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Stocks for the long run? Evidence from emerging markets

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A B S T R A C T

We estimate the myopic (single-period) and intertemporal hedging (long-run) demand for stocks in 20 growth-leading emerging market economies during the 1999–2012 period. We consider two types of investors: a domestic investor who invests in emerging-market assets only (with returns in local currency) and an international investor who invests in both US and emerging-market assets (with returns in US dollars). We establish economically relevant short-run and long-run demand for stocks in several emerging market economies, for both domestic and international investors. From a welfare perspective, however, the myopic demand for emerging-market stocks is much more important than the hedging demand. Further international diversification and foreign currency hedging by the international investor do not alter this conclusion. Hence, for both domestic and international investors emerging-market stocks are mainly assets for the short run.

1. Introduction

For both domestic and international investors, emerging markets may offer attractive investment opportunities. According to the Global Financial Stability Report (IMF, 2011) emerging markets' growth prospects are among the main considerations for asset allocation by long-term real-money investors. Also from a diversification perspective, emerging markets provide potentially interesting investment opportunities (Harvey, 1994; Bekaert and Harvey, 2003).

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The aforementioned considerations suggest that emerging market equities can be an interesting portfolio component for both domestic and international investors with a multi-period investment horizon. The present study therefore analyzes the intertemporal effects of return predictability on optimal consumption and portfolio choice for long-term emerging-market investors. We decompose the demand for emerging-market stocks in a myopic and an intertemporal hedging part. The myopic demand owes to the current risk premium in a single-period setting, whereas the intertemporal hedging demand stems from the investor's strategic objective to hedge against adverse future events in a multi-period setting. To our best knowledge, the impact of myopic and intertemporal hedging motives on the total demand for stocks as proposed by Campbell et al. (2003a) has not yet been applied to emerging markets.[1]

In Campbell et al. (2003a) the intertemporal hedging demand for US stocks stems from the predictability of stock returns from the dividend yield, due to which negative stock returns are associated with positive expected returns in the future. In this way, stocks can be used to hedge the variation in their own future returns. The empirical evidence for return predictability is mixed though, even for the US and other developed markets. For example, Goyal and Welch (2008) and Boudoukh et al. (2008) present evidence against return predictability in the US, whereas Campbell and Thompson (2008) establish evidence in favor of it. Schrimpf (2010) investigates return predictability in an international context and finds large differences across markets. In his study of four industrialized stock markets, he finds weak evidence in favor of stock return predictability in Germany, Japan and the United Kingdom.

There is even more ambiguity in the literature about return predictability in emerging markets. Harvey (1994) finds that emerging-market equity returns are more predictable than stock returns in developed economies, while Karemera et al. (1999) cannot reject the random walk model for equity returns in their study of fifteen emerging markets. Bekaert and Harvey (2007) establish more evidence in favor of predictability of emerging market stock returns, whereas Hjalmarsson (2010) finds only little evidence for predictability. There is also uncertainty about mean-reversion effects in emerging market stock returns; see e.g. Chaudhuri and Wu (2003) and Malliaropulos and Priestley (1999). Mean reversion is defined as negative autocorrelation in asset returns and arises in the presence of strong return predictability. Because of the mixed results regarding predictability and mean reversion in emerging-market stock returns, it is not a priori clear whether emerging-market stocks will turn out to be assets 'for the long run'.

The goal of this study is to analyze the intertemporal effects of return predictability in emerging markets. We focus on the group of the emerging and growth-leading economies (known as EAGLEs and EAGLEs Nest countries), created in 2010 by Banco Bilbao Vizcaya Argentaria.[2] The EAGLEs group includes economies whose expected contribution to the world's economic growth in the next 10 years is larger than the average of the G-6 economies (i.e., G-7 excluding the US). The performance of group members is reviewed annually for possible inclusion or removal. A related classification is the EAGLEs Nest, which includes countries whose expected incremental GDP in the next decade is lower than the average of the G-6 economies but higher than that of the smallest G-6 group's contributor. Currently, there are 9 countries in the EAGLEs group (Brazil, China, India, Indonesia, Mexico, Russia, South Korea, Taiwan, and Turkey), while there are 15 countries in the EAGLEs Nest group (Argentina, Bangladesh, Chile, Colombia, Egypt, Malaysia, Nigeria, Pakistan, Peru, Philippines, Poland, South Africa, Thailand, Ukraine, Vietnam). Motivated by data availability considerations, we study the demand for stocks in 20 of these countries, from June 1999 until July 2012.

We analyze the intertemporal portfolio choice problem for two types of emerging-market investors: a domestic investor with returns in the local currency and an international investor whose returns are denominated in US dollars. Both investors have an asset menu consisting of a benchmark asset and a stock index. The domestic investor invests in the local market only, whereas the international investor can invest in both the local market and the US. The benchmark asset for each country's domestic investor is a local short-term money market instrument, while the international investor's

[1] A notable exception is De Vries et al. (2011), who apply the approach of Campbell et al. (2003a) to South Africa.
[2] See http://www.bbvaresearch.com/KETD/ketd/ing/nav/eagles.jsp.

benchmark asset is a 3-month US T-bill. For various levels of risk aversion, we analyze the relevance of the hedging and myopic demand for emerging-market stocks from a welfare perspective. This allows us to assess whether these assets are investments for the long run or the short run, or both. We use the expected utility per unit of wealth, evaluated in the optimal consumption-wealth ratio, as a welfare measure (Campbell and Viceira, 1999, 2001; Campbell et al., 2003a). In addition to point estimates of the welfare measures, we provide statistical confidence intervals to quantify the amount of parameter uncertainty involved with the point estimates. Accounting for estimation uncertainty is particularly relevant in emerging markets, which are relatively volatile and often suffer from limited data availability.

Our study builds on the work of Rapach and Wohar (2009) who apply the approach of Campbell et al. (2003a) to the US and six other developed countries (Australia, Canada, France, Germany, Italy, and the UK). They find that the intertemporal hedging motive explains a significant portion of the domestic demand for US and UK stocks, whereas the hedging demand for domestic stocks turns out insignificant in the other countries under consideration. For international investors, the hedging and myopic demand for Australian, Canadian, French and Italian stocks is significant. We extend the study by Rapach and Wohar (2009) to emerging markets. Moreover, we take a welfare perspective and zoom in on the economic relevance of the hedging and myopic demand, instead of considering the portfolio weights only.

We establish the following main results. In several emerging market economies the hedging demand is substantial from a welfare perspective, emphasizing the importance of accounting for time variation in investment opportunities. Stock returns in these countries are predictable to some extent, which explains the long-run demand for these assets and the associated welfare effects. The main predictor of stock returns turns out to be the book-to-market ratio, which may proxy for a firm's risk of distress. Also for international investors, whose asset menu contains both US stocks and emerging-market equity in one particular emerging country, the hedging demand for emerging-market stocks tends to be economically relevant. From a welfare perspective, however, the myopic demand for emerging-market stocks is much more important than the hedging demand. Further international diversification and foreign currency hedging by the international investor do not alter this conclusion. Hence, for both domestic and international investors emerging-market stocks are mainly assets for the short run.

The remainder of the paper is organized as follows. Section 3 provides some background to the multi-period asset allocation problem, followed by a model description in Section 3. The details of emerging markets data are given in Section 4. The estimation results are discussed in Sections 5 (domestic investor) and 6 (international investor). Finally, Section 7 concludes. An appendix with supplementary material is available.

2. Literature review

Ever since the seminal work of Markowitz (1952) on mean-variance analysis, financial economists have investigated various facets of portfolio choice. The traditional mean variance analysis is myopic in nature and is appropriate only for a single-period investment horizon with constant investment opportunities. In practice, however, most investors face multi-period investment horizons with time-varying investment opportunities (Campbell and Viceira, 1999).

In a multi-period setting, an investor looks beyond the single-period investment horizon and seeks protection against adverse events affecting future returns. Mossin (1968) was among the first to examine the multi-period portfolio choice problem. His study showed that myopic portfolio choice is optimal for an investor with log utility in terminal wealth and unhedgeable investment opportunities that are either constant or time-varying. Samuelson (1969) and Merton (1969) incorporated the role of consumption in the multi-period portfolio choice problem and highlighted the difference between myopic and multi-period portfolio choice. They showed that myopic portfolio choice is optimal for an investor with either log utility or unpredictable (idd) asset returns.

During the last two decades a large volume of literature has documented predictability of equity returns, particularly for longer investment horizons (e.g., Keim and Stambaugh, 1986; Campbell, 1987, 1991; Fama and French, 1988, 1989; Harvey, 1994; Barberis, 2000; Lynch, 2001; Bekaert and Ang, 2002;

Chapados, 2011; Ang and Bekaert, 2007). Merton (1973) introduced the concept of intertemporal hedging demand and showed that the variation in expected returns over time can lead to horizon effects for long-term investors. Intertemporal hedging demand arises when an investor wants to hedge against future shocks in investment opportunities (Campbell and Viceira, 2002).

Despite the theoretical soundness of Merton's model, analytical solutions of the model (in terms of portfolio weights as a function of state variables) were not available for a long time. The progress in advanced computing towards the end of the 20th century has led to the development of a number of numerical solutions of the Merton model that were calibrated to US data (see Balduzzi and Lynch, 1999; Barberis, 2000; Brennan et al., 1997; Lynch, 2001). Campbell and Viceira (1999) go one step further by incorporating consumption in the portfolio choice problem. They develop an approximate analytical solution to the Merton model for an infinitely-lived investor with one risky asset and one state variable. They show that accounting for the hedging motive can almost double the total demand for US stocks, with substantial welfare gains. Campbell et al. (2003a) extend Campbell and Viceira (1999) model to include more assets and state variables by applying a simple numerical procedure in conjunction with an approximate analytical solution. They calculate the myopic and the intertemporal hedging component of the total optimal asset demand for an infinitely lived investor with Epstein-Zin utility. The myopic demand corresponds to the single-period demand for an asset when there are no changes in the investment opportunity set. The myopic demand is similar to the demand in the traditional single-period portfolio choice problem. The hedging demand reflects the additional demand for an asset when the changes in the investment opportunity set are incorporated into the portfolio choice problem, as in the multi-period portfolio choice problem of Merton (1973). The empirical implementation of the Campbell et al. (2003a) approach uses a vector autoregressive (VAR) model to capture the time-varying nature of expected asset returns. There are no borrowing or short-selling constraints on asset allocations to isolate the intertemporal effects of return predictability. The authors show that the intertemporal hedging demand motive explains a substantial part of the total demand for US stocks.

Campbell et al. (2003a) explain the intertemporal hedging demand from the positive coefficient of the lagged dividend yield in the VAR model's stock excess return equation and the strongly negative correlation between the innovations of the stock return and dividend yield equations. Investors are generally long in stocks that have high Sharpe ratios. A negative shock to stock excess returns implies a deterioration of investment opportunities for such investors. A strongly negative correlation between the innovations of the stock excess return and dividend yield equations means that a negative shock to stock excess returns is generally accompanied by a positive shock to the dividend yield. The positive coefficient of the lagged dividend yield in the stock excess return equation implies that the positive dividend yield will have a positive impact on expected excess returns in the next period. Therefore, low stock returns in the present tend to be followed by higher expected excess returns in the future, thus providing a hedge in the long run. Hence, predictability of asset returns is crucial in explaining the hedging demand. We will formalize this in the next section.

3. Methodology

This section outlines the approach of Campbell et al. (2003a).

3.1. Theoretical framework

Let $R_{p,t+1}$ be the real return of a portfolio of n assets, for an infinitely long-lived investor with Epstein-Zin preferences defined over a fixed stream of consumption. Let $R_{1,t+1}$ be the simple real return on the benchmark asset (a short-term money instrument) and $R_{i,t+1}$ ($i = 2,3,\ldots,n$) the simple real return on the remaining $n-1$ assets. The portfolio return is given by

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

where $\alpha_{i,t}$ is the portfolio weight for asset i. The log real return is denoted as $r_{i,t+1} = \log(R_{i,t+1}+1)$, for all i. Let x_{t+1} be the vector of excess returns such that

$$x_{t+1} = \left[r_{2,t+1} - r_{1,t+1}, \ldots, r_{n,t+1} - r_{1,t+1}\right]'. \tag{2}$$

Let s_{t+1} be the vector of the other state variables (also referred to as instruments), such as the dividend yield and the short rate. We stack $r_{1,t+1}$,x_{t+1} and s_{t+1} in a $m \times 1$ vector, z_{t+1}, yielding the state vector

$$z_{t+1} = \left[r_{1,t+1}, x_{t+1}, s_{t+1}\right]'. \tag{3}$$

The system of state variables is assumed to follow a first-order vector autoregression for z_{t+1}, such that

$$z_{t+1} = \phi_0 + \phi_1 z_t + \nu_{t+1}, \tag{4}$$

where ϕ_0 is the $m \times 1$ vector of intercepts, and ϕ_1 is the $m \times m$ matrix of slope coefficients, and ν_{t+1} is an m-dimensional vector of shocks that is iid normally distributed with mean 0 and covariance matrix Σ_ν, such that

$$\Sigma_\nu = \mathbb{V}\mathrm{ar}_t(\nu_{t+1}) = \begin{pmatrix} \sigma_1^2 & \sigma_{1x}' & \sigma_{1s}' \\ \sigma_{1x} & \Sigma_{xx} & \Sigma_{xs}' \\ \sigma_{1s} & \Sigma_{xs} & \Sigma_{ss} \end{pmatrix}. \tag{5}$$

Innovations are assumed to be homoscedastic and independently distributed over time, but cross-sectional correlation is allowed. σ_1^2 denotes the variance of the innovations to the return on the benchmark asset; σ_{1x} is the vector of covariances between the innovations to the benchmark asset returns and the other asset returns (with $(n-1)$ elements); σ_{1s} is the vector of covariances between the innovations to the benchmark asset returns and the instruments (with $(m-n)$ elements); Σ_{xx} is the covariance matrix of the innovations to the excess returns (with $(n-1) \times (n-1)$ elements); Σ_{xs} is the covariance matrix of the innovations to the excess returns and the instruments (with $(m-n) \times (n-1)$ elements); Σ_{ss} is the covariance matrix of the innovations to the instruments (with $(m-n) \times (m-n)$ elements).

The homoskedasticity assumption is restrictive in the sense that it rules out the possibility that the state variables predict changes in risk. However, the literature has shown that the impact of the state variables on risk seems modest relative to their influence on expected returns; see Campbell et al. (2003a).

Following Epstein and Zin (1989, 1991); Campbell et al. (2003a) define the recursive preferences of an investor over an infinite investment horizon as

$$U(C_t, \mathrm{IE}_t(U_{t+1})) = \left((1-\delta)C_t^{(1-\gamma)/\theta} + \delta\left(\mathrm{IE}_t\left(U_{t+1}^{1-\gamma}\right)\right)^{1/\theta}\right)^{\theta/(1-\gamma)}, \tag{6}$$

where C_t is the consumption at time t, $\mathrm{IE}_t(\cdot)$ is the conditional expectation given all information at time t, $0<\delta<1$ is the time-discount factor, $\gamma>0$ is the coefficient of relative risk aversion, $\theta\equiv(1-\gamma)/(1-\psi^{-1})$ and $\psi>0$ is the elasticity of intertemporal substitution. A higher value of δ reflects a more patient investor and a higher value of γ corresponds with a more risk averse investor. One notable advantage of using this utility function is the separation of the notion of risk aversion (γ) from that of the elasticity of intertemporal substitution (ψ).[3]

[3] Equation (6) reduces to a special case of time-separable power utility when $\gamma = \psi^{-1}$ and to log utility under the additional constraint $\gamma = \psi^{-1} = 1$.

The budget constraint for an investor with wealth W_t is

$$W_{t+1} = (W_t - C_t)R_{p,t+1}. \tag{7}$$

Given the budget constraint defined in Equation (7), Epstein and Zin (1989, 1991) derive the Euler equation for consumption of asset i in portfolio p as

$$\mathrm{IE}_t\left(\left(\delta\left(\frac{C_{t+1}}{C_t}\right)^{-1/\psi}\right)^{\theta} R_{p,t+1}^{-(1-\theta)} R_{i,t+1}\right) = 1 \tag{8}$$

For the power utility case (with $\gamma = \psi^{-1}$ and $\theta = 1$), the first-order condition in Equation (8) reduces to the standard one. Campbell et al. (2003a) point out that the optimal portfolio choice with constant investment opportunities is the same as the single-period or myopic portfolio. However, with time varying investment opportunities, exact analytical solutions are generally not available except for specific values of γ and ψ. Campbell et al. (2003a) combine the approximate analytical solution of Campbell and Viceira (1999, 2001) with a simple numerical procedure to calculate the optimal portfolio and consumption choices for any values of γ and ψ. Campbell et al. (2003a) approximate the log real return on the portfolio in a way that is exact in continuous time and highly accurate for short time intervals. Furthermore, log-linear approximations of the budget constraint (first order) and the Euler equation (second order) are used.[4] The optimal portfolio (α_t) and consumption ($c_t - w_t$) rules are given by

$$\alpha_t = A_0 + A_1 z_t; \quad c_t - w_t = b_0 + B_1' z_t + z_t' B_2 z_t, \tag{9}$$

where c_t and w_t are the log levels of C_t and W_t, respectively. A_0 (dimension $(n-1) \times 1$), A_1 ($(n-1) \times m$), b_0 (1×1), B_1 ($m \times 1$) and B_2 ($m \times m$) are constant coefficient matrices that are functions of γ, ψ, δ, ρ, ϕ_0, ϕ_1 and Σ_ν, with $\rho = 1 - \exp[\mathrm{IE}(c_t - w_t)]$.

3.2. Myopic and intertemporal hedging demand

Because we focus on an investor's portfolio choice, we are interested in the parameters of Equation (9). Following Merton (1969, 1971), Campbell et al. (2003a) derive expressions for A_0 and A_1 in (9) that divide the total demand into myopic and intertemporal hedging components:

$$A_0 = \underbrace{(1/\gamma)\sum_{xx}^{-1}\left(H_x\phi_0 + 0.5\sigma_x^2 + (1-\gamma)\sigma_{1x}\right)}_{\text{myopic demand}} + \underbrace{(1-(1/\gamma))\sum_{xx}^{-1}(-\Lambda_0/(1-\psi))}_{\text{intertemporal hedging demand}} \tag{10}$$

and

$$A_1 = \underbrace{(1/\gamma)\sum_{xx}^{-1} H_x\phi_1}_{\text{myopic demand}} + \underbrace{(1-(1/\gamma))\sum_{xx}^{-1}(-\Lambda_1/(1-\psi))}_{\text{intertemporal hedging demand}}, \tag{11}$$

where H_x denotes the selection matrix that selects the vector of excess returns (x_t) from z_t. σ_x^2 denotes the vector of diagonal elements of Σ_{xx}; Λ_0 and Λ_1 denote matrices whose values depend on B_0, B_1, B_2 γ, ψ, δ, ρ, ϕ_0, ϕ_1 and Σ_ν. For full details we refer to Campbell et al. (2003a). The two terms related to the myopic demand in Equations (10) and (11) sum to the total myopic demand for an asset. The myopic demand refers to the demand for an asset in a single-period context, similar to the demand derived in a

[4] These approximations are exact for $\psi = 1$.

static mean-variance framework, with a constant investment opportunity set. The two terms related to the intertemporal hedging demand in Equations (10) and (11) sum to the total intertemporal hedging demand. The latter demand arises in a multi-period portfolio choice problem, when an investor accounts for changes in the investment opportunity set and tries to hedge against adverse future shocks.

When the benchmark asset is riskless ($\sigma_{1x} = 0$) the myopic demand equals the vector of expected excess returns on the risky assets, scaled by the inverse of the covariance matrix of the risky asset returns and the reciprocal of the coefficient of relative risk aversion. When the benchmark asset is risky, investors use the term $(1-\gamma)\sigma_{1x}$ to adjust this allocation. An investor with logarithmic utility (i.e., $\gamma = 1$ and $\theta = 0$) will have a zero hedging demand. The hedging demand will also be zero when investment opportunities are constant over time. More specifically, Rapach and Wohar (2009) point out two necessary conditions for the existence of intertemporal hedging demand in a multi-period portfolio choice framework with non-logarithmic utility: (1) the returns should be predictable and (2) the variance-covariance matrix for the VAR innovations (Σ_ν) should not be diagonal.

The more risk-averse the investor, the more eager she is to hold assets that deliver wealth when investment opportunities are poor. Consequently, the hedging demand is usually positive for sufficiently risk-averse investors. By contrast, a more risky investor prefers to hold assets when investment opportunities are favorable. For such an investor the hedging demand tends to be negative. Hence, the risk-averse investor is usually long in stocks. However, if the expected stock excess returns are sufficiently negative, it becomes attractive for the investor to take a short position in equity. With a short position in stocks, a drop in expected future stock returns provides an improvement in the investment opportunity set. In this scenario the hedging demand becomes negative.

As noticed by Rapach and Wohar (2009), the estimated asset demands can be given a normative or positive interpretation. According to the normative interpretation, the optimal asset demand for a given asset return process corresponds to an investor whose investment preferences coincide with the assumptions made by Campbell et al. (2003a). The positive interpretation, following Lynch (2001), states that the optimal asset demand reflects the behavior of a unique individual or of a small group of investors, who exploit the return predictability created by a large number of other investors with different preferences, such as the habit-formation preferences of Campbell and Cochrane (1999).

Finally, we discuss the welfare losses associated with suboptimal or restricted asset allocations. Epstein and Zin (1989, 1991) consider the value function, which is defined as the utility function per unit of wealth evaluated in an optimal consumption-wealth ratio. They show that the value function can be expressed as a power function of the optimal consumption-wealth ratio[5]:

$$V_t = U_t/W_t = (1-\delta)^{-\psi/(1-\psi)}(C_t/W_t)^{1/(1-\psi)}. \tag{12}$$

The value function can be used to assess the welfare loss due to suboptimal or restricted asset allocation, provided that consumption is chosen optimally given the suboptimal portfolio rule (Campbell and Viceira, 1999, 2001; Campbell et al., 2003a). We obtain the Expected Value Loss (EVL) as the relative difference between the expected value of V_t corresponding to the suboptimal or restricted allocation (denoted $\mathrm{IE}(V_t^{restr})$) and the expected value of V_t corresponding to the optimal asset allocation (denoted $\mathrm{IE}(V_t^{\mathrm{opt}})$):

$$\mathrm{EVL} = 1 - \frac{\mathrm{IE}\left(V_t^{\mathrm{restr}}\right)}{\mathrm{IE}\left(V_t^{\mathrm{opt}}\right)}. \tag{13}$$

The EVL takes values between 0 and 1 and measures the welfare loss due to suboptimal asset allocation. An EVL of 0 indicates that there is no welfare loss relative to the optimal asset allocation, while an EVL of 1 corresponds with the largest welfare loss possible. For example, when applied to the hedging demand for an asset, the associated EVL measures the welfare loss per unit of wealth due to

[5] The value function reaches a finite limit for $\psi \to 1$.

ignoring the hedging demand. In the same way we can obtain the EVL corresponding to ignoring the myopic demand. As we will see later, a statistically significant hedging demand does not necessarily imply large welfare losses due to removing this component from the portfolio. Conversely, ignoring statistically insignificant myopic demand can lead to a large drop in expected utility per unit of wealth. Stated differently, portfolio weights (and their statistical significance) are not necessarily informative about welfare effects. Furthermore, the estimated myopic demand tends to exhibit much more parameter uncertainty than the EVL due to ignoring the myopic demand.[6] We therefore focus on the EVL to evaluate the economic importance of both the myopic and hedging demand for emerging-market stocks.

3.3. Limitations of the approach

Campbell et al. (2003a) discuss several limitations of their approach that we briefly summarize here. First, their approach boils down to a partial equilibrium model, focusing on the demand-side of the asset allocation problem. For a given exogenous asset return process and a set of investor preferences, a long-term investor's optimal demand for assets is calculated. This partial approach assumes that asset returns are exogenous, which implies (among others) that the asset demand by individual investors does not have any market impact. The implied model of investor behavior is not used to explain observed asset returns such as in e.g. Lynch (2003). Second, the approach of Campbell et al. (2003a) provides an approximate solution, which is only exact under certain assumptions. Although it has been shown that this solution is generally accurate, the approximation error increases when the state variable is more than two standard deviations away from its mean.

4. Data

We consider two main types of investors: A domestic investor with returns denominated in the local currency and an international investor whose returns are denominated in US dollars. Both investors can invest in a short-term money market asset (the benchmark asset) and a stock market index. The domestic investor's benchmark asset is a domestic money market instrument, while it is a 3-month US T-bill for the international investor. Lastly, we also consider a domestic US investor, whose investment set is restricted to 3-month US T-bills and a US stock market index.

4.1. Data choices

The relevant data series on equity indices, money market instruments, and inflation rates have been obtained from Thompson Reuters Datastream and the IMFs International Financial Statistics (IFS). We use Datastream's Global Equity total return indices to obtain the stock returns in each country under consideration. Throughout, we work with continuously compounded returns and inflation rates. Real returns are calculated by subtracting the monthly inflation rate from the monthly nominal return. We obtain stock excess returns by subtracting the nominal return on the short-term money market instrument from the nominal stock return. For the domestic investor, we use the inflation rate of the relevant domestic market to calculate real returns. For the international investor we use the US inflation rate.

We opt for the longest sample available in our data sources. This is the period June 1999–July 2012, resulting in 158 monthly observations for the emerging economies of Argentina, Brazil, Chile, China, Colombia, Egypt, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Russia, South Africa, South Korea, Taiwan, Thailand, and Turkey. The sample includes the aftermath of the financial crises in East Asia, Russia and Latin America, the dot-com crisis in the US and the subsequent recovery, and the global financial crisis that started with the US subprime crisis in 2007–2008.

[6] We thank an anonymous referee for observing this.

The first panel of Table 1 lists the domestic investor's benchmark asset in each country, which is a short-term money market instrument. The choice of the money market instrument in each country is mainly driven by data availability. The inflation series are listed in the second panel of Table 1 and the equity indices are given in the first panel of Table 2. The second panel of Table 2 also lists the equity indices used by the international investor, whose returns are denominated in US dollars. This investor's benchmark asset is a 3-month US T-bill. The equity indices for Colombia, Egypt, India, Pakistan, Peru and Russia are available in local currency only. To calculate the international investor's excess returns, we therefore use the relevant exchange rate to convert the local currency return to the US dollar equivalent (see again the third panel of Table 2).

4.2. Sample statistics

Tables 1 and 2 report monthly sample means and standard deviations for the various data series at hand. The money market instrument in Turkey has the highest average monthly return of 0.92%, whereas the benchmark assets for Russia and Chile have the lowest average return of −0.10% and −0.22%, respectively (all in local currency). The returns on the benchmark assets for India and Malaysia have the lowest volatility of 0.34% and 0.41%, respectively, whereas the returns on the benchmark assets for Argentina and Turkey have the highest volatility of 1.2% and 2.3%, respectively.

Domestic investors in Chile and Colombia (with returns in the local currency) have the highest mean excess return on stocks, which equal 1.0% and 0.95%, respectively. Argentina, China, Poland, Taiwan, and Turkey all have negative excess returns on average. Excess returns in Russia and Turkey show the highest volatility: 12.5% and 9.9%, respectively. With 4.8% and 3.9% excess returns in the US and Chile have the lowest volatility.

International investors in Colombia and Russia (with returns in US dollars) have the highest mean excess returns on stocks (1.4% and 1.3%, respectively). The average excess return is lowest in Argentina, where it equals 0.38% during the sample period. In Turkey and Russia excess returns are the most volatile, with monthly sample volatilities of 15.0% and 11.1%, respectively. Chile and Malaysia have the lowest volatility during the sample period (0.07% and 0.18%, respectively). For 14 out of 20 countries,

Table 1
Sample statistics.

Country	Benchmark asset (real return)				Nominal yield		Inflation rate		
	Type of money market asset	Mnemonic	Mean	Std. dev.	Mean	Std. dev.	Mnemonic	Mean	Std. dev.
Argentina	90-day deposit	AG90DPP	0.32	1.17	1.008	0.894	AGCONPRCF	0.69	1.03
Brazil	Selic target rate	BRSELIC	0.74	0.46	1.273	0.362	BRCONPRCF	0.53	0.41
Chile	CD 90-day	CLCD90D	−0.22	0.44	0.031	0.014	CLCONPRCF	0.25	0.44
China	3-month Relending rate	CHDIS3M	0.26	0.66	0.287	0.031	CHCONPRCF	0.03	0.65
Colombia	90-day CD rate	CB90CDR	0.24	0.45	0.684	0.286	CBCONPRCF	0.44	0.43
Egypt	T-bills	IFS database	0.15	0.82	0.770	0.168	EYCONPRCF	0.62	0.78
India	91- day T-bills	INTB91D	0.02	0.34	0.545	0.151	INCPANNL	0.52	0.26
Indonesia	1-month SBI discount rate	IFS database	0.25	0.90	0.842	0.314	IFS database	0.60	0.86
Malaysia	3-month T-bills	IFS database	0.06	0.41	0.232	0.035	MYCONPRCF	0.18	0.41
Mexico	91-day cetes	MXCTM91	0.36	0.42	0.758	0.375	MXCONPRCF	0.40	0.35
Pakistan	Money Market rate	IFS database	0.01	0.80	0.706	0.302	IFS database	0.70	0.79
Peru	Interbank rate	PEINBIR	0.21	0.46	0.422	0.328	PECONPRCF	0.22	0.31
Philippines	91-day T-bills	PHTBL3M	0.06	0.46	0.462	0.218	PHCONPRCF	0.40	0.42
Poland	Interbank rate	POIBKON	0.32	0.54	0.607	0.435	POCONPRCF	0.29	0.42
Russia	Interbank rate	RSIBK90	−0.10	0.67	0.865	0.593	RSCONPRCF	0.97	0.66
South Africa	91-day T-bills	SATBL3M	0.25	0.46	0.715	0.178	SACONPRCF	0.46	0.45
South Korea	91-day COD	KOCD91D	0.12	0.41	0.373	0.111	KOCONPRCF	0.25	0.40
Taiwan	Money market rate	TAMM90D	0.09	0.80	0.182	0.118	TWCONPRCF	0.09	0.79
Thailand	Interbank rate	THBTIBN	−0.02	0.57	0.198	0.095	IFS database	0.22	0.55
Turkey	Money Market rate	IFS database	0.92	2.32	2.379	2.899	IFS database	1.46	1.67
US	3-month T-bills	FRTBS3M	−0.01	0.42	0.191	0.166	IFS database	0.20	0.41

Notes: This table shows monthly sample statistics. The sample mean and standard deviations are in percentage and on a monthly basis.

Table 2
Sample statistics.

Stocks (excess returns local currency)				Stocks (excess returns US dollars)				
Mnemonic	Mean	Std. dev.	SR	Mnemonic	Exchange rate	Mean	Std. dev.	SR
TOTMKAR	−0.23	8.94	−0.03	TOTMAR$		−0.38	9.17	−0.04
TOTMKBR	0.16	6.59	0.02	TOTMBR$		1.13	10.36	0.14
TOTMKCL	1.02	3.94	0.26	TOTMCL$		0.87	6.10	0.18
TOTMKCH	−0.04	8.40	0.00	TOTMCA$		0.22	8.34	0.08
TOTMKCB	0.95	5.91	0.16	TOTMKCB	COLUPE$	1.39	7.80	0.13
TOTMKEY	0.36	8.31	0.04	TOTMKEY	EGYPTN$	0.58	8.48	0.09
TOTMKIN	0.59	8.60	0.07	TOTMKIN	INDRUP$	0.78	9.74	0.06
TOTMKID	0.15	7.94	0.02	TOTMID$		0.70	10.96	0.12
TOTMKMY	0.52	4.90	0.11	TOTMMY$		0.75	5.58	0.07
TOTMKMX	0.56	5.37	0.10	TOTMMX$		0.93	6.98	0.08
TOTMKPK	0.70	9.24	0.08	TOTMKPK	PAKRUP$	0.83	9.59	0.09
TOTMKPE	0.76	5.82	0.13	TOTMKPE	PERUSO$	1.14	6.29	0.18
TOTMKPH	0.23	5.93	0.04	TOTMPH$		0.44	6.97	0.06
TOTMKPO	−0.14	7.09	−0.02	TOTMPO$		0.38	9.86	0.04
TOTMKRS	0.83	9.87	0.08	TOTMKRS	CISRUB$	1.34	11.07	0.12
TOTMKSA	0.61	5.26	0.12	TOTMSA$		0.95	8.13	0.12
TOTMKKO	0.43	7.92	0.05	TOTMKO$		0.64	9.72	0.07
TOTMKTA	−0.05	7.47	−0.01	TOTMTA$		0.00	8.23	0.00
TOTMKTH	0.60	8.27	0.07	TOTMTH$		0.71	9.49	0.08
TOTMKTK	−0.72	12.51	−0.06	TOTMTK$		0.53	14.97	0.04
TOTMKUS	0.02	4.82	0.00	TOTMKUS		0.02	4.82	0.00

Notes: This table shows monthly sample statistics. The sample mean and standard deviations are in percentage and on a monthly basis. SR stands for the (sample) Sharpe ratio. Because of unavailability of the book-to-market ratio, we report the dividend yield for Brazil.

the US dollar Sharpe ratio (corresponding to the emerging-market stock index) is higher than the local currency equivalent.

In addition to sample means and standard deviations, we also report the ratio of the mean excess return and the standard deviation for stocks. We refer to this as the (sample) Sharpe ratio (SR) in Table 2. A higher value of the Sharpe ratio implies a higher myopic demand for stocks, ceteris paribus. In local currency, Chile has the highest Sharpe ratio (0.26), followed by Colombia (0.16). Argentina, China, Poland, Taiwan, and Turkey have negative Sharpe ratios. In US dollars the equity indices of Chile and Russia exhibit the highest Sharpe ratio (both 0.18), whereas Argentina's Sharpe ratio of −0.04 is lowest across all countries under consideration.

All in all, the risk-return profiles of the money market instruments and the equity indices show substantial variation across countries.

5. Empirical results: domestic investor

This section considers domestic investors in the various emerging market countries (domestic emerging market investors) and the US (domestic US investor). We analyze the economic importance of the hedging and myopic demand for emerging-market stocks to assess whether these investments are assets for the long-run or the short-run, or both.

5.1. Specification search

We use a VAR model to capture time-varying investment opportunities. Apart from the real return on the money market instrument (the benchmark asset) and the excess return on the stock index, this model involves several predictor variables or instruments. Stock return predictability is one of the most extensively discussed topics in the finance literature; for a recent survey see Rapach and Zhou (2013). Among the potential predictors of stock returns are dividend yields and dividend growth rates, book-to-market ratios, term spreads, credit spreads, and nominal interest rates. Datastream provides both dividend yields and book-to-market ratios for the emerging-market indices mentioned in Section 4.

The domestic investor's term spread is also available from Datastream and calculated as the difference in nominal yield between domestic country's JP Morgan Government Bond Index-Emerging Markets bond index and the benchmark asset.[7]

For each country we start with a VAR model including all of the aforementioned predictor variables. For the sake of parsimony we also estimate smaller VAR models by leaving out one or more predictor variables. Subsequently, we compare the estimated demand for assets with the estimated demand based on the initial model. This specification search makes clear that it is crucial to include the book-to-market ratio as an instrument in each country's VAR model. More specifically, the VAR model containing the book-to-market ratio as the only predictor results in virtually the same demand for stocks as the bigger model involving all predictor variables. We will therefore use the 3-dimensional first-order VAR model for each country in our sample, including the real yield on the money market instrument (the benchmark asset), the excess return on the stock index, and the natural logarithm of the book-to-market ratio of the stock index.[8] We will illustrate and discuss the role of the book-to-market ratio in more detail in Section 5.4.

5.2. Model parameters

Complete OLS estimation results for the domestic investor's VAR models are provided in the appendix with supplementary material; see Table I (the VAR models' estimated coefficients) and Table II (the VAR models' residual correlations) of the latter document. In addition to the VAR coefficients, we need realistic values of ψ (the elasticity of intertemporal substitution), γ (the coefficient of relative risk aversion), and δ (annual time-discount factor) to estimate Equation (9). Campbell et al. (2003a) calculate the mean optimal demand for US stocks for $\psi = 0.5,1$ while Rapach and Wohar (2009) use values of $\psi = 0.3,1,1.5$ for developed markets. Buffie et al. (2009) show that the elasticity values tend to be relatively low for developing countries, where they range between 0.1 and 0.5. We therefore start our analysis with $\psi = 1$ and later also obtain results for $\psi = 0.1$, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, and 0.8. Regarding the coefficient of relative risk aversion (γ), Campbell et al. (2003a) use values of 1, 2, 5 and 20, while Rapach and Wohar (2009) consider values 4, 7 and 10. We calculate the demand for assets using the values 2, 5, 7, and 10. Campbell et al. (2003a) and Rapach and Wohar (2009) use an annual time-discount factor $\delta = 0.92$ for developed markets. We opt for discount factors of 0.92, 0.95 and 0.99 to cater for different time preferences across investors.[9]

5.3. Welfare effects: hedging and myopic demand

We start with a domestic investor in each of the emerging market countries and (for the sake of comparison) the US. The domestic investors can invest in a stock index and a short-term money market instrument, both available in the domestic market and denominated in the local currency. We calculate the total, hedging and myopic demand for assets on the basis of Equation (9) using the time average of z_t (Campbell et al., 2003a). To assess the economic importance of the myopic and hedging components in the total demand for stocks, we calculate the EVL that arises from ignoring the optimal myopic or hedging demand according to Equation (13).[10]

The point estimates of EVL are subject to parameter uncertainty, because they boil down to functions of the estimated VAR-model parameters. We estimate 95% confidence intervals in addition to the point estimates using a wild bootstrap (Mammen, 1993), which are reported in the appendix with supplementary material. The confidence intervals are informative about the sampling variation in the estimated utility losses. We notice that the EVLs are always significantly different from 0, since the

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[7] The term spread is only available for Brazil, India, Malaysia, Mexico, Poland, South-Africa, Thailand, and the US.

[8] We use the dividend yield for Brazil anyhow, because of the unavailability of book-to-market ratio data in Datastream.

[9] Fuentes and Gredig (2011) report discount factors between 0.97 and 0.99 for Chile, while Rebelo and Vegh (1995) use a value of 0.99 for Argentina. A comprehensive review of time-discount factors is provided by Frederick et al. (2002).

[10] We notice that a zero myopic demand is optimal for an infinitely risk averse investor, while no hedging demand is optimal in the absence of any instruments.

latter value never falls in the confidence interval: the suboptimal or restricted asset allocations always have a smaller expected value than the optimal allocation.

The first, second and third panels of Table 3 report the domestic investor's welfare losses due to ignoring the myopic, hedging and total demand for domestic stocks, respectively, for $\psi = 1$ (intertemporal elasticity of substitution), $\delta = 0.92$ (annual time-discount factor) and $\gamma = 2,5,7,10$ (coefficient of relative risk aversion). We start with the welfare implications for the domestic US investor. The welfare losses arising from not investing myopically in US stocks are large, in particular for more risky investors. For a US investor with coefficient of risk aversion $\gamma = 1$ we find an EVL of 88.7%. The 95% confidence interval for this point estimate equals [71.5%, 99.7%]; see Table III. Hence, the domestic investor faces a welfare reduction of almost 90% by ignoring the myopic demand for US stocks. Although the welfare losses of ignoring the hedging demand are smaller, they are still substantial, especially for more conservative investors. For a US investor with coefficient of risk aversion $\gamma = 10$ we establish an EVL of 25.6% (with 95% confidence interval [6.3%, 57.6%]). Hence, a US investor loses more than 25% of her welfare by ignoring the hedging demand for domestic stocks. When a US investor does not invest in US stocks at all her welfare loss increases to 53.9% (with 95% confidence interval [33.0%, 84.4%]), which is larger than the welfare loss of 38.0% ([25.1%,68.1%]) due to not investing myopically in US stocks. Given our modest data sample, it comes as no surprise that the sampling uncertainty in the EVLs is considerable.

In all countries except for Brazil, Chile, Colombia, Egypt, Indonesia, Peru and Thailand the welfare losses from ignoring the hedging demand for domestic stocks are larger than 10% for at least one value of the coefficient of relative risk aversion. The welfare losses due to not investing myopically are substantial in all countries, especially for more risky investors. Hence, in several emerging market countries the economic relevance of both the myopic and the hedging demand is considerable. Nevertheless, the welfare losses from not investing myopically tend to be considerably larger than those due to ignoring the hedging demand. Only in Argentina, Malaysia and Russia the hedging demand is economically more important than the myopic demand, but only for the most conservative investors (with $\gamma = 10$). A comparison of the first, second and third panels of Table 3 confirms that the welfare losses due to ignoring the total demand for domestic stocks are mainly driven by the lack of myopic demand for domestic stocks, especially for more risky investors. Hence, although emerging-market stocks can add long-run value to a domestic investor's portfolio, they are particularly attractive for short-run investors.

Table 3
Welfare losses due to ignoring the myopic, hedging and total demand for stocks (domestic investor).

CRRA	ARG	BRA	CHI	CHIN	COL	EG	INDIA	INDO	MAL	MEX	PAK	PERU	PHIL	POL	RUS	SA	SK	TAI	THAI	TUR	US
										No myopic demand for stocks											
2	82.7	95.1	99.1	85.0	87.2	91.2	91.4	99.2	98.7	88.0	90.8	73.1	83.2	91.3	92.2	81.0	97.7	94.6	94.3	89.8	88.7
5	46.1	68.6	85.7	56.0	56.3	62.1	67.3	84.0	81.9	60.3	61.7	47.8	51.9	64.1	63.9	52.5	80.2	72.1	69.7	64.1	60.6
7	30.7	55.8	75.0	44.5	46.1	50.7	57.0	72.5	70.0	49.4	48.1	41.0	40.7	52.4	50.0	41.3	68.8	60.3	57.6	52.6	49.0
10	13.0	43.0	61.7	33.7	37.3	40.1	47.3	59.0	56.1	38.9	34.3	35.5	29.9	41.0	35.5	30.4	56.0	47.9	45.3	41.2	38.0
										No hedging demand for stocks											
2	3.0	1.4	5.2	16.5	1.0	0.2	14.2	9.4	52.2	5.1	19.7	0.1	3.3	7.3	19.0	9.2	23.5	18.2	7.5	9.6	18.2
5	12.4	1.6	7.2	29.7	0.3	0.7	24.6	8.3	69.5	11.8	31.5	1.5	10.9	11.8	34.9	18.8	34.6	30.5	9.1	16.5	30.6
7	17.8	1.5	6.7	28.9	0.1	1.2	24.3	6.8	66.5	13.8	30.5	2.6	14.3	11.0	36.4	20.2	31.9	28.8	7.9	15.7	29.0
10	25.1	1.4	6.1	26.4	0.0	1.9	23.0	5.4	60.6	16.3	28.3	4.4	18.8	9.6	37.5	21.4	27.6	25.2	6.7	14.2	25.6
										No demand for stocks											
2	83.3	95.2	99.2	87.5	87.3	91.2	92.6	99.3	99.4	88.6	92.6	73.2	83.7	92.0	93.7	82.7	98.3	95.6	94.7	90.8	90.8
5	52.8	69.1	86.7	69.0	56.4	62.4	75.4	85.3	94.5	65.0	73.8	48.6	57.1	68.4	76.5	61.4	87.0	80.6	72.4	70.0	72.7
7	43.0	56.4	76.6	60.5	46.2	51.2	67.5	74.4	89.9	56.4	63.9	42.6	49.2	57.6	68.2	53.2	78.8	71.7	61.0	60.0	63.8
10	34.9	43.8	64.0	51.2	37.3	41.2	59.4	61.3	82.7	48.8	53.0	38.4	43.1	46.6	59.7	45.3	68.1	61.0	49.0	49.6	53.9

Notes: This table shows the Expected Value Loss (EVL) corresponding to several suboptimal asset allocations, assuming optimal consumption given the suboptimal portfolio rule. The EVL is expressed in % and defined as the relative difference between the expected utility per unit of wealth evaluated in the suboptimal allocation and the expected utility per unit of wealth evaluated in the optimal asset allocation. It serves as a measure for the welfare loss due to suboptimal or restricted asset allocation. For example, the first panel gives the domestic investors' EVLs that arise from ignoring the myopic demand for stocks. In all cases, the value functions corresponding to the optimal and suboptimal asset allocations (both needed to calculate the EVL) are based on the same VAR model.

The economic relevance of the myopic demand arises from short-term investment options offered by positive or negative Sharpe ratios. Investors will go long in stocks with positive Sharpe ratios, while they will otherwise go short. The economic importance of the hedging demand for stocks stems from the predictability of stock returns from the book-to-market ratio and the negative correlation between the innovations of the stock excess return and the book-to-market ratio equations. We will extensively discuss the predictability effects in Section 5.4.

Table IV in the appendix with supplementary material reports the estimated mean optimal equity demand. The 95% confidence bounds reported in these tables are based on a wild bootstrap and reveal a large degree of estimation uncertainty; so large that not all of them are significantly different from zero. An insignificant hedging demand for stocks does not necessarily imply that the hedging demand is irrelevant from a welfare perspective, and vice versa. For example, the hedging demand is not significant in Argentina, but the welfare losses due to ignoring the hedging demand are nevertheless substantial for conservative investors (up to 25%). Conversely, the hedging demand is significant in Thailand for conservative investors, but the welfare losses from ignoring the hedging demand are limited. In none of the countries the myopic demand is statistically significant, yet it is always relevant in terms of welfare effects. These findings illustrate our earlier statement that it is important to study the economic relevance of the myopic and hedging demand, instead of looking at the portfolio weights only.

As a robustness check, we redo our analysis for different parameter values. We calculate the optimal demand for stocks for $\psi = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8$ (intertemporal elasticity of substitution) and $\delta = 0.95, 0.99$ (time-discount factor). The general trend is that a ceteris paribus increase in δ results in an increase in the magnitude of the hedging demand for stocks. This result is intuitive because an investor with a focus on the present uses a lower discount factor than a more future-oriented consumer. Thus, a consumer who is more future-oriented will forego more consumption today in exchange for a better future return. Another effect that we observe is that a ceteris paribus increase in ψ results in an increase in the magnitude of the hedging demand for stocks. The intuition for this result is that investors are willing to hold more stocks for higher values of the intertemporal elasticity of substitution. Because the myopic demand is independent of the latter two parameters (Campbell et al., 2003a), their effect on the myopic demand is minor. Throughout, the previously observed patterns in the EVLs remain qualitatively the same.

5.4. *Determinants of the hedging demand*

In our VAR model predictability stems from the positive coefficient of the lagged book-to-market ratio in the VAR model's stock return equation. In combination with a strongly negative correlation between the innovations of the stock return and book-to-market ratio equations (see Table II in the appendix with supplementary material), this results in intertemporal hedging demand for stocks. Investors are generally long in stocks that have high Sharpe ratios. A negative shock to stock excess returns implies a deterioration of investment opportunities for such investors. A strongly negative correlation between the innovations of the stock excess return and the book-to-market ratio equations means that a negative shock to stock excess returns is generally accompanied by a positive shock to the book-to-market ratio. The positive coefficient of the lagged book-to-market ratio in the stock excess return equation implies that the positive book-to-market ratio will have a positive impact on expected excess returns in the next period. Therefore, low stock returns in the present tend to be followed by higher expected excess returns in the future, thus providing a hedge in the long run. The extent to which the hedging demand turns out economically important depends on the exact magnitude of the predictability effects and the negative correlation.

Campbell et al. (2003a) show that the dividend yield is the most influential determinant of the hedging demand for stocks, while the term spread and the nominal yield on the benchmark asset have a negligible effect. With respect to the latter two predictors we find the same result as Campbell et al. (2003a), yet in our analysis the book-to-market ratio turns out to be the hedging demand's most important driver. To illustrate the crucial role of the book-to-market ratio in the VAR models, Table IV in the appendix with supplementary material shows the demand for stocks in Malaysia, based on the VAR model that only contains the dividend yield as the predictor of stock excess returns (see the caption

'Malaysia (without book-to-market ratio)'). The hedging demand for stocks reported here is substantially lower than the demand based on the VAR model including the book-to-market ratio; see also Table IV. The relatively low (hedging) demand for stocks, arising in the absence of the book-to-market ratio, is due to the two factors. First, the impact of the dividend yield on excess returns is less positive than the impact of the book-to-market ratio. Second and more importantly, the correlation between the innovations of the stock return and dividend yield equations is substantially less negative than the correlation between the innovations of the stock return and book-to-market equations. The inclusion of the book-to-market ratio in the VAR model results in more sizable and significant total and hedging demand for stocks. This does not only hold for Malaysia, but also for e.g. South Africa and South Korea; see again Table IV. In these countries the hedging demand based on the model without the book-to-market ratio is not even significant. As mentioned before, the VAR model including the dividend yield, the book-to-market ratio, the term spread and the nominal yield on the benchmark asset results in very similar outcomes as the model including the book-to-market ratio only. Given our relatively modest sample we strongly prefer the most parsimonious specification to limit estimation uncertainty. We therefore only use the book-to-market ratio as instrument.

The impact of the dividend yield on stock returns is usually explained in the context of the dividend growth model of Campbell and Shiller (1988), which relates the dividend yield to the present value of expected future stock returns and dividend growth rates. Chan and Chen (1991) argue that the book-to-market ratio acts as a proxy for a firm's relative level of distress. According to Fama and French (1992), the book-to-market equity premium stems from the higher risk premiums assigned to high book-to-market firms due to their increased risk of distress. Given that our sample spans a turbulent period in both developed and emerging economies, this seems a plausible explanation for the importance of the book-to-market ratio in our analysis. An alternative explanation is the mispricing hypothesis, which states that market participants underestimate future earnings for high book-to-market stocks and overestimate future earnings for low book-to-market stocks (Ali et al., 2003; Griffin and Lemmon, 2002). The role of the book-to-market ratio can also be viewed from a fundamental value perspective. In the accounting-based present-value model of Vuolteenaho (2002) the log book-to-market ratio equals the discounted sum of expected future excess returns minus profitability.

6. Empirical results: international investor

This section discusses the demand for emerging-market stocks by an international investor whose returns are denominated in US dollars. The international investor can invest in US stocks and T-bills, as well as in foreign stocks in a single emerging market country. Again we use a VAR model to capture this investor's time-varying investment opportunities. In line with Rapach and Wohar (2009), we keep this model tractable by imposing that the investor can only invest in one emerging market country at a time. Throughout, we focus on the economic relevance of the hedging and myopic demand to assess whether these assets are investments for the long run or the short run, or for both. We additionally analyze the welfare implications of further international diversification and foreign currency hedging.

6.1. Specification search

We include the following variables in the international investor's VAR model: the real yield on the 3-month US T-bill (the benchmark asset), the US stock excess return, the emerging market's stock excess return, the log book-to-market ratio on the US stock index, and the log book-to-market ratio on the emerging market stock index. As for the domestic investor, the latter VAR model produces virtually the same demand for assets as the larger VAR model that also contains the dividend yield, the term spread and the nominal yield on the benchmark asset as instruments.[11] Estimation results for the international investor's 5-dimensional VAR model can be found in the appendix; see Tables V (estimated coefficients and p-values) and Table VI (residual correlations).

[11] The term spread is only available for Argentina, Brazil, Chile, China, Colombia, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, and Turkey and calculated from the yields on the relevant JP Morgan Emerging Markets Bond Index.

6.2. Welfare effects: hedging and myopic demand

We proceed in a similar way as before and focus on the economic relevance of the hedging and myopic demand for emerging-market stocks. The first, second and third panels of Table 4 report the international investor's welfare losses due to ignoring the myopic, hedging demand and total demand for emerging-market stocks, for $\psi = 1$ (intertemporal elasticity of substitution), $\delta = 0.92$ (annual time-discount factor) and $\gamma = 2,5,7,10$ (coefficient of relative risk aversion). The associated 95% confidence intervals are reported in Table VII of the appendix with supplementary material. Table VIII in the same appendix provides point estimates of the total, myopic and hedging demand with corresponding confidence intervals.

For all countries apart from Argentina, Brazil, Chile, Colombia, Egypt, Poland and South Africa the international investor's hedging demand for emerging-market stocks is economically relevant. As for the domestic investor, the economic relevance of the hedging demand in the relevant countries stems from the positive coefficients of the book-to-market ratio in the stock return equations, as well as negative residual correlations. The welfare losses caused by not investing myopically are considerable in all countries, especially for more risky investors.

For comparison Table 5 considers the welfare losses due to ignoring the myopic, hedging and total demand for US stocks. We observe that the welfare losses due to ignoring the hedging demand for US stocks are substantial for all international investors, although the welfare losses due to not investing myopically in US stocks tend to be larger, especially for more risky investors. Furthermore, the welfare losses due to ignoring the hedging demand for US stocks are generally larger than the welfare losses due to ignoring the hedging demand for emerging-market stocks. By contrast, the myopic demand for US stocks tends to be economically less relevant than the myopic demand for emerging-market stocks. Overall, emerging-market stocks tend to be economically more important than US stocks; see the third panels of Tables 4 and 5.

These results place the economic relevance of the hedging and myopic demand for emerging-market stocks in a new perspective: the hedging demand for emerging-market stocks tends to be economically relevant, but not as relevant as the hedging demand for US stocks. On the other hand, the myopic demand for emerging-market stocks tends to be economically more relevant than the myopic demand for US stocks. Moreover, the welfare losses due to not investing myopically in emerging-

Table 4
Welfare losses due to ignoring the myopic, hedging and total demand for emerging-market stocks (international investor).

CRRA	ARG	BRA	CHI	CHIN	COL	EG	INDIA	INDO	MAL	MEX	PAK	PERU	PHIL	POL	RUS	SA	SK	TAI	THAI	TUR	Index
No myopic demand for EM stocks																					
2	97.5	93.7	97.6	75.7	99.8	92.9	98.7	99.7	98.9	98.8	94.2	99.4	99.6	67.3	98.9	94.2	99.4	90.9	98.9	99.1	99.9
5	75.0	66.2	77.9	46.4	90.5	60.1	81.8	87.0	83.2	81.6	68.8	87.0	89.3	36.9	80.8	69.4	86.0	62.2	82.7	84.4	93.8
7	62.1	53.5	66.1	36.1	80.9	47.0	70.0	75.8	71.3	69.1	56.6	76.9	80.3	27.9	68.2	57.4	74.9	50.0	71.2	73.3	85.6
10	48.7	41.0	53.3	26.7	68.4	34.9	56.5	62.2	57.1	54.7	44.4	64.6	68.5	20.2	54.1	45.3	61.2	38.2	57.8	60.2	73.4
No hedging demand for EM stocks																					
2	0.4	5.1	6.0	18.4	5.4	3.7	25.6	9.4	38.5	22.2	19.9	21.7	8.3	3.7	28.8	4.5	32.6	13.4	8.4	15.5	30.2
5	1.3	5.7	7.9	36.4	7.3	4.7	35.2	10.4	57.4	28.9	25.7	27.0	12.5	4.9	29.7	6.7	38.5	18.8	12.5	18.9	35.0
7	1.5	5.0	7.2	36.5	6.7	4.4	32.5	9.1	55.5	26.8	22.5	24.6	11.9	4.3	25.1	6.5	34.3	17.0	11.8	16.1	31.3
10	1.4	4.3	6.2	34.3	5.9	3.8	28.6	7.6	51.1	23.7	18.2	21.4	10.5	3.6	20.0	6.3	28.9	14.4	10.7	12.7	26.9
No demand for EM stocks																					
2	97.5	94.0	97.8	80.1	99.8	93.1	99.0	99.7	99.3	99.1	95.4	99.5	99.6	68.5	99.2	94.5	99.6	92.1	99.0	99.2	100.0
5	75.3	68.1	79.6	65.9	91.2	62.0	88.2	88.4	92.9	86.9	76.8	90.5	90.6	39.9	86.5	71.5	91.4	69.3	84.9	87.3	96.0
7	62.7	55.9	68.6	59.4	82.2	49.3	79.8	78.0	87.2	77.4	66.3	82.6	82.6	31.0	76.1	60.2	83.5	58.5	74.6	77.6	90.1
10	49.4	43.5	56.2	51.8	70.3	37.4	68.9	65.0	79.1	65.4	54.5	72.2	71.8	23.1	63.3	48.7	72.4	47.1	62.3	65.3	80.5

Notes: This table shows the Expected Value Loss (EVL) corresponding to several suboptimal asset allocations, assuming optimal consumption given the suboptimal portfolio rule. The EVL is expressed in % and defined as the relative difference between the expected utility per unit of wealth evaluated in the suboptimal allocation and the expected utility per unit of wealth evaluated in the optimal asset allocation. It serves as a measure for the welfare loss due to suboptimal or restricted asset allocation. In all cases, the value functions corresponding to the optimal and suboptimal asset allocations (both needed to calculate the EVL) are based on the same VAR model. The column captioned 'Index' applies to an equally-weighted overall emerging-market stock index based on the individual stock indices in each of the 20 emerging markets under consideration.

Table 5
Welfare losses due to ignoring the myopic, hedging and total demand for US stocks (international investor).

CRRA	ARG	BRA	CHI	CHIN	COL	EG	INDIA	INDO	MAL	MEX	PAK	PERU	PHIL	POL	RUS	SA	SK	TAI	THAI	TUR	Index
No myopic demand for US stocks																					
2	87.7	92.4	63.7	90.5	69.2	81.7	90.9	61.9	81.2	98.1	97.5	74.2	46.6	94.0	90.9	89.4	94.2	86.9	85.4	95.2	95.9
5	58.6	61.7	24.9	62.0	38.9	51.2	60.2	31.2	47.2	74.2	75.2	37.1	18.7	66.8	55.3	57.2	64.8	53.1	51.1	69.3	65.3
7	47.0	48.9	16.8	49.7	30.1	40.3	47.5	23.4	35.6	59.8	62.3	27.5	13.3	54.2	43.0	44.6	51.5	40.8	39.6	56.5	50.4
10	36.2	37.1	11.1	37.9	22.5	30.5	35.6	17.0	25.7	45.2	49.0	19.9	9.4	42.0	32.4	33.2	38.7	30.0	29.5	43.8	36.6
No hedging demand for US stocks																					
2	19.0	29.0	27.2	19.1	48.9	20.6	20.3	24.8	12.0	34.1	23.5	41.6	46.8	23.2	47.5	22.2	15.3	20.9	28.6	18.8	21.9
5	29.2	39.3	38.9	35.1	49.3	31.4	30.9	28.4	25.1	39.4	35.8	48.2	52.3	34.3	45.9	36.8	22.5	30.7	36.1	30.4	35.4
7	27.3	36.6	36.4	34.4	43.9	29.4	29.1	25.3	25.4	36.1	33.5	43.7	47.6	32.2	40.3	35.2	21.0	28.4	32.9	28.9	33.6
10	23.8	32.0	32.0	31.3	37.2	25.9	25.7	21.2	23.8	31.5	29.3	37.6	41.1	28.3	33.9	31.5	18.5	24.6	28.3	25.6	29.9
No demand for US stocks																					
2	90.1	94.6	73.6	92.3	84.3	85.5	92.7	71.4	83.4	98.8	98.1	84.9	71.6	95.4	95.2	91.7	95.1	89.6	89.5	96.1	96.8
5	70.7	76.7	54.1	75.3	69.0	66.5	72.5	50.7	60.4	84.4	84.0	67.4	61.2	78.2	75.8	72.9	72.7	67.5	68.7	78.7	77.5
7	61.5	67.6	47.1	67.0	60.8	57.9	62.7	42.8	52.0	74.3	74.9	59.2	54.6	68.9	66.0	64.1	61.7	57.6	59.5	69.1	67.1
10	51.4	57.2	39.5	57.4	51.3	48.5	52.1	34.6	43.4	62.4	63.9	50.0	46.6	58.4	55.3	54.2	50.0	47.2	49.4	58.2	55.6

Notes: This table shows the Expected Value Loss (EVL) corresponding to several suboptimal asset allocations, assuming optimal consumption given the suboptimal portfolio rule. The EVL is expressed in % and defined as the relative difference between the expected utility per unit of wealth evaluated in the suboptimal allocation and the expected utility per unit of wealth evaluated in the optimal asset allocation. It serves as a measure for the welfare loss due to suboptimal or restricted asset allocation. In all cases, the value functions corresponding to the optimal and suboptimal asset allocations (both needed to calculate the EVL) are based on the same VAR model. The column captioned 'Index' applies to an equally-weighted overall emerging-market stock index based on the individual stock indices in each of the 20 emerging markets under consideration.

market stocks are usually much larger than those of ignoring the hedging demand for emerging-market stocks, especially for more risky investors. In sum, although emerging-market stocks add some long-run value to an international investor's portfolio, they are mainly attractive as a short-run instrument.

6.3. *Welfare effects: international diversification*

For all international investors we quantify the total benefits of international diversification. We do this by calculating each international investor's optimal asset allocation, conditional on the restriction that she cannot invest in emerging-market stocks at all. The resulting welfare implications are based on the associated EVLs and displayed in the third panel of Table 4, while the confidence intervals can be found in Table IX of the appendix with supplementary material. We observe that the welfare losses due to no international diversification are substantial.

For the sake of tractability we have restricted our analysis to international investors who invest in a single emerging market at a time. In practice, however, investors will often invest in multiple emerging markets. To assess the welfare gains from additional international diversification the last column in Table 4 (captioned 'Index') applies to an equally-weighted overall emerging-market stock index based on the individual stock indices in each of the 20 emerging markets under consideration. In the third panel of Table 4 this column allows us to assess the welfare losses that arise from not investing in the overall emerging-market stock index. These welfare losses due to not investing in the overall emerging-market index are larger than the welfare losses caused by not investing in a single emerging-market. Hence, further international diversification results in substantial welfare gains for international investors. As already observed in Section 6.2, emerging-market stocks tend to be economically more important than US stocks.

Is further international diversification attractive for both short-term and long-term investors? To answer this question we consider the welfare implications of ignoring the hedging or myopic demand for the overall emerging-market index (see the last column of Table 4 captioned 'Index'). The economic relevance of the myopic demand for the overall emerging-market equity index is very large; larger than for any individual country (see the first panel of Table 4). The welfare losses from ignoring the hedging demand for the overall index are substantial in an absolute sense, but small in comparison with the

Table 6
Welfare losses due to ignoring the demand for emerging-market stocks in an optimally hedged portfolio (international investor).

CRRA	ARG	BRA	CHI	CHIN	COL	EG	INDIA	INDO	MAL	MEX	PAK	PERU	PHIL	POL	RUS	SA	SK	TAI	THAI	TUR	Index
No demand for hedged EM stocks																					
2	95.6	99.9	99.9	100.0	85.4	95.1	64.4	98.6	91.8	97.4	99.8	91.0	69.3	93.4	97.3	98.0	71.5	98.3	75.9	99.9	78.6
5	69.0	94.2	96.9	99.8	49.1	66.2	35.0	79.9	68.8	78.2	87.8	62.2	34.7	63.8	70.3	80.4	46.7	84.0	40.5	91.1	40.6
7	56.2	87.6	92.6	98.7	37.3	53.8	27.7	67.6	58.9	67.2	76.8	49.8	26.0	51.7	57.0	68.7	38.3	74.5	30.7	81.4	30.8
10	43.6	77.9	84.8	95.1	27.2	41.9	21.4	54.0	48.5	54.9	63.3	37.8	18.9	40.2	44.2	55.3	30.3	63.1	22.5	68.7	22.5
No demand for unhedged EM stocks																					
2	79.2	99.9	87.9	100.0	69.8	97.2	76.1	92.5	89.3	96.5	99.8	97.3	82.3	93.0	99.2	66.3	81.0	96.8	84.7	100.0	66.9
5	42.0	94.7	59.6	99.8	34.7	70.7	39.8	61.4	61.9	76.4	88.3	77.2	46.2	62.2	80.9	39.9	47.7	74.5	49.2	94.7	42.9
7	31.6	88.2	48.2	98.8	26.0	57.7	29.8	48.8	51.3	65.5	77.5	65.4	35.6	49.6	68.5	31.9	37.0	62.5	37.9	87.3	35.0
10	23.0	78.4	37.3	95.5	19.1	44.9	21.5	37.1	41.1	53.5	64.0	52.5	26.4	37.7	54.9	25.1	27.7	49.9	28.1	76.1	27.4
No demand for EM stocks																					
2	99.9	100.0	100.0	100.0	100.0	99.9	99.7	100.0	100.0	100.0	100.0	100.0	99.9	98.0	100.0	99.9	99.9	99.9	99.8	100.0	100.0
5	94.1	99.3	99.5	99.9	96.4	91.7	92.1	98.6	98.9	97.5	97.2	96.8	94.3	78.5	98.3	94.5	96.7	96.4	91.0	98.9	97.6
7	86.4	97.1	98.0	99.5	90.4	82.7	84.8	95.0	96.9	93.3	92.3	91.9	87.7	66.9	94.5	87.6	91.9	91.4	82.4	95.9	93.0
10	74.9	92.0	94.1	97.6	80.4	70.4	74.7	87.4	92.6	85.4	83.4	83.7	77.9	54.2	86.7	77.1	83.6	83.0	70.8	89.3	84.7

Notes: This table shows the Expected Value Loss (EVL) corresponding to several suboptimal asset allocations, assuming optimal consumption given the suboptimal portfolio rule. The EVL is expressed in % and defined as the relative difference between the expected utility per unit of wealth evaluated in the suboptimal allocation and the expected utility per unit of wealth evaluated in the optimal asset allocation. It serves as a measure for the welfare loss due to suboptimal or restricted asset allocation. In all cases, the value functions corresponding to the optimal and suboptimal asset allocations (both needed to calculate the EVL) are based on the same VAR model. The column captioned 'Index' applies to an equally-weighted overall emerging-market stock index based on the individual stock indices in each of the 20 emerging markets under consideration.

Table 7
Welfare losses due to ignoring the myopic and hedging demand for (hedged + unhedged) emerging-market stocks in an optimally hedged portfolio (international investor).

CRRA	ARG	BRA	CHI	CHIN	COL	EG	INDIA	INDO	MAL	MEX	PAK	PERU	PHIL	POL	RUS	SA	SK	TAI	THAI	TUR	Index
No myopic demand for EM stocks																					
2	99.9	100.0	100.0	100.0	100.0	99.9	99.6	100.0	100.0	100.0	100.0	100.0	99.9	97.9	100.0	99.9	99.9	99.9	99.7	100.0	100.0
5	93.7	99.2	98.3	99.8	96.1	89.8	88.3	97.9	96.3	95.7	96.1	95.8	93.4	77.1	97.7	92.3	94.0	93.5	89.9	98.6	96.4
7	85.5	96.9	94.3	98.9	89.8	79.5	78.1	93.2	90.3	88.9	89.8	89.7	86.0	64.8	92.9	83.4	86.4	85.6	80.3	95.1	90.2
10	73.5	91.5	86.3	95.9	79.4	66.1	65.2	83.9	80.3	77.7	79.3	79.9	75.2	51.5	83.9	70.8	74.8	74.1	67.6	87.6	79.6
No hedging demand for EM stocks																					
2	5.2	9.7	59.1	70.9	5.8	22.6	22.1	32.7	49.8	29.0	25.2	19.1	8.2	3.2	24.0	22.3	35.7	36.3	7.6	24.5	21.3
5	6.7	9.4	69.9	59.3	6.8	18.3	32.7	32.2	69.7	41.6	28.2	24.0	13.0	6.1	26.3	28.2	44.5	44.3	11.4	21.5	31.4
7	6.1	7.7	64.6	51.7	6.0	15.6	30.7	27.2	67.6	39.1	24.5	21.7	12.3	6.1	22.1	25.4	40.4	40.2	10.9	17.5	28.8
10	5.2	5.9	56.6	43.3	5.2	12.8	27.4	21.8	62.7	34.8	19.9	18.8	10.8	5.6	17.4	21.8	34.7	34.4	10.0	13.5	25.2

Notes: This table shows the Expected Value Loss (EVL) corresponding to several suboptimal asset allocations, assuming optimal consumption given the suboptimal portfolio rule. The EVL is expressed in % and defined as the relative difference between the expected utility per unit of wealth evaluated in the suboptimal allocation and the expected utility per unit of wealth evaluated in the optimal asset allocation. It serves as a measure for the welfare loss due to suboptimal or restricted asset allocation. In all cases, the value functions corresponding to the optimal and suboptimal asset allocations (both needed to calculate the EVL) are based on the same VAR model. The column captioned 'Index' applies to an equally-weighted overall emerging-market stock index based on the individual stock indices in each of the 20 emerging markets under consideration.

losses due to ignoring the myopic demand (see the first and second panels of Table 4). This result suggests that further international diversification across different emerging markets is particularly attractive for short-term investors. Hence, further international diversification does not alter the previously drawn conclusions.

6.4. *Welfare effects: hedging foreign currency risk*

Until sofar our analysis of the international investor's demand for assets has been restricted to *unhedged* portfolio returns; i.e., portfolio returns based on emerging-market stock returns in US dollars. By analyzing unhedged portfolios we have been able to isolate the pure intertemporal effects of return predictability.

Unhedged portfolios are exposed to currency risk, which raises the question whether the international investor's hedging demand for emerging-market stocks will change if she can hedge the exchange rate exposure (for example, by means of a foreign-currency forward contract position). The effect of currency hedging on the hedging demand for stocks is not a priori clear. The difference between the hedged and unhedged emerging-market stock returns is the currency return, whose presence might weaken the predictability of the unhedged equity returns (Killian and Taylor, 2003; Wright, 2008). On the other hand, Campbell et al. (2003b) show that foreign currency can act as a hedge against domestic real interest rate risk.

To assess the international investor's demand for emerging-market stocks in an optimally hedged portfolio, we first have to determine how much currency risk should be hedged. The optimally hedged portfolio can be obtained by treating *hedged* and *unhedged* emerging-market stocks as two separate asset classes (Ang and Bekaert, 2002). The returns on the hedged investment in emerging-market stocks boil down to the stock returns in local currency, while the returns on the unhedged investment are the returns in US dollars. The total foreign equity position is the sum of hedged and unhedged equity. We follow the approach of Campbell et al. (2003a) as before and estimate the optimal demand for assets in a portfolio consisting of the benchmark asset, as well as hedged and unhedged emerging-market stocks. The first and second panels of Table 6 show the welfare losses due to ignoring the demand for hedged and unhedged emerging-market stocks, respectively. The third panel of Table 6 displays the welfare losses that arise from investing neither in hedged nor in unhedged emerging-market equity. The confidence intervals corresponding to the EVLs in Table 6 are given in Table X of the appendix with supplementary material.

The estimation results in Table 6 show that ignoring the demand for hedged emerging-market equity has considerable welfare effects for the international investor. The EVLs due to not hedging foreign currency risk are substantial in all countries, especially for more risky investors. At the same time we observe that ignoring the demand for unhedged emerging-market equity can also lead to substantial welfare losses. For some investors the welfare losses due to ignoring the demand for emerging-market equity are driven by the lack of hedged emerging-market stocks. This is the case for investors in Argentina, Chile, Colombia, Indonesia, Malaysia (more conservative investors), South Africa and Taiwan (more conservative investors). For other investors hedged and unhedged emerging-market stocks are economically about equally relevant. This holds for investors in Brazil, China, Egypt, India (more conservative investors), Malaysia (risky investors), Mexico, Pakistan, Poland, Russia (risky investors), South Korea (more conservative investors), Taiwan (risky investors) and Turkey (risky investors). For the remaining investors unhedged emerging-market equity is the most important portfolio component from a welfare perspective. We notice that, whenever the welfare losses of having no unhedged (hedged) emerging-market equity are small in comparison with having no hedged (unhedged) emerging-market equity, also the welfare losses of ignoring either the myopic or the hedging demand for unhedged (hedged) emerging-market equity must be relatively small.

By analyzing the economic importance of the hedging and myopic demand for emerging-market stocks in the optimally hedged portfolio, we can investigate whether foreign-currency hedging influences the attractiveness of emerging-market stocks for short-run and long-run investors. The relevant EVLs are displayed in the first and second panels of Table 7 and the associated confidence intervals can be found in Table XI of the appendix with supplementary material. For several countries the economic relevance of the hedging demand for the total of hedged and unhedged emerging-market stocks turns out more substantial in the optimally hedged portfolio than in the unhedged portfolio. These countries are Chile, China, Egypt, Indonesia, Malaysia, Mexico, South Africa and Taiwan. For the other countries the economic relevance of the hedging demand is hardly affected by hedging foreign currency risk. Hence, hedging the exchange rate exposure makes emerging-market stocks slightly more attractive for long-term investors. As before, however, the economic relevance of the myopic demand is considerably larger than that of the hedging demand. Moreover, for all emerging-market investors the myopic demand in the hedged portfolio is economically even more relevant than in the unhedged portfolio. In sum, we conclude again that the welfare losses due to ignoring the hedging demand for emerging-market stocks are relatively small in comparison with the welfare losses due to ignoring the myopic demand. Consequently, also the welfare losses due to ignoring the hedging demand for either hedged or unhedged emerging-market equity must be relatively small.

By combining the aforementioned results, we arrive at the following conclusions. From a welfare perspective the myopic demand for emerging-market equity is the most important component in the optimally hedged portfolio. Whether the myopic demand for *hedged* or *unhedged* emerging-market equity is the most important component depends on the investor's target market and degree of risk averseness. The myopic demand for hedged emerging-market equity is the most important component in the optimally hedged portfolio of investors in Argentina, Chile, Colombia, Indonesia, Malaysia (more conservative investors), South Africa and Taiwan (more conservative investors). The myopic demands for hedged and unhedged emerging-market are economically about equally relevant for investors in Brazil, China, Egypt, India (more conservative investors), Malaysia (risky investors), Mexico, Pakistan, Poland, Russia (risky investors), South Korea (more conservative investors), Taiwan (risky investors) and Turkey (risky investors). For the remaining investors the myopic demand for unhedged emerging-market equity is the most important portfolio component from a welfare perspective.[12] Hence, also for the optimally hedged portfolios we maintain the previously drawn conclusion that emerging-market stocks are mainly attractive for short-run investors.

7. Conclusions

This paper investigates the myopic and hedging demand for stocks in 20 emerging markets from the perspective of a domestic investor (whose returns are denominated in the local currency) and an international investor (with returns in US dollars) during the period 1999–2012. In several emerging market economies the hedging demand is substantial from a welfare perspective, emphasizing the importance of accounting for time variation in investment opportunities. Also for international investors, whose asset menu contains both US stocks and emerging-market equity in a single emerging country, the hedging demand for emerging-market stocks tends to be economically relevant. However, the economic importance of the myopic demand for emerging-market stocks is much more substantial than that of the hedging demand. Further international diversification and foreign-currency hedging by the international investor do not alter these conclusions. Hence, for both domestic and international investors emerging-market stocks are mainly assets for the short run.

Our model of emerging-market equity returns reveals that local-currency emerging market stock returns are to some extent predictable. These predictability effects accounts for the domestic investor's significant hedging demand for emerging-market stocks. We find the book-to-market ratio to be the main determinant of the hedging demand for stocks, rather than the dividend yield that has often been

[12] As before, we could use the EVLs to quantify the welfare implications of ignoring the hedging (myopic) demand for hedged (unhedged) emerging-market stocks. However, doing so poses a problem. There is strongly positive correlation between the returns on hedged and unhedged emerging-market equity. Consequently, in the optimally hedged portfolio the hedging (myopic) demand for *hedged* emerging-market stocks is strongly negatively correlated with the hedging (myopic) demand for *unhedged* emerging-market stocks. When the hedging (myopic) demand for either hedged or unhedged emerging-market stocks is ignored in the restricted portfolio rules, we run into problems in the sense that the resulting welfare effects make no sense anymore. When we impose constraints on both hedging (myopic) components (i.e., for *both* hedged and unhedged equity) there are no such problems; see the estimation results in Table 7. It therefore seems that the problem is due to the strong correlation between the two asset classes, due to which it is not possible to impose a restriction on the hedging (myopic) demand for only one of them. We have therefore derived the economic importance of the hedging (myopic) demand for hedged and unhedged emerging-market equity in an indirect way.

used as a predictor of stock excess returns in previous studies. The literature relates the book-to-market ratio to a firm's relative level of distress. The turbulent sample analyzed in this paper may explain why the book-to-market ratio acts as the main predictor of stock excess returns.

Throughout, we provide statistical confidence intervals in addition to the point estimates of the welfare effects. Because data availability for emerging-market assets is still limited, the amount of parameter uncertainty turns out to be considerable. As a consequence, the estimation results have to be interpreted with some caution.

There are several directions for future research. More parsimonious models could help to reduce the amount of estimation uncertainty. Furthermore, regime-switching models (possibly with endogenous states) could help analyzing the changes in asset demand over time, although this would require longer samples than the ones considered in this paper.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jimonfin.2014.06.003.

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