Multi-Period Portfolio Choice and the Intertemporal Hedging Demands for Stocks and Bonds: International Evidence

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Abstract

In this paper, we investigate the intertemporal hedging demands for stocks and bonds for investors in the U.S., Australia, Canada, France, Germany, Italy, and U.K. Employing the recently developed methodology of Campbell, Chan, and Viceira (2003), we solve a multi-period portfolio choice problem 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 who can invest in domestic bills, stocks, and bonds, where the dynamics governing asset returns are described by a vector autoregressive process. Most notably, we find sizable mean intertemporal hedging demands for domestic stocks in the U.S. and U.K. and considerably smaller mean hedging demands for stocks in the other countries. 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 sizable mean intertemporal hedging demands for U.S. stocks, while the mean hedging demands for foreign stocks and bonds are limited. In another multi-period portfolio choice problem, 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 mean intertemporal hedging demands for U.S. stocks. We augment the Campbell, Chan, and Viceira (2003) approach with a parametric bootstrap procedure to compute 90% confidence intervals for the estimated mean asset demands. While the confidence intervals are often quite wide, the mean intertemporal hedging demands for U.S. stocks are consistently significant according to the 90% confidence intervals. Overall, our results point to important intertemporal hedging demands for U.S. stocks.

JEL classifications: C32, G11

Key words: Intertemporal hedging demand; Multi-period portfolio choice problem; Parametric bootstrap; Return predictability
1. Introduction

There has been a recent resurgence of interest in portfolio choice problems. In particular, the body of empirical evidence accumulated over the last two decades indicating that stock and bond returns have important predictable components has reinvigorated interest in multi-period portfolio choice problems. As initially recognized by Samuelson (1969) and Merton (1969, 1971), return predictability has potentially important implications for multi-period portfolio choice problems. More specifically, return predictability can give rise to intertemporal hedging demands for assets, so that—in contrast to the canonical static portfolio choice problem of 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. 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

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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.

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 multi-period portfolio choice 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 in real bill returns, excess stock returns, excess bond returns, as well as the nominal bill yield, dividend yield, and term spread. A number of studies find that the latter three variables have predictive ability with respect to stock and bond returns.\(^4\) CCV 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 important 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

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\(^3\) 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.

domestic investments in U.S. assets. In the present paper, we extend the extant empirical literature and use the CCV approach to analyze dynamic asset allocation across domestic bills, stocks, and bonds for investors in Australia, Canada, France, Germany, Italy, and the U.K., as well as the U.S. As in 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. Using a set of plausible assumed values for the parameters relating to intertemporal preferences—including CRRA values of 4, 7, and 10—we use the CCV approach to estimate the 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 90% 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 a multi-period portfolio choice problem 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 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.\footnote{Ang and Bekaert (2002) consider a multi-period portfolio choice problem where an investor in the U.S. can invest in domestic stocks as well as stocks from one or two foreign countries. Unlike most of the literature, Ang and Bekaert (2002) do not characterize return predictability using a VAR(1) process that includes instruments such as the dividend yield but instead use a Markov-switching process for the moments of the returns. Also see Campbell, 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.} 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. 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 sizable mean intertemporal hedging demands for domestic stocks for investors in the U.S. and U.K., while the mean hedging demands for domestic stocks are decidedly smaller for investors in Australia, Canada, France, Germany, and Italy. When an investor in the U.S. has access to foreign stocks and bonds, in addition to domestic bills, stocks, and bonds, the mean intertemporal hedging demands for domestic stocks remain sizable; in contrast, with the exception of U.K. stocks, the mean hedging demands for foreign stocks and bonds are small for 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 mean intertemporal hedging demands for U.S. stocks. The 90% confidence intervals show that sampling uncertainty can make it difficult to estimate asset demands with precision. Nevertheless, the estimated mean intertemporal hedging demands for U.S. stocks are consistently significant according to the confidence intervals. Overall, we discover important similarities and differences in the optimal intertemporal hedging demands for stocks and bonds across countries, and our results point to especially important intertemporal hedging demands for U.S. stocks. We also discuss how the excess stock return-dividend yield relationship in the U.S. helps to explain the sizable intertemporal hedging demands for U.S. stocks by investors in different countries.

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.⁶ 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 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. Multi-Period Portfolio Choice Problem

In this subsection, we outline the multi-period portfolio choice problem faced by the investor. Details are provided in Section 2 of CCV. The investor has access to $n$ risky assets. Let $R_{1,t+1}$ be the real

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⁶ 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.
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.\(^7\) The real return on the investor’s portfolio (\( R_{p,t+1} \)) can be expressed as

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

(1)

where \( \alpha_{i,t} \) is the portfolio weight on asset \( i \) at time \( t \).\(^8\) Letting \( r_{t+1} = \log(R_{t+1}) \), 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 \( s_{t+1} \) comprises the state variables. The \( m \)-vector of state variables is given by

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

(2)

As in a number of other studies,\(^9\) 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

\[
z_{t+1} = \Phi_0 + \Phi_1 z_t + v_{t+1},
\]

(3)

where \( \Phi_0 \) is an \( m \)-vector of VAR intercepts; \( \Phi_1 \) 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 \( N(0_{m \times 1}, \Sigma_v) \). The variance-covariance matrix \( \Sigma_v \) can be partitioned such that

\[
\Sigma_v = \begin{bmatrix}
\sigma_i^2 & \sigma_{1x}' & \sigma_{1x}' \\
\sigma_{1x} & \Sigma_{xx} & \Sigma_{xs}' \\
\sigma_{1x} & \Sigma_{xs} & \Sigma_{ss}
\end{bmatrix},
\]

(4)

where \( \sigma_i^2 \) is the variance of the innovation to the benchmark asset return; \( \sigma_{1x} \) is an \((n-1)\)-vector of covariances between innovations to the benchmark asset return and innovations to the excess returns on

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\(^7\) While we follow CCV and use a 3-month Treasury bill as the benchmark asset, the designation of the benchmark asset is arbitrary.

\(^8\) The portfolio weight on the benchmark asset at time \( t \) is \( 1 - \sum_{i=2}^{n} \alpha_{i,t} \).

the remaining assets; \( \sigma_{1s} \) is an \((m-n)\)-vector of covariances between innovations to the benchmark asset return and innovations to the instruments; \( \Sigma_{xx} \) is the \((n-1) \times (n-1)\) variance-covariance matrix for the innovations to the excess returns; \( \Sigma_{ss} \) is the \((m-n) \times (n-1)\) matrix of covariances between innovations to the excess returns and innovations to the instruments; \( \Sigma_{ss} \) 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.\(^{10}\)

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

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

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.\(^{11}\) 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 \( \alpha_t = [\alpha_{2,t}, \ldots, \alpha_{n,t}]' \) in order to maximize equation (5), using all available information at time \( t \), subject to the intertemporal budget constraint,

\[
W_{t+1} = (W_t - C_t) R_{t+1},
\]

where \( W_t \) is wealth at time \( t \).

\(^{10}\) Assuming that the vector of VAR innovations is homoskedastic is standard in much of the literature, such as the studies cited in footnote 9 above. Chacko and Viceira (2003) solve a multi-period portfolio choice problem with stochastic volatility.

\(^{11}\) 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.
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 log real return on the portfolio. This approximation is exact in continuous time, and CCV observe that it is highly accurate for short time intervals.\textsuperscript{12} CCV also employ first- and second-order log-linear approximations of the budget constraint and Euler equation, respectively. These approximations are exact when $\psi = 1$, so that the solution to the approximate model is appropriate when $\psi$ is near unity. CCV show that the solution to the approximate model can be expressed in terms of policy functions for $\alpha_t$ and $c_t - w_t$, where $c_t$ and $w_t$ are the log-levels of $C_t$ and $W_t$:

$$\alpha_t = A_0 + A_1 z_t,$$

$$c_t - w_t = B_0 + B_1 z_t + z_t' B_2 z_t,$$

where $A_0 \ [ (n-1) \times 1 ]$, $A_1 \ [ (n-1) \times m ]$, $B_0 \ [ 1 \times 1 ]$, $B_1 \ [ m \times 1 ]$, and $B_2 \ [ m \times m ]$ are coefficient matrices that are constant through time and functions of $\gamma$, $\psi$, $\delta$, $\rho$, $\Phi_0$, $\Phi_1$, and $\Sigma_v$, where $\rho = 1 - \exp[E(c_t - w_t)]$.\textsuperscript{13} CCV use an iterative numerical procedure to compute estimates of $A_0$, $A_1$, $B_0$, $B_1$, and $B_2$; the procedure is described in detail in Campbell, Chan, and Viceira (2002). We are primarily interested in the estimates of the parameters in equation (7), which govern the investor’s optimal asset allocations.

In our applications in Section 3 below, we use the CCV approach to estimate equations (7) and (8) for an 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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\textsuperscript{12} Our use of monthly data in Section 3 below should help to ensure the accuracy of the approximation in our empirical applications. While the CCV framework does not impose borrowing or short-sales constraints, the approximation to the log real return on the portfolio used by CCV has the effect of ruling out the possibility of bankruptcy; see Campbell and Viceira (2002, pp. 28-29).

\textsuperscript{13} 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.
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 $z_{t+1} = [rtbr_{t+1}, xsr_{t+1}, xbr_{t+1}, bill_{t+1}, div_{t+1}, spread_{t+1}]’$. We assume $\delta = 0.92$ on an annual basis (so that the discount factor equals $0.92^{1/12}$ on a monthly basis) and $\psi = 1$, and we estimate the VAR parameters in equation (3) using maximum likelihood. We consider three values for $\gamma$: 4, 7, and 10. These $\gamma$ values are similar to those considered in other studies, 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 $\gamma$ value using $\alpha = \hat{A}_0 + \hat{A}_1 \bar{z}$, where $\hat{A}_0$ and $\hat{A}_1$ are the estimates of $A_0$ and $A_1$, respectively, in equation (7) obtained using the CCV numerical procedure and $\bar{z} = \sum_{t=1}^{T} z_t$, where $T$ is the number of available sample observations for the state vector.

We are especially interested in the intertemporal hedging demands for the various assets. CCV derive the following result that is useful for dividing the total demand into its myopic and intertemporal hedging components, following Merton (1969, 1971):

$$A_0 = (1/\gamma)\Sigma_x^{-1}[H_x \Phi_0 + 0.5\sigma_x^2 + (1-\gamma)\sigma_{1x}] + [1 - (1/\gamma)]\Sigma_x^{-1}[-\Lambda_0/(1-\psi)], \quad (9)$$

$$A_1 = (1/\gamma)\Sigma_x^{-1}H_x \Phi_1 + [1 - (1/\gamma)]\Sigma_x^{-1}[-\Lambda_1/(1-\psi)], \quad (10)$$

14 When $\psi = 1$, the optimal consumption-wealth ratio is constant (Giovannini and Weil, 1989), and this assumption slightly simplifies the numerical procedure. In their empirical applications, CCV note that the solutions to problems with $\psi = 0.5$ are similar to the solutions to problems with $\psi = 1$.

15 OLS estimation of $\Phi_0$ and $\Phi_1$ in equation (3) is equivalent to maximum likelihood estimation.

16 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 $\gamma = 4$. 
where $H_x = [0_{(n-1)\times 1}, I_{n-1}, 0_{(n-1)\times (n-m)}]$ is a matrix that selects $x_i$ from the state vector $z_i$; $\sigma_x^2$ is the vector of diagonal elements in $\Sigma_{xx}$; $\Lambda_0$ and $\Lambda_1$ are matrices that depend on $B_0$, $B_1$, and $B_2$, as well as $\gamma$, $\psi$, $\delta$, $\rho$, $\Phi_0$, $\Phi_1$, and $\Sigma_\nu$. The first term on the right-hand-side (RHS) of equations (9) and (10) 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 (9) and (10) 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 (9) and (10) 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 ($\Phi_1$) is a zero matrix—so that there is no return predictability—the second term on the RHS of each equation will also vanish. 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.

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.

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17 CCV observe that $\Lambda_0$ and $\Lambda_1$ are zero matrices when $\Phi_1$ is a zero matrix, so that the second term on the RHS of equations (9) and (10) vanishes.

18 Actually, an additional condition needs to be satisfied: the variance-covariance matrix for the VAR innovations, $\Sigma_\nu$, 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.
2.2. Parametric Bootstrap Procedure

Apparently due to computational costs, most extant studies (including CCV) report only point estimates of asset demands. To get a sense of the sampling uncertainty associated with the point estimates of the mean total, myopic, and hedging demands for each asset in each country, we construct 90% confidence intervals for the mean demands using a parametric bootstrap procedure. We assume that the state vector \( z_{t+1} \) is generated by equation (3), where the parameters of the VAR are set to their maximum-likelihood estimates. In order to generate a series of innovations to use in constructing a pseudo-sample of observations for \( z_t \), we make \( T + 100 \) independent draws from a \( N(0_{m+1}, \hat{\Sigma}_v) \) 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 CCV approach to estimate equations (7) and (8) and the mean total, myopic, and hedging demands for each asset. We repeat this process 500 times, giving us an empirical distribution for each of the mean asset demands. We construct 90% confidence intervals for each mean asset demand from the empirical distributions using the percentile method described in Davidson and MacKinnon (1993, p. 766).

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.\(^\text{19}\) The sample ends in 2004:05 for each country. We measure the log real return on a 3-month

\(^{19}\) 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.
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. 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 bill yield is the yield on a 3-month Treasury bill, and the term spread is the difference between the yields on a 10-year government bond and 3-month Treasury bill.

Table 1 reports summary statistics (mean, standard deviation, first-order autocorrelation coefficient) for the three risky asset returns and three instruments for each of the seven countries. 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 return for the U.S., Australia, and U.K. is between 5% and 6%. Canada, Germany, and France exhibit lower mean excess stock returns, while Italy has the lowest mean excess stock return of 1.89%. The mean excess bond returns range from 0.92% to 2.63%. The mean excess bond return is lower than the mean excess stock return for each country, although the mean excess stock return is less than 1 percentage point higher than the mean excess bond return for France, Germany, and Italy. For all seven 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 return for each country.

The U.S., Australia, and U.K. have the highest Sharpe ratios for excess stock returns (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. Note that the Sharpe

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20 Due to data availability, we use the wholesale price index for Australia.
21 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.
22 Names and descriptions of the Global Financial Data files used to construct all of the variables are provided in an on-line data appendix.
ratio for excess stock returns is approximately 1.5 to 2.5 times higher 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 equal, the Sharpe ratios lead us to expect a higher 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 seven countries (first-order autocorrelation coefficients between 0.03 and 0.12). Excess bond returns typically appear more persistent than excess stock returns, with Italy and the U.K. displaying the most persistent excess bond returns. The real bill return is 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. Domestic Asset Demands for Investors in Different Countries

Table 2 reports the mean total, myopic, and intertemporal hedging demands (in percentages) for domestic bills, stocks, and bonds and $\gamma$ values of 4, 7, and 10 in each country generated using the CCV approach. Table 2 also reports 90% 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 mean total and intertemporal hedging demands for stocks for each reported $\gamma$ value. As we would expect, the mean total demand for stocks—the most risky asset—decreases as $\gamma$ increases. While the mean hedging demand for stocks also decreases as $\gamma$ increases, the mean hedging demand for stocks as a share of the total demand actually increases as $\gamma$ increases. 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 $\gamma$ value, so that the investor typically shorts bills. The results in Table 2 for the mean hedging demands for stocks 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 2 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 2 (and in CCV) is the substantial mean 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, 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 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. 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.

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23 See, for example, the discussion in Brandt (2004, Section 2.2.1).
24 To conserve space, we do not report the complete VAR estimation results.
25 Furthermore, $div_t$ is a persistent process so that there will be a persistent increase in the expected dividend yield, leading to a persistent increase in expected excess stock returns.
As a cautionary note, observe that the 90% confidence intervals for the mean asset demands tend to be quite wide for the U.S. in Table 2, 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. Of course, substantial sampling uncertainty can be a problem in general with regard to asset allocation problems; see, for example, Brandt (2004, Section 3.1.2). Nevertheless, it is important to observe that while many of the confidence intervals for the U.S. are quite wide in Table 2, the 90% confidence intervals for the mean hedging demands for stocks are tight enough to conclude that the mean hedging demands for stocks are significant and large in the U.S. for the reported $\gamma$ values. However, we cannot reject the null hypothesis that the mean hedging demands for bonds are zero according to the 90% confidence intervals.

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 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 2, 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 also much smaller than the corresponding demands in the U.S., and the 90% 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 closer to zero than in the U.S. As in the U.S., the 90% confidence intervals for the mean hedging demands for bonds do not indicate rejection of the null hypothesis of zero mean hedging demands.
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 2 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 stocks and bonds in Canada according to the 90% confidence intervals. Panel C of Figure 1 shows that the hedging demand for bonds is much more volatile than the hedging demand for stocks in Canada when $\gamma = 7$.

With respect to the results for France in Table 2, the mean total and hedging demands for stocks are much smaller in magnitude than those in any country, with the exception of Italy, and we clearly cannot reject the null hypothesis that the mean total and hedging demands for stocks are zero in France according to the 90% 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 we cannot reject the null hypothesis of zero mean total and hedging demands for bonds in France. 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 and hedging demands for stocks in Germany in Table 2 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. We cannot reject the null hypothesis of zero mean hedging demands for stocks and bonds in Germany. 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 $\gamma = 7$.

The mean total demands for stocks in Italy in Table 2 are even lower than those in France, and the mean hedging demands for stocks are also very small in magnitude in Italy. Not surprisingly, we cannot
reject the null hypothesis that the mean total and hedging demands for stocks are zero in Italy according to the 90% confidence intervals. The mean hedging demands for bonds in Italy are similar to, although slightly smaller in magnitude than, those in the U.S., and as in the U.S., we cannot reject the null hypothesis of zero mean hedging demands for bonds. 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 2 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 substantial. According to the 90% confidence intervals, it is reasonable to conclude that, as in the U.S., the mean hedging demands for stocks in the U.K. are significant 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 according to the 90% 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.

We next discuss some of the factors contributing to the smaller intertemporal hedging demands for domestic stocks in some countries 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, the coefficients on the lagged dividend yield in the excess stock return equations are the smallest for France and Italy, limiting the hedging ability of the dividend yield in France and Italy and thereby contributing further to the weak hedging demands for stocks in these two countries relative to the U.S.

Recall from Table 1 that the Sharpe ratio for stocks in the U.K. is relatively large. The coefficient on the lagged dividend yield in the excess stock return equation is also large relative to the other countries, and innovations to excess stock returns and the dividend yield are strongly negatively correlated (-0.79). These factors help to explain why, like the U.S., there are sizable hedging demands for domestic stocks in the U.K.

3.3. 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 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.\(^\text{26}\) 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

\[
z_{t+1} = \begin{bmatrix} rtbr_{t+1}, xsr_{t+1}, xbr_{t+1}, xbr^*_t, xsr^*_t, bill^*_{t+1}, div^*_{t+1}, spread^*_{t+1}, bill^*_{t+1}, div^*_{t+1}, spread^*_{t+1} \end{bmatrix}. \tag{11}
\]

\(^{26}\) 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, and \( \psi = 1 \). We again consider \( \gamma \) values of 4, 7, and 10 and use the CCV numerical procedure to estimate the asset demands. The mean asset demands, along with 90% confidence intervals (generated using a suitably modified version of the parametric bootstrap procedure described in Section 2.2 above), are reported in Table 3.\(^{27}\)

A number of results stand out in Table 3. First, an investor in the U.S. continues to have substantial mean total and intertemporal 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 sizable mean total and hedging demands for domestic stocks. While the confidence intervals are again generally quite wide in Table 3, the hedging demands for domestic stocks are significant according to the 90% confidence intervals when Australia, Canada, France, Italy, or the U.K. serves as the foreign country. We also see fairly large negative intertemporal hedging demands for domestic bonds when France, Germany, or Italy is the foreign country, although these demands are not significant according to the 90% confidence intervals. It is interesting to note that, with the possible exceptions of Canadian stocks and U.K. stocks and bonds, the intertemporal hedging demands for the foreign assets are quite small in magnitude. In no case can we reject the null hypothesis of zero mean hedging demands for foreign stocks and bonds according to the 90% confidence intervals, although the mean intertemporal hedging demands for foreign stocks are nearly significantly positive when the U.K. serves as the foreign country.

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 those for the U.S. in Panel A of Figure 1. We see that

\(^{27}\) In order to conserve space, we do not report the summary statistics or complete VAR estimation results for these models.
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.

The sizable intertemporal hedging demands for domestic stocks for U.S. investors who also have access to foreign stocks and bonds can again be explained to a large extent by the relatively high Sharpe ratio for U.S. stocks in conjunction with the relationship between excess stock returns and the dividend yield. The high Sharpe ratio makes domestic stocks attractive to U.S. investors, while the positive effect of the lagged dividend yield on excess stock returns and the strong negative correlation between innovations to excess stock returns and the dividend yield make domestic stocks a good hedge against themselves. This creates a strong intertemporal hedging demand for domestic stocks for investors in the U.S., and the strong hedging demand for domestic stocks is evident whether or not an investor in the U.S. has access to foreign stocks and bonds.

One way to quantify the gains from international diversification is to compute the expected value of the value function per unit of wealth, which is readily available using the CCV approach; see Campbell, Chan, and Viceira (2002). For a CRRA equal to 7, an investor in the U.S. who invests in domestic assets alone would require the following factor increases in wealth in order to enjoy the same utility as she realizes when she can invest in both domestic assets and asset from a foreign country: Australia, 2.47; Canada, 7.63; France, 3.00; Germany, 2.53; Italy, 3.26; U.K., 4.89.

3.4. 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. 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 4 reports the mean asset demands and corresponding 90% confidence intervals (again generated using a suitably modified parametric bootstrap procedure) for \( \gamma \) values of 4, 7, and 10.

A number of results stand out in Table 4. With the exception of the U.K., the mean intertemporal hedging demands for domestic stocks are fairly small in magnitude in all of the countries. According to the 90% confidence intervals, we cannot reject the null hypothesis that the mean hedging demands for domestic stocks are zero in Australia, Canada, France, Germany, and Italy. A similar situation holds with respect to the mean intertemporal hedging demands for domestic bonds, and although these demands are typically larger in magnitude than the mean hedging demands for domestic stocks, we cannot reject the null hypothesis that the mean hedging demands for domestic bonds are zero for any country. The only case where we see a sizable and significant mean hedging demand for a domestic asset is domestic stocks in the U.K.

While the mean intertemporal hedging demands for domestic assets are typically small in Table 4, the mean hedging demands for U.S. stocks are substantial. The mean hedging demands for U.S. stocks are significant according to the 90% confidence intervals in Australia, Canada, Italy, and the U.K. There are also sizable and sometimes significant mean hedging demands for U.S. bonds. Overall, the results in Table 4 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 4. The largest

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28 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.

29 Again in order to conserve space, we do not report summary statistics or the complete VAR estimation results for these models.
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.

What accounts for the sizable intertemporal hedging demand for U.S. stock that emerges when investors in Australia, Canada, France, Germany, Italy, and the U.K. have access to U.S. stocks and bonds? In the previous two subsections, we have discussed how the high Sharpe ratio for U.S. stocks, together with the relationship between U.S. excess stock returns and the dividend yield, create sizable intertemporal hedging demands for domestic stocks for investors in the U.S. When investors outside the U.S. have access to U.S. stocks, the relatively high (local-currency) Sharpe ratio for U.S. stocks makes U.S. stocks relatively attractive to these investors. From the standpoint of investors outside the U.S., there is again a positive relationship between the lagged U.S. dividend yield and excess U.S. stock returns and a strong negative correlation between innovations to U.S. excess stocks returns and the U.S. dividend yield, making U.S. stocks an attractive hedge. All of this creates a strong intertemporal hedging demand for U.S. stocks for investors outside the U.S.

We can again quantify the gains from international diversification using the expected value of the value function per unit of wealth. For a CRRA equal to 7, an investor in a given country who invests in domestic assets alone would require the following factor increases in wealth in order to enjoy the same utility as she realizes when she can invest in both domestic and U.S. assets: Australia, 7.50; Canada, 9.08; France, 4.00; Germany, 4.09; Italy, 4.00; U.K., 7.52. Note that these factors are larger than the corresponding factors reported in Section 3.3 above, implying that investors outside the U.S. have more to gain by having access to U.S. stocks and bonds than U.S. investors do by having access to foreign stocks and bonds.

4. Conclusion

In this paper, we investigate 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. When we analyze allocations across domestic bills, stocks, and bonds for
investors in each country, the sizable mean 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., she continues to have sizable mean hedging demands for U.S. stocks, and the only foreign asset for which she exhibits relatively large 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 substantial intertemporal hedging demands for U.S. stocks. The excess stock return-dividend yield relationship in the U.S. helps to account for the strong intertemporal hedging demands for U.S. stocks. Overall, our results indicate that U.S. stocks provide especially attractive intertemporal hedging instruments for international investors with Epstein-Zin-Weil preferences and infinite horizons.

Finally, we suggest some areas for future research. First, it would be useful to investigate methods for obtaining more efficient estimates of asset demands, as our parametric bootstrap procedure shows that confidence intervals for the estimated asset demands generated by the CCV approach can be quite wide. In addition, 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.30 Another area 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, while in practice there is considerable uncertainty surrounding the parameters of the data-generating process.31 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

30 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.

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. Further advances in solving complex portfolio choice problems could provide additional insights to international investors with long horizons.
References


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

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<td>Sharpe ratio</td>
<td>Mean</td>
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<td>1.98</td>
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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)]. $\rho_1$ is the first-order autocorrelation coefficient.
Table 2: Mean demands for domestic assets for investors in different countries

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<th>CRRA</th>
<th>Stocks</th>
<th>Bonds</th>
<th>Bills</th>
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<tbody>
<tr>
<td></td>
<td>Total demand</td>
<td>Myopic demand</td>
<td>Hedging demand</td>
</tr>
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</table>

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 $0.92^{1/2}$, and coefficients of relative risk aversion ($\gamma$) equal to 4, 7, and 10. The table also reports the mean myopic and hedging demands for each asset class. Bootstrapped 90% confidence intervals for the mean asset demands are given in brackets. A bold entry indicates significance according to the 90% confidence interval.
Table 2 (continued)

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<th>Bonds</th>
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<td>Myopic Demand</td>
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<td>Hedging demand</td>
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<tr>
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<td>72.15</td>
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</table>
Table 3: Mean asset demands for an investor in the United States who can also invest in foreign stocks and bonds

| CRRA | Domestic stocks | | | | Foreign stocks | | | | Foreign bonds | | | | Domestic bills |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 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 |
| $\gamma = 4$ | | | | | | | | | | | | | | | |
| | 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 |
| $\gamma = 7$ | | | | | | | | | | | | | | | |
| | 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 |
| $\gamma = 10$ | | | | | | | | | | | | | | | |

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, and coefficients of relative risk aversion ($\gamma$) equal to 4, 7, and 10. The table also reports the mean myopic and hedging demands for each asset class. Bootstrapped 90% confidence intervals for the mean asset demands are given in brackets. A bold entry indicates significance according to the 90% confidence interval.
Table 3 (continued)

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Table 4: 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

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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 $0.92^{12}$, and coefficients of relative risk aversion ($\gamma$) equal to 4, 7, and 10. The table also reports the mean myopic and hedging demands for each asset class. Bootstrapped 90% confidence intervals for the mean asset demands are given in brackets. A bold entry indicates significance according to the 90% confidence interval.
Table 4 (continued)

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Domestic country: Italy, 1952:04-2004:04

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Domestic country: United Kingdom, 1952:04-2004:04

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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 $\gamma = 7$. 


D. Foreign country: Germany, 1967:02–2004:04


F. Foreign country: United Kingdom, 1952:04–2004:04
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 $\gamma = 7$. 