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ABSTRACT

The growing presence of financial operators in the oil markets has modified oil price dynamics. The diffusion of techniques based on extrapolative expectations – such as feedback trading – leads to departures of prices from their fundamental values and increases their variability. Oil price changes are here associated with changes in stocks, bonds and effective USD exchange rate. The feedback trading mechanism is combined with an ICAPM and provides a model which is then estimated in a CCC GARCH-M framework, both the risk premium and the feedback trading components of the conditional means being nonlinear functions of the system's conditional variances and covariances. The empirical analysis identifies a structural change in the year 2000. From then on oil returns tend to become more reactive to the remaining assets of the model and feedback trading more pervasive. A comparison is drawn between three and four asset minimum variance portfolios in the two sub-periods, 1992-1999 and 2000-2008. Oil acquires in the second period, besides its standard properties as a physical commodity, the characteristics of a financial asset. Indeed, the trade-off between risk and returns – measured here by the average return per unit of risk index – indicates that in the last decade oil diversifies away the empirical risk of our portfolio.

Keywords: oil price dynamics; feedback trading; multivariate GARCH-M; portfolio allocation.

JEL Classification: G11 G12 G18 Q40
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1. Introduction

Systematic deviations from the tenets of the efficient markets hypothesis are commonly accepted in the financial literature and are often attributed to trading techniques based on extrapolative expectations. This kind of market behavior is conducive to feedback trading: "positive" if investors buy when prices rise and sell when they fall and "negative" if investors buy when prices fall and sell when they rise.

Positive feedback trading is considered irrational, since it moves prices away from their equilibrium values and raises market risk. Lakonishok et al. (1992) and Nofsinger and Sias (1999), among many others, attribute this trading behavior to specific groups of market operators, such as foreign institutional investors. It was detected in the US stock market by Cutler et al. (1991) and Sentana and Wadhwani (1992) in two classic articles and in later studies by Koutmos (1997) and Koutmos and Saidi (2001) in, respectively, European and emerging equity markets. The growing number of financial operators entering the oil market suggests that this paradigm be extended to the modeling of oil price behavior.

Shiller (1984) and Sentana and Wadhwani (1992) analyse feedback trading in the context of a behavioral CAPM, a single factor model which fails to capture the risk return components due to cross asset linkages. We adopt, therefore, Merton's (1973) multifactor ICAPM parameterization, which introduces additional measures of risk and allows the covariance between the assets under investigation and the variables that enter the investment opportunity set to influence the behavior of returns over time. This framework is used here to assess the role of oil in financial portfolio hedging decisions.

Oil price dynamics is often associated with stock and bond markets and exchange rate behavior. Several studies ascertain a negative linkage between oil and bond and stock prices, i.e. a negative covariance risk between oil and a diversified portfolio of financial assets.[1]

[1] See, among others, Sadorsky (1999) and Bhar and Nikolova (2009).

Alternatively, it is claimed that there is a positive real sector linkage between the value of financial assets and oil via production and business cycle, expansionary periods (related to asset price increases) being associated with oil price rises.
The dollar exchange rate too is strongly interlinked with oil prices. From a macroeconomic point of view, higher oil prices raise trade deficits, weaken the dollar, and bring about compensatory price increase policies by oil exporting countries. From a financial point of view, the correlation between oil and financial asset prices is likely to be negative. As noted by Roache (2008), commodities (such as oil) behave differently from stocks and bonds and provide risk diversification opportunities. Traders that expect a dollar depreciation will sell dollar denominated financial assets and buy oil (and vice-versa if they are bullish on the dollar) in order to diversify their portfolio. Indeed, crude oil seems to have attracted funds away from financial markets in periods of stress.
This study analyses the behavior of weekly changes in the WTI crude oil price over a time period spanning the last fifteen years and provides estimates of the financial interrelation between oil, US stocks, bonds, and dollar effective exchange rate changes. We check for the presence of speculative components in oil pricing using long and homogeneous time series which encompass large shifts in market sentiment. Our multivariate investigation builds on the parameterization of feedback trading by Sentana and Wadhwani (1992) and on the two factor ICAPM of Scruggs (1998). The main goal is to assess if (and how) the different behavior of oil brings about a reduction of the unpriced risk of a financial portfolio.
The remainder of this paper is structured as follows. After briefly introducing the theoretical model mentioned above, the empirical results are set forth. The multivariate GARCH analysis - carried on the two sample periods 1992-1999 and 2000-2008 - reveals that feedback trading mechanisms gain momentum in the crude oil market from 2000 to 2008. The potential diversification effect of oil is then analyzed through a comparison of modified Sharpe's ratios (average return per unit of risk indexes) obtained from multi asset-class portfolios which provides support for our hypotheses.

2. The behavioral ICAPM

Merton's (1973) dynamic Intertemporal Capital Asset Pricing Model, in spite of its sophistication, does not account for the serial correlation of the returns, a standard stylized characteristic of asset and commodity pricing. We follow therefore Dean and Faff (2008) and insert the feedback trading paradigm of Cutler et al. (1991), among others, into the ICAPM.

Two types of agents enter our model, as in Sentana and Wadhwani (1992), feedback traders or trend chasers, and smart money investors. The former react to past price changes only while the latter respond to expected risk-return considerations using an ICAPM framework.

According to Merton investors price an asset in relation not only to the expected systematic risk, but also in relation to the expected future change in the investment opportunity set, proxied by n state variables. The analysis is set in a continuous time framework, where the returns and the state variables follow standard diffusion processes. Risk averse investors maximize the utility of wealth function $J(W(t),\overline{F}(t),t)$ where $W(t)$ is wealth and $\overline{F}(t)$ is a $n\times 1$ vector of state variables ($F_1, F_2, \ldots\ldots, F_n$) that represent the behavior over time of the investment opportunity set.

In equilibrium the expected market risk premium for asset M is given by [2]

$$E_{t-1}[r_{M,t}-\alpha]=\left[\frac{-J_{WW}W}{J_W}\right]\sigma^2_{M,t}+\left[\frac{-J_{WF_1}}{J_W}\right]\sigma_{MF_1,t}+\ldots.+\left[\frac{-J_{WF_n}}{J_W}\right]\sigma_{MF_n,t} \qquad (1)$$

where α is the risk free rate $E_{t-1}[.]$ is the expectation operator, $r_{M,t}$ is the return of asset M, $\sigma^2_{M,t}$ and σ_{MF_it} are the corresponding conditional variance and covariance with the state variable F_i, where $i=1,\ldots,n$. The first coefficient $\left[\frac{-J_{WW}W}{J_W}\right]$ quantifies the degree of relative risk aversion.[3] It is always positive since $J_W>0$ and $J_{WW}<0$, which suggests a positive

[2] Equation (1) is derived from Merton's first order conditions. See Merton (1973, equation (15), page 876).

[3] Low case letters indicate partial derivatives.

relationship between risk premium and conditional variance. The sign of the impact on excess returns of the i^{th} state variable will depend upon the interaction of the signs of J_{WF_i} and $\sigma_{MF_i,t}$, which are both a priori indeterminate. If J_{WF_i} and $\sigma_{MF_i,t}$ are of the same sign, i.e. either both positive or both negative, $J_{WF_i}\sigma_{MF_i,t}$ is positive and investors will demand a lower risk premium. If J_{WF_i} and $\sigma_{MF_i,t}$ are of the opposite sign, $J_{WF_i}\sigma_{MF_i,t}$ is negative and investors will demand a higher risk premium.

In the empirical analysis it will be assumed that the risk premium is a linear function of market variance and of the covariances between the returns and the state variables. Equation (1) can then be rewritten as follows

$$E_{t-1}[r_{M,t} - \alpha] = \Phi_t \tag{2}$$

where

$$\Phi_t = \Phi_1(\sigma^2_{M,t}) + \Phi_2(\sigma_{MF_1,t}) + ... + \Phi_{n+1}(\sigma_{MF_n,t}) \tag{3}$$

The proportionate demand for asset M by smart money traders, DS_t, is governed by standard mean-variance considerations:

$$DS_t = \frac{E_{t-1}[r_{M,t} - \alpha]}{\Phi_t} \tag{4}$$

The demand of risky asset M rises with the expected excess return and declines when its riskiness Φ_t increases.

If $DS_t = 1$ equation (4) reverts to the standard ICAPM equilibrium equation (2).

The relative asset demand by feedback traders, DF_t, is formulated as

$$DF_t = \gamma r_{M,t-1} \tag{5}$$

If $\gamma > 0$ we have positive feedback trading. Agents buy (sell) when the rate of change of the price of the previous period is positive (negative) and may destabilize the market if asset prices overshoot their equilibrium values based on fundamentals. When $\gamma < 0$, with negative feedback trading, agents sell (buy) when prices are rising (falling) in the previous period and tend to stabilize the market.

Equilibrium requires that the two investor groups clear the market and $DS_t + DF_t = 1$. Adding equations (4) and (5) and replacing Φ_t by its determinants according to equation (3), we obtain the following feedback trading equation

$$\begin{aligned} E_{t-1}[r_{M,t} - \alpha] &= \Phi_1(\sigma^2_{M,t}) + \Phi_2(\sigma_{MF_1,t}) + ... + \Phi_{n+1}(\sigma_{MF_n,t}) \\ &\quad - \gamma[\Phi_1(\sigma^2_{M,t}) + \Phi_2(\sigma_{MF_1,t}) + ... + \Phi_{n+1}(\sigma_{MF_n,t})]r_{M,t-1} \end{aligned} \qquad (6)$$

Equation (6) is the behavioral ICAPM relationship that shall be used to parameterize the dynamics of the assets analyzed in the paper. The sign of the coefficient of the lagged rate of return $r_{M,t-1}$ will depend upon (a) the nature of the feedback trading behavior, either positive of negative, (b) the sign of the conditional covariances with the state variables $\sigma_{MF_{i,t}}$, $i = 1,...,n$, and (c) the sign of the corresponding $\Phi_2,...,\Phi_{n+1}$ risk loadings.

3. Empirical results

The empirical evidence relies on the multivariate CCC GARCH-M parameterization of the ICAPM model. Feedback trading mechanisms are accounted for in a four asset portfolio context.

3.1 Description of the series

The weekly observations used in this study span the 6 October 1992 – 10 June 2008 time period. The data set includes oil spot prices (S_t, the WTI Spot Price fob expressed in US dollars per barrel) and futures oil prices

(F_t, the contract 1 price) which are provided by the EIA database. The Dow Jones Industrial index (J_t), the US dollar nominal effective exchange rate (Z_t) and the US All Lives Government Bond Total Return index (Δk_t) are taken from Bloomberg, Fred Database, and Datastream International respectively.

The descriptive statistics are reported in Table 1.[4] Over the full sample period oil returns are higher, on average, than stock returns but smaller than bond ones. The standard deviation of the oil price rate of change is significantly greater than that of the returns of the remaining assets. All the series are mildly skewed and leptokurtic, and the Jarque Bera test statistics reject the normality of distribution hypothesis. Their stationarity, tested with the ADF procedure, stands out clearly. Inter-temporal dependency of weekly returns (with the exception of the rate of change of the effective exchange rate and of US bond index return) and squared weekly returns is confirmed by the Ljung Box Q-statistics. Volatility clustering affects all the time series while asymmetries are present only in the case of the equity and bond returns.

According to the Andrews (1993) Wald tests (for parameter stability) with unknown switch point, the time series do not show any sign of regime shifts. The null hypothesis of no break point - with the usual trimming of 15% of the data at the endpoints – cannot be rejected.[5]

On the contrary the correlation between the time series does not seem to be constant over the whole sample. A standard Jenrich (1970) χ^2 stability test detects unequivocally a structural break in the correlation matrix of returns at the end of the year 1999.[6] We split therefore the data in two

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[4] Percentage rates of return are used in the empirical analysis, computed multiplying by 100 the first logarithmic differences of the original series. The US All Lives Government Bond Total Return index time series too is multiplied by 100.

[5] The tests are based on a first order autoregression with a constant in the case of oil and equity returns and on a regression on a constant term for the remaining time series. The statistics are available from the authors upon request.

[6] The maximum value of test is 86.72 under the alternative of a breakpoint on 28 December 1999. It strongly rejects the null hypothesis (that two 4-variate normal populations have correlation matrices that have a common non-singular value), the $\chi^2(6)$ 5% critical value being 12.6. In order to deal with potential distortions due to non-normality, we repeated the test using the standardized residuals of a full sample estimation of our CCC-GARCH behavioral ICAPM system and obtained qualitatively similar results.

sub-samples; the first goes from 6 October 1992 to 28 December 1999 (378 observations) and the second from 4 January 2000 to 10 June 2008 (441 observations).

Table 1: Descriptive statistics

	Oil price rate of change	Stock price index rate of change	Effective exchange rate rate of change	Oil futures price rate of change	US Govt Bond Return Index
Mean	0.2237	0.1602	-0.0209	0.2244	0.2831
Std. Dev.	4.7873	2.1679	0.8587	4.8052	1.6362
Skewness	-0.447	-0.199	-0.008	-0.331	-0.077
Kurtosis	4.589	6.984	3.574	4.535	5.566
Jarque Bera	112.635*	544.473*	11.542*	94.581*	225.389*
ADF	-32.04*	-31.53*	-28.30*	-32.14*	-15.21*
$Q_x(1)$	10.20*	8.26*	0.12	10.81*	1.42
$Q_x(12)$	38.02*	41.85*	11.610	34.83*	19.30
$Q_x^2(12)$	38.89*	203.89*	31.04*	38.22*	151.41*
J.T.A.	1.31	65.14*	2.92	6.97	27.64*

Notes: * significant at the 5 percent level; ADF: Augmented Dickey Fuller unit root test statistic; $Q_x(k)$: Ljung Box Q-statistic for kth order serial correlation of the x variable; $Q_x^2(k)$: Ljung Box Q-statistic for kth order serial correlation of the squared variable x^2; J.T.A.: Joint Wald test of the null hypothesis of no asymmetry distributed as χ^2 with 3 degrees of freedom (Engle and Ng, 1993). Data have a weekly frequency over the sample period 6/10/1992 – 10/6/2008. The full sample includes 819 observations.

3.2 First period results - The role of oil in the nineties

We estimate simultaneously four ICAPM asset pricing relationships, one for each asset, over the 6 October 1992 – 28 December 1999 time period. A multivariate GARCH is used to parameterize the conditional second moments since the time series are conditionally heteroskedastic. The following operational version of equation (6) is introduced in order to model the conditional means

$$\begin{aligned}\Delta x_{1t} &= b_{0x_1} + b_{1x_1} h^2_{x_1,t} + b_{2x_1} h_{x_1x_2,t} + b_{3x_1} h_{x_1x_3,t} + b_{4x_1} h_{x_1x_4,t} \\ &\quad + (b_{5x_1} + b_{6x_1} h^2_{x_1,t} + b_{7x_1} h_{x_1x_2,t} + b_{8x_1} h_{x_1x_3,t} + b_{9x_1} h_{x_1x_4,t})\Delta x_{t-1} + u_{x_1,t}\end{aligned} \quad (7)$$

where $\Delta x_{1t},...,\Delta x_{4t}$ are the rates of return of the four assets analyzed in the paper and $h^2_{x_{1,t}}$ and $h_{x_1x_i,t}$, i=2,3,4, are, respectively, the conditional variance and covariances obtained with the GARCH model. $b_{1x_1}h^2_{x_1,t}+b_{2x_1}h_{x_1x_2,t}+b_{3x_1}h_{x_1x_3,t}+b_{4x_1}h_{x_1x_4,t}$ corresponds to $\Phi_1(\sigma^2_{M,t})+\Phi_2(\sigma_{MF_1,t})+\Phi_3(\sigma_{MF_2,t})+\Phi_4(\sigma_{MF_3,t})$ in equation (6), while $b_{5x_1}+b_{6x_1}h^2_{x_1,t}+b_{7x_1}h_{x_1x_2,t}+b_{8x_1}h_{x_1x_3,t}+b_{9x_1}h_{x_1x_4,t}$ corresponds to $\gamma[\Phi_1(\sigma^2_{M,t})+\Phi_2(\sigma_{MF_1,t})+\Phi_3(\sigma_{MF_2,t})+\Phi_4(\sigma_{MF_3,t})]$.

The relevance of the feedback trading component and the number of factors affecting the pricing of each asset are determined empirically. If, as is the case for the bond return and the rate of change of the exchange rate time series, no evidence is found of serial correlation, the feedback trading component is dropped from the corresponding conditional mean parameterization. In the same way we remove the variables with insignificant coefficients at the standard 5 percent level or that correspond to insignificant conditional covariances.[7] The conditional second moments are parameterized using a CCC-GARCH(1,1) model. The behavior of the rate of change of the spot oil prices (Δs_t), the Dow Jones sock index (Δj_t), the US dollar effective exchange rate (Δz_t), and of the US Government bond index total return (Δk_t) are then modelled using the system (A).

$$\begin{aligned}
\Delta s_t &= b_{0s}+b_{1s}h^2_{s,t}+b_{2s}h_{sj,t}+(b_{6s}h^2_{s,t}+b_{7s}h_{sj,t})\Delta s_{t-1}+u_{s,t}\\
\Delta j_t &= b_{0j}+b_{1j}h^2_{j,t}+b_{2j}h_{sj,t}+b_{3j}h_{jz,t}+b_{4j}h_{jk,t}\\
&\quad +(b_{5j}+b_{6j}h^2_{j,t}+b_{7j}h_{sj,t}+b_{8j}h_{jz,t}+b_{9j}h_{jk,t})\Delta j_{t-1}+u_{j,t}\\
\Delta z_t &= b_{0z}+b_{1z}h^2_{z,t}+b_{3z}h_{jz,t}+u_{z,t}\\
\Delta k_t &= b_{0k}+b_{1k}h^2_{k,t}+b_{3k}h_{jk,t}+u_{k,t}
\end{aligned}$$

[7] This parsimonious approach is motivated by need to reduce the large number of parameters entering our nonlinear system.

$$u_t = \begin{bmatrix} u_{s,t} \\ u_{j,t} \\ u_{z,t} \\ u_{k,t} \end{bmatrix}$$

$$u_t | \Omega_{t-1} N(0, H_t) \qquad \text{(A)}$$

$$H_t = \Delta_t R \Delta_t$$

$$R = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} \\ \rho_{21} & 1 & \rho_{23} & \rho_{24} \\ \rho_{31} & \rho_{32} & 1 & \rho_{34} \\ \rho_{41} & \rho_{42} & \rho_{43} & 1 \end{bmatrix} \qquad \Delta_t = \begin{bmatrix} h_{s,t} & 0 & 0 & 0 \\ 0 & h_{j,t} & 0 & 0 \\ 0 & 0 & h_{z,t} & 0 \\ 0 & 0 & 0 & h_{k,t} \end{bmatrix}$$

$$h_{s,t}^2 = \varpi_s + \alpha_s u_{s,t-1}^2 + \beta_s h_{s,t-1}^2; \; h_{j,t}^2 = \varpi_j + \alpha_j u_{j,t-1}^2 + \beta_j h_{j,t-1}^2; h_{z,t}^2 = \varpi_z + \alpha_z u_{z,t-1}^2 + \beta_z h_{z,t-1}^2$$

$$h_{k,t}^2 = \varpi_k + \alpha_k u_{k,t-1}^2 + \beta_k h_{k,t-1}^2$$

The QML estimates are set out in Table 2. The conditional mean determinants that are associated with the conditional covariances between oil returns and exchange rate changes, $h_{sz,t}$, between oil and US bond returns, $h_{sk,t}$, and between exchange rate changes and bond returns, $h_{zk,t}$, are removed since the corresponding conditional correlation coefficients estimates $\rho_{13}, \rho_{14}, \rho_{34}$ do not significantly differ from zero.

The quality of fit is satisfactory. Almost all coefficients are statistically significant and the usual tests for misspecification suggest that the standardized residuals ν_t are well behaved. For each equation we find that $E[\nu_t]=0$ and $E[\nu_t^2]=1$, and that both ν_t and ν_t^2 are serially uncorrelated. The sign bias tests by Engle and Ng (1993) support the choice of a symmetric conditional variance model. Asymmetry, a stylized characteristic of stock return volatility, is filtered out by the feedback trading conditional mean parameterization.

For the sake of notational simplicity let λ_i, where $i = s, j, z, k$, be the CAPM component - i.e. $\lambda_{s,t} = b_{1s} h_{s,t}^2 + b_{2s} h_{sj,t}$, $\lambda_{j,t} = b_{1j} h_{j,t}^2 + b_{2j} h_{sj,t} + b_{3j} h_{jz,t} + b_{4j} h_{jk,t}$, $\lambda_{z,t} = b_{1z} h_{z,t}^2 + b_{3z} h_{jz,t}$, and $\lambda_{k,t} = b_{1k} h_{k,t}^2 + b_{3k} h_{jk,t}$ - and ϕ_i be the feedback trading coefficient - i.e. $\phi_s = b_{6s} h_{s,t}^2 + b_{7s} h_{sj,t}$, and $\phi_j = b_{5j} + b_{6j} h_{j,t}^2 + b_{7j} h_{sj,t} + b_{8j} h_{jz,t} + b_{9j} h_{jk,t}$.

In both the oil and stock returns conditional mean equations the overall CAPM component λ and the feedback trading coefficient ϕ – computed with historical simulations which use the values of the conditional second moments - turn out to be, respectively, positive and negative on average. (Their behavior over time is set out in Graph 1 and their unconditional average values can be found in Table 3). The negative sign of the feedback trading coefficient is due to the presence of destabilizing speculation, which tends to raise the volatility of the returns of the asset.

As for the rate of change of the US dollar effective exchange rate and the US bond returns, the overall CAPM component is negative. The negative sign of $\lambda_{z,t}$ implies that an increase in the conditional variance of the rate of change of the effective exchange rate $h_{z,t}^2$ and of its conditional covariance with the stock returns $h_{jz,t}$, brings about a depreciation of the US effective exchange rate as traders sell dollars (see Graph 1). Similarly the negative value of $\lambda_{k,t}$ means that an increase in the bond return conditional variance $h_{k,t}^2$, possibly due to a rise in inflation risk and/or in general economic uncertainty, will lead to a decline in bond returns as traders sell bonds which are losing their safe asset characteristics.[8]

[8] Viceira (2007) finds that bond return volatility is positively related to the level and the slope of the yield curve, factors that proxy for inflation risk and overall economic uncertainty.

Table 2: Multivariate ICAPM, October 1992-December 1999

System (A) Conditional mean equations

	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	$E[v_t]$	$E[v_t^2]$	Sk.	Kurt.	LM(1)	LM(10)	J.T.A.
Δs_t	-1.40 (-7.37)	0.04 (3.49)	1.57 (1.41)				-0.014 (-2.61)	0.50 (1.86)			-0.008	1.00	-0.004	0.63	0.005 [0.94]	12.64 [0.24]	2.70 [0.43]
Δj_t	0.22 (0.97)	0.08 (2.11)	-1.98 (-2.51)	-9.37 (-29.15)	2.93 (18.70)	-0.44 (-1.93)	-0.16 (-3.53)	0.45 (2.10)	6.61 (5.82)	-0.54 (-14.73)	-0.012	1.00	-0.64	1.48	1.46 [0.22]	4.00 [0.94]	4.69 [0.19]
Δz_t	1.86 (30.22)	-2.52 (-19.50)		-1.00 (-2.99)							-0.001	1.00	-0.09	1.55	2.04 [0.15]	27.31 [0.002]	3.44 [0.32]
Δk_t	0.79 (8.77)	-0.40 (-16.02)		0.49 (3.50)							0.007	1.00	0.06	0.77	2.15 [0.14]	8.35 [0.59]	3.64 [0.30]

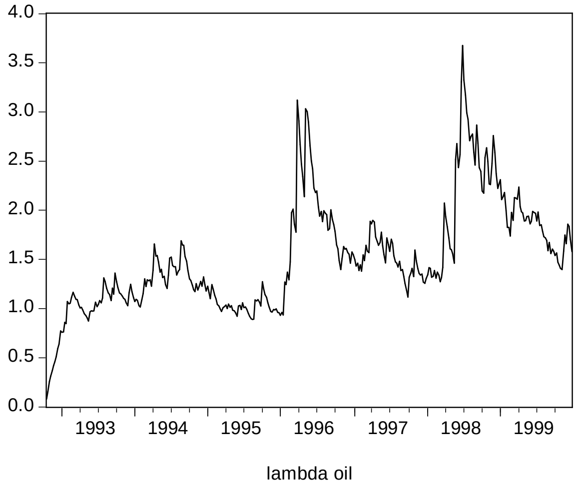
Conditional variance equations

	ϖ	α	β	ρ_{12}	ρ_{13}	ρ_{14}	ρ_{23}	ρ_{24}	ρ_{34}	LLF
$h_{s,t}^2$	1.02 (4.34)	0.87 (39.37)	0.08 (3.63)	0.06 (2.54)	-0.04 (-0.91)	-0.06 (-1.36)	0.12 (7.24)	0.30 (7.76)	0.04 (1.01)	-2941.60
$h_{j,t}^2$	0.17 (5.95)	0.88 (113.86)	0.07 (7.83)							
$h_{z,t}^2$	0.16 (9.89)	0.74 (35.53)	0.01 (1.81)							
$h_{k,t}^2$	0.82 (13.82)	0.55 (24.80)	0.12 (5.09)							

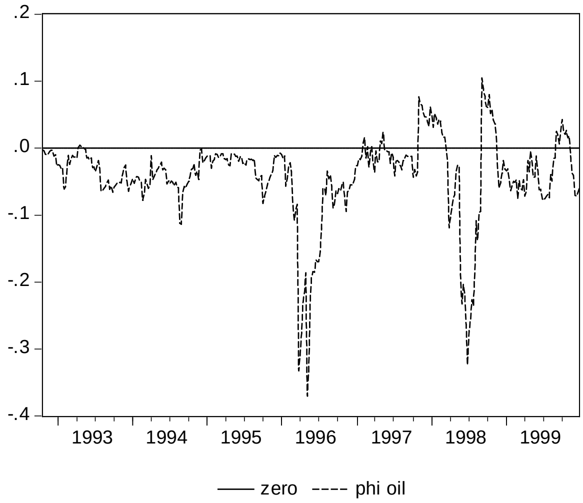
Notes: $v_t = u_t / \sqrt{h_t^2}$; Sk.: Skewness; Kurt.: Kurtosis; LM(k): Lagrange Multiplier test for kth order ARCH; J.T.A.: Joint Wald test of the null hypothesis of no asymmetry, distributed as χ^2 with 3 degrees of freedom (Engle and Ng, 1993); t-statistics are in parentheses and probabilities in square brackets; the t-ratios are based on the robust standard errors computed with the Bollerslev and Wooldridge (1992) procedure. These notes apply also to Table 4.

Graph 1. First period CAPM components and feedback trading coefficients

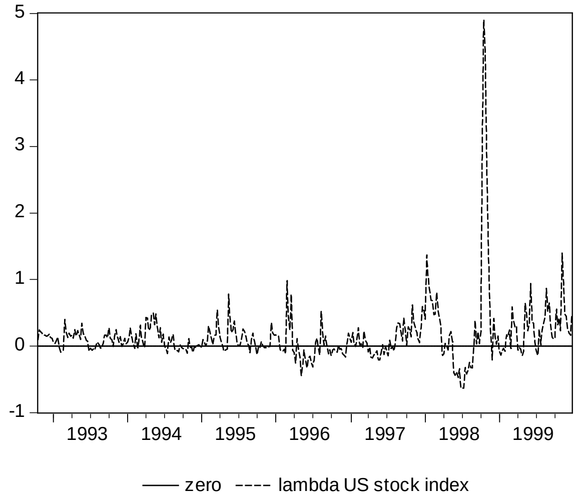
Oil return equation CAPM component



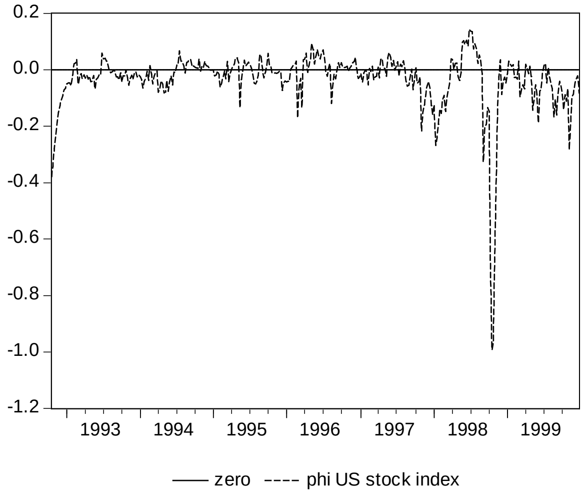
Oil return equation Feedback trading coef.



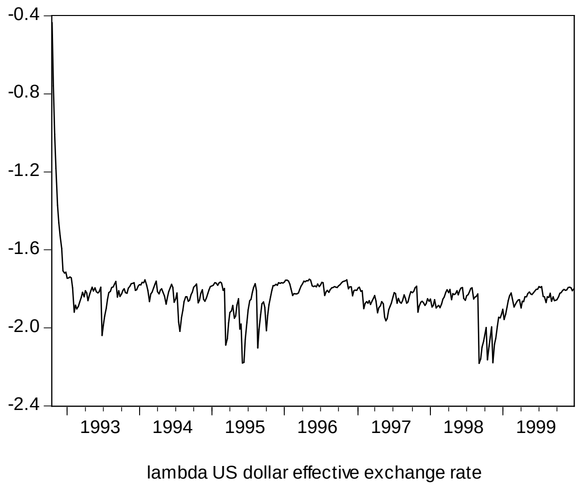
US stock return equation CAPM component



US stock return equation Feedback trading coef.



US dollar equation CAPM component



US bond return index equation CAPM component

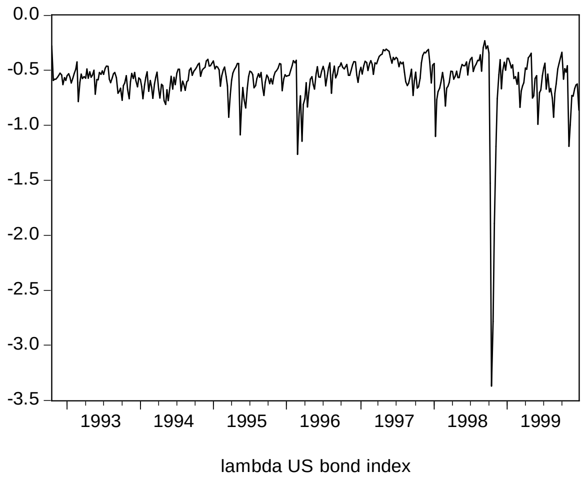


Table 3: Average values of the conditional mean CAPM components (CAPM comp.) **and feedback trading coefficients** (Fbt coef.)

Oil returns		**US dollar changes**	
CAPM comp.	1.52 (52.57)*	CAPM comp.	-1.83 (-256.51)*
Fbt coef.	-0.043 (-12.62)*		
US stock returns		**US bond returns**	
CAPM comp.	0.16 (6.30)*	CAPM comp.	-0.58 (-44.85)*
Fbt coef.	-0.035 (-6.23)*		

Notes. t-statistics (H_o: average = 0) are in parentheses; *: significant at the 5% level.

During the nineties, the link between oil prices and the other assets investigated in the paper is limited to a positive interaction between oil and stock returns, which can be attributed to a real (macroeconomic) channel. A rise in stock returns during the expansionary phase of the business cycle is associated with an increase in the demand for oil and a corresponding upward pressure on oil returns. The latter are responding moreover to a rationale that could connect the convenience yield to volatility along the lines of the model of Pindyck (2001, 2003) where volatility and other variables enter the equation of spot returns as proxies of the convenience yield. As is the case for call options, the greater the volatility of the cash commodity price, the greater the chance it will exceed the corresponding futures price and, as a consequence, the greater the convenience yield. By affecting the size of convenience yields, cash price volatility is expected to affect positively oil price returns.[9]

The two spikes that can be detected in the graphs of the CAPM component and of the feedback trading coefficient of the oil price rate of change equation (see Graph 1) are caused by sharp increases in oil price variability. The first price shock in 1996 is idiosyncratic and can be attributed to a mismatch between actual and expected oil demand. It affects only the oil return equation by raising the pricing risk premium and

[9] On this topic, see also Milonas and Henker (2001).

magnifying the feedback trading effects as the traders' uncertainty rises.[10] The second shock is mainly connected to the Asian crisis and affects all of the remaining assets conditional mean equations by increasing the risk premium that is required to price both the oil and stock rates of return. As expected, since they are negatively related to volatility shifts of the CAPM component, the oil shock has a negative impact (via stocks) on the US bond returns and on the rate of change of the effective exchange rate.[11]

3.3 Second period results - Oil as a financial asset

A preliminary analysis of the data in the second time period reveals that the rates of change of the spot oil prices and of the US effective exchange rate are homoskedastic, the remaining time series being heteroskedastic, as in the first time period.[12]

The exchange rate and oil return variabilities are thus measured as the unconditional variances of their respective conditional mean residuals. The variance covariance matrix of system (B) combines the unconditional variances of the homoskedastic time series with the conditional variances of the heteroskedastic ones in a modified CCC-GARCH framework.

---

[10] A few historical details are of interest here. Despite the ban on Iraqi exports (a consequence of the first Gulf war), low levels of production in Iran, Libya, and especially Russia, following the collapse of the Soviet Union, world oil supply exceeds demand in the first half of the nineties and brings about a reduction in prices. Towards the end of 1996, however, oil prices increase unexpectedly, because of a rebound in US consumption and of an upsurge of demand by the Asian Tigers.

[11] At the beginning of 1998, in the aftermath of the financial turmoil, South Korea's refiners cut output below maximum capacity. The OPEC, in the same year, reduces twice its production target level in order to boost oil prices, which tend to subside because of a reduction in demand from Asia. For more details on this confusing period, see Maugeri (2006, chapter 14, pp. 169-181).

[12] These findings are obtained with the help of Ljung Box Q-tests for k^{th} order serial correlation (k=1,…,24). With the squared rates of change of oil price and effective exchange rate, these statistics are never significant at the 5% level. They are strongly significant in the case of the remaining squared return time series.

$$\Delta s_t = b_{0s} + b_{1s}h_{s,t}^2 + b_{2s}h_{sj,t} + b_{3s}h_{sz,t} + b_{4s}h_{sk,t} + (b_{6s}h_{s,t}^2 + b_{7s}h_{sj,t} + b_{8s}h_{sz,t} + b_{9s}h_{sk,t})\Delta s_{t-1}$$
$$+ b_{10s}D_1 + b_{11s}\Delta f_{t-1} + u_{s,t}$$
$$\Delta j_t = b_{0j} + b_{1j}h_{j,t}^2 + b_{2j}h_{sj,t} + b_{3j}h_{jz,t} + b_{4j}h_{jk,t} + (b_{5j} + b_{6j}h_{j,t}^2 + b_{7j}h_{sj,t} + b_{8j}h_{jz,t})\Delta j_{t-1} + u_{j,t}$$
$$\Delta z_t = b_{0z} + b_{1z}h_{z,t}^2 + b_{2z}h_{sz,t} + b_{3z}h_{jz,t} + b_{4z}h_{zk,t} + u_{z,t}$$
$$\Delta k_t = b_{0k} + b_{1k}h_{k,t}^2 + b_{2k}h_{sk,t} + b_{3k}h_{jk,t} + b_{4k}h_{zk,t} + u_{k,t}$$

$$u_t = \begin{bmatrix} u_{s,t} \\ u_{j,t} \\ u_{z,t} \\ u_{k,t} \end{bmatrix}$$
$$u_t | \Omega_{t-1} N(0, H_t) \qquad \text{(B)}$$
$$H_t = \Delta_t R \Delta_t$$

$$R = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} \\ \rho_{21} & 1 & \rho_{23} & \rho_{24} \\ \rho_{31} & \rho_{32} & 1 & \rho_{34} \\ \rho_{41} & \rho_{42} & \rho_{43} & 1 \end{bmatrix} \qquad \Delta_t = \begin{bmatrix} h_{s,t} & 0 & 0 & 0 \\ 0 & h_{j,t} & 0 & 0 \\ 0 & 0 & h_{z,t} & 0 \\ 0 & 0 & 0 & h_{k,t} \end{bmatrix}$$
$$h_{s,t}^2 = \hat{\sigma}_s^2; \quad h_{j,t}^2 = \varpi_j + \alpha_j u_{j,t-1}^2 + \beta_j h_{j,t-1}^2; \quad h_{z,t}^2 = \hat{\sigma}_z^2$$
$$h_{k,t}^2 = \varpi_k + \alpha_k u_{k,t-1}^2 + \beta_k h_{k,t-1}^2$$

D_1 is a dummy accounting for the steep price rise in the years 2007-2008.

The estimates of system (B) are set out in Table 4. The second period variance covariance matrix points to a very intricate interrelation pattern. The conditional correlation coefficients are significant and negative and suggest that all the assets can be used for portfolio risk diversification. As for the final specification of the model, all the cross covariances are kept in the parameterization of the feedback trading coefficients even if, following our parsimonious approach, the regressors with coefficients that are not significantly different from zero are dropped from the estimation. No feedback trading component appears in the conditional means of the rate of change of the US effective exchange rate and of the US bond returns, as these time series turn out to be serially uncorrelated.

The shifts over time of the CAPM component and feedback trading coefficient time series, computed using historical simulations, are set forth in Graph 2. Their respective unconditional means are collected in Table 5.

The graphical analysis detects two major shocks to oil prices. The first is associated with the financial turmoil caused by the military operations against Iraqi oil infrastructures of 2001 and the second is a direct consequence of the stock market collapse of 2002.[13]

The CAPM component of the oil conditional mean equations is mostly negative from 2000 to 2002. The weighted sum of the variance of oil returns and of the covariance between oil and bond returns and between oil returns and the rate of change of the US effective exchange rate is overcompensated by the negative covariance between oil and stock market returns.

Indeed, shifts in portfolio composition between stock and oil tend to reduce risk. The oil risk premium in Graph 2 declines and becomes negative as investors sell oil and buy stocks, whose CAPM component, in turn, rises as uncertainty increases. This behavior corroborates our hypothesis that oil is now a truly financial asset, as suggested by the significance of all the conditional covariance coefficients in its conditional mean estimates.

From 2003 onwards the variability of stock returns declines and the oil CAPM component is mostly positive. The feedback trading coefficient, on the contrary, is always strongly negative since the loadings of the covariances between oil returns and the returns of the other assets of the model are all positive. An inspection of Tables 3 and 5 shows that positive feedback trading is, on average, more relevant in the second than in the first time period. Destabilizing speculation becomes a major driver of oil price movements.

In the US dollar effective exchange rate conditional mean, b_{1z} is negative; an increase in volatility brings about a depreciation of the US effective exchange rate as traders sell dollars. The average negativeness of the overall CAPM coefficient $\lambda_{z,t}$, however, is mitigated by the impact of the covariance between the oil prices and the US dollar.

[13] Having recovered from the lows which followed September 11 2001, the US stock indices started to slide from March 2002 onwards. The dramatic declines in July and September led to lows last reached in 1997 and/or 1998.

The sign of the CAPM component of the conditional mean equation of the US bond index return can be mainly attributed to the influence of two major factors. The oil channel, $b_{2k}h_{sk,t}$, which identifies a joint nature of bonds and oil as safe assets, and the exchange rate channel, $b_{4k}h_{zk,t}$, which accounts for the foreign demand of US Treasuries. When the USD depreciates US bonds become cheaper and their demand rises. Indeed, the large purchases of Treasuries by foreigners such as the Central Bank of the Peoples' Republic of China, or analogous institutions of emerging market economies, bring about a substantial flattening of the yield curve and invalidate at least temporarily, the standard relationship between risk and returns.

Table 4: Multivariate ICAPM, January 2000-June 2008

System (B) Conditional mean equations

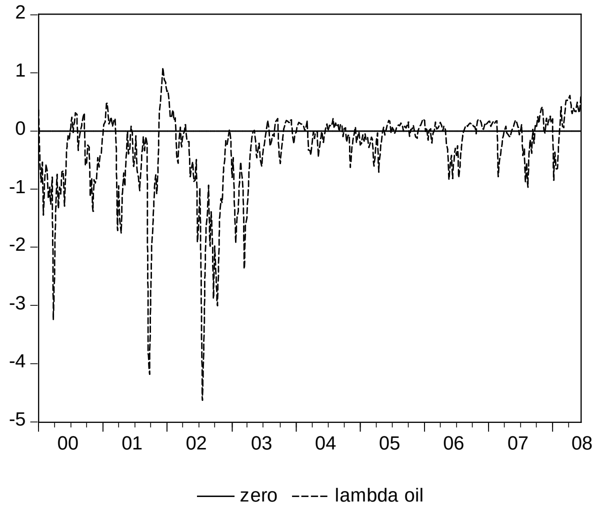
	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	b_{11}	$E[\nu_t]$	$E[\nu_t^2]$	Sk.	Kurt.	LM(1)	LM(10)	J.T.A.
Δs_t	0.50	0.04	2.64	-1.74	-1.88		-0.006	0.17	0.29	0.34	0.86	0.26	0.00	1.36	-0.70	11.05	2.48	16.22	4.25
	(2.43)	(3.00)	(2.98)	(-1.67)	(-2.06)		(-3.33)	(2.81)	(2.40)	(1.94)	(2.53)	(3.76)					[0.11]	[0.09]	[0.23]
Δj_t	-1.45	-0.12	-3.58	-11.43	0.42	-0.54	-0.04	-0.46	-9.31				-0.12	1.00	-0.60	2.21	0.18	4.75	9.46
	(-8.27)	(-3.49)	(-11.88)	(-1.75)	(2.39)	(-4.97)	(-4.41)	(-10.5)	(-9.63)								[0.66]	[0.90]	[0.02]
Δz_t	-0.13	-0.31	-0.09	-3.99	-0.24								-0.00	1.36	0.10	0.02	1.42	13.59	3.15
	(-4.28)	(-4.48)	(-0.51)	(-1.23)	(-1.76)												[0.23]	[0.19]	[0.36]
Δk_t	-1.10	-0.42	-9.74	-0.02	4.01								0.05	1.01	0.02	0.69	3.21	22.62	4.76
	(-5.78)	(-6.57)	(-24.51)	(-0.12)	(5.20)												[0.07]	[0.01]	[0.19]

Conditional variance equations

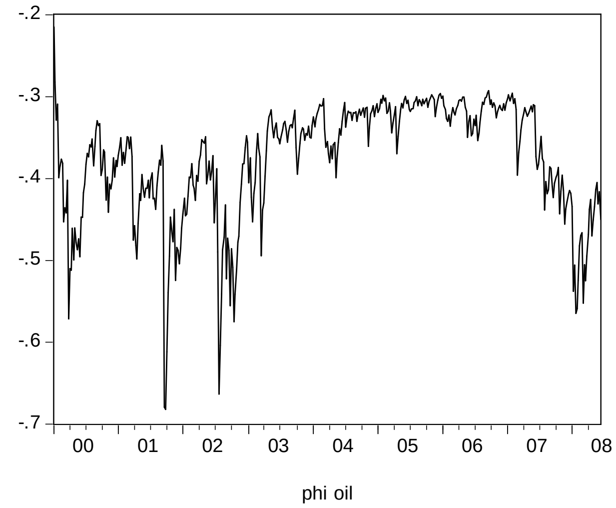
	ϖ	α	β	ρ_{12}	ρ_{13}	ρ_{14}	ρ_{23}	ρ_{24}	ρ_{34}	LLF
$h_{s,t}^2$				-0.09	-0.08	-0.06	-0.02	-0.31	-0.19	-3718.17
				(-7.30)	(-2.82)	(-41.89)	(-3.55)	(-5.93)	(-6.82)	
$h_{j,t}^2$	0.77	0.59	0.28							
	(2.41)	(5.68)	(3.48)							
$h_{z,t}^2$										
$h_{k,t}^2$	0.11	0.81	0.14							
	(3.46)	(30.89)	(6.80)							

Graph 2. Second period CAPM components and feedback trading coefficients

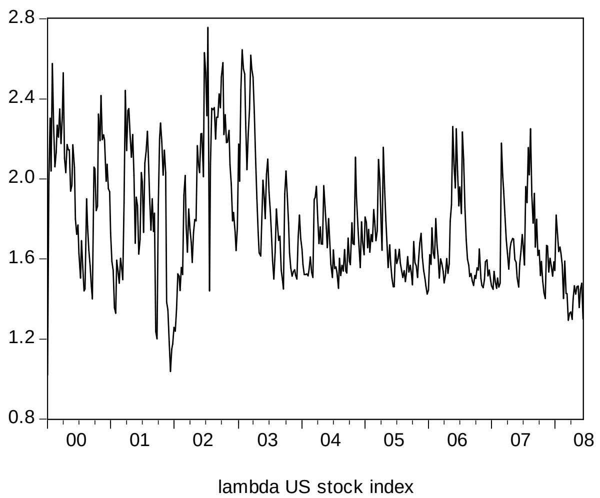
Oil return equation CAPM component



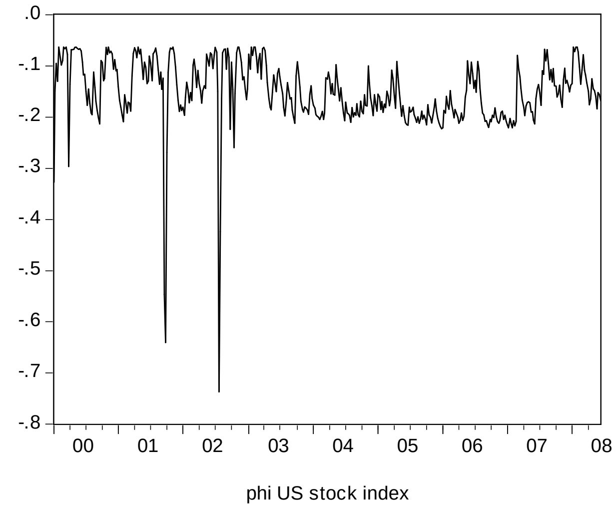
Oil return equation Feedback trading coef.



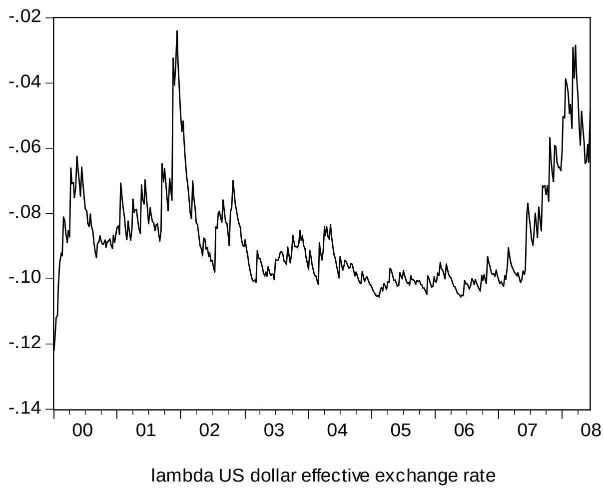
US stock return equation CAPM component



US stock return equation Feedback trading coef.



US dollar equation CAPM component



US bond return index equation CAPM component

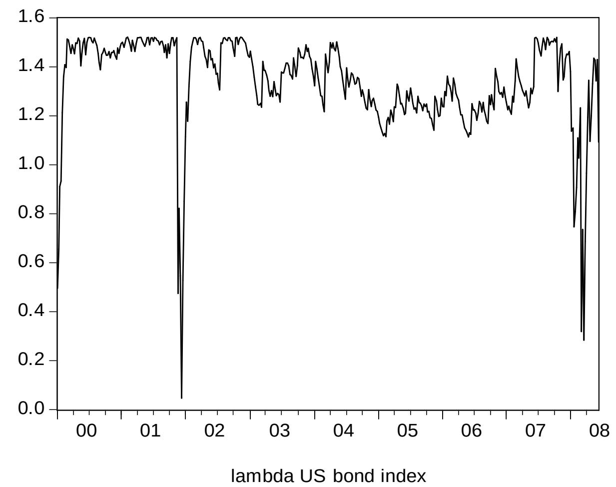


Table 5: Average values of the conditional mean CAPM components (CAPM comp.) **and feedback trading coefficients** (Fbt coef.)

Oil returns		**US dollar changes**	
CAPM comp.	-0.31 (-8.94)*	CAPM comp.	-0.09 (-114.51)*
Fbt coef.	-0.37 (-111.68)*		
US stock returns		**US bond returns**	
CAPM comp.	1.77 (119.30)*	CAPM comp.	1.34 (146.94)*
Fbt coef.	-0.15 (-48.40)*		

Notes. t-statistics (H_o: average = 0) are in parenteses; *: significant at the 5% level.

4. Portfolio analysis

The paper focuses on the important issue of a change in WTI oil spot pricing in the last decade. If the hypothesis that in recent years oil behaved more and more as a financial asset is correct, its inclusion in a portfolio, given the signs of the correlation coefficients computed in the previous section, should have a beneficial effect on the corresponding risk/return trade-off.

We assess this proposition using a straightforward Markowitz procedure, with no short-selling restrictions, no borrowing and no lending, and base the portfolio composition on risk minimization criteria.

If $w = (w_1, \ldots\ldots, w_N)'$ is a Nx1 vector of portfolio weights and Σ is the NxN variance-covariance matrix of the returns, the portfolio variance is then $w'\Sigma w$. The global minimum variance portfolio is the solution of the minimization problem $min_w \; w'\Sigma w \;\; s.t. \;\; w'\underline{1} = 1$, where $\underline{1}$ is a Nx1 column vector of ones. The weights $w_{MV} = (w_{MV,1}, \ldots\ldots, w_{MV,N})'$ of the global minimum variance portfolio take the value $w_{MV} = \Sigma^{-1}\underline{1} / \underline{1}'\Sigma^{-1}\underline{1}$.

The expected return μ_{MV} and the variance σ^2_{MV} of the global minimum variance portfolio read as

$$\mu_{MV} = \mu' w_{MV} = \frac{\mu'\Sigma^{-1}\underline{1}}{\underline{1}'\Sigma^{-1}\underline{1}} \quad (8)$$

and

$$\sigma_{MV}^{2} = w_{MV}^{'} \Sigma w_{MV} = \frac{1}{\underline{1}^{'} \Sigma^{-1} \underline{1}} \tag{9}$$

where μ is a Nx1 column vector of asset returns. The corresponding expected return per unit of risk index is then computed as $\left(\mu_{MV} \Big/ \sqrt{\sigma_{MV}^{2}} \right)$.

The lower variance bound (9) can be attained only if the variance-covariance matrix of the asset returns is known. Typically, historical return observations are used for this estimation. We construct the portfolios either keeping the weights constant over each sub-sample or rebalancing them every week, mimicking a tactical asset allocation behavior. (Weekly portfolio rebalancing is also meant to account for the volatility clustering of the time series.) Every week the constrained variance minimization described above is performed over a predetermined data interval *j* and the corresponding global minimum variance weights, (expected) portfolio returns $\mu_{MV,j}$, portfolio return variance $\sigma_{MV,j}^{2}$ and (expected) return per unit of risk index $\left(\mu_{MV,j} \Big/ \sqrt{\sigma_{MV,j}^{2}} \right)$ are computed. The following week the same procedure is repeated over a sample interval shifted forward by one time period (i.e. one week). This iterative process continues until the end of the sub-period. A set of three time series for each portfolio holding period is obtained in this way. We selected here a 12 month and a 6 month holding period. In Table 6 are set out the unconditional means and the average return per unit of risk, over the two sub-samples, of these time series.

The entries suggest that, over the last decade, the introduction of oil into a multi asset-class portfolio improves the risk/return performance.

In the first sub-period the three asset portfolio (without oil) outperforms the four asset one, which includes oil. This result holds considering both the unconditional mean returns and the average return per unit of risk, with and without portfolio rebalancing.

Table 6: Portfolio analysis

	Holding period	Unconditional mean		Unconditional variance		Average return per unit of risk (Mean/Standard error)	
		First sub-sample 6/10/1992 12/28/1999	Second sub-sample 4/1/2000 10/6/2008	First sub-sample 6/10/1992 12/28/1999	Second sub-sample 4/1/2000 10/6/2008	First sub-sample 6/10/1992 12/28/1999	Second sub-sample 4/1/2000 10/6/2008
No portfolio rebalancing							
Without oil	**Sub-sample***	0.0937	0.0491	0.5270	0.3815	0.1292	0.0796
With oil spot price	**Sub-sample**	0.0909	0.0618	0.5016	0.3440	0.1283	0.1053
With oil futures price	**Sub-sample**	0.0908	0.0627	0.5037	0.3440	0.1279	0.1068
Weekly portfolio rebalancing							
Without oil	**Twelve months***	0.1010	0.0619	0.4953	0.2683	0.1496^{+}	0.1249^{+}
With oil spot price	**Twelve months**	0.0924	0.0712	0.4631	0.2438	0.1410^{+}	0.1505^{+}
With oil futures price	**Twelve months**	0.0940	0.0714	0.4679	0.2437	0.1432^{+}	0.1499^{+}
Without oil	**Six months***	0.1050	0.0760	0.4440	0.2469	0.1699^{+}	0.1585^{+}
With oil spot price	**Six months**	0.0966	0.0897	0.4042	0.2147	0.1629^{+}	0.1968^{+}
With oil futures price	**Six months**	0.0978	0.0901	0.4082	0.2152	0.1640^{+}	0.1959^{+}

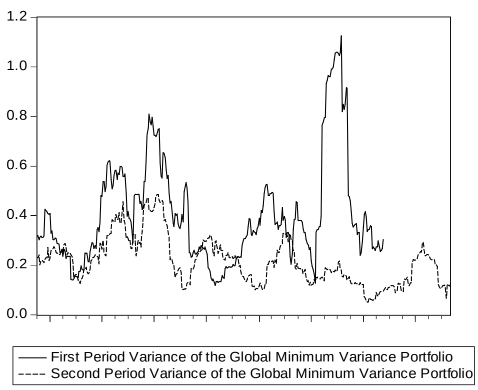
Notes. *: The optimal weights are computed minimizing the variance of a three asset portfolio, which does not include oil; $^{+}$: approximation to the exact index according to Jobson and Korkie (1981, page 893).

In the second period, when oil progressively acquires financial characteristics, we obtain the opposite results. The unconditional portfolio mean and variance and the average return per unit of risk detect a clear-cut dominance of the four asset portfolio, independently of the presence of a rebalancing mechanism and of the length of the holding period. The analysis is then repeated replacing WTI spot prices with the corresponding one month to expiration (contract 1) futures prices and provides similar results, a finding which further corroborates the hypothesis on oil spot pricing mentioned above.[14]

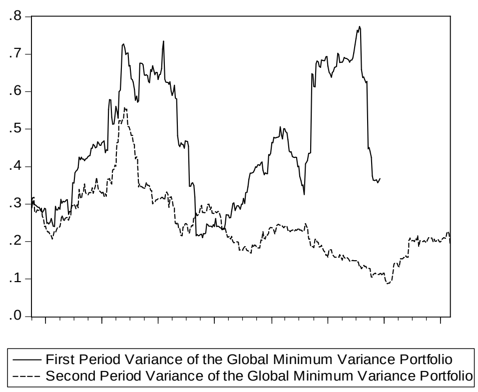
In the same way, the visual inspection of Graph 3, which depicts the behavior over time of the first and second sub-sample variances of the global minimum variance four asset portfolio with annual and semi-annual holding periods, shows that in the second period oil reduces significantly portfolio risk. In both panels the graphs identify the same volatility peaks and point to a dominance of the second period portfolio. Differences in volatility size are due to "ghost features" in the sense of Alexander (2001), since extreme events are averaged over fewer observations in the case of the six month holding period.

Graph 3. Variance of the global minimum variance portfolio with weekly rebalancing and semi-annual and annual holding periods

Six month holding period



Twelve month holding period



5. Conclusion

At the beginning of the year 2000 a regime shift is detected within a highly nonlinear behavioral ICAPM assumed to describe the interconnection between crude oil contracts, US stocks, bonds and effective dollar exchange rate. Indeed, the parsimonious estimates of the model over the 1992-1999 and 2000-2008 time periods differ

[14] Also Geman and Kharoubi (2008) find that WTI crude oil futures contracts can be used to efficiently diversify equity portfolios.

considerably. The conditional correlations change in sign, absolute value, and statistical significance. The oil return conditional mean acquires a complex feedback trading component in the second sub-period and becomes similar in structure to the conditional mean of the stock returns. Oil contracts seem to behave as financial assets, which interact with stocks, bonds, and exchange rates.

In order to further investigate this hypothesis we construct global minimum variance portfolios containing standard financial assets along with WTI crude oil contracts. It stands out clearly – comparing return per unit of risk measures – that the introduction of oil has been of help in diversifying away the unpriced risk of the portfolios.

The paper thus suggests that, in the second sub-period, traders hedge their portfolios considering oil as a component of their wealth allocation.

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