

The Index Investor

Invest Wisely... Get an Impartial Second Opinion.

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A Note from the Publisher

Welcome to our newest edition of *The Index Investor*, for investors whose functional currency is Swiss Francs. This extra-long initial issue contains, in addition to our regular features, additional material on our approach to asset allocation, the asset class assumptions we use in our analyses, and the derivation of our model portfolios.

Besides this new edition (and one in Indian Rupee), we are making other important changes to our offerings in 2006. We will soon be adding a search engine to our site, and the same type of model portfolio “pull-down” menus that subscribers to our sister publication, *Retired Investor*, have found so useful. As part of this improvement, we have added new 6%, 4%, and 2% target real return portfolios to compliment our current 7%, 5%, and 3% offerings. All these portfolios come in two versions: one uses only index funds (i.e., the “pure beta” version) and the other allows up to a ten percent allocation to equity market neutral funds (i.e., the “alpha-beta separation” version). In addition, this year we will be benchmarking our model portfolios’ performance each month not only against cash (which we have defined as the yield on a one year government security purchased on the last day of 2005), but also against a portfolio that gives equal weight to the asset classes we use. This portfolio’s implicit

assumption is that it is not possible to forecast the risk or return of any asset class beyond simple luck. While we disagree with this, we recognize that the equally weighted portfolio is an intellectually honest benchmark for us to use.

Later this year, we will launch a new publication called *Advanced Investor*. As was the case with *Retired Investor*, we are doing this to better satisfy the needs of our subscriber base, which now contains an equal mix of individual investors and professional investment managers and advisers. This new publication will enable us to better target our offerings and our writing to the respective target audiences of these two publications. As always, subscribers to our existing publications will be given the option to transfer their subscriptions to *Advanced Investor* when it is launched at no additional charge.

Last but not least, I apologize to you for the delay in publishing this month's issue, and take responsibility for it. In the middle of all the other changes underway, we have received over the past month a large number of email enquiries about the implications of the uncertainties facing the world today. Trying to be responsive to our subscribers, I (rather too late in the game, as it turned out) changed our editorial plan to speed up the publication of this month's article on forecasting (which we had planned for later in the year) and produce the asset class/scenario matrix you will find in this month's letters section. I hope you find the delay was worthwhile. Having learned our lesson about scheduling, we will endeavor to get next month's issue to you on time!

Susan Miller
Publisher

This Month's Issue: Key Points

This month's feature article explores recent research in an area that lies at the heart of investment management: forecasting. An investor who believes that it is impossible to accurately forecast risk or return (beyond simple luck), even at the asset class level, should logically hold an equally weighted portfolio of asset class index funds. An investor who believes that it is possible to forecast asset class risks and/or returns (either absolutely or relatively) will logically assign different portfolio weights to different asset class index funds. Finally, an investor who believes it is possible to forecast risk and return for individual securities will invest part of his or her portfolio in actively managed products (or pick individual securities herself).

We review the key elements of a forecast, including the model (i.e., the variables that are important to the outcome of interest, and how they are related to each other) and parameter estimates (i.e., the future values of the variables included in the model). We then note the different approaches we use to develop forecasting models, ranging from intuitively drawing on experience to exhaustively examining the internal logic of a novel situation. We next highlight research findings on the most common source of forecast errors, and what, if anything, human beings can do to avoid or at least minimize them. We conclude that there is a reasonable basis for deviating from the equally weighted asset class index portfolio. However, in light of recent findings about forecasting, we are still highly skeptical of the value of active management for most investors.

In this month's product and strategy notes, we highlight Yale Endowment Fund chief David Swensen's agreement with this conclusion. We also take a look at another, and more pessimistic forecast of the potential economic impact of an H5N1 Avian Influenza pandemic. From there we move on to a discussion of a fascinating speech recently given by Mervyn King, Governor of the Bank of England, on the still mysterious causes of the very low real interest rates in the world today. And last but not least, we analyze the new commodity index ETF recently launched in the United States. We conclude that it offers no compelling reason to switch away from the use of existing commodity index mutual funds.

This Month's Letters to the Editor

Investing in volatility is clearly not an easy subject. Could you please explain the difference between futures contracts on implied and realized volatility?

We agree that this is a complicated subject, and we stress that we too look forward to the introduction of a retail futures-based fund (like commodity index funds) that will make it easier for individual investors to access this asset class. To address your question, there are two futures contracts traded on the Chicago Board Options Exchange. One is on the “implied volatility” of the S&P 500 (as measured by traded options contracts), which is known as the VIX index. The other futures contract is on the actual “realized variance” of the S&P 500, which is known as the VT. Note that volatility is another name for standard deviation, which is the square root of the variance. So, despite the different names, we’re still talking about the same statistic. Though both started in 2004, the market for VIX (as measured by outstanding futures contracts) is about one hundred times as big as the market for VT. In the construction of our model portfolios, we used the VIX as our proxy for equity market volatility as an asset class, since it is the deeper market.

As we have noted in our writing, over different time periods, the standard deviation of returns on the S&P 500 (or any analogous equity index in another currency zone) is not stable over time. In addition, historical data shows an inverse relationship between realized volatility and returns. When volatility is high, returns are typically low, and vice versa. However, VIX futures contracts are a biased predictor of future spot values of the VIX index. Futures prices are typically lower than the eventual spot price. The reason for this is economically logical: since the returns on holding equity (as measured by the S&P 500 Index) are negatively correlated with investors want to invest in VIX futures to offset some of the risk of owning equity. However, the party on the other side of that trade – the one selling the VIX futures – is taking on a lot of risk, since probability suggests that he or she will be losing money on the futures contract at the same time that he or she will be losing money on the equities they own. Hence, the seller of a VIX futures contract requires a substantial risk premium. The form this risk premium takes is a VIX futures contract price that is lower than it otherwise would be if it was an unbiased predictor of the future spot VIX index value.

So, to sum up, one set of our model portfolios allows allocations to equity market volatility as an asset class. As we have noted, until retail volatility products are introduced, these portfolios are very much experimental. An investor implementing this allocation today would have to continuously buy and rollover VIX futures contracts. Because of the risk premium required by the sellers of those contracts, they tend to underestimate the final spot price of the VIX at their expiration date.

On its own, this would cause the investors returns on the VIX contracts to be less than the returns on the spot VIX index that we used in the calculation of our model portfolios. However, as is the case with commodity index futures, VIX futures contracts can be purchased “on margin” at less than their full face value. This enables an investor to invest the difference in some other asset class. In the case of retail commodity index funds, this is typically government bonds. In practice, the earnings on these bond investments usually come close to offsetting the risk premium on the futures contract, so that the realized return by the investor in the commodity index fund is close to the realized return on the spot index. We believe that, in the case of VIX futures, this also would usually be the case.

With the recent unrest over Iran’s nuclear ambitions, I was reminded of your past article on how to position a portfolio if this crisis escalates. Have you given anymore thought to that or to other dangerous scenarios we could face?

As noted above, we received many requests recently that were similar to yours. In response, we have prepared the following table, which we hope succinctly summarizes our views on the likely impact of three different scenarios on returns in different asset classes. The three scenarios are (1) a rapid unwinding of current imbalances in the global economy (this scenario was described in detail in our March and September 2005 issues); (2) a scenario that we call “escalating tensions between the West and the Islamic World (which could include oil problems, terrorism, or military actions related to Iran’s nuclear program); and (3) a global H5N1 avian influenza pandemic. The table below shows the key variables found in the pricing model for each asset class, and our assessment of the likely impact of the three different scenarios. At the bottom of the table is a listing of the asset classes we believe would perform best under each scenario. Finally, we have included two asset classes not found in our model

portfolios: gold coins and residential real estate. We did this because the former always seems to come up when downside scenarios are discussed, and the latter represents many people's biggest single investment. We hope you find the table useful.

Asset Class	Key Variables in Asset Pricing Model	Impact of Sudden Unwinding of Global Imbalances	Impact of Escalating Tensions Between West and Islamic World	Impact of Global H5N1 Influenza Pandemic
Real Return Bonds	<ul style="list-style-type: none"> • Productivity growth • Division of increased output (wages, profits, lower prices) • Investor risk aversion • Investor willingness to delay consumption 	<ul style="list-style-type: none"> • Increase in risk aversion and fall in productivity growth both drive real rates lower, causing modest price gains (because real rates are already so low) • Slight positive returns 	<ul style="list-style-type: none"> • Increase in risk aversion and delayed consumption both drive real rates lower • Slight positive returns 	<ul style="list-style-type: none"> • Fall in productivity, increase in labor's share of output, increase in risk aversion and increase in delayed consumption all drive real rates lower • Slight positive returns
Bonds	<ul style="list-style-type: none"> • Change in real rate • Change in expected inflation • Change in average duration • Also, credit and prepayment risk for non-government bonds 	<ul style="list-style-type: none"> • Flow out of US dollar drives down bond prices and forces interest rates to rise • Negative returns in USD • Flow into non-US currencies causes their bond prices to 	<ul style="list-style-type: none"> • Flight to quality causes rising gov't bond prices and falling yields; positive returns • But widening credit spreads between gov't and non-gov't 	<ul style="list-style-type: none"> • Flight to gov't bonds, with tilt towards economies believed best positioned to recover (Anglo Saxon countries? Switzerland?) • Positive returns on

Asset Class	Key Variables in Asset Pricing Model	Impact of Sudden Unwinding of Global Imbalances	Impact of Escalating Tensions Between West and Islamic World	Impact of Global H5N1 Influenza Pandemic
		<p>rise and rates to fall</p> <ul style="list-style-type: none"> • Positive Returns in Non - USD • Exchange rate changes affect returns on foreign bonds; positive for USD based investors, negative for others holding USD bonds • Credit problems rise as economy slows; negative returns on riskier assets 	<p>bonds causes negative returns on riskier assets</p> <ul style="list-style-type: none"> • This accelerates if oil is disrupted and world enters recession • Differential conflict intensity (e.g., US but not others at center of conflict would trigger move out of USD assets) 	<p>gov't bonds, negative on riskier assets</p>
Commercial Property	<ul style="list-style-type: none"> • Occupancy rates (lower means lower returns) • Rental Rates (lower means lowers returns) • Level of interest rates (higher means lowers returns) 	<ul style="list-style-type: none"> • Weakening economy would lower occupancy rates; • Interest rate increases in US would hurt; negative returns • Falls in rates elsewhere would help valuations; non-U.S. 	<ul style="list-style-type: none"> • Falling interest rates would be positive • To some extent offset by falling occupancy rate if economy slows • Neutral to negative returns 	<ul style="list-style-type: none"> • Falling occupancy rates and rent defaults would swamp impact of falling interest rates • Negative returns

Asset Class	Key Variables in Asset Pricing Model	Impact of Sudden Unwinding of Global Imbalances	Impact of Escalating Tensions Between West and Islamic World	Impact of Global H5N1 Influenza Pandemic
		<p>returns neutral to negative</p> <ul style="list-style-type: none"> Flow out of USD would affect foreign commercial property 	<ul style="list-style-type: none"> XR changes could affect foreign property returns 	
Commodities	<ul style="list-style-type: none"> Change in expected spot price Positive “roll yield” (risk premium) as long as futures prices are below expected spot price Return on surplus cash invested in bonds 	<ul style="list-style-type: none"> Weakening global economy would lead to lower spot commodity prices Since most commodities are priced in dollars, falling USD XR would hurt foreign investors Rising USD rates would increase return on surplus cash Depending on commodity, reduced speculative trading should improve risk premiums Negative to weakly positive returns 	<ul style="list-style-type: none"> Positive for oil; high returns Negative for other commodities, if slowing economy caused spot price declines Falling gov’t bond yields reduces return on surplus cash Flight from XR would hurt foreign investor returns 	<ul style="list-style-type: none"> Falling global demand would drive down spot prices Liquidity in derivative markets would sharply contract; risk premiums would increase Falling gov’t bond yields reduces return on surplus cash Negative returns initially, but then moderately positive

Asset Class	Key Variables in Asset Pricing Model	Impact of Sudden Unwinding of Global Imbalances	Impact of Escalating Tensions Between West and Islamic World	Impact of Global H5N1 Influenza Pandemic
Timber	<ul style="list-style-type: none"> • Physical growth of trees (12% per year in early stage – first 10 years; 9% in established stage 11-20 years; 3% when mature) • Change in timber prices (function of age of trees and overall economic growth) • Discount rate for expected cash flows 	<ul style="list-style-type: none"> • Weakening global economic demand (bad for timber prices if no inflation) and rising US rates cause returns to fall • However, positive returns if inflation rises sharply 	<ul style="list-style-type: none"> • Impact of weakening demand on prices has to be balanced against falling discount rate • Modest positive to negative returns 	<ul style="list-style-type: none"> • Weakening economy forces sharp fall in prices that offsets fall in interest rates • Negative returns
Equity	<ul style="list-style-type: none"> • Current dividend • Total factor productivity growth • Real interest rates • Equity market risk premium 	<ul style="list-style-type: none"> • Economic slowdown bad for productivity growth, and will likely lead to higher risk premium, even as real rates fall • Compounded for foreign investors by weakening US dollar • Negative returns 	<ul style="list-style-type: none"> • Economic slowdown bad for productivity growth, and will likely lead to higher risk premium, even as real rates fall • Negative returns 	<ul style="list-style-type: none"> • Economic slowdown bad for productivity growth, and will lead to higher risk premium, even as real rates fall • Negative returns

Asset Class	Key Variables in Asset Pricing Model	Impact of Sudden Unwinding of Global Imbalances	Impact of Escalating Tensions Between West and Islamic World	Impact of Global H5N1 Influenza Pandemic
Equity Market Neutral	<ul style="list-style-type: none"> • Manager’s ability to forecast company specific risk 	<ul style="list-style-type: none"> • Depends on manager skill; however since no fund is completely “market neutral” negative pressure on returns would increase 	<ul style="list-style-type: none"> • Depends on manager skill; however since no fund is completely “market neutral” negative pressure on returns would increase 	<ul style="list-style-type: none"> • Depends on manager skill; however since no fund is completely “market neutral” negative pressure on returns would increase
Equity Volatility	<ul style="list-style-type: none"> • Change in value of futures contract on implied volatility of S&P 500 (could also use contract on realized volatility) • Return on surplus cash invested in bonds 	<ul style="list-style-type: none"> • Economic instability should cause volatility to increase • Rising US rates will increase return on surplus cash • Strong positive returns 	<ul style="list-style-type: none"> • Economic instability should cause volatility to increase • Falling US rates will decrease return on surplus cash • Moderate positive returns 	<ul style="list-style-type: none"> • Economic instability should cause volatility to increase • Falling US rates will decrease return on surplus cash • Moderate positive returns • Rising volatility
Gold Coins	<ul style="list-style-type: none"> • Change in price of gold • Rises if confidence in paper money is undermined • Storage costs reduce returns 	<ul style="list-style-type: none"> • High return if unwinding of imbalances leads to sharp rise in global inflation 	<ul style="list-style-type: none"> • Rise in gold price due to flight to safety concerns 	<ul style="list-style-type: none"> • Rise in gold price due to falling confidence in paper money and banking system if pandemic is severe

Asset Class	Key Variables in Asset Pricing Model	Impact of Sudden Unwinding of Global Imbalances	Impact of Escalating Tensions Between West and Islamic World	Impact of Global H5N1 Influenza Pandemic
Residential Property	<ul style="list-style-type: none"> • Supply of new houses • Demand for houses • Incomes of potential buyers • Interest rates 	<ul style="list-style-type: none"> • Flat to negative returns in US under pressure from declining economic growth and rising rates • Falling rates will help elsewhere, but be offset by flat to negative economic growth • Strongly positive (especially if financed with fixed rate mortgage) if this scenario leads to a sharp rise in global inflation 	<ul style="list-style-type: none"> • Falling rates will be offset by declining economic growth • Flat to negative returns 	<ul style="list-style-type: none"> • Negative returns as demand disappears, and oversupply is created by deaths of homeowners
Best Performing Asset Classes Under Scenario		<ul style="list-style-type: none"> • Real Return Bonds • Domestic Bonds for non USD investors • Foreign Bonds for USD investors 	<ul style="list-style-type: none"> • Real Return Bonds • Government Bonds • Energy Commodities • Equity Market Volatility • Perhaps Gold 	<ul style="list-style-type: none"> • Real Return Bonds • Government Bonds • Equity Market Volatility • Gold Coins

Asset Class	Key Variables in Asset Pricing Model	Impact of Sudden Unwinding of Global Imbalances	Impact of Escalating Tensions Between West and Islamic World	Impact of Global H5N1 Influenza Pandemic
		<ul style="list-style-type: none"> • Equity Market Volatility • Timber, Gold Coins, and Residential Real Estate if inflation rises 	Coins	

Global Asset Class Returns

YTD 31Jan06	<u>In USD</u>	<u>In AUD</u>	<u>In CAD</u>	<u>In EURO</u>	<u>In JPY</u>	<u>In GBP</u>	<u>In CHF</u>	<u>In INR</u>
Asset Held								
US Bonds	-0.10%	-3.51%	-2.18%	-2.74%	-0.64%	-3.49%	-2.76%	-2.67%
US Prop.	7.50%	4.09%	5.42%	4.86%	6.96%	4.11%	4.84%	4.93%
US Equity	3.50%	0.09%	1.42%	0.86%	2.96%	0.11%	0.84%	0.93%
AUS Bonds	-3.18%	-6.59%	-5.26%	-5.82%	-3.73%	-6.58%	-5.85%	-5.75%
AUS Prop.	1.34%	-2.07%	-0.75%	-1.30%	0.79%	-2.06%	-1.33%	-1.23%
AUS Equity	8.45%	5.04%	6.37%	5.82%	7.91%	5.06%	5.79%	5.89%
CAN Bonds	1.18%	-2.23%	-0.90%	-1.46%	0.64%	-2.21%	-1.48%	-1.39%
CAN Prop.	7.10%	3.69%	5.01%	4.46%	6.55%	3.70%	4.43%	4.53%
CAN Equity	9.04%	5.63%	6.96%	6.41%	8.50%	5.65%	6.38%	6.47%
Euro Bonds	2.39%	-1.02%	0.31%	-0.25%	1.85%	-1.00%	-0.27%	-0.18%
Euro Prop.	9.20%	5.79%	7.12%	6.57%	8.66%	5.81%	6.54%	6.63%
Euro Equity	6.74%	3.33%	4.65%	4.10%	6.19%	3.34%	4.07%	4.17%
Japan Bonds	0.53%	-2.88%	-1.55%	-2.11%	-0.01%	-2.86%	-2.13%	-2.04%
Japan Prop.	5.20%	1.79%	3.12%	2.56%	4.66%	1.81%	2.54%	2.63%
Japan Equity	3.70%	0.29%	1.62%	1.06%	3.16%	0.30%	1.03%	1.13%
UK Bonds	4.50%	1.09%	2.42%	1.86%	3.96%	1.11%	1.84%	1.93%
UK Prop.	7.97%	4.56%	5.89%	5.33%	7.43%	4.58%	5.31%	5.40%
UK Equity	6.08%	2.67%	4.00%	3.45%	5.54%	2.69%	3.42%	3.51%
World Bonds	0.90%	-2.51%	-1.18%	-1.74%	0.36%	-2.49%	-1.76%	-1.67%
World Prop.	6.58%	3.17%	4.50%	3.94%	6.04%	3.19%	3.92%	4.01%
World Equity	5.20%	1.79%	3.12%	2.56%	4.66%	1.81%	2.54%	2.63%
Commodities	1.60%	-1.81%	-0.48%	-1.04%	1.06%	-1.79%	-1.06%	-0.97%
Timber	3.91%	0.50%	1.83%	1.28%	3.37%	0.52%	1.25%	1.34%
EqMktNeutral	1.79%	-1.62%	-0.29%	-0.85%	1.25%	-1.61%	-0.87%	-0.78%
Volatility	7.29%	3.88%	5.21%	4.66%	6.75%	3.90%	4.63%	4.72%
Currency								
AUD	3.41%	0.00%	1.33%	0.77%	2.87%	0.02%	0.75%	0.84%
CAD	2.08%	-1.33%	0.00%	-0.55%	1.54%	-1.31%	-0.58%	-0.49%
EUR	2.64%	-0.77%	0.55%	0.00%	2.09%	-0.76%	-0.03%	0.07%
JPY	0.54%	-2.87%	-1.54%	-2.09%	0.00%	-2.85%	-2.12%	-2.03%
GBP	3.39%	-0.02%	1.31%	0.76%	2.85%	0.00%	0.73%	0.83%
USD	0.00%	-3.41%	-2.08%	-2.64%	-0.54%	-3.39%	-2.66%	-2.57%
CHF	2.66%	-0.75%	0.58%	0.03%	2.12%	-0.73%	0.00%	0.10%
INR	2.57%	-0.84%	0.49%	-0.07%	2.03%	-0.83%	-0.10%	0.00%

Equity and Bond Market Valuation Update

Our market valuation analyses are based on the assumption that markets are not perfectly efficient and always in equilibrium. This means that it is possible for the supply of future returns a market is expected to provide to be higher or lower than the returns investors logically demand. In the case of an equity market, we define the future supply of returns to be equal to the current dividend yield plus the rate at which dividends are expected to grow in the future. We define the return investors demand as the current yield on real return government bonds plus an equity market risk premium. As described in our May, 2005 issue, people can and do disagree about the “right” values for these variables. Recognizing this, we present four valuation scenarios for an equity market, based on different values for three key variables. First, we use both the current dividend yield and the dividend yield adjusted upward by .50% to reflect share repurchases. Second, we define future dividend growth to be equal to the long-term rate of total (multifactor) productivity growth, which is equal to either 1% or 2%. Third, we use two different values for the equity risk premium required by investors: 2.5% and 4.0%. Different combinations of these variables yield high and low scenarios for both the future returns the market is expected to supply, and the future returns investors will demand. We then use the dividend discount model to combine these scenarios, to produce four different views of whether an equity market is over, under, or fairly valued today. The specific formula is $(\text{Current Dividend Yield} \times 100) \times (1 + \text{Forecast Productivity Growth})$ divided by $(\text{Current Yield on Real Return Bonds} + \text{Equity Risk Premium} - \text{Forecast Productivity Growth})$. Our valuation estimates are shown in the following tables, where a value greater than 100% implies overvaluation, and less than 100% implies undervaluation:

<i>Australia</i>	Low Demanded Return	High Demanded Return
High Supplied Return	68%	106%
Low Supplied Return	108%	152%

<i>Canada</i>	Low Demanded Return	High Demanded Return
High Supplied Return	82%	144%
Low Supplied Return	157%	235%

<i>Eurozone</i>	Low Demanded Return	High Demanded Return
High Supplied Return	65%	116%
Low Supplied Return	121%	183%

<i>Japan</i>	Low Demanded Return	High Demanded Return
High Supplied Return	92%	205%
Low Supplied Return	274%	460%

<i>United Kingdom</i>	Low Demanded Return	High Demanded Return
High Supplied Return	45%	89%
Low Supplied Return	88%	139%

<i>United States</i>	Low Demanded Return	High Demanded Return
High Supplied Return	115%	185%
Low Supplied Return	215%	307%

<i>Switzerland</i>	Low Demanded Return	High Demanded Return
High Supplied Return	70%	145%
Low Supplied Return	163%	241%

<i>India</i>	Low Demanded Return	High Demanded Return
High Supplied Return	53%	124%
Low Supplied Return	134%	229%

Our government bond market valuation update is based on the same supply and demand methodology we use for our equity market valuation update. In this case, the supply of future fixed income returns is equal to the current nominal yield on ten-year government bonds. The demand for future returns is equal to the current real bond yield plus the historical average inflation premium (the difference between nominal and real bond yields) between 1989 and 2003. To estimate of the degree of over or undervaluation for a bond market, we use the rate of return supplied and the rate of return demanded to calculate the present values of a ten year zero coupon government bond, and then compare them. If the rate supplied is higher than the rate demanded, the market will appear to be undervalued. This information is contained in the following table:

	Current Real Rate	Average Inflation Premium (89-03)	Required Nominal Return	Nominal Return Supplied (10 year Govt)	Return Gap	Asset Class Over or (Under) Valuation, based on 10 year zero
Australia	2.19%	2.96%	5.15%	5.93%	0.78%	-7.16%
Canada	1.52%	2.40%	3.92%	4.19%	0.27%	-2.58%
Eurozone	1.43%	2.37%	3.80%	3.48%	-0.32%	3.16%
Japan	0.71%	0.77%	1.48%	1.57%	0.09%	-0.84%
UK	1.07%	3.17%	4.24%	4.15%	-0.09%	0.89%
USA	1.97%	2.93%	4.90%	4.55%	-0.35%	3.37%
Switz.	0.89%	2.03%	2.92%	2.19%	-0.73%	7.38%
India	1.61%	7.57%	9.18%	7.11%	-2.07%	21.13%

It is important to note some important limitations of this analysis. First, it uses the current yield on real return government bonds (or, in the cases of Switzerland and India, the implied real yield if those bonds existed). Over the past forty years or so, this has averaged around 3.00%. Were we to use this rate, bond markets would generally look even more overvalued. It also uses historical inflation as an estimate of expected future inflation. This may not produce an accurate estimate, if the historical average level of inflation is not a good predictor of average future inflation levels.

Second, this analysis looks only at ten-year government bonds. The relative valuation of non-government bond markets is also affected by the extent to which their respective credit spreads (that is, the difference in yield between an investment grade or high yield corporate bond and a government bond of comparable maturity) are above or below their historical averages (with below average credit spreads indicating potential overvaluation). Today, in many markets credit spreads are at the low end of their historical ranges, which would make non-government bonds appear even more overvalued.

Third, if one were to assume a very different scenario, involving a prolonged recession, accompanied by deflation, then one could argue that government bond markets are actually undervalued.

Finally, for an investor contemplating the purchase of foreign bonds or equities, the expected future annual percentage change in the exchange rate is also important. Study after study has shown that there is no reliable way to forecast this. At best, you can make an estimate that is justified in theory, knowing that in practice it will not turn out to be accurate. That is what we have chosen to do here. Specifically, we have taken the difference between the yields on ten- year government bonds as our estimate of the likely future annual change in exchange rates between two regions. This information is summarized in the following table:

Annual Exchange Rate Changes Implied by Bond Market Yields

	To AUD	To CAD	To EUR	To JPY	To GBP	To USD	To CHF	To INR
From								
AUD	0.00%	-1.74%	-2.45%	-4.36%	-1.78%	-1.38%	-3.74%	1.18%
CAD	1.74%	0.00%	-0.71%	-2.62%	-0.04%	0.36%	-2.00%	2.92%
EUR	2.45%	0.71%	0.00%	-1.91%	0.67%	1.07%	-1.29%	3.63%
JPY	4.36%	2.62%	1.91%	0.00%	2.58%	2.98%	0.62%	5.54%
GBP	1.78%	0.04%	-0.67%	-2.58%	0.00%	0.40%	-1.96%	2.96%
USD	1.38%	-0.36%	-1.07%	-2.98%	-0.40%	0.00%	-2.36%	2.56%
CHF	3.74%	2.00%	1.29%	-0.62%	1.96%	2.36%	0.00%	4.92%
INR	-1.18%	-2.92%	-3.63%	-5.54%	-2.96%	-2.56%	-4.92%	0.00%

Sector and Style Rotation Watch

The following table shows a number of classic style and sector rotation strategies that attempt to generate above index returns by correctly forecasting turning points in the economy. This table assumes that active investors are trying to earn high returns by investing today in the styles and sectors that will perform best in the next stage of the economic cycle. The logic behind this is as follows: Theoretically, the fair price of an asset (also known as its fundamental value) is equal to the present value of the future cash flows it is expected to produce, discounted at a rate that reflects their relative riskiness.

Current economic conditions affect the current cash flow an asset produces. Future economic conditions affect future cash flows and discount rates. Because they are more numerous, expected future cash flows have a much bigger impact on the fundamental value of an asset than do current cash flows. Hence, if an investor is attempting to earn a positive return by purchasing today an asset whose value (and price) will increase in the future, he or she needs to accurately forecast the future value of that asset. To do this, he or she needs to forecast future economic conditions, and their impact on future cash flows and the future discount rate. Moreover, an investor also needs to do this before the majority of other investors reach the same conclusion about the asset's fair value, and through their buying and selling cause its price to adjust to that level (and eliminate the potential excess return).

We publish this table to make an important point: there is nothing unique about the various rotation strategies we describe, which are widely known by many investors. Rather, whatever active management returns (also known as "alpha") they are able to generate is directly related to how accurately (and consistently) one can forecast the turning points in the economic cycle. Regularly getting this right is beyond the skills of most investors. In other words, most of us are better off just getting our asset allocations right, and implementing them via index funds rather than trying to earn extra returns by accurately forecasting the ups and downs of different sub-segments of the U.S. equity and debt markets. That being said, the highest year-to-date returns in the table give a rough indication of how investors employing different strategies expect the economy and interest rates to perform in the near future. The highest returns in a given row indicate that most investors are anticipating the economic and interest rate conditions noted at the top of the next column (e.g., if long maturity bonds have the

highest year to date returns, a plurality of bond investor opinion expects rates to fall in the near future). Comparing returns across strategies provides a rough indication of the extent of agreement (or disagreement) investors about the most likely upcoming changes in the state of the economy.

Year-to-Date Returns on Classic Rotation Strategies in the U.S. Markets

YTD 31Jan06

<i>Economy</i>	Bottoming	Strengthening	Peaking	Weakening
<i>Interest Rates</i>	Falling	Bottom	Rising	Peak
<i>Style Rotation</i>	Growth (IWZ) 2.20%	Value (IWW) 3.99%	Value (IWW) 3.99%	Growth (IWZ) 2.20%
<i>Size Rotation</i>	Small (IWM) 8.44%	Small (IWM) 8.44%	Large (IWB) 2.47%	Large (IWB) 2.47%
<i>Style and Size Rotation</i>	Small Growth (DSG) 7.99%	Small Value (DSV) 7.32%	Large Value (ELV) 2.81%	Large Growth (ELG) 3.44%
<i>Sector Rotation</i>	Cyclicals (IYC) 1.26% Technology (IYW) 4.16%	Basic Materials (IYM) 6.73% Industrials (IYJ) 1.48%	Energy (IYE) 13.12% Staples (IYK) 0.77%	Utilities (IDU) 2.56% Financials (IYF) 1.38%
<i>Bond Market Rotation</i>	High Risk (VWEHX) 0.90%	Short Maturity (VBISX) 0.10%	Low Risk (VIPSX) 0.20%	Long Maturity (VBLTX) -0.90%

Forecasting

Investors are confronted with a myriad of difficult choices -- for example, about asset allocation policy and the funds that should be used to implement it. In our October 2005 issue, we reviewed the types and sources of uncertainty that make these decisions so difficult. In this article, we will look at the extent to which forecasting can penetrate this uncertainty.

A person's beliefs about forecasting are (or should be) central to his or her approach to investment management. An investor who believes that it is impossible to accurately forecast risk or return (beyond simple luck), even at the asset class level, should logically hold an equally weighted portfolio of asset class index funds. An investor who believes that it is possible to forecast asset class risks and/or returns (either absolutely or relatively) will logically assign different portfolio weights to different asset class index funds. Finally, an investor who believes it is possible to forecast risk and return for individual securities will invest part of his or her portfolio in actively managed products (or pick individual securities herself).

Given the importance of forecasting, or, more specifically, beliefs about its accuracy, this article will summarize recent research in this area. Let's start with the basics. A forecast for a given target (or "dependent") variable (say, the rate of return next year on an equity market index) contains three elements: (1) "independent" variables that affect the future value of the target; (2) a description of how these variables are related to each other; and (3) estimates of the future values of the independent variables. Together, (1) and (2) are often referred to as the "forecasting model." This is, in essence, a theory about how a given system works. In contrast, assumptions about the future values of the independent variables are known as "parameter estimates."

We use forecasting models every day. A few are deliberately created and explicit; most are formulated intuitively, and their terms are implicit. Broadly speaking, people typically draw on three sources when creating a forecasting model. The first is analogy and experience. Most day-to-day decisions we make are based on this approach, because it has the great advantage of conserving our scarce cognitive resources. Experience teaches us to direct our attention to certain cues in certain familiar situations (e.g., look for a traffic light if you round a sharp curve while driving your car, and see an intersection ahead). When those cues are present (e.g., a

traffic light is present, and the light is red), they trigger the automatic use of forecasting models that have been used so often that they have become intuitive (e.g., the driver of the car behind me will also see the light and slow down; there is significant probability of getting into an accident or receiving a traffic ticket if I do not stop for the red light; the light will eventually turn to green, etc.).

However, there are times when we don't recognize a situation, either because the situation is unfamiliar, or the cues differ from our expectation. A classic example of this is the first time a newly arrived Canadian or American driver confronts a simultaneous red/yellow traffic light in the United Kingdom. The failure of experience and analogy to quickly provide an appropriate forecasting model typically triggers a quick mental search for a theory that can be used to create one. For example, "red means stop; yellow means caution; therefore I should stop with extra caution." In this case, our driver will quickly learn that the red/yellow combination actually means "the light is about to change to green." The red/yellow combination will be consciously added to the driver's mental forecasting model, whose use will again become automatic, in keeping with the principle that human beings try to conserve scarce cognitive resources.

Now consider what would happen if our driver was confronted with a signal containing three lights arranged in a triangle, with the top one flashing blue. Clearly, experience is not helpful here, nor is there likely to be a readily available theory that can be used to quickly construct a forecasting model. In this case, considerable cognitive effort is required to identify the key variables in the situation, develop a theory about how they are related to each other, estimate their most likely future values, predict the future values of the target variables (e.g., how will the car in back of me behave, or the truck coming towards me, or the cars crossing in front of me?), and decide how to act (e.g., stop, slow down, etc.). Clearly, a lot of assumptions are involved here, which differ not only in their potential importance but also in their degree of uncertainty. This triggers yet another mental process, which identifies the critical "linchpin" assumptions that are both highly important and highly uncertain (e.g., the car behind me will also slow down, even though the driver is talking on his mobile), which must be monitored with scarce cognitive resources while carrying out the chosen course of action. It is easy to see how situations like this produce anxiety and mental exhaustion.

In sum, forecasting models and parameter estimates come from three sources, in ascending order of cognitive difficulty: analogy/experience, theory, and analysis of a specific (and usually novel) situation. To move back into the realm of finance, let's now consider the different ways someone could approach this question: what will be the rate of return on domestic equities over the next year?

A professional equities trader at an investment bank might answer on the basis of an intuitive model grounded in her experience. Another investor might use a theory that says the rate of return the equity market is expected to supply is equal to the current dividend yield plus the rate at which dividends are expected to grow in the future.

A third investor might take a much more deliberate approach, and consider not only the fundamental variables that will affect equity values over the next year (e.g., the outlook for economic growth, interest rates, corporate cash flow, and the like), but also those affecting the future actions of other investors (e.g., current momentum and mood, the potential for near-term political crises, changes in the balance of fear versus greed, etc.). This could take the form of either a substantive qualitative analysis (e.g., as is often found in brokers' investment strategy reports), or an elaborately specified quantitative model.

Regardless of the approach used to develop a forecast, the three potential sources of forecast errors remain constant. The first is known as "model error", which includes getting the independent variables and/or the relationships between them and the target variable wrong. The second is known as "estimation error" which means making an incorrect assumption about the future value of one or more independent variables.

The third source of error is known as "non-stationarity." This refers to a situation in which a model that accurately explains the past values for the target variable fails to do so in the future because either the relationships between the independent variables or the processes driving their future values have changed in an unanticipated way. In the context of the three approaches to forecasting model formation described above, non-stationarity refers to the use of an approach that has worked in the past (e.g., experience), even when the current situation is so different that it no longer applies, and an alternative approach (e.g., explicitly assessing a situation) would make more sense. In our view, there are two reasons humans seem particularly vulnerable to this source of forecast error. First, given our limited cognitive resource, we have a tendency to err on the side of conserving them, preferring easier

approaches to forecasting model development to ones that require more energy. Closely related to this is the so-called “confirmation bias” which causes us to give greater weight to information which confirms our current view, and less weight to information that conflicts with it. Indeed, the confirmation bias is fully consistent with the old saying that “it takes twice as much information to change an opinion as it does to form one.”

Indeed, our susceptibility to non-stationarity error and the confirmation bias may have neurochemical roots. In “Uncertainty, Neuromodulation and Attention,” Yu and Dayan begin by asserting that “making inferences about the state of the world and predictions about the future based on many different kinds of uncertain information sources is one of the most fundamental computational tasks facing the [human] brain.” They then note that Bayesian statistical theory quantifies this problem, and provides a rational approach to updating our views based on the receipt of new information. Yu and Dayan distinguish between “expected uncertainty” and “unexpected uncertainty.” The former “arises from known unreliability of predictive relationships within a familiar environment”, while “unexpected uncertainty is induced by gross changes in the environment that ...strongly violate expectations.” The authors go on to show how two different brain chemicals – acetylcholine and norepinephrine – are involved when we confront expected and unexpected uncertainty. This suggests that anything that affects their levels and functioning will affect our susceptibility to non-stationarity error and the confirmation bias.

Outside the world of neurochemistry, other researchers have recently provided us with new insights into the extent and causes of forecasting error. In “Economic Forecasting: Some Lessons from Recent Research”, David Hendry and Michael Clements (two leaders in the field) conclude that the most important sources of forecast error are related to non-stationarity. Another recent paper, “Tactical Asset Allocation and Model Uncertainty”, David Rey uses historical data from the Swiss equity market, and examines the relative contribution to forecast error over time of model error, parameter error, and non-stationarity. He finds that “the relative contributions are highly dependent on the time period under consideration.” We view this finding as consistent with our view that financial markets function as a complex adaptive system, which are characterized by varying periods of high and low average forecast errors.

Bacchetta and van Wincoop provide further evidence of this in their paper “Higher Order Expectations in Asset Pricing.” They start with a view we strongly share: that accurately

forecasting future asset prices involves consideration not only of the fundamental factors driving their value (e.g., the current dividend yield, expected dividend growth, current real government bond yield, and equity market risk premium), but also the variables that will affect the future actions of other investors. The authors show how incorrect assumptions about future investor behavior can cause asset prices to substantially diverge from their fundamental value.

An important question in finance theory is whether forecast errors are random or whether some investors make them in a predictable way. In “Predictability in Financial Markets: What Do Survey Expectations Tell Us?” Bacchetta, Mertens, and van Wincoop analyze survey data on investors expectations in the stock, bond, money and foreign exchange markets. They “find systematic evidence of predictable expectational errors across markets, sample periods and countries.”

This raises an obvious question: what causes these predictable forecast errors? Broadly speaking, there are two schools of thought. The “behavioral school” believes the underlying cause is investors’ limited cognitive resources, and less than perfect rationality, as evidenced by the confirmation bias. In “Does Adaptive EPS Forecasting Make Analysts Forecasts Redundant?” Dimitri Kantsyrev provides interesting new evidence on this point. He compares the accuracy of stock analysts’ earnings forecasts with ones produced by a statistical forecasting model. In the past, these types of comparison have typically used a time series forecasting model whose terms do not change over time. Unsurprisingly, these studies have found that, because analysts can adapt to new information, their forecasts are more accurate than those produced by unchanging statistical models. Kantsyrev’s innovation is the use of an adaptive neural network model. Made possible by modern high-powered computers, neural network models constantly “learn”, in the sense that they automatically identify changing patterns in historical data, use them to specify a forecasting model, examine their own forecasting errors, and then update the forecasting model accordingly. In this manner, they minimize the impact of non-stationarity as a source of forecasting error.

Kantsyrev found that the adaptive neural network model outperformed analyst forecasts for companies with highly volatile earnings and over longer time horizons. The adaptive neural network model was particularly good at predicting downward changes in earnings. In contrast, the “analysts’ forecast bias [errors] increased with the volatility of earnings.” In our view, this vividly demonstrates, how the impact of non-stationarity is magnified by the confirmation bias.

Kantsyrev draws an even more aggressive conclusion: “financial analysts mainly predict the overall market behavior, and have a lack of ability to predict firm-specific fluctuations.” Not exactly a ringing endorsement of active management (at least by humans!).

The second school of thought sees predictable forecasting errors as caused not by cognitive shortcomings, but rather by a rational process. In “Rational Inattention: A Solution to the Forward Discount Puzzle”, Bacchetta and van Wincoop start with a question that has puzzled many analysts (ourselves included): why does uncovered interest rate parity (UIP) not seem to hold in the short term? For those of you who are scratching your heads, UIP refers to the theoretical relationship between interest rates and exchange rates in two countries. In theory, a difference in interest rates should be offset (less any transaction costs) by an opposite difference in exchange rates, to eliminate the possibility of earning a higher profit (in one currency) by investing in the other country’s bonds. For example, if Australian bonds yield 5% more than U.K. bonds, UIP suggests that the Australian dollar should depreciate by 5% against the U.K. pound.

Bacchetta and van Wincoop note “there are significant costs associated with collecting information, processing information, and making decisions based on that information. These costs are added to the usual transaction costs.” Since investors vary in the size of the trades they can make, they also vary in their ability to profit from the collection of information. “This makes it optimal for many investors to only infrequently assess the available information and revise their portfolios. [Many] investors may therefore be ‘rationally inattentive’, which gives rise to predictable expectational errors” and deviations from uncovered interest rate parity.

A somewhat different line of research has addressed whether or not equity market returns are predictable in advance. Needless to say, there are competing and very strongly held views on this critical question. In “A Comprehensive Look at the Empirical performance of Equity Premium Prediction”, Goyal and Welch conclude that the answer is “no.” They find that none of the forecasting models they examined “would have helped an investor with access only to information [about predictor variables] available [in real time] to time the market.” They conclude that a simple forecast based on historical returns is the best approach. This view is challenged by Campbell and Thompson in “Predicting the Equity Premium Out of Sample: Can Anything Beat the Historical Average?” They conclude that some forecasting variables (e.g., the Price/Earnings ratio) can outperform the historical average, though “their predictive power

is small but [still] economically meaningful.” However, the authors also note “a variable is quite likely to have poor [forecasting] performance for an extended period of time even when the variable genuinely predicts returns with a stable coefficient.” They wisely conclude that “the saying ‘if you’re so smart, why aren’t you rich?’ applies with great force here, and should lead investors to suspect that highly successful [forecasting models] are spurious.”

In “Reconciling the Return Predictability Evidence”, Lettau and Nieuwerburgh show that taking non-stationarity of the predictor variables into account resolves the apparently contradictory findings of the “predictable returns” versus “unpredictable returns” schools. So far, so good. However, this still leaves the investor with the challenge of forecasting non-stationarity, for which the authors offer some initial suggestions. As you can see, rather than solving the fundamental forecasting problem, this approach simply shifts it to another level.

Finally, no discussion of forecasting error would be complete without mention of Philip Tetlock’s outstanding new book, Expert Political Judgment. It is a massive analysis of over twenty years of forecasts produced by a wide variety of experts. Unsurprisingly, it finds that experts are subject to the confirmation bias, find it difficult to learn from their forecasting mistakes, and are outperformed by forecasts made by quantitative models unaffected by emotion or a scarcity of (not always perfectly rational) cognitive resources. In most cases, they perform no better than non-experts.

Tetlock’s most intriguing finding is what he calls the contrast between the “hedgehog” and the “fox” styles of forecasting, which are used by experts and non-experts alike. The former tends to apply a single theory to make forecasts under different circumstances. In contrast, rather than relying on a single theory, the fox tries to make sense of situations based on their own logic. Tetlock finds that while hedgehogs are more popular with the media because of the simplicity and certainty of their views, their actual forecasts are outperformed by those made by the foxes. He notes that “the foxes’ self-critical, point-counterpoint style of thinking prevented them from building up the sorts of excessive enthusiasm for their predictions that hedgehogs, especially well-informed ones, displayed for theirs. Foxes were more sensitive to how contradictory forces can yield stable equilibria, and, as a result, “overpredicted” fewer departures from the status quo. But foxes did not mindlessly predict the past. They recognized the precariousness of many equilibria, and hedged their bets by rarely ruling out anything as impossible.” On the other hand, Tetlock cautions that foxes can be

excessively open minded and prone to confusion caused by “seeing too much merit in too many stories.” On balance, however, Tetlock concludes that “the dominant danger remains hubris, the mostly hedgehog vice of closed-mindedness, of dismissing dissonant possibilities too quickly.”

All of these analyses beg a final question: what can be done to improve our forecasting performance? The key seems to be the ability to adapt one’s forecasting model quickly once non-stationarities are discovered. Anticipating in advance these abrupt changes in the structure of the environment seems to be out of the question; the best we can hope to do is quickly react to them. In “Economic Forecasting: some Lessons From Recent Research”, Hendry and Clements make the important point that the use of simple models is not the same as adaptability. To be sure, simple forecasting models facilitate adaptability but they are not one in the same. For example, Kantsyrev’s earnings forecasting model, while highly adaptive, is anything but simple. Moreover, Tetlock cautions us against the hubris and over-confidence bias (and, perhaps, neurochemical changes!) that simple, successful models often create in their users.

Another technique that has been shown to minimize the risk of non-stationarity errors is the combination of forecasts made using different models. This is the approach we use in our asset allocation models, which combine asset class forecasts made using both historical data and a forward looking asset pricing model. In “Structural Breaks and the Performance of Forecast Combinations”, Aiolfi and Timmerman show why combining forecasts, often using very simple equal weighting schemes, usually works better than relying on a forecasting single model.

Finally, forecast combination does not automatically require the use of quantitative models. In the world of defense and intelligence, “Red Teaming” (also known as “competitive analysis”) is becoming more widely used. In this process, an outside team is used to explicitly challenge a forecast made by an organization. While this can take many forms, two of the most common are (a) assuming a critical uncertain variable has turned out differently than the base case plan assumes, and developing an alternative action plan, and (b) assuming (in hindsight) that the base case plan has failed, and developing a detailed story of why this happened, what could have been done differently, and what warning indicators were missed. In both cases, the end result is a comparison of the base case plan with the alternative one, leading to insights

about the implications for key decisions facing the organization (e.g., wait, hedge, go ahead, etc.), and the most important warning indicators to monitor.

So where does this leave us as investors? We began with two questions, whose answers depend on our beliefs about the efficacy of forecasting. Is there any reason to hold something other than an equally weighted portfolio of broadly defined asset class index funds? And is there any reason to pursue active management, either by opportunistically changing asset class weightings, or going long and short individual securities within them?

Our answer to the first question is a qualified “yes.” We start with the assumption, that, because of differing goals and risk preferences, investors will want to hold portfolios with differing risk/return characteristics. This is true even in the absence of differing investor forecasts about different asset classes’ and securities’ risks and returns. We then make four observations. First, there is evidence that over the long term, investors are compensated with higher returns for holding riskier assets. “The Risk Return Trade Off in the Long Run: 1836 to 2003” by Christian Lundblad is a good example of this research. The second observation, however, is that study after study has found that it is very hard to accurately forecast future asset class returns. On the other hand, the third observation is that the ranking of asset classes by their relative riskiness is quite consistent over time. Triumph of the Optimists by Dimson, Marsh and Staunton is one of the best studies on this point. The fourth observation is another cautionary one, in that the correlation of returns between different asset classes (a key component, along with individual asset class risk, of aggregate portfolio risk) is not stable over time.

These four observations lead us to two conclusions. First, there appears to be a strong case for departing from an equally weighted asset class portfolio, in order to better satisfy investors’ differing risk preferences, based on the observations that asset class risk rankings are relatively stable and that higher risk asset classes tend to earn higher returns. We do not believe this argument is undone by changing return correlations over time.

Our second conclusion is less strongly held: that there is also a case for departing from an equally weighted asset class portfolio in order to better satisfy investors’ differing return goals, within their specified risk constraints. While we believe that, over time, higher risk is rewarded with higher returns, and while we have taken prudent steps to limit the possibility and potential impact of forecast error (e.g., using asset class return forecast combinations, as well as

constraints on the maximum weight for different asset classes), we have no doubts about the inherent difficulty of the task. For that reason, we stress that our asset allocation recommendations are in no sense optimal; rather, our objective is that they are robust enough to achieve, with a minimum probability, a given long-term real return under a wide range of possible future asset class return scenarios.

And what of the second question? Does our review of the latest research about forecasting change the generally unfavorable evaluation of active management we presented in our book [Indexing Versus Active Management: The Trial of a Prudent Investor?](#) On the one hand, there is a high probability that in a rapidly changing world economy, non-stationarities are becoming more frequent. At the same time, Philip Tetlock provides ample evidence that human beings' forecasting skills have not similarly improved. On the other hand, Kantsyrev's paper, along with ample anecdotal evidence about the quantitative modeling arms race now underway in the hedge fund world suggest that highly adaptable forecasting models exist. In addition, there is also the possibility that an active manager can make a superior forecast not because he or she has a superior model, but because, due to superior information, he or she can more accurately estimate the value of key model parameters.

However, this gives rise to three more questions: (1) can investors forecast, with any accuracy, which hedge funds that possess accurate forecasting models or information advantages? (2) More important, can investors forecast with any accuracy the probability that these models or information advantages will be able to successfully adapt to future non-stationarities? And, finally, (3), even if an investor answers "yes" to the first two questions, can he or she forecast with any accuracy that the hedge fund's fees will not fully offset the additional returns (above an index fund) the superior forecasting model and/or information will generate? We do not doubt that some investors will answer, "yes" again, and will, through luck or skill turn out to be right. On the other hand, we are highly skeptical that, in the face of financial markets that function as a complex adaptive system, the great majority of investors, and in particular individual investors, can play this active management game for many years and come out ahead.

In the interest of intellectual honesty, we are putting these views to the test in our model portfolios. As you can see elsewhere in this issue, we are including each month the year-to-date results of an equally weighted portfolio. In our March 2005 issue, we showed how the

historical returns on this portfolio, in most currencies, were quite close to those on our five percent target real return portfolio. We will see if this remains the case going forward.

At the other end of the spectrum, we also include a set of model portfolios that includes “uncorrelated alpha” funds as a possible investment option, along with asset class index funds. As the separation of alpha from beta investing grows more common (see our June 2005 issue or the “Separating Alpha from Beta” button on our home page for more on this), new retail products are being introduced that attempt to deliver uncorrelated alpha. That is, they attempt to deliver returns that have a low or zero correlation with “beta” returns on asset class index funds. This year, we are using the equally weighted return on five of these funds as a proxy for allocating a portion of one’s portfolio to uncorrelated alpha investments. Over time, we will see whether the target real return model portfolios that contain these investments outperform their counterparts that invest only in index products.

Product and Strategy Notes

Another Look at Avian Flu

In our December 2005 issue, we summarize a study by the U.S. Congressional Budget Office on the potential impact of H5N1 avian influenza pandemic. Based on assumptions of a 30% infection rate, and, of those, a 2.5% mortality rate, it concluded that the economic impact of an influenza pandemic would be approximately equal to an average post-World War Two recession. In theory, these assumptions reflect the CBO’s estimate of the historical trade-off between how easy it is to transmit an influenza strain from one human to another, and how deadly it is. Historically, as transmissibility increased, mortality declined.

To check the sensitivity of the CBO’s economic forecast to its assumption about H5N1’s mortality rate, we turned to another source, the International Futures Model developed for the United States National Intelligence Council as part of its “2020” future scenarios project. IFS is a global economic and political forecasting model, which can be accessed on www.ifsmodel.org. Absent any influenza pandemic, the IFS Model’s baseline forecast is that real world gross domestic product should grow at a compound annual rate of 3.38% between 2006 and 2010. We adjusted its mortality assumptions upward as far as the model allowed, beginning in 2006, peaking in 2007 and 2008, and returning to normal thereafter. By our

calculations, this is equivalent to increasing the death rate from H5N1 from the 2.50% assumed by the CBO to 12.66% (assuming no change in the 30% infection rate, which may well be conservative). This reduced real global GDP growth between 2006 and 2010 to a compound annual rate of just 1.66% , which included a two- year global recession in 2008 and 2009. While all the caveats mentioned in this month's article on forecasting clearly apply to this estimate, it is a worrying one nonetheless. Any increase in the human-to-human transmissibility of H5N1 without evidence of a sharp reduction in its mortality rate (which, by some estimates, is still between 33% and 50% of those infected) should be a cause for serious concern.

Mervyn King's Fascinating Speech

On January 16, Mervyn King, Governor of the Bank of England, gave a fascinating speech to a business dinner in Kent. Its principal focus was the substantial fall in real interest rates seen around the world in recent years. Recall that in theory, the real rate of interest on government bonds is the price that balances the supply of and demand for risk free savings. In principle, three factors should interact to determine its level. The first is the growth rate of total factor productivity in the economy. As it increases, a dollar of investment produces more output than before. Assuming no change in the division of this increased output between labor, capital, government (taxes) and consumers (in the form of lower prices), an increase in TFP increases the profitability of investment. Assuming no increase in the supply of savings, this leads to a rise in real interest rates.

The second factor that affects the real interest rate is consumers' time preference – that is, the rate of return they require in order to put off a dollar of consumption today until tomorrow. Impatient consumers – who want it all, right now – lead to higher real interest rates. On the other hand, consumers with a high time preference have more patience, and lead to lower real rates.

The third factor affecting real interest rates is consumers' risk aversion. The less risk averse they are, the less they will save. Assuming no change in the desired level of investment, this will cause an increase in the real rate of interest.

In his speech, Dr. King noted that there were “broadly two types of explanation for the fall in long-term real rates around the world.” The first “explains low real rates as the outcome of an increased propensity to save and lower willingness to invest in the world as a whole.” He noted that the past few years have seen an increased propensity to save in the world, particularly in Asia. Whether this reflects a high willingness to delay consumption or a high degree of risk aversion is an unresolved issue. The permanence of this situation is also open to question. Dr. King speculated “as their people become more prosperous, domestic demand in China and elsewhere in Asia will become the primary driver of those countries’ growth, so they may want to save less.” On the other hand, he also noted that “the growing recognition that increasing longevity will mean we need to save more for retirement may sustain or even lift world savings rates.”

On the investment side of the equation, Dr. King noted “business investment in developed economies has been weak in recent years for reasons we do not fully understand.” He went on to note that “although there are signs of a pick-up in business investment in the U.S. and Euro area, investment remains weak in the U.K. and a recovery of world investment spending is not assured.” It is interesting, in the context of our theoretical model, to speculate on the possible reasons for the observed weakness in global investment spending. Logically, it should be related to either expectations of a decline in total factor productivity growth, or a reduction in the share of output going to capital, and an increase in the share going to some combination of labor, taxes, and lower prices for consumers.

Frankly, you could make an argument for any and all of these. Total factor productivity growth could slow if we are approaching the point where it is constrained by the increasingly poor performance of public school systems in many countries. A severe influenza pandemic that reduced the supply of labor, or simply the affect of declining fertility rates in developed countries could lead to labor receiving a higher share of total output. Given the size of the unfunded liabilities for state pensions and national health insurance benefits facing many developed countries (and, as usual, we commend Australia for having addressed these issues better than most), it is reasonable to assume that taxes as a share of total output could increase in the future (which might well have a knock on negative effect on total factor productivity growth). Finally, the entry of Chinese (and, increasingly, Indian) production into world markets has put downward pressure on prices in multiple industries, reducing the increase in

returns to capital caused by rising total factor productivity. This only confirms Dr. King's point that the decline of global investment spending is a phenomenon "we do not fully understand." However, he also went on to state in his speech that "there is another, very different, explanation for recent low long-term interest rates."

Dr. King noted that "rapid growth of money – as central banks have kept official interest rates very low – has helped to push up asset prices as investors 'search for yield.' Data from the IMF suggest that world broad money in 2003 and 2004 was growing at its fastest rate since the late 1980s. Across the world, the prices of all kinds of assets have risen – not just of government bonds, but also of equities, houses, and other real estate, commodities, gold and other precious metals. Moreover, risk premiums have become unusually compressed and the expansion of money and credit may have encouraged investors to take on more risk than hitherto without demanding a higher return."

Dr. King pointedly noted, "it is questionable whether such behavior can persist. At some point, the ratio of asset prices to the prices of goods and services will revert to more normal levels. That could come about in one of two ways: either the prices of goods and services rise to 'catch up' with asset prices as the increased money leads to higher inflation, or asset prices fall back as markets reassess the appropriate levels of risk premia. In neither case would it be easy to keep inflation close to the 2% target."

He closed his speech with appropriate words of caution. "I do not pretend to know whether...low long-term interest rates are primarily related to underlying preferences for savings and investment, or to the global growth of money and a possible under-pricing of risk, or, in all probability, to some combination of the two. Nor, since we do not know the causes of low long-term rates, can we be sure for how long they will persist."

New U.S. Commodity ETF

After much delay, the United States finally has an exchange traded fund that tracks a commodity index. The new DB Commodity Index Tracking Fund (ticker DBC) is keyed to the Deutsche Bank Liquid Commodities Index. The DBLCI includes fewer commodities than either the Goldman Sachs Commodities Index or the Dow Jones AIG Commodities Index. Its

weighting of major commodity groups lies in between the GSCI and DJAIG, as shown in the following table:

	GSCI	DBLCI	DJ AIG
Energy	73%	55%	33%
Agricultural	16%	22.5%	41%
Metals	11%	22.5%	26%
Total	100%	100%	100%

As a practical matter, this difference in weightings turns out to be somewhat less than this table would suggest; between 1992 and 2004, the correlation between the GSCI and DBLCI was an impressive .91; their respective correlations with the DJAIG were .89 and .86. Moreover, the standard deviation of the returns on the GSCI and DBLCI were indistinguishable over this period, at, respectively, 17.60% and 17.63%, compared to 11.88% on the DJAIG.

The annual expense charge on the new ETF initially will be about 1.45% per year; as initial offering expenses are amortized over three years, this should decline to something closer to 1%.

For tax purposes, it is critical to note that, as described in the DBC prospectus, and unlike other Exchange Traded Funds, it is expected that DBC will be treated as a pass through entity, and the shareholders in DBC will be deemed to own a portion of the underlying Master partnership that actually trades the commodity futures contracts. This means that taxable investors will have to report their pro-rata share of the Master Fund's gains and losses, even if they do not correspond to the cash flows the investors have received. Moreover, because the Master Fund is a partnership, cash flows received will become taxable once they exceed the investor's initial cost basis in the DBC shares.

While we plan to run a longer review article next month on the valuation of commodity, timber, and property funds, our initial take on DBC is that, while it makes sense for investors committed to using ETFs, to implement their asset allocation strategy, there is no compelling case for investors in PCRDX or QRAAX to switch to it.

Yale and Harvard

Along with Stanford, Yale and Harvard are the giants in the world of university endowment investing. Over the past month, both of them have made some interesting news. At a recent meeting of the National Association of College and University Business Officers, David Swensen, who runs Yale's endowment, strongly urged his peers, particularly those running smaller endowment funds, to index their holdings. He stressed that actively managed funds were rarely worth the fees they charged, and "absolute return [hedge funds] don't belong in your portfolio unless you can identify the top 25% or top 10% [of managers]." He went on to note that while Yale and other very large endowments can spend the time and money required to identify top quality active managers, smaller funds lack the necessary resources. In this regard, "the distinction between institutional investors and individual investors is overrated."

Meanwhile, Jack Meyer, the former manager of Harvard's endowment, has left to start his own hedge fund, Convexity Capital. What we find most admirable about Mr. Meyer's new fund is the fee structure he has chosen to use. While the typical hedge fund charges "2 and 20" (2% of the assets under management, plus 20% of all profits), Meyer will charge a base fee of only 1.25%, and peg his 20% incentive fee to returns above a relevant index – that is, to real alpha. As we move towards a world in which alpha and beta investing are increasingly separated, we applaud this step towards more rational pricing.

Asset Class Assumptions

Our asset allocation conclusions critically depend on the assumptions we make about future asset class risks and returns. There is an irreducible level of uncertainty that accompanies this process. In fact, the only thing we can say with confidence is that our estimates will most likely turn out to be wrong. It is for this reason that we use an equally weighted portfolio as our ultimate performance benchmark, since it assumes that neither future returns nor risks can be forecast with any accuracy beyond luck. This raises an obvious question: why do we believe this is not the case?

The most important reason is that basic differences in the return generating processes for different asset classes (e.g., bonds, commercial property, and equity) suggest that there will

be stable differences in the dispersion (i.e., riskiness) of their returns. This means that the ranking of asset classes according to their standard deviations should remain relatively stable over time. This economic hypothesis is supported by the statistical fact that you can improve the accuracy of an estimate of standard deviation by increasing the frequency with which data from a given period (e.g., 1989 to 2004) are sampled (e.g., by using monthly instead of annual data). To be sure, this isn't a perfect approach, as volatility (standard deviation) varies (or "clusters") over time. But even so, a ranking of asset classes by their relative volatility is still much more stable over time than a ranking of asset classes by their relative returns.

We are much less confident about our -- or anybody else's -- ability to accurately forecast future asset class returns; there is simply too much uncertainty involved. At best, we can take steps to limit the size and impact of the inevitable estimation errors we will make. To do this we combine two unavoidably flawed approaches to the estimation problem: historical data and the outputs from a forecasting model.

The use of historical data contains a number of pitfalls. The first is uncertainty about the extent to which the sample of data you are using represents the "true" distribution of results that may be produced by the return generating process. This is a particular concern with respect to so-called "extreme events", or periods in which large gains or losses are experienced. Does your sample contain all the extreme events a return process might produce? It is for this reason that the arcane subject of "extreme value theory" is so popular with hedge fund managers who trade in highly leveraged derivative instruments.

One way to deal with this problem is to convert your sample into a distribution of returns that can be described using just a few variables -- e.g., the mean (average) and standard deviation (a measure of dispersion around the mean) for a normal distribution, or "bell curve." However, this raises another issue: what is the right distribution to use? The normal distribution has some real attractions, because it simplifies a number of calculations. Unfortunately, a look at the data shows that the distributions of returns for many financial assets aren't quite normal. Typically, they are "off center" (technically, they are "skewed") and they have "fatter tails" (technically, they have excess "kurtosis") than a normal distribution. In practice, this leads to arguments about (a) what other distribution to use (e.g., a lognormal or Student's T), and (b) whether it matters. The latter question is addressed by Cremers, Krtizman and Page in their paper "Optimal Hedge Fund Allocations: Do Higher Moments Matter?" They find that the

question turns on the shape of what is known as an investor's "utility" function, which is a measure of their sensitivity toward investment gains and losses. They find that for the most common models of investor utility (technically, power utility functions), using the normal distribution in asset allocation will produce an acceptable result.

Yet another issue is whether the returns generating process underlying the historical data you use has remained constant (or "stationary") over time. If it has not, then estimates derived from historical data that includes the previous process will be poor predictors of future returns. Unfortunately, statisticians continue to argue about the best way to test for these so-called "structural breaks" or "non-stationarities." Some analyses find them, and others don't, leaving investors with more uncertainty. Our instinct is that insofar as the economy is a complex adaptive system, the return generating process for many asset classes is likely to have some structural breaks, raising questions about the wisdom of relying solely on historical data to project future returns.

One technique that has been invented to deal with the problem of estimation errors when using historical data is called "shrinkage." Its basic intuition is that the accuracy of an estimate will be improved if outlying data are "shrunk" towards a common reference point. One such point is known as the "grand mean", which in our case would be the average return on all the asset classes included in our analysis. However, this raises two other issues. The first is how much to shrink each asset class's average return. Different authors have produced many different equations that attempt to improve on the everyday "let's split the difference" heuristic (see, for example, "Bayes-Stein Estimation for Portfolio Analysis" by Philippe Jorion, and "Optimal Estimation of the Risk Premium for the Long Run" by Jacquier, Kane and Marcus). Other authors have argued that the simple approach works quite well in many situations.

The second issue is the fact that even the "grand mean" – the average of the average expected return for each asset class – is still based on the original sample data. This has led to a search for other "shrinkage targets" that would add new information, and in so doing hopefully raise the accuracy of the resulting estimate. In finance, one approach to this is to use the output from a forward-looking return forecasting model as the shrinkage target.

However, this introduces another source of uncertainty: model error. As we have seen, in a complex adaptive system that gives rise to non-linear results, is difficult if not impossible to construct an accurate model of the return generating process for most asset classes. And

even if we could, changes in that process (or copying by other investors) would inevitably invalidate our model at some point in the future. And how can one be certain that the model one decides to use is the most accurate one available? The simple answer is that you can never be sure of this. So what is an investor to do?

Our solution to this problem is to use an equilibrium model to forecast future returns. We know that most of the time, financial markets will not be in equilibrium. However, we also believe that markets are at least attracted to equilibrium, even if they rarely attain it. Specifically, we ask the question, what real rate of return would an investor require, in equilibrium (where the returns supplied equaled the returns demanded), to hold this asset class? To answer it, we take a so-called “building block” approach, that begins with the current yield on real return bonds (our proxy for the risk free rate), and adds various return premia to them based on the relative riskiness of different asset classes. These premia are shown in the table below:

Asset Class	Risk Premia to Generate Equilibrium Return
Real Return Bonds	None. Current yield is used.
Domestic Nominal Return Bonds	1% above real return bond yield
Foreign Currency Bonds	Weighted expected returns on other countries' domestic bonds, adjusted for expected annual exchange rate changes estimated from the current difference in yields on ten year government bonds.
Domestic Commercial Property	2.5% above real return bond yield (half the difference between the expected return on domestic bonds and domestic equity)
Foreign Commercial Property	Weighted expected returns on other countries' domestic commercial property, adjusted for expected annual exchange rate changes estimated from the current difference in yields on ten year government bonds.
Commodities	Equal to expected return on domestic equity, which is roughly in line with historical data
Timber	Equal to expected return on commodities

Asset Class	Risk Premia to Generate Equilibrium Return
Domestic Equity	4% above real return bond yield
Foreign Equity	Weighted expected returns on other countries' domestic equity, adjusted for expected annual exchange rate changes estimated from the current difference in yields on ten year government bonds.
Emerging Equity	2% above expected return on foreign equity
Equity Market Volatility	Equal to domestic equity
Equity Market Neutral	Proxy for sources of alpha whose returns have a low correlation with beta returns on core asset classes. 2% below expected return on domestic equity.

For all these asset classes, our estimates of future risk (standard deviation) were based on the combination of the historical 1989-2004 results, plus a set of results for domestic equities and bonds covering 1900 to 2004 that is found in the Global Investment Returns Yearbook by Dimson, Marsh and Staunton. These were rounded to avoid the appearance of excessive precision on our part.

This leaves us with the issue of how to combine our historically based return estimates with estimates derived from our forecasting model. A recent paper "Forecast Combinations" by Allan Timmerman (an acknowledged expert in the field) concludes that simple methods often work best. Another paper, "Structural Breaks and the Performance of Forecast Combinations" by Timmerman and Marco Aiolfi presents evidence that forecast combinations are more accurate than individual forecasts because they better incorporate the affect of structural breaks. We are also persuaded by the inherent logic of the "KISS" (keep it simple, stupid) principle. All of this leads us to the use of a simple approach (50/50 weighting) to combine our historical and model based return estimates.

The following tables show our historical and model based estimates of future real returns on different asset classes. The historical table shows returns from 1989 to 2004. This period covers a relatively wide range of financial market events (e.g., the 1998 debt market problems, and the internet bubble). However, we also note that the underlying economic

conditions were relatively benign during this period, with inflation generally declining, and real growth fairly steady. As a result, estimates derived from the 1989 to 2004 data probably have some limitations with respect to their coverage of the entire return generating process for most asset classes (especially the extreme events that may be possible).

Four additional qualifications are also in order. First, the data for commercial property reflects traded property securities, and not property that is directly owned. Hence, our estimates will differ from those produced by companies that measure property returns (usually using appraisal based methods, that understate risk). Second, the data for timber is based on a U.S. index. In the past, the returns on this index have diverged from those on other national indexes. Unfortunately, we have no easy basis for combining the returns on these different indexes. However, we also note that in recent years, as investment in timberland has become more popular among institutions, these differences seem to be narrowing. Third, we used the Goldman Sachs Commodities Index for that asset class, as it has the longest available data series. Finally, for equity market volatility we used the VIX index, which measures the implied volatility on S&P 500 options. This has a longer data series than similar indexes (e.g., the VSTOXX) that measure volatility in other equity markets.

Last but not least, in the following tables we present three pieces of data for each asset class. First, its average arithmetic annual return. Second, the standard deviation of those returns. We then adjust the average annual return to reflect relative risk (technically, we subtract one half the variance, which is the standard deviation squared) to derive an estimate of the compound annual (or geometric average) return that would be realized by an investor who held that asset class (and no other) over a long period of time.

Historical Data
CHF Real Returns

Asset Class	Period	Average Annual Return	Standard Deviation	Compound Return
Real Return Bonds	N/A	N/A	N/A	N/A
Domestic Bonds	1989-2004	3.3%	3.9%	3.2%
Foreign Bonds	1989-2004	3.3%	8.1%	2.9%
Domestic Property	1989-2004	8.6%	15.4%	7.4%
Foreign Property	1989-2004	3.8%	18.7%	2.0%
Commodities	1989-2004	6.2%	21.2%	4.0%
Timber	1989-2004	9.3%	16.4%	8.0%
Domestic Equity	1989-2004	10.3%	17.8%	8.7%
Foreign Equity	1989-2004	4.2%	18.6%	2.4%
Emerging Equity	1989-2004	9.8%	27.7%	6.0%
Equity Mkt Neutral	1990-2004	6.2%	11.4%	5.5%
Equity Volatility	1994-2004	7.5%	56.9%	-8.7%

Forecast Data
CHF Real Returns

Asset Class	Average Annual Return	Standard Deviation	Compound Return
Real Return Bonds	0.8%	5.0%	0.7%
Domestic Bonds	1.8%	10.0%	1.3%
Foreign Bonds	1.5%	10.0%	1.0%
Domestic Property	3.3%	12.0%	2.6%
Foreign Property	2.5%	20.0%	0.5%
Commodities	4.8%	20.0%	2.8%
Timber	4.8%	15.0%	3.7%
Domestic Equity	4.8%	20.0%	2.8%
Foreign Equity	4.0%	20.0%	2.0%
Emerging Equity	6.0%	25.0%	2.9%
Equity Mkt Neutral	2.8%	10.0%	2.3%
Equity Volatility	4.8%	55.0%	-10.3%

As you can see, our forecasting model predicts lower real returns on most asset classes than they have delivered over the past sixteen years, along with somewhat higher volatility in some cases. This is not inconsistent with history, which has seen regimes of low returns and high volatility alternate with regimes of higher returns and lower volatility. Our simulation optimization model captures this, testing potential asset allocations against a 50/50 mix of scenarios generated from each distribution.

However, as we said in the first article in this month's issue, there is an irreducible level of uncertainty associated with these estimates, and with the results of our asset allocation analyses. At best, we can raise the probability of achieving a long-term financial goal; neither we, nor anyone else, can guarantee it.

Model Portfolios for 2006-2007

The tables at the end of this article present the results of our biennial asset allocation review. In the following pages, we will review the optimization methodology and input assumptions we used to generate our model portfolios, discuss potential criticisms of our approach, and summarize the main conclusions we reached, and what they mean to you.

Methodology

Our target real return model portfolios assume the existence of an investor who seeks to achieve multiple objectives over a multi-year time horizon. Specifically, we assume an investor who wants to have accumulated a portfolio worth a specific multiple of its current value by a certain date in the future, while saving a fixed amount per year. In order to achieve these goals, our investor must earn a minimum compound annual rate of return on his or her portfolio. In turn, this portfolio return will be a function of the weights given to different asset classes in the portfolio, the sequence of annual returns on these asset classes, the extent to which they are related to each other, and the methodology used to rebalance the portfolio when actual asset class weights deviate from their long-term targets.

We use a technique known as “simulation optimization” to identify a robust asset allocation for this investor. By “robust”, we mean an asset allocation that has a high probability of achieving the investor’s goals while minimizing the amount of risk taken on (which we define as the volatility of annual returns).

Our model works as follows: We first begin with a “candidate” asset allocation and rebalancing strategy. Asset allocation is defined in terms of the weights placed on different asset classes. Rebalancing strategy is defined by two variables: (a) the amount by which one or more asset classes must deviate from their target weights in order to trigger a rebalancing of the portfolio; and (b) an “adjustment factor” that determines whether a rebalanced asset class is returned to its target weight, or to a weight slightly over or under it. For example, assume the “trigger factor” is 10% and the “adjustment factor” is 5%. At the end of each year, the actual asset class weights are compared to their targets. If an asset class deviates by 10% or more from its target weight (e.g., if it is at 35% instead of 25%), a rebalancing is triggered. In this

case, it is rebalanced back to its target less the adjustment factor. Therefore, it would be rebalanced back to 20% (25% less 5%). On the other hand, if the asset class had been more than 10% below its target weight, it would be rebalanced back to 5% above it.

There are two logics at work in this system. The first is a desire to minimize the transaction costs associated with rebalancing, which are deducted from portfolio returns (we do not consider the tax effects of rebalancing). The second is the desire to exploit, in a very controlled manner, the tendency of real world markets to vacillate between overvaluation and undervaluation, caused by the interaction of “momentum” and “value” investors. When the returns on an asset class have caused its weight in the portfolio to grow significantly above its target, we allow for rebalancing to an underweighted position on the theory that it will soon overcorrect. We allow for the exact opposite rebalancing for asset classes that are significantly below their target weights.

For each candidate asset allocation/rebalancing strategy, we then generate 2,000 twenty-year return scenarios. Each scenario contains twenty independent returns for up to twelve different asset classes – i.e., up to 240 different returns per scenario. The interaction of these asset class returns and the rebalancing strategy produces a compound annual return for the scenario. The 2,000 scenarios produce a distribution of annual (single period) and compound (long-term) returns for the candidate asset allocation/rebalancing strategy.

The model next generates another candidate asset allocation/rebalancing strategy, and repeats the process. When it is completed, it retains the asset allocation/rebalancing strategy that has the highest probability of achieving the target compound annual return. If two strategies are tied, it chooses the one with the lower standard deviation of annual returns (i.e., the one with the lowest annual volatility).

So far, so good. However, as the old saying goes, if something seems too easy, it's not. The problem we face is that, because of the number of asset classes and constraints we use (see below), there is a very large number of possible asset allocation/rebalancing strategies to be analyzed. Too many, in fact, for a “brute force” (or “check them all”) approach to work. Thus, the model uses evolutionary algorithms to intelligently search the space of possible asset allocation/rebalancing strategies in order to generate a robust solution in a reasonable amount of time (on average, about 1,000 different strategies are tested, using 2,000 scenarios for each one). We cannot say this solution is “optimal”, because we cannot be sure that there is not

another solution that is better. What we can say, however, is that the solution generated by the model is “robust”, in the sense that, relative to all possible strategies, it has one of the highest probabilities of achieving the compound rate of return target. For more information on simulation optimization, we recommend the short paper “Practical Introduction to Simulation Optimization” by April, Glover, Kelly and Laguna.

Asset Classes Used

In various articles this year, we have explored the use of four new asset classes in our model portfolios: foreign commercial property, timber, equity market neutral strategies, and equity market volatility. In the analysis that follows, we present three different cases. The first uses ten asset classes: real return bonds, domestic investment grade bonds, foreign currency investment grade bonds, domestic commercial property, foreign commercial property, commodities, timber, domestic equity, foreign developed market equity, and emerging markets equity.

The second case adds equity market neutral to the first ten asset classes. Our logic here is based on the growing trend toward separating alpha from beta investing. The returns on traditional long-only actively managed funds are compensation for taking both systemic (non-diversifiable) asset class risk (also known as “beta”), and non-systematic security-specific risk (also known as “alpha”). The problem is that the high fees charged by these funds cover both beta and alpha returns. With the growth of index products (mutual and exchange traded funds, unit trusts, etc.) it is now possible to pay much less for beta. This has led to what is known as the separation of alpha and beta investing (see the button labeled "Separating Alpha from Beta Investing" in the free section of www.indexinvestor.com). In this emerging approach, investors divide their portfolios between a mix of low-cost asset class index funds and funds that focus only on generating alpha returns (and charge much higher prices for doing this). The key attraction of these “pure alpha” funds is that they say that their returns have a low correlation with those on various asset class beta products. As our proxy for this strategy, we have used the average return on equity market neutral hedge funds. (For more on this, please see “Fund of Hedge Funds Portfolio Selection: A Multi-Objective Approach” by Davies, Kat and Lu. It

reaches the same conclusion we do about the relative attractiveness of EMN compared to other hedge fund strategies).

The third case we use adds the return on the implied volatility of the Standard and Poor's 500 ("equity market volatility") to the original ten plus equity market neutral. This return is calculated as the change in the value of the VIX index. The potential attraction of this asset class is its negative correlation with other types of equity; its drawback is its very high volatility. While no retail volatility funds are available today, we expect that they will be introduced before our next asset allocation review in two years time; hence, we are including volatility as one of this year's model portfolios.

Asset Class Risk and Return Assumptions

In an overview of portfolio optimization methodologies ("The Limits of Certainty"), the Consulting Group at Smith Barney notes that "the combination of Monte Carlo simulation and stochastic optimization offers enticing benefits. It is not a panacea, however. Any optimization process, no matter how sophisticated, remains vulnerable to the limitations of the data inputs fed into it. Given the considerable uncertainty surrounding future asset returns, it would be a serious mistake to believe technology alone can eliminate investment risk."

In the previous article, we reviewed the methodology we used to develop the asset class risk and return assumptions we have used in our simulation optimization models. We have taken two steps in our analyses to limit the potential impact of estimation and model error. The first is to set constraints on the maximum amount of a portfolio that can be allocated to a given asset class. These constraints are as follows: real return bonds (100%); domestic bonds (100%); foreign bonds (20%); domestic commercial property (20%); foreign commercial property (20%); commodities (20%); timber (10%, plus commodities and timber together cannot exceed 20%); domestic equity (80%); foreign equity (30%); emerging markets equity (10%); equity market neutral (10%); and volatility (10%).

The second step we took was to conduct two separate optimizations for each compound real return target: one based on the historical assumptions, and one based on the forecast assumptions. We then combined the resulting asset class weights using a 50/50 weighing scheme. Research has shown that in many cases, the simplest approach to combining forecasts

works the best. However, we have also tried to make it easy for people to use different weighing schemes to combine the portfolios derived from both sets of input assumptions.

To generate the probability distribution of the weighted portfolio's future returns, we had to take a different approach, and let our simulation model switch between the assumptions of the historical and forecast regimes, using our 50/50 weighting scheme.

Possible Criticisms of our Approach

As noted above, no asset allocation methodology is perfect, and ours is no exception. However, unlike many others, we go out of our way to highlight the potential shortcomings of our approach. Here they are, along with our responses:

Why didn't you use a longer historical data series?

For some asset classes (e.g., real return bonds, domestic and foreign commercial property securities, commodities, timber, emerging markets equity, equity market neutral and volatility), 1989 is at or beyond the limit of the available data. Long data series really only exist for domestic bonds and equity. In statistical terms, use of a longer data series improves the accuracy of an estimate only if it does not contain so-called "structural breaks." These are changes in the nature of the time-series that suggest a fundamental change in the underlying return generating process. A good example of this is the U.S. Treasury – Federal Reserve Accord of March 1951. Before that date, the Treasury compelled the Fed to manage monetary policy to stabilize government bond prices. After that date, the Federal Reserve was freed from this obligation, and was able to conduct a much more independent monetary policy. A similar agreement was struck in May, 1997 between the U.K. Treasury and the Bank of England (although inflation targeting was started in 1992, after the UK left the European Monetary System). Academic research has found evidence of structural breaks in many long-term equity and bond return data series. For this reason, we decided to use the shorter series, even when longer ones were available.

Why did you use a normal distribution for asset class returns?

A “normal distribution” is the fancy name for the so-called “bell curve” that results when different returns are graphed according to the frequency of their occurrence in the historical data. Because the normal distribution is symmetric, it can be described using only two statistics, the average (i.e., the mean) of the different returns, and their standard deviation (also known as volatility), which measures the extent to which returns fall closer to or farther away from the average. Standard deviation is often used as a proxy for “risk”, in the sense that an asset class whose returns have a wider distribution around the mean (i.e., whose returns are more volatile) is believed to be riskier than an asset class whose returns are more tightly grouped.

In reality, most asset class returns are not normally distributed; they are typically slightly asymmetrical (statistically, this is known as “skewness”) and have somewhat fatter tails than the normal distribution (statistically, this is known as “positive kurtosis”). Rather than the normal distribution, they are better described by other types of distribution (e.g., a multivariate T, for the technically inclined). However, researchers have concluded that, for most investors (e.g., who invest in broad asset classes rather than options) this distinction is of little practical importance (see, for example, “Portfolio Formation with Higher Moments and Plausible Utility” by Cremers, Kritzman and Page, and “On the Out-of-Sample Importance of Skewness and Asymmetric Dependence for Asset Allocation” by Andrew Patton). For this reason, we chose to assume asset class returns are normally distributed, since that substantially simplifies the math in our models. On the other hand, we will also be presenting, in a later article, the results of some asset allocation experiments using a multivariate T distribution.

Did you assume asset class returns are independent and identically distributed over time?

Another feature of real life asset class returns is that they are not independent from year to year; the return in one year often has a slight statistical relationship with returns in one or more previous years. Technically, this is known as “serial correlation.” Another real life phenomenon is that average asset class returns and standard deviations tend to vary over time between different so-called “regimes.” This phenomenon is also referred to as “volatility

clustering.” In the simplest version of this, one can identify two regimes in the historical data. One is usually characterized by low returns and high volatility, while the other has higher returns and lower volatility (of course, this could also be said of a lot of other aspects of life, but that’s a story for another day). In other words, real life differs from the assumption used in many models that asset class returns are independent and identically distributed over time.

Here is how we addressed these issues in our models. As previously noted, our models are based on two different regimes, one derived from historical data and one from our forecasting model. These two regimes closely resemble the high return/low volatility and low return/high volatility regimes found in the historical data series for many asset classes. That being said, one could certainly question the 50/50 probability we have used for each regime. As we noted, it is the statistical way of saying, “we really can’t forecast this with any confidence beyond luck.”

Regarding serial correlation, we included a one-year .20 serial correlation term for real return bonds. This simplified the calculation of our models (compared to using serial correlation for multiple asset classes and/or multiple years of previous returns), while still generating (via the interaction of real return bonds with the cross-correlation of asset classes in any single year) trending in some simulation scenarios.

Why did you use the same correlation assumptions for both regimes?

Another aspect of the regime switching phenomenon is that returns between some asset classes tend to be higher during the low return/high volatility regime, and lower during the high return/low volatility regime. We use a correlation matrix based on the overall historical data series that tends to average out these two extremes. While we would have liked to include two different correlation matrices in our model, it would have required a substantial amount of additional programming. Given scarce resources and competing priorities (e.g., adding rebalancing strategy options, more asset classes, and rewriting our model to take advantage of faster software), we decided that the additional benefits this would generate wasn’t worth the effort it would have required. Again, this is something we hope to experiment with in the future.

Conclusions

Deciding on an asset allocation and rebalancing strategy are two of the most important decisions an investor makes. Unfortunately, all the tools available to help investors make these decisions suffer from shortcomings, particularly around their assumptions about future asset class risks and returns. In addition, the sheer mathematical difficulty of a multi-year optimization problem only adds to the irreducible uncertainty we face when choosing an asset allocation and rebalancing strategy. We are the first ones to say that our approach to this problem still has room for improvement. However, we also think it provides a valuable framework for helping people to think logically about the challenges they face, and in so doing raise the probability that they will achieve their financial goals.

With that in mind, and after reviewing the results of our asset allocation reviews in our eight functional currencies, we offer the following observations.

One important conclusion from our analysis is that, compared to two years ago, it looks like it will be harder in the future to achieve high compound real return targets, and more risk will have to be taken on to have even a diminished probability of success. Practically, this confronts investors with a number of choices, all of which will reduce one's minimum required compound rate of return: (a) reduce the size of your accumulation goal; (b) stretch out the time required to meet it; and/or (c) save more.

Another interesting conclusion from our analyses relates to changes made in the allocations to different asset classes, compared to our previous model portfolios. Real return bonds generally receive less weight. There are two logical reasons for this. The first is that across most markets, the yield to maturity on real return bonds (which we take as our proxy for expected return) is at historically low levels. This means that a rise in real yields (which, would cause a fall in bond prices, and therefore low or negative total returns) is more likely than a further fall in yields (which would cause a rise in bond prices, and a positive total return). In the context of our distribution of returns for the real return bond asset class, this view is reflected in the low level of expected return relative to expected volatility. In addition, we have also added new asset classes (foreign commercial property and timber in our base portfolio, and EMN and volatility in the others) that create further opportunities for obtaining robust asset allocation solutions with relatively low allocations to real return bonds.

Domestic investment grade (nominal return) bonds also seem to have picked up some of the allocations that previously went towards real return bonds. However, at a time when many asset classes appear to be (at least in historical terms) fully or overvalued, this raises an important issue. There are three big ways to get hurt from holding domestic investment grade bonds. The first is a rise in real interest rates. Unless this is offset by a fall in inflation, it will cause a fall in the price of domestic nominal return bonds as surely as it will cause a fall in the price of real return bonds. The second danger is a rise in inflation, which, absent a further fall in real rates, would also cause a decline in the price of domestic bonds. The third danger, assuming one's domestic bond allocation is not limited to government securities (i.e., it includes corporate credit and mortgage backed bonds), is a rise in defaults linked to a downturn in economic conditions. This would logically lead to a widening of credit spreads (i.e., a rise in the yields on non-government bonds), which would cause their price to fall and total returns on holding them to be negative. If one does choose to increase one's allocation to domestic bonds at this time, doing it via short term government bonds (which are least likely to get hurt by rising inflation, but which could still be hurt by rising real interest rates) seems the prudent course of action in the near term.

We have written at length (in our August, 2005 issue) on the pros and cons of foreign currency bonds. While they are still used in a number of our new model portfolios, their weighting has tended to be reduced by the introduction of other asset classes that provided better expected diversification benefits (e.g., timber and volatility) and the fact that we capped the maximum allocation this year at 20% of the total portfolio. That being said, we remain attracted to this asset class for one key reason: historically, its returns have been negatively correlated to returns on most domestic equity markets.

Both domestic and foreign commercial property receive weightings in multiple portfolios. The latter seems attractive in some cases because its expected returns are superior to those on foreign commercial property, without too much additional penalty in terms of higher volatility and correlation with other asset classes.

Commodities and timber both receive positive weightings in most portfolios because of the diversification benefits they provide. However, investors considering an increase in their allocations to these asset classes are again confronted with questions about their current valuation levels.

The same issue arises with respect to our model portfolios' allocations to domestic, foreign, and emerging markets equity. We again stress the important point that our equity market return forecasts are based on an "equilibrium" approach – that is, they assume that over the long term, markets will tend toward equilibrium, and asset classes will therefore tend to deliver the returns that investors demand for holding the risk they represent. However, as we have repeatedly written, we also believe that financial markets are a complex adaptive system in which the equilibrium condition is less likely to hold in the short term. In other words, we believe that all financial markets, and equity markets in particular (because of the greater uncertainties inherent in equity valuation) can and do become under and overvalued from time to time. As we note in our market valuation update, at the current time, in many markets, overvaluation seems more likely to be the case than undervaluation. We base this conclusion on the observation that the returns equity markets are currently expected to supply (as estimated by their current dividend yield plus expected rate of total factor productivity growth) are below those we estimate investors would require in equilibrium (as estimated by the current yield on real return bonds plus a four percent equity market risk premium). This implies that a decline in equity prices (which would raise their dividend yield) will be required to bring supplied returns into line with the equilibrium returns demanded by investors.

Based on the hedge fund community's enthusiastic arguments about the joys of "uncorrelated alpha" investments, one would expect to see the portfolios that contain this asset class all receiving full (up to the constraint level) allocations to it. However, this turns out not to be the case. There appear to be a number of reasons for this. First, we have used the return on the CSFB Tremont Equity Market Neutral hedge fund index as our proxy for the average return on this strategy (technically, it is not an asset class). These are reported in U.S. dollars, so currency effects could offset some of this asset class's attractions to investors in other currency regions. Second, while EMN's correlation of returns with equity and other asset classes is low, it is not zero; in some cases, other asset classes turn out to be more effective means of reducing a portfolio's volatility without imposing too much of an expected return penalty. Commodities and timber certainly seem to play this role, as does volatility when it is included.

In those portfolios where it is a possible asset class, equity volatility often receives a positive weighting, even when its risk and return is measured using the U.S. VIX index (which

tracks changes in the implied volatility on S&P 500 options), rather than a local equivalent like the VSTOXX in the Eurozone. In effect, the inclusion of volatility allows some of the risk of other equity asset classes to be hedged away, while leaving their higher expected returns. Thus, the typical pattern is for equity market weightings to go up when volatility is included as a possible asset class.

Finally, there is the all-important “so what?” question to address. Should you switch your portfolio’s allocation to match one of our new model portfolios? The only accurate answer is, “it depends.” First, it depends on your tax situation. If the assets being switched are held in a taxable account, changing your asset allocation could trigger substantial capital gains tax payments. Since we have noted the potential estimation and model errors inherent in our (and everyone else’s) asset allocation methodology, if your current weights are reasonably close to those in our model portfolio, it probably makes sense to avoid incurring the very real tax cost for what might turn out to be not much of a relative improvement in your portfolio’s performance.

Second, let’s suppose that your investments are largely in tax advantaged accounts, and the difference in portfolio weightings is significant. Does this mean you should reallocate now? Perhaps not, if it means moving into an asset class (like many equity markets) that today appear overvalued. Again, it may well be better to wait and see, and reallocate only after equity or bond prices have fallen.

Third, let’s assume that your assets are in tax advantaged accounts, and the reallocation in question would not involve increasing your exposure to an asset class that today has a high probability of being overvalued (note to readers: in the coming months, we will be expanding our current market valuation outlook section to cover all the asset classes we use in our model portfolios

For example, suppose you wanted to reallocate a small portion of your portfolio into timber. In this case, a move today, or perhaps a gradual one using dollar cost averaging (to further reduce the risk of getting your market timing wrong) might well make sense. In sum, we believe that investors should take both taxes and current asset class valuations into account when rebalancing their portfolios.

The following tables present two different asset allocations for compound annual real return targets of 7%, 5%, and 3%. The first table presents three asset allocations using our ten

“base case” asset classes. The first column shows an allocation based on assumptions derived from historical data, and the second column one based on assumptions derived from our asset class return forecasting model. The third column shows an asset allocation based on a 50/50 weighting of the previous two. Where the rebalancing strategies differed, we chose the one with the higher trigger percentage, on the theory that it would minimize transaction costs. Underneath this weighted asset allocation, we present the rounded probability of achieving the compound annual real return target (CAGR), as well as the expected real annual return and standard deviation for the portfolio. The second table repeats this for our ten basic asset classes plus equity market neutral. We have not shown this table as our model makes no allocation to equity market neutral when it is an available asset class. We caution that this may be due to our use of the return on the CSFB Tremont Equity Market Neutral hedge fund index as our proxy for this strategy. Had we used a domestic Swiss EMN index, the outcome may have been different. We will present the results for portfolios that include equity market volatility in next month’s issue.

7% Compound Real Return Target

10 Asset Classes, 7% Target	Historical Inputs, 10 Asset Classes	Forecast Inputs, 10 Asset Classes	Weighted Portfolio, 10 Asset Classes
Rebalancing Trigger	0.0%	10%	10.0%
Rebalancing Adjustment	2.5%	5%	5.0%
Real Return Bonds	0%	0%	
Domestic Bonds	0%	0%	0.0%
Foreign Bonds	0%	0%	0.0%
Domestic Commercial Prop.	20%	0%	10.0%
Foreign Commercial Prop.	0%	0%	0.0%
Commodities	5%	10%	7.5%
Timber	10%	5%	7.5%
Domestic Equity	65%	75%	70.0%
Foreign Equity	0%	0%	0.0%
Emerging Markets Equity	0%	10%	5.0%
Equity Market Neutral	0%	0%	
Equity Volatility	0%	0%	
<i>Total</i>	100%	100%	100%
Probability of Achieving CAGR TGT	72%	20%	43%
Expected Annual Real Return			7.2%
Standard Deviation of Annual Returns			15.7%

5% Compound Real Return Target

10 Asset Classes, 5% Target	Historical Inputs, 10 Asset Classes	Forecast Inputs, 10 Asset Classes	Weighted Portfolio, 10 Asset Classes
Rebalancing Trigger	0.0%	5%	5%
Rebalancing Adjustment	0.0%	0.0%	0%
Real Return Bonds	0%	0%	0%
Domestic Bonds	0%	0%	0.0%
Foreign Bonds	0%	0%	0.0%
Domestic Commercial Prop.	20%	5%	12.5%
Foreign Commercial Prop.	0%	0%	0.0%
Commodities	10%	20%	15.0%
Timber	10%	0%	5.0%
Domestic Equity	60%	65%	62.5%
Foreign Equity	0%	0%	0.0%
Emerging Markets Equity	0%	10%	5.0%
Equity Market Neutral	0%	0%	0%
Equity Volatility	0%	0%	0%
<i>Total</i>	100%	100%	100%
Probability of Achieving CAGR TGT	89%	38%	60%
Expected Annual Real Return			7.0%
Standard Deviation of Annual Returns			14.4%

3% Compound Real Return Target

10 Asset Classes, 3% Target	Historical Inputs, 10 Asset Classes	Forecast Inputs, 10 Asset Classes	Weighted Portfolio, 10 Asset Classes
Rebalancing Trigger	0.0%	5.0%	5%
Rebalancing Adjustment	2.5%	0.0%	2.5%
Real Return Bonds	0%	0%	0%
Domestic Bonds	50%	10%	30.0%
Foreign Bonds	0%	0%	0.0%
Domestic Commercial Prop.	15%	20%	17.5%
Foreign Commercial Prop.	0%	0%	0.0%
Commodities	5%	15%	10.0%
Timber	10%	5%	7.5%
Domestic Equity	20%	40%	30.0%
Foreign Equity	0%	0%	0.0%
Emerging Markets Equity	0%	10%	5.0%
Equity Market Neutral	0%	0%	0%
Equity Volatility	0%	0%	0%
<i>Total</i>	100%	100%	100%
Probability of Achieving CAGR TGT	98%	61%	76%
Expected Annual Real Return			5.5%
Standard Deviation of Annual Returns			9.7%

2006-2007 Model Portfolios Year-to-Date Performance

Our model portfolios are constructed using a simulation optimization methodology. They assume that an investor understands the long-term compound real rate of return he or she needs to earn on his or her portfolio to achieve his or her long-term financial goals. We use SO to develop multi-period asset allocation solutions that are “robust”. They are intended to maximize the probability of achieving an investor’s compound annual return target under a wide range of possible future asset class return scenarios. More information about the SO methodology is available on our website. Using this approach, we produce model portfolios for six different compound annual real return targets: 7%, 6%, 5%, 4%, 3%, and 2%. We produce two sets of these portfolios: one assumes only investments in broad asset class index funds. These are our “all beta” portfolios. The second set of model portfolios includes equity market neutral (uncorrelated alpha) funds as a possible investment. These assume that an investor is primarily investing in index funds, but is willing to allocate up to ten percent of his or her portfolio to equity market neutral investments.

We use two benchmarks to measure the performance of our model portfolios. The first is cash, which we define as the yield on a one year government security purchased on the last trading day of the previous year. For 2006, our Swiss Franc cash benchmark is 1.48% (in nominal terms). The second benchmark we use is a portfolio equally allocated between the ten asset classes we use (it does not include equity market neutral). This portfolio assumes that an investor believes it is not possible to forecast the risk or return of any asset class. While we disagree with that assumption, it is an intellectually honest benchmark for our model portfolios’ results.

The year-to-date nominal returns for all these model portfolios are shown in the tables on the following pages. Mutual and exchange traded funds that can be used to implement these model portfolios’ asset allocations are listed on our website.

<i>These portfolios seek to maximize the probability of achieving at least the target real return over twenty years, at the lowest possible risk.</i>			
	YTD 31Jan06	Weight	Weighted Return
	In CHF		In CHF
7% Target Real Return	<i>YTD Returns are Nominal</i>		
<i>Asset Classes</i>			
Swiss Real Return Bonds	0.0%	0.0%	0.0%
Swiss Bonds	-2.6%	0.0%	0.0%
Global Bonds	-1.8%	0.0%	0.0%
Domestic Commercial Property	5.0%	10.0%	0.5%
Foreign Commercial Property	3.9%	0.0%	0.0%
Commodities	-1.1%	7.5%	-0.1%
Timber	1.2%	7.5%	0.1%
Swiss Equity	3.2%	70.0%	2.2%
Foreign Equity (US)	0.8%	0.0%	0.0%
Foreign Equity (UK)	3.4%	0.0%	0.0%
Foreign Equity (Eurozone)	4.1%	0.0%	0.0%
Foreign Equity (Japan)	1.0%	0.0%	0.0%
Emerging Mkt. Equity	8.8%	5.0%	0.4%
Equity Market Neutral	-0.9%	0.0%	0.0%
		100.0%	3.2%

	YTD 31Jan06	Weight	Weighted Return
	In CHF		In CHF
6% Target Real Return	<i>YTD Returns are Nominal</i>		
<i>Asset Classes</i>			
Swiss Real Return Bonds	0.0%	0.0%	0.0%
Swiss Bonds	-2.6%	0.0%	0.0%
Global Bonds	-1.8%	0.0%	0.0%
Domestic Commercial Property	5.0%	10.0%	0.5%
Foreign Commercial Property	3.9%	0.0%	0.0%
Commodities	-1.1%	7.5%	-0.1%
Timber	1.2%	7.5%	0.1%
Swiss Equity	3.2%	70.0%	2.2%
Foreign Equity (US)	0.8%	0.0%	0.0%
Foreign Equity (UK)	3.4%	0.0%	0.0%
Foreign Equity (Eurozone)	4.1%	0.0%	0.0%
Foreign Equity (Japan)	1.0%	0.0%	0.0%
Emerging Mkt. Equity	8.8%	5.0%	0.4%
Equity Market Neutral	-0.9%	0.0%	0.0%
		100.0%	3.2%

	YTD 31Jan06	Weight	Weighted Return
	In CHF		In CHF
5% Target Real Return	<i>YTD Returns are Nominal</i>		
<u>Asset Classes</u>			
Swiss Real Return Bonds	0.0%	0.0%	0.0%
Swiss Bonds	-2.6%	0.0%	0.0%
Global Bonds	-1.8%	0.0%	0.0%
Domestic Commercial Property	5.0%	12.5%	0.6%
Foreign Commercial Property	3.9%	0.0%	0.0%
Commodities	-1.1%	15.0%	-0.2%
Timber	1.2%	5.0%	0.1%
Swiss Equity	3.2%	62.5%	2.0%
Foreign Equity (US)	0.8%	0.0%	0.0%
Foreign Equity (UK)	3.4%	0.0%	0.0%
Foreign Equity (Eurozone)	4.1%	0.0%	0.0%
Foreign Equity (Japan)	1.0%	0.0%	0.0%
Emerging Mkt. Equity	8.8%	5.0%	0.4%
Equity Market Neutral	-0.9%	0.0%	0.0%
		100.0%	3.0%

	YTD 31Jan06	Weight	Weighted Return
	In CHF		In CHF
4% Target Real Return	<i>YTD Returns are Nominal</i>		
<u>Asset Classes</u>			
Swiss Real Return Bonds	0.0%	0.0%	0.0%
Swiss Bonds	-2.6%	10.0%	-0.3%
Global Bonds	-1.8%	0.0%	0.0%
Domestic Commercial Property	5.0%	17.5%	0.9%
Foreign Commercial Property	3.9%	0.0%	0.0%
Commodities	-1.1%	20.0%	-0.2%
Timber	1.2%	0.0%	0.0%
Swiss Equity	3.2%	47.5%	1.5%
Foreign Equity (US)	0.8%	0.0%	0.0%
Foreign Equity (UK)	3.4%	0.0%	0.0%
Foreign Equity (Eurozone)	4.1%	0.0%	0.0%
Foreign Equity (Japan)	1.0%	0.0%	0.0%
Emerging Mkt. Equity	8.8%	5.0%	0.4%
Equity Market Neutral	-0.9%	0.0%	0.0%
		100.0%	2.4%

	YTD 31Jan06	Weight	Weighted Return
	In CHF		In CHF
3% Target Real Return	<i>YTD Returns are Nominal</i>		
<u>Asset Classes</u>			
Swiss Real Return Bonds	0.0%	0.0%	0.0%
Swiss Bonds	-2.6%	30.0%	-0.8%
Global Bonds	-1.8%	0.0%	0.0%
Domestic Commercial Property	5.0%	17.5%	0.9%
Foreign Commercial Property	3.9%	0.0%	0.0%
Commodities	-1.1%	10.0%	-0.1%
Timber	1.2%	7.5%	0.1%
Swiss Equity	3.2%	30.0%	1.0%
Foreign Equity (US)	0.8%	0.0%	0.0%
Foreign Equity (UK)	3.4%	0.0%	0.0%
Foreign Equity (Eurozone)	4.1%	0.0%	0.0%
Foreign Equity (Japan)	1.0%	0.0%	0.0%
Emerging Mkt. Equity	8.8%	5.0%	0.4%
Equity Market Neutral	-0.9%	0.0%	0.0%
		100.0%	1.5%

	YTD 31Jan06	Weight	Weighted Return
	In CHF		In CHF
2% Target Real Return	<i>YTD Returns are Nominal</i>		
<u>Asset Classes</u>			
Swiss Real Return Bonds	0.0%	0.0%	0.0%
Swiss Bonds	-2.6%	80.0%	-2.1%
Global Bonds	-1.8%	5.0%	-0.1%
Domestic Commercial Property	5.0%	0.0%	0.0%
Foreign Commercial Property	3.9%	0.0%	0.0%
Commodities	-1.1%	0.0%	0.0%
Timber	1.2%	10.0%	0.1%
Swiss Equity	3.2%	5.0%	0.2%
Foreign Equity (US)	0.8%	0.0%	0.0%
Foreign Equity (UK)	3.4%	0.0%	0.0%
Foreign Equity (Eurozone)	4.1%	0.0%	0.0%
Foreign Equity (Japan)	1.0%	0.0%	0.0%
Emerging Mkt. Equity	8.8%	0.0%	0.0%
Equity Market Neutral	-0.9%	0.0%	0.0%
		100.0%	-1.9%

	YTD 31Jan06	Weight	Weighted Return
	In CHF		In CHF
Equally Weighted Portfolio	<i>YTD Returns are Nominal</i>		
<i>Asset Classes</i>			
Swiss Real Return Bonds	0.0%	10.0%	0.0%
Swiss Bonds	-2.6%	10.0%	-0.3%
Global Bonds	-1.8%	10.0%	-0.2%
Domestic Commercial Property	5.0%	10.0%	0.5%
Foreign Commercial Property	3.9%	10.0%	0.4%
Commodities	-1.1%	10.0%	-0.1%
Timber	1.2%	10.0%	0.1%
Swiss Equity	3.2%	10.0%	0.3%
Foreign Equity (US)	0.8%	6.0%	0.1%
Foreign Equity (UK)	3.4%	1.0%	0.0%
Foreign Equity (Eurozone)	4.1%	2.0%	0.1%
Foreign Equity (Japan)	1.0%	1.0%	0.0%
Emerging Mkt. Equity	8.8%	10.0%	0.9%
		100.0%	1.9%