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Oil market modelling: A comparative analysis of fundamental and latent factor approaches

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ABSTRACT

We formally compare fundamental factor and latent factor approaches to oil price modelling. Fundamental modelling has a long history in seeking to understand oil price movements, while latent factor modelling has a more recent and limited history, but has gained popularity in other financial markets. The two approaches, though competing, have not formally been compared as to effectiveness. For a range of short- medium- and long-dated WTI oil futures we test a recently proposed five-factor fundamental model and a Principal Component Analysis latent factor model. Our findings demonstrate that there is no discernible difference between the two techniques in a dynamic setting. We conclude that this infers some advantages in adopting the latent factor approach due to the difficulty in determining a well specified fundamental model.

1. Introduction

The modelling of prices in oil markets has received considerable attention in the literature. A particular focus of studies has been the identification of fundamental factors that drive oil markets. Everything from internal market characteristics, to linkages with other traded markets, to a wide range of macroeconomic factors, has been tested to determine an optimal fundamental model. In contrast to fundamental modelling a more recent development is based on identifying latent factors. These capture market dynamics using, for instance, principal component analysis of historical data in a purely statistical manner. Latent factors bypass the need to identify a fundamental model; especially useful given the debate as to precisely what fundamental variables should be in such a model. This paper sets out to determine whether fundamental modelling or the latent factor technique offers a better approach to modelling oil prices.

In terms of fundamental factors, as noted, many different lines of investigations have been pursued. Macroeconomic factors have been considered by Hamilton (1983); Bernanke, Gertler, Watson, Sims, and Friedman (1997); Hamilton (2003) and (Barsky and Lutz (2004). How supply and demand imbalances, along with the movements in the business cycle, impact on oil prices has been investigated in depth (Askari & Krichene, 2008; Kaufmann, 2011; Kilian, 2006; Kilian, 2007; Kilian, 2008). Heath (2016) provides a contemporary study on the macroeconomic factors that drive oil prices, showing that measures of real economic activity forecast oil futures prices and, most notably, that real economy shocks have a resulting impact on oil prices.

The link between equity markets and oil markets has also been well studied, with the former representing a proxy for overall economic activity. Kilian and Park (2009) show that US equity markets respond differently to demand and supply shocks in oil markets, and that in the aggregate both forms of shock account for a high percentage (22%) of the long-run variation in stock returns. Arouri (2011) examines the European stock markets and shows a similar link between the markets, although the strength of association is shown to vary significantly across sectors. Hammoudeh and Choi (2006) examine Gulf region stocks and show that, among other factors, oil price shocks influence equity prices. In the case of Oman and Saudi Arabia, oil prices are reported to account for up to 30% of the variation in stock returns. Other such studies that examine the interdependence between equity markets and oil markets include Hammoudeh and Aleisa (2004); El-Sharif, Brown, Burton, Nixon, and Russell (2005); Filis, Degiannakis, and Floros (2011). Several related studies investigate a similar question from the perspective of volatility transmission and spillover (Arouri, 2011; Creti, Joëts, & Mignon, 2013; Malik & Hammoudeh, 2007).

Given that the global currency for oil trade is the USD, much research has focused on foreign exchange effects. Lizardo and Mollick (2010) demonstrate that oil prices significantly explain movements in the value of the USD against major currencies, with particular evidence that rises in oil prices lead to an appreciation (depreciation) of net

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exporter (importer) country currencies against the USD. Reboredo (2012) finds the dependence between oil prices and exchange rates to be weak in general, although it is found that this dependence rose substantially in the aftermath of the global financial crisis. Using a copula-GARCH approach, Aloui, Assa, and Nguyen (2013) find rises in oil prices to be associated with the depreciation of the USD. Utilising alternative wavelet multi-resolution analysis, Reboredo and Rivera-Castro (2013) find that oil prices and exchange rates were not dependent in the pre-crisis period but that this changed to negative dependence with the onset of the crisis. Oil prices are shown to lead exchange rates and vice versa in the crisis period, but not in the pre-crisis period.

In addition to these identifiable fundamental factors, there is significant ongoing discourse over the increasing participation of financial players in the oil markets, and so the impact of speculation on both oil prices and volatility. The diversification benefits of commodities have been argued by many authors (Bodie & Rosansky, 1980; Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006) and as a result, the oil markets, and broader commodity markets, have seen increased financial player participation. The evidence on the effects of speculation is mixed. In some studies, speculation is shown to have a statistically significant effect on price and volatility in oil markets, particularly in the lead up to the historically high oil prices achieved pre-crisis (Cifarelli & Paladino, 2010; Du, Cindy, & Hayes, 2011; Kaufmann & Ullman, 2009; Sornette, Woodard, & Zhou, 2009). In contrast, Büyüksahin and Harris (2011) find no evidence that non-commercial positions, including hedge fund positions, have a causal effect on oil prices. Sanders, Irwin, and Merrin (2010); Irwin and Sanders (2012); Irwin (2013) similarly find no evidence for the influence of speculation across commodity markets, which is corroborated by the surveyed evidence reported by Irwin and Sanders (2011).

In light of this wide and sometimes contradictory literature on the fundamental factors in oil markets, the real challenge with fundamental factor approaches lies in the process of searching out and identifying appropriate variables and then testing their relevance in contemporaneously and dynamically modelling oil price movements. In contrast to fundamental factor approaches, latent factor approaches have been proposed as a purely statistical way of capturing market dynamics. Such methodologies circumvent the need for the explicit identification of fundamental factors. Latent factor approaches have been used to capture the complex movement in commodity forward curves (Casassus & Collin-Dufresne, 2005; Casassus, Liu, & Tang, 2013; Gibson & Schwartz, 1990; Hamilton & Wu, 2014; Schwartz, 1997; Trolle & Schwartz, 2009) and to forecast future oil prices (Cabbibo & Fiorenzani, 2004; Chantziara & Skiadopoulos, 2008); much of the the former literature focused on derivatives pricing and risk management applications. Chantziara and Skiadopoulos (2008) argue that principal component analysis (PCA) provides a parsimonious, non-parametric methodology to describe commodity forward curve dynamics, and should contain full information on the underlying economic drivers of oil prices. In contrast, Heath (2016) argues that real economic activity has material effects on risk premiums and forecasts of oil futures prices, over and above the information in current futures prices.

Linking the two strands of modelling approach remains a gap in the literature to a large extent. Dempster, Medova, and Tang (2012) consider the problem of linking latent factors to economic variables within the context of a proposed three-factor model for spot crude oil prices. Log spot prices are defined as an affine combination of latent short-, medium- and long-term factors, from which an analytic expression for log forward prices is derived as a function of all three factors. Using an EM algorithm combining Kalman filtering and MLE to extract out the latent factors, the authors formally test the relationships of these factors with a range of financial variables (including USD, S&P500, and VIX indices, as studied here), business cycle variables, demand variables, and trading variables. It is shown that the short-term factor links to the demand and trading variables, the medium-term factor links to the business cycle variables, and the long-term factor links to the financial variables. Thus there is some evidence of a link between latent factors and fundamental models as a technique to modelling, however as yet it has not been determined which approach is superior.

Motivated by the work of Dempster et al. (2012), we make a number of contributions. In a first contribution, we conduct a formal model comparison of alternative fundamental factor and latent factor model specifications for oil futures returns. Specifically, for our fundamental factor model, we consider the five factors examined by Andreasson, Bekiros, Nguyen, and Uddin (2016): the S&P 500 index; VIX volatility index; FRED trade-weighted USD currency index; US economic uncertainty index; and Working's T speculation index. For our latent factor model, we employ standard PCA methods to filter out the three most important principal components of the oil forward curve and use these as appropriate latent factors. Given the non-nested nature of the linear model specifications, we employ the non-nested model selection test of Vuong (1989) for our analysis. To the author's knowledge such a formal comparison of fundamental factor and latent factor models has not been conducted to date and so our study fills this gap.

In a second contribution, we conduct our model comparison exercise across the term structure of oil prices to examine whether there is a difference in model fit based on contract maturity. As noted already, Dempster et al. (2012) argue a difference in the factors impacting on the short-, medium- and long-term. Our analysis across the forward curve provides insights into the ability of the respective fundamental and latent factor models to capture term structure movements.

Finally, in a third contribution, we explore the relevance of the speculation factor to the specification of the fundamental factor model for oil prices. Our model comparison set up facilitates an examination of speculation in two ways. Firstly, we drop the speculation variable from the five factor fundamental model and in this four factor setting we re-test against the principal components based model. Any deterioration in the fundamental model fit relative to the principal components model would point to the influence of speculation. Secondly, and more formally, we use the nested model version of the Vuong (1989) test to perform a direct model comparison of the five factor and four factor fundamental models.

For our analysis we consider the continuous monthly WTI futures CL1–CL9, CL12 and CL18 (corresponding to the 1–9, 12 and 18 month maturities respectively), with the sample spanning 10th January 2007 to 4th March 2016. Applying the non-nested model selection test of Vuong (1989) we find that for all contract maturities, the fundamental factor model, whether inclusive of speculation or not, and the latent factor model are equivalent in fit. This finding is relevant as latent factor based linear models have not received the same level of attention as fundamental factor based linear models for oil price modelling, yet there are some clear advantages: avoiding the need to search out and identify appropriate economic factors; avoiding criticisms about omitted variable and/or irrelevant variable bias; and being purely driven by data. As argued by Chantziara and Skiadopoulos (2008), the principal components should contain all of the information contained in the underlying economic variables that actually drive oil prices, and so should capture as much, if not more, information than a well specified fundamental factor model.

A secondary finding from our analysis is that speculation does not emerge as an important factor in the fundamental model specification, despite recent suggestions that it should be included in fundamental models. In our non-nested test involving the four-factor fundamental model, which excludes the speculation variable, we find that this reduced form model specification is also equivalent in terms of model fit to the principal components model. In our direct comparison of the five-factor and four-factor fundamental models, we find no evidence that the former model offers a superior model fit.

The remainder of the paper is organised as follows. Section 2 presents the fundamental factor and latent factor model specifications, along with the technical detail of the Vuong (1989) non-nested model selection test. Section 3 presents the results of our model comparison testing. Section 4 concludes.

2. Modelling and testing methodology

The fundamental factor model we consider is motivated by the analysis of Andreasson et al. (2016). The authors investigate economic, financial and speculation based variables for modelling a range of commodities, including crude oil. Excess speculation, USD exchange rates and S&P 500 equity index returns are all shown to have some form of causal relationship with the commodities considered, with crude oil showing additional relationships with the VIX volatility index and an economic uncertainty index. The economic uncertainty index is an innovative inclusion and is motivated by a set of studies that establish a link between oil price shocks and economic policy uncertainty (Antonakakis, Chatziantoniou, & Filis, 2014; Kang & Ratti, 2013a; Kang & Ratti, 2013b). We use all five factors in our fundamental model specification.

As in Andreasson et al. (2016), excess speculation is captured via the usual Working's T index (Working, 1960) defined as follows:

$$WT = 1 + \frac{SS}{HL + HS} \quad if \quad HS \geq HL$$

$$WT = 1 + \frac{SL}{HL + HS} \quad if \quad HS < HL$$

where SS (SL) is the number of short (long) positions held by speculators and HH (HL) is the number of short (long) positions held by hedgers.

The S&P 500 index is used here, as commonly done, as a barometer of economic activity in the US. Foreign exchange effects are captured via the USD basket of currencies index sourced from Federal Reserve Economic Data (FRED). The trade weighted index comprises the currencies of major economic regions such as the Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden. The VIX index obtained from the CBOE provides a measure of forward looking market volatility, i.e. the market expectation of near-term volatility conveyed by S&P 500 stock index option prices. The Economic Policy Uncertainty Index is that developed by Baker, Bloom, and Davis (2015). The index quantifies economic policy uncertainty based on newspaper coverage frequency. Drawing on 10 leading newspapers in the US,[1] the index is constructed by means of article counts that contain the following trio of word groups: uncertainty or uncertain; economic or economy; and one of the following policy terms: congress, deficit, Federal Reserve, legislation, regulation or White House (including variants like uncertainties, regulatory or the Fed). The raw counts are scaled by the total number of articles in the same newspaper, standardised, and then averaged across the ten papers. The series is then normalised to a mean of 100 from 1985 to 2009, and is continuously updated to the present day at the author's website.[2]

The dynamic fundamental model for oil returns we consider is therefore specified as follows:

$$\Delta CL_t^M + \beta_0 + \beta_{SP500}\Delta \mathrm{SP500}_{t-1} + \beta_{VIX}\Delta \mathrm{VIX}_{t-1} + \beta_{USD}\Delta \mathrm{USD}_{t-1} + \beta_{EPU}\Delta \mathrm{EPU}_{t-1} + \beta_{Spec}\Delta \mathrm{Spec}_{t-1} + \varepsilon_t,$$

where ΔCL denotes the log return of the continuous WTI crude oil (CL) contract of maturity M; $\Delta SP500$ denotes the log return of the S&P 500 index; ΔVIX denotes the log change in the VIX volatility index; ΔUSD denotes the log return of the trade weighted US dollar index; ΔEPU denotes the log change in the economic policy uncertainty index for the US; and $\Delta Spec$ is the change in the Working's T speculation index.

To examine whether speculation is indeed a driving factor of oil prices, we reduce the five-factor fundamental model down by means of excluding the speculation variable. We therefore specify the following nested four-factor fundamental model:

$$\Delta CL_t^M = \beta_0 + \beta_{SP500}\Delta \mathrm{SP500}_{t-1} + \beta_{VIX}\Delta \mathrm{VIX}_{t-1} + \beta_{USD}\Delta \mathrm{USD}_{t-1.} + \beta_{EPU}\Delta \mathrm{EPU}_{t-1} + \varepsilon_t.$$

Any deterioration in the fit of the four factor model relative to the five factor model, as measured against the latent factor model, would point to an important influence of speculation. While this provides indirect evidence on how well specified the two fundamental models are, we go further and conduct a direct model comparison of the models through the nested model version of the test of Vuong (1989).

In contrast to the above, latent factor approaches offer a purely statistical alternative to the objective of oil market modelling. A rationale for such methods is that they circumvent the need for the explicit identification of fundamental factors. PCA is one of the primary tools used for this purpose, providing abstract orthogonalised factors derived directly from the data and reproducing the original correlation matrix of the observed variables (Chantziara & Skiadopoulos, 2008); in our case, the forward curve of oil prices. Chantziara and Skiadopoulos (2008) use PCA in this way and consider the potential of the extracted principal components for forecasting across four commodity markets, including the benchmark WTI and Brent crude oils.

Closely aligned to the Chantziara and Skiadopoulos (2008) method of PCA extraction, but given our focus on crude oil only, we propose the following dynamic latent factor model for oil returns:

$$\Delta CL_t^M = \beta_0 + \beta_{PC1}PC1_{t-1} + \beta_{PC2}PC2_{t-1} + \beta_{PC3}PC3_{t-1} + \varepsilon_t,$$

where $PC1$, $PC2$, $PC3$ denote the first, second and third principal components extracted from the log returns of the futures contracts.

The next section describes the formal model comparison framework and the use of the Vuong test (Vuong, 1989).

2.1. Vuong test of non-nested models

Consider two non-nested (or indeed nested or overlapping) models $F_\theta = \{f(y|z;\theta); \theta \in \Theta\}$ and $G = \{g(y|z;\gamma); \gamma \in \Gamma\}$. Vuong (1989) tests the null hypothesis that the two models are equivalent, in the sense that

$$E^0[\log f(y|z;\theta_*)] = E^0[\log g(y|z;\gamma_*)],$$

against the alternative hypothesis that F_θ is better than G_γ, in the sense that

$$E^0[\log f(y|z;\theta_*)] > E^0[\log g(y|z;\gamma_*)],$$

or the alternative hypothesis that G_γ is better than F_θ, in the sense that

$$E^0[\log f(y|z;\theta_*)] < E^0[\log g(y|z;\gamma_*)].$$

Here $E^0[\cdot]$ is the expectations operator with respect to the true joint distribution of (y,z), and θ_* and γ_* are the pseudo-true values of θ and γ respectively.

[1] The 10 newspaper sources are USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times, and Wall Street Journal.

[2] www.policyuncertainty.com.

Table 1
Descriptive Statistics: WTI CL log-return series.

	Mean	Std Dev	Skew	Kurt
ΔCL1	0.0043%	0.0025	0.3022	5.6212
ΔCL2	0.0025%	0.0024	0.0356	3.7477
ΔCL3	0.0016%	0.0022	−0.0085	3.4223
ΔCL4	0.0013%	0.0022	−0.0113	3.2885
ΔCL5	0.0010%	0.0021	−0.0362	3.2501
ΔCL6	0.0019%	0.0021	−0.0232	3.2661
ΔCL7	0.0014%	0.0020	−0.0172	3.2785
ΔCL8	0.0009%	0.0020	−0.0207	3.2780
ΔCL9	0.0006%	0.0019	−0.0181	3.3825
ΔCL12	0.0014%	0.0018	−0.0301	3.3491
ΔCL18	−0.0011%	0.0017	−0.0736	3.6792

CL1-CL9, CL12 and CL18 are the WTI continuous monthly futures contracts with corresponding 1–9, 12 and 18 month maturities respectively. Δ denotes daily log return.

The appropriate test statistic is the likelihood ratio (LR) for model F_θ against model G_γ defined as

$$LR_n(\theta_n,\gamma_n) \equiv L_n^f(\theta_n) - L_n^g(\gamma_n) = \sum_{t=1}^{n} \log \frac{f(Y_t|Z_t;\theta_n)}{g(Y_t|Z_t;\gamma_n)},$$

where θ_n and γ_n are the maximum likelihood (ML) estimates of θ_* and γ_* respectively. The model selection test proposed by Vuong (1989) states that if F_θ and G_γ are strictly non-nested then

$$\begin{aligned}&\text{under}\, H_0 : LR_n(\theta_n,\gamma_n)/\omega_n\sqrt{n} \to N(0,1)\\&\text{under}\, H_f : LR_n(\theta_n,\gamma_n)/\omega_n\sqrt{n} \to +\infty\\&\text{under}\, H_g : LR_n(\theta_n,\gamma_n)/\omega_n\sqrt{n} \to +-\infty\end{aligned}$$

where H_0 is the null hypothesis that F_θ and G_γ are equivalent

$$H_0 : E^0\left[\log\frac{f(Y_t|Z_t;\theta_*)}{g(Y_t|Z_t;\gamma_*)}\right] = 0$$

tested against the alternative hypotheses H_f that F_θ is better than G_γ

$$H_f : E^0\left[\log\frac{f(Y_t|Z_t;\theta_*)}{g(Y_t|Z_t;\gamma_*)}\right] > 0$$

or H_g that F_θ is worse than G_γ

$$H_g : E^0\left[\log\frac{f(Y_t|Z_t;\theta_*)}{g(Y_t|Z_t;\gamma_*)}\right] < 0.$$

ω_n^2 is the sample analog of the log-likelihood variance $\omega_*^2 \equiv var^0[\log\frac{f(Y_t|Z_t;\theta_*)}{g(Y_t|Z_t;\gamma_*)}]$ defined as follows:

$$\omega_n^2 \equiv \frac{1}{n}\sum_{t=1}^{n}\log\left[\frac{f(Y_t|Z_t;\theta_n)}{g(Y_t|Z_t;\gamma_n)}\right]^2 - \left[\frac{1}{n}\sum_{t=1}^{n}\log\frac{f(Y_t|Z_t;\theta_n)}{g(Y_t|Z_t;\gamma_n)}\right]^2,$$

which is used in the variance test of Vuong (1989) to discriminate

Table 2
Descriptive statistics: fundamental variables.

	Mean	Std Dev	Skew	Kurt
Δ*SP*500	0.00019%	0.0134	−0.3554	8.0117
Δ*VIX*	0.00309%	0.0773	1.3242	5.9370
Δ*USD*	0.00006%	0.0049	−0.3509	4.3325
Δ*EPU*	0.06711%	0.5855	3.3724	28.2354
Spec	1.11873%	0.0361	0.7540	0.7308

*SP*500 is the S&P 500 index, *VIX* is the VIX volatility index, *USD* is the trade weighted US dollar index, *EPU* is the economic policy uncertainty index for the US, and *Spec* is the speculation variable, defined here as the Working's T index (see Section 2). Δ denotes daily log return/log change.

Table 3
Five-factor fundamental model: regression results.

	β_0	β_{SP500}	β_{VIX}	β_{USD}	β_{EPU}	β_{Spec}
CL1	−0.0177	0.2504***	0.0202*	0.4125***	0.0005	0.0157
	(0.0165)	(0.0610)	(0.0104)	(0.1099)	(0.0009)	(0.0147)
CL2	−0.0149	0.2031***	0.0165*	0.2953***	−0.0001	0.0132
	(0.0152)	(0.0564)	(0.0096)	(0.1016)	(0.0008)	(0.0136)
CL3	−0.0139	0.2040***	0.0152	0.2484**	−0.0002	0.0124
	(0.0146)	(0.0539)	(0.0092)	(0.0972)	(0.0008)	(0.0130)
CL4	−0.0129	0.2048***	0.0151*	0.2105**	−0.0003	0.0115
	(0.0146)	(0.0539)	(0.0092)	(0.0972)	(0.0008)	(0.0130)
CL5	−0.0116	0.2072***	0.0145*	0.1953**	−0.0003	0.0104
	(0.0136)	(0.0504)	(0.0086)	(0.0909)	(0.0008)	(0.0122)
CL6	−0.0106	0.2060***	0.0143*	0.1716*	−0.0004	0.0094
	(0.0133)	(0.0491)	(0.0084)	(0.0884)	(0.0007)	(0.0118)
CL7	−0.0097	0.2075***	0.0139*	0.1704**	−0.0004	0.0084
	(0.0130)	(0.0480)	(0.0082)	(0.0865)	(0.0007)	(0.0116)
CL8	−0.0091	0.2124***	0.0160**	0.1517*	−0.0003	0.0081
	(0.0127)	(0.0470)	(0.0080)	(0.0847)	(0.0007)	(0.0113)
CL9	−0.0083	0.1725***	0.0107	0.1359	−0.0002	0.0074
	(0.0124)	(0.0459)	(0.0079)	(0.0828)	(0.0007)	(0.0111)
CL12	−0.0065	0.2032***	0.0138*	0.1357*	−0.0002	0.0058
	(0.0117)	(0.0433)	(0.0074)	(0.0780)	(0.0006)	(0.0104)
CL18	−0.0032	0.1897***	0.0107	0.1157	−0.0003	0.0028
	(0.0107)	(0.0397)	(0.0068)	(0.0715)	(0.0006)	(0.0096)

Regression results for the five-factor fundamental model specified as follows: $\Delta CL_t^M = \beta_0 + \beta_{SP500}\Delta SP500_{t-1} + \beta_{VIX}\Delta VIX_{t-1} + \beta_{USD}\Delta USD_{t-1} + \beta_{EPU}\Delta EPU_{t-1} + \beta_{Spec}\Delta Spec_{t-1} + \varepsilon_t$ where Δ*CL* denotes the log return of the continuous WTI crude oil (CL) contract of maturity M; Δ*SP*500 denotes the log return of the S&P 500 index; Δ*VIX* denotes the log change in the VIX volatility index; Δ*USD* denotes the log return of the trade weighted US dollar index; Δ*EPU* denotes the log change in the economic policy uncertainty index for the US; and Δ*Spec* is the change in the speculation variable, defined here as the Working's T index (see Section 2). Standard errors in parenthesis.
*** Denotes statistical significance at 1%.
** Denotes statistical significance at 5%.
* Denotes statistical significance at 10%.

Table 4
Four-factor fundamental model: regression results.

	β_0	β_{SP500}	β_{VIX}	β_{USD}	β_{EPU}
CL1	−0.0001	0.2482***	0.0198*	0.4117***	0.0004
	(0.0005)	(0.0609)	(0.0104)	(0.1099)	(0.0009)
CL2	−0.0001	0.2013***	0.0162*	0.2946***	−0.0001
	(0.0005)	(0.0563)	(0.0096)	(0.1016)	(0.0008)
CL3	−0.0001	0.2023***	0.0149	0.2477**	−0.0002
	(0.0005)	(0.0539)	(0.0092)	(0.0972)	(0.0008)
CL4	−0.0001	0.2032***	0.0149*	0.2099**	−0.0003
	(0.0005)	(0.0521)	(0.0089)	(0.0940)	(0.0008)
CL5	−0.0001	0.2057***	0.0143*	0.1948**	−0.0003
	(0.0004)	(0.0504)	(0.0086)	(0.0909)	(0.0007)
CL6	−0.0000	0.2047***	0.0141*	0.1711*	−0.0005
	(0.0004)	(0.0490)	(0.0084)	(0.0884)	(0.0007)
CL7	−0.0000	0.2063***	0.0137*	0.1700**	−0.0005
	(0.0004)	(0.0480)	(0.0082)	(0.0865)	(0.0007)
CL8	−0.0001	0.2113***	0.0158**	0.1512*	−0.0003
	(0.0004)	(0.0470)	(0.0080)	(0.0847)	(0.0007)
CL9	−0.0001	0.1715***	0.0105	0.1355	−0.0002
	(0.0004)	(0.0459)	(0.0079)	(0.0828)	(0.0007)
CL12	−0.0001	0.2024***	0.0136*	0.1354*	−0.0003
	(0.0004)	(0.0432)	(0.0074)	(0.0780)	(0.0006)
CL18	−0.0001	0.1893***	0.0107	0.1155	−0.0003
	(0.0003)	(0.0396)	(0.0068)	(0.0715)	(0.0006)

Regression results for the four-factor fundamental model specified as follows: $\Delta CL_t^M = \beta_0 + \beta_{SP500}\Delta SP500_{t-1} + \beta_{VIX}\Delta VIX_{t-1} + \beta_{USD}\Delta USD_{t-1} + \beta_{EPU}\Delta EPU_{t-1} + \varepsilon_t$ where Δ*CL* denotes the log return of the continuous WTI crude oil (CL) contract of maturity M; Δ*SP*500 denotes the log return of the S&P 500 index; Δ*VIX* denotes the log change in the VIX volatility index; Δ*USD* denotes the log return of the trade weighted US dollar index; and Δ*EPU* denotes the log change in the economic policy uncertainty index for the US (see Section 2). Standard errors in parenthesis.
*** Denotes statistical significance 1%.
** Denotes statistical significance 5%.
* Denotes statistical significance at 10%.

Table 5
Principal component variance statistics.

	PC1	PC2	PC3
Standard deviation	0.0680	0.0113	0.0052
Proportion of variance	0.9637	0.0267	0.0056
Cumulative proportion	0.9637	0.9903	0.9959

between two models if not equivalent in the sense that $f(\cdot|\cdot;\theta_*)\neq g(\cdot|\cdot;\gamma_*)$. The associated hypotheses are $H_0^\omega:\omega_*{}^2=0$ versus $H_A^\omega:\omega_*{}^2\neq 0$.

The implementation of the Vuong (1989) test is quite straightforward involving selecting an appropriate critical value c from the standard normal distribution. When the test statistic $LR_n(\theta_n,\gamma_n)/\omega_n\sqrt{n}$ is higher than c then F_θ is deemed the better model, when it is lower than $-c$ then G_γ is deemed the better model, and when it lies in the intermediate region one cannot discriminate between the two models.

3. Empirical results

For our analysis, we use the continuous monthly contracts CL1–CL9, CL12 and CL18 obtained from the CME. These contracts span the 1–9, 12 and 18 month maturities and allow us to consider a range of short-, medium- and long-term movements in the WTI forward curve. For the model comparison exercise to follow, this gives sufficient flexibility to examine whether there is a difference in model fit based on contract maturity. The sample covers the period 10th January 2007 to 4th March 2016, observed daily. Table 1 provides summary statistics for the CL log returns series. Table 2 provides summary statistics for the five fundamental variables considered in our study.

Tables 3 and 4 present the regression results for the five-factor and four-factor fundamental models respectively. Notable in the former case is that speculation is not found to be statistically significant for any of the maturities considered. Economic uncertainty likewise is also found not to have a statistically significant effect on next period oil returns across the term structure. When speculation is dropped in the four-factor case, no effect from economic uncertainty is again observed. The speculation finding aligns with the linear causality testing of Andreasson et al. (2016), who find no causality in either direction between speculation and oil returns. In contrast though to our finding on economic uncertainty, Andreasson et al. (2016) confirm a causal effect of this variable on oil returns. However, our result is found to be consistent for all maturities considered.

Broad equity performance, as a proxy for overall economic activity, can be seen to be a consistent driving factor of oil prices across the contract maturities, having a positive effect. Market volatility and USD currency exposure are also found to be statistically significant, although the positive effects reported are not observed across the entire forward curve. In fact, up to eight months both factors play a role, while the effects thereafter are only seen for the 12-month contract maturity. For the medium-term CL9 and the long-term CL18 contracts neither factor seems to emerge as having an influence.

For the latent factor model, Table 5 first provides the variance statistics for the first three principal components extracted from the forward returns data. The first principal component explains 96.4% of the variance, with the cumulative proportion rising to 99% with the inclusion of the second principal component and to 99.6% with the further inclusion of the third principal component. Table 6 reports the regressions results for the latent factor model specification based off these three estimated principal components.

Notable in the findings is that the first principal component emerges as being a statistically significant driver of oil returns for all maturities. Only for CL2 does the second principal component appear to be relevant, while only for CL1 does the third principal component display significance. This contrasts starkly with the analysis of Chantziara and Skiadopoulos (2008). While their analysis is broader in scope, in that a

Table 6
Latent factor model: regression results.

	β_0	β_{PC1}	β_{PC2}	β_{PC3}
CL1	0.0000	−0.0247***	0.0577	0.2888***
	(0.0005)	(0.0078)	(0.0469)	(0.1024)
CL2	0.0000	−0.0267***	0.0919***	0.0752
	(0.0005)	(0.0072)	(0.0433)	(0.0945)
CL3	0.0000	−0.0237***	0.0624	0.1104
	(0.0005)	(0.0069)	(0.0415)	(0.0905)
CL4	0.0000	−0.0222***	0.0500	0.1097
	(0.0005)	(0.0067)	(0.0401)	(0.0876)
CL5	0.0000	−0.0205***	0.0435	0.1081
	(0.0004)	(0.0065)	(0.0388)	(0.0847)
CL6	0.0000	−0.0185***	0.0293	0.1167
	(0.0004)	(0.0063)	(0.0378)	(0.0825)
CL7	0.0000	−0.0187***	0.0381	0.1157
	(0.0004)	(0.0062)	(0.0370)	(0.0807)
CL8	0.0000	−0.0184***	0.0281	0.0999
	(0.0004)	(0.0060)	(0.0362)	(0.0790)
CL9	0.0000	−0.0177***	0.0233	0.0949
	(0.0004)	(0.0059)	(0.0354)	(0.0771)
CL12	0.0000	−0.0158***	0.0085	0.0732
	(0.0003)	(0.0056)	(0.0334)	(0.0728)
CL18	−0.0000	−0.0132***	−0.0081	0.0199
	(0.0003)	(0.0051)	(0.0306)	(0.0668)

Regression results for the latent factor model specified as follows: $\Delta CL_t^M=\beta_0+\beta_{PC1}PC1_{t-1}+\beta_{PC2}PC2_{t-1}+\beta_{PC3}PC3_{t-1}+\varepsilon_t$, where $PC1$, $PC2$, $PC3$ denote the first, second and third principal components extracted from the log returns of the WTI futures contracts (see Section 2). Standard errors in parenthesis.
*** Denotes statistical significance at 1%.
** Denotes statistical significance at 5%.
* Denotes statistical significance 10%.

Table 7
Vuong test results.

	F_θ:PC v G_θ:5F			F_θ:PC v G_θ:4F		
	$H_0^\omega;H_A^\omega$	$H_0;H_f$	$H_0;H_g$	$H_0^\omega;H_A^\omega$	$H_0;H_f$	$H_0;H_g$
CL1	0.04	−0.46		−0.07	−0.41	
	(0.051)	(0.676)	(0.324)	(0.050)	(0.658)	(0.342)
CL2	−0.02	−0.09		0.24	−0.04	
	(0.047)	(0.534)	(0.466)	(0.046)	(0.516)	(0.484)
CL3	−0.48	−0.28		−0.36	−0.24	
	(0.044)	(0.610)	(0.390)	(0.044)	(0.594)	(0.406)
CL4	−0.21	−0.36		−0.55	−0.32	
	(0.045)	(0.640)	(0.360)	(0.044)	(0.625)	(0.375)
CL5	0.05	−0.50		0.31	−0.47	
	(0.048)	(0.691)	(0.309)	(0.047)	(0.680)	(0.320)
CL6	−0.07	−0.61		0.18	−0.58	
	(0.047)	(0.729)	(0.271)	(0.047)	(0.720)	(0.280)
CL7	−0.24	−0.61		−0.47	−0.59	
	(0.052)	(0.730)	(0.270)	(0.051)	(0.723)	(0.277)
CL8	−0.07	−0.65		0.19	−0.63	
	(0.053)	(0.743)	(0.257)	(0.052)	(0.737)	(0.263)
CL9	0.26	−0.45		−0.44	−0.43	
	(0.041)	(0.675)	(0.325)	(0.041)	(0.668)	(0.332)
CL12	0.23	−0.87		0.33	−0.86	
	(0.056)	(0.807)	(0.193)	(0.056)	(0.804)	(0.196)
CL18	0.36	−1.10		0.19	−1.10	
	(0.058)	(0.864)	(0.136)	(0.058)	(0.864)	(0.136)

Results for the variance test and non-nested model selection test of (Vuong, 1989). The variance test is used to discriminate between two models, F_θ and G_γ, if not equivalent in the sense that $f(\cdot|\cdot;\theta_*)\neq g(\cdot|\cdot;\gamma_*)$. The associated hypotheses are $H_0^\omega:\omega_*{}^2=0$ versus $H_A^\omega:\omega_*{}^2\neq 0$, where ω_* is the log-likelihood variance. See Section 2.1 for details. The non-nested model selection test tests the null hypothesis that F_θ and G_γ are equivalent, $H_0:E^0\left[\log\frac{f(Y_t|Z_t;\theta_*)}{g(Y_t|Z_t;\gamma_*)}\right]=0$, against the alternative hypotheses that F_θ is better than G_γ, $H_f:E^0\left[\log\frac{f(Y_t|Z_t;\theta_*)}{g(Y_t|Z_t;\gamma_*)}\right]>0$, or that F_θ is worse than $G\gamma$, $H_g:E^0\left[\log\frac{f(Y_t|Z_t;\theta_*)}{g(Y_t|Z_t;\gamma_*)}\right]<0$. See Section 2.1 for details. We designate F_θ to be the latent (PC) factor model and $G\gamma$ to be either the five-factor (5F) or four-factor (4F) fundamental model. P-values in parenthesis.

Table 8
Vuong AIC and BIC confidence intervals: latent (PC) factor v five-factor (5F) models.

	BIC PC	BIC 5F	95% CI lower	95% CI upper	AIC PC	AIC 5F	95% CI lower	95% CI upper
CL1	−10,270.5	−10,264.9	−47.8	36.5	−10,299.2	−10,305.0	−36.3	48.0
CL2	−10,638.7	−10,625.0	−54.2	26.8	−10,667.4	−10,665.2	−42.8	38.3
CL3	−10,837.7	−10,827.9	−49.3	29.7	−10,866.4	−10,868.0	−37.8	41.1
CL4	−10,986.2	−10,978.0	−48.1	31.7	−11,014.9	−11,018.1	−36.6	43.2
CL5	−11,137.8	−11,132.8	−46.0	35.8	−11,166.5	−11,172.9	−34.5	47.3
CL6	−11,261.0	−11,258.2	−43.5	38.0	−11,289.7	−11,298.3	−32.1	49.4
CL7	−11,361.9	−11,359.8	−44.7	40.4	−11,390.6	−11,399.9	−33.2	51.9
CL8	−11,456.7	−11,455.6	−44.2	41.9	−11,485.4	−11,495.7	−32.7	53.4
CL9	−11,565.4	−11,558.8	−44.7	31.3	−11,594.1	−11,598.9	−33.2	42.8
CL12	−11,829.0	−11,833.2	−40.3	48.7	−11,857.7	−11,873.4	−28.8	60.1
CL18	−12,220.4	−12,230.2	−35.3	54.9	−12,249.1	−12,270.4	−23.8	66.4

95% CI lower and 95% CI upper respectively denote the lower and upper 95% confidence intervals for the AIC/BIC statistic, consistent with the theory of Vuong (1989).

more expansive twelve-latent factor model is considered using the first three principal components extracted from each of WTI, Brent, (NYMEX) heating oil and (NYMEX) gasoline futures returns, the authors report that it is only the third principal component derived from Brent returns, rather than WTI returns, that explains movements in WTI, and this is only evidenced for the intermediate CL3–CL5 contracts. The effect of the first principal component in our case is consistently observed across all maturities.

We proceed now to the formal model comparison exercise using the non-nested test of Vuong (1989)).[3] For completeness, we initially implement the variance test as proposed by Vuong (1989) to confirm that the two model specifications are not equivalent in the conditional density sense as outlined in Section 2.1. The results of the variance and non-nested model selection tests are presented in Table 7.

From the variance test results it can be seen that, whether comparing the principal component model against the five-factor or four-factor fundamental model, the competing models are deemed to be distinguishable, in the sense that the respective conditional densities are not equivalent; this is found at the 5% or 10% significance level across contract maturity, although in the latter case the *p*-values are marginally outside the 5% threshold. This justifies and prompts our use of the Vuong (1989) non-nested test of model selection in the next step. In all cases, without exception, the latent factor model and fundamental factor model, whether inclusive of speculation or not, appear to have equal fit to the population. The reported *p*-values exceed the 10% threshold and so we fail to reject the null hypothesis that the models are equivalent.

To explore the robustness of this finding, and in an attempt to discriminate between the two models, we generate confidence intervals for the model AIC and BIC statistics that are consistent with the Vuong (1989) theory. The 95% confidence intervals are presented in Tables 8 and 9; the former involving the five-factor fundamental model, the latter involving the four-factor fundamental model. Here again it can be observed that the models are not distinguishable in terms of fit, and so one cannot be selected over the other in each pairwise case. We therefore conclude with confidence that there is no discernible distinction between our fundamental factor and latent factor specification in capturing movement in WTI crude oil prices.

This model comparison finding is significant given the fundamentally different approaches taken to modelling oil prices. In particular, while latent factor based linear models have not received the same level of attention as fundamental factor based linear models for oil price modelling, there as some clear advantages: avoiding the need to search out and identify appropriate economic factors; in so doing, avoiding criticisms about omitted variable and/or irrelevant variable bias; and being purely driven by data. In principle, the principal components should contain all of the information contained in the underlying economic variables (Chantziara & Skiadopoulos, 2008) that drive oil prices, and so should in theory capture as much, if not more, information than a well specified fundamental factor model.

As a secondary finding, it is notable that there is no notable distinction between the five-factor fundamental model and the four-factor counterpart, which excludes the speculation variable. This gives some indirect evidence to the absence of a role for speculation in driving oil prices. Given that this evidence is indirect in nature, we complete our analysis in this section with a direct application of the nested Vuong (1989) test to the two model specifications. Table 10 presents the results. The variance test shows that the five-factor and four-factor models are distinguishable, in the sense that the models respective conditional densities are not equivalent. However, the nested test results show that, for almost all maturities, we fail to reject the null hypothesis that the five-factor and four-factor models are indistinguishable. Only in the case of the 18-month maturity contract is the five-factor model deemed a better fit; this being concluded at the 10% significance level. So we conclude overall that speculation does not have a significant influence on oil futures prices.

4. Conclusion

In this study, we conduct a formal model comparison of fundamental factor and latent factor modelling approaches to capturing oil market movements. To the author's knowledge such a formal comparison has not been conducted to date and so our study fills this gap. We additionally contribute by means of conducting our model comparison exercise across the term structure of oil prices to examine whether there is a difference in model fit based on contract maturity. Prior literature (Dempster et al., 2012) suggests that different factors impact on the short-, medium- and long-term, and so our analysis across the forward curve provides insights into the ability of the respective fundamental and latent factor models to capture these term structure movements. In a final contribution, we use our model comparison setting to formally test whether speculation is a fundamental factor affecting oil prices.

We find the fundamental factor model and latent factor model specifications to be of equal fit to the overall population of oil futures prices. This finding is significant given the fundamentally different

[3] The Vuong (1989) test is implemented in R using the *nonnest2* package. The package guide is available at https://cran.r-project.org/web/packages/nonnest2/nonnest2.pdf. Supporting documentation describing implementation and interpretation is available at https://cran.r-project.org/web/packages/nonnest2/vignettes/nonnest2.pdf.

Table 9
Vuong AIC and BIC Confidence Intervals: Latent (PC) Factor v Four-Factor (4F) Models.

	BIC PC	BIC 4F	95% CI lower	95% CI upper	AIC PC	AIC 4F	95% CI lower	95% CI upper
CL1	−10,270.5	−10,271.5	−40.9	42.8	−10,299.2	−10,305.9	−35.1	48.5
CL2	−10,638.7	−10,631.8	−47.2	33.3	−10,667.4	−10,666.2	−41.4	39.1
CL3	−10,837.7	−10,834.7	−42.1	36.1	−10,866.4	−10,869.1	−36.4	41.9
CL4	−10,986.2	−10,984.9	−40.8	38.2	−11,014.9	−11,019.3	−35.1	44.0
CL5	−11,137.8	−11,139.8	−38.6	42.5	−11,166.5	−11,174.2	−32.9	48.2
CL6	−11,261.0	−11,265.3	−36.1	44.7	−11,289.7	−11,299.7	−30.4	50.5
CL7	−11,361.9	−11,366.9	−37.2	47.3	−11,390.6	−11,401.3	−31.5	53.0
CL8	−11,456.7	−11,462.8	−36.7	48.9	−11,485.4	−11,497.2	−31.0	54.6
CL9	−11,565.4	−11,566.0	−37.1	38.3	−11,594.1	−11,600.4	−31.4	44.1
CL12	−11,829.0	−11,840.7	−32.7	55.9	−11,857.7	−11,875.1	−26.9	61.7
CL18	−12,220.4	−12,237.9	−27.6	62.5	−12,249.1	−12,272.3	−21.8	68.2

95% CI lower and 95% CI upper respectively denote the lower and upper 95% confidence intervals for the AIC/BIC statistic, consistent with the theory of Vuong (1989).

approaches taken to modelling oil prices. Latent factor models, which have received much less attention in the literature, outside of derivatives applications, offer real merit it seems relative to the popular approach of fundamental modelling. In particular, latent factor models avoid the need to search out and identify appropriate economic factors, in so doing avoid criticisms about omitted variable and/or irrelevant variable bias, and are accessible and easily implemented being purely driven by the data of interest. In principle, the principal components should contain all of the information contained in a well specified fundamental factor model.

The novelty of our study is the formal model comparison of fundamental factor and latent factor approaches. The work should motivate further research to appraise the two alternative strands of modelling, using an extended range of fundamental and latent factors. This should be performed on a more expansive cross-commodity basis to see if the findings observed here hold across markets.

Table 10
Vuong nested test results: five-factor v four-factor fundamental models.

	F_θ:5F v G_γ:4F	
	$H_0^\omega;H_A^\omega$	$H_0^{nested};H_A^{nested}$
CL1	−0.07	0.23
	(0.00)	(1.00)
CL2	−0.18	−0.58
	(0.00)	(0.95)
CL3	0.72	−0.07
	(0.00)	(0.91)
CL4	0.13	0.01
	(0.00)	(0.83)
CL5	0.01	−0.28
	(0.00)	(0.72)
CL6	−0.12	0.02
	(0.00)	(0.63)
CL7	−0.12	0.10
	(0.00)	(0.56)
CL8	−0.34	0.00
	(0.00)	(0.51)
CL9	−0.01	−0.05
	(0.00)	(0.44)
CL12	0.60	0.25
	(0.00)	(0.30)
CL18	−0.07	0.00
	(0.00)	(0.08)

Results for the variance test and nested model selection test of Vuong (1989). The variance test is used to discriminate between two models, F_θ and G_γ, if not equivalent in the sense that $f(\cdot|\cdot;\theta_*)\neq g(\cdot|\cdot;\gamma_*)$. The associated hypotheses are $H_0^\omega:\omega_*{}^2=0$ versus $H_A^\omega:\omega_*{}^2\neq 0$, where ω_* is the log-likelihood variance. See Section 2.1 for details. The nested model selection test tests the null hypothesis H_0^{nested} that G_γ fits as well as F_θ against the alternative hypothesis H_A^{nested} that F_θ fits better than G_γ. We designate F_θ to be the five-factor (5F) fundamental model and G_γ to be the four-factor (4F) fundamental model. *P*-values in parenthesis.

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