



Explaining the convenience yield in the WTI crude oil market using realized volatility and jumps[☆]



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ARTICLE INFO

Article history:

Accepted 14 October 2014

Available online 10 November 2014

Keywords:

Convenience yield

Realized volatility

Jump

Inventory

ABSTRACT

In this paper, we first provide an empirical evidence of the existence of intraday jumps in the crude oil price series. We then show that these jumps, in conjunction with realized volatility measures, are important in modeling the convenience yield over the 2001–2010 period. Our empirical results indicate that lagged jump mean only explains around 16% of the weekly convenience yield. Our best specification, including variation in inventories, 8-week realized variance and the 250-day jump mean is able to explain around 61% of the weekly convenience yield. Importantly, our results are not driven by the simultaneous determination of the various variables at work as we only use lagged variables in all regressions.

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1. Introduction

Our paper aims at modeling the convenience yield using measures of volatility and jumps computed using intraday data in the WTI oil futures market. We add these new measures to other measures previously used in the literature (see Pindyck (2004)) such as the 5-week moving average of volatility computed using daily returns, as well as inventory level and shocks to the spot price. We provide evidence that intraday data are helpful in modeling the 1-month convenience yield and that the distinction between volatility and jumps further increases the explanatory power.

Recent mathematical finance literature suggest to model the convenience yield as a mean-reverting process (see Gibson and Schwartz (1990), Schwartz (1997), Hilliard and Reis (1998), Schwartz and Smith (2000) and Casassus and Collin-Dufresne (2005) among the most representative contributions). Liu and Tang (2011) propose an affine model for the oil price with three state variables (spot price, interest rate, and the convenience yield). Their model is able, among other things, to capture an essential characteristic of oil futures, i.e. the positive relationship between volatility and the convenience yield. Mirantes et al. (2013) develop a four-factor model and emphasize the seasonal feature of the convenience yield in addition of its stochastic behavior.

The stochastic nature of the convenience yield calls attention to its modeling, what we attempt in the present paper. Gorton et al. (2013) show that the convenience yield is a decreasing and non-linear function

of inventories. As such, inventories may have predictive power for the convenience yield. Also, Pindyck (1994, 2001, 2004) shows that the convenience yield should be a function of the level of spot price, the level of inventories and the level of volatility.¹ Because all these variables are jointly determined, we only use in our empirical applications lagged explanatory variable to avoid the simultaneity issue. Other papers modeling the convenience yield using similar variables are Chiou Wei and Zhu (2006) and Borak et al. (2006), but none use realized measures and their explanatory variable for the volatility component is generally not significant.

This paper is the first to model the convenience yield using the rich information in high-frequency data. The existing work uses at best daily data. Because realized estimators provide a more robust measure of the latent volatility, we expect to improve the empirical results by using these estimates. As such, we extend the analysis in Pindyck (1994, 2004).² In addition, we distinguish between the information in the continuous component and the jump component from high-frequency prices. This distinction has proven to be very useful in the volatility forecasting literature (see Andersen et al. (2007)) and we investigate its usefulness here for modeling the convenience yield.

We consider the weekly 1-month convenience yield for the most traded commodity futures contract in the world, namely the WTI crude oil futures from CME-NYMEX. Our main results are as follows. First, realized volatility measures computed over the last i weeks for

[☆] This research was initiated while the author was a visiting scholar at the London Business School (MSO Department), whose support and hospitality have been greatly appreciated. Comments by Derek Bunn are gratefully acknowledged as well as the very detailed comments by an anonymous referee which help to improve significantly the paper.

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¹ The general relationship between inventories, volatility, prices and the convenience yield is nicely presented in Geman (2005), but using informal arguments. Knittel and Pindyck (2013) and earlier references cited therein provide theoretical support for such a relationship.

² In contrast with Pindyck (1994), Pindyck (2004) explicitly takes account for price volatility as a factor determining the convenience yield.

$i = 1, \dots, 8$ have a good explanatory power, better than the 5-week measure using daily data in Pindyck (2004) when i equals 5 or above. Second, the explanatory power of the jump mean statistic alone is around 16%. As jumps are representative of large and rapid changes in oil futures prices, our results point to a relationship between large intraday returns (jumps) and the convenience yield. As the latter describes needs and expectations of economic agents in the oil market, our study partly explains how investors react to large changes in oil futures prices through their trading strategy.

Our finding about the existence of a relationship between the 1-month convenience yield and lagged volatility and jumps has implications for the modeling of oil returns. Indeed, two- or three-factor models now systematically include the convenience yield risk as a risk factor to fit futures price data better.³ As we show that the convenience yield risk is related to other risk factors such as jump and volatility risk, these risks should not be modeled independently from the convenience yield risk any more as is often the case in stochastic modeling of energy prices.

As a further implication, it should be emphasized that if a stochastic convenience yield leads to market incompleteness as pointed out in Geman (2005) then the link between volatility (or jumps) and the convenience yield may help to implement optimal hedging strategies using the existing instruments such as the oil volatility index (OVX) that has been developed to track the model-free implied volatility for the WTI oil market. These hedging strategies would be developed on the basis of a statistical relationship between volatility and the convenience yield and would help to reduce the overall price exposure when no financial instrument exists to specifically deal with the convenience yield risk. This kind of strategy, coined as “cross-hedging”, relates to the early contribution of Anderson and Danthine (1981), where the authors show how an optimal hedging policy can be implemented using hedging tools whose underlying asset is not the same as the asset for which the original risk is bear.⁴

Our results may also be of interest for policy-makers as we emphasize a link between the volatility (and jumps) and the future convenience yield. Recall that the convenience yield is determined on the basis of the subsequent futures prices. Our results thus show that volatility and jumps play a major role in explaining the term structure on the oil market. Moreover, the volatility has explanatory power for the future storage policy by firms as this storage policy explains the price gap between futures contracts of different maturities. Policy-makers may then influence the storage policy of firms in periods of high volatility, where the convenience is expected to increase, by managing oil strategic reserves according to their objectives.

1.1. Relevant literature

Following the recent availability of intraday data for most existing financial markets, and in particular commodity markets, recent research has investigated various properties of oil financial markets using this data. Wang et al. (2008) investigate the distributional properties of realized volatility and standardized returns in the WTI futures market over the 1995–1999 period. Tseng et al. (2009) use pseudo long memory time series models to evaluate the contribution of jumps to forecasting the conditional volatility in the WTI futures market for the 2000–2007 period. More recently, Liu and Wan (2012) study the long-range dependence in the Shanghai fuel oil futures market over the 2004–2011 period and emphasize the role of tick-by-tick data to forecasting conditional volatility. The authors also highlight the role of trader activity which has a very significant impact on the level of volatility in the futures market. Chevallier and Sévi (2012) empirically study the volatility–volume

relationship using intraday data and show the role of jumps in bearing this relation over the period 2006–2010. Sévi (2014) provides an extensive study of the predictive properties of various HAR-class models for long 1987–2010 period and shows that the basic HAR model provides very good forecast performance out-of-sample relatively to more sophisticated models, thereby questioning the interest to disentangle the jump component from the continuous component for the purpose of forecasting oil price volatility. Finally, Baum and Zerilli (2013) use nonparametric estimates of jumps in the WTI oil markets to estimate the parameters of a continuous-time stochastic volatility model with jumps. The authors provide strong empirical evidence of the importance of jumps in adequately modeling the oil return process.

Other papers have investigated the issue of jumps using daily data. Those papers are Askari and Krichene (2008), Lee et al. (2010) and Gronwald (2012). Askari and Krichene (2008) estimate the various components of a stochastic process and provide evidence of jumps. Lee et al. (2010) and Gronwald (2012) investigate and estimate the presence of jumps relying on the methodology in Chan and Maheu (2002). Our paper improves upon these last two by using nonparametric methods along with intraday data.

Our measures of jump distribution use the recent contribution by Tauchen and Zhou (2010) who suggest to use the characteristics of the distribution of jumps to predict credit spreads. To our best knowledge, these tools have only been used in Wright and Zhou (2009), Zhang et al. (2009) and Evans (2011) to date. The idea behind these papers is that characteristics of jump distribution may be helpful in explaining some financial variables such as credit spread (at the aggregate or firm level) or the bond premia because the returns are a function of agents' aversion to large losses. We use the same measures as in Tauchen and Zhou (2010) along with measures of realized volatility to model the 1-month convenience yield.

Symeonidis et al. (2012) provide empirical evidence of the relationship between inventory and the shape of the forward curve. The convenience yield is related to the forward curve and, as such, the authors also analyze the link between inventory and the convenience yield. The authors also highlight the relationship between inventory and conditional volatility. In our investigation of the predictive properties of various predictors of the convenience yield, we also explore the forecasting performance of inventory and volatility. However, we distinguish between the continuous component and the jump component to enrich our set of predictors.

The convenience yield is also included in dynamic models of the oil storage as in Pieroni and Ricciarelli (2008) who extend the Pindyck (1994, 2001) model. Because all the variables such as the price, the volatility, the convenience yield and the inventory level are endogenously determined, we use lagged variables to deal with the issue of simultaneity.

In the next Section, we provide some details about the econometric approach. Section 3 presents the main empirical findings of our regression analysis and discusses some robustness checks that we also computed. Section 4 provides some concluding remarks and suggestions for future research about the empirical properties of the convenience yield.

2. Empirical approach

We present in this Section how we estimate realized quantities that will be used in the next Section for regression analysis. We first develop the concept of bi-power variation which is used along with realized volatility to detect jumps. Next, we explain the computation of jumps statistics.

2.1. Detecting jumps in oil returns

Jumps are defined as large returns that could be of interest to investors that face the convenience yield risk in commodity markets.

³ Convenience yield risk refers to the risk of change in the convenience yield level, not the risk related to the volatility of the convenience yield which is a very different concept.

⁴ The idea here would be to hedge the convenience yield risk using oil volatility futures (futures on OVX) exploiting the existing correlation between the convenience yield and the oil volatility that we highlight in the present study.

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