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Risk premium, price of risk and expected volatility in the oil market: evidence from survey data

Georges Prat * and Remzi Uctum *†

* EconomiX, CNRS/University Paris Nanterre, France
 † Corresponding author

Abstract – This paper contributes to the literature on crude oil risk premiums by providing ex-ante measures of these premiums using survey oil price expectations over an extended period. These ex-ante premiums are uncorrelated with ex-post premiums commonly used in existing studies, whereas they are more relevant as they directly influence investors' decision-making. Utilizing a portfolio choice model, we explain the ex-ante premium as the product of the price of risk and the expected variance, both varying over time and across horizons. We estimate this relationship using a multivariate state-space framework. From our estimated risk prices we find, on average, that investors exhibit risk-seeking behavior in the short term and risk aversion in the long term. It follows that the term structure of oil risk premiums are prominently upward-sloping. Additionally, consistent with the prospect theory, investors are found to be predominantly risk averse in a context of expected gains and risk-seeking in a context of expected losses. Finally, the dynamics of risk prices are shown to be driven by identifiable economic, financial, and oil market-related factors.

Keywords: oil price expectations, ex-ante oil risk premium, survey data, prospect theory **JEL classification :** D81, G11, Q43

[†] Corresponding author: Remzi Uctum, EconomiX, CNRS/University Paris Nanterre, 200 av.
de la République 92001 Nanterre, France, <u>uctum@parisnanterre.fr</u>, +33 623766635.

1. Introduction

Using futures contracts to hedge oil price risk, commercial producers in the oil market offer to speculators and arbitrageurs, who are the counterparties of these contracts, an income to offset the risk they bear. This compensation is the oil risk premium (ORP), defined as the relative difference between expected oil prices and oil futures prices. Risk premiums are a key concern of market participants since they add to the costs supported by producers and influence investors' decisions regarding the structure of their portfolios. Analyzing their determination is therefore of considerable interest. In this paper, we use survey-based consensus data to measure oil price expectations for the 3- and 12-month horizons, which enables us to construct for each horizon an observable market ORP that we model within a portfolio choice theory framework. We show that, once estimated using nonlinear techniques, our ORP model has various interesting implications in terms of the measure of risk prices, their determinants, investors' risk attitudes and the term structure of risk premiums.

By their definition involving expected oil prices, ORPs are a forward-looking concept and this justifies their being qualified as "ex ante". Our approach focuses on ex-ante ORPs and departs from an extensive literature employing an "ex-post" measure of risk premiums where the expected value of oil price at time t for time $t + \tau$ is replaced by the spot oil price observed at time $t + \tau$.¹ These ex-post risk premiums express in fact excess oil returns, which are employed as endogenous variables to estimate the unobservable ex-ante ORP using information available at time t. In this line, different modeling strategies can be distinguished. which are detailed section 2.

Despite their great interest in analyzing the dynamics of oil spot and futures prices, one can question the ability of studies based on ex-post ORPs to produce reliable measures of exante risk premiums. First, using the ex-post ORP as the dependent variable amounts to measuring the ex-ante ORP from the fitted deterministic part of an excess return regression model. Unsurprisingly, Baumeister (2022) documents that strong disparities are evidenced between the signs and the magnitudes of 25 different ORP models of the literature assumed to be stable over time when they are re-estimated over the period 1998-2018 and for the 12-month horizon. This acutely raises the question of what model is to be chosen to represent exante ORPs. Second, the ex-post ORP is formally equal to the value of the ex-ante risk

¹ Note that when the futures markets are concerned, the ex-post ORP is the relative difference between the frontmonth contract (i.e., the one-month to maturity futures price observed at month $t + \tau - 1$, where $\tau > 1$) and the riskless contract (the τ -month to maturity futures price observed at month t).

premium plus the ex-post forecast error,² which is clearly unknown to the investor at time t. When expectations are rational, the forecast error is white noise; in this case, it is captured by the residuals of the model so that the explanatory factors of the model specification are indeed those of the ex-ante ORP. However, when expectations are not rational, the factors that are found to be significant comprise those driving the ex-ante ORP and those contained in the forecast error, implying a misidentification of the ex-ante ORP factors and thus a biased estimation of this premium. As to whether or not expectations are rational, a large body of empirical studies from a variety of approaches comes to the conclusion that the rational expectations hypothesis (REH) does not hold. First, many authors find evidence that ex-post ORPs are horizon-dependent (see, among others, Melolinna, 2011). However, Cochrane (1999a,b) demonstrates on theoretical grounds that under the REH, ex-post risk premiums are not conditioned by the horizon. Consequently, the observed horizon-dependence of ex-post ORPs is not compatible with the REH, implying that these premiums include persistent forecast errors and thus provide biased measures of the "true" premiums. Second, many authors show that oil returns are partially predictable, hence suggesting that oil price is not expected rationally in an efficient market.³ Third, studies using various survey data on expected oil spot price strongly reject REH whatever the horizon considered.⁴ These studies show that backward looking processes such as the traditional adaptive, extrapolative and mean-reverting mechanisms are relevant in explaining oil price expectations (MacDonald and Marsh, 1993; Reitz et al., 2010; Prat and Uctum, 2011, have reached these results using Consensus Economic survey data while Bianchi, 2021, used Bloomberg surveys).⁵ Overall, it comes out from these various results that, whatever the horizon, the ex-post ORP is not an appropriate dependent variable to use in order to identify the relevant factors of the ex-ante ORP.

These limitations inherent to ex-post ORPs have motivated some authors to consider directly exogenous measures of ex-ante ORPs. This approach has led to two different ways of

² This can be made trivial using the identity $p_{t+\tau} - f_{t,\tau} = (E_t p_{t+\tau} - f_{t,\tau}) + (p_{t+\tau} - E_t p_{t+\tau})$, where $E_t p_{t+\tau}$ and $p_{t+\tau}$ are the expected and the ex-post realized oil spot log-prices and $f_{t,\tau}$ is the τ -month to maturity oil futures log-price.

³ The crude oil futures price is found to be a biased predictor of the future spot price (Moosa and Al-Loughani, 1994; Sadorsky, 2002; Alquist and Kilian, 2010; Baumeister, 2022) while macroeconomic variables appear to be partial predictors. Recent studies show that models including economic determinants of oil price such as changes in oil inventories, oil production and global real economic activity may provide more accurate out-of-sample forecasts than oil futures prices (Alquist et al., 2013; Baumeister et al., 2014; Baumeister and Kilian, 2012, 2014, 2015). This finding holds even in a real-time forecasting environment, where oil price predictors become available only with a delay and are subsequently revised.

⁴ Some studies show that it is possible to improve the quality of oil return forecasts by combining forecast variables with surveys (Alquist et al., 2013; Baumeister et al., 2014; Sanders et al., 2009), but none of them can reach predictions that are consistent with the REH.

⁵ Alquist and Arbatli (2010) show that the 3 month (12 month) ahead expected change in oil price is correlated with the log-ratio between the 3 month (12 month) to maturity oil futures price and the spot price, hence suggesting that futures price could also help explaining expectations.

investigation (see section 2 for a thorough discussion). The first class of models consists in determining option-based risk premiums in the oil market. In these models, the market's forward-looking views on oil return volatility are assessed using the information provided by option prices on the distribution at expiry of the underlying spot oil price. The main merit of the option-based ORP approach compared to the ex-post ORP is that no more confusion between risk premium and forecast error is of concern. However, a drawback is that it requires binding assumptions on market completeness, risk neutral probability density functions and diffusion process specifications describing the dynamics of spot and option prices. The second way of tackling ex-ante ORPs consists in using professional experts' oil price forecasts provided by survey data to quantify oil price expectations and thus to obtain observable measures of ex-ante premiums since futures prices are given by the market. This approach allows disentangling risk premiums and forecast errors by contrast to the previous models and helps to circumvent the binding assumptions needed by the option-based ORP analysis. Care must be taken, nonetheless, about how accurately survey forecasts represent market expectations. In this regard, the sample size of respondents, their being informed agents and the degree of attrition are among the important conditions of an adequate representativeness.⁶

Surprisingly, the literature on ex-ante ORPs using survey data is very scarce. These data are particularly suitable for examining investors' forward-looking decision-making behavior in a portfolio choice context. In this paper we address this issue. We measure ex-ante crude oil risk premiums for the 3 and 12-month horizons using expected oil price data provided by Consensus Economics surveys (London) over the period spanning from November 1989 to April 2024. As an important preliminary result, we find that the REH is rejected for both horizons, implying that ex-post ORP is not an unbiased measure of the true premium because its forecast error component is not white noise. Consistently with the portfolio choice theory, the ex-ante ORP is expressed as the price of risk times the expected variance. We estimate our ORPs for the two horizons using a state-space model where the unobservable risk prices are represented by stochastic state variables while the expected variances depend on actual and lagged instantaneous volatilities of unknown order. We show that this model represents adequately our 3- and 12-month horizon ex-ante ORPs aims at estimating for different

⁶ Many studies show that consensus survey-based price expectations can be fairly represented by a combination of standard forecast heuristics, which invalidates the idea that these surveys would not convey authentic beliefs. Comparing expected stock returns provided by different surveys, Greenwood and Shleifer (2014) find that they are strongly correlated between them, with past returns and with investor inflows into mutual funds. This result leads the authors to argue that "survey measures of investor expectations are not meaningless noise but are rather reflections of widely shared beliefs about future market returns".

horizons the effects at any time of these two components of the ORP. Regarding investors' attitudes toward risk, it comes out from our results that while risk seeking behavior (represented by positive values of the risk price) is mostly associated with the short horizon, risk aversion (negative values of the risk price) is dominant in the longer horizon. It follows that a dominant upward sloping term structure of ex-ante ORPs over our extended period is evidenced. We also consider risk attitudes according to expected changes in oil prices, and find that investors are prominently risk-averse when they expect a rise in oil prices and risk seeking in a context of expected decrease in oil prices. This is a particularly interesting issue of our paper since it makes our estimated values of risk prices consistent with the predictions of the prospect theory. A last contribution of our study consists in exploring the empirical relationship between the risk prices and various economic and oil market-related factors.

The remainder of the paper is organized as follows. Section 2 provides a survey of the literature on crude oil risk premium modeling. Section 3 presents the theoretical model of ORP in the light of the portfolio choice theory. The survey data used to assess our ex-ante ORPs are discussed in section 4. The results of the estimation of our 2-horizon state-space model are outlined in section 5. Section 6 concludes.

2. A survey of the literature

Several strands of the empirical literature have attempted to measure ORPs using different methods. We can group the different approaches in two broad categories: the expost ORP models where the observed excess return of oil is employed to identify the determinants of the unobserved true premium and the ex-ante ORP models where the true premium is made observable using option-based or survey-based approaches.

A first class of studies from the ex-post approach examines the factors of risk premiums based on univariate or multivariate regression analyses. Pagano and Pisani (2009) document that the US business cycle, represented by the degree of capacity utilization in manufacturing, is a significant factor of the futures ORPs, while Hambur and Stenner (2016) emphasize the effect of net hedging pressure on excess return using panel modeling. Haase and Zimmermann (2013) point out the role of the physical scarcity of oil with respect to demand. Performing an impulse response analysis from a structural VAR model, Valenti et al. (2020) find that ex-post ORPs are related to shocks on fundamentals such as inflation, production and interest rate spreads. Assuming that oil futures prices represent expected oil spot prices, Coimbra and Esteves (2004) show that oil forecast errors - which in this case formally equal the ex-post ORPs - are correlated with forecast errors in world economic activity. Melolinna

(2011) documents that crude oil stock level, net speculative positions and the correlation between share prices and crude oil prices have explanatory power on ORPs. Using the GMM to account for errors in expectations and measurement, Considine and Larson (2001) show that ORP is sensitive to price volatility together with a convenience yield that is inversely correlated with stock levels.

Another important strand of studies uses the (G)ARCH framework to analyze ex-post ORPs. Estimating a GARCH-in-mean model, Moosa and Al-Loughani (1994) find support for a significant effect of the expected conditional variance on the ex-post premium. Estimating a multivariate GARCH model under the REH, Jalali-Naini and Manesh (2006) find support for the existence of a time-varying risk premium in the crude oil market. Using **a** CCC trivariate GARCH-M model, Cifarelli and Paladino (2010) show that oil price changes depend on a speculative component represented by the expected variance and on stock prices and foreign exchange rates. Sadorsky (2002) implements an ARMAX-GARCH model for different petroleum futures returns and finds that time-varying risk premium is significant only for heating oil but not for crude oil.

In factor affine models of risk prices, ex-post ORPs in the futures oil market are constructed as the relative difference between the price of the futures contract at t + s with maturity $\tau - s$, $0 < s < \tau$) and the price at t of the futures contract with maturity τ . Using multi-factor affine models, Bhar and Lee (2011) find that the term structure of futures oil prices involves the same risk factors as equities and bonds. Considering a standard asset pricing model, Hamilton and Wu (2014) show that interactions between commercial producers who hedge against risk and risk averse arbitrageurs acting as hedgers' counterparties can produce an affine factor structure to the prices of futures contracts; the authors find that differences in the risk prices across horizons as well as the levels of risk prices can take positive or negative values over time. In the same vein, Heath (2019) develops an affine futures pricing model and shows that the ORPs term structure is most often procyclical. Gao et al. (2022) points out that risk prices and thus ORPs in the futures market often take negative values and find that they are related to the US crude oil commercial stock, inflation, economic uncertainty, and hedging pressure.

Given that oil return is a main component of the ex-post ORP, the literature addressing the effects of speculative and fundamental factors on oil prices is also of indirect but essential interest for ORP modeling. Coleman (2012) documents that oil prices are impacted by fundamentals such as bond yield, economic growth, oil market shocks and geopolitical measures; they also depend on speculative activities and on events such as terrorist attacks and industry events. Kaufmann and Ullman (2009) also evidence both speculative and fundamental effects. Some authors attribute the rise in crude oil price between 2003 and 2008 more on financial speculation than on economic fundamentals (Kaufmann, 2011; Weiner, 2002 and Sanders et al., 2004). Conversely, Fattouh et al (2013) and Liu et al (2016) are more supportive of the role of macroeconomic factors in driving oil spot price after early 2000s, while Hamilton (2009) comes to the same conclusion in analysing the 2007-2008 oil price shock. Some authors emphasize the role of speculative behaviour in expected variance. This variable is indeed correlated with indicators of speculative activity such as black market trade, market share of non-commercial traders, trading volume, open interest (see, among others, Du et al., 2011; Nicolini et al., 2013). Another acknowledged factor of volatility is heterogeneity of beliefs and preferences (Li and Muzere, 2010; Weinbaum, 2009). These studies suggest that the greater the speculation in the market, the higher the volatility.⁷

Studies relaxing the ex-post modeling of ORPs and emphasizing the ex-ante nature of these premiums can be classified into two groups: option-based models and survey-based models. Option-based ORP models infer market expectations on oil return volatility from the distribution at expiry of the underlying spot oil price. Chiang et al. (2015) develop a four factors affine model estimated using data on futures and option prices. Supposing a risk-neutral Ito diffusion process, the authors calculate the implied variances of oil returns and show that option-based ORPs are significantly related to macroeconomic variables such as production and the VIX index. Li (2018) finds that the risk aversion coefficient can take any sign and varies with the speculative activity represented by the expected volatility of oil returns. By focusing on the tails of ORPs distributions, Ellwanger (2017) suggests that fears of future extreme oil returns contribute to explaining premiums.

Very few studies have attempted to model ex-ante ORPs by exploiting survey data. In these studies, ORPs are calculated using professional experts' oil price forecasts, supposed to provide an acceptable representation of market expectations. Bianchi (2021) employ monthly forecasts on oil and other commodity prices provided by Bloomberg surveys from January 1997 to April 2020 to assess ex-ante ORPs for three horizons in commodity markets. Performing dynamic linear regressions, they find that the net positions of hedgers, the number of outstanding contracts held by market participants and past oil returns are significant factors of ORPs. Using WTI oil price forecasts data from Bloomberg and from the U.S. Energy Information Administration, Cortazar et al. (2019, 2022) implement a three-factor affine model of ex-ante ORPs and calculate weekly premiums for many horizons over the period 2010-2017. Assuming that volatilities are constant over time (but variable across horizons)

⁷ Of course, the data cannot allow distinguishing between the possibility that hedgers make market prices while speculators are hedgers' counterparties, nor the opposite possibility that speculators drive price movements (Weiner, 2002).

and futures prices correspond to the expected value of the spot price under the risk-adjusted probability measure, the authors show that, in average, short-term ex-ante ORPs are higher than long-term ones because their volatility is structurally higher. Although the time invariance of volatilities is of course a very restrictive hypothesis, the authors interestingly show that financial variables such as stock returns, level and spreads of interest, and oil market-related variables such as open interest, hedging pressure or inventory changes are significant factors of their survey-based ex-ante ORPs.

3. The theoretical model

The ex-ante crude oil risk premium is defined as the log-difference between expected and futures oil prices, which identically can be written as the difference between the expected change in spot price and the so-called "basis" defined as the log-difference between futures and spot prices. Accordingly, let p_t be the logarithm of the spot oil price and $f_{t,\tau}$ the logarithm of the τ -term maturity futures oil price. E_t stands for the conditional expectation operator at time *t*. The ex-ante ORP for a τ -month horizon investment is, in percent per month:

$$\phi_{t,\tau} = \frac{100}{\tau} \left[(E_t(p_{t+\tau}) - p_t) - (f_{t,\tau} - p_t) \right]$$
(1)

where the first term in the bracket is the expected rate of change in oil price at t for $t + \tau$ while the second term is the basis.

Because oil is a physical asset, the basis encompasses costs and advantages of oil inventories. In this respect, when the market is in "contango", the spread between the futures and spot prices must be large enough to compensate for the costs of carry (including storage cost) and thus to make oil holding profitable.⁸ This situation occurs when the spot price is expected to rise, which translates into an upward sloping futures curve. Conversely, the market is in "normal backwardation" when available stock levels are low, futures prices are lower than the spot price because the current price is expected to fall. This implies a downward sloping futures curve. To complete the theory of normal backwardation, Kaldor (1939) adds the concept of "convenience yield", which represents the advantages associated with holding the physical commodity.⁹ Indeed, holding physical oil allows for reducing costs related to delivery delays, enhances the ability of responding to unexpected demand and

⁸ The total oil storage costs depend on the opportunity cost of not investing in another asset, on the cost of maintaining buildings and facilities (including rents), on the risk of inventories depreciation and on taxes.

⁹ Number of authors find evidence for the existence of convenience yields (see, among others, Considine and Larson, 2001; Alquist and Kilian, 2010; Alquist et al., 2013)

hence keeping regular customers satisfied. Under the no-arbitrage condition, the basis is equal to the total cost of carry (interest paid on the loan used to purchase oil at the spot price plus the marginal storage cost) minus a convenience yield, thus allowing the basis to be positive in case of contango and negative in backwardation (see, among others, Fama and French, 1987; Melolinna, 2011; Gorton et al., 2013). :

$$\frac{100}{\tau}(f_{t,\tau} - p_t) = r_{t,\tau} + sc_{t,\tau} - cy_{t,\tau}, \quad sc_{t,\tau} > 0, \quad cy_{t,\tau} > 0$$
(2)

where $r_{t,\tau}$ is the τ -month maturity risk-free rate at time t, $sc_{t,\tau}$ is a τ -month duration marginal oil storage cost and $cy_{t,\tau}$ is the convenience yield associated with this storage, all variables being in % per month. We assume that expected oil return includes these costs and advantages related to oil holdings:

$$E_t(R_{t+\tau}) = \frac{100}{\tau} [E_t(p_{t+\tau}) - p_t] + cy_{t,\tau} - sc_{t,\tau}$$
(3)

Because the magnitudes $sc_{t,\tau}$ and $cy_{t,\tau}$ are not directly observable, the expected return can be given a more tractable specification by solving Eqs.(2) and (3):

$$E_t(R_{t+\tau}) = \frac{100}{\tau} [E_t(p_{t+\tau}) - p_t] - \frac{100}{\tau} (f_{t,\tau} - p_t) + r_{t,\tau}$$
(4)

Putting together (1) and (4) yields to an alternative expression of the ex-ante ORP defined as the difference between the expected return and the risk-free rate:

$$\phi_{t,\tau} = E_t(R_{t+\tau}) - r_{t,\tau} \tag{5}$$

Eq.(5) says of course nothing about the question of how the risk premium is explained. To address this issue, we refer to the portfolio choice theory where we distinguish the behaviour of the representative investor when they adopt a risk averse attitude and when they are risk seeking. In the standard expected utility theory, risk attitudes are characterized by the utility function: an agent is risk averse if their utility function is concave while a convex utility function implies risk seeking behaviour. The risk premium, defined as the difference between the expected value of the uncertain payment and the certainty equivalent, is positive in the former case (investors require a premium for betting) and negative in the latter case (investors accept to pay a premium for betting). Interestingly, based on multiple experimental lotteries, the (cumulative) prospect theory by Kahneman and Tversky (1979) and Tversky and Kahneman (1992) sheds light on the *conditions* under which an individual may adopt risk-averse or risk-seeking attitude. According to the theory, risk aversion and risk seeking are determined jointly by a value function of outcomes (gains and losses) and by some decision weights. Relative to some reference point (e.g., the initial wealth), the value function is

concave in the region of gains and convex in the region of losses; moreover, due to the loss aversion bias it is steeper over losses than over gains of the same magnitude. Individuals weight the value function not by the objective probabilities associated with the outcomes, but by an inverse-S shaped weighting function of these probabilities. These decision weights state the certainty equivalents in a way that, for both gains and losses, low probabilities are overweighted and high probabilities are underweighted. The weighting and the value functions imply a fourfold pattern of risk attitudes for nonmixed prospects¹⁰: risk aversion for gains and risk seeking for losses of moderate and high probabilities, risk seeking for gains and risk aversion for losses of small probabilities.

The prospect theory is originally designed to describe decision making under risk in experimental settings and based on lottery-like gambles. As stated by Barberis (2013), there are very few attempts to apply it in economics,¹¹ mostly due to the unclearness of how its components can be conceptualized in different economic contexts - e.g., which reference point should be chosen, how gains and losses should be defined and what should be the associated objective probabilities. On the other hand, prospect theory does not state how the coefficients of risk aversion and risk preference can be assessed, as these coefficients are the key ingredients of the portfolio choice model which we will introduce later. In this paper, we do not aim at proposing an application of the prospect theory in risk premium modelling. Rather, we examine the investor's behaviour with regard to risk in an expected utility theory framework. By matching the behaviours towards risk with the perspectives of gains and losses, our empirical results are interpreted in the light of the prospect theory.

We consider a representative investor whose portfolio is composed of a risky asset made of a quantity of oil barrels and a risk-free asset. At time *t*, the investor's horizon is of duration τ and the value of the portfolio corresponds to their wealth $W_{t,\tau}$. The share of the risky asset in the portfolio is $\theta_{t,\tau}$ with $0 \le \theta_{t,\tau} \le 1$. We denote $U_A(W_{t,\tau})$ the utility function of the investor when the state of nature they perceive leads them to be risk averse and $U_S(W_{t,\tau})$ the utility function of the investor when they are risk seeking. At any time *t*, $U_A(W_{t,\tau})$ and $U_S(W_{t,\tau})$ are both increasing functions of wealth $(U'_A > 0, U'_S > 0)$. In the state of risk aversion, this function is concave $(U''_A < 0)$ and the Arrow-Pratt approximation of the expected utility leads to the absolute coefficient of risk aversion $\lambda_{t,\tau}^A = -\frac{U''_A(W_{t,\tau})}{U'_A(W_{t,\tau})} > 0$.¹² Risk

¹⁰ Typically, a nonmixed prospect consists in a gain (loss) of probability p against zero gain (loss) of probability 1-p.
¹¹ See Barberis et al. (2001, 2016) for applications of prospect theory to financial markets and Barberis (2013)

¹¹ See Barberis et al. (2001, 2016) for applications of prospect theory to financial markets and Barberis (2013) for a survey of such studies.

¹² Our assumption that the coefficient of risk aversion depends on the horizon is in line with Eisenbach and Schmalz (2016) who find experimental evidence that risk aversion is horizon-dependent and documents the various origins of horizon-dependent risk aversion preferences.

seeking attitude implies a convex utility function $(U_S'' > 0)$, and through a similar calculation as for the risk aversion coefficient, the expected utility leads to define the absolute risk preference coefficient as $\lambda_{t,\tau}^S = -\frac{U_S'(W_{t,\tau})}{U_S'(W_{t,\tau})} < 0$. At any time *t*, the investor determines the optimal value of $\theta_{t,\tau}$ maximizing the expected utility of their wealth for $t + \tau$ conditionally on the set of information used. Assuming that $W_{t,\tau}$ is normally distributed¹³, we can put the expected utility in the expectation-variance form so that the investor's program is written as:

$$\max_{\theta_{t,\tau}} E_t \{ U(W_{t+\tau,\tau}) \} = \max_{\theta_{t,\tau}} \left\{ E_t(W_{t+\tau,\tau}) - \frac{\lambda_{t,\tau}}{2} V_t(W_{t+\tau,\tau}) \right\}$$
(6)
s.t. $W_{t+\tau,\tau} = W_{t,\tau} [1 + \theta_{t,\tau} R_{t+\tau} + (1 - \theta_{t,\tau}) r_{t,\tau}]$

where U and $\lambda_{t,\tau}$ correspond to U_A and $\lambda_{t,\tau}^A$ if at time t the investor is risk averse and to U_S and $\lambda_{t,\tau}^S$ if they are risk-seeking. E_t and V_t stand for the conditional expectations operator and conditional expected variance operator, respectively, while $R_{t+\tau}$ is the oil return between t and $t + \tau$. The solution of the program (6) can straightforwardly be written as:

$$W_{t,\tau}\left[E_t(R_{t+\tau}) - r_{t,\tau} - \kappa_{t,\tau} \; \theta_{t,\tau}^* V_t(R_{t+\tau})\right] = 0 \tag{7}$$

where $\kappa_{t,\tau} = \lambda_{t,\tau} W_{t,\tau}$ is the coefficient of relative risk aversion or preference and $V_t(R_{t+\tau})$ is the expected variance of oil return at *t* for $t + \tau$.¹⁴ Using Eq(5), the solution of the investor can be written in the form:

$$\phi_{t,\tau}^* = \gamma_{t,\tau} V_t(R_{t+\tau}) \tag{8}$$

where

$$\gamma_{t,\tau} = \kappa_{t,\tau} \theta_{t,\tau}^* \tag{9}$$

is the price of risk at the equilibrium and $\phi_{t,\tau}^*$ the corresponding equilibrium or required value of the ex-ante ORP. Assuming that the premium offered by the market adjusts instantly to its required value ($\phi_{t,\tau} = \phi_{t,\tau}^*$), the structural Eq.(7) allows specifying the ex-ante ORP as¹⁵:

$$\phi_{t,\tau} = \gamma_{t,\tau} V_t(R_{t+\tau}) \tag{10}$$

¹³ Note that Jondeau and Rockinger (2006) show that even under moderate non-normality, the mean-variance criterion provides a good approximation of the expected utility.

¹⁴ Note that V_t being an *expected* variance operator, we have $V_t(r_t) = 0$. It is easy to check that since the second order condition is negative, the first order condition corresponds to a maximum.

¹⁵ Eq.(10) is formally still valid under the hypothesis of no monetary illusion. In this case, the left hand side remains unchanged since the expected rate of inflation must be subtracted from both the expected oil return and the risk-free rate. In the right hand side, however, the expected variance of real oil returns is of concern.

Thus, according to whether the agent has a risk aversion $(\lambda_{t,\tau} > 0)$ or a risk preference $(\lambda_{t,\tau} < 0)$ profile, the coefficient of relative risk attitude $\kappa_{t,\tau}$, and hence the price of risk $\gamma_{t,\tau}$ and the risk premium $\phi_{t,\tau}$ are positive or negative, respectively. To make Eq.(10) operational, additional hypotheses must be adopted about the determination of the expected variance of oil returns $V_t(R_{t+\tau})$ and the representation of the time-varying price of risk $\gamma_{t,\tau}$ which both are unobservable components. Both the price of risk and the volatility can a priori convey speculative or fundamental effects on the ORP. We will present in section 4 the empirical approach we adopted to assess these magnitudes.

4. Data

Concerning oil price expectations, « Consensus Economics » (CE) asks at the beginning of each month about 180 economy and capital market specialists in about 30 countries to predict values for different horizons of a large number of variables, among which oil prices. Respondents are commercial or investment banks, industrial firms and forecast companies, whose forecasts influence many market participants' decisions. These experts are identified with a confidential code which only mentions their country. They are asked to answer only when the oil market concerns them enough. Therefore, the consensus (arithmetic average of the individually expected values of oil price) is not biased a priori by noise traders since only informed agents do respond.¹⁶ Besides, since the individual answers are confidential (i.e. only the consensus is disclosed to the public with a time lag) and because each individual is negligible within the consensus, it does not seem to be justified to object that, for reasons which are inherent to speculative games, individuals might not reveal their « true » opinion. At each monthly survey, CE requires a very specific day for the answers. This day is as a rule the same for all respondents, located between the 1st and the 7th of the month from the beginning of the survey until March 1994 and between the 4th and the 16th of the month since April 1994.¹⁷ The consensus predictions are published in the monthly CE newsletter for two horizons only, the 3-month and the 12- month horizons, along with the oil prices observed at the time the forecasts are made. These consensus and observed price time series are used in this paper over the period November 1989 to April 2024.

¹⁶ In fact, about two thirds of the 180 experts answer the questions concerning future values of oil price, and this confirms that responding experts are those who are informed about the oil market.

¹⁷ The effective horizons, however, always remain equal to 3 and 12 months. If, for instance, the answers are due on the 3rd of May (which was the case in May 1993), the future values are asked for August 3, 1993 (3 month-ahead expectations) and for January 3, 1994 (12 month-ahead expectations).

More precisely, experts are requested by CE to forecast the US\$ spot price per barrel of the West Texas Intermediate (WTI) from the beginning of the survey (October 1989) until December 2012. Since January 2013, the price which is asked to be forecasted is that of the Brent. This switch in the survey oil benchmark can be understood within the following context. Historically, the prices for WTI and Brent have moved together very closely until the US shale oil boom triggered a raise in crude oil inventories in Cushing (Oklahoma). As a result, since the end of 2010, the WTI spot price shrank at levels which were considered as being excessively low, boosting Brent to become the international oil reference. Although the spread between WTI and Brent prices substantially narrowed at the end of 2014 after the increase in Seawave Pipeline oil transporting capacities from Cushing to US Gulf Coast, Brent remained the most widely used benchmark because it is easy to refine into high-demand products such as petrol and, since it is extracted in the North Sea, it is easy to transport to distant locations.

The shift from WTI to Brent as oil benchmark operated by CE occurred at a date when the gap between the two oil prices was still persistent. Unsurprisingly, a similar gap exists between the two expected oil prices provided by the CE respondents. However, by concatenating the rate of change series from the two benchmarks, we can build whole-period series of observed changes in crude oil price irrespective of whether the benchmark is WTI or Brent. Continuity at the January 2013 break date is achieved provided that the log-difference between December 2012 and November 2012 values of the WTI price is followed by the logdifference between January 2013 and December 2012 values of the Brent price. As for the expected change in oil price, because WTI and subsequently Brent price expectations are formed at the same dates as WTI and Brent observed prices, taking the log-difference between the expected price and the spot price for each oil product raises no problem of continuity at the January 2013 break date. In order to check for the statistical validity of our continuity assertion in the expected changes in WTI and Brent oil prices, we regressed the concatenated expected rate of change in oil price on the concatenated observed rate of change and performed the Quandt-Andrews unknown breakpoint test over the whole period. Any disruption in the regression estimates at the junction point of the series should be interpreted by the test as a structural break. However, while the null of no breakpoint was failed to be rejected for the 12-month horizon, the only significant breakpoint for the 3-month horizon was found to be located at January 2009.¹⁸ As a result, no breakpoint has been depicted at January 2013 for none of our horizons.

¹⁸ This estimated breakdate is consistent with the sharp increase in the WTI oil return volatility during the financial crisis and its stabilization afterward (Joo et al, 2020).

CE data also provide at time t the standard deviation of expected prices across respondents; the coefficient of variation (i.e. the ratio of the standard deviation to the consensus) at each point in time lies between 2.3% and 24.4% for the 3-month horizon and between 4.3% and 23.25% for the 12-month horizon. This implies that some heterogeneity is present in individual expectations without, however, compromising the statistical sense of the consensus.

We now turn to the crude oil futures prices and risk-free interest rates data. Consistently with the 3- and 12-month time horizons of price expectations, we consider the prices of 3- and 12-month to maturities futures contracts quoted in NYMEX, both extracted from Macrobond database at the same days as the survey expectations. To represent the risk-free interest rates, we use the US Treasury Bills market rates. Our choice is motivated by the following key features. T-Bills are short-term zero-coupon debt instruments issued by the U.S. Department of the Treasury with a maturity of one year or less. They are regarded as having no default risk as they are backed by the U.S. government. Their interest income is exempt from state and local taxes but subject to federal taxes. They are easily marketable in the secondary bond market and highly liquid, enabling investors to easily manage their liquidity constraints. The 3- and 12-month US T-Bills rates have been retrieved from Consensus Economics so as to maintain, here again, the same reference dates.

With these survey-based expected oil price and crude oil futures data in hand, we can construct the series of ex-ante ORPs for our two horizons according to Eq.(1). Figure 1 presents these magnitudes for the 3-month (panel A) and 12-month (panel B) horizons, respectively. It can be seen that ex-ante ORPs exhibit significant disparities regarding the horizons, with much higher amplitudes for the 3-month horizon than for the 12-month horizon. On the other hand, note that both the expected change in oil price and the basis play a significant role in the measurement of ex-ante oil risk premium.

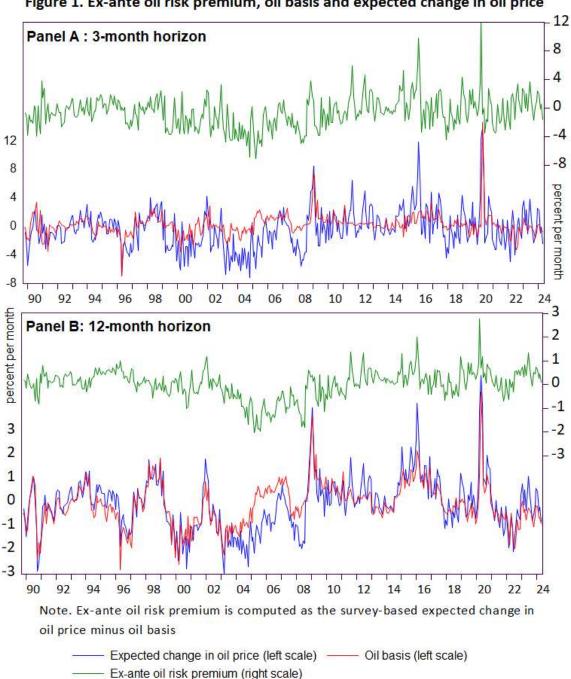
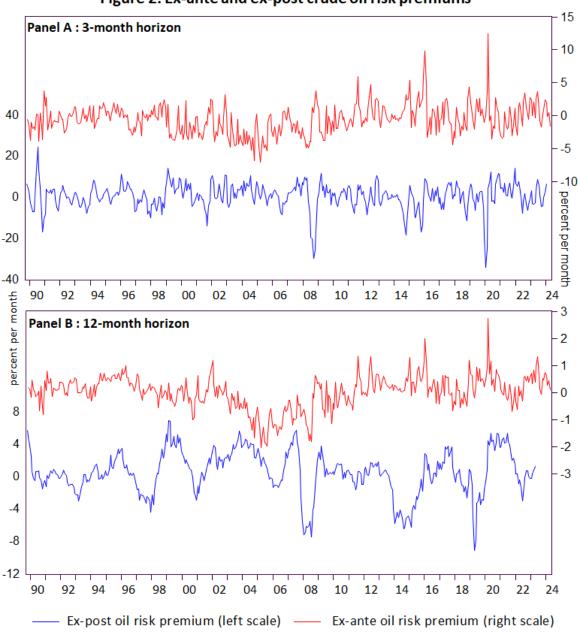


Figure 1. Ex-ante oil risk premium, oil basis and expected change in oil price

It is also instructive to compare ex-ante and ex-post ORPs.¹⁹ Figure 2 displays these two premiums for each horizon and exhibit three striking features. First, risk premiums may take positive or negative values, due to the investors' dominant attitude toward risk (see section 3) and consistent with the empirical literature (Bianchi, 2021; Baumeister, 2022). Second, there is no significant correlation between the two types of risk premiums: the correlation coefficients are -0.06 for the 3-month horizon and = -0.01 for the 12-month horizon. Third, the ex-post ORPs exhibit much broader variability compared to the ex-ante

¹⁹ The τ -month horizon ex-post risk premium at time t is calculated as the log-difference between the τ -month horizon ex-post crude oil price and the τ -month maturity oil futures price.

ORPs: the standard deviations of the former are about 3 times higher than those of the latter for the 3-month horizon, and about 4 times for the 12-month horizon. These very different time patterns between ex-ante and ex-post premiums result from large forecast errors in oil price expectations. This provides support to our emphasis towards the ex-ante approach in modeling ORPs.





5. Empirical analysis

If expectations were rational, ex-post ORPs would provide an unbiased measure of risk premiums. We must thus examine whether the REH, strongly rejected by previous surveybased studies, is still invalidated by our CE survey data over our extended period. We conduct a powerful test that controls for potential biases due to measurement errors in expectations (see Appendix). Our findings reject the REH, aligning with those obtained by, e.g., Prat and Uctum (2011) and Mac Donald and Marsh (1993) who employed simpler test procedures over much shorter timeframes. We conclude that ex-ante premiums are more suitable than ex-post premiums for analyzing investors' decision-making.

5.1 Estimating the state-space model

We must first determine how the expected variance and the price of risk at the RHS of Eq.(10) are determined. The price of risk represents the sensitivity of the risk premium to the expected variance, the latter reflecting the "quantity of risk" felt by the investor. As indicated in Eq.(9), this sensitivity is defined as the product of the coefficient of relative risk aversion (or preference) by the share of the risky asset in the portfolio. These two components being time-varying, the price of risk is also time varying. In particular, recall from Eqs(9) and (10) that our price of risk (and thus our risk premium) can take positive or negative values depending on whether investors are predominantly risk-averse ($\kappa_{t,\tau}$ > 0), or risk-seeking ($\kappa_{t,\tau}$ < 0). Support is provided to these views by, for example, Bhar and Lee (2011) who estimate a time-varying price of risk in a three-factor ex-post crude oil risk premium model and Li (2018) who finds, in an *implied* risk premium framework, that the risk aversion and therefore the price of risk are state-dependent and can take alternate signs.

Unfortunately, it seems not possible to know at time *t* how the representative investor behaves against risk and what makes them change their risk attitude from one period to another. Even assuming that this risk-averse or risk-seeking attitude could be known, the extent of its effect on the price of risk would remain undetermined. This is why we cannot determine a priori the sign and the magnitude of the coefficient of risk aversion (or preference) $\kappa_{t,\tau}$, and thus the value of the price of risk. To tackle this indetermination, we represent for each horizon the price of risk as an unobservable stochastic state variable associated with a measurement equation describing the ex-ante ORP relationship. The general form of our state equation is an autoregressive process with drift. Estimated using the Kalman filter methodology, our 2-horizon multivariate state-space model lets the signs and the amplitudes of the state variables be determined freely at each point in time so that our risk prices fit at best the ex-ante ORPs. Note that such a risk price dynamics is general enough to collapse to a simple random walk or to a constant as particular cases.

From its constituent components (the share of the risky asset in the portfolio and the relative coefficient of risk aversion/preference), it seems intuitive that the price of risk $\gamma_{t,\tau}$ in our ex-ante ORP model might depend on the economic environment perceived by investors. Accordingly, the aforementioned risk price autoregressive process can be thought of as including additional exogenous variables, namely macroeconomic and oil market-specific factors. However, adding such variables into the AR process would constraint the impacts of all these macroeconomic variables to follow identically the same geometric decay – although adjusted by individual multiplicative coefficients - as we move into the past. To avoid this strong assumption, we choose not to include them into the risk price state equations and to examine the links between the risk prices and economic variables in a subsequent stage, once the values of the risk prices are estimated over the whole period.

We now focus on the question of how to measure the conditional expected variance of oil return. In this paper, we assume that agents determine their volatility expectations and risk price simultaneously at both horizons. Therefore, the 3- and 12-month expected variances and risk prices must be estimated jointly, and our bivariate state-space model is suitable to fulfil this prerequisite. In this context, the standard assumption that the expected variance follows a GARCH process is not a relevant option for two reasons. First, consistently with our monthly data, implementing a GARCH process would only allow calculating one-month ahead expected variance whereas we need to evaluate the 3- and 12-month horizon expectations of the conditional variance. Second, employing the GARCH methodology would necessarily imply assessing the expected variances prior to filtering our ex-ante ORP model, which we want to avoid.

An alternative popular approach for proxying the expected variance would consist in constructing for each horizon a monthly realized volatility (RV) measure employing daily squared returns and inferring expected volatility from autoregressive (AR) forecasting.²⁰ Reduced form AR-based dynamic forecast processes can then be used for the 3- and the 12- month ahead expected RVs in the measurement equations of ex-ante ORPs. These two forecast processes are based on actual and past RVs whose composite coefficients can be fully specified employing the lag parameters up to a given lag order. However, since in our setup the lag orders are not known a priori and must be determined endogenously, the composite coefficients cannot be given explicit formulations to complete the model prior to estimation.

²⁰ More recent studies use heterogenous autoregressive (HAR) models for RV forecasting, proposed by Corsi et al. (2012). The same arguments developed in the case of AR forecasting apply.

A feasible approach is to represent expected volatility as a weighted average of the actual and lagged instantaneous variances defined by the squared returns.²¹ In this way, individual lag weights can be estimated in the course of the estimation of the structural model and their orders endogenously determined using a double grid search. Our conditional expected variance based on this weighted average approach writes:

$$V_t(R_{t+\tau}) = \sum_{j=0}^{m_{\tau}} \omega_{j,\tau} \ R_{t-j}^2, \quad \text{with} \ \sum_{j=0}^{m_{\tau}} \omega_{j,\tau} = 1$$
(11)

where $\omega_{j,\tau} = \beta_{j,\tau} / \sum_{j=0}^{m_{\tau}} \beta_{j,\tau}$ is the weight at the *j*'th lag and $\beta_{j,\tau}$'s its constituent parameters to be estimated. R_t^2 is the instantaneous variance proxy observed at time *t*. We define the instantaneous return R_t as the last one-month risk-free interest rate plus the basis-adjusted change in oil price:

$$R_t = 100(p_t - p_{t-1}) - 100(f_{t-1,1} - p_{t-1}) + r_{t-1,1}$$
(12)

so that after appropriate rearrangement the τ -month horizon expected return (4) can be derived.²²

Our 2-horizon multivariate state-space model is built upon two measurement equations describing the ex-ante ORP relationships obtained by reporting Eq.(5) into Eq.(10), and two state equations specifying the AR dynamics of the price of risk:

$$E_t(R_{t+3}) - r_{t,3} = \gamma_{t,3} V_t(R_{t+3}) + \varepsilon_{t,3}$$
(13a)

$$E_t(R_{t+12}) - r_{t,12} = \gamma_{t,12} V_t(R_{t+12}) + \varepsilon_{t,12}$$
(13b)

$$\gamma_{t,3} = \delta_{0,3} + \sum_{i=1}^{p_3} \delta_{i,3} \gamma_{t-i,3} + \eta_{t,3}$$
(14a)

$$\gamma_{t,12} = \delta_{0,12} + \Sigma_{i=1}^{p_{12}} \delta_{i,12} \gamma_{t-i,12} + \eta_{t,12}$$
(14b)

where $V_t(R_{t+\tau})$ is given by Eq.(11) and where $\varepsilon_{t,3}$, $\varepsilon_{t,12}$, $\eta_{t,3}$ and $\eta_{t,12}$ are *Niid* innovations with mean zero and constant variances σ_3^2 , σ_{12}^2 , s_3^2 and s_{12}^2 , respectively, with possible correlation within signal errors $(cov(\varepsilon_{t,3}, \varepsilon_{t,12}) = \rho)$ and within state errors $(cov(\eta_{t,3}, \eta_{t,12}) = \varphi)$ but with no cross-correlation at any lag between signal errors, state errors and between signal and state errors.

Starting from initial values for the price of risk and for the vector of parameters $\psi = \{\sigma_{\tau}^2, s_{\tau}^2, \rho, \varphi, \delta_{0,\tau}, \delta_{i,\tau}, \beta_{j,\tau}; \tau = 3,12; i = 1,2, ..., p_{\tau}; j = 1,2, ..., m_{\tau} \}$, the Kalman filter calculates predicted and updated (filtered) values of the state variables and their covariances

²¹ Considine and Larson (2001) use a similar approach in evaluating the conditional variance by monthly averaging daily standard deviations of prices using the previous 20 trading days.

²² From Eq.(12), take the 1-month ahead expectation $E_t R_{t+1} = 100(E_t p_{t+1} - p_t) - 100(f_{t,1} - p_t) + r_{t,1}$ and form the τ -month expected return by extending up to τ the horizon subscripts of the expected return and price and the maturity subscript of the futures, thus obtaining Eq(4).

at any time t = 1, ..., T based on actual and past observations. Given these predicted values, the log-likelihood (*L*) of the system is maximized to find new optimal values for ψ . Using the latter vector new sets of predicted states and of their covariances are generated, and so on. It is shown that the likelihood *L* is increased as ψ is updated across iterations (Dempster et al, 1977). Since this paper is concerned with a structural model, we perform smoothed estimates of the state variables, which use all the information in the sample.

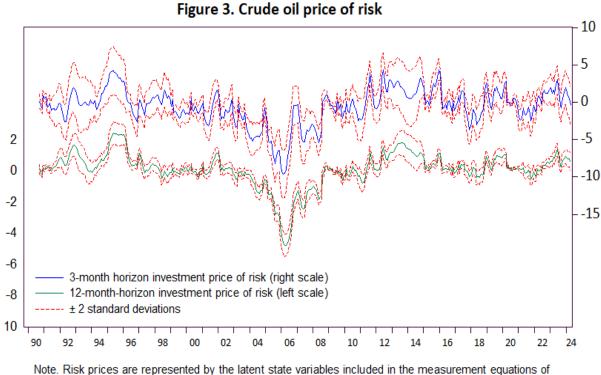
Table 1 summarizes the estimation results. Both state equations were found to take an AR(1) form without drift, that is, only $\delta_{1,3}$ and $\delta_{1,12}$ were significant. The estimated 0.86 and 0.94 values of these slope parameters imply that any shock on the risk price innovations have rather persistent effects, which are especially long-lasting in the case of the one-year horizon. The covariance values between the two signal residuals and between the two state disturbances are significant, reflecting the relevance of including them into the vector of parameters ψ . Robust and significant lag orders in the conditional expected variance (11) were found to be $m_3 = 5$ and $m_{12} = 9$ for the 3- and 12-month horizons, respectively. For both horizons, a downward overall trend is observed in the lag parameters $\beta_{j,\tau}$.

The high values of R^2 and R_D^2 measures indicate that our model of ex-ante ORPs fit well the data for both horizons and outperform by far a simple random walk with drift. To check for the statistical properties of the signal residuals, we perform appropriate diagnostic tests upon the smoothed signal disturbances standardized by their time-varying standard errors. Harvey's (1989) Ljung-Box Q* test fails to reject the null of no serial autocorrelation in the signal residuals at the 5% level of significance for $\tau = 3$ and at the 1% level for $\tau = 12$, corroborating that our model is well specified. From McLeod and Li's (1983) Ljung-Box statistics applied to squared residuals (Q^{ARCH}), we conclude that no ARCH effects are present in the residuals for both horizons at the 5% level. Non-rejection of the null of homoskedasticity is consistent with the time-invariant (or time-homogenous) feature of our state-space model, which assumes that the slope parameters and the parameters of the residual covariance matrices are constant. According to the Bowman-Shenton normality statistic, the signal residuals have a normal distribution over the whole sample at the 5% level irrespective of the horizon, indicating that no significant number of outliers is present. Overall, these favourable residual properties suggest that it would not be relevant to add explanatory factors to Eqs.(14a) and (14b).

Table 1: Kalman filter estimation results				
	τ=3	$\tau=12$		
Signal equations				
$eta_{\mathtt{l}, au}$	0.65*** (0.16)	0.85*** (0.11)		
$\beta_{2,\tau}$	0.90*** (0.21)	0.95*** (0.13)		
$\beta_{3,\tau}$	0.80*** (0.20)	0.99*** (0.17)		
$\beta_{4, au}$	0.74*** (0.19)	1.04*** (0.17)		
$\beta_{5,\tau}$	0.49*** (0.16)	0.99*** (0.16)		
$\beta_{6,\tau}$		0.72*** (0.13)		
$\beta_{7,\tau}$		0.69*** (0.13)		
$\beta_{8,\tau}$		0.61*** (0.11)		
$\beta_{9,\tau}$		0.38*** (0.09)		
$k_{\varepsilon,\tau}$	0.24** (0.14)	-3.09*** (0.13)		
State equations				
$\delta_{1, au}$	0.86*** (0.02)	0.94*** (0.01)		
$k_{\eta, au}$	0.49*** (0.18)	-2.19*** (0.12)		
Residual covariances:				
within signal eqns. ρ	0.21**	** (0.03)		
within state eqns. φ	0.36*	** (0.06)		
R^2	0.86	0.94		
R_D^2	0.85	0.88		
$Q^{*}(6)$	14.20	16.23		
$Q^{ARCH}(6)$	5.71	6.76		
BS	9.17	6.51		
AIC		.01		
SC	4.23			
HQ	4.09			
L	-78	-787.71		

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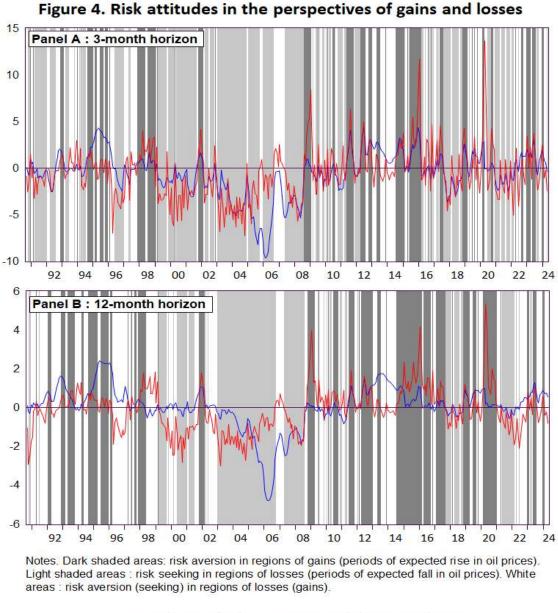
Notes: The data covers the period November 1989 – April 2024 (404 observations after lag adjustments). The Table presents final estimations of Eqs.(13a) to (14b) after eliminating the state intercepts $\delta_{0,\tau}$ which were found to be insignificant. The $\beta_{j,\tau}$'s in Eq.(12) are normalized such that $\beta_{0,\tau} = 1$. To ensure positivity, the variances of $\varepsilon_{t,\tau}$ and $\eta_{t,\tau}$ ($\tau = 3,12$) are calculated as $\exp(k_{\varepsilon,\tau})$ and $\exp(k_{\eta,\tau})$, respectively, where the scalars $k_{\varepsilon,\tau}$ and $k_{\eta,\tau}$ are estimated freely. R_D^2 is a goodness of fit measure which states that the model does better (worse) than a random walk with drift if the statistic is positive (negative) (Harvey, 1989). *AIC*, *SC* and *HQ* stand for the Akaike, Schwarz and Hannan-Quinn information criteria, respectively. *L* is the log-likelihood value. Q^* is a Ljung-Box form statistic to test for residual autocorrelation in the signal equation. Q^{ARCH} is a Ljung-Box form statistic applied to squared residuals to test for the presence of an ARCH effect in the signal residuals (Harvey, 1989). Both Q^* and Q^{ARCH} are distributed as $\chi^2(p)$ (McLeod and Li, 1983) where *p*, the number of lags, is set to ln(404)=6 as suggested by Harvey (1989) and 2. The *BS* statistic is distributed as $\chi^2(2)$. Asymptotic critical values for χ^2 with (2; 6) d.o.f. are (5.99; 12.59) at the 5% level and (9.21; 16.81) at the 1% level. ** and *** stand for significance at the 5% and 1% levels, respectively. Numbers in brackets are the standard errors of estimation.



ex-ante risk premiums and are obtained by jointly filtering the 2-horizon state-space model (Eqs (14)-(15))

Figure 3 displays the estimated values of the price of risk generated by the state equations for the 3- and 12-month horizons. It can be seen that the risk prices are either positive or negative, depending on the periods. Two observations can be made from these results. First, 59,7% of the values of risk price are negative (40,3% are positive) for the 3month horizon while 60,1% of these values are positive (39,9% are negative) in the case of the 12-month horizon. This suggests that at the shorter horizon investors are more frequently prone to be risk seeking than risk averse, while in the longer horizon they are barely more frequently risk averse than risk seeking. This result conforms to the evidence that speculators' horizon favors the short term. Second, the alternating dynamic of the price of risk can be given a state dependent risk attitude interpretation in accordance with the prospect theory. As a result of their gamble-based experiments, Kahneman and Tversky (1979) found that 84% of individuals are risk-averse in the area of gains while 69% of them are risk-seeking in the area of losses. For comparison purposes, we must discuss how we can represent the patterns of preferences "risk aversion in the region of gains" and "risk-seeking in the region of losses" in the case of our representative investor. Recall from Eq.(9) that in the state of risk aversion $(\kappa_{t,\tau} > 0)$ the price of risk is positive, while it is negative in the state of risk-seeking $(\kappa_{t,\tau} < 0)$ 0). Let the region of gains be represented in our context by the subset of opinions S_1 where agents expect a positive change in oil price and the region of losses by the subset of opinions S_2 where agents expect a negative change in oil price. We can then consider the joint event E_1 : "the price of risk and the expected change in oil price are both positive" and the joint event E_2 : "the price of risk and the expected change in oil price are both negative" as the states from our context that are analogous to Kahneman and Tversky's patterns of preference mentioned above. For the two horizons, Figure 4 exhibits respectively the occurrences of E_1 (dark shaded areas) and of E_2 (light shaded areas).²³ To express these occurrences in percentage terms, we divided the numbers of realizations of E_1 and E_2 by the number of bullish expectations in S_1 and the number of bearish expectations in S_2 , respectively. We obtained 71% for E_1 and 79% for E_2 at the 3-month horizon and 79% for E_1 and 55% for E_2 at the 12-month horizon, averaging 75% for E_1 and 67% for E_2 across both horizons. These two magnitudes are consistent with Kahneman and Tversky's experiments, since there is a large majority of risk averse investors in the region of gains and a large majority of risk seeking agents in the region of losses. This deserves emphasis in that it makes our results concerning investors' contextual risk attitudes compatible with the prospect theory predictions.

²³ In the unshaded areas, the price of risk and the expected change in oil price have opposite signs. These fewer cases are not of interest here, since they correspond to the Kahneman and Tversky's remaining two patterns of preference (risk aversion in the context of losses and risk seeking in the context of gains) that were adopted by a minority of individuals.



— Oil price of risk — Expected change in oil price

In particular, we can interpret in this context the troughs in the negative region drawn by the price of risk between 2002 and 2008 at both horizons in Figure 3. This period was characterized by an upsurge in oil price as a result of the strong growth in global economic activity driven by emerging market economies (and especially China), on the one hand, and of geopolitical tensions in Middle East, on the other hand, together with an increasingly tight oil supply since 2004 (Hamilton, 2009). We can also observe that although oil price expectations for both horizons were steadily revised upwards as the spot price rose, expected values were almost systematically lower than actual values (Figure 5, zoomed area). One interpretation of this may be the following: agents who had in mind the stability of the mean value of oil price around US\$30 up to 2002 might not have expected the bullish oil market to last long and might have believed that it will end up by a trend reversion in the near future, thus forming negative expected returns. Such downward oil price expectations would lead them to believe that they are potentially facing a loss. According to the prospect theory, this suggests that they will prominently tend to be risk seeking, consistently with the negative risk price troughs in Figure 3.

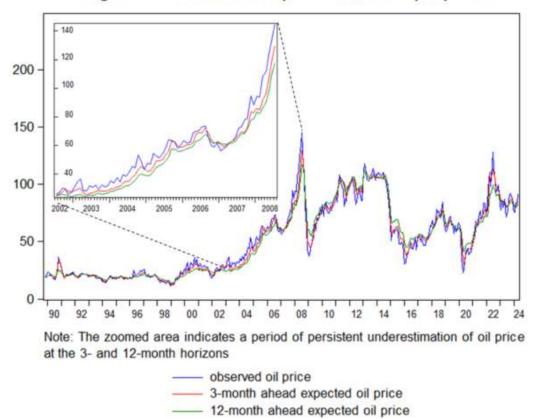


Figure 5. Observed and expected crude oil spot price

Figure 6 displays for each horizon the expected conditional variance of oil returns as described in Eq.(11), calculated using the Kalman estimates of $\omega_{j,\tau}$'s (Table 1). As expected, a peak is formed during the global financial crisis and the post-Covid period for both horizons and the 12-month horizon variance appears to be tighter than the 3-month horizon variance. As a result, the expected variance is not significantly correlated with the price of risk, since the coefficients of correlation are 0.046 for the 3-month horizon and -0.039 for the 12-month horizon. This shows that the two elements contributing to describe the dynamics of risk premiums are independent and therefore fully complementary components. This statistical property suggests that the expected variance mainly reflects the speculative component while the price of risk mainly conveys economic factors of the ex-ante ORPs, these being macroeconomic as well as oil market specific factors.

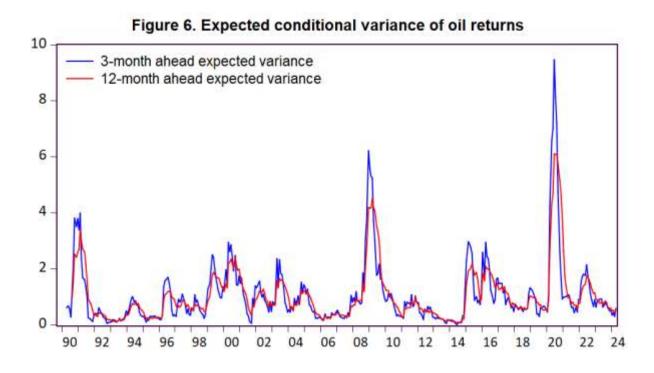


Figure 7 compares the observed and fitted values of the ex-ante ORPs. Fitted values were obtained from the estimation by Kalman filtering of the measurement equations (13a) and (13b) along with the state variables (14a) and (14b) and the expected variance (11), for the 3- and 12-month horizons, respectively. For both horizons, it can be seen that the estimated values closely follow the main fluctuations of the observed values, with a finer adjustment for the 12-month horizon, as indicated by the R^2 statistics (Table 1). Specifically, our model provides good fits to the largest peaks in both ORPs, such as the one associated with the collapse in oil price due to the Covid-19 crisis in mid-2020. Overall, regarding the well-behaved residuals of our state-space model, we can conclude that, despite its relative simplicity, our model accurately describes the dynamics of ex-ante ORPs.

A natural extension of our ORP analysis is to study the term structure of ORPs. This is a central issue in that observing and understanding this structure conditions the decision-making of an investor who wants to choose the most relevant horizon for investing in crude oil. Figure 8 displays the term spread between the survey-based observed values of 12- and 3- month ex-ante ORPs and the spread between the estimated values of ORPs from our estimated state-space model. Although less volatile, the calculated spread reproduces the major trends of the observed values.

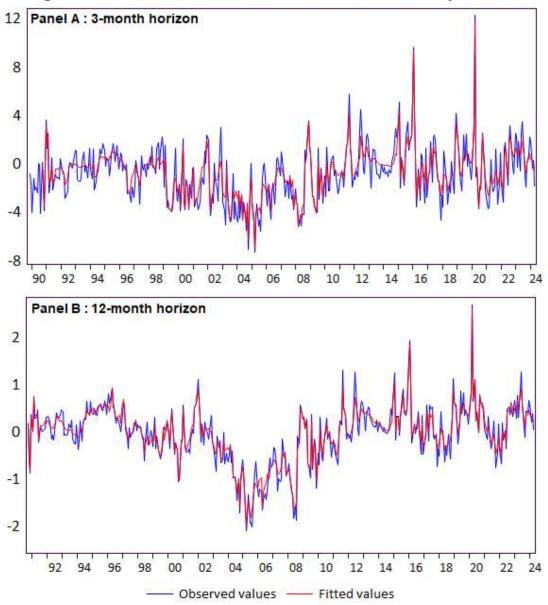
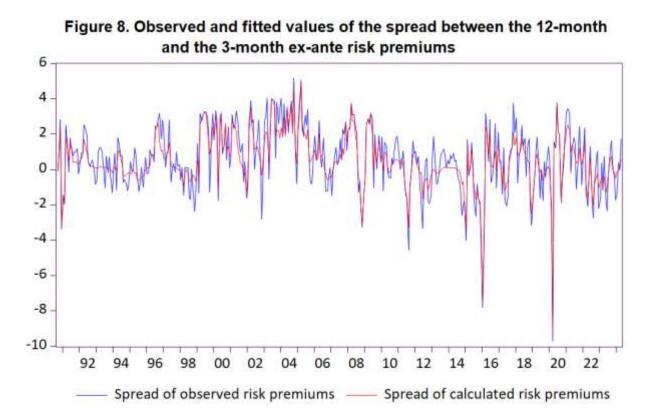


Figure 7. Observed and fitted values of the ex-ante risk premiums



It can be seen that, even though the sign of the spread alternates over time, the dominant slope of our term structure of oil risk premiums is clearly positive. Over the whole period, we find a proportion of 66% of positive values for the spread with median and mean values of 0.65% and 0.61% per month, respectively.²⁴ This upward term structure stems from our result that, consistently with our risk price estimations, the 12-month and 3-month horizons are characterized by a dominant risk aversion and dominant risk preference, respectively; the positive slope is not explained by the volatility patterns, which on average exhibit higher volatility for the 3-month horizon than for the 12-month horizon (see Figure 6). Contrary to these findings, using different survey data (Bloomberg) and different methodologies, Cortazar et al. (2022) found a downward slope in the ex-ante ORP term structure over the periods spanning from January 2010 to June 2017. Note, however, that this finding is specific to the sample period used, which is much shorter than ours. The sign of the term structure slope can obviously change depending on the period – as is the case with interest rate term spreads – and only an extended period such as ours can help detect a dominant sign.

²⁴ By comparison, due to the presence of a risk or liquidity premium in long term rates, the term structure of interest rates is also known to be most often upward sloping. Contrariwise, the term structure of equity risk premiums is mostly found to be downward sloping (see, among others, Binsbergen and Koijen, 2017).

5.2 Empirical identification of risk price driving factors

In Section 5.1, we measured our unobservable risk prices through the estimation of our state variables. However, the economic factors underlying these variables remain unidentified. Our goal here is to empirically investigate whether risk prices are associated with relevant economic factors. Developing a theoretical framework to explain the determinants of risk prices is beyond the scope of this study.

We tested a number of factors which were found to be significant in explaining ORPs (see section 2). Among these, macroeconomic factors include the expected CPI-based and observed WPI-based rates of inflation, the rate of change in US GDP, the expected change in the industrial production to GDP ratio, and NBER probabilities of US recessions. Financial factors are the term spreads of US Treasury Bill rates and the CBOE crude oil volatility index (OVX)²⁵. We also consider oil market-related factors, that are the rate of change in crude oil price, the log of US oil stock, the utilization rate of refinery capacity (calculated as the log ratio of refinery throughput to refinery capacity or maximum throughput), the US oil reserves lifetime (constructed as the log ratio of proved oil reserves to oil production, see Coleman, 2012), and OPEC relative oil supply (defined as the log ratio of OPEC and US oil productions). As an indicator of forecast heterogeneity, we considered the coefficient of variation of CE experts' oil price expectations, defined at any time as the ratio of the crosssection standard error of oil price expectations to the cross-section mean. Expected macroeconomic variables (expectations are for the end of the current year, expressed as percent per month) are extracted from CE at the survey date. Observed macroeconomic and oil market-related variables are collected from Datastream and financial indices and recession probabilities are obtained from the Federal Reserve of Saint Louis (FRED). We test all these factors as potential economic drivers of our risk price variables for both the 3- and 12-month horizons. These two equations are estimated by using the seemingly unrelated regression (SUR) methodology which is appropriate when the errors are mutually correlated and heteroskedastic.²⁶ Our SUR estimation results are displayed in Table 2. The two regression residuals are found to be stationary at the 1% level for both horizons, which ensures that our SUR is not spurious. Due to inevitable missing factors in modeling price of risk, residuals are

²⁵ Since the OVX is only available from May 2007 onward, incorporating it among the other regressors would roughly halve our sample period, resulting in a significant loss of power in the system estimation. Instead, we regard the inexistence of the OVX prior to May 2007 as evidence that it could not have influenced the price of risk before that point in time, given that investors could not refer to this decision-making tool. We address this ineffectiveness by imputing zeros for the OVX before May 2007, similar to a dummy variable taking zero values at times the event in question did not impact the dependent variable. This allows us to conduct our analysis over the full timeframe.

²⁶ Note that if the two equations have identical right-hand-side variables, the SUR method does not add to the estimator efficiency and becomes equivalent to performing two separate OLS regressions. As our final sets of significant regressors are not identical, the SUR approach applies.

autocorrelated, implying that our estimates are unbiased but inefficient. However, we can admit that this inefficiency is offset by the high level of significance of almost all the estimated parameters. Overall, based on the \overline{R}^2 values, the economic factors we identified explain about half of the dynamics of the risk prices for each horizon.

We interpret the impact mechanism of many variables on the oil risk price through their effects on the share of the risky asset in the portfolio $\theta_{t,\tau}^*$ or on the relative risk aversion (or risk preference) coefficient $\kappa_{t,\tau}$, see Eq.(9).

Table 2: Seemingly unrelated regression of oil price of risk				
	τ=3	τ=12		
Intercept	18.33*** (3.35)	22.80*** (10.17)		
WPI-based 3 month inflation	-0.61*** (-3.12)	-0.20** (-2.49)		
CPI-based expected current annual inflation	-0.38*** (-4.54)	-0.30*** (-9.03)		
Expected change in the ratio of industrial production to GDP	0.33*** (5.39)	0.07*** (2.74)		
Expected growth in GDP	-0.34*** (-4.59)	-0.11*** (-3.53)		
NBER probabilities of US recessions	-	0.005*** (3.73)		
Term spread of interest rates ^(a)	-1.14* (-1.93)	0.29*** (3.89)		
OVX	0.02*** (3.57)	0.01*** (3.61)		
Heterogeneity of oil price expectations (lagged)	-0.07*** (-2.78)	-0.10*** (-7.05)		
Rate of change in oil price	-0.05*** (-5.50)	-0.01** (-1.98)		
Utilization rate of refinery capacity	8.07*** (3.03)	3.41*** (3.13)		
US oil reserves lifetime	2.19** (2.39)	2.16*** (5.66)		
Log of US oil stock (lagged)	-3.92*** (-4.14)	-4.20*** (-10.86)		
OPEC relative oil supply	-5.61*** (-9.58)	-4.02*** (-16.36)		
\bar{R}^2	0.44	0.55		
DW	0.26	0.24		
ADF	-5.42	-5.47		

Table 2: Seemingly	unrelated	regression	of	oil	price	of	ris	k
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Notes. Numbers in brackets are the *t*-statistics. The dependent variable (the price of risk) is generated as a state variable using the Kalman filter estimation. The hyphen indicates that the corresponding variable is not significant for the specified horizon; the results presented are obtained after excluding this regressor. The *ADF* statistic tests the null of the presence of a unit root in the residuals and compares to the residual-based critical values of MacKinnon (2010), which are calculated as -4.33, -3.76 and -3.45 at the 1%, 5% and 10% levels, respectively. Symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. (a) The term spread of interest rates is defined as the difference between the 3-month US Treasury Bill (TB) and the 1-month TB for the 3-month horizon, and the difference between the 12-month TB and the 3-month TB for the 12-month horizon.

Macroeconomic factors

When the production growth rate is expected to increase, two opposite effects on price of risk can be envisaged: a positive ripple effect and a negative confidence effect. Concerning the first effect, an increase in expected industrial production growth reflects a higher expected oil demand, as the industrial sector is the most energy-consuming sector. Such an outlook of rising demand for oil should directly increase the holdings of barrels of crude oil and consequently elevate the share of the risky asset in portfolios, implying a higher price of risk. Our finding that expected growth in the ratio of industrial production to GDP is positively related to the price of risk is in line with this conjecture. As for the second channel, when they expect a higher level of economic activity, investors in general and oil asset holders in particular may feel more confident, so that they may become less risk averse, or more risk seeking, depending on their risk attitude at that period. It follows that the coefficient $\kappa_{t,\tau}$ and thus the price of risk should tend to decline. This result conforms to the widely agreed outcome of the empirical financial literature that the market risk premium is countercyclical (Pagano and Pisani, 2009; Alquist et al, 2013; Chin and Liu, 2015).

In the same vein, the influence of the probability of recessions in the US economy is positive for the 12-month horizon, signalling a rise in the perceived uncertainty over longer horizons and a consequent upward adjustment in $\kappa_{t,12}$, and hence on the price of risk.

Concerning the impact of the current and expected inflation on the oil price of risk, we would expect their sign to be positive under the assumption that investors use crude oil future contracts as a hedging tool against inflation (increase in $\theta_{t,\tau}^*$), and negative if they rather rely on the risk-free debt securities as safe haven investments against inflation (decrease in $\theta_{t,\tau}^*$). Our negative estimates support the latter case.

Financial factors

The impact of the term spread of interest rates on the price of risk can be explained through the effects of its components, which are the expected change in the short rate and the liquidity premium. An increase in the former variable leads, all other things being equal, to a fall in the share of the oil asset in the portfolio $\theta_{t,\tau}^*$. Conversely, a liquidity premium reflects a rise in the liquidity constraint which raises the risk aversion $\kappa_{t,\tau}$. At the 12-month horizon, the positive sign of the spread suggests that the second effect dominates while the first effect seems to prevail at the 3-month horizon.²⁷

²⁷ Spreads between 10-year TB bonds and 3-month TB rates and between 12-month and 3-month TB rates were alternatively introduced in the 3-month risk price equation but none of them was found to be significant.

A positive impact on the price of risk is also provided by the OVX index. A surge in this factor reflects increasing market uncertainty, which primarily drives up risk aversion, which in turn raises the price of risk.

Oil market-related factors

To describe the effect of forecast heterogeneity on oil risk prices, we assume that when forming their opinions investors are reluctant to deviate from the market opinion (Orléan, 1992; Laurent, 1995). Consequently, individuals who realize that they overestimated or underestimated future oil price at time t-1 with regard to market expectations should be prompted to adjust their opinions towards the market opinion. As a result, the sum of the downward and upward adjustments towards the consensus between time t-1 and t should lower heterogeneity, the size of this contraction being proportional to the level of the initial heterogeneity. Investors who revise their forecasts downwards will accordingly reduce the share of the oil asset in their portfolios at time t, this leading to a decrease in the price of risk. Conversely, those who update their opinions upward will purchase new oil assets, thereby tending to push up the risk price.²⁸ One can expect a positive overall impact of forecast heterogeneity on the price of risk if overestimating agents are dominant in average during the period and a negative effect if underestimating agents dominate the market. We find support for the latter case since the estimated slope of the lagged value of the coefficient of variation is negative for both horizons.

When oil market is bullish, investors may wish to increase their oil holdings with the expectation of selling them at a higher price in the future. Such a long position implies a rise in the share of the risky asset in their portfolios. In the meantime, if investors believe this strategy to be profitable, they may be motivated to take on more risk, which translates into a lower risk aversion parameter. Thus, two simultaneous but controversial influences of $\theta_{t,\tau}^*$ and $\kappa_{t,\tau}$ can be seen as affecting the price of risk. Our finding that oil price returns negatively impact the price of risk for both horizons suggest that the effect of the parameter $\kappa_{t,3}$ is dominant. This interpretation is consistent with Hoffmann and Post (2017).²⁹

Similarly, the level of oil stocks can have contradictory effects on the price of risk depending on whether they are more influenced by marginal storage costs or by convenience yield. An increase in marginal storage costs is a powerful disincentive for maintaining oil

 $^{^{28}}$ If, because of individuals' aversion to deviating from the consensus, the dispersion of individual opinions shrinks during the time span between t-1 and t, the arrival of new information at time t will of course give rise to a new oil price forecast heterogeneity that may be greater or smaller than the one prevailing at time t-1.

²⁹ The authors use brokerage records and investor surveys to show that investors' past personal portfolio returns have a positive impact on their return expectations and risk tolerance (i.e., a negative impact on their risk aversion).

holdings; in this case a fall in $\theta_{t,\tau}^*$ reduces the price of risk. Convenience yield represents the benefits gained from reducing the risk of non-delivery to oil consumers in the event of an unexpected rise in oil demand, which is a motive to build up physical inventories of oil; in this case the risk price increases with $\theta_{t,\tau}^*$. Our results suggest that the marginal cost effect outperforms the convenient yield effect, since a rise in oil inventories reduces oil price of risk at both horizons.

When oil production approaches full capacity, the expected oil production shortages may push investors into a precautionary strategy by consolidating their stocks, which results in a rise in $\theta_{t,\tau}^*$. This allows explaining the positive relationship we evidenced between the rate of refinery capacity utilization and the price of risk.

An increase in the lifetime of oil reserves, driven by a slower rise in oil production compared to the growth of proved reserves, may lead investors to believe in a faster shift towards alternative energies that are becoming more competitive. This belief can reduce confidence in oil assets (raising $\kappa_{t,\tau}$) and lead them to lower their oil holdings in their portfolios (decreasing $\theta_{t,\tau}^*$). The positive effect of oil reserve lifetime on the risk price across both horizons suggests that, on average, the influence of the first effect is dominant.

The negative sign of OPEC's relative oil supply is consistent with OPEC's strategy to regulate oil production and prices through coordinated efforts among its member countries, particularly by establishing a system of production quotas. Consequently, an increase (decrease) in the OPEC's share of the total oil supply can lead to a decrease (increase) in investors' risk aversion, as they approve of the cartel's regulatory intent.

6. Conclusion

This article aims at modeling ex-ante risk premiums in the crude oil market for the 3and 12-month horizons. We calculate these ex-ante premiums using oil price expectations provided by Consensus Economics surveys over thirty-five years, a timeframe that gives our results a broader scope than the shorter periods considered by the few previous studies. It is shown that oil price expectations are not rational, implying that in driving decision- making, the ex-ante approach to the risk premium is more relevant than the ex-post approach.

We model ex-ante crude oil risk premium for each of the two horizons within the portfolio choice theory framework, where the representative investor maximizes the expected utility of their future wealth made of a combination of barrels of oil and risk-free asset (T-Bills). The solution of this program determines the risk premium as the product of the

expected variance of oil returns and the price of risk, both assumed to be time-varying and horizon-dependent. While the expected variance depends on actual and past instantaneous variances, the price of risk is represented as an unobservable stochastic state variable within a two-horizon state-space model of ex-ante risk premiums that we estimate using the Kalman filter methodology.

We find significant disparities in ex-ante oil risk premiums between horizons, with much higher amplitudes for the 3-month horizon compared to the 12-month horizon. Risk prices take positive or negative values, reflecting alternating risk attitudes over time. Risk seeking behaviour is more pronounced in the short horizon, while risk aversion dominates in the longer horizon. Investors are shown to be prominently risk averse over gains (expected rise in oil price) and risk seeking over losses (expected drop in oil price), which is consistent with the predictions of prospect theory. The resulting spread between the two risk premiums exhibits a dominant upward slope over our extended period. Finally, we identify various factors influencing the price of risk. Macroeconomic and financial factors include expected growth, inflation, term spread of interest rates, and OVX. Factors that are specific to the oil market are the heterogeneity of oil price expectations, the rate of change in oil price, oil stocks, the rate of utilization of refinery capacity, oil reserves lifetime, and OPEC's relative oil production. Overall, these influences explain about half of the variation in the price of risk and offer a comprehensive understanding of the fundamental and speculative effects on risk pricing.

Appendix : Testing the rational expectation hypothesis

Testing for the REH requires that unbiasedness and orthogonality tests be performed, given that the latter test is not needed if the former test is rejected. Our unbiasedness test equation is :

$$p_{t+\tau} - p_t = a + b[E_t(p_{t+\tau}) - p_t] + v_{t+\tau}$$

where the null a = 0, b = 1 is jointly tested and $v_{t+\tau}$ must be white noise to insure residual orthogonality. Note that the reverse causality in the unbiasedness test equation would lead to an endogenous regressor problem. To ensure that our estimates are robust to heteroskedasticity and autocorrelation, we estimated our test equation using the Newey-West methodology. Results are reported in Table A, columns 2 and 4. For the two horizons, *a* is not significantly different from zero. For the 3-month horizon, *b* significantly differs from 1, leading to a strong rejection of the null. However, the null is not rejected for the 12-month horizon. However, the test equation includes an expectation variable with a potential measurement error, causing an attenuation bias in *b*. We use the ΔJ statistics within the TSLS methodology to test for this bias. The null hypothesis of zero measurement error bias is rejected for the 3-month horizon but not for the 12-month horizon. Thus, testing the hypothesis that b = 1 is inconclusive for the 3-month horizon, while the test is not rejected for the 12-month horizon. In any case, DW statistics suggest that residuals are not white noise, invalidating the residual orthogonality hypothesis and thus the REH. Therefore, the ex-ante ORP measure is appropriate.

Table A. Unblasedness with no measurement error blas test results				
	τ=3		τ=	12
	OLS	TSLS	OLS	TSLS
а	0.49 (0.53)	0.75 (0.59)	0.41 (0.31)	0.50 (0.37)
b	0.31** (0.16)	0.36** (0.16)	0.73*** (0.25)	0.90*** (0.30)
R^2	0.02	0.02	0.09	0.08
DW	0.55	0.54	0.13	0.12
ΔJ -statistic p-value	-	0.001	-	0.61

Table A. Unbiasedness with no measurement error bias test results

Notes. Numbers between square brackets are the standard errors of the estimates of the test equation above. Values in columns 2 and 4 are the standard (OLS) unbiasedness test results. Values in columns 3 and 5 are the Two Stage Least Squares (TSLS) estimation results which are appropriate to testing for the presence of a measurement bias due to $E_t(p_{t+\tau}) - p_t$. The ΔJ statistic is the difference between the TSLS objective function J including the IVs plus the regressor under test and the objective function J' with the IVs only. Under the null of no measurement error bias $\Delta J = J - J'$ is distributed as a χ^2 with 1 d.o.f. (number of regressors tested). All estimates are performed using the Newey-West heteroskedasticity and autocorrelation-consistent covariance matrix. **, *** stand for significance at the 5%, 1% level, respectively.

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