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Stavros Degiannakis
Timotheos Angelidis
George Filis

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BANK OF GREECE
Economic Research Department – Special Studies Division
21, E. Venizelos Avenue
GR-102 50 Athens
Tel: +30210-320 3610
Fax: +30210-320 2432

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OIL PRICE SHOCKS AND VOLATILITY DO PREDICT STOCK MARKET REGIMES

Stavros Degiannakis
Bank of Greece

Timotheos Angelidis
University of Peloponnese

George Filis
Bournemouth University

Abstract

The paper investigates whether oil price shocks and oil price volatility provide predictive information for the state of the US stock market returns and volatility. The disaggregation of oil price shocks according to their origin allows us to assess whether they contain incremental forecasting power on the state of the stock market returns and volatility, a case that does not hold for the oil price returns. Overall, the results suggest that oil price returns and volatility possess the power to forecast the state of stock market returns and volatility. The full effects of oil price returns, though, can only be revealed when the oil price shocks are disentangled and as such we claim that the oil price shocks have an incremental power in forecasting the state of the stock market. The findings are important for stock market forecasters and investors dealing with stock and derivatives markets.

Keywords: Decomposition of shocks, oil price shocks, oil price volatility, regime switching, stock market volatility, US stock market.

JEL classification: C13, C32, C58, G10, Q40.

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Correspondence:
Stavros Degiannakis
Bank of Greece
21, El. Venizelos Ave.
10250 Athens, Greece
Tel.: 0030-210-3202371
Email: sdegiannakis@bankofgreece.gr

1. Introduction and review of the literature

Since Hamilton’s (1983) seminar paper there is a growing interest in the effects of oil prices on stock market returns, as well as, on the economy. The aim of this paper is to examine the relationship between the oil prices and the stock market from a different angle. In particular, we define a regime switching model specification and investigate whether oil price shocks and oil price volatility can predict states of the stock market.

A large body of the academic literature has provided mounting empirical evidence regarding the relationship between oil prices and macroeconomic variables. In the main, the results suggest that oil prices exert a very significant impact on the economy either due to their effects on pricing and production costs or due to their effects on aggregate demand (i.e. via inflation and monetary policy channels) and aggregate supply (i.e. via output). Important studies include those by Segal (2011), Rahman and Serletis (2011), Tang et al. (2010), Nakov and Pescatori (2010), Jbir and Zouari-Ghorbel (2009), Blanchard and Gali (2007), Hamilton (2008, 1996), Hamilton and Herrera (2004), Barsky and Kilian (2004), Jones et al. (2004), Leduc and Sill (2004), Brown and Yucel (2002), Bernanke et al., (1997), Rotemberg and Woodford (1996), Huang et al. (1996), Mork et al. (1994), Mork (1989) and Burbidge and Harrison (1984).

Notwithstanding this general conclusion that oil prices influence the economy, a strand in the literature over the last decade or so has been shaping around the concept that the relationship between oil prices and the economy changed after the 80s (see, *inter alia*, Lescaroux and Mignon, 2008; Blanchard and Gali, 2007; Hooker, 2002, 1996; Bernanke et al., 1997; Darrat et al., 1996). Specifically, they maintain that oil price changes are no longer inflationary, and do not significantly impact output levels and, thus, do not constitute a source of recessionary periods.

Even though there is an extended literature on the relationship between oil prices and the macroeconomy, research in the area of oil prices and stock markets is still growing. The bulk of the literature finds a negative relationship between changes in oil prices and stock market returns (see, *inter alia*, Filis, 2010; Chen, 2010; Miller and Ratti, 2009; Driesprong et al., 2008; Nandha and Faff, 2008; O'Neill et al., 2008; Park and Ratti, 2008; Bachmeier, 2008; Henriques and Sadorsky, 2008; Sadorsky, 2001; Papapetrou, 2001; Ciner, 2001; Gjerde and Sættem, 1999; Huang et al., 1996; Jones and Kaul, 1996).

By contrast, part of the literature finds no relationship between oil price changes and stock market performance (see, *inter alia*, Jammazi and Aloui, 2010; Apergis and Miller, 2009; Cong et al., 2008).

Malik and Ewing (2009), Oberndorfer (2009) and Sadorsky (1999) argue further that, apart from oil prices, oil price volatility also impacts on stock returns. They provide evidence that higher oil price volatility tends to cause a negative effect on stock market returns. Chiou and Lee (2009) also show that oil price volatility exerts a negative impact on the S&P500 index.

Nevertheless, the aforementioned effects of oil stock market performance are far from definite. The status of the country as a net oil-importer or net oil-exporter provides information additional to these effects. Many authors subscribe to the belief that stock markets in oil-exporting countries tend to benefit from an oil price increase, whereas the reverse is true for the oil-importing countries (see, among others, Arouri and Rault, 2012; Mohanty et al., 2011; Korhonen and Ledyaeva, 2010; Bjornland, 2009; Lescaroux and Mignon, 2008 and Hammoudeh et al., 2004).

Furthermore, as suggested by Hamilton (2009a,b) and Kilian (2008a,b), not all oil price changes originate from the same source and, thus, they do not cause the same response from the financial markets. More specifically, the authors distinguish between supply-side and demand-side oil price shocks. Supply-side oil price shocks take place due to changes in the world oil supply, whereas demand-side oil price shocks are caused by changes in aggregate demand, arising mainly from the industrialisation of developing countries like China (Hamilton 2009a,b). Kilian (2009) suggests that demand-side shocks could be further disentangled into aggregate demand shocks and oil specific demand shocks. The latter shock arises due to the uncertainty of the future availability of oil, whereas the former is the equivalent to Hamilton's demand-side shock. The general consensus from the literature regarding the oil price shocks and their impact is as follows (assuming a positive shock): (a) supply-side shocks do not seem to exert any impact on the economy or the stock market. This is mainly due to the fact that disruptions/increases in oil supply do not cause significant changes in oil prices, possibly because OPEC's decisions on oil supply levels are nowadays anticipated by the markets, (b) demand-side shocks seem to trigger positive responses from the stock markets and the economy, as these shocks are considered to be positive news, whereas, (c) oil specific demand shocks tend to exercise a negative effect. Some notable papers of authors who have considered the different origin of oil price shocks in their studies, are those by Baumeister and Peersman (2012), Basher et al. (2012), Lippi and Nobili (2012), Kilian and Lewis (2011), Filis et al. (2011), Kilian and Park (2009), Apergis and Miller (2009), Lescaroux and Mignon (2008), Kilian (2008a) and Barsky and Kilian (2004).

Even though the oil literature is still growing, past findings do not provide evidence about whether oil prices can predict the probability of a stock market being bullish or bearish. Thus, adding to this literature, this study examines whether oil price shocks and oil price volatility can predict bullish stock market behaviour, using the state probabilities of a Markov-Switching model.

Some studies related to the aforementioned hypothesis include the papers by Chen (2010) and Aloui and Jammazi (2009). Aloui and Jammazi (2009) using a regime Markov-Switching EGARCH model were able to find evidence supporting the view that higher oil prices can explain higher stock market volatility and the transition from a stable to a volatile regime. In the same vein as Aloui and Jammazi (2009), Chen (2010) used a time varying transition probability Markov-Switching model to examine whether upward movements in oil prices could lead to bearish stock markets. The results suggest that higher oil prices increase the probability of the stock market moving from a low variance regime to a high variance regime. Even more, the results show that higher oil prices force the stock market to remain in a high variance regime for a longer period of time.

This paper extends the work of Chen (2010) and Aloui and Jammazi (2009), following a different methodological approach, influenced by Chen (2009). Specifically, we do not assume that the transition probabilities are time-varying but we forecast the state of the stock market by using oil variables, as well as a set of macroeconomic and financial indicators, which are used as control variables. This methodology gives us the ability to predict in advance when and why a switch is expected to occur and not what affects the transition probabilities *per se*.

Overall, the contributions of this paper to the existing literature can be described succinctly. First, we disaggregate oil price shocks according to their origin; that is depending whether the oil price shock is supply side in origin, demand side or an oil specific demand shock. The disaggregation enable us to examine which component affects the state of the stock market and hence to uncover hidden relations. Second, we examine whether the disaggregated oil price shocks contain incremental forecasting power on the state of the stock market in contrast to the oil prices.

In short, we show that oil price returns and volatility have the power to forecast the state of stock market returns and volatility. Nevertheless, we highlight that the full effects of oil price returns can be revealed only if we disentangle the oil price shocks. Thus, we suggest that oil price shocks have an incremental power in forecasting the state of the stock market. Finally, a clear distinction is made between the oil price shocks that affect the state probability of stock market returns and those that affect the state probability of stock market volatility.

The rest of the paper is organised as follows: Section 2 describes the dataset, while Section 3 decomposes the oil price shocks. Section 4 presents the econometric model employed and reports the empirical results. Section 5 provides evidence that the findings can be utilised by investors. Section 6 concludes the paper and discusses points for further research.

2. Data description

Monthly data from January, 1989 to December, 2011 from the US stock market are used. The Dow Jones index returns (RDOW), its dividend yield (DY), the US seasonally adjusted inflation (INF), the unemployment rate (UNEMP), interest rates (INT), as well as, the US default spread (DS) are considered. The interest rates used in this study are the 3-month Treasury bill rates. The U.S. default spread is defined as the difference between Moody's seasoned Baa corporate bond yield and the ten-year Treasury constant maturity rate. Finally, the monthly stock market realised volatility (VOLDOW) is equal to:

$$VOL_{\mathrm{t}} = \sqrt{n_t Var\left(r_{t,d}\right)}, \qquad (1)$$

where n_t is the number of days in month t and $r_{t,d}$ is the daily return of Dow index in day d of month t. We estimate similarly the monthly oil price volatility (VOLOIL).

Furthermore, we take into account monthly data for changes in oil production (OP), oil price returns (ROP) and real global economic activity (GEA), which are used to estimate the three oil price shocks (the supply-side oil price shock, aggregate demand shocks and the oil specific demand shock). More specifically, we collect data from Brent crude oil, which represents the 60% of the world oil daily consumption and, thus, can be used as a proxy for world oil prices (Maghyereh, 2004). We use oil production data, as a proxy for world oil supply. Finally, Kilian's (2009) measurement of global economic activity is considered, which is based on dry cargo freight rates[1].

The data for the Brent crude oil prices and oil production have been collected from the Energy Information Administration. Stock market prices, Dow Jones dividend yield, US default spread, interest rates, inflation and unemployment are collected from *Datastream*®. Stock market prices, oil prices and interest rates are expressed in real terms. Stock market returns, oil price changes, as well as, changes in oil production are estimated as the first log-difference. A visual representation of the variables can be seen in Figure 1.

[FIGURE 1 HERE]

In Figure 1 we observe the effects of the 2007 Great Recession which resulted in peaks for stock market and oil price volatilities, default spreads and unemployment, as well as, troughs in stock and oil prices, inflation, interest rates and global economic activity. In addition, abrupt changes of oil prices, oil production and oil volatility can be also identified in the early 90s, which are associated with the first war in Iraq and the collapse of the Soviet Union.

[TABLE 1 HERE]

According to Table 1, the characteristics of the variables differ greatly. As expected, the financial variables along with the oil variables exhibit the highest volatility compared with the macroeconomic variables. Furthermore, the Global Economic Activity exhibits the significant impact of the Great Recession to the global demand, as this is depicted by the significant decrease of the index during 2008. In addition, notable information that we can extract from Table 1 is that both the Dow

[1] The data can be found in Lutz Kilian personal website; http://www-personal.umich.edu/~lkilian/.

Jones returns and interest rates have fluctuated into negative levels, as this is suggested by their minimum values. None of the variables are normally distributed as evident by the Jarque Bera test, as well as, the skewness and kurtosis measures.

[TABLE 2 HERE]

Table 2 reports the correlation matrix of the variables under consideration. We notice that the highest correlation is between the US default spread and the Dow Jones realised volatility (positive). The latter figure is expected considering that the higher the default spread of a country the higher the uncertainty in the stock market. Some additional expected correlations are those among the Dow Jones index returns and realised volatility and the US default spread. Regarding the oil variables, a negative coefficient exists between oil price returns and Dow Jones index returns, as well as, between oil price returns and Dow Jones realised volatility. Finally, oil price volatility is exhibiting a positive correlation with Dow Jones realised volatility and a negative relationship with Dow Jones index returns.

Overall, from this preliminary analysis we can observe that the oil price changes and oil price volatility have a negative relationship with stock market performance, as suggested by the literature.

3. Oil price shocks and historical decomposition

As noted above, the aim of this paper is to examine whether the decomposition of oil price shocks according to their origin contain incremental forecasting power on the state of the stock market returns and volatility. We adopt Kilian's (2009) decomposition framework, which allows the identification of three oil price shocks (i.e. supply-side, aggregate demand and oil specific demand). A structural VAR model of order *p* is applied:

$$\boldsymbol{A}_0 \boldsymbol{y}_{\mathrm{t}} = \boldsymbol{c}_0 + \sum_{i=1}^{p} \boldsymbol{A}_{\mathrm{i}} \boldsymbol{y}_{\mathrm{t-i}} + \boldsymbol{\varepsilon}_{\mathrm{t}} \qquad (2)$$

where, $\boldsymbol{y}_{\mathrm{t}} = [op_t \quad gea_t \quad rop_t]'$ is a 3×1 vector of endogenous variables (changes in oil production, real global economic activity and oil price changes), $\boldsymbol{A}_0$ represents the 3x3 contemporaneous matrix, $\boldsymbol{A}_{\mathrm{i}}$ are 3×3 autoregressive coefficient matrices, $\boldsymbol{\varepsilon}_{\mathrm{t}}$ is the vector of structural disturbances, assumed to have zero covariance. The covariance matrix of the structural disturbances has the form $E[\boldsymbol{\varepsilon}_{\mathrm{t}}\boldsymbol{\varepsilon}_t'] = \boldsymbol{D} = \begin{bmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & 0 \\ 0 & 0 & \sigma_3^2 \end{bmatrix}$. In order to get the reduced form of the structural model, we multiply both sides with $\mathbf{A}_0^{-1}$, such as that:

$$\boldsymbol{y}_{\mathrm{t}} = \boldsymbol{a}_0 + \sum_{i=1}^{p} \boldsymbol{B}_{\mathrm{i}}\boldsymbol{y}_{\mathrm{t-i}} + \boldsymbol{e}_{\mathrm{t}}, \tag{3}$$

where, $\boldsymbol{a}_0 = \boldsymbol{A}_0^{-1}\boldsymbol{c}_0$, $\boldsymbol{B}_{\mathrm{i}} = \boldsymbol{A}_0^{-1}\boldsymbol{A}_{\mathrm{i}}$, and $\boldsymbol{e}_{\mathrm{t}} = \boldsymbol{A}_0^{-1}\boldsymbol{\varepsilon}_{\mathrm{t}}$. The reduced form errors $\mathbf{e}_t$ are linear combinations of the structural errors $\boldsymbol{\varepsilon}_t$, with a covariance matrix of the form $E[\boldsymbol{e}_{\mathrm{t}}\boldsymbol{e}_t'] = \boldsymbol{A}_0^{-1}\boldsymbol{D}\boldsymbol{A}_0^{-1\prime}$.

The structural disturbances can be derived by imposing suitable restrictions on $\boldsymbol{A}_0$. The short-run restrictions that are applied in this model as the following:

$$\begin{bmatrix} \varepsilon_{1,t}^{SS} \\ \varepsilon_{2,t}^{ADS} \\ \varepsilon_{3,t}^{SDS} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \times \begin{bmatrix} e_{1,t}^{op} \\ e_{2,t}^{gea} \\ e_{3,t}^{rop} \end{bmatrix},$$

where, SS = supply-side oil price shock, ADS = aggregate demand shock and SDS = oil specific demand shock.

The model restrictions are incorporated for the identification of the oil price shocks. Oil production does not responding contemporaneously to changes in oil demand due to the high adjustment costs. Oil supply changes can contemporaneously influence global economic activity and the price of oil. Global economic activity is not contemporaneously influenced by oil prices, as it requires time for the world economy to react to oil price changes. Nevertheless, changes in economic activity will have an immediate impact on oil prices due to the immediate reaction of the commodities markets. Finally, the oil price innovation could be triggered by supply-side events, aggregate demand-side events, as well as, oil specific demand events. Thus, oil production shocks, as well as aggregate demand shocks, can contemporaneously impact oil prices.

The historical decomposition of oil price returns, according to the origin of the shock can be summarized in three steps (for more details please refer to Kilian and Park, 2009 and Burbidge and Harrison, 1985). First, the structural VAR model in eq.3 is estimated, which allows identification of the three oil price shocks. Second, the estimated SVAR model is used to forecast the endogenous variables for periods $t+1, t+2, \ldots, t+s$. Finally, the forecast errors are decomposed into the cumulative contributions of the structural oil price shocks. For example, a $t+1$ vector of forecast errors, $\boldsymbol{e}_{\mathrm{t}+1}$, can be decomposed as $\boldsymbol{e}_{\mathrm{t}+1} = \sum_{i=1}^{3} \boldsymbol{e}_{t+1}^{(i)}$, where i denotes the contribution of the i^{th} structural shock to each element in the vector of forecast errors. We then use the cumulative effects of the supply-side (SS), aggregate demand (ADS) and oil specific demand shocks (SDS) on oil price log-returns as predictive variables of the state of the US stock market returns and volatility.

4. Forecasting the state of the stock market returns and volatility

In this section, the incremental power of the oil price shocks and oil price volatility in forecasting the state of the stock market returns and volatility is investigated. In order to achieve this goal, we, first, extract the states of the stock market by using a regime switching model. Then, the regimes of the stock market are predicted by using the lag values of the oil price shocks, oil volatility and a set of control variables.

It is well documented (see for example Schaller and van Norden, 1997; Guidolin and Timmerman, 2005) that stock returns are characterised by at least two distinct regimes (*bull* and *bear* markets). Therefore, we estimate a two-state regime switching model for the returns and the volatility of Dow Jones index. The model is written as:

$$\begin{aligned} y_{i,t} &= \mu_{i,1} + \varepsilon_{i,t,1}, \quad \varepsilon_{i,t,1} \sim \mathrm{N}\left(0, \sigma_{i,1}^2\right) \\ y_{i,t} &= \mu_{i,2} + \varepsilon_{i,t,2}, \quad \varepsilon_{i,t,2} \sim \mathrm{N}\left(0, \sigma_{i,2}^2\right), \end{aligned} \tag{4}$$

where $y_{i,t}$ is the variable of interest (return or volatility of Dow Jones for i=1,2, respectively), $\mu_{i,j}$ and $\sigma_{i,j}$ are the conditional mean and the standard deviation for state j=1,2. We assume that the return dispersion is a first order Markov, which is described by a binary variable $\mathrm{S}_t = 1,2$ and the constant probabilities p, q.

We calculate the regime classification measure that has been proposed by Ang and Bekaert (2002) to evaluate the quality of regime classification:

$$RCM = 400 \frac{1}{T} \sum_{t=1}^{T} p_t (1 - p_t) , \tag{5}$$

where $p_t = (S_t|\mathcal{J}_T)$ and $\mathcal{J}_T$ is the information set for the entire sample. The RCM statistic takes values between 0 and 100 with low values indicating good regime classification. For the return (volatility) index the measure equals 26 (19) and, therefore, there are strong indications that the two-state regime switching model classifies correctly the periods of high and/or low risk.

Table 3 exhibits the estimated coefficients of the regime switching models, while Figure 2 plots the probability of state 1 (low risk environment) conditioned on all information in the sample based on Kim's (1994) algorithm. In the figure, the Dow Jones return and volatility are also plotted.

[TABLE 3 HERE]

[FIGURE 2 HERE]

The average monthly return during low volatility periods is statistically significant, while during periods of high risk the return is lower and statistically insignificant with standard deviation that is two times greater. The regimes are quite persistent as the probability of staying in the low (high) risk environment is equal to 98.36% (97.35%). The same picture emerges for the states of the volatility of Dow Jones returns. The annual volatility during high risk periods is 2.3 times greater than that of moderate periods while the volatility of volatility is almost 4 times greater. As expected, Figure 2 reveals that times of turbulence in market returns coincide with times of turbulence in risk (late 80s, 1998-2002, and 2008-2009).

To explore the role of the variables of interest in the prediction of the future state of the Dow Jones returns and realised volatility, we estimate the following probit regression:

$$P(\mathrm{d_t} = 1) = \Phi(\beta_i \boldsymbol{OIL}_{t-1}, \gamma_i VOLOIL_{t-1}, \boldsymbol{\delta}_i \boldsymbol{X}_{t-1}), \tag{6}$$

where, $\mathrm{d_t} = 1$ when the state probability is greater than 50%, and $\mathrm{d_t} = 2$ otherwise and Φ is the cumulative distribution function of the standard normal distribution. The explanatory variables include the $\boldsymbol{OIL_t}$ variable (either the oil price shocks (SS_t, ADS_t, SDS_t) or the real oil price returns (ROP_t) – depending on the model specification) and oil price volatility ($VOLOIL_t$). We also include a vector $\boldsymbol{X}_t$, which includes the control variables that have been described in section 2; $\boldsymbol{X}_t =$

$[DS_t, INT_t, CPI_t, DY_t, UNEMP_t, DOW_t]'$, where DOW_t is the $RDOW_t$ ($VOLDOW_t$) on the returns (realised volatility) probit regression model.[2]

Table 4 presents the estimated coefficients of the probit regressions for the Dow Jones returns. Overall, the oil price volatility is negative and statistically significant on all specifications, suggesting that the higher the oil volatility the lower the probability of stock market returns being in state 1. On the contrary, the real oil price returns do not seem to exercise a significant effect, as suggested by specifications 1 and 3.

[TABLE 4 HERE]

Interestingly, when real oil price returns are decomposed into the individual oil price shocks, the supply side and aggregate demand side shocks exercise a significant effect (see specifications 4 and 5). The positive coefficients imply that these shocks are regarded as positive information by the market, suggesting that the stock market will be in a bullish state. Positive changes in these two shocks are affirmative information as (i) changes in the world oil production trigger lower oil prices and (ii) positive aggregate demand shocks, despite the fact that they tend to raise oil prices, originate from the increase in the global economic activity. These findings complement the conclusions of Basher et al. (2012), Lippi and Nobili (2012), Kilian and Lewis (2011), Filis et al. (2011) and Kilian and Park (2009). The control variables suggest that the default spread, real interest rates, inflation and the dividend yield have a significant effect on the probability of the state on all specifications, although inflation is not significant in specification (2). In particular, the default spread, real interest rates and inflation exercise a negative effect suggesting that as their values increase the stock market tends to move away from the low risk environment. Furthermore, the dividend yield has a positive coefficient, which is once again expected.

Based on Table 4, we maintain that unless we disentangle the oil price shocks, we cannot paint a complete picture of the ability of oil prices to predict the state of the stock market. Thus, we argue the oil price shocks carry an incremental power in forecasting the state of the stock market returns compared to real oil price changes.

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[2] Similar methodology has been incorporated by Chen (2009), who showed that yield curve spreads and inflation rates predict bear markets.

[TABLE 5 HERE]

Subsequently, we examine the estimated coefficients of the probit regressions for the Dow Jones volatility, as these are presented in Table 5. The model specifications suggest that oil price volatility does not exercise a significant effect on Dow Jones volatility when all variables are taken into consideration (see specification 3 and 5). Nevertheless, the opposite result is observed for oil prices. Dow Jones volatility is negatively associated with real oil price returns, implying that increased oil prices tend to drive stock market volatility away from the low risk environment. Once again, though, unless we disentangle the origin of the oil price changes, we can only gain a partial inference, as demonstrated in specification 5. More specifically, focusing on the oil price shocks, we find that only the oil specific demand shock has any incremental power in forecasting the state of the stock market volatility. Thus, the effects of the oil price returns noted on specification 3, is mainly a consequence of the oil specific demand shocks. This is an important finding, considering that oil specific demand shocks have been characterised as uncertainty bearing shocks. Such claim stems from the fact that the events which cause oil specific demand shocks are related to political uncertainty, wars or changes in the inventory policies of the oil sector.

In terms of the control variables, the evidence reveals that all variables are significant with the expected signs. In particular, we report that default spreads, interest rates and unemployment tend to decrease the probability that volatility will remain in the low risk environment, whereas the reverse hold true for the remaining control variables.

Overall, the results provide evidence that oil price returns and volatility possess the power to forecast the state of stock market returns and volatility, as changes in these variables cause stock market returns and volatility to switch to a different state. Nevertheless, we show that the full effects of oil price returns can only be revealed when the oil price shocks are isolated and as such we claim that the oil price shocks have an incremental power in forecasting the state of the stock market. An interesting finding is that there is a clear distinction between the oil price shocks that affect the state probability of the stock market returns (i.e. only the supply-side and aggregate demand shocks) and the state probability of the stock market volatility (i.e. only the oil specific demand shock).

5. Portfolio performance based on the predicted market regimes

This section provides solid evidence in favour of the use of oil shocks and oil price volatility to predict the stock market regimes by examining portfolio performance. We compare two traders that adjust their portfolios according to their information for the state of the market. The first trader uses the predicted market regimes based on equation (4) to adjust her portfolio, whereas the second trader uses the forecasted market regimes based on the forecast of the state of the market from the probit regression (equation 6). The traders assume a long position when the market is in the low risk environment and a short position when the market is in the high risk environment. Portfolio returns are computed as the cumulative log-returns for the investment horizon which coincides with the period being examined.

Table 6 summarises the cumulative returns for both traders for the Dow Jones index, as well as, its volatility, whereas Figure 3 exhibits the line graph of the cumulative returns. It is evident that in both cases the trader who uses the forecasted market regimes based on oil price shocks and oil price volatility enjoys higher portfolio returns. This is particularly apparent for the volatility portfolio. The volatility trading strategy has been replicated using the Dow Jones implied volatility index (VXD) instead of Dow Jones realised volatility and the results are qualitatively similar[3]. The VXD index has launched in October, 1997, thus the investment period is shorter: October, 1997-December, 2011. Overall, this example verifies the importance of using oil price shocks and volatility to forecast market regimes and make portfolio adjustments accordingly.

[TABLE 6 HERE]
[FIGURE 3 HERE]

6. Conclusion

The study investigates whether oil price shocks and oil price volatility can predict the stock market low risk state, as this is approximated by positive returns and low volatility, using a regime switching model. To identify the oil price shocks we follow a similar methodology with Kilian and Park (2009).

[3] The VXD, or CBOE DJIA Volatility Index, is based on real-time prices of options on the Dow Jones Industrial Average. The VXD index reflects investors' consensus view of future (30 calendar days) expected stock market volatility. The VOLDOW is the estimate of the realised volatility; hence, its actual replication in a portfolio is not a straightforward task. However, the volatility trading strategy is directly applied with the VXD, as the CBOE Futures Exchange has introduced futures on the VXD Index (the CBOE DJIA Volatility Index Futures).

The paper extends the work by Chen (2010) and Alou and Jammazi (2009), although a different methodological approach is followed, based on Chen (2009). Specifically, we do not assume time-varying transition probabilities, but we forecast the state of the stock market by using oil variables and a set of macroeconomic and financial indicators, which serve as control variables.

The contributions of the paper are: (i) We disaggregate oil price shocks, which enables us to examine how different kinds of shocks affect the state of the stock market and, hence, we are able to reveal relationships between oil prices and the stock market which would otherwise remain hidden. (ii) We examine whether the decomposed oil price shocks contain incremental forecasting power on the state of the stock market compared to oil price returns.

The regime switch results allow us to detect two episodes of stock market behaviour. The low risk environment is related to high returns and low volatility, whereas the reverse holds for the high risk environment.

The findings from the probit regressions suggest that oil price shocks and volatility have incremental power in forecasting US stock market returns and volatility. In addition, we show that there is a clear distinction between those oil price shocks that affect the state probability of stock market returns and those that affect the state probability of stock market volatility. These findings are important for investors who want to predict the state of the market and adjust accordingly the weights of the assets they hold, i.e. switch to low risk investment (cash) when a high risk state is anticipated. In addition, these results can be utilised by investors who trade options as volatility is the key component of option prices.

An interesting question that future study could examine is whether oil price shocks have incremental forecasting ability on the state of other financial variables (such as the Amihud's illiquidity) or economic variables (such as, interest rate, bond returns, term spread, default spread). Finally, another avenue for further research would be the examination of the forecasting ability of oil price shocks for the state of returns and volatility in various industrial sectors.

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Tables

Table 1. Descriptive statistics of the variables under investigation. The sample period runs from January 1989 to December, 2011.

	Dow Jones Returns	*Dow Jones Realised Volatility*	*Div. Yield*	*Inflation*	*Interest Rates*	*Un/ment*	*Default Spread*	*Oil Price Returns*	*Oil Pr/tion*	*Global Ec. Activity*	*Oil Price Vol/ty*
Mean	0.003	0.157	0.020	0.028	0.009	0.059	0.022	0.005	0.001	-0.004	0.333
Median	0.010	0.135	0.018	0.028	0.010	0.055	0.020	0.021	0.001	-0.039	0.307
Maximum	0.110	0.789	0.039	0.064	0.044	0.100	0.061	0.444	0.044	0.550	1.467
Minimum	-0.186	0.044	0.009	-0.020	-0.041	0.380	0.012	-0.502	-0.060	-0.506	0.112
Std. Dev.	0.045	0.098	0.006	0.013	0.020	0.015	0.008	0.109	0.010	0.228	0.156
Skewness	-0.771	2.646	0.671	-0.274	-0.489	1.092	1.902	-0.621	-0.976	0.451	2.650
Kurtosis	4.396	13.560	2.568	4.504	2.404	3.343	8.083	5.280	9.880	2.662	15.144
Jarque-Bera	49.7	1604.5	22.8	29.4	15.1	56.1	463.6	77.5	588.1	10.6	2019.0
Probability	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.005	0.000

Table 2. Correlation coefficients of the variables under investigation. The sample period runs from January 1989 to December, 2011.

	RDOW	VOL DOW	DY	INF	INT	UNEMP	DS	ROP	OP	GEA	VOL OIL
Dow Jones Returns	1.000										
Dow Jones Realised Volatility	-0.366	1.000									
Dividend Yield	-0.044	-0.135	1.000								
Inflation	-0.124	-0.197	0.433	1.000							
Interest Rates	0.148	-0.275	0.108	-0.027	1.000						
Unemployment	0.047	0.100	0.338	-0.285	-0.544	1.000					
Default Spread	-0.160	0.762	-0.111	-0.381	-0.512	0.394	1.000				
Oil Price Returns	-0.087	-0.139	-0.045	-0.041	0.025	-0.003	-0.088	1.000			
Oil Production	0.021	-0.005	-0.040	-0.012	-0.030	0.014	0.002	-0.076	1.000		
Global Economic Activity	0.039	-0.130	-0.046	0.157	-0.349	0.047	-0.056	0.069	0.052	1.000	
Oil Price Volatility	-0.088	0.402	-0.001	0.016	0.006	-0.112	0.317	-0.091	-0.148	-0.189	1.000

Table 3. The estimated coefficients of the regime switching model.

The model is $y_{i,t} = \mu_{i,j} + \varepsilon_{i,t,j}$, $\varepsilon_{i,t,j} \sim N(0, \sigma^2_{i,j})$, where $y_{i,t}$ is the variable of interest (return or volatility of Dow Jones for i=1,2, respectively), $\mu_{i,j}$ and $\sigma_{i,j}$ are the conditional mean and the standard deviation for state j=1,2. The sample period runs from January, 1989 to December, 2011.

	μ_1	μ_2	σ_1	σ_2	p	q	RCM
Dow Jones Returns	0.008***	0.0005	0.025***	0.054***	98.36%***	97.35%***	26.4
($y_{1,t}$)	(0.0027)	(0.0047)	(0.0021)	(0.0032)	(0.0154)	(0.0217)	
Dow Jones Realised	0.105***	0.231***	0.030***	0.111***	96.13%***	95.30%***	19.8
volatility ($y_{2,t}$)	(0.0025)	(0.0179)	(0.0021)	(0.0057)	(0.0162)	(0.0248)	

***, ** and * denote statistical significance at the 1%, 5% and the 10% level, respectively.

Note: p, q are constant probabilities of stay in regime 1 or 2, respectively. RCM is the regime classification measure proposed by Ang and Bekaert (2002) to evaluate the quality of regime classification.

Table 4. Probit regression results: $P(\mathrm{d_t}=1)=\Phi(\beta_i \boldsymbol{OIL}_{t-1}, \gamma_i VOLOIL_{t-1}, \boldsymbol{\delta}_i \boldsymbol{X}_{t-1})$ where, $\mathrm{d_t}=1$ when the state probability for the Dow Jones returns is greater than 50%, and $\mathrm{d_t}=2$ otherwise. Φ is the cdf of the standard normal distribution, $\boldsymbol{OIL_t}$ denotes either the oil price shocks (SS_t, ADS_t, SDS_t) or the real oil price returns (ROP_t), $VOLOIL_t$ is the oil price volatility, and $\boldsymbol{X}_t$ includes the control variables $DS_t, INT_t, CPI_t, DY_t, UNEMP_t, RDOW_t$. The sample period runs from January, 1989 to December, 2011.

Independent Variables:	(1)		(2)		(3)		(4)		(5)	
Constant	0.9911	***	10.0343	***	11.6304	***	0.9777	***	12.5420	***
	(0.2872)		(1.0242)		(1.2695)		(0.2933)		(1.4341)	
Supply Side Shock $_{t-1}$							5.2151		15.3078	**
							(4.3846)		(6.1956)	
Aggregate Demand Shock $_{t-1}$							7.1377	**	14.0791	***
							(3.6001)		(5.2716)	
Oil Specific Demand Shock $_{t-1}$							-0.6270		-0.7019	
							(0.7984)		(1.2262)	
Oil Price Returns$_{t-1}$	-0.3347				-0.3511					
	(0.7709)				(1.2145)					
Oil Price Volatility$_{t-1}$	-3.9458	***			-3.7873	***	-4.0920	***	-4.1368	***
	(0.9132)				(1.2045)		(0.9439)		(1.2352)	
Default Spread$_{t-1}$			-4.0663	***	-4.1420	***			-4.4475	***
			(0.3921)		(0.4063)				(0.4661)	
Interest Rates$_{t-1}$			-90.5936	***	-90.9008	***			-97.1331	***
			(9.8405)		(9.9403)				(11.7862)	
Inflation$_{t-1}$			-20.0316		-37.5639	**			-44.6543	**
			(14.5105)		(18.9521)				(19.6781)	
Dividend Yield$_{t-1}$			56.4481	***	36.7082	*			48.2223	**
			(17.7016)		(19.7332)				(20.6517)	
Unemployment$_{t-1}$			0.4284		2.4084				0.5216	
			(4.5086)		(4.7094)				(4.7497)	
Dow Jones Returns$_{t-1}$			0.2241		-0.5937				0.2261	
			(2.8812)		(3.2761)				(3.5041)	
R^2	0.0911		0.4965		0.5231		0.1065		0.5567	

Note: In each specification, the dependent variable $P(d_t=1)$ is the probability of the Dow Jones returns to be in state 1. ***, ** and * denote statistical significance at the 1%, 5% and the 10% level, respectively. Huber (1967) and White (1980) robust standard errors are reported in parentheses.

Table 5. Probit regression results: $P(\mathrm{d_t} = 1) = \Phi(\beta_i \boldsymbol{OIL}_{t-1}, \gamma_i VOLOIL_{t-1}, \boldsymbol{\delta}_i \boldsymbol{X}_{t-1})$ where, $\mathrm{d_t} = 1$ when the state probability for the Dow Jones volatility is greater than 50%, and $\mathrm{d_t} = 2$ otherwise. Φ is the cdf of the standard normal distribution, $\boldsymbol{OIL_t}$ denotes either the oil price shocks (SS_t, ADS_t, SDS_t) or the real oil price returns (ROP_t), $VOLOIL_t$ is the oil price volatility, and $\boldsymbol{X_t}$ includes the control variables $DS_t, INT_t, CPI_t, DY_t, UNEMP_t, VOLDOW_t$. The sample period runs from January, 1989 to December, 2011.

Independent Variables:	(1)		(2)		(3)		(4)		(5)	
Constant	1.1165	***	7.63432	***	7.6633	***	1.1406	***	7.7027	***
	(0.3013)		(1.2790)		(1.3564)		(0.3351)		(1.3521)	
Supply Side Shock $_{t-1}$							-2.2823		-1.5243	
							(4.2252)		(6.8760)	
Aggregate Demand Shock $_{t-1}$							-2.2927		-4.6069	
							(3.2401)		(6.0706)	
Oil Specific Demand Shock $_{t-1}$							-1.1121		-3.1675	**
							(0.8132)		(1.4150)	
Oil Price Returns$_{t-1}$	-1.1722				-3.1380	**				
	(0.7702)				(1.3312)					
Oil Price Volatility$_{t-1}$	-2.3752	***			0.0396		-2.5178	**	-0.0106	
	(0.8993)				(0.7966)		(1.0043)		(0.8177)	
Default Spread$_{t-1}$			-2.2169	***	-2.2910	***			-2.2893	***
			(0.4068)		(0.4544)				(0.4542)	
Interest Rates$_{t-1}$			-39.5687	***	-42.5199	***			-42.6276	***
			(11.1179)		(11.9248)				(12.0045)	
Inflation$_{t-1}$			91.6441	***	97.9308	***			98.6602	***
			(24.3316)		(22.3027)				(22.2139)	
Dividend Yield$_{t-1}$			134.5263	***	139.9043	***			140.4472	***
			(28.4715)		(28.0132)				(27.7792)	
Unemployment$_{t-1}$			-8.2814	*	-9.7905	*			-10.0118	*
			(5.0883)		(5.5289)				(5.7772)	
Dow Jones Realised Volatility$_{t-1}$			-24.3339	***	-23.7152	***			-23.7669	***
			(4.8904)		(5.1172)				(5.2051)	
R^2	0.0642		0.7513		0.7643		0.0713		0.7645	

Note: In each specification, the dependent variable $P(d_t = 1)$ is the probability of the Dow Jones volatility to be in state 1. ***, ** and * denote statistical significance at the 1%, 5% and the 10% level, respectively. Huber (1967) and White (1980) robust standard errors are reported in parentheses.

Table 6. Cumulative returns of the trading strategy based on the predicted market regimes according to i) the two-state regime switching model; equation (4), and ii) the probit regression model; equation (6), specification (5), for the returns and the volatility of Dow Jones index. The investment period runs from January, 1989 to December, 2011. For the VXD index, the investment period runs from October, 1997 to December, 2011.

	Portfolio		
	Dow Jones index	Volatility of Dow Jones index	VXD index
Model			
Two-state regime switching model	20.3%	398%	180%
Probit regression model	25.2%	1426%	290%

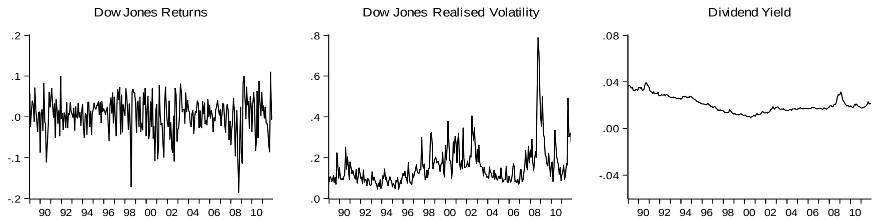
Note: The regime switching model is $y_{i,t} = \mu_{i,j} + \varepsilon_{i,t,j}$, $\varepsilon_{i,t,j} \sim \mathrm{N}(0, \sigma^2_{i,j})$, where $y_{i,t}$ is the return or volatility of Dow Jones for i=1,2, respectively, $\mu_{i,j}$ and $\sigma_{i,j}$ are the conditional mean and the standard deviation for state j=1,2.

The Probit model is $P(\mathrm{d_t} = 1) = \Phi(\beta_i \boldsymbol{OIL}_{t-1}, \gamma_i VOLOIL_{t-1}, \boldsymbol{\delta}_i \boldsymbol{X}_{t-1})$ for $\boldsymbol{OIL_t}$=(SS_t, ADS_t, SDS_t) and $\boldsymbol{X}_t = DS_t, INT_t, CPI_t, DY_t, UNEMP_t, DOW_t$.

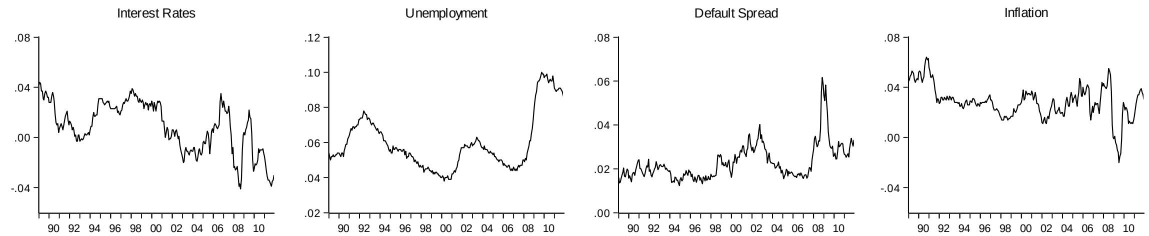
Figures

Figure 1: Growth rates plots for the variables under investigation. The sample period runs from January, 1989 to December, 2011.

Panel A: Stock market variables



Panel B: Macroeconomic variables



Panel C: Oil variables

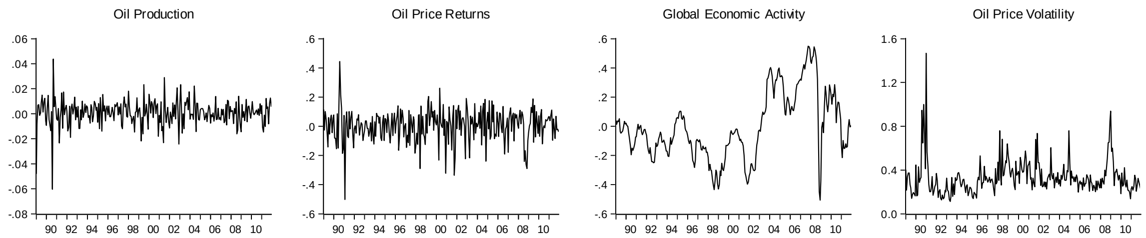
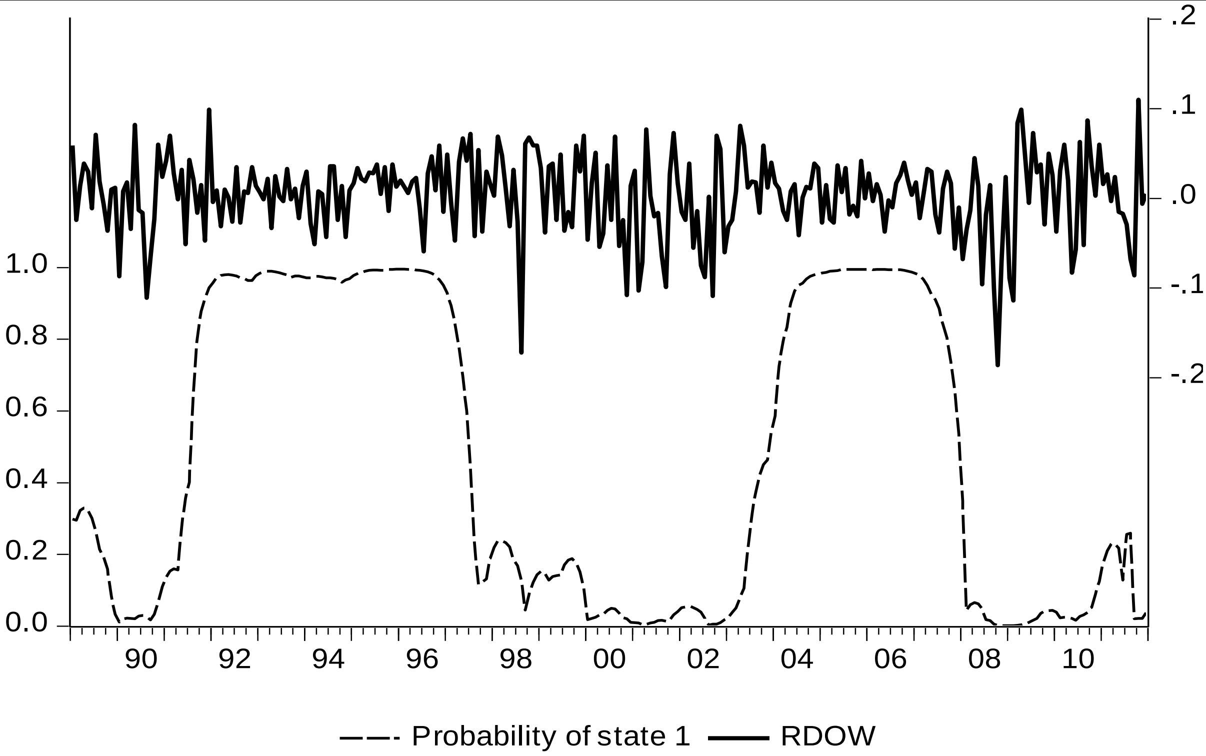
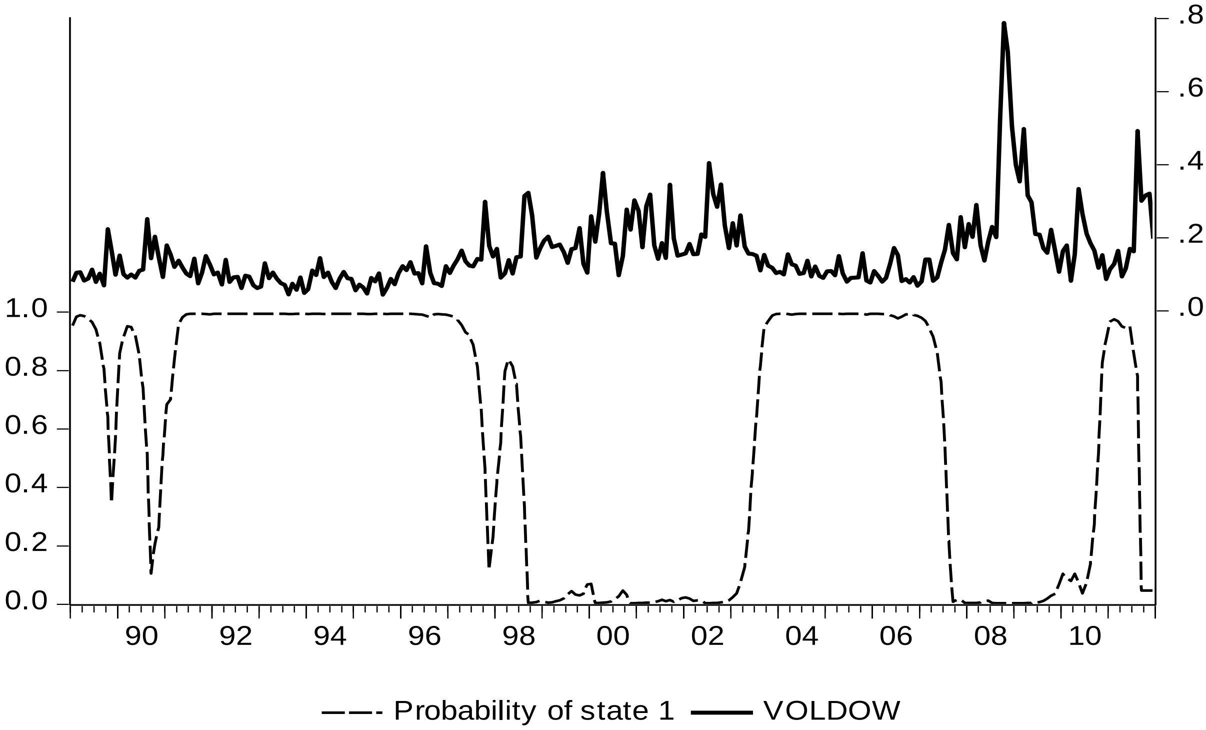


Figure 2: Smoothed probabilities of State 1 and of State 2 of Dow Jones returns and volatility. The sample period runs from January, 1989 to December, 2011.

Panel A: Dow Jones returns.



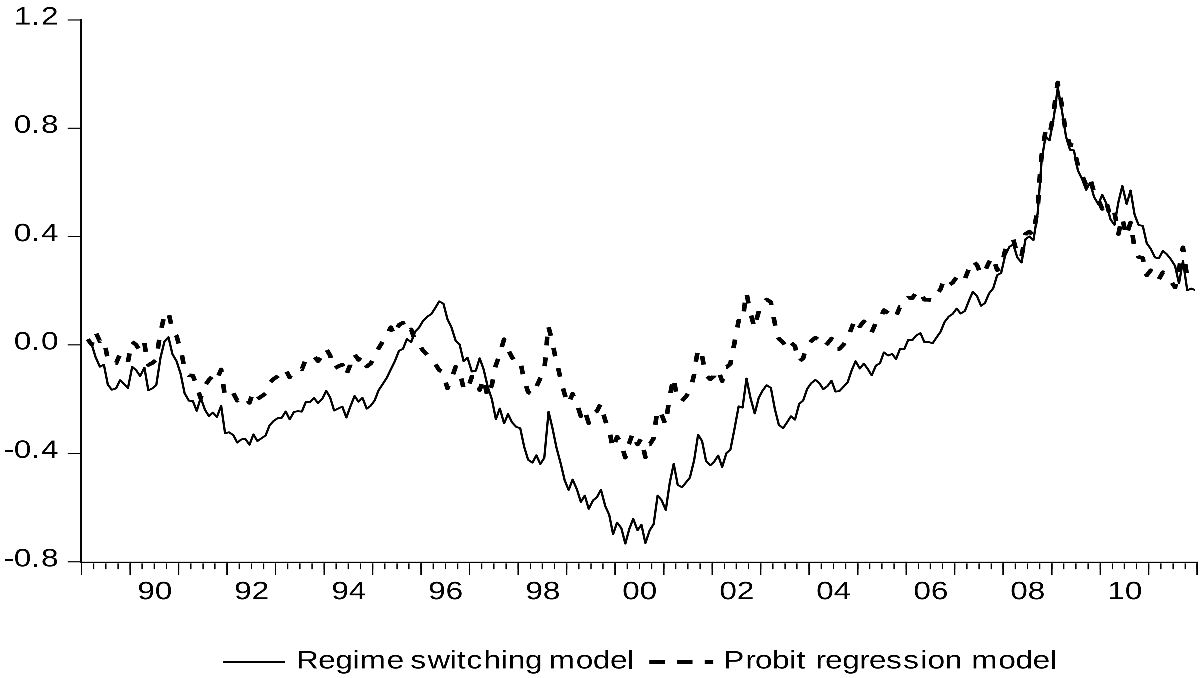
Panel B: Dow Jones volatility.



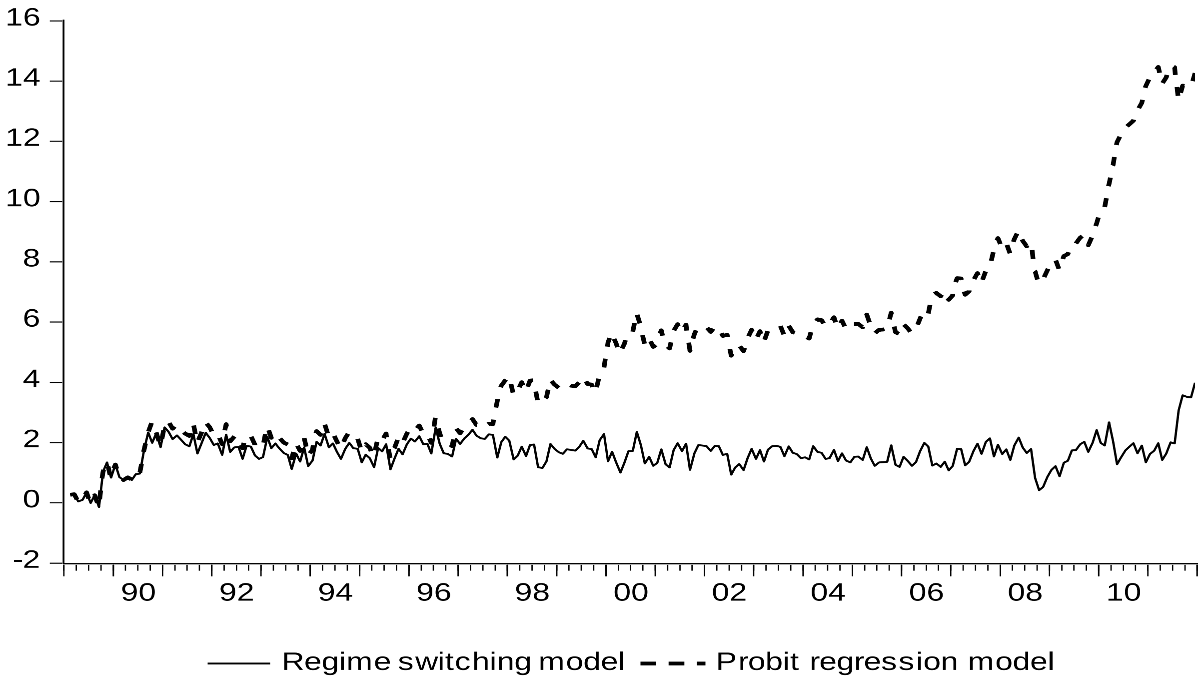
Note: For the Dow Jones returns, regime 1 is the high mean/low volatility, whereas regime 2 is the low mean/high volatility regime. For the Dow Jones volatility, regime 1 is the low mean/low volatility regime, whereas regime 2 is the high mean/high volatility regime.

Figure 3: Cumulative returns of the trading strategies

Panel A: Cumulative returns of the trading strategy based on the predicted market regimes according to i) the two-state regime switching model; equation (4), and ii) the probit regression model; equation (6), specification (5), for the returns of Dow Jones index. The investment period runs from January, 1989 to December, 2011.



Panel B: Cumulative returns of the trading strategy based on the predicted market regimes according to i) the two-state regime switching model; equation (4), and ii) the probit regression model; equation (6), specification (5), for the volatility of Dow Jones index. The investment period runs from January, 1989 to December, 2011.



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