

Financially Diversified Portfolios with Alternative Investments: *The Impact of Life Settlements*

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The recent international financial crisis complicated the management of investment portfolios. As a result, investment alternatives for surplus funds in financial markets became marked with uncertainty in terms of risk and reward. This study examines the effectiveness of including life settlement (LS) funds in combination with fixed income and equity funds and gold, energy, and agricultural commodities to form efficient portfolios to mitigate market risk. In our analysis, we create efficient portfolios by using Markowitz's [1952] portfolio selection theory to investigate the optimal weighting allocation of these assets and their contribution to the return and risk of the portfolio.

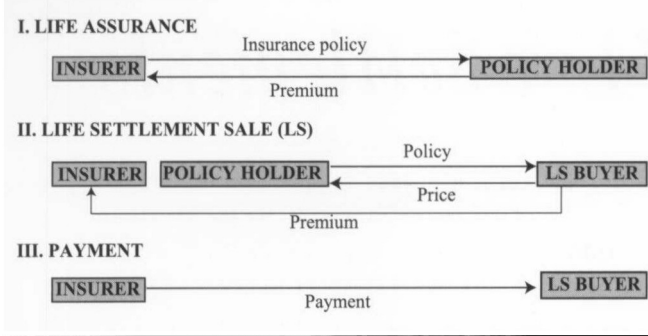
In the U.S., a secondary market has recently developed related to life insurance policies, whose evolution does not depend on the stock market, governmental bonds, or traditional financial assets. LSs are created by an agreement between a severely ill beneficiary of a life insurance policy that covers the risk of death and a third party who purchases the rights of that policy from the beneficiary. The insured individual receives a sum of money, and the investing company becomes the owner of the policy. When an investment fund buys a portfolio of these insurance policies, it acquires the rights and obligations of each contract. As manager, the fund must pay the corresponding premium each year; when

the insured dies, the investment fund receives the value of the policy.

LSs are considered financial assets and can be negotiated in a secondary market. LSs developed as a secondary market to offer liquidity to morbidly ill policyholders as a consequence of the review of their mortality risk. This modification in mortality risks has generated different financial indexes and LS derivatives and has even created the possibility of portfolio securitization (Bozanic [2008]). In this sense, LS funds are investment funds that invest the contributions from the participants in financial instruments such as equity, fixed income, and LSs.

LSs as a secondary market offer a series of advantages to both the original policyholder and the investment firm. First, they make available liquidity to the original policyholders, which may, in turn, result in a beneficial effect on the primary market insofar as it may increase the number of clients willing purchase these policies (Doherty and Singer [2002] and Frank [2004]). Second, their inclusion in investment portfolios may increase the efficiency of portfolio management by improving the diversification and performance of the portfolio due not only to their low correlation with traditional assets but also their ability to reduce portfolio volatility (Rosenfeld [2009]). The typical scheme of LSs is described in Exhibit 1.

EXHIBIT 1 The Life Settlement Process



The remainder of this study is structured as follows. After we review the literature on LSs and the generation of efficient portfolios based on alternative investments, we describe the data. We then present the portfolio optimization method that we use to generate our efficient portfolios and our main results. Finally, we offer our conclusions.

LITERATURE REVIEW

The literature review is divided into two areas. Using portfolio theory (Markowitz [1952], who introduced the concepts of efficient portfolios and efficient frontiers), we first discuss the use of alternative investment portfolios in the efficient management of portfolios. Second, we identify those studies related to the inclusion of LSs in the calculation of efficient portfolios.

The use of alternative investment assets to enhance portfolio performance is currently a growing trend (Russell Investments Inc. [2010]). Robichek, Cohn, and Pringle's [1972] pioneering work proposed the advantages of diversified allocation in portfolio conglomeration. They found that diversified investment holdings with low correlations, in combination with other underlying financial instruments (i.e., stocks, bonds, and indexes) and commodity derivatives, improve portfolio performance.

Jensen, Johnson, and Mercer [2000] advanced Robichek et al.'s study by examining the role of raw materials as an asset to create efficient portfolios, thus showing the ability to create portfolio value during time periods of restricted liquidity. Schweizer [2008] studied the process of efficient portfolio formation by using mainly nonconventional (alternative) assets together with the traditional combinations of stocks and bonds. He found that these

nonconventional assets played a complementary role in portfolio performance, independent of the risk level assumed by the investor. In sum, these studies suggest that portfolio performance can be improved by the inclusion of alternative investment allocations.

Literature on LSs specifically related to their inclusion in efficient portfolios is rather limited, principally due to their recent introduction to financial markets, although several studies are available. In particular, Perera and Reeves [2006] outlined the transfer of the inherent risk of LSs, and Smith and Washington [2006] studied the process of risk diversification using LS allocations. However, none of them integrates these assets into efficient portfolios. Dorr [2008] studied LSs in relation to the extension of the efficient frontier model. Finally, Rosenfeld [2009] obtained the correlation matrix of an index linked to mortality with fixed income and equity indexes. Nevertheless, these previous contributions do not develop portfolio optimization processes with LSs.

Most recently Braum, Gatzert, and Schmeiser [2012] analyze "profitability and risk" in LS funds. Distinguishing between closed-end funds and open-end funds, they point out advantages of the open-end funds in terms of liquidity, larger scope of market growth, more transparency, and standardization. They assume a gradual migration to open-end LS funds as the market consolidates.

DATA

We select 14 funds to replicate fixed income and equity indexes in the U.S. and Europe. These 14 funds obtained the highest performance ranking, according to Bloomberg, and had the largest amount of liquidation value data depending on fund type. Our sampling period ranges from January 2007 to November 2010 (47 months), a period that coincides in part with the international financial crisis and whose selection is conditioned by the availability of data on funds linked to LSs.

The selected funds invest in fixed income and equity indexes, commodities (gold, oil, energy, and agricultural), and LSs under different types of currencies (euro, U.S. dollar [USD], and sterling pound [GBP]). Bloomberg provides monthly data, given as net asset values, for 14 funds covering six indexes: S&P500, Eurostoxx50, AGG:US iShares Barclays Bond Fund, SCHEAIE:IX Schroder International Selection Fund Corporate Bond, FTSE 100, and Madrid Stock Exchange General Index

(IGBM). Exhibit 2 shows the funds' average returns, risk, and currency. In addition, graphs of the funds' monthly liquidation values are provided in the Appendix.

We filter the sample based on the results prior to the generation of efficient portfolios with equities, the distorting effect of IS funds that pay dividends, the negative correlation between prices, and price data availability. First, we generate efficient portfolios that integrate IS funds and investment funds that replicate fixed income and equity indexes from the U.S. and Europe. These portfolios are created with exact monthly price data from January 2007 to February 2010 (i.e., months in which all fund data are available), and we obtain efficient frontiers in all of the IS funds that improved the risk-reward of fixed income and equity portfolios. Following the process of generating the efficient portfolios, the weight of the funds that replicate the IGBM and FTSE100 is zero; therefore, these two funds are eliminated from our study.

Second, we attend to the distortion of IS funds that pay dividends. Both EPICLSS GU US and EPICLSC GU US funds were among the highest according to performance and pricing data. However, we retain only the EPICLSC GU US fund and eliminate the EPICLSS GU IA fund, given the distortion caused by the evolution of prices related to the payment of periodic dividends.

Third, we analyze the monthly prices of the 14 funds and find negative correlations between most funds. Specifically, we find negative correlations between the

IS fund (SC) and all other sample funds; Eurostoxx50 and the two gold funds; the U.S. bond index and oil and energy funds; and the Euro Bond Index and gold, oil, and energy funds. Because we did not find a correlation between the agricultural funds and any other fund, we eliminated them from our study.

Finally, liquidation values for the oil fund (USL:US)12Oil (US\$) did not coincide with the analyzed time horizon (47 months), so we eliminated it from the sample. This filtering process reduced our sample size to nine funds. Using these nine funds, we generate an efficient frontier for an observation period of 47 months (January 2007–November 2010).

Exhibit 3 shows the returns of the nine funds. The two gold funds have the highest return—1.78%. Data are obtained with prices from different currencies: the EPICLSC GU US fund is quoted in GBP; the funds that replicated the Eurostoxx50 and SCHEA1E C Bond indexes, in euros; and the (GLD:US)SPDR Gold, (IAU:US)iShares Gold, (DBE:US) Energy and DBC Commodity, and the funds that replicate the S&P500 and AGG:US Bond indexes, in USD. In addition, we use data of the calculated performance and standard deviations after considering the conversion to euros of the liquidation values, starting with the exchange rates for the euro–USD and the euro–GBP. The values in euros of the nine funds, in terms of average return and risk, are shown in Exhibit 4.

Exhibit 4 also presents the returns of the nine funds. Again, the two gold funds have the highest return—1.77%. The table also shows the effects of the exchange rates on the risk–return of each fund: positive in bold, and negative in gray. The effect of the conversion to euros of the liquidation values results in a reduction in

EXHIBIT 2

Average Monthly Return and Standard Deviation of 14 Funds (May 2008–November 2010)

	Average (%)	Desvestp (%)
EPICLSS GU Life Settlement (GBP)	-0.07	1.9960
EPICLSC GU Life Settlement	0.78	0.1424
S&P500 (\$)	-0.28	6.5227
Eurostoxx50 (€)	-0.94	6.7769
AGG:US Bond (\$)	0.15	1.5983
SCHEA1E, € Bond (€)	0.31	1.6922
FTSE100 (GBP)	-0.15	5.6177
IGBM (€)	-1.17	7.3790
(GLD:US)SPDR Gold (\$)	1.64	6.0491
(IAU:US)iShares Gold (\$)	1.64	6.0159
(USL:US)12Oil (\$)	-1.07	10.2678
(DBE:US)Energy (\$)	-1.26	10.0591
DBC, Commodity (\$)	0.95	7.9076
(DAG:US), Agriculture (\$)	-0.92	15.860

EXHIBIT 3

Average Monthly Return and Standard Deviation of Nine Funds (January 2007–November 2010)

	Average (%)	Desvestp (%)
EPICLSC GU Life Settlement (£)	0.78	0.1580
S&P500 (\$)	-0.25	5.6649
Eurostoxx50 (€)	-0.79	6.1183
AGG:US Bond (\$)	0.17	1.4189
SCHEA1E, € Bond (€)	0.18	1.4911
(GLD:US)SPDR Gold (\$)	1.78	5.7172
(IAU:US)iShares Gold (\$)	1.78	5.6975
(DBE:US)Energy (\$)	0.47	9.0771
DBC, Commodity (\$)	0.45	7.1795

EXHIBIT 4

Average Return and Standard Deviation of the Values in Euros of Nine Funds (January 2007–November 2010)

	Average (%)	Desvestp (%)
EPICLSC GU Life Settlement (£)	0.32	3.1947
S&P500 (\$)	-0.30	4.8820
Eurostoxx50 (€)	-0.79	6.1183
AGG:US Bond (\$)	0.22	3.4500
SCHEA1E, € Bond (€)	0.18	1.4911
(GLD:US)SPDR Gold (\$)	1.77	5.6568
(IAU:US)iShares Gold (\$)	1.77	5.6189
(DBE:US)Energy (\$)	0.37	8.0154
DBC, Commodity (\$)	0.35	5.7059

Notes: Positive effects are in bold. Negative effects are in gray.

return for almost all of the funds that are not quoted in euros and a risk reduction for almost all of the funds.

Exhibit 5 shows the correlations between the nine funds without considering the effect of exchange rates (i.e., with each fund represented in its respective currency). Here we find that the correlation between the LS fund and all other funds is negative. There is also a negative correlation between the two gold funds and the Eurostoxx50, between the energy fund and the two fixed income indexes, and between the DBC Commodity fund and the euro fixed income index. Clearly, the correlations between the nine funds in the study show different results when considering the effect of the euro exchange rates (all data expressed in euros), as shown in Exhibit 6.

When considering the impact of the euro exchange rate, the correlation of the SCHEA1E €-bond index is negative with seven of the eight funds. The LS fund, with prices converted to euros is the only fund with a negative correlation with the Eurostoxx50 and SCHEA1E €-bond indexes. We also find a negative correlation between the S&P500 (USD) and the two gold funds (USD) and the S&P500 and the SCHEA1E €-bond index. In addition, the gold funds (USD) are negatively correlated with the Eurostoxx50 and the SCHEA1E €-bond indexes. Finally, the energy funds (USD) and commodities (USD) are negatively correlated with the two fixed income indexes from the U.S. and Europe.

METHOD AND RESULTS

We use Markowitz's [1952] model for portfolio selection to examine the appropriateness of adding LS

funds to a portfolio of fixed income and equity funds and gold, energy, and commodity assets to optimize the diversification and performance of a portfolio. Portfolio theory structures the management process of financial investments into five stages (Goetzmann [1996]): setting the investment objective, establishing investment policy, selecting the portfolio strategy, selecting the assets, and measuring evaluating performance.

In the first stage, we obtain a specific return assuming minimum risk. In the second stage, we determine the funds in which to invest. In the third stage, we develop a portfolio strategy; namely, we select the fund allocation. We make decisions regarding the weighting allocation of each fund based on Markowitz's portfolio optimization model, which determines the most appropriate portfolio based on an investor risk-reward profile. In the fourth stage, portfolio asset selection, the three previous stages are applied during a set time period with new data and the model is measured for portfolio goodness of fit. The fifth stage, performance evaluation, provides a comparison of the optimal portfolio with other alternatives.

As previously discussed, we obtain a specific return assuming minimum risk and select nine funds. We now analyze the weighting allocation of the funds that make up efficient portfolios, based on risk-reward and diversification. To do so, we carry out the following process.

First, we analyze the funds that make up the portfolios by estimating the risk and return so that the risk and return of each fund can be included into the set of the portfolio risk-reward. We also include the effect of exchange rate variation effect into the portfolio risk-reward by considering the financial asset prices, in GBP and USD, which are converted into euros. Portfolio risk-reward depends on the return of each fund, allocation or weight (W_i) of each fund, the volatility (σ_i) of each fund, and the covariance (σ_{ij}) among all pairs of funds that make up the portfolio. Thus, we obtain covariances among the funds and the correlation coefficients ρ_{ij} . We establish return constraints and conduct portfolio selection in agreement with the minimum desired return level.

Second, we analyze the portfolios considering the effect of the interaction between the funds and the currencies in which they are listed. Portfolio diversification allows systematic (market) and unsystematic (unique) risk to be mitigated, while maintaining the same return. Unsystematic risk is reduced due to existent diversified

EXHIBIT 5

Correlation Coefficient Matrix, without Euro Exchange Rate Effect

	1	2	3	4	5	6	7	8	9
1. EPICLSC GU Life Settlement	1								
2. S&P500	-0.36463600	1							
3. Eurostoxx50	-0.27859291	0.89901566	1						
4. AGG:US Bond	-0.18679680	0.17334035	0.12513750	1					
5. SCHEA1E, € Bond	-0.18848006	0.10975367	0.13859192	0.32589184	1				
6. (GLD:US)SPDR Gold	-0.22274432	0.04556238	-0.09640190	0.42004455	0.09276765	1			
7. (IAU:US)Shares Gold	-0.22861765	0.04819557	-0.09576260	0.42425864	0.09531642	0.99960991	1		
8. (DBE:US)Energy	-0.30984155	0.53190874	0.38001769	-0.13600590	-0.09719840	0.27936155	0.27882564	1	
9. DBC, Commodity	-0.38142590	0.56183022	0.39656215	0.06218534	-0.01147720	0.42756074	0.42876587	0.94275627	1

Source: Author research.

EXHIBIT 6

Correlation Coefficient Matrix, Including Euro Exchange Rate Effect

	1	2	3	4	5	6	7	8	9
1. EPICLSC GU Life Settlement	1								
2. S&P 500	0.25576873	1							
3. Eurostoxx50	-0.15515977	0.6922419	1						
4. AGG:US Bond	0.49291633	0.10481454	-0.46933484	1					
5. SCHEA1E, € Bond	-0.05686565	-0.01983995	0.13859192	-0.07767223	1				
6. (GLD:US)SPDR Gold	0.25390031	-0.12305187	-0.41217453	0.38801138	-0.04043293	1			
7. (IAU:US)Shares Gold	0.25155551	-0.12411035	-0.41387877	0.38663424	-0.03855613	0.99961454	1		
8. (DBE:US)Energy	0.38889602	0.37556002	0.22649266	-0.23703854	-0.19584809	0.11354928	0.11085498	1	
9. DBC, Commodity	0.28233823	0.33637205	0.20761111	-0.24479553	-0.13886185	0.22652615	0.22497401	0.94282058	1

funds, in addition to fund diversification in the portfolios; that is, a measure that affects one fund value also affects, to a lesser degree, the fund portfolios. With regard to systematic risk, some variables (interest rates) affect all markets (L.Ss, fixed income, and equity) and their influence cannot be mitigated, but other variables (life expectancy and exchange rate) affect only some markets (L.Ss) and not others (fixed income and equities in the same currency). The overall effect of these portfolio changes is reduced with diversification.

Third, we select the optimal portfolios based on the application of the Markowitz [1952] model, which requires a calculation of the optimal weight of the funds that make up the portfolio to mitigate risk, guaranteeing a fixed return. In our empirical analysis, we obtain a covariance matrix between the nine funds and, based on them, apply mathematical optimization programs (Excel solver), which minimize the portfolio risk for specified returns. We carried out optimization processes (Fama and Miller [1972]), whereby the objective function to be minimized is the return volatility of the portfolios and one constraint of the program is expected return:

$$\begin{aligned} \text{Min Var}(r_p) &= \left(\sum_i W_i^2 \sigma_i^2 \right) + \left(\sum_i \sum_j W_i W_j \sigma_{ij} \right) \\ \text{subject to } E(r_p) &= \sum_i W_i E(r_i) = r^* \\ \sum_i W_i &= 1 \end{aligned} \quad (1)$$

$$W_i > 0 \text{ (otherwise, } W_i = 0)$$

The outputs from the optimization models are portfolios that minimize volatility with a predetermined return. As a result, different values for return r^* are generated, leading to the generation of additional combinations of optimal risk-reward, which become the efficient portfolios that define the efficient frontier. We obtain the efficient frontiers or curves that connect the points of minimal risk for each return level by carrying out the first two stages of the portfolio analysis according to Markowitz's [1952] model: namely, separate the efficient frontiers from the non-efficient frontiers and present the optimal combinations or efficient frontiers.

The Markowitz [1952] model allows us to choose among our nine funds, which originate from various markets (L.Ss, fixed income and equity indexes, gold, oil, energy, and commodities). This model assumes that the variable exhibits normal behavior. Thus, any portfolio return (r_p) is also a random variable associated with a normal probability distribution. We use volatility and standard deviation of the performance return σ_p to measure portfolio risk. The formation of efficient portfolios with nine funds ($i = 1 \dots 9$) requires the calculation of the volatility of the portfolio using nine performance return volatilities from the funds and the covariances between these performance returns. Thus, we calculate nine fund volatilities and 36 covariances, which we show in matrix form (Harvey [1995]). The negative correlation between the funds is observed in the correlation coefficient matrices that measure the dependence between the different funds. The correlation analysis allows us to minimize total portfolio risk, VAR (Rp), by properly combining all funds.

The model spreadsheet shown in Exhibits 7 and 8 generates portfolios by means of optimization. These tables summarize performance returns and volatility of each of the nine funds that make up the portfolio, risk, and performance reward of the equally weighted portfolio ($W_i = 1/9 = 0.11$) and the variance and covariance matrices. Panel A of both the spreadsheet (Exhibit 7) and covariance matrix (Exhibit 8) does not consider the euro exchange rate (i.e., each fund is listed in its original currency), whereas in Panel B of both tables, the data are calculated based on the liquidation values converted into euros.

The equally weighted portfolio hypothesis is applied only to produce a model from which the optimal weighting fund allocations are obtained to form efficient portfolios. Nevertheless, in Exhibit 7, note that the advantages of diversification are clear because the portfolio formed from the nine funds in equal parts has a positive return, which is greater than some of the fund returns, and has less risk.

We use spreadsheet models to calculate the asset weight allocation that mitigates portfolio risk, VAR (Rp), subject to a specified return level. The performance return constraint is successively modified to generate efficient portfolios. Possible results are risk-reward combinations that make up the efficient frontier. Panels A and B of Exhibit 9 show the efficient frontiers for the

EXHIBIT 7

Model Spreadsheets to Calculate Optimization, with and without Euro Exchange Rate Effect

FUND (I)	WI (1/9)	E(Ri) (%)	WI E(Ri)
Panel A: With euro exchange rate effect			
EPICLSC GU Life Settlement	0.11	0.780	0.0009
S&P500	0.11	-0.252	-0.0003
Eurostoxx50	0.11	-0.791	-0.0009
AGG:US Bond	0.11	0.167	0.0002
SCHEA1E, € Bond	0.11	0.179	0.0002
(GLD:US)SPDR Gold	0.11	1.779	0.0020
(IAU:US)Shares Gold	0.11	1.778	0.0020
(DBE:US)Energy	0.11	0.468	0.0005
DBC, Commodity	0.11	0.453	0.0005
	Sum Wi	E(Rp) (%)	Var(Rp)
	1.00	0.51	0.0010369
FUND (I)	WI (1/9)	E(Ri) (%)	WI E(Ri)
Panel B: Without euro exchange rate effect			
EPICLSC GU Life Settlement	0.11	0.325	0.0004
S&P500	0.11	-0.297	-0.0003
Eurostoxx50	0.11	-0.791	-0.0009
AGG:US Bond	0.11	0.216	0.0002
SCHEA1E, € Bond	0.11	0.179	0.0002
(GLD:US)SPDR Gold	0.11	1.770	0.0020
(IAU:US)Shares Gold	0.11	1.769	0.0020
(DBE:US)Energy	0.11	0.371	0.0004
DBC, Commodity	0.11	0.351	0.0004
	Sum Wi	E(Rp) (%)	Var(Rp)
	1.00	0.43	0.0006735

nine funds without considering the euro exchange rate and with price data in euros. The points represented in the efficient frontiers are the efficient portfolios. Exhibit 10 provides the variations of the weighting of the nine funds that generate the efficient frontiers.

Once we carry out the portfolio analysis from the Markowitz [1952] model, we obtain the portfolios and efficient frontiers. We now introduce the investor utility functions into the allocation decision. This process entails an analysis of the utility combinations based on indifference curves to determine the efficient portfolio that maximizes investor utility (i.e., point of tangency between the indifference curve and the efficient frontier curve).

Overall, our empirical analysis shows that the inclusion of US funds in efficient portfolio formation improves portfolio performance. Specifically, we find negative correlations between the US fund in our study and our other eight funds that replicate fixed income and equity indexes, gold, oil, energy, and commodities. Although we report the performance improvement in euros, the improvement is even more notable if the financial position is reported in GBP. The conversion of the liquidation

values to euros, given the evolution of the exchange rates, partially reduces this beneficial effect.

In addition, if we do not consider the exchange rate effect, US funds form part of each portfolio with returns that are greater than the average during the period under study and for the funds used in the study (specifically, 0.51% for the portfolios of the nine funds using the same allocation weight). Finally, our results suggest that the performance returns of US funds are less correlated with fixed income and equity index funds than these funds from these indexes are with each other. However, the correlation between US funds and funds from fixed income and equity indexes increases when we convert the currency of all liquidation values into euros. (Exhibit 4 provides original currencies of the funds).

CONCLUSIONS

This study investigates whether the inclusion of US funds in the formation of efficient portfolios contributes to the mitigation of market risk and improves portfolio performance. We form efficient portfolios from approximations based on Markowitz's [1952] portfolio theory by using US funds in combination with fixed income and equity funds, gold, energy, and agricultural commodities. We find that US funds are an effective approach to investment diversification, given their low correlation with other fund types.

Specifically, our analysis leads to two main findings. First, our results suggest that US funds can reduce portfolio risk. In particular, US funds possess tremendous potential to reduce portfolio risk in combination with fixed income and equity indexes and commodities; US funds improve performance to the greatest extent in these portfolios. This is particularly relevant in financial crisis periods, characterized by high levels of market risk. In the same sense, a future line of investigation will study the impact of portfolio risk in US funds with a combination of hedge funds or funds of hedge funds. Second, the inverse correlations between US funds and fixed income and equity funds are

EXHIBIT 8

Covariance Matrix for Model Spreadsheets to Calculate Optimization, with and without Euro Exchange Rate Effect

	1	2	3	4	5	6	7	8	9
Panel A: With euro exchange rate effect									
1. EPICLSC GU Life Settlement	0.000002497								
2. S&P500	-0.000032639	0.003291210							
3. Eurostoxx50	-0.000026933	0.003115977	0.003743415						
4. AGG:US Bond	-0.000004188	0.000139333	0.000108638	0.000250134					
5. SCHEA1E, € Bond	-0.000004441	0.000092707	0.000126437	0.000068950	0.000222333				
6. (GLD:US)SPDR Gold	-0.000020122	0.000147564	0.000337210	0.000340750	0.000079082	0.003268596			
7. (IAU:US)Shares Gold	-0.000020582	0.000155555	0.000333820	0.000342984	0.000080975	0.003256069	0.003246123		
8. (DBE:US)Energy	-0.000044440	0.002735139	0.002110508	-0.000175173	-0.000131556	0.001449761	0.001441997	0.008239453	
9. DBC, Commodity	-0.000043271	0.002285041	0.001741972	0.000063350	-0.000012287	0.001754988	0.001753874	0.006143904	0.005154560
Panel B: Without euro exchange rate effect									
1. EPICLSC GU Life Settlement	0.001020629								
2. S&P500	0.000398913	0.002383382							
3. Eurostoxx50	-0.000303282	0.002067706	0.003743415						
4. AGG:US Bond	0.000543277	0.000176536	-0.000990675	0.001190225					
5. SCHEA1E, € Bond	-0.000027089	-0.000014442	0.000126437	-0.000039956	0.000222333				
6. (GLD:US)SPDR Gold	0.000458848	-0.000339826	-0.001426548	0.000757234	-0.000034104	0.003199944			
7. (IAU:US)Shares Gold	0.000451567	-0.000340455	-0.001422859	0.000749496	-0.000032304	0.003177302	0.003157254		
8. (DBE:US)Energy	0.000995847	0.001469608	0.001110742	-0.000655479	-0.000234070	0.000514850	0.000499270	0.006424664	
9. DBC, Commodity	0.000514667	0.000937000	0.000724782	-0.000481882	-0.000118143	0.000731160	0.000721290	0.004311982	0.003255708



EXHIBIT 9

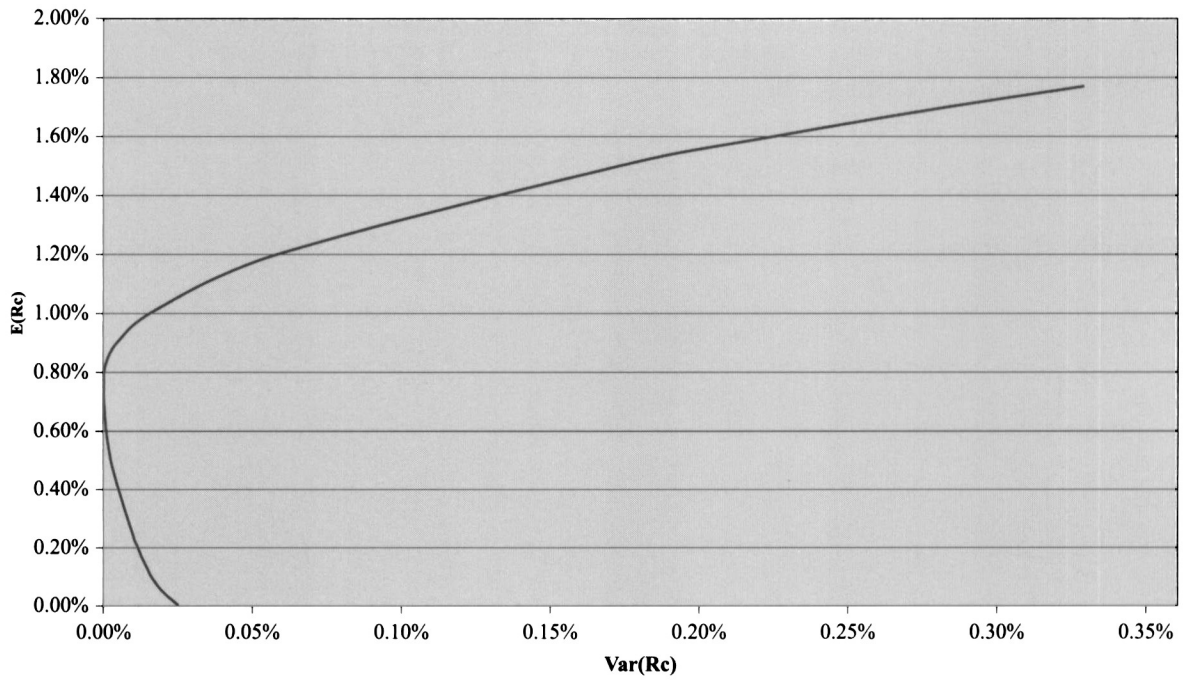
Efficient Portfolios, Excluding and Including Euro Exchange Rate

E(Rp) (%)	EPICLSC			AGG:US Bond (%)	SCHEA1E, € Bond (%)	(GLD:US)	(IAU:US)	(DBE:US) Energy (%)	DBC, Commodity (%)
	GU LS (%)	S&P500 (%)	Eurostoxx50 (%)			SPDR Gold (%)	iShares Gold (%)		
Panel A: Portfolios excluding euro exchange rate									
0.01	0	0	17	48	35	0	0	0	0
0.01	0	0	17	48	35	0	0	0	0
0.02	0	0	16	48	35	0	0	0	0
0.02	0	0	16	49	36	0	0	0	0
0.04	0	0	14	49	37	0	0	0	0
0.06	0	0	12	50	38	0	0	0	0
0.07	0	0	11	50	39	0	0	0	0
0.09	0	0	9	51	41	0	0	0	0
0.11	0	0	7	51	41	0	0	1	0
0.12	1	0	6	50	41	0	0	1	0
0.14	4	0	6	47	40	0	0	1	0
0.17	8	0	5	44	38	0	0	1	0
0.21	14	0	5	42	36	0	0	1	0
0.23	17	0	3	22	34	0	0	1	0
0.50	58	0	1	6	17	0	0	1	0
0.70	88	0	0	2	5	0	0	1	0
0.75	95	0	0	0	2	0	0	0	1
0.77	97	1	0	0	1	0	1	0	0
0.78	98	1	0	0	0	0	1	0	0
0.80	98	0	0	0	0	0	2	0	0
0.85	93	0	0	0	0	0	7	0	0
0.90	88	0	0	0	0	0	12	0	0
1.00	78	0	0	0	0	0	22	0	0
1.20	58	0	0	0	0	0	42	0	0
1.50	28	0	0	0	0	0	72	0	0
1.60	18	0	0	0	0	0	82	0	0
1.70	8	0	0	0	0	0	92	0	0
1.77	1	0	0	0	0	0	99	0	0
Panel B: Portfolios including euro exchange rate									
0.01	0	0	20	28	50	0	0	0	3
0.01	0	0	19	28	50	0	0	0	3
0.02	0	0	19	27	51	0	0	0	3
0.02	0	0	18	27	51	0	0	0	4
0.04	0	0	16	26	53	0	0	0	4
0.06	0	0	14	25	55	0	0	0	5
0.07	0	0	13	25	57	0	0	0	5
0.09	0	0	11	24	59	0	0	0	6
0.11	0	0	9	23	61	0	0	0	7
0.12	0	0	8	23	62	0	0	0	7
0.14	1	0	6	21	64	0	0	0	8
0.17	2	0	5	19	65	0	1	0	7
0.21	2	0	5	17	66	0	4	2	5
0.23	2	0	5	16	66	0	5	2	4
0.50	8	0	1	1	68	0	19	3	0
0.70	5	0	0	0	61	0	32	3	0
0.75	4	0	0	0	59	0	35	2	0
0.77	3	0	0	0	58	0	37	2	0
0.78	3	0	0	0	57	0	37	2	0
0.80	3	0	0	0	57	0	39	2	0
0.85	2	0	0	0	54	0	42	2	0
0.90	0	0	0	0	52	0	45	2	0
1.00	0	0	0	0	47	0	51	2	0
1.20	0	0	0	0	35	0	64	1	0
1.50	0	0	0	0	17	0	83	0	0
1.60	0	0	0	0	11	0	89	0	0
1.70	0	0	0	0	4	0	96	0	0
1.77	0	0	0	0	0	73	27	0	0

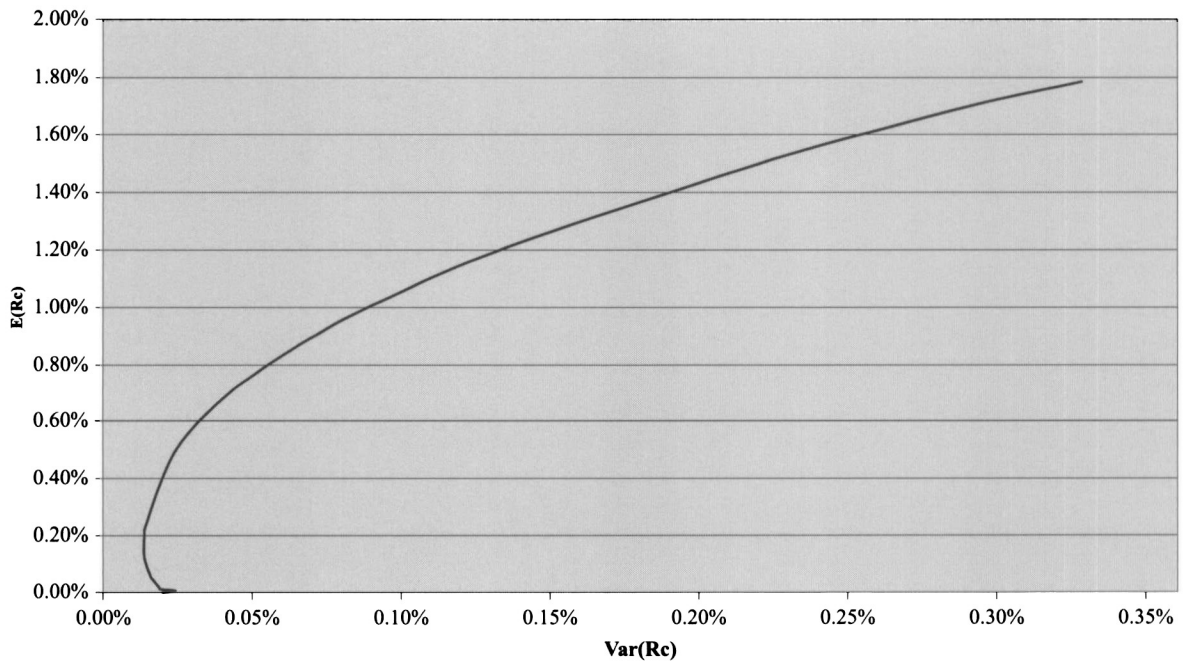
Source: Author research.

EXHIBIT 10

Panel A. Efficient Frontier, Excluding Euro Exchange Rate



Panel B. Efficient Frontier, with Price Data in Euros



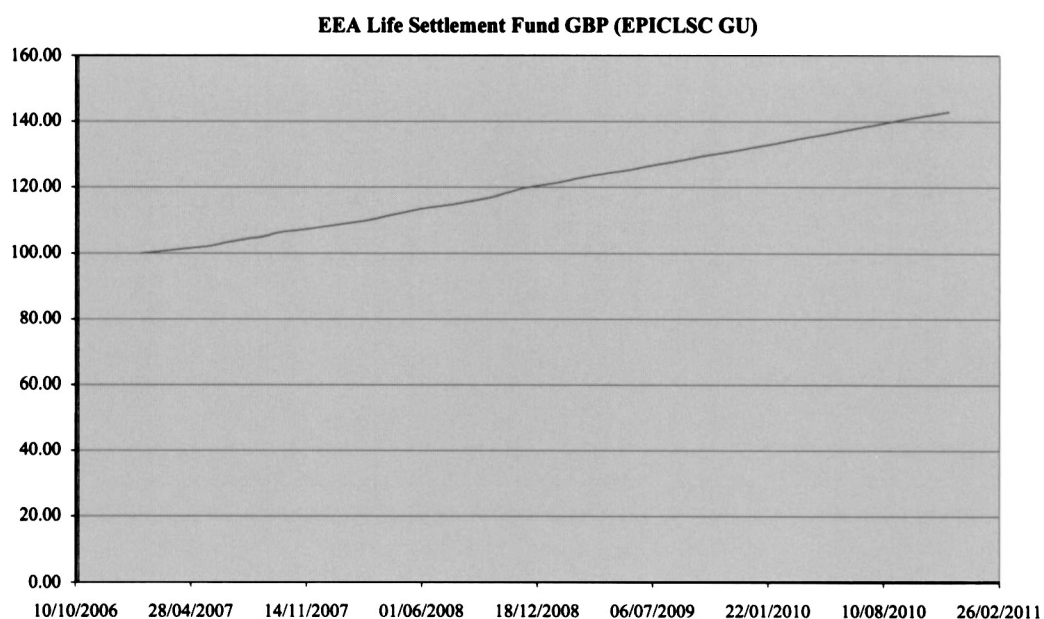
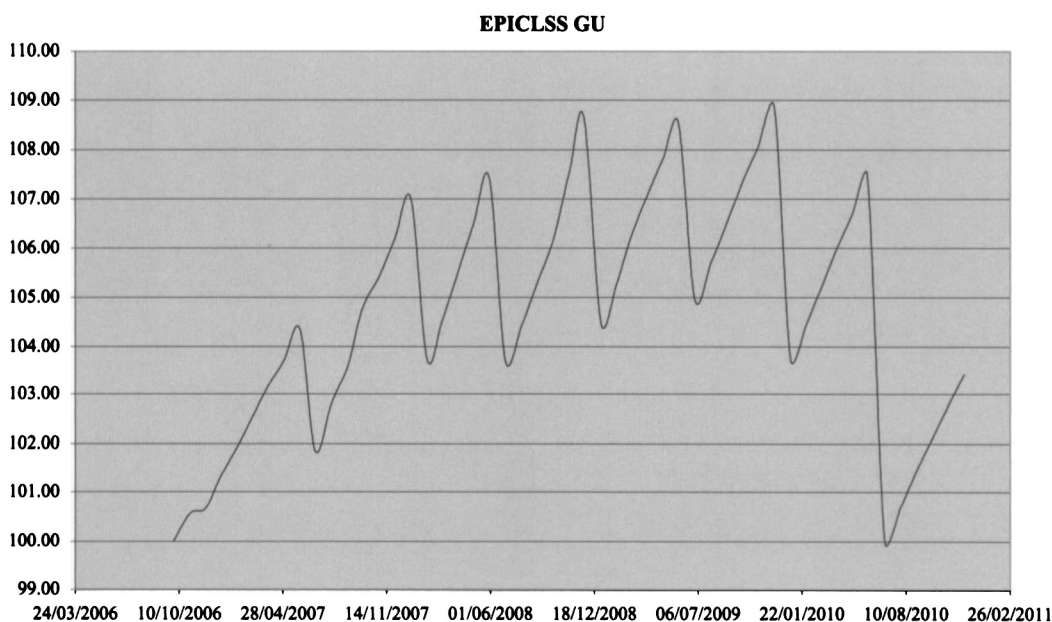
very important for diversification, but the effect is reduced when the exchange rate effect is considered.

One limitation of our study is the simplification of the selection criteria with regard to the risk and return analysis using historical data. Access to longer time periods of observable data will allow future studies to

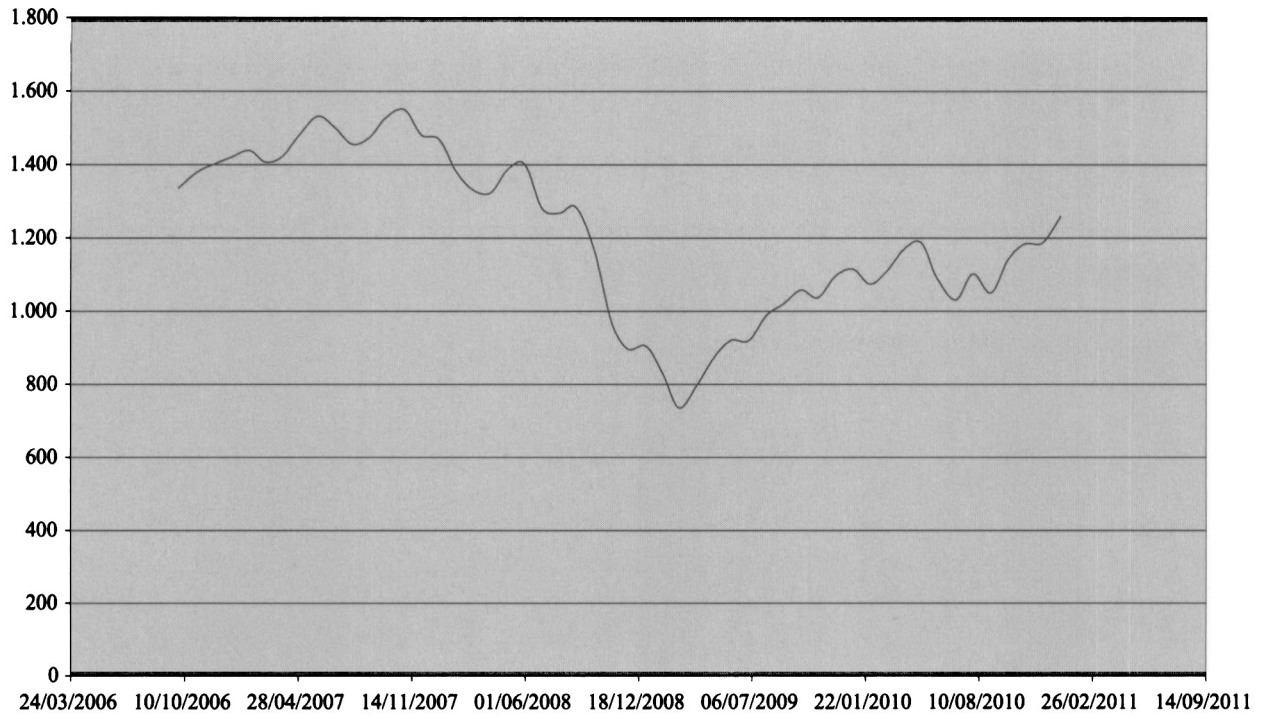
apply other models in the calculations of returns and expected returns. Another path for future research may be an investigation of alternative investments in gold and commodity funds, which we find improve performance in portfolios based on fixed income and equities (unreported).

APPENDIX

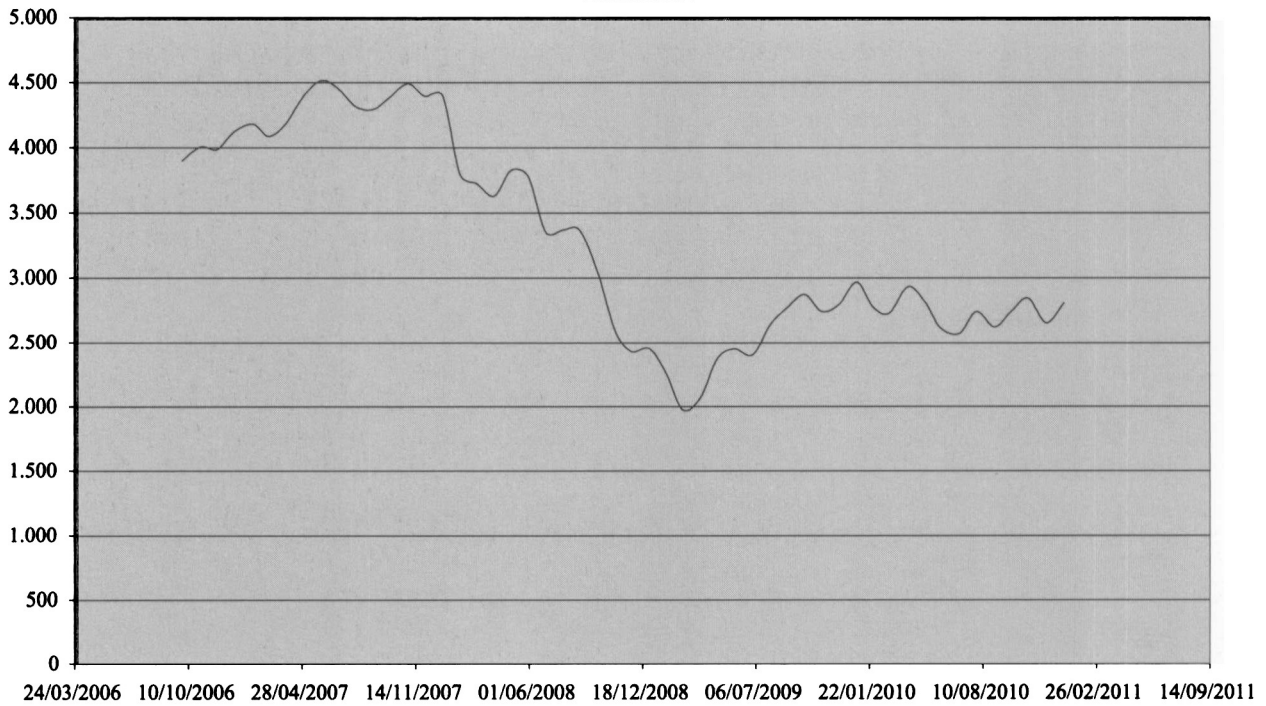
Graphs of Monthly Liquidation Values of 14 Funds



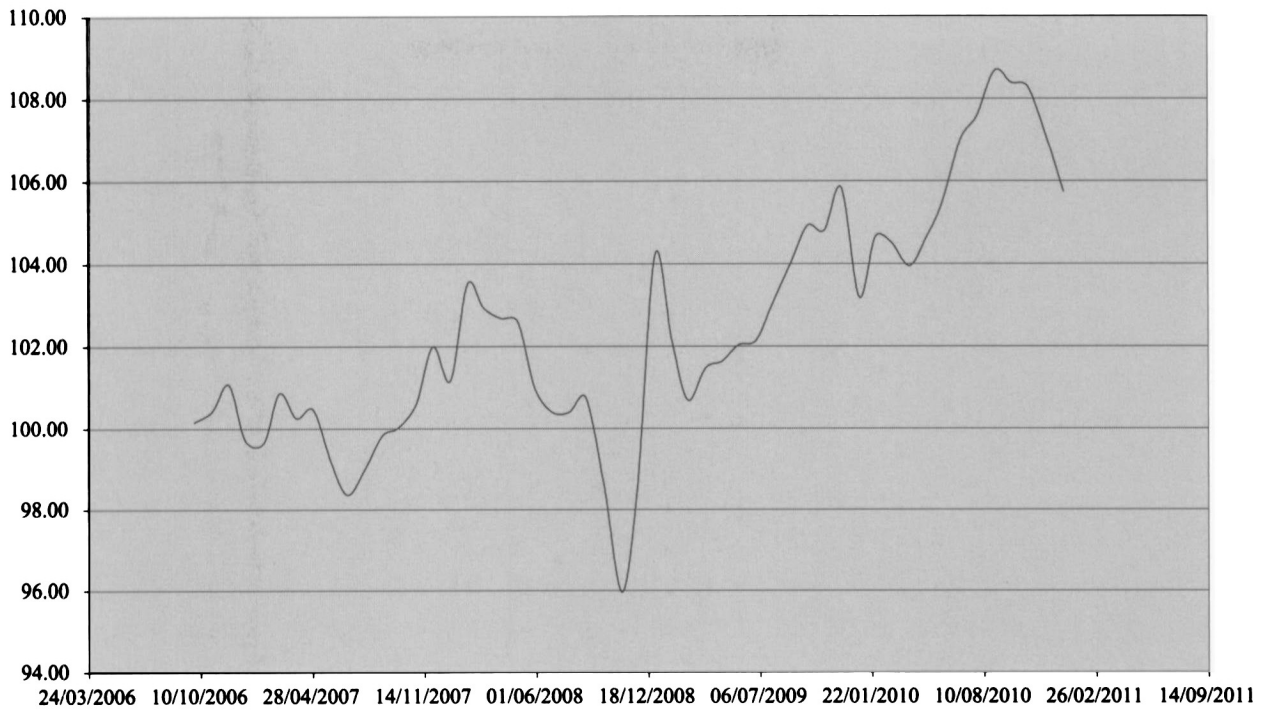
S&P500



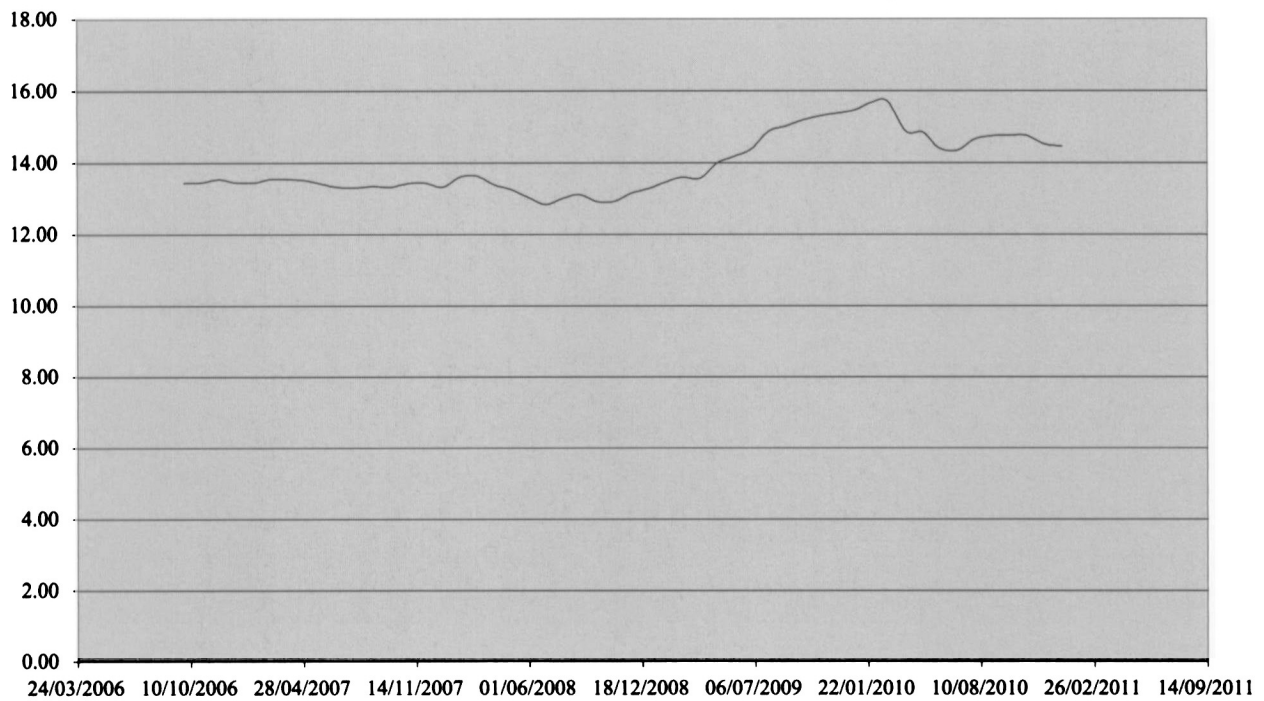
Eurostoxx50

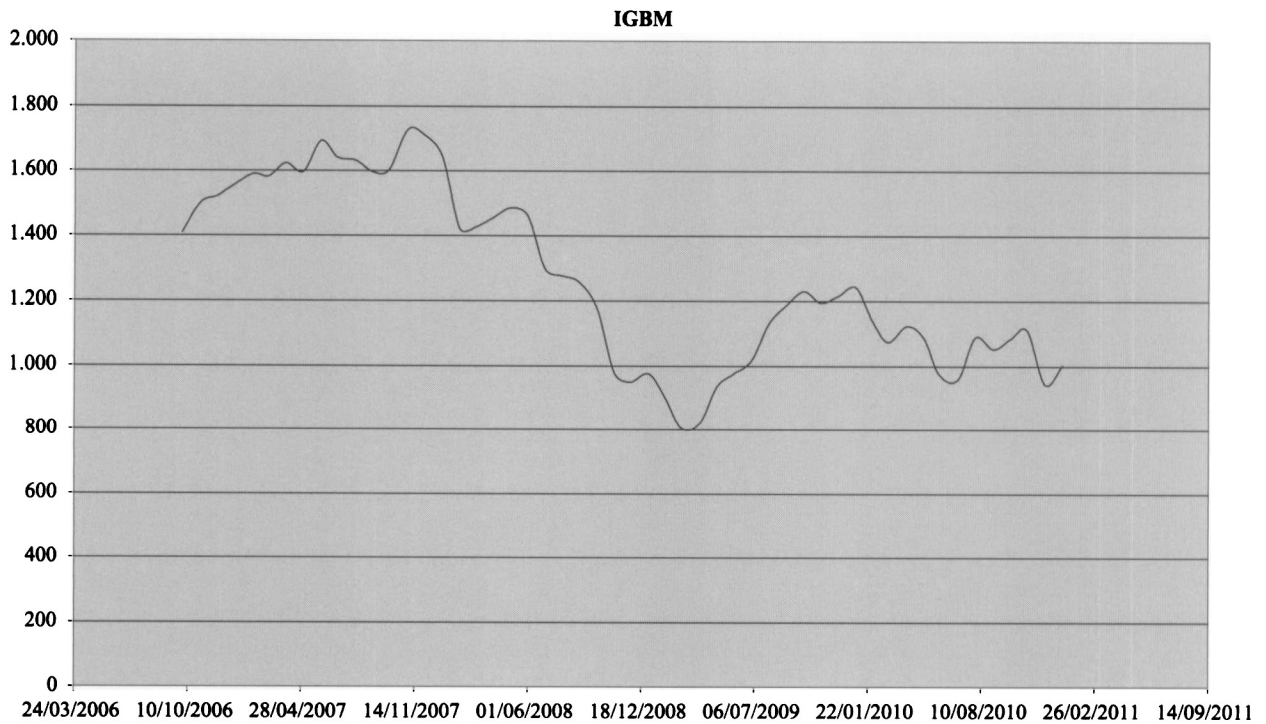
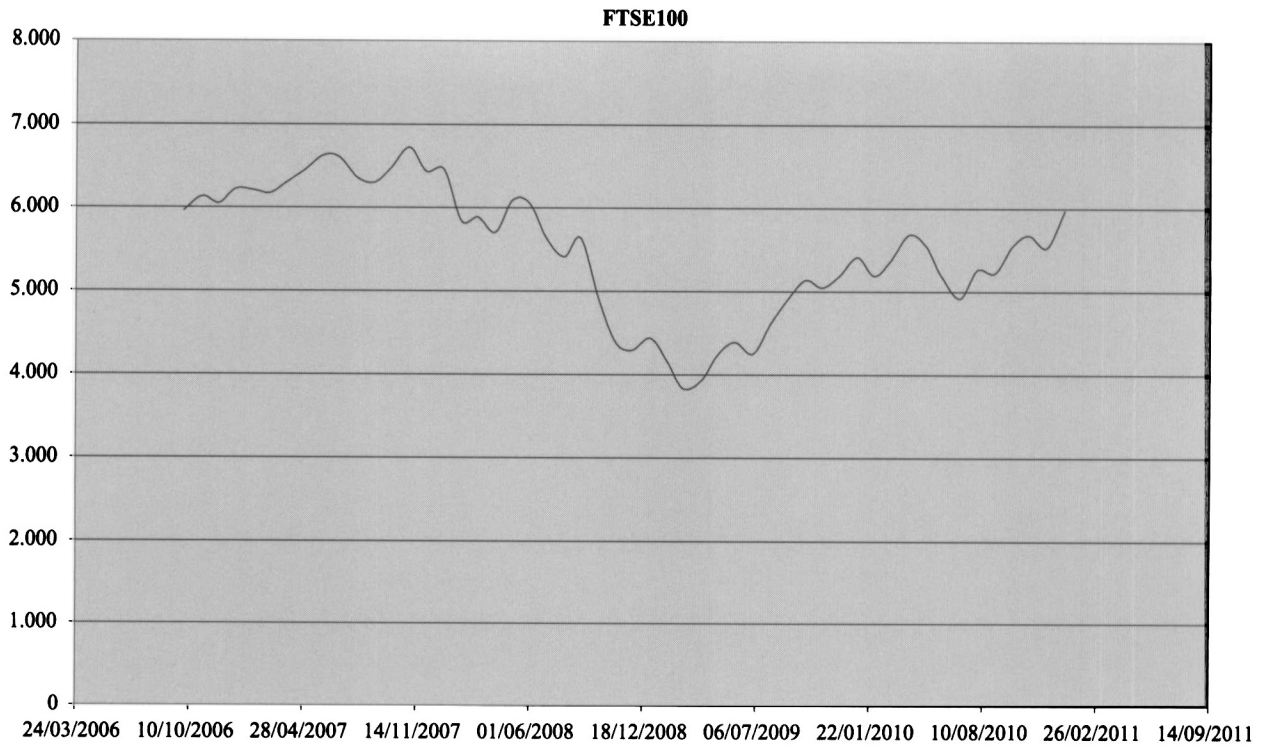


AGG:US iShares Barclays Aggregate Bond Fund

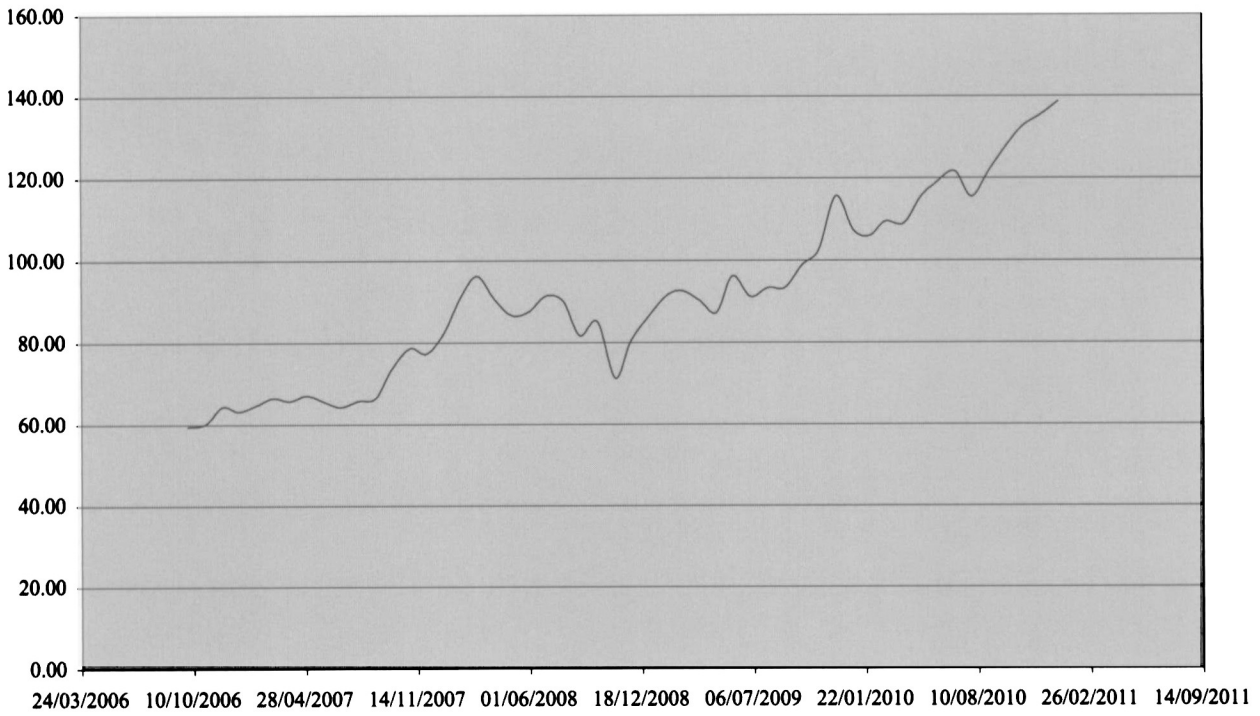


SCHEA1E:LX Schroder International Selection Fund - EURO Corporate Bond

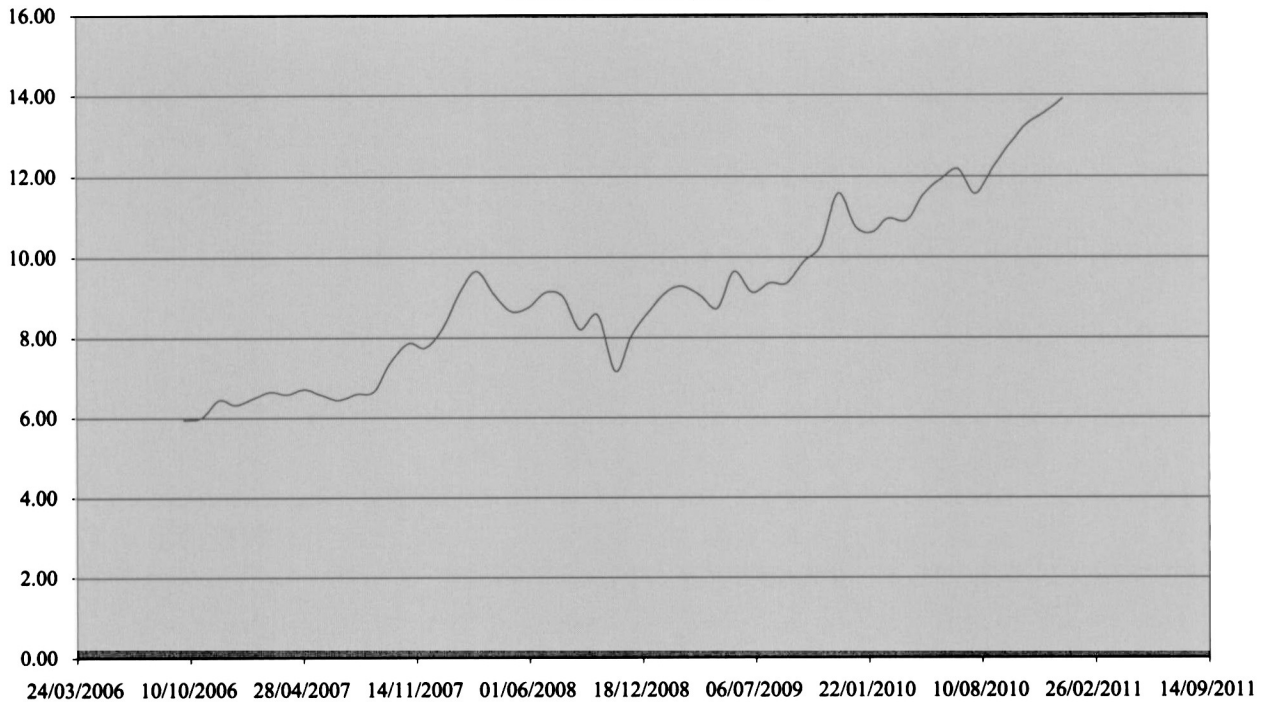




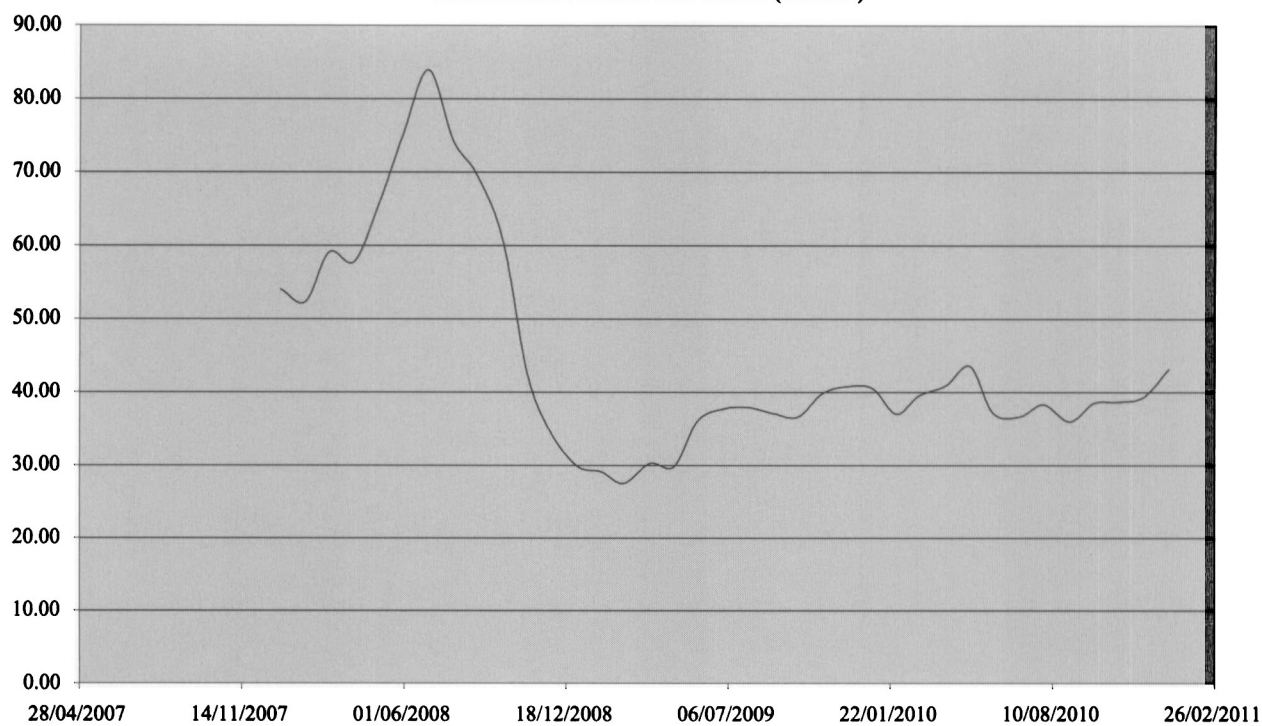
SPDR Gold Shares (GLD:US)



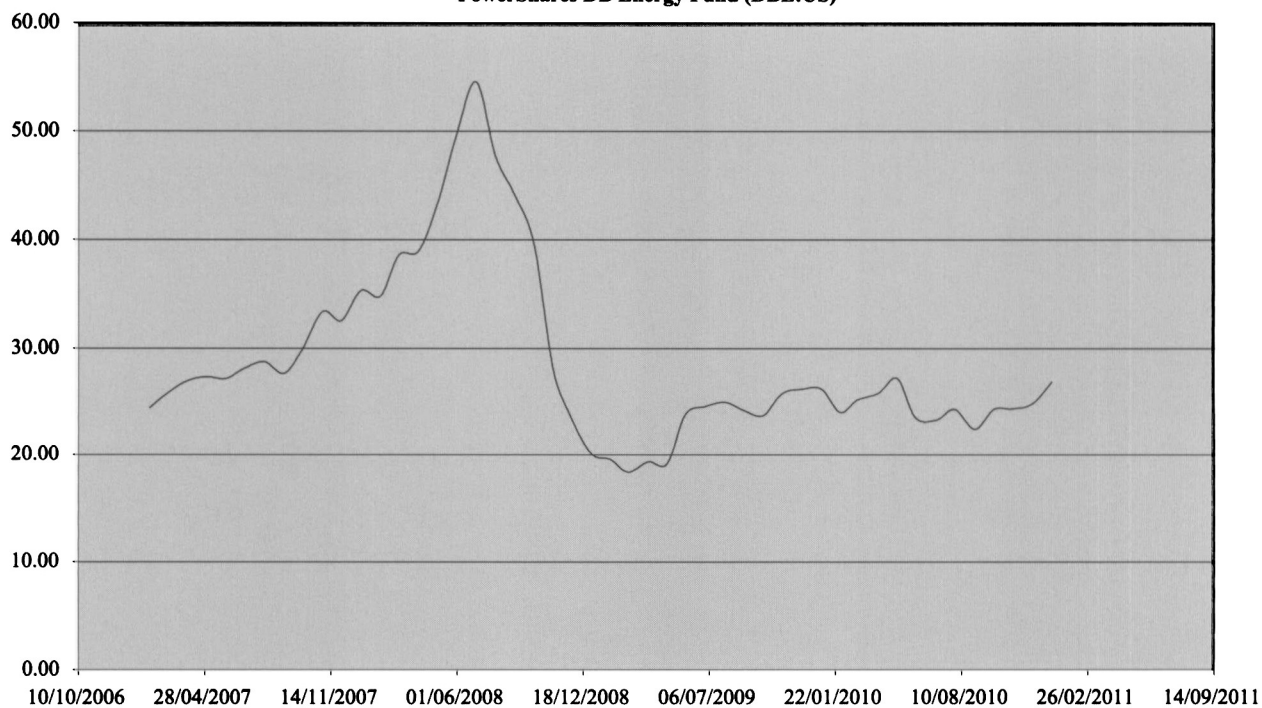
iShares Gold Trust (IAU:US)



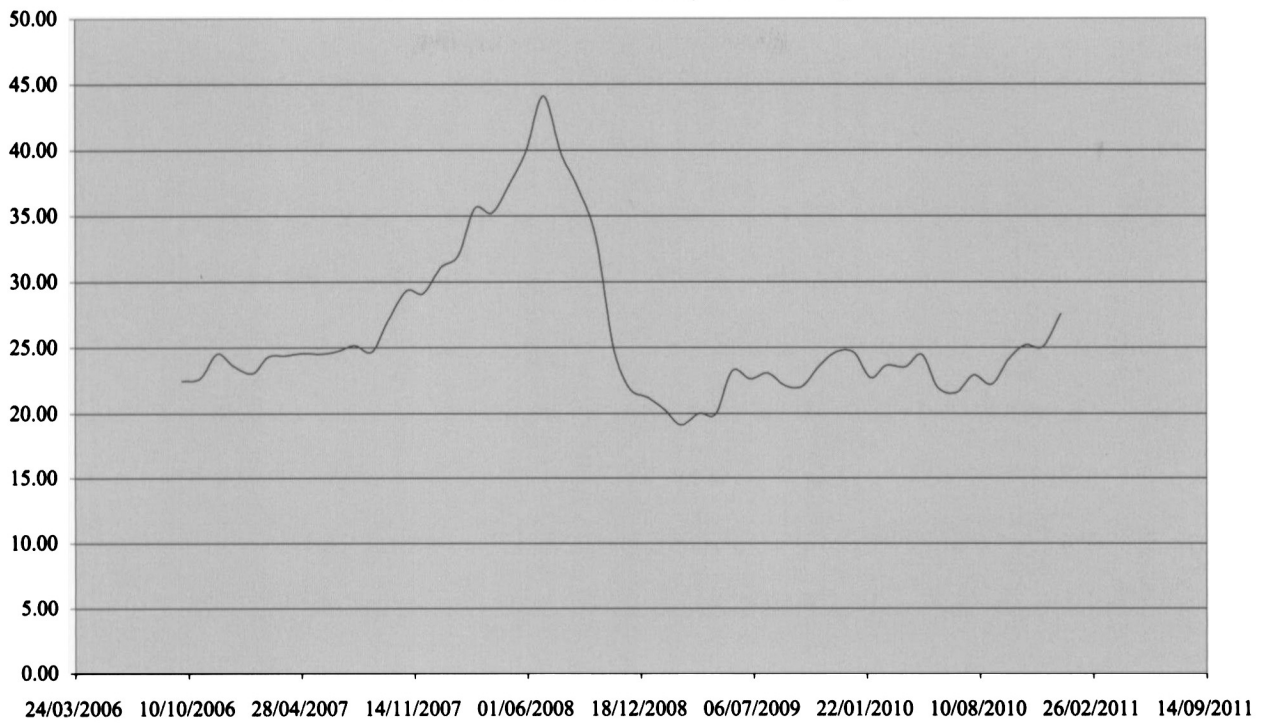
United States 12 Month Oil Fund LP (USL:US)



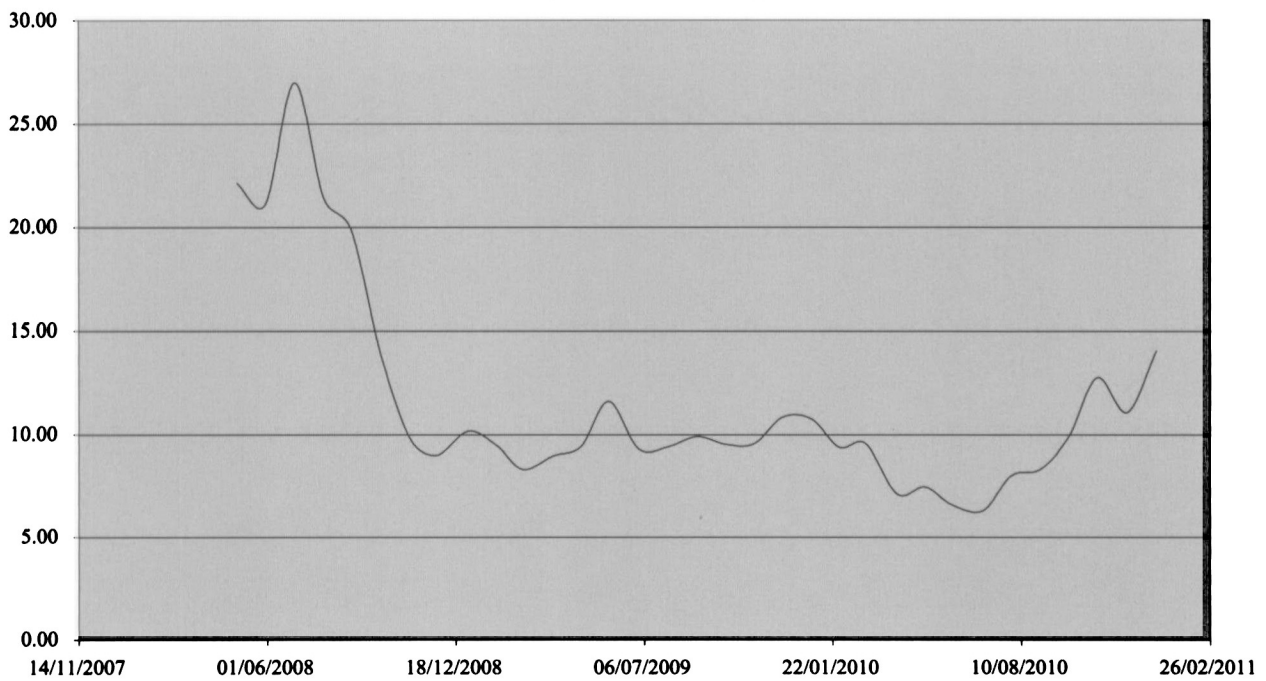
PowerShares DB Energy Fund (DBE:US)



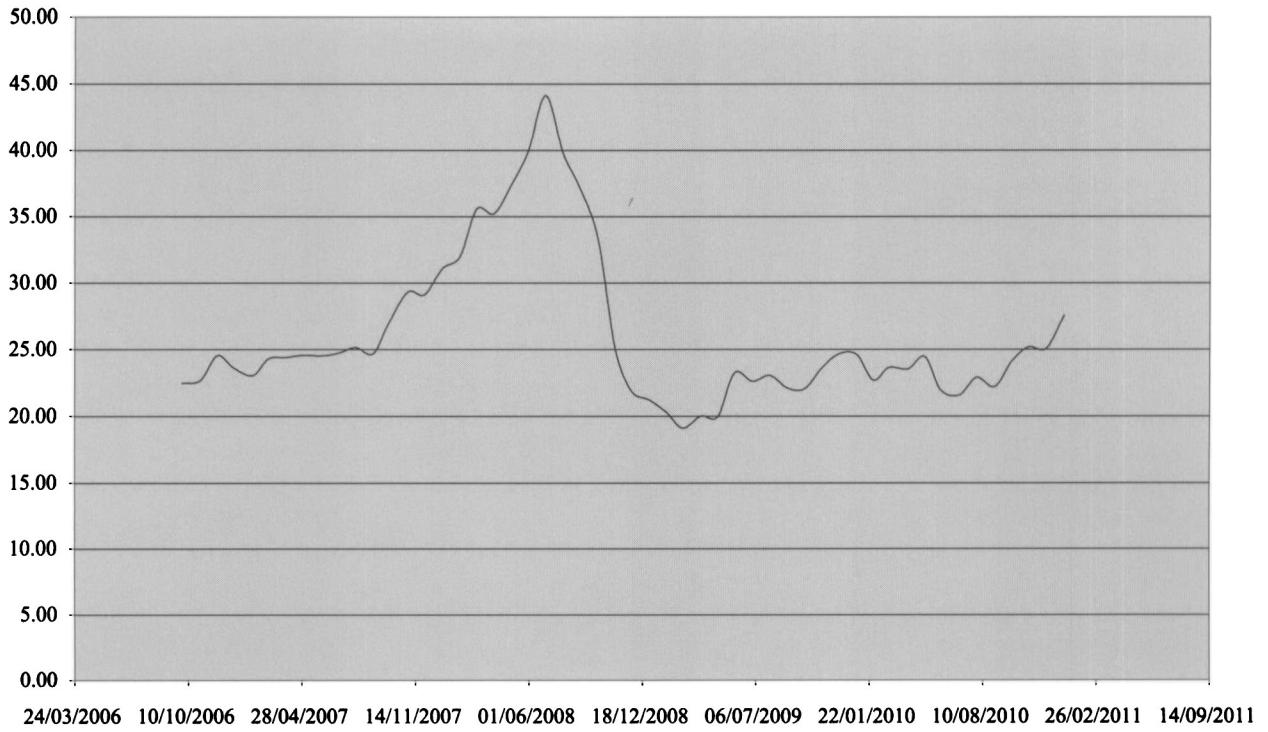
DBC: PowerShares DB Commodity Index Tracking Fund



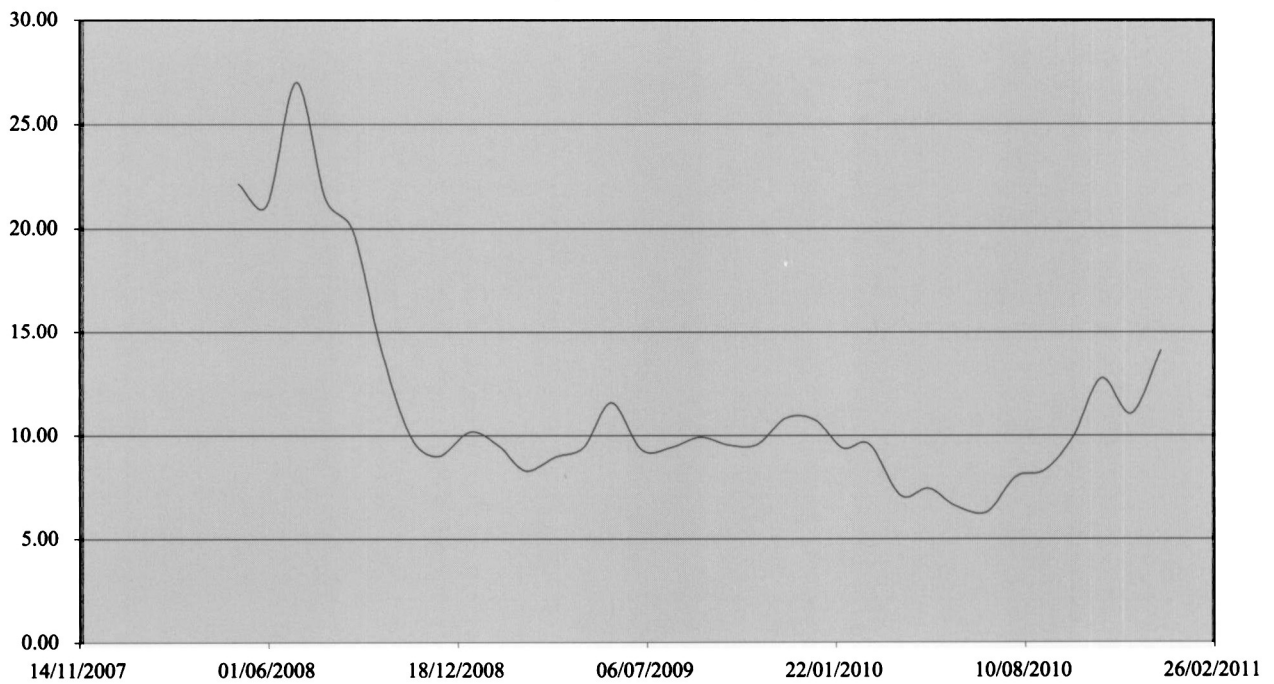
PowerShares DB Agriculture Double Long ETN (DAG:US)



DBC: PowerShares DB Commodity Index Tracking Fund



PowerShares DB Agriculture Double Long ETN (DAG:US)



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The Journal of Wealth Management

PORTFOLIO SIZE REVISITED 49

JAMES CHONG AND G. MICHAEL PHILLIPS

Using a sophisticated sampling technique, the authors compare randomly constructed stock portfolios with portfolios using the underlying population and evaluate them with 18 different measures. The randomization included portfolio size and portfolio start date to eliminate timing bias from the analysis. By comparing the 18 statistics across the portfolios, average portfolio sizes to reproduce the population characteristics were computed. The optimal portfolio size depended greatly on the criterion being used to judge the adequacy of diversification.

BAD BOND MATH: *An Object Lesson Using Bloomberg's After-Tax Yields on Market Discount Bonds* 61

DONALD J. SMITH

Defining information to be a subset of data (information is data that has utility in decision making), the author offers an object lesson to demonstrate the challenge facing an investor using after-tax yield data presented on a widely viewed Bloomberg page. He demonstrates that users of "black box" technologies need to be able to confirm the numbers that are presented to them by data suppliers and check those calculations and underlying assumptions on a regular basis. Failure to understand these assumptions can lead investors to erroneous conclusions, as illustrated in the comparison of two categories of bonds, deeply discounted U.S. corporate bonds, distressed tax-exempt U.S. municipal bonds, and the projected after-tax rates of return on all of the securities under consideration (given assumed tax rates on ordinary income and capital gains and, of course, assuming no default).

FINANCIALLY DIVERSIFIED PORTFOLIOS WITH ALTERNATIVE INVESTMENTS: *The Impact of Life Settlements* 69

NURIA BAJO DAVÓ, CARMEN MENDOZA RESCO, AND MANUEL MONJAS BARROSO

This study investigates whether the inclusion of life settlement (LS) funds in the formation of diversified portfolios contributes significantly to the mitigation of market risk and enhances portfolio performance. The authors construct efficient portfolios from approximations based on Markowitz's portfolio theory by using LS funds in combination with fixed income and equity funds, gold, energy, and agricultural commodities. With nine funds representative of seven international financial markets, they find that LS funds are an effective approach to investment diversification, given their low correlation with the other proposed assets. Specifically, their results suggest that LS funds provide the largest diversification and risk-reduction benefit in combination with fixed income, equity, and commodities funds. The benefit is reduced, however, when the exchange rate effect is considered.

BIOTECHNOLOGY ETFs: *Performance Analysis and Demystifying the Correlation Matrix* 88

MANU SHARMA, RAJNISH AGGARWAL, AND ESHA PRASHAR

The authors investigate the performance of biotechnology ETFs relative to the S&P 500 and NASDAQ Biotechnology indexes during the past five years. They show that the biotechnology ETFs and NASDAQ Biotechnology Index had higher five-year average returns than that of the market