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Abstract

Purpose – The purpose of this paper is to investigate and test for changes in investor risk aversion and the stochastic discount factor (SDF) using options data on the West Texas Intermediate crude oil futures contract during the 2007-2011 period.

Design/methodology/approach – Risk aversion functions and SDFs are estimated using parametric approaches before and after four specific dates of interest. The dates are: the summer 2008 end of the bull market regime; the late 2008 credit freeze trough; the BP Deepwater Horizon explosion; and the Libyan uprising.

Findings – Absolute risk aversion functions and SDFs are significantly flatter (less decreasing in wealth) after the end of the bull market and the credit freeze trough. After these two market reversals, oil market participants were less risk-averse for low levels of wealth but more risk-averse for high wealth levels. Oil market investors also increased their valuation of anticipated future wealth in average states of nature relative to very high or very low-asset return states after reversals. The BP explosion and the Libyan uprising led to steeper risk aversion functions (decreasing more rapidly in wealth) and SDF. Oil market investors were more risk-averse for lower future wealth, but less risk-averse for higher future wealth. Oil market investors increased their valuation of anticipated future wealth in extreme states of nature relative to average states of nature after both dates.

Originality/value – Documenting statistically and economically significant changes in oil market investors' attitude toward risk and inter-temporal appetite for risk in relation to changes in financial and political conditions.

Keywords Loss aversion, Options, Risk aversion, Crude oil, Risk-neutral density

Paper type Research paper

1. Introduction

Oil markets have experienced in recent years heightened uncertainty and a severe boom-and-bust cycle associated with the financialization of commodities and the financial crisis of 2007-2009 (Carter *et al.*, 2011; Cheng and Xiong, 2014; Singleton, 2013).

This paper studies the risk attitudes of oil market participants during this volatile period by documenting changes in their tolerance for risk (risk aversion) and inter-temporal appetite for risk (stochastic discount factor, or SDF) linked to varying financial and political conditions. After first estimating physical and risk-neutral return densities using options and futures data for the West Texas Intermediate (WTI) crude oil contract over 2007-2011, this paper tests for changes in investor risk aversion and the SDF during four significant periods for the oil market. The methodology builds on Jackwerth (2000) and, to reduce the impact of market noise on the results, is applied to short windows of 15 days before and after each date of interest, but omitting the date itself. We present graphical, statistical and economic evidence, together with several robustness checks, to support our findings.

Our results show similarities in the adjustment of oil market participants' risk attitudes following the market reversal dates (the end of the bull cycle and the credit freeze trough). Absolute risk aversion functions and SDFs are significantly flatter after

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these dates. These findings imply that, after the two market reversals, oil market participants are less risk-averse than before for low levels of wealth but more risk-averse for high wealth levels. The flatter U-shaped SDF implies that oil market participants increase their valuation of anticipated future wealth in average states of nature (relative to extreme states of nature, i.e. very high- or very low-asset returns) after reversals, suggesting they view another major reversal (an extreme state of nature) as less likely. Our results also suggest that both the BP explosion and the Libyan uprising shocks have similar impacts on risk aversion and time preferences. After these shocks, the risk aversion function and SDF are steeper, such that an investor was more risk-averse for lower future wealth but less risk-averse for higher future wealth. The steeper U-shaped SDF implies that oil market participants after these events increase their valuation of anticipated future wealth in extreme states of nature relative to that received in average states of nature, as these shocks could signify a higher probability of similar events (extreme states of nature) in the future.

1.1 Oil markets and the financialization of commodities

Crude oil is an important market. As an asset, it represents 48.67 percent of the value of the Goldman Sachs Commodity Index in 2014 (see 2013 S&P indices) and WTI futures and options are very liquid, as measured by transaction volumes. WTI options trade for a wide range of strike prices and maturities that have nontrivial trading volume (see 2015 CME Group bulletins). Indeed, WTI crude oil options are the most heavily traded among commodities. WTI option annual trading volume is 32 percent greater than for natural gas, 46 percent greater than corn, almost three times greater than soybeans, nine times greater than gold and 25 times greater than silver. Thus, crude oil is a key asset to better understand the financialization of commodities.

As a key commodity, crude oil is also of considerable importance in the global economy. It is well established that oil prices tend to be pro-cyclical and endogenous to the real business cycle, and moreover, that oil price increases have led nine out of ten US post-war recessions (Kilian, 2009). Furthermore, evidence suggests that crude oil prices and its forward curve have predictive power for stock market indices and global economic activity (Hong and Yogo, 2012). Finally, as our objective is to identify and measure changes in risk preferences, oil is an appropriate reference asset given that market and political events can be readily and accurately identified based on financial news.

Four important dates for the oil market, presented in Table I, are considered: the end of the commodity bull cycle on July 11, 2008, associated with a switch from a bull-to-bear market (see, e.g. Carter *et al.*, 2011; Cheng and Xiong, 2014; Singleton, 2013); the oil futures

Window	End of the commodity bull cycle	Credit freeze trough	Deepwater Horizon explosion	Libyan uprising
15 days prior the date	June 12, 2008	November 28, 2008	March 29, 2010	January 31, 2011
Date of interest	July 3, 2008	December 19, 2008	April 20, 2010	February 22, 2011
15 days after the date	July 25, 2008	January 13, 2009	May 11, 2010	March 15, 2011

Note: The table reports the time windows considered before and after each of the four dates of interest considered

Table I.
Dates of interest and pre- and post-15-day windows

price trough occurring on December 19, 2008 and linked to the credit freeze crisis and switching from a bear to a bull market; the explosion of the BP Deepwater Horizon oil platform on April 20, 2010; and the beginning of the "Libyan uprising" (Jasmine revolution) on February 22, 2011. Dates are chosen based on the magnitude of WTI oil futures price movements and the importance of commodity-related news as reported on Bloomberg.

This sample covers a period of turbulence in the oil market. In particular, Baker and Routledge (2012) document that during the bull market regime leading up to the June 2008 price spike, oil prices exceeded in real terms the OPEC price shocks of the 1970s. Moreover, they report that this increase in prices lasted much longer than the effect of the Persian Gulf Crisis in 1990-1991. It is worth noting that the credit freeze trough of December 19, 2008 followed the first wave of quantitative easing and an OPEC announcement to reduce production[1]. Whether or not these announcements contributed to the onset of the market reversal is a question beyond the scope of this paper and regarding which the macroeconomic literature still has not reached a consensus. We assume that the oil futures market is semi-efficient and proceed based on the principle that these events were incorporated at their announcement dates, which are outside our window of interest. Finally, while there are several notable events related to the "Jasmine revolution," the chosen date (February 22, 2011) marks the start of the insurrection in Tripoli. News about oil prices on Bloomberg show that February 22, 2011 was the date at which the uncertainty regarding future oil supplies was at its highest.

1.2 Literature review

Since Breeden and Litzenberger (1978), a large financial literature has emerged focussing on option-implied information on investor risk aversion and the SDF[2]. The literature on crude oil options documents the evolution of oil price returns, volatility and risk-neutral densities (Melick and Thomas, 1997; Flamouris and Giamouridis, 2002; Giamouridis, 2005; Hog and Tsiaras, 2011).

With respect to this literature, our main contribution is to go beyond reporting only risk-neutral densities and to document and test for the significance of short-run changes in risk aversion and SDFs following important market reversals and shocks to the oil market. Several studies document how market participant risk aversion and time preferences vary in the long run (e.g. Chabi-Yo *et al.*, 2008; Rosenberg and Engle, 2002; Jackwerth, 2000; Ross, 2015). In particular, Jackwerth (2000) examines the long-term stability of the absolute risk aversion function implied by S&P 500 index options and finds that it changes dramatically after the 1987 crash. However, little is known about short-run changes in risk aversion. This paper develops a methodology capable of measuring such changes for crude oil or other reference assets. We test a first hypothesis based on the evidence presented by Jackwerth (2000):

H1. In addition to the changes in risk aversion reported in the long run in Jackwerth (2000), the risk aversion function changes significantly after a market crash and reversal in the short term.

Moreover, we build on the results presented in Melick and Thomas (1997), who examine how risk-neutral distributions implied from crude oil options have reacted to events during the 1990-1991 Persian Gulf Crisis. Based on their evidence, we test the following hypothesis:

H2. Geopolitical events such as the Libyan uprising and idiosyncratic shocks such as the BP platform explosion will significantly affect the risk aversion function and SDF, through their impact on the risk-neutral density of oil price returns.

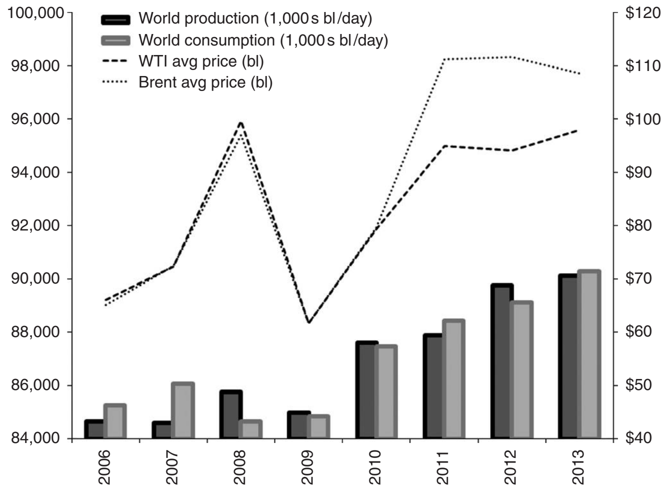
While our results provide additional evidence that the risk-neutral distribution quickly incorporates geopolitical news as found in Melick and Thomas (1997), our analysis also shows that oil derivative investors revise their attitudes toward risk as well as their expectations.

Lastly, the behavioral finance literature provides further context for our analysis. Barone-Adesi *et al.* (2012) study how investor sentiment affects risk aversion and the rate of time preference. Relatedly, Tanha *et al.* (2014) find that in-the-money and out-of-the-money options respond differently (through implied volatility) to macroeconomic announcements. Based on the close link between financial and commodity markets and the importance of energy in the economy, this paper makes a contribution by documenting changes in risk attitudes implied by options markets, which have been under-studied in the behavioral finance literature.

2. Data

Figure 1 presents the evolution of the WTI and Brent oil spot prices as well as world oil production and consumption. Daily price data on futures and options on futures for the WTI crude oil contract traded on the NYMEX/CME market are used over the period of June 1, 2007-October 25, 2011 for options and January 3, 2000-October 25, 2011 for futures. The futures data are extracted from the Bloomberg database while the options data are obtained from the Commodity Research Bureau (Bridge). To estimate physical densities, gross returns of the second nearby WTI futures contract over a one-month horizon are used. The time series data are obtained by rolling over the second nearby contract. The rollover to the next contract occurs on the 15th of each month. Table II presents the empirical moments for the gross returns in each sub-period.

To recover the risk-neutral density, data on NYMEX (now CME) American options written on the WTI futures contract are extracted from June 2007 until December 2011. Table III presents descriptive statistics related to options data for each window of interest. On average, the sample contains between 1,436 and 2,066 option observations for each trading day with over 200 strikes daily. As these options are American-style



Source: Energy information administration

Figure 1. Production, consumption, WTI and Brent spot oil prices during the 2006-2013 period

Table II.
Descriptive statistics for the NYMEX WTI oil futures contract one-month gross return

	End of the commodity bull cycle	Credit freeze trough	Deepwater Horizon explosion	Libyan uprising
Number of observations	252	131	317	214
Minimum	0.789	0.586	0.821	0.813
Maximum	1.225	1.289	1.491	1.206
Mean	1.059	0.826	1.056	1.007
SD	0.0757	0.109	0.119	0.0718
Skewness	−0.165	−0.0883	0.570	−0.595
Kurtosis	2.220	2.622	3.304	3.016

Notes: The table presents the descriptive statistics for gross returns over a one-month investment period of the WTI futures contract over the different sub-periods considered. Descriptive statistics for the non-overlapping period prior to the event are presented. The first line reports the number of observations (trading days) in each sub-period. The data on the WTI futures contract are extracted from Bloomberg

Table III.
Descriptive statistics for the options data used to obtain the risk-neutral densities before and after each significant date

	End of the commodity bull market	Credit freeze trough	BP Deepwater Horizon	Libyan uprising
Number of options				
Mean	1,958	1,912	1,475	1,578
Min.	1,834	1,827	1,436	1,513
Max.	2,066	1,983	1,553	1,671
Implied volatility				
Mean	0.41	0.56	0.31	0.32
Min.	0.21	0.23	0.06	0.17
Max.	0.74	1.00	0.75	1.00
Strike prices				
Mean	114.44	95.88	95.11	99.46
Min.	35	20	25	25
Max.	300	400	250	200
Number of strikes				
Mean	272	269	217	204
Min.	256	254	211	200
Max.	280	280	223	207
Time-to-maturity (years)				
Mean	1.18	1.23	1.16	1.06
Min.	0.01	0.01	0.01	0.01
Max.	4.59	5.04	4.81	4.97
Number of maturities				
Mean	53	48	36	39
Min.	52	47	35	39
Max.	54	49	37	40

Notes: The table presents descriptive statistics for options on the WTI futures contract used to obtain the risk-neutral densities. The data were obtained from the Commodity Research Bureau (Bridge). Reported in this table are the means of the daily means for the options inside the 15-day windows and written on futures, the early exercise option value (Trolle and Schwartz, 2009) is adjusted using the Barone-Adesi and Whaley (1987) analytic approximation. As the procedure does not allow for redundant assets, the data need to be filtered (Rebonato, 2004, p. 254). In-the-money options are excluded as they tend to be more thinly traded. Out-of-the-money call options are used together with out-of-the-money put options. Put-call parity is used to convert out-of-the-money puts into in-the-money calls. Options for which the implied volatility is non-positive or above 100 percent are excluded. Data for the last three days before maturity for each contract are also excluded. Lastly, to avoid stale prices spurious effects, observations are excluded for options that have a price of \$0.01. It is unlikely that stale prices would affect our results. Indeed, CME Group options and futures trade alongside and are well synchronized (Arnold *et al.*, 2007). In the end, the number of excluded options in each day is negligible.

3. Methodology

3.1 Probability densities, SDF and risk aversion function

Risk aversion functions and SDFs are required for each of the 15 days before and after each date of interest. Therefore, physical and risk-neutral densities are estimated for 120 dates. In the baseline case, a log-normal distribution is considered for oil futures gross returns. Robustness tests are performed on both densities to ensure that the distributional assumptions made are not driving our results. A summary of the methodology is presented in Table AI.

3.1.1 The physical density. Following Christoffersen *et al.* (2013), we estimate a GARCH model of the daily series of one-month returns using WTI crude oil second nearby futures prices. This approach accommodates the time dependence across overlapping return observations. For each date of interest *t*, the estimation uses all past return observations beginning from January 3, 2000. The time-*t* conditional density of returns for a horizon T (i.e. one month) is:

$$\hat{f}\left(R_{t,T}\right) = \hat{f}\left(\overline{R} + \sigma_t Z_i\right) \tag{1}$$

where $\overline{R}$ is the fixed long-run mean return, σ_t is the conditional standard deviation for a one-month investment horizon estimated from the GARCH model and Z_i are realizations of i.i.d. $N(0, 1)$ innovations. Following Jackwerth (2000), we demean gross returns, then set the long-run mean $\overline{R}$ equal to the risk-free rate plus the commodity risk premium, which is fixed at 6 percent annually, based on previous research (Baker and Routledge, 2012; Gorton and Rouwenhorst, 2006).

Fixing the mean to its long-run historical value is a conservative approach to investigating changes in risk aversion functions and SDFs. It reduces the likelihood of spurious findings, for example during periods when the sample mean is briefly below the risk-free rate. In particular, this approach implies that the results in July 2008 and December 2008 are not driven by short-run changes in mean returns. In the robustness check, instead of assuming normality, a non-parametric kernel density is fitted using the Epanechnikov kernel and Silverman's bandwidth.

3.1.2 The risk-neutral density. A parametric, non-structural approach is adopted to estimate the risk-neutral density given the data constraints of estimating a different density each day (see Jondeau *et al.*, 2007 for a survey). In the baseline case, a log-normal density function is fitted to monthly gross return data. The risk-neutral drift is measured by the risk-free rate over a one-month horizon. The diffusion parameter $\sigma(\beta)$ is estimated using the fitted implied volatility $\hat{\sigma}_{IV}$.

Specifically, Black-Scholes (Black, 1976) implied volatilities are regressed over corresponding values of (log) moneyness (MN), time-to-maturity, their squared values, an interaction term and a constant. Time-to-maturity is calculated as the ratio of business days before contract expiry over 252. Log-MN is the natural logarithm of the ratio of strike price over futures price. The following estimated regression is performed each day i over the observed options:

$$\sigma_{BSi} = \beta_0 + \beta_1 TM + \beta_2 MN + \beta_3 TM^2 + \beta_4 MN^2 + \beta_5 (TM \times MN) + e_i \tag{2}$$

From (2), the fitted implied volatility $\hat{\sigma}_{IV}$ is used to estimate the risk-neutral density:

$$\hat{\sigma}_{IVi} = \hat{\beta}_0 + \hat{\beta}_1 TM + \hat{\beta}_2 MN + \hat{\beta}_3 TM^2 + \hat{\beta}_4 MN^2 + \hat{\beta}_5 (TM \times MN) \tag{3}$$

For purposes of robustness analysis, daily risk-neutral densities are estimated using the Generalized Beta-2 distribution (henceforth GB2), allowing for higher-order moments to be modeled (e.g. Bookstaber and McDonald 1987; Liu *et al.*, 2007). For each date, a GB2 risk-neutral density is estimated from the daily cross-section of option data using all available strikes and a one-month time-to-maturity. We use the constrained optimization routine under the martingale restriction presented in Liu *et al.* (2007) to estimate the four parameters of interest defining the GB2 distribution. The GB2 seems preferable to the mixture of log-normals used by Melick and Thomas (1997), because the mixture of log-normals involves difficult-to-resolve complications in the estimation procedure due to nuisance parameters (see Jondeau *et al.*, 2007, p. 391-393).

3.1.3 SDF and risk aversion function. The risk-neutral density $Q(S)$, physical density $P(S)$, SDF $m(S)$ and the Arrow-Pratt coefficient of (absolute) risk aversion $ARA(S)$ associated with a wealth index (S) are related as follows (e.g. Ross, 2015):

$$Q(S) = m(S)P(S) \tag{4}$$

$$ARA(S) = \frac{P'(S)}{P(S)} - \frac{Q'(S)}{Q(S)} \tag{5}$$

Below, we follow established practice and use MN as a proxy for wealth (S) (see, e.g. Jackwerth, 2000; Giamouridis, 2005).

3.2 Statistical robustness assessment

This section describes the methodology used to establish the robustness of the statistical analysis. Our tests are designed to differentiate the pre and post physical densities as well as the pre and post fitted risk aversion distributions.

3.2.1 Non-parametric tests on physical return densities. Kolmogorov-Smirnov (KS) and Cramer-Von-Mises (CVM) two-sample non-parametric tests are used to assess whether the physical distribution has changed before and after each significant date. We use observations that are non-overlapping across sub-periods.

3.2.2 Tests on fitted risk aversion distributions. Next, we derive a distribution of risk aversion values from the option data to enable statistical tests of changes in risk aversion around each important date. These densities are fitted using option *MN* as a proxy for one-month-ahead wealth. Specifically, using estimated risk aversion functions (5), each possible future wealth level as a proportion of initial wealth is matched with the corresponding computed value of absolute risk aversion. The wealth levels range from 0.45 to 1.48 (the range of one-month horizon gross returns in the sample data) using increments of 0.005. Then, risk aversion values are fitted to a regression that is quadratic in the wealth measure, *MN*:

$$ARA_i = b_0 + b_1 MN_i + b_2 MN_i^2 + e_i. \tag{6}$$

From (6), the coefficients of slope (b_1) and curvature (b_2) are recovered. This regression can be compared to the estimation of a volatility surface, whereby coefficients on *MN* and MN^2 on the original "unweighted" function are similar to the coefficients in (3) fitting the implied volatility to a quadratic function of *MN* and time-to-maturity. Lastly, an additional step is needed to "weight" the observations and obtain a distribution of risk aversion values before and after each date of interest. In fact, not all future levels of wealth are equally likely. For each option in the sample, *MN* is used to proxy for future wealth (i.e. the gross return on initial wealth). Then, estimated coefficients from (6) are used to compute risk aversion values associated with each option j in the sample according to the following correspondence:

$$\text{fitted } ARA_j = \hat{b}_0 + \hat{b}_1 MN_j + \hat{b}_2 MN_j^2. \tag{7}$$

Repeating this step for each option j generates a corresponding series of "weighted" fitted risk aversion values in terms of the future wealth levels implied by the options, for each of the 120 days examined.

This distribution of risk aversion values is used to perform statistical tests. KS and CVM two-sample distributional tests are conducted on the densities of fitted risk aversion values before and after each significant date. The tests are performed at the midpoint of the 15-day window[3]. This is done in order to rule out the possibility that statistical significance is due to the large number of observations (over 20,000 for the full window) (e.g. Berger and Sellke, 1987). As the number of observations is still over 1,500 observations each day, the analysis is also performed on random sub-samples obtained from draws without replacement from the observations of the eighth day. Results based on this sampling approach are reported for 5,000 draws where the number of observations (n) in each draw is 100, 250 or 500.

4. Results

4.1 Baseline case

Figures 2-5 present figures for the physical and risk-neutral densities, SDFs and risk aversion functions. Following Jackwerth (2000), the mean distribution is presented for the 15 days before and after each date of interest, with empirical confidence intervals representing ±0.5 standard deviations from the mean.

The physical densities have heavier tails after the July 2008 bull-to-bear and the December 2008 bear-to-bull market changes[4], reflecting higher volatility in the oil

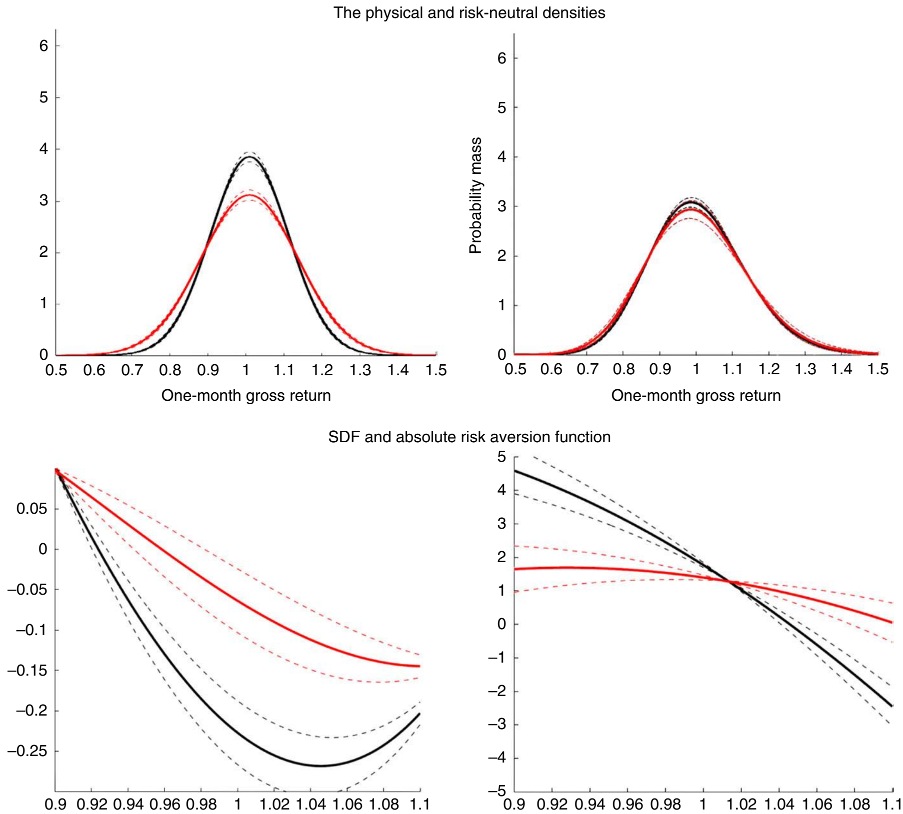


Figure 2.
Physical densities, risk-neutral densities, SDFs and absolute risk version functions for the end of the bull commodity cycle (Gaussian baseline case)

Notes: The date July 3, 2008 captures the end of the commodity bull cycle. The top- left figure represents the physical densities of the WTI futures price return. The top-right figure represents the risk-neutral densities estimated from options on the WTI future second nearby contract. The bottom-left figure represents the mean SDF and the bottom-right figure represents the mean absolute risk aversion function. Regarding results: for Figures 2-9, the solid black curves represent the mean of the daily densities or functions during each of the 15 days prior to the date of interest while the solid red curves represent the mean of the daily densities or functions during the 15 trading days after the date of interest. The dashed lines represent the associated empirical confidence intervals (the mean ±0.5 standard deviation). The Gaussian baseline case: for Figures 2-5, the parametric assumption is the log-normality of the physical (fitted from GARCH conditional standard deviations and IID innovations) and risk-neutral (Black-Scholes model following Dumas *et al.*, 1998) densities of gross returns

futures price, as well as a greater likelihood of extreme returns. However, there is no corresponding increase in volatility in the risk-neutral densities, suggesting that the option market participants did not change their expectations after these dates. In our sample, as bull markets turn to bear or vice versa, anticipations in the economy "crystallize" and leave the forward-looking risk-neutral density relatively intact.

The estimated SDF is flatter and less quadratic, though still U-shaped, after both end-of-cycle dates. A U-shaped SDF is consistent with much of the empirical literature and

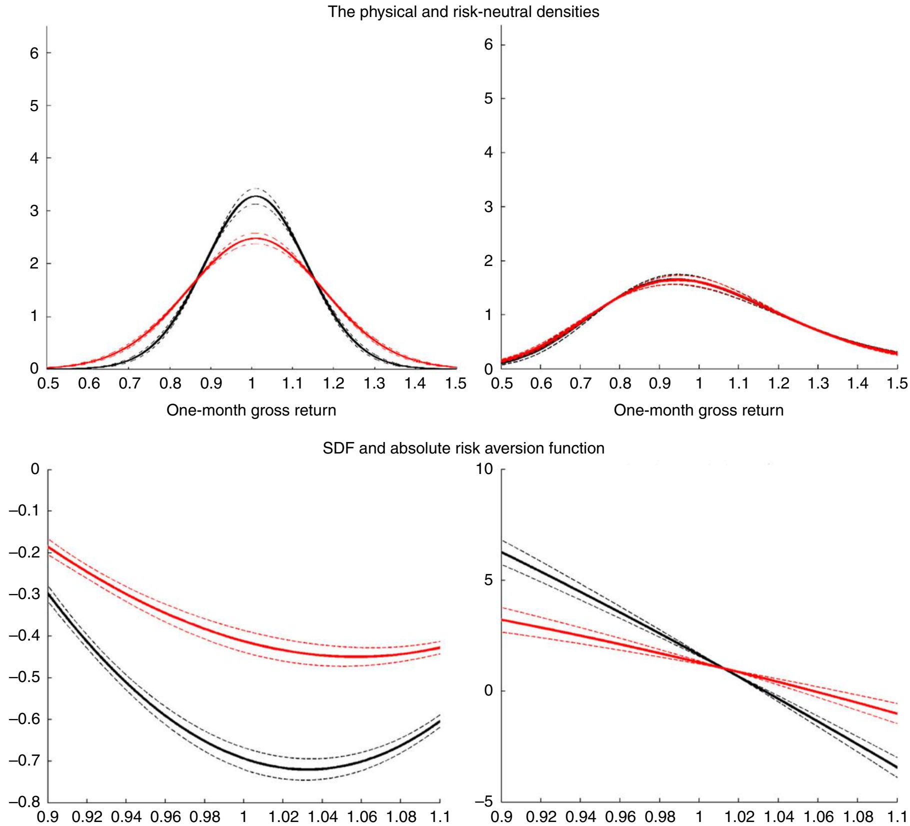


Figure 3.
Physical densities, risk-neutral densities, SDFs and absolute risk version functions for the credit freeze trough (Gaussian baseline case)

Notes: The date December 19, 2008 captures the credit freeze trough. The top-left figure represents the physical densities of the WTI futures price return and the top-right figure represents the risk- neutral densities estimated from options on the WTI futures third nearby contract. The bottom-left figure represents the mean SDF and the bottom-right figure represents the mean absolute risk aversion function estimated around the date of interest using the historical WTI futures price and related options data

can be explained by a negative variance risk premium (see, e.g. Christoffersen *et al.*, 2013). A flattening SDF implies that investors place lower value on extreme states of nature (i.e. large decreases or increases in wealth) relative to maintaining their original wealth. Thus, the U-shape flattens as the variance risk premium decreases in absolute value. That is, state prices fall substantially for both low-return and high-return states of nature relative to the state price associated with small changes in wealth. Our empirical results suggest that investors consider another reversal unlikely in the short run after each of these dates.

Although the first two dates capture different types of market reversals, as evidenced by different risk aversion functions, they both were followed by similar and important changes in the absolute risk aversion function. Indeed, in both cases there are significant changes in risk aversion over a short-term horizon, consistent with the long-term changes reported by Jackwerth (2000). This finding provides support for *H1* with respect to the existing literature.

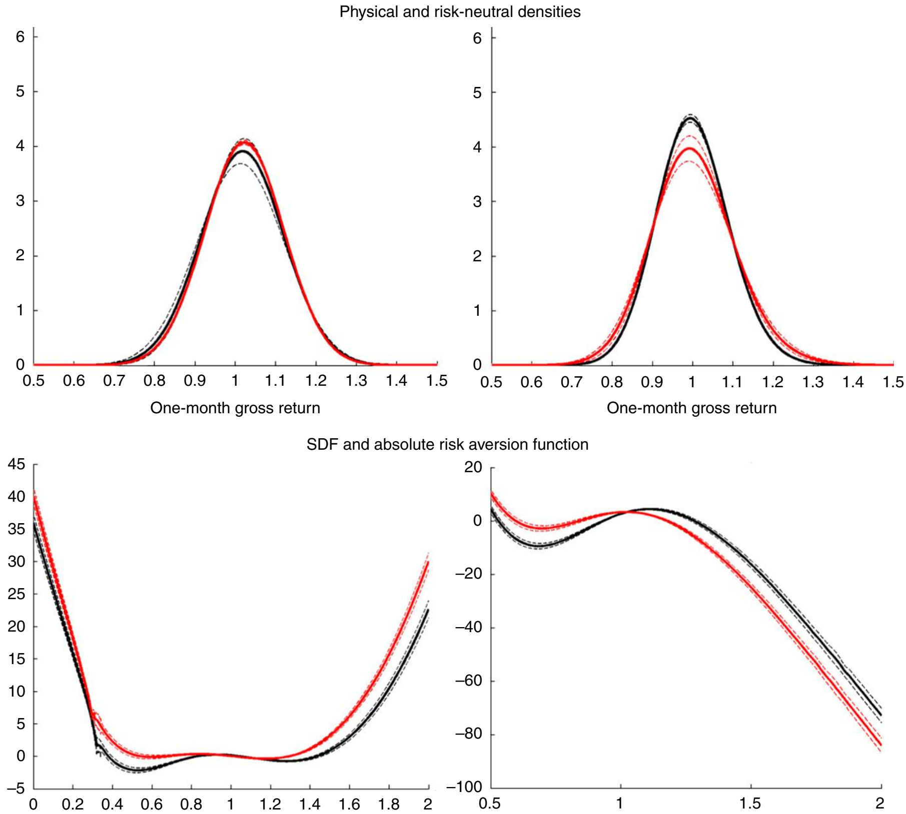


Figure 4.
Physical densities, risk-neutral densities, SDFs and absolute risk version functions for the BP Deepwater Horizon platform explosion (Gaussian baseline case)

Notes: The date is April 20, 2010 and captures the explosion of the BP Deepwater Horizon platform. The top-left figure represents the physical densities of the WTI futures price return and the top-right figure represents the risk-neutral densities estimated from options on the WTI futures third nearby contract. The bottom-left figure represents the mean SDF and the bottom-right figure represents the mean absolute risk aversion function estimated around the date of interest using the historical WTI futures price and related options data

For the July 2008 price peak, the risk aversion function is decreasing before but nearly flat (i.e. constant) afterward. For the credit freeze trough, the risk aversion function flattens and goes from strongly decreasing to only slightly decreasing. With flatter risk aversion functions, both changes of regime seem to make the representative investor less risk-averse for low future wealth levels, a finding consistent with a "double or nothing" strategy and prospect theory (e.g. Benartzi and Thaler, 1995). However, investors become more risk-averse regarding higher future wealth levels, suggesting cautiousness and a desire to hold onto gains after a market regime change.

The BP Deepwater Horizon explosion and the Libyan uprising are idiosyncratic shocks. Their impact on the physical densities is limited, as can be seen in Figures 4 and 5. In the case of the Libyan crisis, the distribution shifts slightly to the right, but this small shift is not upheld by the robustness tests. Since Libya is a small but

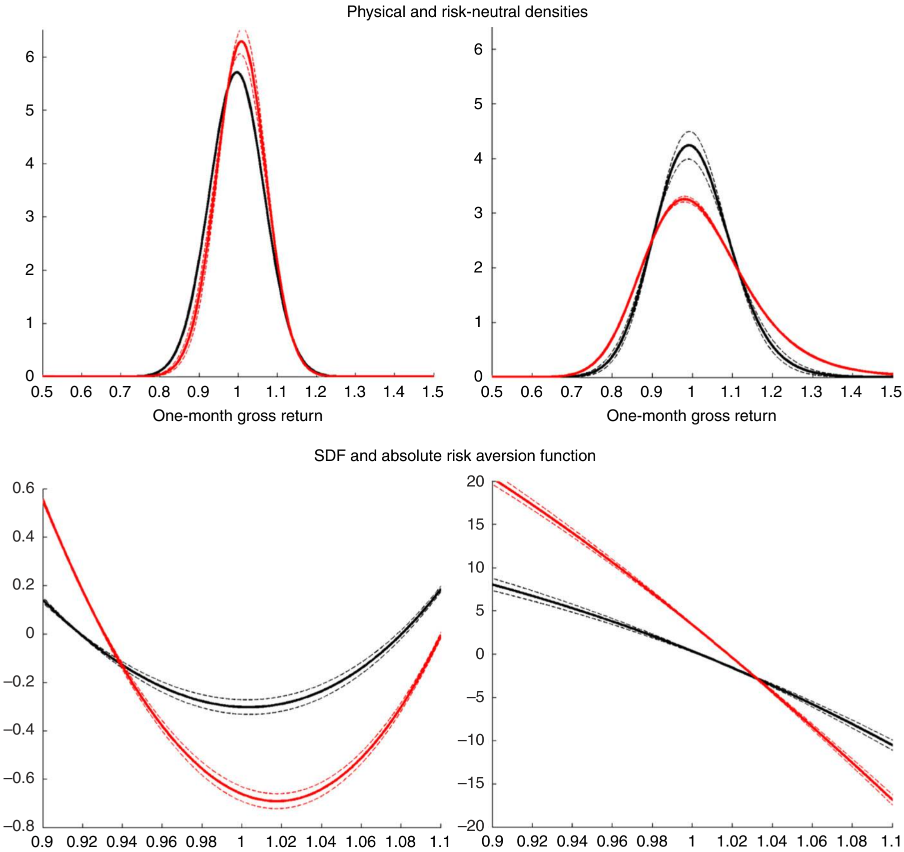


Figure 5.
Physical densities, risk-neutral densities, SDFs and absolute risk version functions for the Libyan uprising (Gaussian baseline case)

Notes: The date is February 22, 2011 and captures the uprising in Libya. The top-left figure represents the physical densities of the WTI futures price return and the top-right figure represents the risk- neutral densities estimated from options on the WTI futures third nearby contract. The bottom-left figure represents the mean SDF and the bottom-right figure represents the mean absolute risk aversion function estimated around the date of interest using the historical WTI futures price and related options data

non-negligible producer, and its contribution to world oil supplies decreased from about 2 to 0.6 percent during the uprising, inventories could have smoothed out the production shock. We find, however, that the lack of change in the physical density is unlikely to be explained by large movements in inventories, as the inventories only decreased by 0.35 percent in the following week.

Although the impact on the physical density turned out to be limited, the realization of both shocks was important to the oil futures market because latent but remote possibilities occurred and were recognized. This is supported by the fatter tails exhibited in post-date risk-neutral densities for both idiosyncratic shocks, resulting in significant changes in terms of attitudes toward risk. The SDFs become more non-linear (quadratic) afterward and the U-shape becomes steeper. This change implies that state prices increase for extreme states of nature (i.e. large decreases or increases in wealth) relative to states associated with little or no change in wealth levels. This result is consistent with the variance risk premium increasing (in absolute value) after the shock, reflecting the market participants' expectations that there could be disruptions in the production. Finally, the risk aversion function is steeper after the BP explosion and the Libyan uprising. The reason why the shape of the risk aversion function is not entirely smooth around the BP explosion event could be due to the assumption of log-normal gross returns, which may be too restrictive for this period.

These empirical results validate stated *H2*, as related to the existing literature. Building on Melick and Thomas (1997), we show that the increased likelihood of disruption implied by political events can not only affect prices but also influence attitudes toward risk. While it may not be possible to conclude that the impact on oil markets was the same for both dates, the similarities in the changes in risk aversion and the SDF can be explained by a common feature. Indeed, the BP explosion and the Libyan uprising signaled a higher probability of similar events elsewhere in the future, such as production shocks in other deep sea oil wells (for BP) and other oil-producing countries (for Libya). These events raised "red flags" in oil derivatives markets regarding possible future disruptions and potential problems on the oil markets.

4.2 Robustness check to higher moments in returns: the alternative case under the GB2 distributional assumption

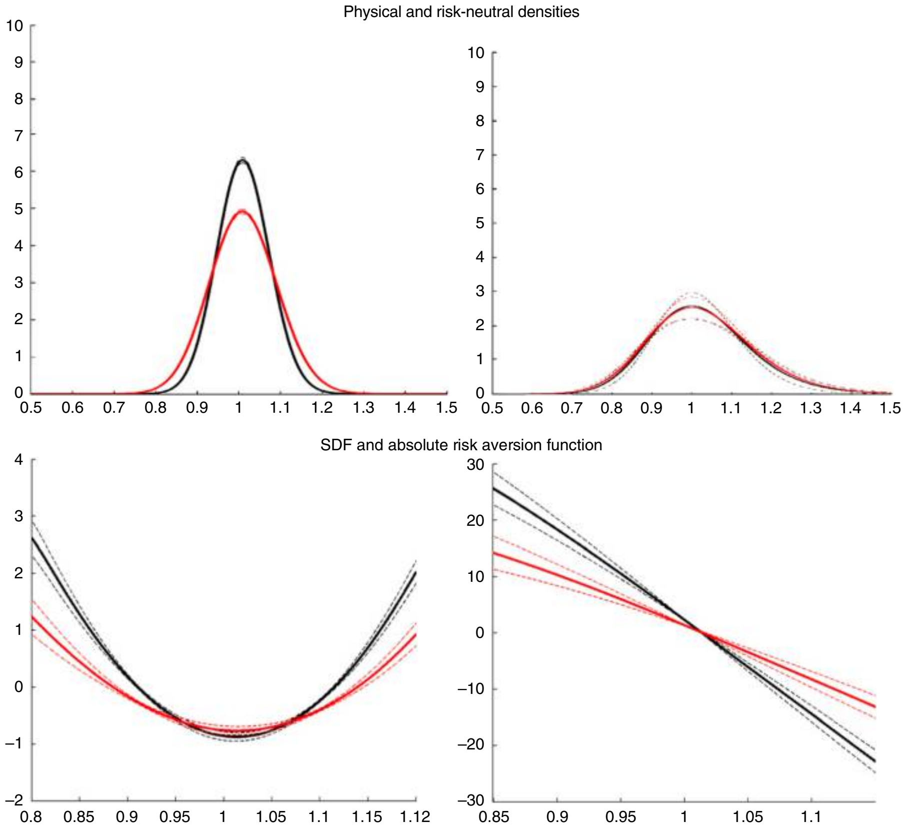
Results are now presented under the distributional assumption of a GB2 density for the risk-neutral density and a kernel estimation for the physical density, using past innovations from the estimated GARCH model. Figures 6-9 report figures for the physical and risk-neutral distributions, SDFs, and absolute risk aversion functions, before and after each date. Although GB2 risk-neutral densities display greater day-to-day variation, the results confirm the baseline findings, allowing for more flexible distributional assumptions for both physical and risk-neutral densities. This greater variation in the risk-neutral densities and some irregularities in the SDF shape can be explained mainly by the greater number of parameters estimated to solve the GB2 distribution option price relative to the baseline case.

The physical densities have heavier tails after the two market reversals but are still unchanged following the BP explosion and the Libyan uprising. The risk-neutral densities exhibit higher dispersion under the GB2 distributional assumption, but are essentially unchanged following the two market reversals. In contrast, the GB2 risk-neutral density has fatter tails after the BP explosion and Libyan uprising, suggesting the recognition of new uncertainty in the market.

4.3 Statistical robustness analysis

Table IV reports results for non-parametric specification tests on the physical densities in support of our graphical analysis. KS and CVM tests reject the null at a 5 and 10 percent confidence level, respectively for the end of the bull market and the credit freeze trough. The null that both densities are drawn from the same distribution is not rejected at the 5 percent level for the BP explosion for both tests and for the Libyan uprising using the CVM statistic.

Table V presents the results for the KS and CVM tests of equality of the before/after densities using the fitted risk aversion values computed from Equation (7). The table reports the results for a pairwise comparison of ARA distributions for the eighth day



Notes: The date July 3, 2008 captures the end of the commodity bull cycle. The top- left figure represents the physical densities of the WTI futures price return. The top- right figure represents the risk-neutral densities estimated from options on the WTI future second nearby contract. The bottom- left figure represents the mean SDF and the bottom- right figure represents the mean absolute risk aversion function. Generalized Beta 2 case: for Figures 6-9: the parametric assumption is a GARCH model with conditional standard deviations and IID innovations (based on Christoffersen *et al.*, 2013) for the physical densities and the generalized Beta-2 for the risk-neutral densities

Figure 6.
Physical densities, risk-neutral densities, SDF and the absolute risk version functions for the end of the bull commodity cycle (Generalized Beta-2 case)

before and the eighth day after the date of interest. Table V presents the p-values for the test over the total number of samplings drawn for both the baseline case and the robustness parametric specification. The equality of the distribution of fitted risk aversion values before and after is strongly rejected for the whole sample and for samplings of 100, 250 and 500 observations. The only exception to the rejection of the null hypothesis of equality is the BP explosion in the log-normal case, where the rejection rate is lower for smaller sub-samples. As irregularities disappear in the robustness check, we conclude that the baseline parameterization is too restrictive for this period as shown in Figure 4. Overall, the results are confirmed by each of the robustness exercises and we conclude that changes in risk aversion and behavior toward risk after the date of interest are statistically significant[5].

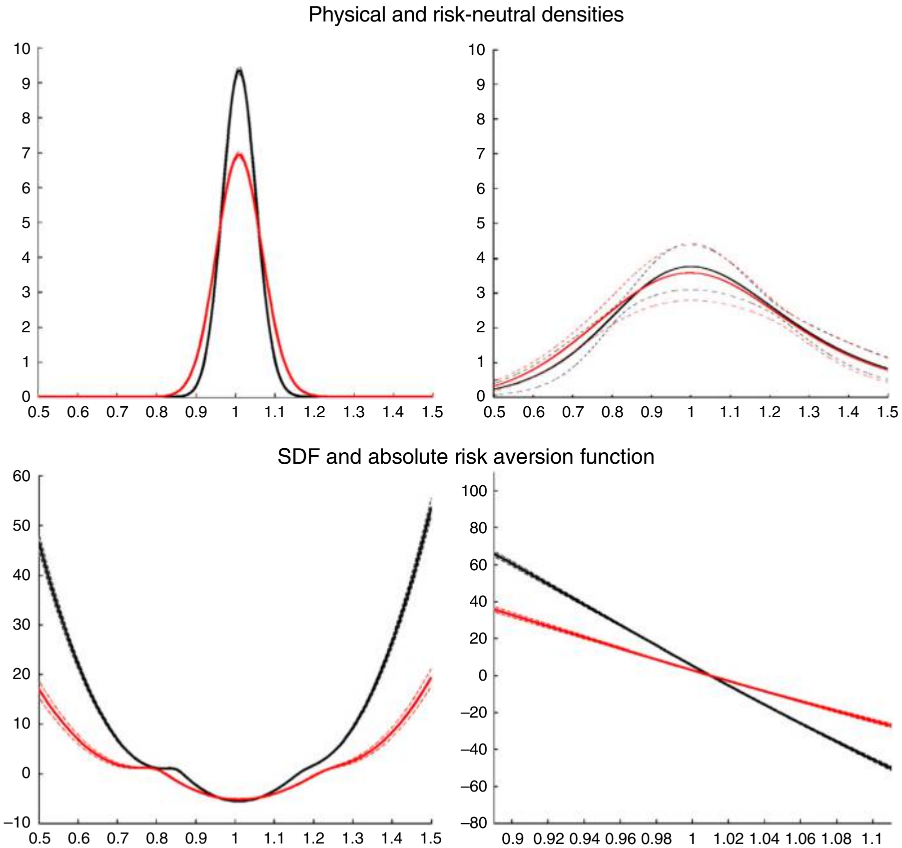
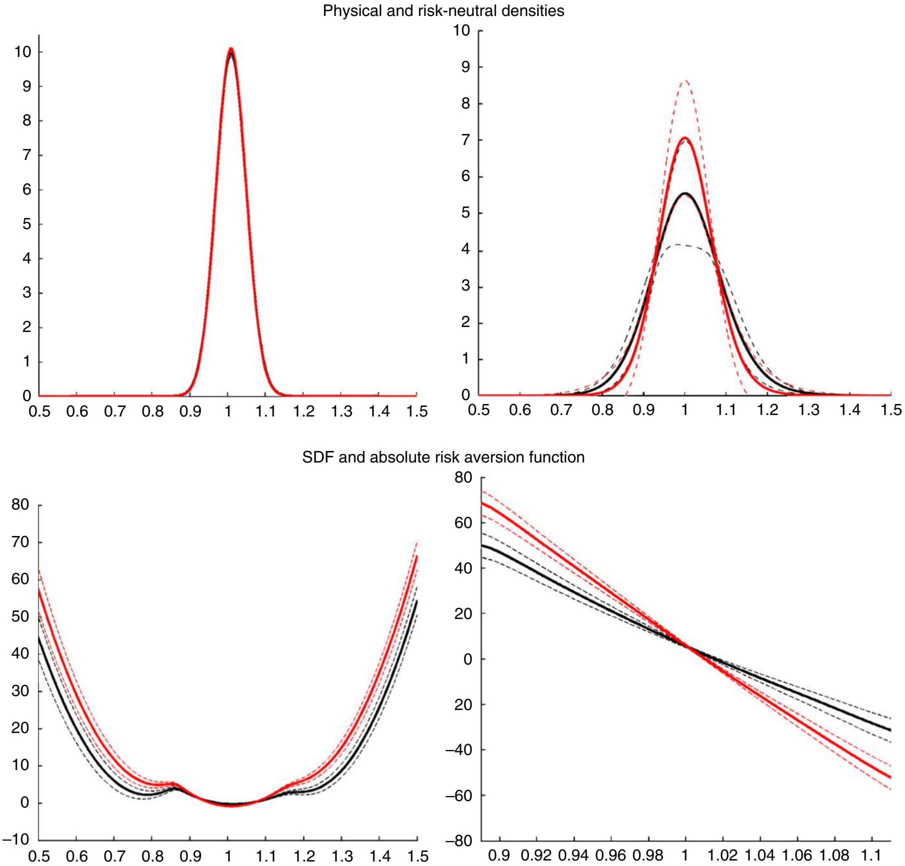


Figure 7.
Physical densities, risk-neutral densities, SDF and the absolute risk aversion functions for the credit freeze trough (Generalized Beta-2 case)

Notes: The date December 19, 2008 captures the credit freeze trough. The top-left figure represents the physical densities of the WTI futures price return and the top-right figure represents the risk-neutral densities estimated from options on the WTI futures third nearby contract. The bottom-left figure represents the mean SDF and the bottom-right figure represents the mean absolute risk aversion function estimated around the date of interest using the historical WTI futures price and related options data

4.4 *Economic significance*

Finally, we present a streamlined portfolio optimization exercise to emphasize the economic significance of our results. We choose a normalized wealth level of 0.95 (i.e. 5 percent monthly loss) as a plausible reference point in the remainder of the analysis [6]. Using the absolute risk aversion functions derived in our previous results, we recover coefficients of relative risk aversion for this wealth level. We find that after each of the first two dates of interest, consistent with a flattening risk aversion function, the coefficient of relative risk aversion becomes smaller in absolute value. The coefficient falls from 9.05 to 4.56 after the first date, and from 27.17 to 14.58 after the second date. The high level of risk aversion around the second date can be explained by the economic context, namely, the financial crisis. On the other hand, the coefficients of relative risk aversion increase in absolute value after the third and fourth dates,



Notes: The date is April 20, 2010 and captures the explosion of the BP Deepwater Horizon platform. The top-left figure represents the physical densities of the WTI futures price return and the top-right figure represents the risk-neutral densities estimated from options on the WTI futures third nearby contract. The bottom-left figure represents the mean SDF and the bottom-right figure represents the mean absolute risk aversion function estimated around the date of interest using the historical WTI futures price and related options data

Figure 8. Physical densities, risk-neutral densities, SDF and the absolute risk version functions for the BP Deepwater Horizon platform (Generalized Beta-2 case)

consistent with a steeper risk aversion function. The coefficient at 0.95 wealth increases from 21.03 to 28.76 after the BP explosion and from 8.93 to 12.58 after the Libyan uprising.

Then, we use the classic portfolio optimization result presented in Merton (1969) to recover, π, the weight allocation to the risky asset:

$$\pi = \frac{E[r_i]-r_f}{\sigma_i^2\gamma} \tag{8}$$

where $(E[r_i]-r_f)$ is the risk premium (assumed to be 6 percent, as in Section 3.1.1), σ_i^2 is the variance of the risky asset (0.09, given our sample annualized volatility of 30 percent) and γ is the coefficient of relative risk aversion.

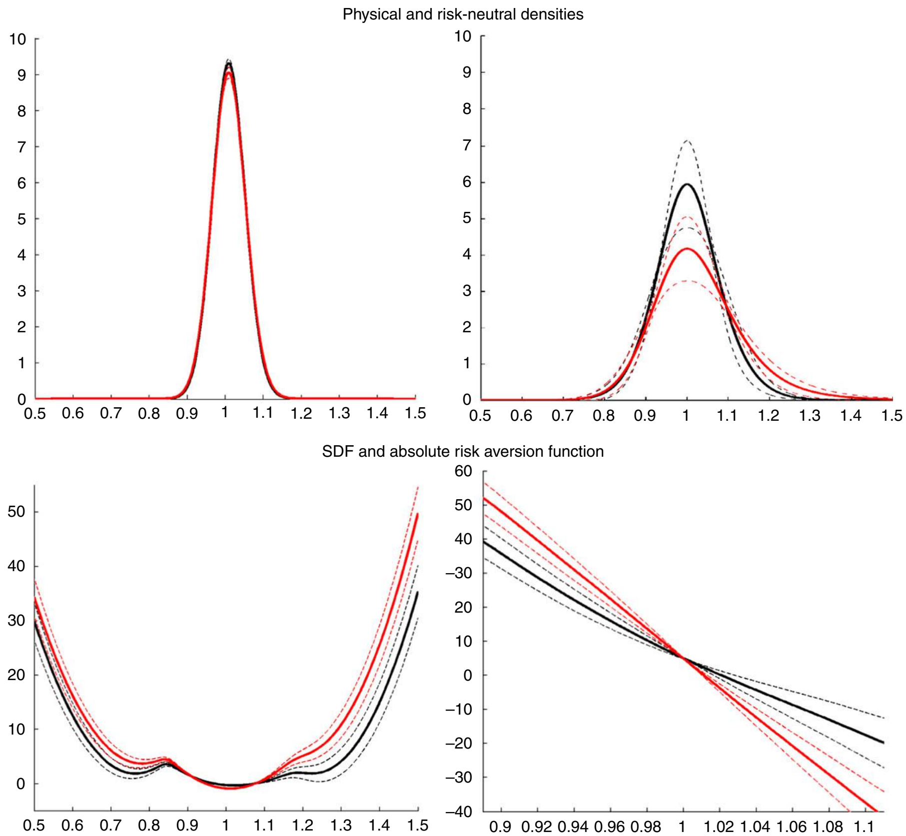


Figure 9.
The physical densities, risk-neutral densities, SDF and the absolute risk version functions for the Libyan uprising (Generalized Beta-2 case)

Notes: The date is February 22, 2011 and captures the uprising in Libya. The top-left figure represents the physical densities of the WTI futures price return and the top-right figure represents the risk-neutral densities estimated from options on the WTI futures third nearby contract. The bottom-left figure represents the mean SDF and the bottom-right figure represents the mean absolute risk aversion function estimated around the date of interest using the historical WTI futures price and related options data

	End of the commodity bull cycle	Credit freeze trough	BP Deepwater Horizon explosion	Libyan uprising
Kolmogorov-Smirnov test of equality	0.05	0.01	0.83	0.05
Cramer-Von-Mises test of equality	0.08	0.06	0.74	0.42

Table IV.
Statistical tests on the physical densities of returns

Notes: The table presents p-values for several tests on the physical densities of (log) gross returns computed from futures price data using GARCH models. The null hypothesis is that the physical densities of the one-month (log) gross returns prior to the event is drawn from the sample continuous distribution as the post-event physical densities

		p-values full sample	100	250	500
Baseline case: GARCH-normal RWD and log-normal RND					
Date	KS	0.00	100	100	100
1	CVM	0.00	100	100	100
Date	KS	0.00	89.2	100	100
2	CVM	0.00	80.7	99.9	100
Date	KS	0.05	71.6	98.4	100
3	CVM	0.02	72.5	98.8	100
Date	KS	0.00	99.9	100	100
4	CVM	0.00	99.9	100	100
Robustness case: GARCH-Kernel RWD and GB2 RND					
Date	KS	0.00	100	100	100
1	CVM	0.00	100	100	100
Date	KS	0.00	98.5	100	100
2	CVM	0.00	93.3	100	100
Date	KS	0.00	99.8	100	100
3	CVM	0.00	99.9	100	100
Date	KS	0.00	90.6	99.9	100
4	CVM	0.00	90.9	100	100

Notes: The Kolmogorov-Smirnov (KS) and the Cramer-Von-Mises (CVM) tests are reported for a pairwise comparison of absolute risk aversion (ARA) distributions for the eighth day before the event and the eighth date after the event. The null hypothesis is that the fitted distribution of ARA prior to the event is drawn from the same sample continuous distribution as the post-event fitted distribution of ARA. For simulations, values represent the number of rejections at a 1 percent level of significance. The sub-samples random samplings without replacement are performed 5,000 times; in each sampling, we randomly draw 100, 250 or 500 observations from the full sample. The number of observations is 1,897 before and 2,048 after date 1; 1,941 before and 1,948 after date 2; 1,479 before and 1,478 after date 3; and 1,540 before and 1,595 after date 4. The top panel reports the results for the baseline case and the bottom panel reports the result for the robustness case

Table V. Statistical tests on distributions of implied risk aversion values for the full sample and random sub-samples

The percent of wealth invested in the risky asset would increase from 35 to 61 percent following the end of the commodity bull cycle, and from 17 to 32 percent following the credit freeze trough. Investors with poor wealth prospects are "doubling-down" on risky investments during these market events. Investors would lower their risky asset allocation from 17.4 to 16.8 percent after the BP platform explosion and from 21.9 to 20.1 percent after the Libyan uprising. It is plausible that portfolio changes would be more important for market-wide events than for idiosyncratic events.

Taken collectively, these findings suggest that the documented changes in risk aversion are economically significant in addition to being statistically significant. Although it is not the main purpose of the paper to describe an optimal portfolio strategy, as other considerations such as transaction costs and liquidity constraints would need to be taken into account, this simple exercise highlights the economic magnitude of the changes in risk aversion reported in the paper.

5. Conclusion

Our results document short-run changes in the behavior of oil market participants in several ways. After both market reversals (end of the bull cycle and credit freeze trough), risk aversion functions and SDFs are significantly flatter and less U-shaped, respectively. This evidence extends to the short-run case Jackwerth's (2000) findings of significant long-run changes in risk aversion following the October 1987 stock market crash. However, after idiosyncratic shocks (BP explosion and Libyan uprising), risk aversion functions and SDFs are significantly steeper and more U-shaped, respectively.

Our findings expand on the literature that analyzes the information contained in crude oil derivatives markets and further document that commodity-specific shocks affect risk-neutral densities (Flamouris and Giamouridis, 2002; Giamouridis, 2005), and our fitted risk-neutral and physical densities are consistent with those in the literature (Hog and Tsiaras, 2011). Our results complement the existing literature by calculating day-by-day risk aversion functions and SDFs and presenting evidence of statistically and economically significant changes.

While the methodology introduced in this paper can be applied and extended to other settings, our results remain sample specific and not directly generalizable. In particular, our analysis covers periods during which inventory levels are close to their historical average. Abnormal levels of inventories could affect the results found in this study.

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Notes

1. The first wave of QE was announced by the Federal Reserve Bank on November 25 and launched on December 16 while the OPEC announcement occurred on October 24, 2008 and on December 17, 2008. The second announcement may have been anticipated by the market since OPEC had previously disclosed that it would cut production until oil prices would recover. The OPEC announcement was met with skepticism by the markets. It turns out that OPEC did not diminish significantly its daily average production significantly in 2008 or 2009 (EIA).
2. While a complete review of this literature is beyond the scope of this paper, a survey can be found in Jondeau *et al.* (2007).
3. The tests are also performed using the second and fifth days before and after the sample. The results are similar to the eighth day and available upon request.
4. The upper left quadrant of Figures 2-9 reports the physical densities using the empirical mean. However, the physical density used for the calculation of ARA is demeaned and fixed at the risk-free rate plus a 6 percent commodity risk premium.
5. Given the direct link between the risk aversion function and the SDF, the analysis performed in the paper could be based on either quantity and should be equivalent. We focus on the risk aversion function, but similar tests for changes in the SDF are performed although not reported here and corroborate our results.

6. We focus our analysis on the 0.95 normalized wealth level because of the negative CRRA sign recovered for some intervals of wealth levels associated with large gains. These negative values of risk aversion are a standard example of a well-known problem in the financial literature, namely, the risk aversion puzzle reported in other papers, e.g. Jackwerth (2000) or Barone-Adesi *et al.* (2012). Given the shape of our risk aversion functions, the changes in CRRA will be more accentuated for extreme levels of wealth. Finally, our results for other wealth levels such as 1.0 show similar changes in the composition of the optimal portfolio.

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Further reading

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Appendix

Data	Parameterization	Approach (steps)
Physical densities		
Gross returns on one-month investment horizon from the WTI crude oil second nearby futures Baseline	Log-normal with GARCH innovations	1. $\overline{R}$: gross returns are demeaned and fixed to r_f+ risk premium 2. σ_t: the conditional variance is obtained with a GARCH model (Christoffersen *et al.*, 2013) 3. The log-normal distribution is then fitted to $\hat{f}\left(\overline{R}+\sigma_t Z\right)$ for the one-month gross returns
Robustness	Non-parametric Kernel estimator	1. Same as baseline 2. Christoffersen *et al.* (2013) approach and use as values of Z all past innovations from the estimated GARCH model 3. A non-parametric kernel density is fitted using the Epanechnikov kernel and Silverman's bandwidth
Risk-neutral densities		
American options on WTI crude oil second nearby futures Baseline	Log-normal	1. Use Black-Scholes to recover implied vol. 2. Fit the log-normal density for each day in the event window with implied vol. and risk-free rate
Robustness	GB2	1. Fit the GB2 density with a daily cross-section of strikes and time-to-maturity matching the one-month horizon 2. Optimization routine

Notes: All the densities are estimated for the one-month investment horizon and are estimated for each day in the event window; Christoffersen *et al.* (2013) refers to the methodology proposed in Christoffersen *et al.* (2013)

Table AI. Summary of the procedures

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