prices adjust, this passive strategy continues to hold 1% of the world market portfolio at the correct weights. The fund need only buy or sell shares to match changes to a firm’s capital structure. A low value of \( \Omega_j \) from Equation (20) indicates large home bias. A high value of \( \Omega_j \) indicates reduced home bias.
of the MSCI World Market Index denominated in US dollars.

**Firm Characteristics:** For each stock, as of December 31, 2002, we obtain the number of shares outstanding, the share price, the number of analysts covering the stock, sales, and the ratio of the book value of debt to total assets. Together with the holdings and return data, our final sample consists of 5,781 stocks. The stocks in our final sample are tabulated by country (Table 1, Panel A) and by sector (Panel B).

### 4.1 Proxy Variables

**Asset Specific Information:** We create a proxy variable to measure the level of a stock’s asset specific information. The following time-series regression is estimated for each stock \( j \) in our sample using up to five years of monthly returns. The data start July 1997 and end June 2002 and we require at least 20 months of returns. Our procedure avoids overlap with the holdings data.\(^\text{14}\)

\[
 r_{j,t} = \alpha + \beta_w r_{w,t} + \beta_k r_{k,t} + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_x r_{x,t} + \varepsilon_{j,t} \tag{21}
\]

\[
 Asset Specific_j \equiv 1 - R^2_j
\]

Above, \( r_{j,t} \) is the return on stock \( j \) in month \( t \), \( r_{w,t} \) is the return on the world market portfolio, \( r_{k,t} \) is the return from a global sector index where \( k \) is determined by the sector of stock \( j \), \( SMB_t \) is the Fama-French small minus big factor, \( HML_t \) is the Fama-French high minus low book-to-market factor, and \( r_{x,t} \) is the return of currency \( x \) which determined by stock \( j \)’s quoted prices. Our proxy variable \( Asset Specific_j \) is defined as one minus the fit from Equation (21)—see Durnev, Morck, and Yeung (2004) for a similar example. Note that co linearity between right-hand side variables such as between \( r_{w,t} \) and \( r_{k,t} \) should not affect our measure of \( R^2_j \) since we are interested in fit and not slope coefficients. A high value of \( Asset Specific_j \) indicates that asset specific information plays a large role in determining asset \( j \)’s prices. A low value of \( Asset Specific_j \) indicates that economy-wide components (and information about these components) play a large role in determining \( j \)’s prices. Using variants of Equation (21) do not materially affect our results.

**Common Component Information:** We create a proxy variable for the information

\(^\text{14}\)Section 4.3 considers an alternative proxy for asset specific information. The alternative is based on sales and does not use return data.
advantage mutual fund managers may have about common components of payoffs. Fund managers in our sample are primarily located in North America. We note the industry \((k)\) for each stock \(j\) in our sample. We calculate the fraction (weight) each industry \(k\) represents of total market capitalization of all United States stocks.\(^{15}\) The fraction (denoted \(Industry \text{ Wgt}_k\)) is used to proxy for information advantages that U.S. fund managers may have about a sector of the economy. The implicit assumption is that larger industries in the United States generate more information about U.S. stocks in that industry and about the industry itself.

\[
Common_{j,k} = 100 \times Industry \text{ Wgt}_k \times \hat{\beta}_{j,k}^2 \tag{22}
\]

Above, \(\hat{\beta}_{j,k}^2\) comes from estimating: \(r_{j,t} = \alpha + \beta_{j,k} r_{k,t} + \varepsilon_{j,t}\) where \(r_{j,t}\) is the return of stock \(j\) in month \(t\) and \(r_{k,t}\) is the return of industry \(k\). The time-series regression is estimated for each stock \(j\) in our sample using up to five years of monthly returns. The data start July 1997 and end June 2002 and we require at least 20 months of returns. Our procedure avoids overlap with the holdings data. Our measure is created without using the price levels or market capitalizations of the 5,781 stocks in our sample. The sector weights are from U.S. stocks which are not in our sample. Most importantly, Equation (22) includes the loading (\(\beta_{j,k}\)) of stock \(j\) on its industry (\(k\)) index. We are interested in knowing if stock \(j\)’s loading is large in magnitude (positively or negatively). Understanding the outlook for an industry does not help analyze the outlook of a firm if the firm’s \(\beta_{j,k} = 0\).

The model in Section 2 suggests using the \(\beta^2\) term in Equation (22). To see why this is the case, note that the variance of \(B \hat{f}\) in the model is \(B' B\). Also, Appendix F shows that investor \(i\)’s portfolio weights are proportional to his conditional variance of payoffs. Intuitively, information about the common component is valuable whenever a stock loads heavily on the component (i.e., when the loading is large positively or negatively). The \(\beta^2\) term in Equation (22) reflects this intuition.

**Overview Statistics:** Table 2 provides overview statistics of the variables used in this paper. Panel A shows that the average stock has \(\Omega_j = 2.76\%\) of its shares held by foreign mutual funds from our dataset. The 25th percentile of holdings is 0.14% and 75th percentile is 3.22%. The difference between the number of Stock \(j\)’s shares held by foreign and domestic mutual funds (normalized by shares outstanding) is denoted \(\Omega_j^*\), has a \(-2.00\%\) average value and a \([-3.40\%, 0.39\%]\) interquartile range. Section 4.3 explains how we use \(\Omega_j^*\) in robustness checks.

\(^{15}\)U.S. stock data come from Datastream. We use only U.S. securities with a primary listing on one of the three major U.S. exchanges (New York Stock Exchange, American Stock Exchange, and Nasdaq).
The average value of our asset specific information proxy $Asset\ Specific_j$—the average value of $1 - R^2_j$ from Equation (21)—is 0.85 with a [0.79, 0.95] inter-quartile range. The average value of our common component information proxy $Common_{j,k}$ is 1.28 with a [0.16, 1.46] inter-quartile range.

Market capitalizations are highly skewed. The average is USD 2.56 billion with a [0.04, 0.47] inter-quartile range. For this reason, we use the natural log of market capitalization in our cross-sectional regressions. The average log of market capitalization is 18.75 with a [17.41, 19.97] inter-quartile range. The average number of analysts covering the foreign stocks is 4.16 and the average book leverage is 0.57.

[ Insert Table 2 About Here ]

Table 2, Panel B shows correlation coefficients for the variables used in this paper. The level of a stock’s foreign ownership ($\Omega_j$) is negatively correlated with the asset specific information proxy (-0.15 coefficient), but positively correlated with the common information proxy (0.14 coefficient), natural log of market capitalization (0.33 coefficient), and number of analysts (0.46 coefficient). $Asset\ Specific_j$ is negatively cross-sectionally correlated with the natural log of market capitalization (-0.28 correlation coefficient). $Asset\ Specific_j$ is also negatively correlated with number of analysts (-0.27 coefficient) indicating that it is likely to be a good proxy for information not observed by mutual fund managers in our dataset. $Common_{j,k}$ is positively correlated with the natural log of market capitalization (0.15 coefficient) and with the number of analysts (0.24 coefficient).

4.2 Cross-Border Holdings and Double Sort Results

We compare the empirical relationship between mutual fund holdings and information proxies with the theoretical relationship shown in Figure 4. We test if cross-border holdings decrease as asset specific information advantages increase and if holdings increase as common component information advantages increase. We sort the 5,781 stocks into quartiles using our proxy variable for asset specific information. We also sort the stocks into quartiles using our proxy variable for common component information.

Table 3 shows the average foreign holdings for the four combinations where the sort variable is either “low” (bottom 25%) or “high” (upper 25%). When there are low-levels of information about common components and high-levels of asset specific information, the average cross-border holding is 0.0139 of shares outstanding. Low-levels of cross-border holdings correspond to situations when home bias is high—see the lower-right
When there are high-levels of information about common components and low-levels of asset specific information, the average cross-border holdings is 0.0490 of shares outstanding. High-levels of cross-border holdings correspond to situations when home bias is low and reverse home bias is possible—see the upper-left hand side of Figure 4 for a graphical example. When asset specific information is “low”, an increase in common component information leads holdings to increase from 0.0293 to 0.0490. The increase is 0.0197 with a 3.51 t-statistic.

Table 3 shows that when information about common components is “high”, an increase in asset specific information leads to an increase of 0.0267 in cross-border holdings (with a 7.39 t-statistic). When information about common components is “low”, an increase in asset specific information leads to an increase of 0.0154 in cross-border holdings (with a 2.99 t-statistic). The increases are both statistically and economically significant.

Sorting stocks by our information proxy variables produces large dispersions in observed cross-border holdings. The dispersions (or differences) shown in Table 3 range from 0.84% to 2.67%. In fact, if we compare the largest ownership group (4.90%) in Table 3 with the lowest group (1.39%), the dispersion is 3.51%. We conclude that sorting by our proxy variables produces holding dispersions that are large and economically significant.

4.3 Cross-Border Holdings and Regression Results

We use regression analysis to examine the relationship between our proxy variables for information advantages and holdings. Table 4 reports results of a regression of holdings on Asset Specific\(_j\) and other variables known to influence cross-border holdings. Table 5 repeats the same regressions but first partitions stocks into those with high and low values of our proxy variable for factor information. The basic regression is:

\[
\Omega_j = \gamma_0 + \gamma_1 (\text{Asset Specific}_j) + \nu_j
\]

The coefficient of interest is \(\gamma_1\). Table 4, Regression 1 shows the estimated value of \(\gamma_1\) is -0.0569 with a -7.87 t-statistic. We use robust (White) standard errors to compute t-statistics. Stocks with high levels of asset specific information (i.e., stocks that move

---

16If the mutual funds in our dataset held the world market portfolio, we should measure similar values of \(\Omega_j\) across all stocks and thus report similar values of \(\bar{\Omega}\) for each of the four bins shown in Table 3.
less with world and sector (indices) have lower levels of cross-border holdings. This finding
of a negative slope coefficient matches the downward sloping graph lines in Figure 4.

[ Insert Table 4 About Here ]

We expand the basic regression to include variables that have previously been linked
to cross-border holdings. The variables include the natural log of equity market value
\((\ln MC_j)\), and the number of analysts following the stock \((\# \text{ of Analysts}_j)\).

\[
\Omega_j = \gamma_0 + \gamma_1 (\text{Asset Specific}_j) + \gamma_2 (\ln MC_j) + \gamma_3 (\# \text{ of Analysts}_j) + \nu_j
\]

In Table 4, Regression 2 shows the results after including two explanatory variables in
the cross-sectional regression. The coefficient on Asset Specific\(_j\) (\(\gamma_1\)) is -0.0224 with a
-3.12 t-statistic. The fit of the regression is 0.11 which is higher than Regression 1.\(^{17}\)

The remainder of Table 4 is a series of robustness checks. We test different regression
specifications and check if the \(\gamma_1\) coefficient remains significantly negative. In Regression
3, the left-hand side variable is changed to \(\Omega^*_j\) which is defined using the difference
between number of shares held by foreign and local institutions in the numerator of Equation
(20). If a stock is particularly attractive to all institutional investors (as opposed to
just cross-border investors), \(\Omega^*_j\) will be low. However, the coefficients in Regression 3 are
broadly similar to those in the first two regressions except that number of analysts is now
significantly positive. Regression 4 includes book leverage as an explanatory variable.
The coefficient is 0.0029 with a 10.35 t-statistic. We conclude that controlling for possibly
(unobserved) characteristics that may be attractive to institutional investors does not
affect our results.

A Sales-Based Measure of Asset Specific\(_j\): We calculate a second measure of Asset
Specific\(_j\) based on sales data as opposed to stock market data. For each company, we
obtain a history of annual sales (in US dollars) and calculate annual sales growth. We next
calculate each industry’s annual sales growth as the equal-weighted average of company
sales growths. The number of firms per industry is given in Table 1, Panel B. The new
measure of Asset Specific\(_j\) (Sales) is simply one minus the correlation of stock \(j\)’s annual
sales growth with its industry’s annual sales growth. We require a company to have six
years of sales growth data to be included which reduces our sample to 3,905 stocks.

In Table 4, Regression 5, the \(\gamma_1\) coefficient is -0.0602 with a -13.69 t-statistic. We continue

\(^{17}\)The fit shown at the bottom of Table 4 is an adjusted \(R^2\) from the cross-sectional regression—not to be
confused with the fit from the time series regression (21) used to construct Asset Specific\(_j\).
to use robust (White) standard errors when calculating t-statistics. In Regression 6, we include country fixed effects (dummy variables). The coefficient on \( Asset \ Specific_{j}(Sales) \) is -0.0076 with a -1.98 t-statistic. Controlling for country fixed effects addresses the possibility that unobserved country-level differences are driving results. If, however, country-level differences are related to information structures, such a regression would not make sense in light of our model. We report results for completeness.

In the final column, Regression 7, we control for the large number of Japanese and UK firms in our sample. We randomly choose 155 of the 2,108 Japanese stocks in our sample and 155 of the 721 UK stocks in the sample (note that 155 is the average number of stocks from other countries in our sample.) The sample size is 1,354 as we have dramatically reduced the number of Japanese and UK stocks used. In addition, some of the 155 stocks that were randomly chosen may not have six years of sales growth data. Regression 7 shows the coefficient on \( Asset \ Specific_{j}(Sales) \) is -0.0186 with a -3.15 t-statistic.

Our regressions show that cross-border holdings decrease as asset specific information becomes more important for a given stock’s returns. We measure the level of asset specific information using both stock return data and sales growth data.

### 4.4 Information about Common Factors and Regressions

We end the empirical analysis by combining our common information proxy variable with the regression analysis. Table 5, Regression 1a considers only stocks with a low degree of information advantage about common factors (bottom 25%). We regress our cross-border holdings (\( \Omega_{j} \)) on a constant and our proxy for asset specific information (\( Asset \ Specific_{j} \)). The coefficient on \( Asset \ Specific_{j} \) is -0.0331 with a -3.70 t-statistic. Regression 1b uses stocks with a high degree of information advantage about common factors (upper 25%). The coefficient on \( Asset \ Specific_{j} \) is -0.0741 with a -3.40 t-statistic.

[ Insert Table 5 About Here ]

The regression results shown in Table 5 parallel the double sort results shown in Table 3. In Table 5, Regressions 1a and 1b, stocks with a high degree of information advantage about common factors are more sensitive to our proxy for asset specific information (e.g., the coefficient is more negative: \(-0.0331 > -0.0741\)). In Table 3, and for stocks with a high common information proxy, stocks with high asset-specific information have 2.67% lower holdings that stocks with low asset-specific information.
Also in Table 5, stocks with a high degree of information advantage about common factors have higher levels of cross-border holdings (when the asset specific proxy is zero)—see the estimated constant term $\gamma_0$ and note that $0.0478 < 0.0821$. An F-test for differences in the asset specific coefficients (only) has a 0.0029 p-value.

Table 5, Regressions 2a and 2b use $\Omega_j^*$ as the dependent variable. Both specifications give the same general picture even after controlling for stock size and leverage. The $\gamma_1$ coefficients become increasingly negative when moving from stocks with low information advantage about the common factor to stocks with high information advantage ($-0.0523 > -0.1001$). The F-test for differences in the asset specific coefficient rejects the hypothesis of coefficient equality at the 3%-level.

5 Conclusion

This paper proposes a rational expectations equilibrium model in which agents are asymmetrically informed about asset specific and common components of payoffs. Our model allows agents to have asset specific information or information about common components or both or neither. The model produces closed-form solutions for prices and the holdings of individual agents. We apply the model to a study of international portfolio choice.

We show that prices in the model collapse to the traditional CAPM (adjusted for the supply uncertainty that exists in our model) when all agents are fully informed about all payoffs in the economy. An asset’s price today equals its discounted future payoffs minus a risk premium. The price discount (risk premium) is a function of risk aversion and the covariance of the asset’s payoffs with the payoffs of all other assets (the market). When agents are asymmetrically informed about an asset’s payoffs, we show the price is below the CAPM value. The discount below a CAPM value is called the information price discount which can (roughly) be thought of as a signal-to-noise measure. When the market has high uncertainty about an asset’s future payoffs (relative to any residual uncertainty) the information price discount is large, and the asset’s price is low. A thorough understanding of information price discounts depends on the market’s uncertainty about a given asset’s payoffs compared with the market’s uncertainty about other assets’ payoffs. Thus, we turn to numerically analyzing our model to gain economic understanding.

Our numerical analysis focuses on international portfolio choice and the home bias puzzle. We consider a simple two-country, two-asset, single-factor setting. Under a typical assumption that American investors have better information about the asset specific component of American stocks and French investors have better information about the asset
specific component of French stocks, we measure a magnitude of home bias that parallels
the existing empirical literature. We next assume that one group of investors has better
information about the common component. Low levels of asset specific information, high
levels of information advantage about the common component, and different factor load-
ings lead to a large dispersion in the home bias measure. Investors from one country may
even overweight assets from the other country—a phenomenon called “reverse home bias.”

We end the paper with an empirical analysis that revisits international portfolio choice.
We create two proxy variables. The first measures the degree of information advantage
about the asset specific component of a stock’s payoffs. The second measures the degree
of information advantage about common components. We show that both a decrease
in the proxy for asset specific information advantage and an increase in the proxy for
common information lead to greater levels of cross-border holdings. In regression analysis,
our information proxies explain holding levels even after including variables that have
previously been linked to home bias (e.g., the market capitalization of a firm’s equity, the
number of analysts following the firm, and the firm’s leverage.)

There are a number of potential avenues for future research. First, one could try to
extend our model to multiple periods. This would provide expressions for net trading as
in Brennan and Cao (1997) as well as suggest empirical tests based on trading (as opposed
to holdings) data. Second, one could work to devise methods of empirically identifying
different information structures. While no small task, structures could then be used to
test relative asset prices using expressions in this paper. Third, our model may be adapted
to better understanding partially segmented markets. In such cases, information is the
“friction” that segments markets. One may be able to model groups of investors who face
low frictions only when trading securities from their home country, groups of investors who
face low frictions when trading securities in a contiguous block of countries (a geographic
region), or groups of investors who face very little frictions when investing in any global
security. None of the three extensions is likely to be easy—all are potentially interesting.
References


Appendix A

The information set of investor \( n \) (formally, investor \( i \) in group \( n \)) consists of the realization of private signals \( M_n\tilde{\eta} \) and of equilibrium prices \( \tilde{P}^0 \). The equilibrium price vector \( \tilde{P}^0 \) is a linear function of the information \( \tilde{\eta} \) and the supply \( \tilde{z} \) with \( \tilde{P}^0 = A_0 + A_1\tilde{\eta} - A_2\tilde{z} \). Since, \( \tilde{w}_n = w_n^0 + X_n'(\tilde{P}^1 - R\tilde{P}^0) \) and \( \tilde{P}^1 \) is a linear function of \( \tilde{\eta} \) and \( \tilde{\varepsilon} \), it follows that \( \tilde{w}_n \) joins the multivariate normal distribution of \( (\tilde{\eta}, \tilde{\varepsilon}, \tilde{z}) \). Consequently, \( \tilde{w}_n \) is a normal random variable conditional on \( M_n\tilde{\eta} \) and \( \tilde{P}^0 \). Properties of normal distributions imply that investor \( n \)’s expected utility can be written as:

\[
E[U(\tilde{w}_n)|M_n\tilde{\eta}, \tilde{P}^0] = U\left\{ E\left[\tilde{w}_n|M_n\tilde{\eta}, \tilde{P}^0\right] - \frac{\alpha}{2} Var\left[\tilde{w}_n|M_n\tilde{\eta}, \tilde{P}^0\right]\right\} = U\left\{ E\left[w_n^0 + X_n'(\tilde{P}^1 - R\tilde{P}^0)|M_n\tilde{\eta}, \tilde{P}^0\right] - \frac{\alpha}{2} Var\left[w_n^0 + X_n'(\tilde{P}^1 - R\tilde{P}^0)|M_n\tilde{\eta}, \tilde{P}^0\right]\right\}
\]

Since the utility function is exponential, maximizing this expected utility is identical to maximizing:

\[
\max_{X_n} \left\{ E\left[w_n^0 + X_n'(\tilde{P}^1 - R\tilde{P}^0)|M_n\tilde{\eta}, \tilde{P}^0\right] - \frac{\alpha}{2} Var\left[w_n^0 + X_n'(\tilde{P}^1 - R\tilde{P}^0)|M_n\tilde{\eta}, \tilde{P}^0\right]\right\} = \max_{X_n} \left\{ X_n' E\left[(\tilde{P}^1 - R\tilde{P}^0)|M_n\tilde{\eta}, \tilde{P}^0\right] - \frac{\alpha}{2} X_n' Var\left[(\tilde{P}^1 - R\tilde{P}^0)|M_n\tilde{\eta}, \tilde{P}^0\right] X_n\right\}
\]

The equation to be solved is:

\[
0 = E\left[(\tilde{P}^1 - R\tilde{P}^0)|M_n\tilde{\eta}, \tilde{P}^0\right] - \alpha Var\left[(\tilde{P}^1 - R\tilde{P}^0)|M_n\tilde{\eta}, \tilde{P}^0\right] X_n
\]

(23)

This implies that investor \( n \)’s demand vector is:

\[
X_n = a^{-1}Var^{-1}\left[\tilde{P}^1|M_n\tilde{\eta}, \tilde{P}^0\right] \times \left(E\left[\tilde{P}^1|M_n\tilde{\eta}, \tilde{P}^0\right] - R\tilde{P}^0\right)
\]

(24)

Appendix B

From Equations (4), (6), and (7), we have:

\[
0 = \sum_{n=1}^{N} \lambda_n V_n^{-1}\left(B_{0n} + B_{1n}M_n\tilde{\eta} + (B_{2n} - RL) (A_0 + A_1\tilde{\eta} - A_2\tilde{z})\right) - a\tilde{z}
\]

By canceling the \( \tilde{z} \), \( \tilde{\eta} \), and constant terms, it is straightforward to show that:
\[ a A_2^{-1} A_0 = \sum_{n=1}^{N} \lambda_n V_n^{-1} B_{0n} \]
\[ a A_2^{-1} A_1 = \sum_{n=1}^{N} \lambda_n V_n^{-1} B_{1n} M_n \]
\[ a A_2^{-1} = \sum_{n=1}^{N} \lambda_n V_n^{-1} (R_{IJ} - B_{2n}) \]  \hspace{1cm} (25)

Appendix C

The vector \((\tilde{P}^{0'} \ M_n \tilde{\eta}^' \ \tilde{P}^{0'})^'\) is normally distributed and its var-cov matrix is:

\[ \text{Var}[ (\tilde{P}^{0'} \ M_n \tilde{\eta}^' \ \tilde{P}^{0'})^' ] = \begin{pmatrix}
CQC' + \Sigma & CQM_n' & CQA_1' \\
M_n QC' & M_n QM_n' & M_n QA_1' \\
A_1 QC' & A_1 QM_n' & A_1 QA_1' + A_2 ZA_2'
\end{pmatrix} \]  \hspace{1cm} (26)

The conditional expectation is:

\[ E_n[\tilde{P}^1|\tilde{M}_n \tilde{\eta}, \tilde{P}^0] = E[\tilde{P}^1] + \text{Cov}[\tilde{P}^1; \left( \begin{array}{c}
M_n \tilde{\eta} \\
\tilde{P}^0 
\end{array} \right)] \times \text{Var}^{-1} \left[ \left( \begin{array}{c}
M_n \tilde{\eta} \\
\tilde{P}^0 
\end{array} \right) - E \left[ \left( \begin{array}{c}
M_n \tilde{\eta} \\
\tilde{P}^0 
\end{array} \right) \right] \right] \]

Normal distributions give \(E_n[\tilde{P}^1|\tilde{M}_n \tilde{\eta}, \tilde{P}^0] = B_{0n} + B_{1n} M_n \tilde{\eta} + B_{2n} \tilde{P}^0\). Hence,

\[ \left( \begin{array}{c}
B_{1n} \\
B_{2n}
\end{array} \right) = \text{Cov}[\tilde{P}^1; \left( \begin{array}{c}
M_n \tilde{\eta} \\
\tilde{P}^0 
\end{array} \right)] \times \text{Var}^{-1} \left[ M_n \tilde{\eta} \right] \]  \hspace{1cm} (27)

\[ \left( \begin{array}{c}
CQM_n' \\
CQA_1'
\end{array} \right) = \left( \begin{array}{c}
B_{1n} \\
B_{2n}
\end{array} \right) \left( \begin{array}{c}
M_n QM_n' \\
A_1 QM_n' \\
M_n QA_1' \\
A_1 QA_1' + A_2 ZA_2'
\end{array} \right) \]  \hspace{1cm} (28)

The variance of returns conditional on \(n\)’s information is:

\[ V_n = \text{Var}[\tilde{P}^1|\tilde{M}_n \tilde{\eta}, \tilde{P}^0] \]
\[ = \text{Var}[\tilde{P}^1] - \text{Cov}[\tilde{P}^1; \left( \begin{array}{c}
M_n \tilde{\eta} \\
\tilde{P}^0 
\end{array} \right)] \times \text{Var}^{-1} \left[ \left( \begin{array}{c}
M_n \tilde{\eta} \\
\tilde{P}^0 
\end{array} \right) \right] \times \text{Cov} \left[ \left( \begin{array}{c}
M_n \tilde{\eta} \\
\tilde{P}^0 
\end{array} \right) ; \tilde{P}^1 \right] \]  \hspace{1cm} (29)

We use Equation (27) to get:

\[ V_n = \text{Var}[\tilde{P}^1] - \left( \begin{array}{c}
B_{1n} \\
B_{2n}
\end{array} \right) \text{Cov} \left[ \left( \begin{array}{c}
M_n \tilde{\eta} \\
\tilde{P}^0 
\end{array} \right) ; \tilde{P}^1 \right] \]
Because $\text{Cov} \left[ \begin{pmatrix} M_n \bar{\eta} \\ \bar{P}^0 \end{pmatrix}, \bar{P}^1 \right] = \begin{pmatrix} M_n QC' \\ A_1 QC' \end{pmatrix}$ we get:

$$V_n = CQC' + \Sigma - B_{1n}M_nQC' - B_{2n}A_1QC'$$ (30)

---

**Appendix D**

In order to determine a closed form solution for $U$, we solve the second equation from the system shown in Equation (8):

$$aA_2^{-1}A_1 = aU = \sum_{n=1}^{N} \lambda_n V_n^{-1}B_{1n}M_n$$ (31)

The following properties apply to matrices $D_n$ and $M_n$:

**P1:** $\sum_{n=1}^{N} D_n = I_J$

**P2:** $\forall n_1 \neq n_2$: $D_{n_1}D_{n_2} = 0_J$, where $0_J$ is the null matrix of order $J$;

**P3:** $M_{n_1}M'_{n_2} = 0_{J_{n_1},J_{n_2}}$, where $0_{J_{n_1},J_{n_2}}$ is the null matrix of order $J_{n_1} \times J_{n_2}$;

**P4:** $D_nD_n = D_n$ and $M_nM_n^{-1} = I_{Jn}$

**P5:** $\forall G_1, G_2$: $g(G_1)g(G_2) = \sum_{n=1}^{N} D_nG_1D_nG_2D_n$

**P6:** $\forall G$: $g(GD) = g(G)D = Dg(G)$

There are three matrices key to obtaining a closed form solution for $U$:

$$M = UQU' + Z$$

$$\Psi = \text{Var} \left[ \bar{\eta} \bar{P}^0 \right] = Q - QU'Q^{-1}UQ$$

$$\Psi_n = M_n\Psi M_n'$$

We first solve Equation (28) for $B_{1n}$ and $B_{2n}$. The two equations to be solved are:

$$B_{1n} (M_nQM_n') + B_{2n} (A_1QM_n') = CQM_n'$$ (32)

$$B_{1n} (M_nQA_1') + B_{2n} (A_1QA_1' + A_2ZA_2') = CQA_1'$$ (33)

Using $M = UQU' + Z$, we obtain $A_1QA_1' + A_2ZA_2' = A_2MA_2'$. This implies:
\[ B_{1n}(M_n Q) + B_{2n}(A_2 M A_2') A_1' = C Q \]
\[ \Leftrightarrow B_{2n} A_2 M U'^{-1} = C Q - B_{1n} M_n Q \]
\[ \Leftrightarrow B_{2n} = (C - B_{1n} M_n) Q U M^{-1} A_2^{-1} \]

In a second step, we solve Equation (32):

\[ B_{1n}(M_n Q M_n') + (C - B_{1n} M_n) Q U M^{-1} A_2^{-1} (A_2' M_n') = C Q M_n' \]
\[ \Leftrightarrow B_{1n} M_n (Q M_n' - Q U M^{-1} U Q M_n') = (C Q - C Q U M^{-1} U Q) M_n' \]
\[ \Leftrightarrow B_{1n} M_n (Q M_n' - Q U M^{-1} U Q) M_n' = C (Q M_n' - Q U M^{-1} U Q) M_n' \]
\[ \Leftrightarrow B_{1n} M_n \Psi M_n' = C \Psi M_n' \]
\[ \Leftrightarrow B_{1n} \Psi_n = C \Psi M_n' \]
\[ \Leftrightarrow B_{1n} = C \Psi M_n' \Psi_n^{-1} \]

We have thus demonstrated that:

\[ B_{1n} = C \Psi M_n' \Psi_n^{-1} \]
\[ B_{2n} = (C - B_{1n} M_n) Q U M^{-1} A_2^{-1} \] (34)

By substituting \( B_{1n} \) and \( B_{2n} \) into Equation (30) we obtain the variance-covariance matrix \( V_n \) as a function of \( \Psi \)

\[ V_n = C Q C' + \Sigma - B_{1n} M_n Q C' - B_{2n} A_1 Q C' \]
\[ \Leftrightarrow V_n = C Q C' + \Sigma - C \Psi M_n' \Psi_n^{-1} M_n Q C' - (C - C \Psi M_n' \Psi_n^{-1} M_n) Q U M^{-1} A_2^{-1} A_1 Q C' \]
\[ \Leftrightarrow V_n = \Sigma + C (Q - Q U M^{-1} U Q) C' - C \Psi M_n' \Psi_n^{-1} M_n Q C' + C \Psi M_n' \Psi_n^{-1} M_n Q U M^{-1} U Q C' \]
\[ \Leftrightarrow V_n = \Sigma + C \Psi C' - C \Psi M_n' \Psi_n^{-1} M_n (Q - Q U M^{-1} U Q) C' \]
\[ \Leftrightarrow V_n = \Sigma + C \Psi C' - C \Psi M_n' \Psi_n^{-1} M_n \Psi C' \] (35)

We use Equation (31) to determine \( U \). Multiplying (31) by \( M_n' \) on the right, we obtain \( \lambda_n V_n^{-1} B_{1n} = a U M_n' \). We then multiply this last equation by \( V_n \) on the left and we replace \( B_{1n} \) with its value from (34):

\[ \lambda_n C \Psi M_n' \Psi_n^{-1} = a V_n U M_n' \] (36)

If we multiply (36) by \( M_n \) on the right and if we sum for \( n = 1, \ldots, N \), we obtain Equation (31). We conclude that Equation (31) is equivalent to Equation (36) for all
If we multiply Equation (36) by $\Psi_n$ and $M_n$ on the right and if we replace $V_n$ with its value in Equation (35) we then obtain:

$$\lambda_n C \Psi D_n = a (\Sigma + C \Psi C' - C \Psi M_n^{-1} M_n \Psi C') U M_n' \Psi_n M_n$$

If we now sum for $n = 1, \ldots, N$ we obtain:

$$\sum_{n=1}^{N} \lambda_n C \Psi D_n = a \left( \Sigma \sum_{n=1}^{N} U M_n' \Psi_n M_n + C \Psi C' \sum_{n=1}^{N} U M_n' \Psi_n M_n - \sum_{n=1}^{N} C \Psi M_n^{-1} M_n \Psi C' U M_n' \Psi_n M_n \right)$$

which is equivalent to:

$$C \Psi D = a \left( \Sigma U \sum_{n=1}^{N} D_n \Psi D_n + C \Psi C' U \sum_{n=1}^{N} D_n \Psi D_n - C \Psi \sum_{n=1}^{N} M_n' \Psi_n^{-1} M_n \Psi C' U M_n' \Psi_n M_n \right)$$

By introducing the function $g(\cdot)$, we obtain:

$$C \Psi D = a \Sigma U g(\Psi) + a C \Psi C' U g(\Psi) - a C \Psi \left( \sum_{n=1}^{N} M_n' \Psi_n^{-1} M_n \Psi C' U M_n' \Psi_n M_n \right)$$

(37)

The reader can easily check that (37) is equivalent to (31). We substitute $U$ in (37) with $U = a^{-1} \Sigma^{-1} C D$ and we have to check the following equality:

$$C \Psi D = CD g(\Psi) + C \Psi C' \Sigma^{-1} CD g(\Psi) - C \Psi \left( \sum_{n=1}^{N} M_n' \Psi_n^{-1} M_n \Psi C' \Sigma^{-1} C D M_n' \Psi_n M_n \right)$$

(38)

Thanks to Lemma 2.1, $\Psi^{-1} + C' \Sigma^{-1} C$ is a $g$-matrix which means by definition, that $g(\Psi^{-1} + C' \Sigma^{-1} C) = \Psi^{-1} + C' \Sigma^{-1} C$. We then replace $C' \Sigma^{-1} C$ by $g(\Psi^{-1} + C' \Sigma^{-1} C) - \Psi^{-1}$ in the right term of Equation (38). This enables us to prove the equality in (38). We conclude $U = a^{-1} \Sigma^{-1} C D$ represents a solution for $U$.

---

**Appendix E**

We replace $B_{2n}$ in the first equation of (8) with its value given in (34). We then obtain $A_2$. We eliminate the $B_{1n}$ coefficients ($n = 1, \ldots, N$) using the second equation in (8). We then directly obtain $A_1$ from the expression for $U$. In order to determine $A_0$, we replace the following in the third equation of (8).
\[ \mathbf{B}_{0n} = (\mathbf{I} - \mathbf{B}_{1n}\mathbf{M}_n - \mathbf{B}_{2n}\mathbf{A}_1) E[\tilde{\theta}] - \mathbf{B}_{2n}(\mathbf{A}_0 - \mathbf{A}_2E[\tilde{z}]) \]

The reader can easily check that the matrix \( \mathbf{A}_2 \) is regular and it follows from Equation (13) that \( \mathbf{A}_2 = a\mathbf{A}_1(\mathbf{CD})^{-1}\Sigma \). The matrices \( \mathbf{C}, \mathbf{D} \) and \( \Sigma \) are, by definition, regular matrices. Moreover, using the properties of positive definite matrices, \( \mathbf{A}_1 \) appears to be a regular matrix.

---

**Appendix F**

We analyze the relationship between model parameters \( \{r_f, a, \lambda_1, \ldots, \lambda_N, \mathbf{B}, \mathbf{T}, \Sigma, \mathbf{Z}\} \) and ex-ante equilibrium holdings. We do this by taking expectations over the random variables in the model \( \{\tilde{\eta}, \tilde{\varepsilon}, \tilde{z}\} \). Taking expectations of Equation (5) and substituting into Equation (15) gives the following expression for investor \( n \)'s holdings:

\[ E[X_n] = a^{-1}\mathbf{V}_n^{-1}\left( E[\tilde{P}\tilde{1}] - RE[\tilde{P}_0]\right) \]

\[ = \mathbf{V}_n^{-1}\mathbf{V}_NE[\tilde{z}] \quad \text{(39)} \]

In a single-stock world with no factors, investor \( n \)'s holdings depends on the ratio of the market’s uncertainty about the future payoff (\( \mathbf{V}_N \)) to his uncertainty about the same payoff (\( \mathbf{V}_n \)). The higher the investor’s uncertainty relative to the market, the lower the ratio, and the lower the weight of the asset in his portfolio.

In a multi-asset framework with uncorrelated residual uncertainty and no factors, the matrices (\( \mathbf{V}_N \)) and (\( \mathbf{V}_n \)) are diagonal. The term \( \mathbf{V}_n^{-1}\mathbf{V}_N \) represents a series of uncertainty ratios. The same intuition described in the paragraph above holds.

In a multi-asset model with correlated residual uncertainties and/or a factor structure of payoffs, thinking about \( \mathbf{V}_n^{-1}\mathbf{V}_N \) as a ratio of two uncertainty measures provides rough intuition only. However, the product of the two matrices includes covariance terms relating to assets’ payoffs. Investor \( n \)'s holdings of a specific asset now depends on his uncertainty about the asset’s payoffs, his uncertainty about other assets’ payoffs, and others’ uncertainty about all assets (including the specific asset in question). Section 3 numerically analyzes equilibrium prices and holdings in an effort to better understand the role of the covariance terms.
Appendix G

We demonstrate that when all investors are informed about all asset specific components and common components, prices reduce to a form of the Capital Asset Pricing Model (CAPM). We subtract $\bar{R}$ times Equation (4) from Equation (3) and take expectations to get:

$$E \left[ \tilde{P}^1 \right] - R E \left[ \tilde{P}^0 \right] = (C - RA_1)E [\tilde{\eta}] + RA_2E [\tilde{z}] - RA_0$$

Equations (11), (12), and (13) enable us to write:

$$RA_1 = (CQC)' + \Sigma - V_N(CDQC')^{-1}CD = C$$

$$RA_2 = a(CQC)' + \Sigma - V_N(CDQC')^{-1}\Sigma = a\Sigma$$

$$RA_0 = (C - RA_1)E [\tilde{\eta}] + (RA_2 - aV_N)E [\tilde{z}] = 0$$

Combining these results gives the CAPM expressed in prices:

$$E \left[ \tilde{P}^0 \right] = \frac{1}{R} \left( E \left[ \tilde{P}^1 \right] - a\Sigma E [\tilde{z}] \right)$$

(40)

We can express the same result in terms of covariance. As all investors are informed, they know the realization $\eta$ of $\tilde{\eta}$. Therefore, $\tilde{P}^1 = C\eta + \tilde{\epsilon}$ and $Var \left[ \tilde{P}^1 \right] = \Sigma$:

$$a\Sigma E [\tilde{z}] = a Var \left[ \tilde{P}^1 \right] E [\tilde{z}] = a Cov \left[ \tilde{P}^1, \tilde{P}^1 \right] E [\tilde{z}] = a Cov \left[ \tilde{P}^1, \left( \tilde{P}^1 \right)' E [\tilde{z}] \right]$$

$$= a Cov \left[ \tilde{P}^1, \tilde{P}^1_m \right]$$

Here, $\tilde{P}^1_m$ is the payoff of the market portfolio (the one that contains all the assets) divided by the number of investors (since $\tilde{z}$ has been defined as the supply per investor). As the supply is unknown by the agents in the market, we consider the expectations of the supply, rather than the supply itself. Using Equation (40) and the above result gives:

$$E \left[ \tilde{P}^1 \right] - R E \left[ \tilde{P}^0 \right] = a\Sigma E [\tilde{z}] = a Cov \left[ \tilde{P}^1, \tilde{P}^1_m \right] .$$

For asset $j$, we get: $E \left[ \tilde{P}^j_1 \right] - R E \left[ \tilde{P}^0_j \right] = a Cov \left[ \tilde{P}^j_1, \tilde{P}^1_m \right]$.
Table 1
Sample Size

The table shows the number of stocks in our data sample. Panel A sorts stocks by country. Panel B sorts the final sample of 5,781 stocks by industry. The table is based on cross-border holdings on December 31, 2002. Holdings data are from Thompson Financial. Price data are from Datastream.

Panel A: Number of Stocks by Country

<table>
<thead>
<tr>
<th>Country</th>
<th>Holdings Data</th>
<th>Holdings and Price Data</th>
<th>Holdings and Firm Char. Data</th>
<th>Holdings, Prices, Firm Char. Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Australia</td>
<td>695</td>
<td>587</td>
<td>307</td>
<td>293</td>
</tr>
<tr>
<td>2 Austria</td>
<td>91</td>
<td>78</td>
<td>65</td>
<td>60</td>
</tr>
<tr>
<td>3 Belgium</td>
<td>191</td>
<td>166</td>
<td>99</td>
<td>95</td>
</tr>
<tr>
<td>4 Denmark</td>
<td>162</td>
<td>124</td>
<td>111</td>
<td>97</td>
</tr>
<tr>
<td>5 Ireland</td>
<td>72</td>
<td>48</td>
<td>37</td>
<td>34</td>
</tr>
<tr>
<td>6 Finland</td>
<td>143</td>
<td>122</td>
<td>109</td>
<td>97</td>
</tr>
<tr>
<td>7 France</td>
<td>686</td>
<td>567</td>
<td>497</td>
<td>448</td>
</tr>
<tr>
<td>8 Germany</td>
<td>744</td>
<td>642</td>
<td>507</td>
<td>467</td>
</tr>
<tr>
<td>9 Greece</td>
<td>299</td>
<td>242</td>
<td>117</td>
<td>110</td>
</tr>
<tr>
<td>10 Hong Kong</td>
<td>196</td>
<td>160</td>
<td>157</td>
<td>150</td>
</tr>
<tr>
<td>11 Italy</td>
<td>302</td>
<td>243</td>
<td>219</td>
<td>189</td>
</tr>
<tr>
<td>12 Japan</td>
<td>2,676</td>
<td>2,370</td>
<td>2,216</td>
<td>2,108</td>
</tr>
<tr>
<td>13 Netherlands</td>
<td>198</td>
<td>137</td>
<td>117</td>
<td>109</td>
</tr>
<tr>
<td>14 New Zealand</td>
<td>79</td>
<td>70</td>
<td>41</td>
<td>41</td>
</tr>
<tr>
<td>15 Norway</td>
<td>178</td>
<td>106</td>
<td>107</td>
<td>88</td>
</tr>
<tr>
<td>16 Portugal</td>
<td>56</td>
<td>46</td>
<td>34</td>
<td>30</td>
</tr>
<tr>
<td>17 Singapore</td>
<td>274</td>
<td>233</td>
<td>214</td>
<td>200</td>
</tr>
<tr>
<td>18 Spain</td>
<td>687</td>
<td>121</td>
<td>118</td>
<td>105</td>
</tr>
<tr>
<td>19 Sweden</td>
<td>326</td>
<td>226</td>
<td>209</td>
<td>174</td>
</tr>
<tr>
<td>20 Switzerland</td>
<td>264</td>
<td>198</td>
<td>184</td>
<td>165</td>
</tr>
<tr>
<td>21 United Kingdom</td>
<td>1,973</td>
<td>1,067</td>
<td>794</td>
<td>721</td>
</tr>
</tbody>
</table>

TOTAL STOCKS | 10,292 | 7,553 | 6,259 | 5,781 |
### Table 1
Sample Size

**Panel B: Industry Break-Down**

<table>
<thead>
<tr>
<th>Industry</th>
<th>Num. of Stocks</th>
<th>Industry</th>
<th>Num. of Stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerospace &amp; Defense</td>
<td>23</td>
<td>Industrial Metals</td>
<td>100</td>
</tr>
<tr>
<td>Auto &amp; Parts</td>
<td>160</td>
<td>Industrial Trans.</td>
<td>149</td>
</tr>
<tr>
<td>Banks</td>
<td>225</td>
<td>Leisure Goods</td>
<td>70</td>
</tr>
<tr>
<td>Beverages</td>
<td>76</td>
<td>Life Insurance</td>
<td>23</td>
</tr>
<tr>
<td>Chemicals</td>
<td>234</td>
<td>Media</td>
<td>219</td>
</tr>
<tr>
<td>Construction</td>
<td>372</td>
<td>Mining</td>
<td>64</td>
</tr>
<tr>
<td>Electricity</td>
<td>54</td>
<td>Mobile Telecom.</td>
<td>33</td>
</tr>
<tr>
<td>Electronic Equip.</td>
<td>315</td>
<td>Nonlife Insur.</td>
<td>66</td>
</tr>
<tr>
<td>Equity Investments</td>
<td>55</td>
<td>Oil &amp; Gas Producers</td>
<td>51</td>
</tr>
<tr>
<td>Fixed Line Telecom.</td>
<td>26</td>
<td>Oil Equip. &amp; Srvcs</td>
<td>18</td>
</tr>
<tr>
<td>Food &amp; Drug Retail</td>
<td>79</td>
<td>Personal Goods</td>
<td>190</td>
</tr>
<tr>
<td>Food Producers</td>
<td>224</td>
<td>Pharm. &amp; Biotech.</td>
<td>154</td>
</tr>
<tr>
<td>Forestry &amp; Paper</td>
<td>47</td>
<td>Real Estate</td>
<td>252</td>
</tr>
<tr>
<td>General Financial</td>
<td>197</td>
<td>Software Services</td>
<td>474</td>
</tr>
<tr>
<td>General Indus.</td>
<td>110</td>
<td>Support Services</td>
<td>253</td>
</tr>
<tr>
<td>General Retailers</td>
<td>293</td>
<td>Tech. Equipment</td>
<td>246</td>
</tr>
<tr>
<td>Health Equipment</td>
<td>110</td>
<td>Tobacco</td>
<td>8</td>
</tr>
<tr>
<td>Household Goods</td>
<td>159</td>
<td>Travel &amp; Leisure</td>
<td>230</td>
</tr>
<tr>
<td>Industrial Engin.</td>
<td>384</td>
<td>Utilities</td>
<td>38</td>
</tr>
</tbody>
</table>

**Total Number of Stocks:** 5,781
Table 2
Overview Statistics

The table shows the overview statistics for the main variables in our empirical analysis. Panel A shows each variable’s cross-sectional mean, standard deviation, 25th, 50th, and 75th percentiles for the 5,781 stocks. Panel B shows correlation coefficients of the variables. “Foreign Holdings (Ωj)” is the number of shares held by foreign funds divided by shares outstanding. “Foreign – Domestic Holdings (Ω*j)” is the number of shares held by foreign funds minus shares held by domestic fund all divided by shares outstanding. We have two proxy variables for information—one is asset specific and one relates to common components. The table is based on cross-border holdings on December 31, 2002. Holdings data are from Thompson Financial. Price data are from Datastream.

Panel A: Cross-Sectional Statistics

<table>
<thead>
<tr>
<th>Units</th>
<th>Mean</th>
<th>Stdev</th>
<th>25th Ptile</th>
<th>50th Ptile</th>
<th>75th Ptile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Foreign Hold (Ωj)</td>
<td>%</td>
<td>2.76</td>
<td>5.20</td>
<td>0.14</td>
<td>0.59</td>
</tr>
<tr>
<td>For-Dom Hold (Ω*j)</td>
<td>%</td>
<td>(2.00)</td>
<td>8.43</td>
<td>(3.40)</td>
<td>(0.36)</td>
</tr>
<tr>
<td>Asset Specific Info Proxy j</td>
<td>--</td>
<td>0.85</td>
<td>0.13</td>
<td>0.79</td>
<td>0.89</td>
</tr>
<tr>
<td>Common Info Proxy j,k</td>
<td>--</td>
<td>1.28</td>
<td>2.18</td>
<td>0.16</td>
<td>0.57</td>
</tr>
<tr>
<td>Market Capitalization j</td>
<td>$ bn</td>
<td>2.56</td>
<td>79.29</td>
<td>0.04</td>
<td>0.11</td>
</tr>
<tr>
<td>ln( Market Cap j )</td>
<td>ln($)</td>
<td>18.75</td>
<td>1.96</td>
<td>17.41</td>
<td>18.55</td>
</tr>
<tr>
<td>Leverage j</td>
<td>--</td>
<td>0.57</td>
<td>0.36</td>
<td>0.39</td>
<td>0.57</td>
</tr>
<tr>
<td>Num. of Analysts j</td>
<td>--</td>
<td>4.16</td>
<td>6.44</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Panel B: Correlation of Variables

<table>
<thead>
<tr>
<th>Ωj</th>
<th>Ω*j</th>
<th>Asset Spec. j</th>
<th>Common j,k</th>
<th>MktCap j</th>
<th>ln(MCj)</th>
<th>Lev j</th>
<th>#Analyst j</th>
</tr>
</thead>
<tbody>
<tr>
<td>Foreign Hold (Ωj)</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For-Dom Hold (Ω*j)</td>
<td>0.52</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asset Specific Info Proxy j</td>
<td>-0.15</td>
<td>-0.14</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Common Info Proxy j,k</td>
<td>0.14</td>
<td>0.06</td>
<td>-0.31</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market Capitalization j</td>
<td>0.03</td>
<td>0.03</td>
<td>-0.05</td>
<td>0.03</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln( Market Cap j )</td>
<td>0.33</td>
<td>0.15</td>
<td>-0.28</td>
<td>0.15</td>
<td>0.12</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Leverage j</td>
<td>-0.01</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.00</td>
<td>0.04</td>
<td>1.00</td>
</tr>
<tr>
<td>Num. of Analysts j</td>
<td>0.46</td>
<td>0.23</td>
<td>-0.27</td>
<td>0.24</td>
<td>0.08</td>
<td>0.65</td>
<td>0.03</td>
</tr>
</tbody>
</table>
Table 3
Cross-Border Holdings and Double Sort Results

The table shows average cross-border holdings as a fraction of a stock’s shares outstanding for four different groups of stocks. We sort stocks into quartiles along two dimensions. The first sort uses our proxy for the information advantage about the asset specific component of a stock’s returns. The second sort uses our proxy for the information advantage of foreign investors with respect to common components of asset payoffs. “Low” indicates a proxy variable is in the lower 25% of its distribution. “High” indicates a proxy variable is in the upper 25% of its distribution. The table is based on cross-border holdings on December 31, 2002. Holdings data are from Thompson Financial.

<table>
<thead>
<tr>
<th>Common Info Proxy</th>
<th>Asset Specific Info Proxy</th>
<th>Low</th>
<th>High</th>
<th>Diff</th>
<th>T-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td></td>
<td>0.0490</td>
<td>0.0223</td>
<td>0.0267</td>
<td>7.39</td>
</tr>
<tr>
<td>Low</td>
<td></td>
<td>0.0293</td>
<td>0.0139</td>
<td>0.0154</td>
<td>2.99</td>
</tr>
<tr>
<td>Diff</td>
<td></td>
<td>0.0197</td>
<td>0.0084</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T-stat</td>
<td></td>
<td>3.51</td>
<td>2.97</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4
Regression Results and Asset Specific Information Proxy

The table shows cross-sectional regression results. The dependent variable in Regressions 1 and 2 is $\Omega$ which is the ratio of shares held by foreign funds divided by shares outstanding. The dependent variable in Regressions 3 – 7 is $\Omega^*$ which is the difference between shares held by foreign funds and domestic funds, all divided by shares outstanding. “Asset Specificj” is our proxy for the information advantage about the asset specific component of a stock’s returns. “Asset Specificj (Sales)” is based on sales growth data instead of returns (methodology described in the text.) The table is based on cross-border holdings on December 31, 2002. Holdings data are from Thompson Financial. Price data are from Datastream.

<table>
<thead>
<tr>
<th>Depend. Var.</th>
<th>Reg. 1</th>
<th>Reg. 2</th>
<th>Reg. 3</th>
<th>Reg. 4</th>
<th>Reg. 5</th>
<th>Reg. 6</th>
<th>Reg. 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Omega_j$</td>
<td>-0.0569</td>
<td>-0.0224</td>
<td>-0.0701</td>
<td>-0.0570</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[7.87]</td>
<td>[3.12]</td>
<td>[7.86]</td>
<td>[6.84]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Omega_j^*$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.0602</td>
<td>-0.0076</td>
<td>-0.0186</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[13.69]</td>
<td>[1.98]</td>
<td>[3.15]</td>
</tr>
<tr>
<td>Asset Spec j (Sales)</td>
<td>0.0083</td>
<td>0.0050</td>
<td>-0.0009</td>
<td>-0.0011</td>
<td>0.0017</td>
<td>0.0016</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[24.12]</td>
<td>[9.55]</td>
<td>[1.18]</td>
<td>[0.95]</td>
<td>[1.56]</td>
<td>[1.03]</td>
<td></td>
</tr>
<tr>
<td>ln(MktCapj)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Num. Analystsj</td>
<td>-0.0031</td>
<td>0.0074</td>
<td>0.0068</td>
<td>0.0110</td>
<td>0.0051</td>
<td>0.0045</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.98]</td>
<td>[3.42]</td>
<td>[3.03]</td>
<td>[2.12]</td>
<td>[1.16]</td>
<td>[0.61]</td>
<td></td>
</tr>
<tr>
<td>Leveragej</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.0693</td>
<td>-0.1107</td>
<td>-0.0660</td>
<td>0.0234</td>
<td>0.0159</td>
<td>Country</td>
<td>-0.0410</td>
</tr>
<tr>
<td></td>
<td>[12.34]</td>
<td>[11.90]</td>
<td>[4.95]</td>
<td>[1.36]</td>
<td>[0.75]</td>
<td>F.E.</td>
<td></td>
</tr>
<tr>
<td># Obs</td>
<td>5,780</td>
<td>5,780</td>
<td>5,780</td>
<td>5,780</td>
<td>3,095</td>
<td>3,095</td>
<td>1,354</td>
</tr>
<tr>
<td>Fit</td>
<td>0.02</td>
<td>0.11</td>
<td>0.03</td>
<td>0.06</td>
<td>0.13</td>
<td>0.46</td>
<td>0.08</td>
</tr>
</tbody>
</table>

40
### Table 5
**Regression Results, Asset Specific Proxy, and Common Component Proxy**

The table shows pairs of cross-sectional regression results. The first regression in the pairs considers stocks with low information advantages vis-à-vis the common factor (bottom 25%). The second regression in the pair considers stocks with high information advantages (upper 25%). The dependent variable in Regressions 1a and 1b is $\Omega_j$ which is the ratio of shares held by foreign funds divided by shares outstanding. The dependent variable in Regressions 2a and 2b is $\Omega_j^*$ which is the difference between shares held by foreign funds and domestic funds, all divided by shares outstanding. The table is based on cross-border holdings on December 31, 2002. Holdings data are from Thompson Financial. Price data are from Datastream.

<table>
<thead>
<tr>
<th>Depend. Var.</th>
<th>Reg. 1a &amp; 1b</th>
<th>Reg. 2a &amp; 2b</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Common Info Proxy</td>
<td>Common Info Proxy</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>$\Omega_j$</td>
<td>-0.0331</td>
<td>-0.0741</td>
</tr>
<tr>
<td>(T-stat)</td>
<td>[3.70]</td>
<td>[3.40]</td>
</tr>
<tr>
<td>$\Omega_j^*$</td>
<td>0.0478</td>
<td>0.0821</td>
</tr>
<tr>
<td>(T-stat)</td>
<td>[7.34]</td>
<td>[4.76]</td>
</tr>
<tr>
<td># Obs</td>
<td>1,445</td>
<td>1,445</td>
</tr>
<tr>
<td>Fit</td>
<td>0.01</td>
<td>0.03</td>
</tr>
</tbody>
</table>

F-Stat for Diff. in Asset-Specific Coefs
(P-value)
8.87 (0.0029) 4.68 (0.0306)
Figure 1
World Market Capitalization

The figure shows the level of world market capitalization for different levels of information advantages about the asset specific components of payoffs and the common component of payoffs. We consider a case with two assets (an American stock and a French stock) and two groups of investors (American people and French people.) Payoffs are generated by a one-factor linear model. Investors have asset specific information about the asset from their home country. The American investors have information about the common component. The X-axis represents different levels of information advantage about the home-country assets. The four curves (labeled 0, 1, 2, 4) represent four levels of information advantage (for the American investor) about the common component. The bottom graph line (thin, purple, with “O” markings) represents the highest levels of information advantage about the common component. Details of the numerical analysis are given in the text.
The figure shows the weight of American assets in the world market portfolio for different levels of information advantages about the asset-specific components of payoffs and the common component of payoffs. The X-axis represents different levels of information advantage about the home-country assets. The four curves (labeled 0, 1, 2, 4) represent four levels of information advantage (for the American investor) about the common component. The top graph line (thin, purple, with “O” markings) represents the highest levels of information advantage about the common component. Details of the numerical analysis are given in the text.
The figure shows weight of the French asset in the American investors’ portfolios minus the weight of the French asset in the world market portfolio (a measure related to the degree of home bias). The X-axis represents different levels of information advantage about the home-country asset. The four curves (labeled 0, 1, 2, 4) represent four levels of information advantage about the common component of payoffs. The top graph line (thin, purple, with “O” markings) represents the highest levels of asymmetry about the common component. Details of the numerical analysis are given in the text.
Figure 4
Shares of French Asset in the American Investors’ Portfolios

The figure shows the number of shares of the French asset in the American investors’ portfolios divided by the number of shares of the French asset outstanding. The X-axis shows the degree of information asymmetry about each asset. The four curves (labeled 0, 1, 2, 4) represent four levels of information advantage about the common component of payoffs. The top graph line (thin, purple, with “O” markings) represents the highest levels of asymmetry about the common component. Details of the numerical analysis are given in the text.