Return Predictability and the Implied Intertemporal Hedging Demands for Stocks and Bonds: International Evidence

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Abstract

In this paper, we investigate return predictability and the implied intertemporal hedging demands for stocks and bonds in the U.S., Australia, Canada, France, Germany, Italy, and U.K. We first estimate predictive regression models for domestic bill, stock, and bond returns in each country, where returns depend on the nominal bill yield, dividend yield, term spread, and lagged returns. Employing the recently developed methodology of Campbell, Chan, and Viceira (2003), we calculate the implied optimal asset demands, including their myopic and intertemporal hedging components, for domestic bills, stocks, and bonds for an investor with an infinite horizon, Epstein-Zin-Weil utility, and a coefficient of relative risk aversion equal to 4, 7, or 10 in each country. We find that return predictability generates sizable positive intertemporal hedging demands for domestic stocks in the U.S. and U.K., while the intertemporal hedging demands for domestic stocks are decidedly smaller in Australia, Canada, and Germany and essentially zero in France and Italy. The intertemporal hedging demands for domestic bonds are negative and reasonably large in magnitude in the U.S., France, Germany, and Italy, while they are considerably smaller in magnitude in Australia, Canada, and the U.K. We also use the Campbell, Chan, and Viceira (2003) approach to calculate optimal asset demands for an investor in the U.S. who, in addition to domestic bills, stocks, and bonds, has access to foreign stocks and bonds. We continue to find a sizable positive intertemporal hedging demand for U.S. stocks, and an important positive intertemporal hedging demand for U.K. stocks emerges. In another exercise, we find that investors in Australia, Canada, France, Germany, Italy, and the U.K. who have access to U.S. stocks and bonds all display sizable positive intertemporal hedging demands for U.S. stocks. Overall, we discover interesting similarities and differences in the implied intertemporal hedging demands for stocks and bonds across countries, and our results indicate that return predictability implies especially strong intertemporal hedging demands for U.S. and U.K. stocks.

JEL classifications: C32, G11

Key words: Asset allocation; Intertemporal hedging demand; Return predictability

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1. Introduction

There has been a recent resurgence of interest in portfolio choice problems. In particular, interest in multi-period portfolio choice (dynamic asset allocation) problems has been reinvigorated by the body of empirical evidence accumulated over the last two decades indicating that stock and bond returns have important predictable components. As initially recognized by Samuelson (1969) and Merton (1969, 1971), return predictability has potentially important implications for multi-period portfolio choice problems.[1] More specifically, return predictability can give rise to intertemporal hedging demands for assets, so that—in contrast to the canonical static portfolio choice problem due to Markowitz (1952)—investors look beyond one-period-ahead when optimally allocating across assets. Intuitively, investors may want to hedge against adverse future return shocks, and return predictability provides a temporal mechanism to accomplish this.

While return predictability can have important implications for multi-period portfolio choice problems, a difficulty in studying these problems is that exact analytical solutions are generally not available.[2] This has led researchers to use different approaches in order to solve multi-period portfolio choice problems in empirical applications. A number of researchers take advantage of gains in computing power and employ computationally intensive numerical procedures to approximate the solutions to multi-period portfolio choice problems in the presence of return predictability. For example, Brennan, Schwartz, and Lagnado (1997), Barberis (2000), and Lynch (2001) use discrete-state approximations to numerically solve portfolio choice problems for investors with long horizons when returns are predictable. Balduzzi and Lynch (1999), Lynch and Balduzzi (2000), and Lynch and Tan (2003) also employ discrete-state approximations to numerically solve similar types of problems when transaction costs are nonzero. Another approach in the empirical literature uses approximate analytical methods to

[1] Note that for our purposes, it is the existence of return predictability itself—and not the reason for its existence—that has potentially important implications for multi-period portfolio choice problems, so we can sidestep the thorny issue of whether return predictability is due to time-varying equilibrium returns or market inefficiencies (Fama, 1991). Campbell (2000) provides a survey of the predictability literature.

[2] Kim and Omberg (1996), Lui (1998, 2001), and Wachter (2002) obtain exact analytical solutions in certain special classes of multi-period portfolio choice problems.

solve portfolio choice problems for investors with infinite horizons when returns are predictable in neighborhoods of known exact solutions (Campbell and Viceira, 1999, 2001, 2002).[3]

In a recent extension of Campbell and Viceira (1999), Campbell, Chan, and Viceira (2003; henceforth, CCV) develop an approach that combines an approximate analytical method with a relatively simple numerical procedure. This approach has the advantage of being able to accommodate dynamic asset allocation problems with a relatively large number of assets and potential return predictors, whereas such problems can quickly become intractable using approaches based on more computationally intensive numerical procedures. CCV use their approach to analyze optimal dynamic asset allocation across U.S. bills, stocks, and bonds when return predictability is described by a first-order vector autoregressive [VAR(1)] process fit to real bill returns, excess stock returns, excess bond returns, the nominal bill yield, dividend yield, and term spread using quarterly U.S. data for 1952:2-1999:4. They consider an investor who maximizes the expected utility of lifetime consumption over an infinite horizon, where the utility function is of the Epstein-Zin-Weil (Epstein and Zin, 1989; Weil, 1989) form. Interestingly, CCV find that return predictability should lead an investor in the U.S. to have a sizable positive mean intertemporal hedging demand for domestic stocks for a range of values of the coefficient of relative risk aversion (CRRA). They also find that return predictability implies a sizable negative intertemporal hedging demand for domestic bonds for an investor in the U.S. Overall, the empirical results in CCV, as well as the other studies cited above, indicate that return predictability can generate significant intertemporal hedging demands for U.S. assets, especially U.S. stocks.

While the existing empirical literature on multi-period choice problems contains important findings relating to the implications of return predictability, the literature focuses almost exclusively on domestic investments in U.S. assets. In the present paper, we extend the extant empirical literature and use the CCV approach to analyze return predictability and its dynamic asset allocation implications for

[3] Using another computationally intensive approach, Brandt (1999) and Aït-Sahalia and Brandt (2001) use non- and semiparametric procedures to analyze Euler equations and approximate the solutions to portfolio choice problems for investors with long horizons in the presence of return predictability. See Brandt (2004) for an extensive survey of the literature on both static and multi-period portfolio choice problems.

investors with Epstein-Zin-Weil utility and infinite horizons in the U.S., Australia, Canada, France, Germany, Italy, and U.K. More specifically, we examine the nature of bill, stock, and bond return predictability in each of these countries and the implied intertemporal hedging demands for domestic bills, stocks, and bonds for investors in each country. Following CCV, we assume that the return dynamics in each country are well-characterized by a VAR(1) process that includes three instruments: the nominal bill yield, dividend yield, and term spread. A number of studies find that these variables have predictive ability with respect to stock and bond returns.[4] Using monthly data for 1952:04-2004:05,[5] we estimate VAR processes for each country and analyze domestic bill, stock, and bond return predictability in each country. Armed with estimates of the dynamic processes governing returns in each country and plausible assumed values for the parameters relating to intertemporal preferences—including CRRA values of 4, 7, and 10—we use the approximate analytical method and numerical procedure developed by CCV to solve the investor's multi-period portfolio choice problem and estimate the implied mean total, myopic, and intertemporal hedging demands for domestic bills, stocks, and bonds in each country. In order to account for sampling uncertainty, we augment the CCV approach with a parametric bootstrap procedure that enables us to compute confidence intervals for the mean total, myopic, and intertemporal hedging demands in each country. We also present estimates of the intertemporal hedging demands for domestic stocks and bonds for each month over the sample in each country.

In addition to examining the implied intertemporal hedging demands for domestic stocks and bonds for investors in a number of different countries, we also consider a multi-period portfolio choice problem for an investor in the U.S. who can invest in stocks and bonds from a foreign country. It is quite feasible to use the CCV approach to solve multi-period portfolio choice problems with five risky assets and six instruments. This allows us to extend the empirical application in CCV and analyze a multi-period portfolio choice problem for an investor in the U.S. who, in addition to domestic bills, stocks, and bonds, has access to stocks and bonds from a foreign country (Australia, Canada, France, Germany, Italy, or the

[4] See, for example, Rozeff (1984), Campbell (1987), Campbell and Shiller (1988), Fama and French (1988, 1989), Hodrick (1992), Solnick (1993), and Lewellen (2004).
[5] Based on data availability, the sample begins in 1961:01 (1967:02) for France (Germany).

U.K.), and where the investor considers six instruments (the domestic and foreign nominal bill yields, dividend yields, and term spreads) that potentially contribute to return predictability.[6] We use the CCV approach to estimate the total, myopic, and intertemporal hedging demands for domestic bills, stocks, and bonds and foreign stocks and bonds for an investor in the U.S. when the return dynamics are characterized by a VAR(1) process that includes the five returns and six instruments.[7] In another extension, we use the CCV approach to analyze a multi-period portfolio choice problem for an investor in Australia, Canada, France, Germany, Italy, or the U.K. who, in addition to domestic bills, stocks, and bonds, can invest in U.S. stocks and bonds.

Previewing our empirical results, we find that return predictability generates sizable positive intertemporal hedging demands for domestic stocks for investors in the U.S. and U.K., while the intertemporal hedging demands for domestic stocks are decidedly smaller for investors in Australia, Canada, and Germany and essentially zero for investors in France and Italy. The intertemporal hedging demands for domestic bonds are negative and reasonably large in magnitude for investors in the U.S., France, Germany, and Italy, while they are considerably smaller in magnitude for investors in Australia, Canada, and the U.K. We relate similarities and differences in return predictability across countries to similarities and differences in the intertemporal hedging demands for stocks and bonds across countries, and the predictive relationships between dividend yields and excess stock returns in the U.S. and U.K. help to account for the sizable intertemporal hedging demands for domestic stocks for investors in these countries. When an investor in the U.S. has access to foreign stocks and bonds, in addition to domestic

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[6] Ang and Bekaert (2002) consider a multi-period portfolio choice problem where an investor in the U.S. can invest in domestic stocks and stocks from one or two foreign countries. Unlike most of the literature, Ang and Bekaert (2002) do not characterize return predictability using a VAR process that includes instruments such as the dividend yield, but instead use a Markov-switching process for the moments of the returns. Also see Cambpell, Viceira, and White (2003), who use the CCV approach to study a multi-period portfolio choice problem where an investor in the U.S. has access to domestic bills and bills from a foreign country (the U.K., Germany, or Japan). The present paper extends these studies by considering a broader range of domestic and foreign assets and a larger number of countries.

[7] The size of the parameter space for the VAR(1) model becomes an issue as additional assets and instruments are included in the multi-period portfolio choice problem. Given our relatively long span of data, it is feasible to reliably estimate a VAR(1) model composed of five asset returns and six instruments. However, it may become necessary to impose restrictions on the VAR(1) model to limit the parameter space if additional returns or instruments are included in the problem.

bills, stocks, and bonds, the positive intertemporal hedging demand for domestic stocks remains sizable, and an important positive intertemporal hedging demand for U.K. stocks emerges. The intertemporal hedging demands for stocks from foreign countries beside the U.K. are typically small, as are the intertemporal hedging demands for foreign bonds from all countries. When investors in Australia, Canada, France, Germany, Italy, and the U.K. have access to U.S. stocks and bonds, we find substantial positive (negative) intertemporal hedging demands for U.S. stocks (bonds). Overall, we discover important similarities and differences in the optimal intertemporal hedging demands for stocks and bonds across countries, and our results indicate that return predictability implies especially strong intertemporal hedging demands for U.S. and U.K. stocks.

It is important to emphasize that the asset demands derived from multi-period portfolio choice problems in the recent empirical literature (including the present paper) are partial equilibrium in nature, as the return processes are treated as exogenous. That is, given an exogenous return process (usually calibrated to U.S. data), researchers calculate the implied optimal asset demands for an individual investor with a long horizon and an assumed set of preferences; no attempt is made to use the implied model of investor behavior to explain observed asset returns.[8] Two ways of interpreting the estimated asset demands in the extant empirical literature have been offered. First, Campbell and Viceira (2002) suggest viewing the estimated asset demands as normative descriptions of investor behavior, so that the estimated asset demands are those that an investor with an assumed set of preferences should have for a given return process. In line with this, CCV (p. 42) motivate the development of their approach by observing that while “[a]cademic research in finance has had a remarkable impact on many aspects of the financial services industry…academic financial economists have thus far provided surprisingly little guidance to financial planners who offer portfolio advice to long-term investors.” Alternatively, we can follow the suggestion of Lynch (2001) and view the estimated asset demands as a positive description of the

[8] Explaining observed asset returns requires embedding a representative investor of this type in a general equilibrium framework where all markets clear. Lynch (2003) makes important progress in this area by embedding a representative investor with a long horizon and access to three stock portfolios sorted on book-to-market ratios in a general equilibrium model and comparing the quantitative properties of asset returns implied by the model to actual U.S. asset returns.

behavior of a unique individual or small group (rather than a representative agent) in the economy who exploits the return predictability created by a large number of other investors with different preferences. These different preferences may be created by habit persistence, as in Campbell and Cochrane (1999), or they may be of the type assumed in models of behavioral finance, such as Barberis, Huang, and Santos (2000).

The rest of the paper is organized as follows: Section 2 describes our empirical approach, including the CCV framework and our parametric bootstrap procedure; Section 3 presents our empirical results; Section 4 concludes with suggestions for future research.

2. Empirical Approach

2.1. The Multi-Period Portfolio Choice Problem

Consider an investor who has access to n risky assets.[9] Let $R_{1,t+1}$ be the real return on a benchmark asset (usually a Treasury bill) from time t to time $t+1$, and let $R_{i,t+1}$, $i=2,\ldots,n$, be the real returns on the $n-1$ additional assets.[10] The real return on the investor's portfolio ($R_{p,t+1}$) can be expressed as

$$R_{p,t+1} = \sum_{i=2}^{n} \alpha_{i,t} (R_{i,t+1} - R_{1,t+1}) + R_{1,t+1}, \tag{1}$$

where $\alpha_{i,t}$ is the portfolio weight on asset i at time t.[11] Letting $r_{i,t+1} = \log(R_{i,t+1})$, define the vector of log excess returns as $x_{t+1} = [r_{2,t+1} - r_{1,t+1}, \ldots, r_{n,t+1} - r_{1,t+1}]'$. In addition to the n returns, a vector of instruments s_{t+1} helps to determine the dynamics of the complete system of state variables. Gathering the returns and instruments into an *m*-vector, the state vector is given by

[9] We adopt the notation of CCV throughout this section.

[10] While we follow CCV and use a 3-month Treasury bill as the benchmark asset, the designation of the benchmark asset is arbitrary.

[11] The portfolio weight on the benchmark asset at time t is $1-\sum_{i=2}^{n} \alpha_{i,t}$. Note that the CCV framework does not impose borrowing or short-sales constraints. The use of equation (8) below to approximate the log real return on the portfolio has the effect of ruling out the possibility of bankruptcy; see Campbell and Viceira (2002, pp. 28-29).

$$z_{t+1} = [r_{1,t+1}, x_{t+1}, s_{t+1}]'. \tag{2}$$

As in a number of other studies,[12] CCV assume that the dynamics of the system of state variables are well-characterized by a VAR(1) process, so that the data-generating process for the state vector z_{t+1} is given by

$$z_{t+1} = \Phi_0 + \Phi_1 z_t + v_{t+1}, \tag{3}$$

where Φ_0 is an *m*-vector of VAR intercepts; Φ_1 is an $m \times m$ matrix of VAR slope coefficients; v_{t+1} is an *m*-vector of VAR innovations that are independently and identically distributed as $N(0_{m\times 1}, \Sigma_v)$. For some of the expressions used below, it is useful to partition Σ_v such that

$$\Sigma_v = \begin{bmatrix} \sigma_1^2 & \sigma_{1x}^{'} & \sigma_{1s}^{'} \\ \sigma_{1x} & \Sigma_{xx} & \Sigma_{xs}^{'} \\ \sigma_{1s} & \Sigma_{xs} & \Sigma_{ss} \end{bmatrix}, \tag{4}$$

where σ_1^2 is the variance of the innovation to the benchmark asset return; σ_{1x} is an $(n-1)$-vector of covariances between innovations to the benchmark asset return and innovations to the excess returns on the remaining assets; σ_{1s} is an $(m-n)$-vector of covariances between innovations to the benchmark asset return and innovations to the instruments; Σ_{xx} is the $(n-1)\times(n-1)$ variance-covariance matrix for the innovations to the excess returns; Σ_{xs} is the $(m-n)\times(n-1)$ matrix of covariances between innovations to the excess returns and innovations to the instruments; Σ_{ss} is the $(m-n)\times(m-n)$ variance-covariance matrix for the innovations to the instruments. Note that the vector of VAR innovations is assumed to be homoskedastic. CCV argue that this is a reasonable assumption, as studies such as Campbell (1987), Harvey (1989, 1991), and Glosten, Jagannathan, and Runkle (1993) find that relative to their effects on expected returns, state variables have only a limited ability to predict risk.[13]

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[12] See, for example, Campbell (1991), Balduzzi and Lynch (1999), Kandel and Stambaugh (1996), Campbell and Viceira (1999), Lynch and Balduzzi (2000), Barberis (2000), and Lynch (2001).

[13] Assuming that the vector of VAR innovations is homoskedastic is standard in much of the literature, such as the studies cited in footnote 12 above. Chacko and Viceira (2003) solve a multi-period portfolio choice problem with stochastic volatility.

The investor is assumed to have Epstein-Zin-Weil utility, which she maximizes over an infinite horizon. The recursive preferences that characterize Epsten-Zin-Weil utility are given by

$$U[C_t, E_t(U_{t+1})] = \{(1-\delta)C_t^{(1-\gamma)/\theta} + \delta[E_t(U_{t+1}^{1-\gamma})]^{1/\theta}\}^{\theta/(1-\gamma)}, \quad (5)$$

where C_t is consumption at time t; $E_t(\cdot)$ is the expectation operator conditional on information available at time t; $\gamma > 0$ is the CRRA; $\psi > 0$ is the elasticity of intertemporal substitution (EIS); $0 < \delta < 1$ is the time discount factor; $\theta = (1-\gamma)/(1-\psi^{-1})$. As emphasized by CCV, Epstein-Zin-Weil utility severs the tight link between the CRRA and EIS that characterizes the popular time-separable power utility function.[14] This is a nice feature of equation (5), as the CRRA and EIS are conceptually distinct notions relating to intertemporal preferences. At each time t, the investor selects C_t and $\alpha_{2,t}, \ldots, \alpha_{n,t}$ in order to maximize equation (5), using all available information at time t, subject to the intertemporal budget constraint,

$$W_{t+1} = (W_t - C_t)R_{p,t+1}, \quad (6)$$

where W_t is wealth at time t. The Euler equation for consumption for this problem is given by (Epstein and Zin, 1989, 1991)

$$E_t\{[\delta(C_{t+1}/C_t)^{-1/\psi}]^{\theta} R_{p,t+1}^{-(1-\theta)} R_{i,t+1}\} = 1, \quad (7)$$

for any asset i. With time-varying investment opportunities, exact analytical solutions for this problem are generally not available. CCV combine an extension of the Campbell and Viceira (1999) approximate analytical solution with a relatively simple numerical procedure to compute the investor's optimal asset allocation and consumption policies.

A key approximation used by CCV involves the equation for the log real return on the investor's portfolio. We approximate the log real return on the portfolio using

$$r_{p,t+1} = r_{1,t+1} + \alpha_t^{'} x_{t+1} + 0.5\alpha_t^{'}(\sigma_x^2 - \Sigma_{xx}\alpha_t), \quad (8)$$

[14] When $\gamma = \psi^{-1}$, equation (5) reduces to the familiar case of time-separable power utility; when $\gamma = \psi^{-1} = 1$, equation (5) reduces to log utility.

where $\alpha_t = [\alpha_{2,t}, \ldots, \alpha_{n,t}]'$, and σ_x^2 is the vector of diagonal elements in Σ_{xx}. This approximation is exact in continuous time, and CCV observe that it is highly accurate for short time intervals.[15] CCV also employ first- and second-order log-linear approximations of the budget constraint and Euler equation, respectively, yielding

$$\Delta w_{t+1} = r_{p,t+1} + [1-(1/\rho)](c_t - w_t) + k\,, \tag{9}$$

$$\begin{aligned} &E_t(r_{i,t+1} - r_{1,t+1}) + 0.5\,\mathrm{var}_t(r_{i,t+1} - r_{1,t+1}) = (\theta/\psi)\,\mathrm{cov}_t(r_{i,t+1}, c_{t+1} - w_{t+1}) + \\ &\gamma[\mathrm{cov}_t(r_{i,t+1}, r_{p,t+1}) - \mathrm{cov}_t(r_{1,t+1}, r_{p,t+1})] - [\mathrm{cov}_t(r_{i,t+1}, r_{1,t+1}) - \mathrm{var}_t(r_{1,t+1})]\,, \end{aligned} \tag{10}$$

where c_t and w_t are the log-levels of C_t and W_t, respectively; $\rho = 1 - \exp[E(c_t - w_t)]$; $k = \log(\rho) + (1-\rho)\log(1-\rho)/\rho$. The approximations to the budget constraint and Euler equation are exact when $\psi = 1$, so that the solution to the approximate model is appropriate when ψ is near unity. The policy functions for α_t and $c_t - w_t$, which constitute the solution to the approximate model, are linear and quadratic, respectively, in z_t:

$$\alpha_t = A_0 + A_1 z_t\,, \tag{11}$$

$$c_t - w_t = B_0 + B_1' z_t + z_t' B_2 z_t\,, \tag{12}$$

where A_0 $[(n-1)\times 1]$, A_1 $[(n-1)\times m]$, B_0 (1×1), B_1 $(m\times 1)$, and B_2 $(m\times m)$ are coefficient matrices that are constant through time and functions of γ, ψ, δ, ρ, Φ_0, Φ_1, and Σ_v.[16] We are primarily interested in the parameters in equation (11), which govern the investor's optimal asset allocations.

2.2. Numerical Solution Procedure

In order to compute estimates of A_0, A_1, B_0, B_1, and B_2, CCV use a numerical procedure. First, they set $\Phi_0 = \hat{\Phi}_0$, $\Phi_1 = \hat{\Phi}_1$, and $\Sigma_v = \hat{\Sigma}_v$, where $\hat{\Phi}_0$, $\hat{\Phi}_1$, and $\hat{\Sigma}_v$ are estimates of the VAR parameters in

[15] Our use of monthly data in Section 3 below should help to ensure the accuracy of the approximation in our empirical applications.
[16] The coefficient matrices are constant through time due to the infinite-horizon assumption. This assumption means that we do not have to solve the problem backward recursively starting from the terminal date.

equation (3). They also set $\delta = 0.92$ on an annual basis (so that the discount factor equals $0.92^{1/12}$ on a monthly basis) and consider different values for γ and ψ. The following result is useful in implementing the numerical procedure:

$$A_0 = (1/\gamma)\Sigma_{xx}^{-1}[H_x\Phi_0 + 0.5\sigma_x^2 + (1-\gamma)\sigma_{1x}] + [1-(1/\gamma)]\Sigma_{xx}^{-1}[-\Lambda_0/(1-\psi)], \tag{13}$$

$$A_1 = (1/\gamma)\Sigma_{xx}^{-1}H_x\Phi_1 + [1-(1/\gamma)]\Sigma_{xx}^{-1}[-\Lambda_1/(1-\psi)], \tag{14}$$

where $H_x = [0_{(n-1)\times 1}, I_{n-1}, 0_{(n-1)\times(m-n)}]$ is a matrix that selects x_t from the state vector z_t; Λ_0 and Λ_1 are matrices that depend on the parameters of equation (12) (B_0, B_1, and B_2), as well as γ, ψ, δ, ρ, Φ_0, Φ_1, and Σ_v. Note that $-\Lambda_0/(1-\psi)$ and $-\Lambda_1/(1-\psi)$ are independent of ψ for a given ρ and that we can define a nonlinear system, $B_0 = \Xi_0$, $B_1 = \Xi_1'$, and $vec(B_2) = \Xi_2$, where Ξ_0, Ξ_1, and Ξ_2 are functions of γ, ψ, δ, ρ, Φ_0, Φ_1, Σ_v, A_0, A_1, B_0, B_1, and B_2.[17]

As described in Campbell, Chan, and Viceira (2002), we implement the iterative process of the numerical procedure as follows. For a given value of γ, we set $\rho = \delta$ and select an arbitrary value for ψ, as well as initial values for B_0, B_1, and B_2. We plug the initial values for B_0, B_1, and B_2 into equations (13) and (14) to obtain an initial set of estimates for A_0 and A_1. Using the initial B_0, B_1, and B_2 values and the initial A_0 and A_1 estimates, we then obtain a new set of estimates for B_0, B_1, and B_2 through the set of equations, $B_0 = \Xi_0$, $B_1 = \Xi_1'$, and $vec(B_2) = \Xi_2$. We begin the process again by plugging the new B_0, B_1, and B_2 estimates into equations (13) and (14) to obtain a new set of A_0 and A_1 estimates. We iterate in the manner until the B_0, B_1, and B_2 estimates (and thus the A_0 and A_1 estimates) converge. Following CCV, we assume $\psi = 1$. In this case, the optimal consumption-wealth

[17] The complete expressions for Λ_0, Λ_1, Ξ_0, Ξ_1, and Ξ_2 are given in Campbell, Chan, and Viceira (2002).

ratio is constant and equal to $1-\delta$ (Giovannini and Weil, 1989), so that $\rho=\delta$, and the numerical procedure can stop.[18]

We can also use equations (13) and (14) to identify the myopic and intertemporal hedging components of asset demand, following Merton (1969, 1971). The first term on the right-hand-side (RHS) of equations (13) and (14) represents the myopic part of asset demand. The myopic component focuses solely on a single-period-ahead and essentially corresponds to the asset demand generated under the static Markowitz problem. The second term on the RHS of equations (13) and (14) represents the intertemporal hedging part of asset demand. In contrast to the static Markowitz problem, an intertemporal hedging demand can arise in a multi-period portfolio choice problem, as a risk-averse investor in a multi-period setting may look beyond a single-period-ahead and be interested in hedging her exposure to adverse future return shocks. Note that a multi-period choice problem is a necessary, but not sufficient, condition for the existence of an intertemporal hedging demand. For example, when $\gamma=1$, the second term on the RHS of equations (13) and (14) vanishes, so that there is no intertemporal hedging demand. In this case, the investor is not sufficiently risk-averse to generate an intertemporal hedging demand. If the matrix of VAR slope coefficients (Φ_1) is a zero matrix—so that there is no return predictability—the second term on the RHS of each equation will also vanish.[19] Thus, in order for an intertemporal hedging demand to exist in a multi-period portfolio choice problem, the investor must be sufficiently risk-averse and returns must be predictable.[20]

In our applications in Section 3 below, we use the CCV procedure to estimate equations (11) and (12) for a infinitely lived investor in the U.S., Australia, Canada, France, Germany, Italy, and U.K. (in turn) who can invest in domestic 3-month Treasury bills, a broad domestic stock market index, and

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[18] If $\psi\neq1$, an additional iterative loop is necessary to find the optimal value of ρ. In their empirical applications, CCV note that the solutions to problems with $\psi=0.5$ are similar to the solutions to problems with $\psi=1$.

[19] CCV observe that Λ_0 and Λ_1 are zero matrices when Φ_1 is a zero matrix, so that the second term on the RHS of equations (13) and (14) vanishes.

[20] Actually, an additional condition needs to be satisfied: the variance-covariance matrix for the VAR innovations, Σ_v, cannot be diagonal; see, for example, Brandt (2004, Section 2.3). The importance of this condition will become evident in the discussion of the empirical results in Section 3 below.

domestic 10-year government bonds. We follow CCV in the basic set-up of the model. Namely, we treat the log real return on a 3-month Treasury bill ($rtbr_t$) as the return on the benchmark asset, so that the two log excess real returns are those on the stock market index and a 10-year government bond (xsr_t and xbr_t, respectively). In addition to lagged returns, three domestic instruments serve as potential return predictors: the nominal yield on a 3-month Treasury bill ($bill_t$), the log of the dividend yield on the stock market index (div_t), and the term spread ($spread_t$). Given these returns and instruments, the state vector is $z_{t+1} = [rtbr_{t+1}, xsr_{t+1}, xbr_{r+1}, bill_{t+1}, div_{t+1}, spread_{t+1}]'$. We assume $\psi = 1$ (so that $\rho = \delta$) and $\delta = 0.92$ on an annual basis, and we estimate the VAR parameters in equation (3) using maximum likelihood, yielding $\hat{\Phi}_0$, $\hat{\Phi}_1$, and $\hat{\Sigma}_v$.[21] We consider three values for γ: 4, 7, and 10. These γ values are similar to those considered in other studies,[22] and they represent plausible values for the CRRA. We report estimates of the mean asset demands for domestic 3-month Treasury bills, stocks, and 10-year government bonds over the sample for each γ value using $\overline{\alpha} = \hat{A}_0 + \hat{A}_1 \bar{z}$, where $\hat{A}_0$ and $\hat{A}_1$ are the estimates of A_0 and A_1, respectively, in equation (11) obtained using the numerical procedure described above and $\bar{z} = \sum_{t=1}^{T} z_t$, where T is the number of available sample observations for the state vector. In addition to the total mean asset demands, we use equations (13) and (14) to estimate the mean myopic and hedging demands for each asset and each value of γ. Given our interest in intertemporal hedging demands in the present paper, we also present figures showing the hedging demands for domestic stocks and bonds for each month over the sample when $\gamma = 7$ in each country.

To get a sense of the sampling uncertainty associated with our point estimates of the mean total, myopic, and hedging demands for each asset in each country, we construct 68% confidence intervals for

[21] OLS estimation of $\hat{\Phi}_0$ and $\hat{\Phi}_1$ in equation (3) is equivalent to maximum likelihood estimation.

[22] For example, CCV include tabulated results for $\gamma = 5$; Balduzzi and Lynch (1999) consider $\gamma = 6$; Barberis (2000) considers $\gamma = 5{,}10$; Lynch (2001) considers $\gamma = 4$.

the mean demands using the following parametric bootstrap procedure.[23] We assume that observations for the state vector z_{t+1} are generated by equation (3) with the parameters of the VAR set to their maximum-likelihood estimates. In order to generate a series of innovations to use in constructing a pseudo-sample, we make $T+100$ independent draws from a $N(0_{m\times 1}, \hat{\Sigma}_v)$ distribution. Using the randomly drawn innovations, equation (3) with $\Phi_0 = \hat{\Phi}_0$ and $\Phi_1 = \hat{\Phi}_1$, and setting the initial z_t observations to zero, we can build up a pseudo-sample of $T+100$ observations for z_t. We drop the first 100 transient start-up observations in order to randomize the initial z_t observations, leaving us with a pseudo-sample of T observations for z_t, matching the original sample. For the pseudo-sample, we use the numerical procedure described above to estimate equations (11) and (12) and the mean total, myopic, and hedging demands for each asset. We repeat this process 1,000 times, giving us an empirical distribution for each of the mean asset demands. We construct 68% confidence intervals for each mean asset demand from the empirical distributions using the percentile method described in Davidson and MacKinnon (1993, p. 766).

2.3. Predictive Regression Model Estimation

Before presenting estimates of the total, myopic, and intertemporal hedging demands for each asset in each country in Section 3.3 below, we report OLS estimation results for the VAR(1) model, equation (3), for each country in Section 3.2 below. The VAR model captures the extent of return predictability in each country that provides the basis for the intertemporal hedging demands. Letting $\Phi_0 = \{\phi_i^0\}$ and $\Phi_1 = \{\phi_{i,j}^1\}$, equation (3) can be expressed in more detail as

$$rtbr_{t+1} = \phi_1^0 + \phi_{1,1}^1 rbtr_t + \phi_{1,2}^1 xsr_t + \phi_{1,3}^1 xbr_t + \phi_{1,4}^1 bill_t + \phi_{1,5}^1 div_t + \phi_{1,6}^1 spread_t + v_{1,t+1}, \tag{15}$$

$$xsr_{t+1} = \phi_2^0 + \phi_{2,1}^1 rbtr_t + \phi_{2,2}^1 xsr_t + \phi_{2,3}^1 xbr_t + \phi_{2,4}^1 bill_t + \phi_{2,5}^1 div_t + \phi_{2,6}^1 spread_t + v_{2,t+1}, \tag{16}$$

$$xbr_{t+1} = \phi_3^0 + \phi_{3,1}^1 rbtr_t + \phi_{3,2}^1 xsr_t + \phi_{3,3}^1 xbr_t + \phi_{3,4}^1 bill_t + \phi_{3,5}^1 div_t + \phi_{3,6}^1 spread_t + v_{3,t+1}, \tag{17}$$

[23] Primarily due to computational costs, most extant studies (including CCV) report only point estimates of asset demands.

$$bill_{t+1} = \phi_4^0 + \phi_{4,1}^1 rbtr_t + \phi_{4,2}^1 xsr_t + \phi_{4,3}^1 xbr_t + \phi_{4,4}^1 bill_t + \phi_{4,5}^1 div_t + \phi_{4,6}^1 spread_t + v_{4,t+1}, \tag{18}$$

$$div_{t+1} = \phi_5^0 + \phi_{5,1}^1 rbtr_t + \phi_{5,2}^1 xsr_t + \phi_{5,3}^1 xbr_t + \phi_{5,4}^1 bill_t + \phi_{5,5}^1 div_t + \phi_{5,6}^1 spread_t + v_{5,t+1}, \tag{19}$$

$$spread_{t+1} = \phi_6^0 + \phi_{6,1}^1 rbtr_t + \phi_{6,2}^1 xsr_t + \phi_{6,3}^1 xbr_t + \phi_{6,4}^1 bill_t + \phi_{6,5}^1 div_t + \phi_{6,6}^1 spread_t + v_{6,t+1}, \tag{20}$$

for $t = 1, \ldots, T-1$. The first three equations of the VAR, equations (15)-(17), can be viewed as predictive regression models for real bill, excess stock, and excess bond returns, respectively. It is well-known that there are a number of econometric difficulties associated with estimating predictive regressions for stock and bond returns (Mankiw and Shapiro, 1986; Stambaugh, 1986, 1999; Nelson and Kim, 1993; Kirby, 1997; Bekaert, Hodrick, and Marshall, 1997). Essentially, these difficulties lead to size distortions in tests of the significance of the slope coefficients in predictive regressions.[24] In order to help correct for possible size distortions when assessing the predictive power of the lagged returns and instruments with respect to bill, stock, and bond returns in each country, we report *p*-values corresponding to the *t*-statistics for the slope coefficients in equations (15)-(17) using a parametric bootstrap procedure similar to the one described in Section 2.2 above, with the exception that we assume real bill, excess stock, and excess bond returns are generated by

$$rtbr_{t+1} = \tilde{\phi}_1^0 + \tilde{v}_{1,t+1}, \tag{15'}$$

$$xsr_{t+1} = \tilde{\phi}_2^0 + \tilde{v}_{2,t+1}, \tag{16'}$$

$$xbr_{t+1} = \tilde{\phi}_3^0 + \tilde{v}_{3,t+1}, \tag{17'}$$

respectively, under the null hypothesis of no return predictability. Using this restricted VAR(1) model as the data-generating process, we can simulate a pseudo-sample of *T* observations for z_t and calculate the *t*-statistic for each of the slope coefficients in equations (15)-(17) for the pseudo-sample.[25] We repeat this process 1,000 times, giving us empirical distributions for the *t*-statistics for each of the slope coefficients

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[24] Relatedly, OLS estimates can be subject to small-sample biases (Stambaugh, 1986, 1999). Given that small-sample bias corrections can be very complicated in the system defined by equations (15)-(20), we follow CCV and assume that investors treat the OLS estimates of the VAR coefficients as given and known.

[25] Like the bootstrap procedure described in Section 2.2 above, we randomize the initial z_t values by including 100 transient start-up observations in each pseudo-sample that we subsequently discard.

in equations (15)-(17) under the null hypothesis of no return predictability. In order to generate *p*-values corresponding to one-sided significance tests, if the *t*-statistic for a given slope coefficient for the original sample is positive, then the *p*-value is the proportion of the bootstrapped *t*-statistics that are greater than the *t*-statistic for the original sample; if the *t*-statistic for the original sample is negative, then the *p*-value is the proportion of the bootstrapped *t*-statistics that are less than the *t*-statistic for the original sample. Inoue and Kilian (2003) argue that more powerful one-sided tests should be preferred in predictive regressions, as theory frequently suggests the sign of a coefficient.[26] For each return equation, we also report a bootstrapped *p*-value corresponding to a Wald test of the null hypothesis that the slope coefficients are jointly zero.

3. Empirical Results

3.1. Data

The data for the U.S., Australia, Canada, France, Germany, Italy, and U.K. are from Global Financial Data. Following CCV, our sample begins in 1952:04 for each country, with the exceptions of France and Germany, where, due to data availability, the sample begins in 1961:01 and 1967:02, respectively.[27] The sample ends in 2004:05 for each country. We measure the log real return on a 3-month Treasury bill for a given month as the difference in the logs of the total return index for bills for the given and previous months minus the difference in the logs of the consumer price index for the given and previous months.[28] The log excess stock (bond) return for a given month is the difference in the logs of the total return index for stocks (10-year government bonds) for the given and previous months minus the difference in the logs of the total return index for bills for the given and previous months. The nominal

[26] While we report *p*-values for one-sided tests, we can simply double the *p*-values to convert them to *p*-values for two-sided tests under the assumptions that the distributions are approximately symmetric.
[27] We had originally planned to include Japan in order to include all of the G-7 countries, but data for all of the necessary series for Japan are not available for a sufficiently long period from Global Financial Data.
[28] Due to data availability, we use the wholesale price index for Australia.

bill yield is the yield on a 3-month Treasury bill,[29] and the term spread is the difference between the yields on a 10-year government bond and 3-month Treasury bill. Names and descriptions of the Global Financial Data files used to construct all of the variables are provided in the Data Appendix.

Table 1 reports summary statistics (mean, standard deviation, and first-order autocorrelation coefficient) for the three risky asset returns and three instruments for each of the seven countries we consider. The mean and standard deviation for the returns are expressed in annualized percentage units, and we include the Sharpe ratio (the ratio of the annualized mean to the annualized standard deviation) for the excess stock and bond returns. The mean excess stock returns for the U.S., Australia, and U.K. are between 5% and 6%. Canada, Germany, and France exhibit lower mean excess returns, while Italy has the lowest mean excess return of 1.89%. Mean excess stock returns for the U.S., Australia, and U.K. are approximately 3 to 4 percentage points higher than mean excess bond returns for these countries. Mean excess stock returns are just over 2 percentage points higher than mean excess bond returns for Canada, and mean excess stock returns are actually less than 1 percentage point higher than mean excess bond returns for France, Germany, and Italy. For all of the countries, the standard deviation of excess stock returns is approximately 2 to 4 times larger than the standard deviation of excess bond returns, and the standard deviation of the real bill return is always considerably below that of excess bond returns for each country.

The Sharpe ratios for excess stock returns are the highest for the U.S., Australia, and U.K. (0.39, 0.32, and 0.29, respectively), while Italy has the smallest ratio (0.09). The Sharpe ratios for excess bond returns are very similar across all of the countries (with the exception of Germany), ranging from 0.15 to 0.19. For Germany, the Sharpe ratio for excess bond returns is considerably higher at 0.44. Observe that the Sharpe ratio for excess stock returns is approximately 1.5 to 2.5 times larger than the Sharpe ratio for excess bond returns for the U.S., Australia, Canada, and U.K., while for France, Germany, and Italy, the Sharpe ratio for excess stock returns is actually less than the Sharpe ratio for excess bond returns. All else

[29] Following a number of other studies, we use deviations in the nominal 3-month Treasury bill yield from a 1-year backward-looking moving average.

equal, the Sharpe ratios lead us to expect a higher myopic demand on average for stocks in the U.S., Australia, Canada, and U.K. This is borne out in the empirical results reported in Section 3.3 below.

Excess stock returns exhibit fairly limited persistence in all countries (first-order autocorrelation coefficients between 0.03 and 0.12). Excess bond returns typically appear somewhat more persistent than excess stock returns, with Italy and the U.K. displaying the most persistent excess bond returns. Real bill returns are moderately persistent for all countries, ranging from 0.21 to 0.51. In contrast to the returns, the instruments appear very persistent for all countries, with the first-order correlation coefficients ranging from 0.88 to 0.93 for the nominal bill yield, 0.98 to 0.99 for the dividend yield, and 0.94 to 0.97 for the term spread.

3.2. VAR Estimation Results

Tables 2 through 8 report estimation results for the VAR(1) model for each country. The top part of each table reports estimates of the slope coefficients and their corresponding *t*-statistics, as well as the R^2 goodness-of-fit measure, for each equation of the VAR. Bootstrapped *p*-values are also reported for the coefficients in the return equations, where the *p*-values are computed using the bootstrap procedure described in Section 2.3 above. In addition, bootstrapped *p*-values for Wald tests of the null hypothesis that the explanatory variables are jointly zero in each of the return equations (that is, no return predictability) are also reported below the R^2 measures. The bottom part of each table reports the cross-correlations of the VAR residuals. We briefly discuss the VAR estimation results.

The R^2 measures for the estimated real bill return equations in Tables 2 through 8 range from 0.093 (Canada) to 0.311 (France), and we are easily able to reject the null hypothesis of no real bill return predictability for each country at conventional significance levels according to the bootstrapped *p*-values. The coefficients on the lagged bill return are positive and significant at conventional levels for all countries. For Australia, Canada, Italy, and the U.K., the three lagged instruments all have negative coefficients that are significant (or nearly significant) at conventional levels. Two (one) of the lagged instruments are significant at conventional levels for France (Germany).

With respect to the estimated excess stock return equations, we see that the R^2 measures are between 0.016 (Italy) and 0.044 (U.K.). These measures are in line with the extant empirical literature, which finds that the degree of predictability in excess stock returns is limited. Nevertheless, the Wald test easily rejects the null hypothesis of no predictability for the U.S., Australia, Canada, France, and U.K. according to the bootstrapped *p*-values, and as indicated in the extant empirical literature—and as we will see below—even a limited degree of predictability can have quantitatively important asset allocation implications. We cannot reject the null hypothesis of no predictability using the Wald test for Germany and Italy at conventional significance levels. Looking at the individual coefficients, at least one of the lagged return coefficients is significant at conventional levels for each country. The lagged nominal bill yield is significant at conventional levels for the U.S. and Germany, where it enters with a negative coefficient. For the U.S., Australia, and U.K., the lagged dividend yield has a positive and significant coefficient in the excess stock return equation, while the lagged term spread is only significant for Canada.

The R^2 measures are somewhat higher for the fitted excess bond return equations than the excess stock return equations for each country, with the excess bond return equation measures ranging from 0.027 (Australia) to 0.155 (Italy). According to the bootstrapped *p*-values, we can reject the null hypothesis of no predictability for the excess bond return equation for each country at conventional significance levels. Either two or three of the lagged returns are significant at conventional levels for the U.S., Canada, France, Germany, Italy, and U.K. The lagged nominal bill yield has a negative and significant coefficient for Australia, France, Germany, and Italy, while the term spread has a positive and significant (or nearly significant) coefficient for the U.S., Canada, France, Germany, Italy, and U.K.

The autoregressive coefficients tend to dominate the estimated equations for each of the instruments for each country. This is in line with the large autocorrelation coefficients reported for the instruments in Table 1. The R^2 measures are quite high for these equations, ranging from 0.791 to 0.988.

With respect to the cross-correlations of the VAR innovations for each country, one notable feature is the strong negative correlation between innovations to excess stock returns and the dividend yield for each country. The strongest correlation is –0.964 (U.S.), while the weakest is still –0.599 (Italy). There are also sizable negative correlations between innovations to the nominal bill yield and term spread for each country (–0.854 to –0.748), as well as a fairly large negative correlation between innovations to excess bond returns and nominal bill yields for each country, ranging from –0.656 (U.S.) to –0.204 (Germany). Innovations to excess stock and bond returns are positively correlated, and while typically smaller than the other correlations we have mentioned in absolute value, they still appear reasonably large (0.132 to 0.291).

Summarizing the VAR estimation results reported in Tables 2 through 8, real bill returns and excess bond returns appear significantly predictable at conventional levels for each of the countries. Excess stock returns appear significantly predictable at conventional levels for the U.S., Australia, Canada, France, and U.K., but not for Germany and Italy. In addition, there are consistent patterns in the correlations of the VAR innovations, with the strong negative correlation between innovations to excess stock returns and the dividend yield a notable feature for each country.

3.3. Domestic Asset Demands for Investors in Different Countries

Table 9 reports the mean total, myopic, and intertemporal hedging demands (in percentages) for domestic bills, stocks, and bonds and γ values of 4, 7, and 10 in each country. To get a sense of sampling uncertainty, the table also reports 68% confidence intervals for the mean asset demands generated using the parametric bootstrap procedure described in Section 2.2 above. Of course, the total mean demands across the three assets sum to 100; the mean myopic demands across assets also sum to 100, while the mean hedging demands sum to 0.

For the U.S., there are large positive mean total and intertemporal hedging demands for stocks for each reported γ value. As we would expect, the mean total demand for stocks—the most risky asset—decreases as γ increases. While the mean hedging demand for stocks also decreases as γ increases, the mean hedging demand for stocks as a share of the total demand actually increases as γ increases. The mean total demands for bonds are noticeably smaller than the mean total demands for stocks. The mean hedging demands for bonds are negative and fairly large in magnitude, contributing to the smaller total demands for bonds vis-à-vis stocks. The mean total demand for bills is negative for each reported γ value, so that the investor typically shorts bills. There is also a fairly sizable negative mean hedging demand for bills for each reported γ value. The results in Table 9 for the mean hedging demands for stock in the U.S. are similar to the mean hedging demand for stocks (100.84) reported in CCV for the U.S. using quarterly data for 1952:2-1999:4 and $\gamma = 5$; the mean hedging demands for bonds in the U.S. in Table 9 are smaller in magnitude than the mean hedging demand for bonds (–122.57) reported in CCV. The most striking result for the U.S. in Table 9 (and in CCV) is the substantial positive total and intertemporal hedging demands for domestic stocks for an investor in the U.S.

What explains the sizable intertemporal hedging demand for domestic stocks in the U.S.? While a number of factors are at work in this multivariate analysis, as emphasized by CCV and others,[30] two factors appear to play especially important roles: (i) the positive coefficient on the lagged dividend yield in the excess stock return equation of the VAR; (ii) the strong negative correlation between innovations to excess stock returns and the dividend yield. To see how these factors generate a strong intertemporal hedging demand for stocks, consider a negative innovation to excess stock returns next period. Due to the large Sharpe ratio for stocks in the U.S., investors are usually long in stocks, so that the negative innovation to excess stock returns represents a worsening of the investor's investment opportunities next

[30] See, for example, the discussion in Brandt (2004, Section 2.2.1).

period. However, a negative innovation to excess stock returns next period tends to be accompanied by a positive innovation to the dividend yield next period, and according to the positive coefficient on the lagged dividend yield in the excess stock return equation of the VAR, the higher dividend yield next period leads to higher expected stock returns two periods from now.[31] Thus, by looking beyond one-period-ahead—as an investor with $\gamma > 1$ will do—and taking into account return predictability, as well as the negative correlation between innovations to stock returns and the dividend yield, stocks become a good hedge against themselves, in that they hedge exposure to future adverse return shocks.

As a cautionary note, observe that the 68% confidence intervals for the mean asset demands tend to be quite wide for the U.S. in Table 9, especially with regard to the mean total demands for each asset and the mean myopic demands for bonds and bills. This suggests that the reporting of point estimates alone can mask considerable sampling uncertainty in empirical multi-period portfolio choice problems.[32] Nevertheless, it is important to observe that while many of the confidence intervals for the U.S. are quite wide in Table 9, the confidence intervals for the mean hedging demands for stocks appear tight enough to conclude that the mean hedging demands for stocks are positive and sizable in the U.S. for the reported γ values. The confidence intervals for the mean hedging demands for bonds in the U.S. also appear tight enough to conclude that the mean hedging demands for bonds are close to zero or negative in the U.S. for the reported γ values. While there is often substantial sampling uncertainty regarding mean asset demands, it is reasonable to view the empirical evidence as supportive of a sizable positive implied intertemporal hedging demand for domestic stocks and a small or negative implied intertermporal hedging demand for domestic bonds in the U.S.

In order to glean additional insight into the intertemporal hedging demands for domestic stocks and bonds in the U.S., Panel A of Figure 1 portrays the estimated hedging demands for stocks and bonds for each month over the sample in the U.S. when $\gamma = 7$. Overall, the hedging demand for stocks appears

[31] Furthermore, the large autoregressive coefficient in the div_{t+1} equation in Table 2 means that there will be a persistent increase in the expected dividend yield, leading to a persistent increase in expected excess stock returns.
[32] Substantial sampling uncertainty can be a problem in general with regard to asset allocation problems; see Brandt (2004, Section 3.1.2).

considerably less volatile than the hedging demand for bonds. The hedging demand for stocks is typically well above the hedging demand for bonds over the sample, with the exception that the hedging demand for bonds does move above the hedging demand for stocks during the late 1990s and 2000.

Turning to the results for Australia in Table 9, while the mean total demands for domestic stocks are moderately large, they are considerably smaller than the mean total demands for domestic stocks in the U.S. The mean hedging demands for stocks in Australia are much smaller than the corresponding demands in the U.S., and the 68% confidence intervals for the mean hedging demands for stocks in Australia do not lead to rejection of the null hypothesis of a zero mean hedging demand. The mean total demands for bonds in Australia are very similar to those in the U.S., while the mean hedging demands for bonds in Australia are much closer to zero than in the U.S. Again, the 68% confidence intervals for the mean hedging demands for bonds in Australia do not indicate rejection of the null hypothesis of zero mean hedging demand for bonds. From Panel B of Figure 1, we see that the hedging demand for stocks is always above the hedging demand for bonds when $\gamma = 7$, although a drop in the average hedging demands for both stocks and bonds in Australia is evident in the early 1980s.

The results for Canada in Table 9 are similar to those for Australia, in that the mean total and hedging demands for stocks are positive but considerably smaller than the corresponding demands for the U.S., while the mean total demands for bonds are similar to, and the mean hedging demands for bonds are considerably smaller in magnitude than, those for the U.S. We cannot reject the null hypothesis of zero mean hedging demands for bonds in Canada according to the 68% confidence intervals. The hedging demand for bonds is much more volatile than the hedging demand for stocks in Canada when $\gamma = 7$ (see Panel C of Figure 1). Turning to the results for Germany in Table 9, the mean total and hedging demands for stocks are similar to the corresponding demands in Australia and Canada, while the mean hedging demands for bonds in Germany are similar to those in the U.S. From Panel E of Figure 1, we also see that the hedging demand for bonds is more volatile than the hedging demand for stocks in Germany when $\gamma = 7$.

With respect to the results for France in Table 9, the mean total and hedging demands for stocks are much smaller than those for the U.S., Australia, Canada, and Germany, and we cannot reject the null hypothesis that the mean total and hedging demands for stocks are zero in France according to the 68% confidence intervals. The mean hedging demands for bonds in France are similar to, but somewhat smaller in magnitude than, those in the U.S. and Germany. Panel D of Figure 1 shows that the hedging demand for stocks is always very close to zero in France when $\gamma = 7$, and that the hedging demand for bonds is much more volatile than the hedging demand for stocks. The mean total demands for stocks in Italy in Table 9 are even lower than the mean total demands in France, and the mean hedging demands for stocks are also very small in magnitude in Italy. Matching the results for France, we cannot reject the null hypothesis that the mean total and hedging demands for stocks are zero in Italy according to the 68% confidence intervals. The mean hedging demands for bonds in Italy are similar to, although slightly smaller in magnitude than, those in the U.S. We see from Panel F of Figure 1 that the hedging demand for stocks in Italy is always very near zero over the sample period when $\gamma = 7$, while the hedging demand for bonds is quite volatile.

The final country for which we report results in Table 9 is the U.K. With respect to the mean total and hedging demands for stocks, the results for the U.K. are very similar to those for the U.S., in that the mean total and hedging demands for stocks are positive and large. According to the 68% confidence intervals, it appears reasonable to conclude, as in the U.S., that the mean hedging demands for stocks in the U.K. are positive and sizable. The mean hedging demands for bonds are very small in magnitude in the U.K., and we cannot reject the null hypothesis that they are zero at reasonable significance levels according to the 68% confidence intervals. Similar to the case for the U.S., we see from Panel G of Figure 1 that the hedging demand for stocks is typically above the hedging demand for bonds over the sample period in the U.K. when $\gamma = 7$. Again similar to the U.S., there is a period in the late 1990s and 2000 where the hedging demand for bonds moves above the hedging demand for stocks for a more extended period.

We next discuss some of the factors contributing to the smaller (similar) intertemporal hedging demands for domestic stocks in Australia, Canada, France, Germany, and Italy (the U.K.) vis-à-vis the U.S. As we discussed above, a large Sharpe ratio for stocks is likely to lead to a long position in stocks, while a positive coefficient on the lagged dividend yield in the excess stock return equation of the VAR, combined with a negative correlation between innovations to excess stocks returns and the dividend yield, help to make stocks a good hedge against future adverse return shocks for an investor long in stocks. With respect to Canada, France, Germany, and Italy, recall from Table 1 that these countries have Sharpe ratios for domestic stocks that are considerably smaller than the Sharpe ratio for stocks in the U.S., so that investors in these countries are likely to hold fewer stocks than an investor in the U.S. This will make investors in these countries less concerned with hedging against adverse future stock return shocks using the dividend yield-excess stock return relationship, thereby contributing to a lower hedging demand for stocks in these countries. This is especially likely to be the case for France and Italy, where the Sharpe ratios for stocks are the lowest. In addition, we see from Tables 5 and 7 that the coefficients on the lagged dividend yield in the excess stock return equations are the smallest for France and Italy. This limits the hedging ability of the dividend yield in France and Italy, contributing further to the very weak hedging demands for stocks in these two countries relative to the U.S. The Sharpe ratios for stocks are reasonably similar for Australia and the U.S. The smaller hedging demand for stocks in Australia vis-à-vis the U.S. could be attributed to the weaker negative correlation between innovations to excess stock returns and the dividend yield in Australia versus the U.S. (–0.737 vs. –0.964). The weaker correlation helps to make domestic stocks a better hedge against future adverse returns shocks in the U.S. than in Australia. Recalling the results for the excess stock return equation for the U.K. in Table 8, we can partly understand why, like the U.S., there are sizable hedging demands for domestic stocks in the U.K.: the coefficient on the lagged dividend yield in the excess stock return equation is very large (relative to the other countries) and highly significant, helping to make stocks a good intertemporal hedge for investors in the U.K., who usually hold long positions in stocks due to the relatively large Sharpe ratio for stocks in the U.K.[33]

[33] While similarities and differences in the relationships between excess stock returns and the dividend yield across

Overall, the results in Table 9 point to interesting similarities and differences across countries with respect to the optimal intertemporal hedging demands for domestic stocks and bonds. There are substantial positive hedging demands for domestic stocks in the U.S. and U.K., considerably smaller (but still positive) hedging demands for stocks in Australia, Canada, and Germany, and essentially zero hedging demand for stocks in France and Italy. We see negative and fairly large hedging demands for domestic bonds in the U.S., France, Germany, and Italy and essentially zero hedging demand for bonds in Australia, Canada, and the U.K. Taking the results in Tables 2-9 together, we see that differences in return predictability across countries can have important implications for the intertemporal hedging demands for domestic stocks and bonds across countries.

3.4. Asset Demands for an Investor in the U.S. Who Can Also Invest in Foreign Stocks and Bonds

We next use the CCV approach to analyze a multi-period portfolio choice problem for an investor in the U.S. who, in addition to domestic bills, stocks, and bonds, has access to stocks and bonds from a foreign country. We take, in turn, Australia, Canada, France, Germany, Italy, and the U.K. to be the foreign country. We take the countries in turn in an attempt to keep the VAR parameter space to a reasonable size. The log real return on a 3-month U.S. Treasury bill again serves as the return on the benchmark asset, and the log excess returns on U.S. stocks and bonds and foreign stocks and bonds constitute the excess returns on the other four assets.[34] The instrument set includes the U.S. nominal bill yield, dividend yield, and term spread, as well as their foreign counterparts. The state vector for the multi-period portfolio choice problem is now given by

$$z_{t+1} = [rtbr_{t+1}, xsr_{t+1}, xbr_{t+1}, xsr^*_{t+1}, xbr^*_{t+1}, bill_{t+1}, div_{t+1}, spread_{t+1}, bill^*_{t+1}, div^*_{t+1}, spread^*_{t+1}]', \qquad (21)$$

countries can help to explain similarities and differences in the intertemporal hedging demands for domestic stocks across countries, it is important to keep in mind that numerous factors are at work in this multivariate framework.

[34] As in, for example, Harvey (1991), we measure the log excess return on foreign stocks or bonds by first converting the foreign stock or bond return to U.S. dollars using exchange rates and then computing the U.S. dollar return in excess of the U.S. dollar return on a U.S. 3-month Treasury bill.

where xsr_{t+1}^{*} (xbr_{t+1}^{*}) is the log excess return in U.S. dollars on foreign stocks (bonds) relative to the U.S. 3-month Treasury bill return, and $bill_{t+1}^{*}$, div_{t+1}^{*}, and $spread_{t+1}^{*}$ are the instruments in the foreign country. We again assume that the state vector is generated by a VAR(1) process, $\delta = 0.92$ on an annual basis, $\psi = 1$, and we again consider γ values of 4, 7, and 10. We use the same numerical solution procedure described in Section 2.2 above, with the exception that the state vector is now given by equation (21). The mean asset demands, along with 68% confidence intervals (generated using a suitably modified version of the parametric bootstrap procedure described in Section 2.2 above), are reported in Table 10.[35]

A number of results stand out in Table 10. First, an investor in the U.S. continues to have very strong mean total and hedging demands for domestic stocks, regardless of the foreign country. That is, it is still optimal for an investor in the U.S. with access to foreign stocks and bonds from Australia, Canada, France, Germany, Italy, or the U.K. to have positive and sizable mean total and hedging demands for domestic stocks. While the confidence intervals are again generally quite wide in Table 10, it remains reasonable to conclude that the mean hedging demands for domestic stocks are positive and sizable for an investor in the U.S. who also considers stocks and bonds from a number of different foreign countries. We also continue to see fairly large negative intertemporal hedging demands for domestic bonds when France, Germany, or Italy is the foreign country.

It is also evident from Table 10 that the mean hedging demands for foreign stocks are typically quite small in magnitude when Australia, Canada, France, Germany, or Italy serves as the foreign country. We cannot reject the null hypothesis of zero mean hedging demands for foreign stocks in these countries according to the 68% confidence intervals, so that foreign stocks in these countries do not present a useful hedging opportunity for an investor in the U.S. In contrast, when the U.K. serves as the foreign country, an investor in the U.S. does have fairly sizable mean hedging demands for foreign stocks, so foreign stocks from the U.K. do appear to present a positive hedging opportunity for an investor in the

[35] In order to conserve space, we do not report summary statistics or the complete VAR estimation results. They are available at http://pages.slu.edu/faculty/rapachde/Research.htm.

U.S. With the possible exception of the U.K., the intertemporal hedging demands for foreign bonds are typically small in magnitude for the different foreign countries.

Figure 2 presents the intertemporal hedging demands for domestic and foreign stocks and bonds for each month over the sample when $\gamma = 7$. The profiles of the hedging demands for domestic stocks and bonds in each panel of Figure 2 are similar to the profiles for the U.S. in Panel A of Figure 1. We see that the hedging demands for foreign stocks and foreign bonds are typically small in magnitude throughout the sample for all foreign countries with the exception of the U.K.

3.5. Asset Demands for Investors in Australia, Canada, France, Germany, Italy, and the U.K. Who Can Also Invest in U.S. Stocks and Bonds

Our final empirical exercise is another extension that analyzes asset demands for an investor in Australia, Canada, France, Germany Italy, or the U.K. who has access to domestic bills, stocks, and bonds, as well as stocks and bonds from the U.S. The log real return on a domestic 3-month Treasury bill acts as the return on the benchmark asset, and the log excess returns on domestic stocks and bonds and U.S. stocks and bonds comprise the excess returns on the other four assets.[36] The investor considers six instruments: the domestic and U.S. nominal bill yields, dividend yields, and term spreads. We continue to assume a VAR(1) structure for the state vector, $\psi = 1$, and $\delta = 0.92$ on an annual basis. Table 11 reports the mean asset demands and corresponding 68% confidence intervals (again generated using a suitably modified parametric bootstrap procedure) for γ values of 4, 7, and 10.[37]

Observe that with the exception of the U.K., the intertemporal hedging demands for domestic stocks and bonds are typically fairly small in magnitude in all of the countries. According to the 68% confidence intervals, we cannot reject the null hypothesis that the intertemporal hedging demands for

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[36] We measure the log excess return on U.S. stocks or bonds by first converting the U.S. dollar stock or bond return to local currency using exchange rates and then computing the local currency return in excess of the local currency return on a domestic 3-month Treasury bill.

[37] Again in order to conserve space, we do not report summary statistics or the complete VAR estimation results. They are available at http://pages.slu.edu/faculty/rapachde/Research.htm.

domestic stocks and bonds are zero in Australia, Canada, France, Germany, and Italy. We do see sizable positive intertemporal hedging demands for domestic stocks in the U.K., so that the strong hedging demands for stocks in the U.K. in the last panel of Table 9 remain in the last panel of Table 11.

We see substantial positive (negative) estimates of the intertemporal hedging demands for U.S. stocks (bonds) in the different countries in Table 11. According to the confidence intervals, it is reasonable to conclude that the intertemporal hedging demands for U.S. stocks are positive and sizable in Australia, Canada, Italy, and the U.K. and that the intertemporal hedging demands for U.S. bonds are negative and sizable in all of the countries. Overall, the results in Table 11 indicate that access to U.S. stocks and bonds for investors in Australia, Canada, France, Germany, Italy, and the U.K. generates sizable intertemporal hedging demands for U.S. assets. Figure 3 presents the intertemporal hedging demands for domestic and foreign stocks and bonds for each month over the sample in each country when $\gamma = 7$, and the figure reinforces the conclusions from Table 11. The largest intertemporal hedging demand among domestic and U.S. stocks and bonds over most of the sample for each country is that for U.S. stocks.

4. Conclusion

In this paper, we investigate return predictability and its implications for the intertemporal hedging demands for stocks and bonds for investors with Epstein-Zin-Weil preferences and infinite horizons in the U.S., Australia, Canada, France, Germany, Italy, and U.K. Our results show that differences in return predictability across countries can lead to important differences in the implied intertemporal hedging demands for domestic stocks and bonds across countries. When we analyze allocations across domestic bills, stocks, and bonds in each country, the sizable positive intertemporal hedging demands for domestic stocks in the U.S. and U.K. stand out. When an investor in the U.S. also has access to stocks and bonds from Australia, Canada, France, Germany, Italy, or the U.K., the only foreign asset for which she exhibits significant positive intertemporal hedging demands is U.K. stocks. When investors in Australia, Canada, France, Germany, Italy, and the U.K. have access to U.S. stocks and bonds, investors in all of these countries display sizable positive intertemporal hedging demands for U.S. stocks and sizable negative intertemporal hedging demands for U.S. bonds. Overall, our results indicate that U.S. and U.K. stocks provide especially attractive intertemporal hedging instruments for international investors with Epstein-Zin-Weil preferences and infinite horizons.

Finally, we suggest two avenues for future research. First, it would be interesting to examine the implications of structural change for the multi-period portfolio choice problems we consider in the present paper, as the predictive relationships between lagged instruments and expected returns may be subject to periodic structural breaks.[38] A second avenue for future research involves the incorporation of investor uncertainty and learning into the multi-period choice problems we consider. In the present paper, we assume that the investor has complete knowledge of the data-generating process governing returns as she takes her allocation decisions. Of course, in practice, there is considerable uncertainty surrounding the parameters of the data-generating process, and the investor may update her views concerning these parameters as she learns about the data-generating process through time.[39] Both structural change and learning add considerable complexity to multi-period portfolio choice problems, especially the types of problems considered in the present paper involving a large number of state variables. At the present time, it appears we need further analytical and computational advances in order to make the analysis of multi-period portfolio choice problems with a large number of state variables, return predictability, structural change, and learning tractable. While the present paper shows that return predictability has important asset allocation implications for international investors with long horizons, structural change and learning have potentially important implications of their own, so that further advances in solving complex portfolio choice problems could provide added insights to international investors with long horizons.

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[38] For progress in this area, see Guidolin and Timmermann (2004), who analyze optimal asset allocation across domestic stocks and bonds for an investor in the U.S. with a long horizon and power utility defined over consumption, and where the VAR(1) process characterizing the return dynamics is subject to regime shifts governed by a Markov-switching process.

[39] Brennan (1998) and Barberis (2000) investigate the role of learning in multi-period portfolio choice problems without return predictability. For progress on the role of learning in multi-period portfolio choice problems with return predictability, see Xia (2001) and Brandt et al. (2003).

Data Appendix

All of the data are from Global Financial Data, Inc. (www.globalfindata.com). A list of the names of all of the Global Financial Data files used to construct the state variables for each country are listed below. A description of each file (provided by Global Financial Data) is given in parentheses.

United States

TRUSABIM (USA Total Return Commercial/T-Bill Index)
_SPXTRM (S&P 500® Total Return Index)
TRUSAGVM (USA 10-year Government Bond Total Return Index)
CPUSAM (USA BLS Consumer Price Index)
ITUSA3SM (USA Government 90-day T-Bills Secondary Market [Yield])
IGUSA10M (USA 10-year Bond Constant Maturity Yield)
SYUSAYM (S&P 500 Monthly Dividend Yield)

Australia

TRAUSBIM (Australia Total Return Bills Index)
_AORDAM (Australia ASX Accumulation Index-All Ordinaries)
TRAUSGVM (Australia 10-year Government Bond Return Index)
WPAUSM (AUS Manufacturing Output Prices)
ITAUS3M (Australia 3-month Treasury Bills [Yield])
IGAUS10M (Australia Commonwealth 10-year Bonds [Yield])
SYAUSYM (Australia ASX Dividend yield)
__AUD_M (Australia Dollar (USD per AUD))

Canada

TRCANBIM (Canada Total Return Bills Index)
_TRGSPTM (Toronto SE-300 Total Return Index)
TRCANGVM (Canada 10-year Total Return Government Bond Index)
CPCANM (Canada Consumer Price Index)
ITCAN3M (Canada 3-month Treasury Bill Yield)
IGCAN10M (Canada 10-year Government Bond Yield)
SYCANYTM (Toronto SE Dividend Yield)
__CAD_M (Canada Dollar)

France

TRFRABIM (France Total Return Bills Index)
TRSBF25M (France SBF-250 Total Return Index)
TRFRAGVM (France 10-year Total Return Government Bond Index)
CPFRAM (France Consumer Price Index)
ITFRA3M (France 3-month Treasury Bill Yield)
IGFRA10M (France 10-year Government Bond Yield)
SYFRAYM (France Dividend Yield)
__FRF_M (France Franc)

Germany

TRDEUBIM (Germany Total Return Bills Index)
_CDAXM (Germany CDAX Total Return Index)
TRDEUGVM (Germany 10-year Government Bond Return Index)
CPDEUM (Germany Consumer Price Index)
ITDEUM (Germany 3-month Treasury Bill Yield)
IGDEU10M (Germany 10-year Benchmark Bond)
SYDEUYM (Germany Dividend Yield)
__DEM_M (Germany Deutschemark)

Italy

TRITABIM (Italy Total Return Bills Index)
_BCIPRM (Italy BCI Global Return Index)
TRITAGVM (Italy 10-year Total Return Government Bond Index)
CPITAM (Italy Consumer Price Index)
ITITA3M (Italy 3-month Treasury Bill Yield)
IGITA10M (Italy 10-year Government Bond Yield)
SYITAYM (Italy Dividend Yield)
__ITL_M (Italy Lira)

United Kingdom

TRGBRBIM (United Kingdom Total Return Bills Index)
_TFTASM (UK FTA All-Share Return Index)
TRGBRGVM (United Kingdom 10-year Government Bond Total Return Index)
CPGBRM (UK Retail Price Index)
ITGBR3M (UK 3-month Treasury Bill Yield)
IGGBR10M (UK 10-year Government Bonds [Yield])
_DFTASM (UK FT-Actuaries Dividend Yield)
__GBP_M (UK British Pound Daily (USD per GBP))

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Table 1: Summary statistics, 1952:04-2004:05

(1) Variable	(2) Mean	(3) Standard deviation	(4) Sharpe ratio	(5) ρ_1	(6) Variable	(7) Mean	(8) Standard deviation	(9) Sharpe ratio	(10) ρ_1
United States, 1952:04-2004:05					*Germany, 1967:02-2004:05*				
$rtbr_t$	1.34	0.99		0.37	$rtbr_t$	2.09	1.15		0.29
xsr_t	5.69	14.62	0.39	0.03	xsr_t	2.98	18.28	0.16	0.08
xbr_t	1.01	5.65	0.18	0.14	xbr_t	2.63	5.97	0.44	0.21
$bill_t$	-0.01	1.03		0.88	$bill_t$	-0.04	1.02		0.93
div_t	1.16	0.39		0.99	div_t	1.19	0.30		0.98
$spread_t$	1.39	1.16		0.94	$spread_t$	1.98	1.27		0.95
Australia, 1952:04-2004:05					*Italy, 1952:04-2004:05*				
$rtbr_t$	2.30	2.86		0.37	$rtbr_t$	1.91	1.62		0.49
xsr_t	5.54	17.43	0.32	0.07	xsr_t	1.89	21.90	0.09	0.09
xbr_t	1.14	7.15	0.16	0.05	xbr_t	1.18	7.08	0.17	0.31
$bill_t$	0.05	1.26		0.89	$bill_t$	-0.01	1.42		0.90
div_t	1.66	0.29		0.99	div_t	1.14	0.40		0.98
$spread_t$	1.35	1.67		0.95	$spread_t$	1.22	1.71		0.94
Canada, 1952:04-2004:05					*United Kingdom, 1952:04-2004:05*				
$rtbr_t$	2.36	1.41		0.21	$rtbr_t$	1.59	2.07		0.28
xsr_t	3.17	15.60	0.20	0.09	xsr_t	5.30	18.53	0.29	0.11
xbr_t	1.10	7.38	0.15	0.10	xbr_t	0.92	4.83	0.19	0.32
$bill_t$	0.01	1.33		0.92	$bill_t$	0.03	1.36		0.90
div_t	1.15	0.36		0.99	div_t	1.51	0.28		0.98
$spread_t$	1.30	1.48		0.95	$spread_t$	0.84	2.07		0.97
France, 1961:01-2004:05									
$rtbr_t$	2.23	1.15		0.51					
xsr_t	2.12	19.44	0.11	0.12					
xbr_t	1.21	6.36	0.19	0.17					
$bill_t$	-0.02	1.33		0.93					
div_t	1.28	0.47		0.99					
$spread_t$	0.94	1.45		0.95					

Notes: $rtbr_t$ = log real 3-month Treasury bill return; xsr_t = log excess stock return; xbr_t = log excess bond return; $bill_t$ = 3-month Treasury bill yield (deviations from 1-year backward-looking moving average); div_t = log dividend yield; $spread_t$ = 10-year government bond yield – 3-month Treasury bill yield. Sharpe ratio is the mean [column (2)] divided by the standard deviation [column (3)]. ρ_1 is the first-order autocorrelation coefficient.

Table 2: VAR estimation results, United States, 1952:04-2004:05

(1) Dependent variable	(2) $rtbr_t$	(3) xsr_t	(4) xbr_t	(5) $bill_t$	(6) div_t	(7) $spread_t$	(8) R^2
VAR slope coefficient estimates and goodness-of-fit measures							
$rtbr_{t+1}$	0.360	0.003	0.009	-0.000	0.000	0.000	0.146
	(9.610)	(1.169)	(1.287)	(-0.681)	(0.251)	(0.608)	[0.000]
	[0.000]	[0.139]	[0.110]	[0.229]	[0.472]	[0.294]	
xsr_{t+1}	0.813	-0.004	0.253	-0.004	0.009	0.001	0.042
	(1.381)	(-0.094)	(2.294)	(-1.874)	(2.156)	(0.760)	[0.000]
	[0.080]	[0.476]	[0.013]	[0.037]	[0.072]	[0.269]	
xbr_{t+1}	0.651	-0.065	0.165	0.001	0.001	0.002	0.070
	(2.901)	(-4.264)	(3.913)	(1.072)	(0.317)	(2.834)	[0.000]
	[0.002]	[0.000]	[0.000]	[0.208]	[0.566]	[0.001]	
$bill_{t+1}$	-10.793	1.635	-6.778	0.881	-0.022	0.048	0.791
	(-1.603)	(3.551)	(-5.372)	(36.718)	(-0.448)	(2.383)	
div_{t+1}	-0.862	0.030	-0.276	0.005	0.992	-0.001	0.988
	(-1.401)	(0.706)	(-2.396)	(2.285)	(223.159)	(-0.328)	
$spread_{t+1}$	-0.626	-0.353	3.125	-0.011	0.000	0.932	0.885
	(-0.111)	(-0.916)	(2.960)	(-0.548)	(0.012)	(55.789)	
Cross-correlations of VAR residuals							
	rtbr	*xsr*	*xbr*	*bill*	*div*	*spread*	
rtbr	1.000						
xsr	0.052	1.00					
xbr	-0.010	0.132	1.00				
bill	0.063	-0.046	-0.656	1.00			
div	-0.081	-0.964	-0.126	0.034	1.00		
spread	-0.100	-0.076	0.050	-0.748	0.087	1.00	

Notes: $rtbr_t$ = log real 3-month Treasury bill return; xsr_t = log excess stock return; xbr_t = log excess bond return; $bill_t$ = 3-month Treasury bill yield (deviations from 1-year backward-looking moving average); div_t = log dividend yield; $spread_t$ = 10-year government bond yield – 3-month Treasury bill yield. *t*-statistics are given in parentheses. Bootstrapped *p*-values corresponding to the reported *t*-statistics under the null hypothesis of no predictability are given in brackets; if the *t*-statistic < 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic less than the original statistic; if the *t*-statistic > 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic greater than the original *t*-statistic. The bootstrapped *p*-values appearing below the reported R^2 measure correspond to a Wald test of the null hypothesis that the explanatory variables are jointly zero. 0.000 indicates $\leq$ 0.0005.

Table 3: VAR estimation results, Australia, 1952:04-2004:05

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	$rtbr_t$	xsr_t	xbr_t	$bill_t$	div_t	$spread_t$	R^2
VAR slope coefficient estimates and goodness-of-fit measures							
$rtbr_{t+1}$	0.323	-0.005	0.007	-0.000	-0.002	-0.001	0.164
	(8.475)	(-0.720)	(0.431)	(-1.345)	(-2.132)	(-3.219)	[0.000]
	[0.000]	[0.230]	[0.325]	[0.077]	[0.007]	[0.000]	
xsr_{t+1}	-0.095	0.091	-0.213	-0.002	0.015	0.000	0.020
	(-0.377)	(2.173)	(-2.035)	(-0.836)	(2.035)	(0.212)	[0.075]
	[0.381]	[0.015]	[0.029]	[0.213]	[0.073]	[0.461]	
xbr_{t+1}	0.111	0.017	0.005	-0.002	0.001	0.001	0.027
	(1.081)	(0.982)	(0.123)	(-2.488)	(0.270)	(1.440)	[0.008]
	[0.123]	[0.151]	[0.423]	[0.005]	[0.503]	[0.112]	
$bill_{t+1}$	-4.051	-0.035	-1.386	0.924	-0.192	0.068	0.802
	(-1.430)	(-0.075)	(-1.176)	(44.702)	(-2.313)	(4.389)	
div_{t+1}	-0.220	-0.111	0.208	0.005	0.981	0.002	0.974
	(-0.946)	(-2.873)	(2.152)	(2.748)	(144.256)	(1.372)	
$spread_{t+1}$	2.087	0.144	0.792	-0.012	0.123	0.940	0.897
	(0.774)	(0.324)	(0.706)	(-0.632)	(1.554)	(63.766)	
Cross-correlations of VAR residuals							
	rtbr	*xsr*	*xbr*	*bill*	*div*	*spread*	
rtbr	1.000						
xsr	0.033	1.000					
xbr	0.063	0.291	1.000				
bill	0.017	-0.212	-0.298	1.000			
div	-0.059	-0.737	-0.250	0.276	1.000		
spread	-0.051	0.068	-0.172	-0.849	-0.119	1.000	

Notes: $rtbr_t$ = log real 3-month Treasury bill return; xsr_t = log excess stock return; xbr_t = log excess bond return; $bill_t$ = 3-month Treasury bill yield (deviations from 1-year backward-looking moving average); div_t = log dividend yield; $spread_t$ = 10-year government bond yield – 3-month Treasury bill yield. *t*-statistics are given in parentheses. Bootstrapped *p*-values corresponding to the reported *t*-statistics under the null hypothesis of no predictability are given in brackets; if the *t*-statistic < 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic less than the original statistic; if the *t*-statistic > 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic greater than the original *t*-statistic. The bootstrapped *p*-values appearing below the reported R^2 measure correspond to a Wald test of the null hypothesis that the explanatory variables are jointly zero. 0.000 indicates $\leq$ 0.0005.

Table 4: VAR estimation results, Canada, 1952:04-2004:05

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	$rtbr_t$	xsr_t	xbr_t	$bill_t$	div_t	$spread_t$	R^2
VAR slope coefficient estimates and goodness-of-fit measures							
$rtbr_{t+1}$	0.152 (3.814) [0.000]	-0.002 (-0.683) [0.235]	0.006 (0.802) [0.209]	-0.000 (-1.450) [0.070]	-0.001 (-2.102) [0.017]	-0.001 (-5.276) [0.000]	0.093 [0.000]
xsr_{t+1}	-0.109 (-0.239) [0.413]	0.064 (1.553) [0.073]	0.168 (1.876) [0.039]	-0.001 (-0.616) [0.265]	0.008 (1.576) [0.154]	0.002 (1.442) [0.091]	0.027 [0.013]
xbr_{t+1}	0.766 (3.639) [0.000]	-0.098 (-5.173) [0.000]	0.134 (3.262) [0.000]	-0.000 (-0.300) [0.282]	0.003 (1.132) [0.269]	0.003 (3.576) [0.000]	0.085 [0.000]
$bill_{t+1}$	-12.132 (-2.383)	1.213 (2.635)	-6.149 (-6.171)	0.944 (50.568)	-0.024 (-0.408)	0.069 (3.974)	0.863
div_{t+1}	-0.194 (-0.413)	-0.038 (-0.898)	-0.198 (-2.150)	0.003 (1.813)	0.990 (183.840)	-0.001 (-0.628)	0.984
$spread_{t+1}$	1.903 (0.427)	0.289 (0.716)	4.193 (4.801)	-0.050 (-3.050)	-0.030 (-0.594)	0.922 (60.929)	0.914
Cross-correlations of VAR residuals							
	rtbr	*xsr*	*xbr*	*bill*	*div*	*spread*	
rtbr	1.000						
xsr	0.018	1.000					
xbr	0.021	0.269	1.000				
bill	0.042	-0.200	-0.449	1.000			
div	-0.068	-0.900	-0.308	0.216	1.000		
spread	-0.051	0.050	-0.167	-0.777	-0.049	1.000	

Notes: $rtbr_t$ = log real 3-month Treasury bill return; xsr_t = log excess stock return; xbr_t = log excess bond return; $bill_t$ = 3-month Treasury bill yield (deviations from 1-year backward-looking moving average); div_t = log dividend yield; $spread_t$ = 10-year government bond yield – 3-month Treasury bill yield. *t*-statistics are given in parentheses. Bootstrapped *p*-values corresponding to the reported *t*-statistics under the null hypothesis of no predictability are given in brackets; if the *t*-statistic < 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic less than the original statistic; if the *t*-statistic > 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic greater than the original *t*-statistic. The bootstrapped *p*-values appearing below the reported R^2 measure correspond to a Wald test of the null hypothesis that the explanatory variables are jointly zero. 0.000 indicates $\leq$ 0.0005.

Table 5: VAR estimation results, France, 1961:01-2004:05

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	$rtbr_t$	xsr_t	xbr_t	$bill_t$	div_t	$spread_t$	R^2
VAR slope coefficient estimates and goodness-of-fit measures							
$rtbr_{t+1}$	0.410 (10.111) [0.000]	-0.002 (-0.975) [0.170]	0.009 (1.277) [0.106]	-0.000 (-2.374) [0.009]	-0.000 (-1.103) [0.123]	-0.001 (-5.666) [0.000]	0.311 [0.000]
xsr_{t+1}	0.014 (0.017) [0.489]	0.098 (2.148) [0.014]	0.198 (1.371) [0.085]	-0.002 (-1.116) [0.159]	0.005 (0.942) [0.386]	0.001 (0.258) [0.422]	0.026 [0.045]
xbr_{t+1}	1.394 (5.454) [0.000]	-0.004 (-0.271) [0.381]	0.129 (2.839) [0.001]	-0.001 (-1.791) [0.019]	0.001 (0.670) [0.380]	0.002 (2.583) [0.008]	0.103 [0.000]
$bill_{t+1}$	-3.832 (-0.583)	-0.469 (-1.279)	-5.695 (-4.873)	0.947 (53.047)	-0.040 (-0.928)	0.083 (4.928)	0.887
div_{t+1}	-0.875 (-0.968)	-0.157 (-3.110)	-0.257 (-1.601)	0.003 (1.176)	0.986 (168.410)	0.000 (0.001)	0.983
$spread_{t+1}$	-14.085 (-2.200)	0.480 (1.344)	4.088 (3.592)	-0.048 (-2.737)	0.005 (0.130)	0.918 (56.105)	0.910
Cross-correlations of VAR residuals							
	rtbr	*xsr*	*xbr*	*bill*	*div*	*spread*	
rtbr	1.000						
xsr	0.008	1.000					
xbr	-0.031	0.255	1.000				
bill	0.128	-0.151	-0.350	1.000			
div	0.028	-0.778	-0.258	0.068	1.000		
spread	-0.110	0.022	-0.208	-0.798	0.065	1.000	

Notes: $rtbr_t$ = log real 3-month Treasury bill return; xsr_t = log excess stock return; xbr_t = log excess bond return; $bill_t$ = 3-month Treasury bill yield (deviations from 1-year backward-looking moving average); div_t = log dividend yield; $spread_t$ = 10-year government bond yield – 3-month Treasury bill yield. *t*-statistics are given in parentheses. Bootstrapped *p*-values corresponding to the reported *t*-statistics under the null hypothesis of no predictability are given in brackets; if the *t*-statistic < 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic less than the original statistic; if the *t*-statistic > 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic greater than the original *t*-statistic. The bootstrapped *p*-values appearing below the reported R^2 measure correspond to a Wald test of the null hypothesis that the explanatory variables are jointly zero. 0.000 indicates $\leq$ 0.0005.

Table 6: VAR estimation results, Germany, 1967:02-2004:05

(1) Dependent Variable	(2) $rtbr_t$	(3) xsr_t	(4) xbr_t	(5) $bill_t$	(6) div_t	(7) $spread_t$	(8) R^2
VAR slope coefficient estimates and goodness-of-fit measures							
$rtbr_{t+1}$	0.224 (4.768) [0.000]	-0.002 (-0.664) [0.240]	-0.011 (-1.178) [0.137]	0.000 (0.111) [0.483]	-0.000 (-0.101) [0.434]	-0.001 (-4.777) [0.000]	0.139 [0.000]
xsr_{t+1}	0.343 (0.433) [0.331]	0.064 (1.320) [0.094]	0.082 (0.540) [0.288]	-0.005 (-1.965) [0.035]	0.010 (1.144) [0.303]	0.002 (0.849) [0.262]	0.023 [0.138]
xbr_{t+1}	0.745 (2.972) [0.003]	-0.044 (-2.877) [0.001]	0.200 (4.200) [0.000]	-0.001 (-1.735) [0.026]	0.002 (0.654) [0.371]	0.001 (1.496) [0.105]	0.088 [0.000]
$bill_{t+1}$	1.260 (0.248)	0.377 (1.218)	-7.687 (-7.942)	0.929 (55.388)	-0.064 (-1.175)	0.068 (4.925)	0.892
div_{t+1}	-0.044 (-0.050)	-0.062 (-1.167)	-0.156 (-0.934)	0.008 (2.609)	0.980 (103.836)	-0.001 (-0.345)	0.962
$spread_{t+1}$	-11.420 (-2.039)	0.347 (1.018)	4.664 (4.374)	-0.035 (-1.874)	0.014 (0.237)	0.940 (61.636)	0.915
Cross-correlations of VAR residuals							
	rtbr	*xsr*	*xbr*	*bill*	*div*	*spread*	
rtbr	1.000						
xsr	-0.014	1.000					
xbr	0.113	0.152	1.000				
bill	0.017	-0.015	-0.204	1.000			
div	0.018	-0.804	-0.132	0.027	1.000		
spread	-0.082	-0.070	-0.435	-0.774	0.044	1.000	

Notes: $rtbr_t$ = log real 3-month Treasury bill return; xsr_t = log excess stock return; xbr_t = log excess bond return; $bill_t$ = 3-month Treasury bill yield (deviations from 1-year backward-looking moving average); div_t = log dividend yield; $spread_t$ = 10-year government bond yield – 3-month Treasury bill yield. *t*-statistics are given in parentheses. Bootstrapped *p*-values corresponding to the reported *t*-statistics under the null hypothesis of no predictability are given in brackets; if the *t*-statistic < 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic less than the original statistic; if the *t*-statistic > 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic greater than the original *t*-statistic. The bootstrapped *p*-values appearing below the reported R^2 measure correspond to a Wald test of the null hypothesis that the explanatory variables are jointly zero. 0.000 indicates $\leq$ 0.0005.

Table 7: VAR estimation results, Italy, 1952:04-2004:05

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	$rtbr_t$	xsr_t	xbr_t	$bill_t$	div_t	$spread_t$	R^2
VAR slope coefficient estimates and goodness-of-fit measures							
$rtbr_{t+1}$	0.458 (12.771) [0.000]	0.000 (0.083) [0.430]	0.006 (0.685) [0.270]	-0.000 (-1.522) [0.060]	-0.001 (-1.494) [0.064]	-0.000 (-2.544) [0.003]	0.262 [0.000]
xsr_{t+1}	0.740 (1.319) [0.092]	0.094 (2.298) [0.006]	-0.025 (-0.187) [0.422]	-0.001 (-0.566) [0.283]	0.006 (0.824) [0.359]	0.002 (0.853) [0.218]	0.016 [0.132]
xbr_{t+1}	0.719 (4.273) [0.000]	0.017 (1.367) [0.109]	0.238 (5.919) [0.000]	-0.002 (-2.857) [0.000]	0.000 (0.124) [0.448]	0.001 (1.699) [0.065]	0.155 [0.000]
$bill_{t+1}$	-28.046 (-5.376)	-0.562 (-1.484)	-2.016 (-1.616)	0.908 (45.865)	-0.162 (-2.520)	0.062 (3.787)	0.830
div_{t+1}	-0.874 (-1.405)	-0.400 (-8.858)	0.280 (1.884)	0.000 (0.069)	0.971 (126.418)	0.001 (0.751)	0.969
$spread_{t+1}$	16.983 (3.368)	0.701 (1.914)	-0.953 (-0.791)	0.002 (0.128)	0.141 (2.255)	0.938 (59.015)	0.891
Cross-correlations of VAR residuals							
	rtbr	*xsr*	*xbr*	*bill*	*div*	*spread*	
rtbr	1.000						
xsr	-0.017	1.000					
xbr	0.009	0.157	1.000				
bill	0.010	-0.089	-0.244	1.000			
div	0.028	-0.599	-0.118	0.001	1.000		
spread	-0.011	-0.019	-0.179	-0.854	0.084	1.000	

Notes: $rtbr_t$ = log real 3-month Treasury bill return; xsr_t = log excess stock return; xbr_t = log excess bond return; $bill_t$ = 3-month Treasury bill yield (deviations from 1-year backward-looking moving average); div_t = log dividend yield; $spread_t$ = 10-year government bond yield – 3-month Treasury bill yield. *t*-statistics are given in parentheses. Bootstrapped *p*-values corresponding to the reported *t*-statistics under the null hypothesis of no predictability are given in brackets; if the *t*-statistic < 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic less than the original statistic; if the *t*-statistic > 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic greater than the original *t*-statistic. The bootstrapped *p*-values appearing below the reported R^2 measure correspond to a Wald test of the null hypothesis that the explanatory variables are jointly zero. 0.000 indicates $\leq$ 0.0005.

Table 8: VAR estimation results, United Kingdom, 1952:04-2004:05

(1) Dependent Variable	(2) $rtbr_t$	(3) xsr_t	(4) xbr_t	(5) $bill_t$	(6) div_t	(7) $spread_t$	(8) R^2
VAR slope coefficient estimates and goodness-of-fit measures							
$rtbr_{t+1}$	0.183 (4.624) [0.000]	0.001 (0.324) [0.377]	-0.003 (-0.181) [0.436]	-0.001 (-3.598) [0.000]	-0.001 (-1.468) [0.083]	-0.001 (-6.154) [0.000]	0.146 [0.000]
xsr_{t+1}	0.845 (2.240) [0.015]	0.093 (2.224) [0.009]	0.210 (1.269) [0.109]	-0.001 (-0.478) [0.299]	0.028 (3.555) [0.003]	0.001 (0.731) [0.269]	0.044 [0.000]
xbr_{t+1}	0.255 (2.732) [0.002]	0.042 (4.018) [0.000]	0.269 (6.572) [0.000]	0.000 (0.284) [0.446]	0.004 (1.918) [0.042]	0.000 (1.553) [0.065]	0.140 [0.000]
$bill_{t+1}$	2.671 (0.661)	-0.106 (-0.236)	-7.124 (-4.022)	0.913 (47.958)	-0.251 (-3.021)	0.054 (4.275)	0.830
div_{t+1}	-0.363 (-1.213)	-0.442 (-13.340)	-0.111 (-0.847)	0.002 (1.515)	0.984 (160.090)	0.000 (0.507)	0.979
$spread_{t+1}$	-7.353 (-1.961)	-0.998 (-2.404)	1.851 (1.126)	-0.031 (-1.761)	0.149 (1.936)	0.950 (80.995)	0.937
Cross-correlations of VAR residuals							
	rtbr	*xsr*	*xbr*	*bill*	*div*	*spread*	
rtbr	1.000						
xsr	-0.111	1.000					
xbr	-0.043	0.279	1.000				
bill	0.097	-0.263	-0.466	1.000			
div	0.082	-0.789	-0.291	0.222	1.000		
spread	-0.098	0.129	0.036	-0.840	-0.083	1.000	

Notes: $rtbr_t$ = log real 3-month Treasury bill return; xsr_t = log excess stock return; xbr_t = log excess bond return; $bill_t$ = 3-month Treasury bill yield (deviations from 1-year backward-looking moving average); div_t = log dividend yield; $spread_t$ = 10-year government bond yield – 3-month Treasury bill yield. *t*-statistics are given in parentheses. Bootstrapped *p*-values corresponding to the reported *t*-statistics under the null hypothesis of no predictability are given in brackets; if the *t*-statistic < 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic less than the original statistic; if the *t*-statistic > 0, the reported *p*-value is the proportion of bootstrapped draws that yield a *t*-statistic greater than the original *t*-statistic. The bootstrapped *p*-values appearing below the reported R^2 measure correspond to a Wald test of the null hypothesis that the explanatory variables are jointly zero. 0.000 indicates $\leq$ 0.0005.

Table 9: Mean demands for domestic assets for investors in different countries

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Stocks			Bonds			Bills		
CRRA	Total demand	Myopic Demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand
United States, 1952:04-2004:04									
$\gamma = 4$	173.79 [102,197]	78.28 [43,76]	95.51 [50,122]	35.59 [-65,124]	70.15 [-55,143]	-34.56 [-46,-6]	-109.37 [-254,-40]	-48.42 [-159,28]	-60.95 [-140,-41]
$\gamma = 7$	124.65 [71,149]	44.58 [24,43]	80.07 [43,109]	15.49 [-41,68]	40.21 [-32,82]	-24.72 [-32,-4]	-40.14 [-136,2]	15.21 [-48,58]	-55.35 [-124,-36]
$\gamma = 10$	98.08 [55,122]	31.10 [17,30]	66.97 [34,92]	8.81 [-29,47]	28.23 [-20,59]	-19.42 [-26,-4]	-6.89 [-84,25]	40.66 [-4,71]	-47.55 [-109,-30]
Australia, 1954:02-2004:04									
$\gamma = 4$	73.60 [30,95]	55.35 [25,67]	18.25 [0,31]	36.73 [-45,78]	28.88 [-62,73]	7.86 [-14,24]	-10.33 [-83,41]	15.78 [-47,69]	-26.11 [-71,-5]
$\gamma = 7$	40.34 [14,56]	31.52 [14,39]	8.81 [-5,20]	13.63 [-32,39]	15.57 [-36,41]	-1.93 [-16,11]	46.03 [-4,75]	52.91 [17,83]	-6.88 [-44,7]
$\gamma = 10$	25.64 [6,39]	22.00 [10,27]	3.64 [-7,15]	3.06 [-29,22]	10.24 [-26,29]	-7.18 [-18,5]	71.30 [31,91]	67.76 [42,89]	3.54 [-29,13]
Canada, 1954:02-2004:04									
$\gamma = 4$	59.46 [21,83]	40.46 [11,48]	19.00 [5,40]	29.99 [-44,92]	43.52 [-51,103]	-13.53 [-24,5]	10.55 [-94,53]	16.02 [-69,70]	-5.47 [-55,-1]
$\gamma = 7$	34.96 [12,53]	23.07 [6,27]	11.89 [2,30]	16.22 [-26,52]	24.73 [-30,59]	-8.51 [-15,4]	45.82 [-19,71]	52.21 [4,84]	-3.38 [-44,-1]
$\gamma = 10$	24.16 [8,39]	16.11 [4,19]	8.05 [-1,22]	11.11 [-17,37]	17.21 [-21,41]	-6.10 [-11,4]	64.73 [14,79]	66.68 [33,88]	-1.95 [-35,0]
France, 1961:01-2004:04									
$\gamma = 4$	23.78 [-3,43]	20.48 [-5,32]	3.30 [-4,16]	56.38 [-51,128]	80.05 [-60,159]	-23.67 [-47,-4]	19.84 [-104,74]	-0.53 [-130,77]	20.37 [-17,26]
$\gamma = 7$	13.11 [-3,27]	11.67 [-3,18]	1.44 [-4,10]	30.82 [-29,71]	45.98 [-37,88]	-15.16 [-30,-3]	56.07 [-14,86]	42.35 [-31,86]	13.72 [-12,17]
$\gamma = 10$	8.70 [-3,19]	8.14 [-2,13]	0.56 [-4,8]	21.11 [-21,49]	32.36 [-25,62]	-11.24 [-23,-2]	70.19 [21,91]	59.50 [8,90]	10.68 [-9,14]
Germany, 1967:02-2004:04									
$\gamma = 4$	49.85 [17,76]	25.77 [1,38]	24.08 [8,44]	151.76 [41,229]	201.22 [68,284]	-49.46 [-76,-18]	-101.61 [-262,-49]	-126.98 [-270,-56]	25.38 [-33,35]
$\gamma = 7$	29.86 [10,48]	14.80 [1,22]	15.06 [3,28]	83.52 [26,132]	114.03 [38,162]	-30.52 [-47,-10]	-13.38 [-109,14]	-28.84 [-111,12]	15.46 [-25,21]
$\gamma = 10$	20.92 [7,35]	10.42 [0,15]	10.50 [2,21]	57.66 [20,93]	79.16 [26,112]	-21.50 [-34,-6]	21.41 [-48,39]	10.42 [-47,39]	10.99 [-21,15]

Notes: The table reports mean monthly total asset demands in percentages for stocks, 10-year government bonds, and 3-month Treasury bills for an investor with a unitary elasticity of intertemporal substitution, a discount factor equal to $0.92^{1/12}$, and coefficients of relative risk aversion (γ) equal to 4, 7, and 10. The table also reports the mean myopic and hedging demands for each asset class. Bootstrapped 68% confidence intervals for the mean asset demands are given in brackets.

Table 9 (continued)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Stocks			Bonds			Bills		
CRRA	Total demand	Myopic Demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand
Italy, 1952:04-2004:04									
$\gamma = 4$	15.68	19.21	-3.53	46.89	72.15	-25.27	37.43	8.63	28.80
	[-5,32]	[1,30]	[-9,4]	[-56,111]	[-69,154]	[-65,-1]	[-74,95]	[-139,92]	[-15,47]
$\gamma = 7$	6.48	11.03	-4.55	23.47	41.12	-17.64	70.04	47.85	22.19
	[-5,17]	[0,17]	[-9,1]	[-35,60]	[-40,88]	[-41,-2]	[8,101]	[-36,95]	[-6,33]
$\gamma = 10$	2.75	7.76	-5.01	14.44	28.70	-14.26	82.81	63.54	19.27
	[-5,11]	[0,12]	[-9,0]	[-27,40]	[-28,61]	[-32,-3]	[39,104]	[5,97]	[-2,27]
United Kingdom, 1952:04-2004:04									
$\gamma = 4$	125.59	48.63	76.97	75.50	73.72	1.78	-101.09	-22.34	-78.75
	[74,147]	[30,57]	[41,94]	[-57,154]	[-80,159]	[-27,22]	[-250,-9]	[-165,70]	[-125,-48]
$\gamma = 7$	88.00	28.27	59.73	44.30	42.36	1.94	-32.30	29.37	-61.67
	[50,106]	[18,33]	[30,75]	[-33,89]	[-46,91]	[-20,15]	[-123,25]	[-52,83]	[-100,-36]
$\gamma = 10$	66.61	20.13	46.48	30.79	29.82	0.97	2.60	50.05	-47.45
	[36,82]	[13,23]	[21,60]	[-24,61]	[-33,64]	[-16,11]	[-65,45]	[-7,87]	[-80,-26]

Table 10: Mean asset demands for an investor in the United States who can also invest in foreign stocks and bonds

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Domestic stocks			Domestic bonds			Foreign stocks			Foreign bonds			Domestic bills		
CRRA	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand
Foreign country: Australia, 1952:04-2004:04															
$\gamma = 4$	148.94	59.39	89.55	75.97	92.51	-16.54	50.36	37.52	12.85	-36.54	-33.26	-3.28	-138.73	-56.15	-82.58
	[68,172]	[19,59]	[41,116]	[-21,167]	[-35,173]	[-37,20]	[8,70]	[3,52]	[-1,21]	[-96,9]	[-90,10]	[-17,3]	[-298,-56]	[-197,40]	[-170,-55]
$\gamma = 7$	110.73	33.68	77.05	40.56	53.14	-12.58	30.18	21.61	8.57	-21.51	-19.21	-2.30	-59.95	10.78	-70.74
	[51,132]	[11,33]	[38,105]	[-13,96]	[-19,99]	[-26,14]	[5,42]	[2,30]	[-1,16]	[-56,5]	[-52,5]	[-12,2]	[-169,-12]	[-70,65]	[-145,-48]
$\gamma = 10$	89.40	23.39	66.01	26.76	37.39	-10.64	21.14	15.24	5.89	-15.15	-13.59	-1.56	-22.15	37.56	-59.70
	[42,110]	[7,23]	[32,88]	[-11,67]	[-13,70]	[-20,10]	[4,31]	[2,21]	[-1,12]	[-39,3]	[-37,3]	[-10,1]	[-105,11]	[-19,76]	[-124,-41]
Foreign country: Canada, 1952:04-2004:04															
$\gamma = 4$	172.01	95.82	76.19	46.28	56.64	-10.36	5.50	-22.32	27.81	13.11	17.27	-4.16	-136.90	-47.42	-89.48
	[54,200]	[29,101]	[12,104]	[-91,149]	[-42,120]	[-60,36]	[-40,55]	[-58,14]	[-2,55]	[-69,75]	[-60,72]	[-27,13]	[-310,-65]	[-157,22]	[-185,-66]
$\gamma = 7$	119.81	54.25	65.57	29.22	32.97	-3.75	9.53	-12.31	21.84	6.24	9.50	-3.26	-64.80	15.59	-80.40
	[42,145]	[14,56]	[16,92]	[-57,94]	[-24,69]	[-42,31]	[-18,42]	[-33,8]	[0,43]	[-43,45]	[-35,41]	[-21,10]	[-183,-19]	[-47,55]	[-162,-60]
$\gamma = 10$	92.87	37.62	55.25	24.18	23.50	0.67	9.65	-8.31	17.95	2.81	6.39	-3.58	-29.50	40.79	-70.30
	[34,116]	[11,40]	[16,80]	[-41,71]	[-16,49]	[-32,27]	[-11,34]	[-23,6]	[2,35]	[-33,31]	[-24,29]	[-17,8]	[-121,4]	[-3,68]	[-141,-53]
Foreign country: France, 1961:01-2004:04															
$\gamma = 4$	145.76	62.97	82.78	-8.42	45.14	-53.56	-15.99	-3.33	-12.66	63.53	57.29	6.24	-84.87	-62.07	-22.79
	[39,173]	[11,62]	[20,109]	[-93,115]	[-52,139]	[-83,-4]	[-50,18]	[-32,17]	[-25,6]	[-19,128]	[-13,123]	[-11,13]	[-305,-30]	[-239,8]	[-120,-5]
$\gamma = 7$	105.92	35.89	70.03	-13.45	25.93	-39.37	-13.08	-2.06	-11.02	38.06	32.86	5.20	-17.45	7.38	-24.84
	[30,129]	[6,36]	[20,95]	[-62,63]	[-29,80]	[-58,-5]	[-34,8]	[-18,9]	[-19,3]	[-11,75]	[-7,70]	[-8,9]	[-152,15]	[-94,47]	[-104,-10]
$\gamma = 10$	84.68	25.06	59.62	-13.39	18.24	-31.64	-11.29	-1.56	-9.74	27.66	23.09	4.57	12.34	35.16	-22.82
	[25,106]	[4,25]	[18,83]	[-47,42]	[-20,56]	[-46,-6]	[-26,5]	[-13,6]	[-16,2]	[-7,53]	[-5,49]	[-6,7]	[-92,34]	[-35,63]	[-89,-9]
Foreign country: Germany, 1967:02-2004:04															
$\gamma = 4$	122.46	50.90	71.56	-18.10	41.65	-59.75	-5.62	4.64	-10.26	66.91	62.96	3.95	-65.66	-60.16	-5.50
	[25,143]	[3,52]	[10,99]	[-103,122]	[-49,140]	[-77,-1]	[-66,15]	[-54,18]	[-23,2]	[-6,111]	[-1,104]	[-14,12]	[-254,-1]	[-189,11]	[-109,6]
$\gamma = 7$	85.28	28.86	56.41	-16.92	24.28	-41.20	-5.13	2.62	-7.75	38.58	35.80	2.78	-1.80	8.44	-10.24
	[17,107]	[1,30]	[10,83]	[-68,67]	[-28,80]	[-52,-2]	[-39,7]	[-31,10]	[-16,1]	[-4,64]	[-1,59]	[-9,8]	[-126,34]	[-65,49]	[-91,0]
$\gamma = 10$	66.21	20.05	46.16	-14.16	17.33	-31.49	-4.61	1.82	-6.43	27.27	24.93	2.34	25.29	35.87	-10.58
	[13,88]	[1,20]	[9,71]	[-49,47]	[-19,56]	[-40,-2]	[-28,5]	[-22,7]	[-13,1]	[-3,45]	[-1,41]	[-7,6]	[-69,52]	[-16,64]	[-78,-1]

Notes: The table reports mean monthly total asset demands in percentages for domestic stocks, domestic 10-year government bonds, foreign stocks, foreign 10-year government bonds, and domestic 3-month Treasury bills for an investor with a unitary elasticity of intertemporal substitution, a discount factor equal to $0.92^{1/12}$, and coefficients of relative risk aversion (γ) equal to 4, 7, and 10. The table also reports the mean myopic and hedging demands for each asset class. Bootstrapped 68% confidence intervals for the mean asset demands are given in brackets.

Table 10 (continued)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Domestic stocks			Domestic bonds			Foreign stocks			Foreign bonds			Domestic bills		
CRRA	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand
Foreign country: Italy, 1952:04-2004:04															
$\gamma = 4$	169.43	77.64	91.79	-6.46	45.59	-52.04	8.26	4.71	3.55	41.14	54.04	-12.90	-112.37	-81.98	-30.39
	[106,202]	[44,79]	[59,128]	[-99,83]	[-59,115]	[-77,-7]	[-18,24]	[-18,18]	[-9,11]	[-24,81]	[-18,95]	[-29,-4]	[-287,-50]	[-220,9]	[-142,-16]
$\gamma = 7$	122.73	44.28	78.45	-8.42	26.07	-34.49	4.01	2.58	1.43	23.05	30.94	-7.90	-41.36	-3.88	-37.48
	[78,153]	[25,45]	[49,110]	[-60,46]	[-34,66]	[-52,-4]	[-12,15]	[-10,10]	[-7,7]	[-16,43]	[-11,54]	[-19,-1]	[-153,-6]	[-83,48]	[-126,-25]
$\gamma = 10$	98.25	30.94	67.31	-8.07	18.27	-26.34	1.69	1.73	-0.04	16.55	21.70	-5.15	-8.41	27.36	-35.78
	[64,127]	[17,32]	[40,94]	[-44,31]	[-24,46]	[-39,-3]	[-9,10]	[-7,7]	[-6,5]	[-10,31]	[-7,38]	[-14,-1]	[-95,16]	[-28,64]	[-110,-25]
Foreign country: United Kingdom, 1952:04-2004:04															
$\gamma = 4$	163.61	64.96	98.65	38.09	53.60	-15.51	57.63	21.38	36.25	17.76	39.82	-22.06	-177.10	-79.77	-97.33
	[94,187]	[33,72]	[56,126]	[-71,112]	[-64,119]	[-42,11]	[0,83]	[-11,34]	[5,50]	[-50,74]	[-22,89]	[-39,-7]	[-336,-87]	[-211,8]	[-170,-65]
$\gamma = 7$	125.07	37.13	87.94	22.13	30.72	-8.59	40.86	11.97	28.90	5.13	22.96	-17.83	-93.19	-2.77	-90.42
	[75,150]	[19,41]	[51,113]	[-41,67]	[-37,69]	[-29,10]	[2,58]	[-6,19]	[4,40]	[-34,39]	[-13,51]	[-33,-6]	[-196,-37]	[-78,47]	[-154,-63]
$\gamma = 10$	102.70	25.99	76.70	15.91	21.57	-5.66	31.00	8.20	22.81	2.02	16.22	-14.19	-51.64	28.02	-79.66
	[60,123]	[13,29]	[45,100]	[-29,47]	[-26,48]	[-22,9]	[1,45]	[-5,13]	[3,33]	[-27,27]	[-9,36]	[-27,-5]	[-130,-10]	[-25,63]	[-137,-56]

Table 11: Mean asset demands for investors in Australia, Canada, France, Germany, Italy, and the United Kingdom who can also invest in United States stocks and bonds

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Domestic stocks			Domestic bonds			Foreign stocks			Foreign bonds			Domestic bills		
CRRA	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand
Domestic country: Australia, 1952:04-2004:04															
$\gamma = 4$	75.42	49.22	26.20	50.28	31.83	18.45	142.81	60.94	81.87	-9.04	67.51	-76.54	-159.48	-109.50	-49.98
	[24,100]	[17,64]	[0,40]	[-46,126]	[-64,110]	[-14,39]	[52,158]	[15.61]	[30,102]	[-53,45]	[34,102]	[-109,-48]	[-280,-94]	[-215,-47]	[-110,-20]
$\gamma = 7$	44.29	28.16	16.14	26.79	17.13	9.66	100.97	34.6	66.36	-21.61	39.23	-60.85	-50.44	-19.13	-31.31
	[12,61]	[9,37]	[-2,27]	[-29,73]	[-38,62]	[-13,26]	[39,115]	[8,35]	[25,84]	[-54,14]	[20,59]	[-88,-38]	[-127,-12]	[-79,16]	[-77,-11]
$\gamma = 10$	29.72	19.73	9.99	14.97	11.26	3.71	79.38	24.07	55.31	-22.21	27.92	-50.13	-1.86	17.02	-18.88
	[6,43]	[6,26]	[-4,20]	[-24,49]	[-27,43]	[-13,18]	[31,92]	[6,24]	[21,70]	[-47,4]	[15,42]	[-75,-31]	[-61,25]	[-25,42]	[-57,-4]
Domestic country: Canada, 1952:04-2004:04															
$\gamma = 4$	-12.69	-10.54	-2.15	168.83	146.24	22.59	161.16	74.58	86.58	-270.70	-179.30	-91.41	53.40	69.01	-15.61
	[-73,41]	[-53,21]	[-32,31]	[47,251]	[23,221]	[-3,46]	[43,183]	[12,80]	[22,106]	[-379,-141]	[-259,-78]	[-139,-52]	[-137,112]	[-78,127]	[-83,1]
$\gamma = 7$	-6.72	-5.79	-0.93	102.19	83.63	18.55	110.8	42.26	68.54	-164.37	-102.64	-61.73	58.10	82.53	-24.43
	[-45,28]	[-30,12]	[-22,23]	[32,154]	[14,126]	[0,38]	[33,131]	[7,45]	[20,87]	[-242,-91]	[-148,-45]	[-105,-35]	[-60,92]	[-2,115]	[-76,-10]
$\gamma = 10$	-3.72	-3.89	0.17	72.70	58.59	14.11	83.51	29.33	54.18	-113.95	-71.97	-41.97	61.46	87.94	-26.49
	[-31,22]	[-21,9]	[-16,19]	[23,112]	[9,88]	[-1,31]	[25,102]	[5,32]	[15,72]	[-177,-63]	[-104,-31]	[-80,-23]	[-27,84]	[29,111]	[-69,-14]
Domestic country: France, 1961:01-2004:04															
$\gamma = 4$	-10.59	-1.14	-9.44	85.10	99.83	-14.73	109.18	50.08	59.10	-98.47	-45.60	-52.87	14.78	-3.16	17.94
	[-42,23]	[-31,16]	[-19,10]	[-37,192]	[-43,206]	[-33,5]	[-2,114]	[-4,49]	[1,67]	[-153,-14]	[-92,8]	[-76,-17]	[-162,77]	[-176,74]	[-29,23]
$\gamma = 7$	-8.32	-0.71	-7.61	48.51	57.40	-8.89	75.63	28.64	46.99	-66.74	-26.20	-40.53	50.92	40.88	10.04
	[-27,14]	[-18,9]	[-14,7]	[-20,109]	[-24,118]	[-21,5]	[2,82]	[-2,28]	[2,54]	[-103,-14]	[-53,5]	[-60,-14]	[-51,84]	[-58,85]	[-24,13]
$\gamma = 10$	-6.77	-0.54	-6.23	34.11	40.43	-6.32	58.38	20.06	38.32	-50.85	-18.44	-32.41	65.12	58.49	6.63
	[-20,10]	[-12,7]	[-11,6]	[-14,77]	[-17,82]	[-16,4]	[2,65]	[-2,20]	[2,45]	[-78,-12]	[-37,3]	[-49,-11]	[-8,88]	[-10,90]	[-20,10]
Domestic country: Germany, 1967:02-2004:04															
$\gamma = 4$	14.65	6.86	7.79	201.53	223.50	-21.97	110.78	42.63	68.15	-104.53	-37.28	-67.26	-122.43	-135.71	13.28
	[-49,27]	[-52,16]	[-9,20]	[47,279]	[41,290]	[-50,13]	[-1,110]	[-6,42]	[-5,74]	[-155,8]	[-81,27]	[-91,-16]	[-268,-23]	[-265,-18]	[-54,26]
$\gamma = 7$	7.99	3.99	4.00	116.64	126.80	-10.16	78.31	24.33	53.99	-72.36	-21.31	-51.05	-30.58	-33.81	3.22
	[-30,16]	[-29,9]	[-7,13]	[27,160]	[25,167]	[-30,12]	[1,81]	[-3,25]	[-3,59]	[-107,-1]	[-46,16]	[-71,-12]	[-115,30]	[-108,33]	[-45,16]
$\gamma = 10$	5.03	2.84	2.18	82.67	88.11	-5.44	61.17	17.00	44.17	-55.76	-14.92	-40.84	6.89	6.96	-0.07
	[-21,12]	[-20,6]	[-6,9]	[17,112]	[16,116]	[-21,12]	[0,64]	[-2,17]	[-2,49]	[-82,-3]	[-32,11]	[-58,-10]	[-55,50]	[-45,54]	[-38,10]

Notes: The table reports mean monthly total asset demands in percentages for domestic stocks, domestic 10-year government bonds, foreign stocks, foreign 10-year government bonds, and domestic 3-month Treasury bills for an investor with a unitary elasticity of intertemporal substitution, a discount factor equal to $0.92^{1/12}$, and coefficients of relative risk aversion (γ) equal to 4, 7, and 10. The table also reports the mean myopic and hedging demands for each asset class. Bootstrapped 68% confidence intervals for the mean asset demands are given in brackets.

Table 11 (continued)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Domestic stocks			Domestic bonds			Foreign stocks			Foreign bonds			Domestic bills		
CRRA	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging demand	Total demand	Myopic demand	Hedging Demand
Domestic country: Italy, 1952:04-2004:04															
$\gamma = 4$	3.26	5.00	-1.74	59.66	78.57	-18.91	126.25	64.07	62.18	-100.43	-53.56	-46.87	11.27	5.92	5.35
	[-23,21]	[-16,19]	[-12,5]	[-64,142]	[-77,181]	[-54,1]	[-62,144]	[27,67]	[29,80]	[-158,-42]	[-101,-5]	[-70,-29]	[-141,81]	[-173,95]	[-40,28]
$\gamma = 7$	0.24	2.92	-2.68	32.87	44.93	-12.06	88.90	36.35	52.55	-68.70	-30.28	-38.42	46.69	46.08	0.61
	[-15,11]	[-9,11]	[-10,3]	[-37,80]	[-44,104]	[-35,1]	[44,103]	[15,38]	[24,66]	[-105,-33]	[-58,-3]	[-56,-25]	[-41,85]	[-56,97]	[-31,16]
$\gamma = 10$	-1.17	2.09	-3.26	22.50	31.47	-8.98	70.56	25.26	45.30	-53.59	-20.96	-32.63	61.71	62.14	-0.43
	[-12,7]	[-6,8]	[-9,2]	[-26,54]	[-31,73]	[-27,1]	[35,82]	[10,27]	[21,56]	[-81,-27]	[-40,-2]	[-48,-21]	[1,89]	[-10,98]	[-25,11]
Domestic country: United Kingdom, 1952:04-2004:04															
$\gamma = 4$	80.43	24.44	56.00	131.34	113.69	17.65	134.35	52.63	81.73	-104.36	-44.06	-60.29	-141.77	-46.69	-95.08
	[0,92]	[-13,36]	[11,60]	[-37,220]	[-65,215]	[-16,33]	[63,146]	[16,59]	[33,90]	[-163,-62]	[-109,-12]	[-81,-35]	[-287,13]	[-215,87]	[-142,-36]
$\gamma = 7$	60.58	14.42	46.17	80.50	65.40	15.10	102.43	30.13	72.30	-77.66	-25.96	-51.71	-65.85	16.01	-81.86
	[4,69]	[-7,21]	[8,49]	[-16,131]	[-35,125]	[-12,27]	[48,111]	[9,33]	[31,80]	[-113,-48]	[-64,-7]	[-69,-30]	[-151,33]	[-79,93]	[-122,-32]
$\gamma = 10$	47.84	10.41	37.43	57.47	46.08	11.39	83.91	21.13	62.78	-63.00	-18.72	-44.28	-26.22	41.09	-67.32
	[4,54]	[-5,15]	[6,40]	[-10,93]	[-24,89]	[-13,19]	[38,91]	[7,24]	[26,69]	[-89,-40]	[-45,-5]	[-59,-25]	[-89,48]	[-25,95]	[-100,-25]

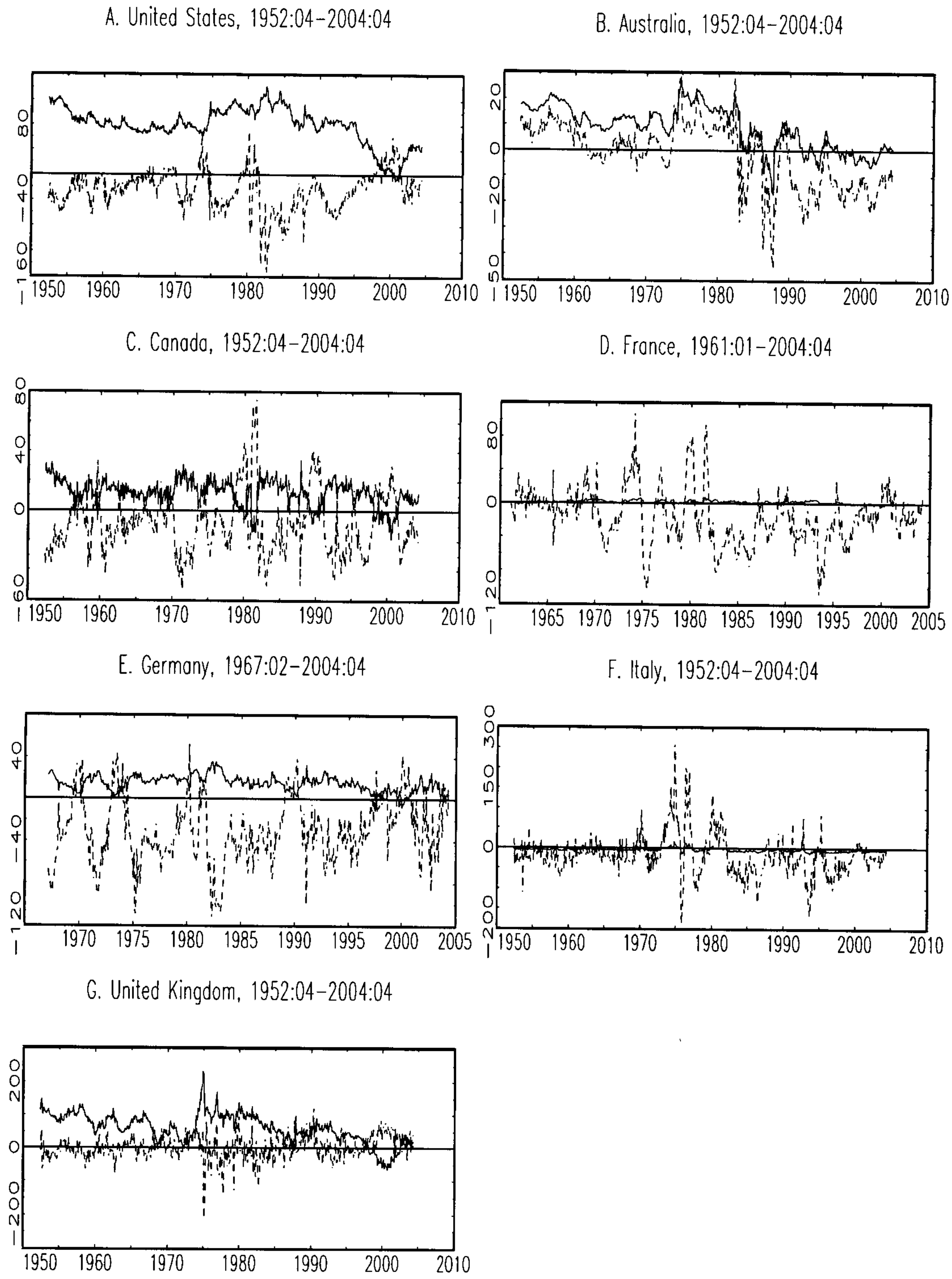

Figure 1: Historical intertemporal hedging demands for domestic stocks (solid lines) and bonds (dashed lines) for investors in different countries when $\gamma = 7$.

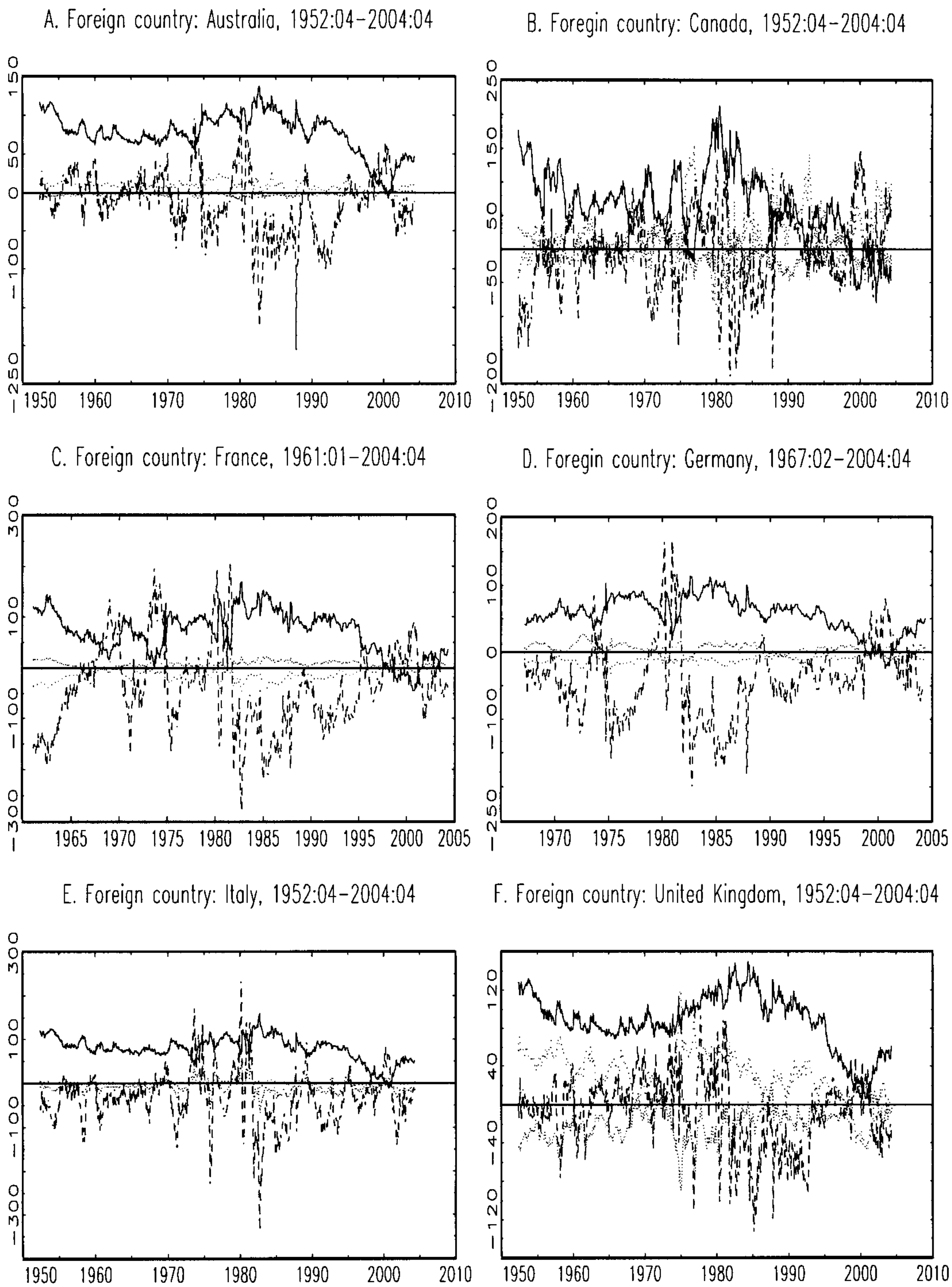

Figure 2: Historical intertemporal hedging demands for domestic stocks (solid lines), domestic bonds (dashed lines), foreign stocks (dotted lines), and foreign bonds (closely spaced dotted lines) for an investor in the United States who can also invest in foreign stocks and bonds when $\gamma = 7$.

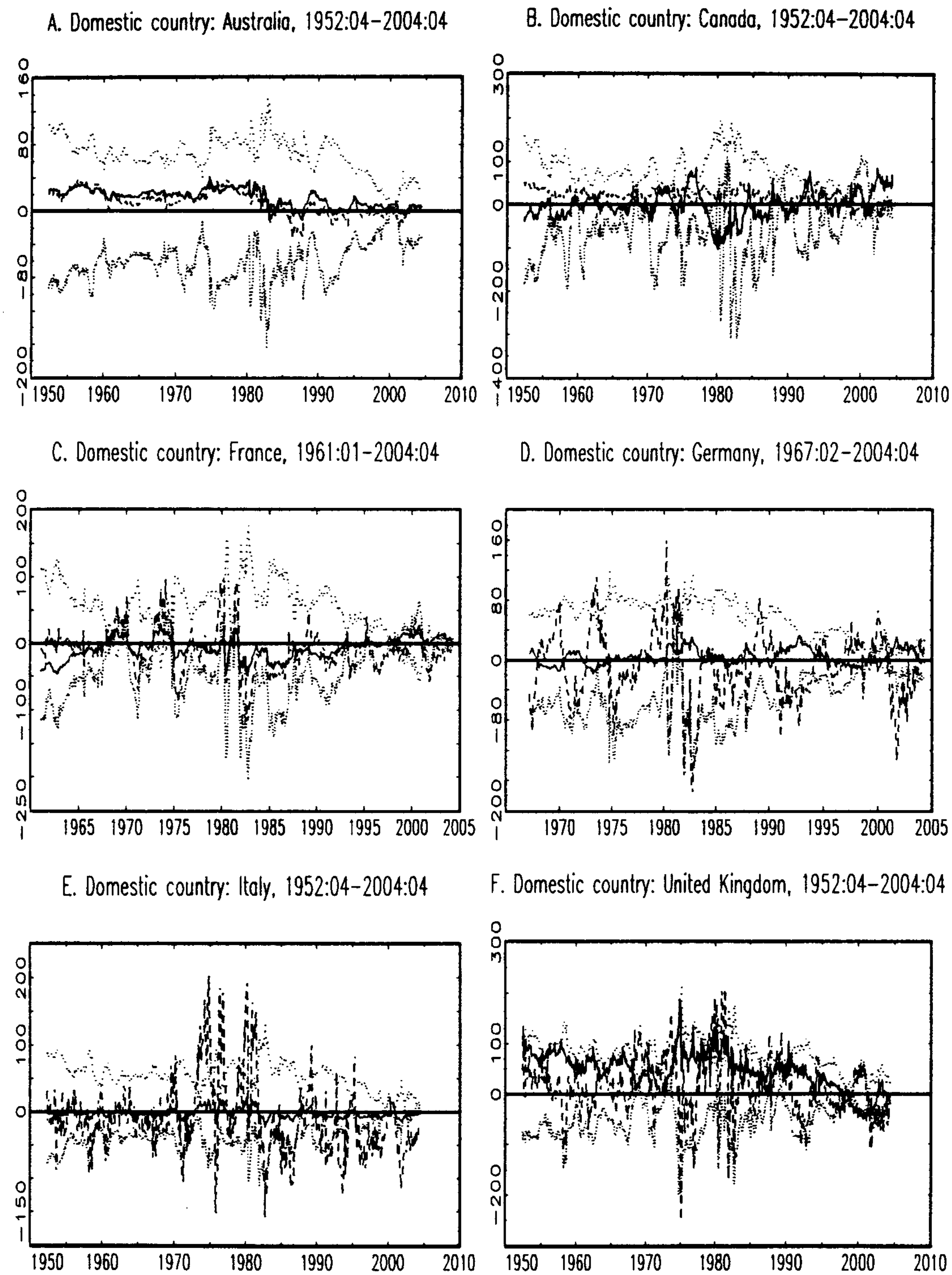

Figure 3: Historical intertemporal hedging demands for domestic stocks (solid lines), domestic bonds (dashed lines), foreign stocks (dotted lines), and foreign bonds (closely spaced dotted lines) for investors in Australia, Canada, France, Germany, Italy, and the United Kingdom who can also invest in United States stocks and bonds when $\gamma = 7$.