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Abstract

We study the role of real oil prices on the directional predictability of excess stock market returns in the U.S. and ten other countries using probit models. Previous studies have shown that oil price shocks have adverse effects on stock returns. We extend this literature by focusing on the sign component of excess returns. Our findings indicate that real oil prices are useful predictors of the direction of stock returns in a number of markets over and above commonly used predictors, but results vary substantially between countries. Interestingly, we find only limited evidence of asymmetric effects of oil price shocks.

JEL Classification: C22, G12, G17, Q49

Keywords: equity returns, real oil prices, sign predictability, probit model

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1 Introduction

In this paper, we study the predictive ability of real oil prices on the sign of excess stock market returns in the U.S. and ten other markets. Several previous studies have suggested that shocks in oil prices have effects on both macroeconomic variables and stock returns. Hamilton (1983) found a negative impact of oil prices on the real economy, and since then, the topic has received wide attention (see, e.g., Serletis and Elder (2011) and references therein). As there is a close relationship between stock return predictability and business-cycle fluctuations (see, e.g., Rapach and Zhou (2013) for discussion on the topic), examining the relationship between oil price shocks and asset prices has been a natural extension to the literature.

Chen et al. (1986) were among the first to study whether oil price risk is priced in U.S. stock markets, and their results suggested no reward for oil price risk. On the other hand, Jones and Kaul (1996) found that oil price changes have significant effects on stock returns in Canada, Japan, U.K., and the U.S., but the reaction in the Canadian and U.S. stock markets is accounted for by the impact of the shocks on current and expected real cash flows. More recently, Driesprong et al. (2008) have shown that oil prices predict stock market returns worldwide, with the evidence being especially strong in developed countries and the world market index (see also Park and Ratti (2008)). Nandha and Faff (2008) studied the effects of oil prices on global industry indices and found that positive oil price shocks have a negative impact on stock returns in all sectors, excluding oil, gas, and mining industries.

We add to the existing literature by studying the relationship between oil prices and stock returns in eleven developed countries using probit models. Different aspects of the oil price–stock return relationship have previously been uncovered using various different methodologies,[1] but our paper is the first one where the focus is on

[1] Sadorsky (1999) used vector autoregressive (VAR) models and found evidence that also oil price volatility has effects on real stock returns, whereas Kilian and Park (2009) employed VAR models and found that U.S. real stock returns react differently to demand and supply driven oil price shocks. Narayan and Sharma (2011) used generalised autoregressive conditional heteroskedastic (GARCH) and threshold models and found strong evidence of lagged effects of oil price on daily firm and industry returns. Finally, Du and He (2015) found extreme risk spillovers between crude oil and stock markets using Value at Risk (VaR) as a measure of market risk, and Sim and Zhou (2015) studied the topic using a novel quantile-on-quantile approach.

the signs of the returns instead of the actual magnitudes. In a slightly different vein, Engemann et al. (2011) studied the effect of oil price shocks on the probability that an economy enters a recession by using a hidden Markov model with time-varying transition probabilities. Their study is methodologically perhaps the closest one to ours so far, since we also examine the effect of lagged oil price changes, but we are interested in the probability of a positive excess return in the stock markets using binary time series models.

The main motivation for the focus on the sign predictability of stock returns is that sign predictability may exist even in the absence of mean predictability (see, e.g., Christoffersen and Diebold (2006), Christoffersen et al. (2007), and Chevapatrakul (2013)). Forecasts based on the binary dependent variable models have also been shown to outperform those obtained by continuous dependent variable models (see e.g. Leung et al. (2000), Nyberg (2011) and Pönkä (2014)). The directional forecasting performance is also important in terms of asset allocation as pointed out by Pesaran and Timmermann (2002), who also study various methods in order to take into account possible parameter breaks in forecasting financial returns. For further discussion on the benefits of our focus and methodology, we refer to Nyberg and Pönkä (2015), who study the role of the U.S. markets in predicting the direction of excess stock market returns in ten other markets.

Our findings indicate that real oil prices are useful predictors for the direction of stock returns in a number of stock markets both in- and out-of-sample, even after accounting for the predictive ability of a set of commonly used predictors of stock returns. However, we also find that the overall level of sign predictability of returns and the predictive power of oil price changes vary substantially between markets. Finally, both increases and decreases in real oil prices seem to affect the direction of return, but in some markets we find evidence of possible asymmetry.

The rest of the paper is organised as follows. In Section 2, we present the econometric framework used in the study. In Section 3, we introduce the data and discuss the set of predictors. In Sections 4 and 5, we report the in-sample and out-of-sample results, respectively. The possible asymmetric effects of real oil price changes are examined in Section 6. Finally, Section 7 concludes the study.

2 Econometric methodology

Throughout this paper, our focus is on the directional component of the excess stock market returns. Let us denote a one-month excess market return for market j as $r_{jt} = r_{jt}^n - r_{jf}$, where r_{jt}^n is the nominal return and r_{jf} is the risk-free rate. The excess return series can be transformed into binary time series of positive and negative returns as follows

$$y_{jt} = \begin{cases} 1, \text{if the excess portfolio return } r_{jt} \text{ is positive,} \\ 0, \text{otherwise.} \end{cases} \tag{1}$$

The conditional expectation and probability are denoted as $E_{t-1}(\cdot)$ and $P_{t-1}(\cdot)$, respectively, and the information set $\Omega_{j,t-1}$ includes information on the past returns and predictive variables. As $y_{jt}|\Omega_{j,t-1}$ follows a Bernoulli distribution, the conditional probability of the positive excess return can be written as $p_{jt} = P_{t-1}(y_{jt} = 1) = E_{t-1}(y_{jt})$, and the conditional probability of negative return (i.e. $y_{jt} = 0$) is the complement probability $1 - p_{jt}$. In this paper, we consider a univariate probit model

$$p_{jt} = \Phi(\pi_{jt}), \tag{2}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution and π_{jt} is a linear function of the variables in Ω_{t-1}. To complete the model, we consider the basic and most commonly used static model specification

$$\pi_{jt} = \omega_j + \boldsymbol{x}'_{j,t-1}\boldsymbol{\beta}_j, \tag{3}$$

where $\boldsymbol{x}_{j,t-1}$ includes the predictive variables and ω_j is the constant for market j.

The parameters of the model can be estimated using maximum likelihood (ML) methods. For more details on the estimation and the calculation of Newey-West type robust standard errors, we refer to Kauppi and Saikkonen (2008), who also introduce dynamic extensions to the static probit model (3). These extensions have subsequently been considered in the context of directional predictability of stock returns by Nyberg (2011) and Pönkä (2014). However, findings from both of these studies indicate that the parsimonious static probit model performs well compared to the extended models. Therefore, as the focus of this study is on the predictive ability of real oil prices, we limit ourselves to the static probit model (3).

We employ a number of different measures to evaluate the in-sample and out-of-sample predictive performance of the probit models. These are the pseudo-R^2 of Estrella (1998), the quadratic probability score (QPS), and the success ratio (SR), which is simply the percentage of correct forecasts. In addition to these conventional measures, we also employ the Area Under the receiver operating characteristic Curve (AUC). The AUC is a useful measure of overall predictive ability of a given model and it has recently gained popularity in economic applications (see, e.g., Nyberg and Pönkä (2015) and the references therein). The AUC is of particular interest in our application, since the level of predictability of stock returns is typically rather low. Therefore, a statistically significant improvement over 0.5 implies sign predictability that may also lead to economic gains in trading strategies (considered in Section 5).

3 Dataset

In this study, we use the same dataset with the sample period 1980M3–2010M12, and the same eleven markets as Rapach et al. (2013) and Nyberg and Pönkä (2015), who focus on the predictive ability of lagged U.S. stock returns for other markets. The markets are Australia (AUS), Canada (CAN), France (FRA), Germany (GER), Italy (ITA), Japan (JPN), the Netherlands (NED), Sweden (SWE), Switzerland (SUI), the United Kingdom (U.K.), and the United States (U.S.).

The binary dependent variables ($RI_{j,t}$) are transformed from the excess market returns ($RM_{j,t}$) as in (1). The real oil price ($OIL_{j,t-1}$) is the main predictor of interest and the explanatory variables in our baseline models include the three-month interest rate ($3MTH_{j,t-1}$), dividend yield ($DY_{j,t-1}$), and the lagged excess stock market return ($RM_{j,t-1}$). We also consider the CPI inflation ($INF_{j,t-1}$), term spread ($TS_{j,t-1}$), and the growth rates in the real exchange rate ($REX_{j,t-1}$) and industrial production ($IP_{j,t-1}$), as well as the lags of the binary returns $RI_{j,t-1}$.

4 In-sample results

In this section, we focus on the in-sample results of static probit models, and in particular, the additional predictive power of the change in real oil prices over and above commonly used predictors of stock returns. Our baseline model includes three predictors, also employed by Rapach et al. (2013); the 3-month interest rate ($3MTH_{j,t-1}$), the dividend yield ($DY_{j,t-1}$), and the lagged stock return ($RM_{j,t-1}$).

The in-sample findings of the baseline probit models indicate that the three predictors perform rather differently between markets. The three-month interest rate has a statistically significant coefficient (at least at the 10% level) in five countries whereas the dividend yield is statistically significant only in models for the U.S. and Netherlands. Overall, the level of predictability is rather modest, as is typical in stock return applications. The results for the success ratios also confirm these findings, as they show statistically significant predictive power (at the 10% level) in only three out of eleven markets.[2]

The results for the benchmark probit models augmented with the lagged real oil price are presented in Table 1. The real oil price variable has a statistically significant coefficient (at least at the 10% level) for four out of eleven markets (Italy, Netherlands, Sweden, and Switzerland). However, the AUC implies improvement in predictive power in ten out of eleven markets when we include the real oil price variable. Similarly, the success ratios imply statistically significant predictability in six markets compared to only three when the real oil price variable was left out.

Since the findings in Table 1 suggest that the predictive power of $RM_{j,t-1}$, $DY_{j,t-1}$, and $3MTH_{j,t-1}$ varies substantially between the markets, we consider the following model selection approach. Instead of using the same three predictors for each market, we select the best predictors among the set of variables described in Section 3 separately for each market using the Akaike information criterion (AIC). These models are then augmented with the real oil price variable, thus allowing us

[2] The full details of the results from the baseline probit models are available upon request, but the success ratios and AUCs are reported in the final panel in Table 1.

to study whether real oil prices have predictive ability over the 'best' predictors.[3]

The findings in Table 2 indicate that the selected predictors and the level of directional predictability of the excess stock returns vary substantially between the markets. For Australia, Italy, and Japan the selected models include only one predictor, whereas for the U.S. there are five predictors. In general, we find improvement in the in-sample fit compared to the results in Table 1. The real oil price variable shows once again a statistically significant coefficient (at least at the 10% level) for four out of eleven markets. However, the AUC (and success ratio) is improved in ten (nine) out of eleven markets and is statistically highly significantly different from the 0.5 benchmark. In conclusion, our in-sample findings generally suggest that the real oil price growth is a useful predictor of the direction of stock market returns.

5 Out-of-sample results

We study the robustness of our in-sample findings by examining out-of-sample forecasts for the period 1995M1-2010M12. Following Nyberg and Pönkä (2015), we use the rolling window and concentrate on one-month-ahead (h=1) forecasts. The results are presented in Table 3 and they indicate that for eight out of eleven markets, models including the lagged change in the real oil price outperform the corresponding models excluding it. Moreover, for seven out of eleven markets we reject the null of AUC = 0.5 at least at the 10% level, implying sign predictability of the returns.

In order to study the economic value of our forecasts, we employ simple trading strategies follow the approach used, e.g., in Nyberg and Pönkä (2015). The static probit models including the oil price variable produce a higher annual return than the model excluding real oil prices (buy-and-hold strategy) in six (seven) out of eleven markets.[4] There is substantial variation in the trading profits in different markets, as the annual trading returns for the model including the oil price variable range from 0.25% for the Japanese to 16.15% for the Swedish markets. Overall,

[3] If we include the real oil prices in the model selection in a similar way as the other predictors, it gets selected into the models in six out of eleven markets.

[4] For the case of Australia, all the models suggest a full weight in stocks for the whole period and the results are therefore the same.

the out-of-sample findings in terms of sign predictability of excess returns are not particularly strong, but they nevertheless lend support to the findings from the previous literature on the adverse effects of oil price changes on future stock returns.

6 The asymmetric effects of oil prices

In this section, we focus on the possible asymmetric effects of oil price increases and decreases on the direction of stock returns, which has previously not been studied. Previous studies have suggested that the effect of oil price shocks on real activity and stock returns is asymmetric and non-linear. Recently, Jiménez-Rodríguez (2015) found evidence of non-linearity between oil price shocks and stock market returns. Kilian (2009) and Kilian and Park (2009) have also suggested that the effect of oil price shocks depends on whether it is driven by demand or supply, and on the state of the economy (Reboredo (2010)).

The asymmetric effects of positive and negative oil price shocks can be studied in a number of ways. Mork (1989) and Mork et al. (1994) propose capturing the effects of positive and negative changes in oil prices:

$$OIL_{POS,t} = \begin{cases} OIL_t, \text{if the real oil price growth is positive,} \\ 0, \text{otherwise,} \end{cases} \tag{4}$$

and similarly for negative real oil price changes. Another alternative is the non-linear oil price index (NOPI), proposed by Hamilton (1996). This variable takes into account only positive shocks in oil prices, and is defined as:

$$NOPI_t = max[0, ln(OIL_t) - max[ln(OIL_{t-1}), ln(OIL_{t-2}), ..., ln(OIL_{t-12})]]. \tag{5}$$

This measure has been used in a number of later studies, e.g. Park and Ratti (2008), Engemann et al. (2011), and Hamilton (2011), but it has been also criticized by Kilian (2009) of being based on behavioral arguments rather than economic theory.

Results based on models including the aforementioned three variables are reported in Table 4. The model for each market includes the same set of predictors as in Table 2 and the given asymmetric oil price variable.[5] Similarly to Park and

[5] As the NOPI variable compares the current oil price to 12 lagged values, we lose 11 observations compared to previous sections. However, the out-of-sample period is the same as previously.

Ratti (2008), we find only little evidence on asymmetric effects on stock returns of positive and negative real oil price changes, although there is some variation in results between markets. For instance, the negative oil price changes have a statistically significant (at least at the 10% level) effect on Swedish markets, whereas the positive changes have an effect for German and Dutch markets. For Italy, both positive and negative changes are important. Overall, the coefficients for both the positive and negative changes are negative, except for the case of the positive real oil price changes on Canadian markets, where the coefficient is positive. This can be partly explained by the fact that Canada is a net exporter of oil. Finally, we do not find the non-linear oil price variable (NOPI) to have predictive power for the direction of stock markets except in the Italian market.

In addition to the in-sample results, we also present the out-of-sample AUC for each model in Table 4. These findings indicate that including the transformed real oil price variables in the models lead to lower out-of-sample AUCs in most studied markets. Exceptions include Germany, where including positive oil prices leads to a higher out-of-sample AUC than when the original variable is included (compare with Table 3). A similar result is obtained for Sweden with the model including the negative real oil price variable and for Japan including the NOPI.

7 Conclusion

In this paper, we have extended the previous literature on the oil price–stock market relationship by studying the predictive power of changes in real oil prices on the sign of excess stock returns in the U.S. and ten other markets. To achieve this, we have used probit models that have not been employed previously in the context of our application. Our findings indicate that real oil prices are indeed useful predictors of the direction of stock returns in a number of markets, even after controlling for the predictive power of commonly used predictors. Finally, we find only little evidence of asymmetric effects of oil price increases and decreases, but are unable to make general conclusions, because the results vary between markets.

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Table 1: In-sample estimation results of probit models with the benchmark predictors and real oil prices.

	AUS	CAN	FRA	GER	ITA	JPN	NED	SWE	SUI	U.K.	U.S.
$CONST$	0.546*	0.228	0.280*	0.229	0.298	-0.140	0.165	0.326	0.438**	0.006	0.210
	(0.291)	(0.215)	(0.156)	(0.205)	(0.245)	(0.195)	(0.163)	(0.177)	(0.211)	(0.273)	(0.169)
$3MTH_{t-1}$	-0.026	-0.024	-0.022	-0.058*	-0.014	0.017	-0.079**	-0.019	-0.067**	-0.022	-0.090***
	(0.019)	(0.028)	(0.020)	(0.030)	(0.009)	(0.026)	(0.033)	(0.015)	(0.034)	(0.024)	(0.031)
DY_{t-1}	-0.035	0.116	0.017	0.066	-0.036	0.144	0.124**	-0.011	0.010	0.107	0.181**
	(0.085)	(0.125)	(0.051)	(0.074)	(0.068)	(0.148)	(0.057)	(0.058)	0.121	(0.092)	(0.082)
RM_{t-1}	0.006	0.019	0.027**	0.024**	0.014	0.031**	0.006	0.012	0.039***	-0.005	0.019
	(0.013)	(0.014)	(0.011)	(0.012)	(0.009)	(0.014)	(0.014)	(0.010)	(0.015)	(0.014)	(0.015)
OIL_{t-1}	0.001	-0.008	-0.013	-0.010	-0.025***	-0.003	-0.015*	-0.014*	-0.014*	-0.011	-0.006
	(0.007)	(0.008)	(0.009)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
$logL$	-250.569	-248.062	-247.212	-248.294	-248.822	-252.293	-243.951	-250.111	-240.533	-246.914	-244.141
AIC	255.569	253.062	252.212	253.294	253.822	257.293	248.951	255.111	245.533	251.914	249.141
psR^2	0.012	0.034	0.029	0.024	0.040	0.020	0.029	0.019	0.046	0.011	0.030
$adj.psR^2$	-0.002	0.020	0.015	0.011	0.026	0.007	0.016	0.005	0.032	-0.002	0.017
SR	0.597*	0.595**	0.570	0.600***	0.586***	0.543	0.622**	0.554	0.608	0.603	0.614**
AUC	0.560**	0.599***	0.599***	0.591***	0.606***	0.596***	0.610***	0.591***	0.632***	0.577***	0.594***
Results from baseline models not including changes in real oil prices											
SR_{NoOil}	0.592	0.597**	0.570	0.584*	0.543	0.549	0.605	0.568*	0.608	0.600	0.597
AUC_{NoOil}	0.560**	0.587***	0.583***	0.569**	0.558**	0.587***	0.587***	0.557**	0.604***	0.543*	0.589***

Notes: This table illustrates the predictive power of the lagged three-month interest rate (TB), dividend yield (DY), excess stock return (RM), and real oil price (OIL). Robust standard errors of the estimated coefficients are reported in brackets (see Kauppi and Saikkonen (2008)). The goodness-of-fit measures are introduced in Section 2. The success ratio (SR) is based on a signal forecast $\hat{y}_t$ receiving the value 1 if $p_t > 0.5$ and 0 otherwise. In the table, *, **, and *** denote the statistical significance of the estimated coefficients and the Pesaran and Timmermann (2009) PT predictability test for the success ratios at 10%, 5% and 1% significance levels, respectively.

Table 2: In-sample estimation results of the selected probit models for different markets.

	AUS	CAN	FRA	GER	ITA	JPN	NED	SWE	SUI	U.K.	U.S.
$CONST$	0.545***	0.428***	0.177***	0.016	0.054	0.057	0.175	0.225	0.349***	-0.105	0.618***
	(0.194)	(0.126)	(0.065)	(0.111)	(0.070)	(0.066)	(0.166)	(0.141)	(0.125)	(0.269)	(0.215)
TB_{t-1}		-0.045***					-0.079**				
		(0.017)					(0.033)				
DY_{t-1}							0.122**			0.123*	0.440***
							(0.060)			(0.069)	(0.121)
RM_{t-1}			0.027**	0.023*	0.015*	0.031**		0.028*	0.068***		0.050**
			(0.011)	(0.012)	(0.009)	(0.014)		(0.016)	(0.021)		(0.024)
RMI_{t-1}								-0.334	-0.379**		-0.328
								(0.212)	(0.190)		(0.219)
IP_{t-1}			0.127**								0.165
			(0.062)								(0.106)
$10Y_{t-1}$	-0.040**										-0.204***
	(0.019)										(0.051)
TS_{t-1}				0.107*				0.121***	0.135***		
				(0.059)				(0.045)	(0.051)		
INF_{t-1}										-0.379***	
										(0.147)	
REX_{t-1}		0.051									
		(0.033)									
OIL_{t-1}	0.001	-0.008	-0.015*	-0.011	-0.024***	-0.003	-0.015*	-0.014**	-0.013	-0.010	-0.007
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.006)	(0.008)	(0.007)	(0.009)	(0.007)	(0.008)
$logL$	-250.395	-248.334	-245.414	-248.208	-249.676	-252.810	-244.054	-246.726	-238.778	-243.989	-239.821
AIC	253.395	252.334	249.414	252.208	252.676	255.810	248.054	251.726	253.562	247.989	246.821
psR^2	0.013	0.032	0.038	0.025	0.035	0.017	0.029	0.037	0.055	0.027	0.054
$adj.psR^2$	0.005	0.021	0.028	0.014	0.027	0.009	0.018	0.024	0.042	0.016	0.035
SR	0.568	0.611***	0.595**	0.614***	0.565**	0.557	0.619*	0.584**	0.627**	0.624***	0.641***
AUC	0.574***	0.595***	0.603***	0.592***	0.597***	0.582***	0.611***	0.615***	0.651***	0.591***	0.630***
Results from models not including changes in real oil prices											
SR_{NoOil}	0.559	0.597	0.597**	0.586*	0.524	0.543	0.608	0.586***	0.614	0.614**	0.638***
AUC_{NoOil}	0.578***	0.588***	0.591***	0.569**	0.543*	0.576***	0.589***	0.587***	0.633***	0.581***	0.620***

Notes: The table presents the in-sample estimation results for the best probit models based on the model selection procedure described in Section 4. See also the notes to Table 1.

Table 3: Out-of-sample forecasting results.

Model	Stat.	AUS	CAN	FRA	GER	ITA	JPN	NED	SWE	SUI	U.K.	U.S.
No oil	SR	0.615	0.620	0.609	0.545	0.443	0.505	0.604	0.599	0.630	0.599	0.625**
	AUC	0.510	0.494	0.559**	0.514	0.420	0.533	0.535	0.543*	0.569**	0.529	0.573**
	RET	10.30%	12.47%	9.82%	9.07%	1.78%	-0.29%	7.84%	14.63%	7.59%	7.95%	10.47%
	SHR	1.24	2.13	1.47	1.04	-0.49	-0.16	0.81	1.89	1.39	0.76	1.69
Oil	SR	0.615	0.615	0.589	0.545	0.542	0.510	0.630**	0.599	0.620	0.589	0.609
	AUC	0.511	0.476	0.572**	0.572**	0.530	0.543*	0.573**	0.571**	0.592***	0.519	0.567**
	RET	10.30%	10.98%	8.72%	7.26%	7.99%	0.25%	11.37%	16.15%	7.77%	7.15%	11.15%
	SHR	1.24	1.82	1.18	0.73	0.96	-0.01	1.48	2.23	1.45	0.57	1.89
B&H	RET	10.30%	9.77%	8.19%	7.04%	6.27%	-1.92%	7.84%	12.12%	7.86%	7.95%	9.77%
	SHR	1.24	1.34	0.92	0.67	0.35	-0.42	0.81	1.37	1.39	0.76	1.34

Notes: This table presents the out-of-sample forecasting results for the period 1995M01–2010M12. The forecasts are based on a rolling estimation window of 15 years. The models "No oil" and "Oil" refer to the models presented in Table 2 excluding and including the real oil price variable. B&H refers to a buy-and-hold strategy, whereas statistics RET and SHR refer to the annual return and the Sharpe ratio of the trading strategies based on the forecasts. See also notes to Table 1.