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The oil price crash in 2014/15: Was there a (negative) financial bubble?

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HIGHLIGHTS

- There was a negative bubble in oil prices in 2014/15.
- This bubble decreased oil prices beyond the level justified by economic fundamentals.
- Several bubble detection methods confirm this evidence.

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ABSTRACT

This paper suggests that there was a negative bubble in oil prices in 2014/15, which decreased them beyond the level justified by economic fundamentals. This proposition is corroborated by two sets of bubble detection strategies: the first set consists of tests for financial bubbles, while the second set consists of the log-periodic power law (LPPL) model for negative financial bubbles. Despite the methodological differences between these detection methods, they provided the same outcome: the oil price experienced a statistically significant negative financial bubble in the last months of 2014 and at the beginning of 2015. These results also hold after several robustness checks which consider the effect of conditional heteroskedasticity, model set-ups with additional restrictions, longer data samples, tests with lower frequency data and with an alternative proxy variable to measure the fundamental value of oil.

1. Introduction

The Brent and WTI prices of crude oil fell by 60% between June 2014 and January 2015, marking one of the quickest and largest declines in oil history. This fall in oil prices is large but it is not an unprecedented event: the oil price fell more than 30% in a seven-month sample already five times in the last three decades (1985–1986, 1990–1991, 1997–1998, 2001, 2008). Of these five episodes, the price slide in 1985–86 has some similarities with the fall in 2014/2015, because it followed a period of strong expansion of oil supply from non-OPEC countries and Saudi-Arabia decided to increase production and to stop defending prices. Several factors have been proposed to explain this latest price crash: Arezki and Blanchard (2014) suggested an important contribution of positive oil supply shocks after June 2014. For example, there was a faster than expected recovery of Libyan oil production due to a lull in the local civil war, as it is visible from the EIA estimated historical unplanned OPEC crude oil production outages:

Moreover, Iraq oil production was not affected by the civil war enraging in the west and in the north of the country, as initially feared. The success of US shale oil production (+0.9 million b/d in 2014) and the OPEC decision in November 2014 to maintain its production level of 30 mb/d, signalling a shift in the cartel's policy from oil price targeting to maintaining market share, put additional pressure on oil prices.

Oil demand seems to have played a minor role compared to

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supply shocks: Arezki and Blanchard (2014) suggested that unexpected lower demand between June and December 2014 could account for only 20–35% of the price decline, while Hamilton (2014) found that only two-fifths of the fall in oil prices was due to weak global demand. Baumeister and Kilian (2016) used the reduced-form representation of the structural oil market model developed in Kilian and Murphy (2014) and argued that, out of a $49 fall in the Brent oil price, $11 of this decline was due to adverse demand shocks in the first half of 2014, $ 16 to (positive) oil supply shocks that occurred prior to July 2014, while the remaining part was due to a "*shock to oil price expectations in July 2014 that lowered the demand for oil inventories and a shock to the demand for oil associated with an unexpectedly weakening economy in December 2014, which lowered the price of oil by an additional $9 and $13, respectively*".

These and other potential factors which could have influenced the oil price decline are discussed in an extensive World Bank policy research note by Baffes et al. (2015). Similarly to previous works, they also found out that supply shocks roughly accounted for twice as much as demand shocks in explaining the fall in oil prices. An alternative explanation is put forward by Tokic (2015) who suggested that the 2014 oil price collapse was partially an irrational over-reaction to the falling Euro versus the dollar. This seems to be consistent with a Bank of International Settlements report (Domanski et al., 2015), which shows that production and consumption alone are not sufficient for a fully satisfactory explanation of the collapse in oil prices. In this regard, Domanski et al. (2015) advanced the idea that "*if financial constraints keep production levels high and result in increased hedging of future production, the addition to oil sales would magnify price declines. In the extreme, a downward-sloping supply response of increased current and future sales of oil could amplify the initial decline in the oil price and force further deleveraging*".

Given this background, we want to propose a potential explanation for the part of the oil price decline which can not be explained using supply and demand alone, particularly in the last months of 2014, as highlighted by Baumeister and Kilian (2016). More specifically, we suggest that there was a negative financial bubble which decreased oil prices beyond the level justified by economic fundamentals. A negative financial bubble is a situation where the increasing pessimism fuelled by short positions lead investors to run away from the market, which spirals downwards in a self-fulfilling process, see Yan et al. (2012) for a discussion.

We employ two approaches to corroborate this proposition: the first approach consists of tests for financial bubbles proposed by Phillips et al. (2016) (hereafter PSY) and Phillips and Shi (2014) (hereafter PS). These tests are based on recursive and rolling right-tailed Augmented Dickey-Fuller unit root test, wherein the null hypothesis is of a unit root and the alternative is of a mildly explosive process. They can identify periods of statistically significant explosive price behavior and date-stamp their occurrence. The second approach consists of the log-periodic power law (LPPL) model for negative financial bubbles developed by Yan et al. (2012). This model adapts the Johansen-Ledoit-Sornette (JLS) model of rational expectation bubbles developed by Sornette et al. (1999); Johansen et al. (1999) and Johansen et al. (2000) to the case of a price fall occurring during a transient negative bubble, which they interpret as an effective random down payment that rational agents accept to pay in the hope of profiting from the expected occurrence of a possible rally. Despite the methodological differences between these bubble detection methods, they provide the same result: the oil price experienced a statistically significant negative financial bubble in the last months of 2014 and at the beginning of 2015. A set of robustness checks finally show that our results also hold with different tests, different model set-ups and alternative datasets.

The paper is organized as follows: the bubble detection methods are presented in Section 2, while the data employed in the empirical analysis are discussed in Section 3. The main results are described in Section 4, while robustness checks are reported in Section 5. Conclusions and policy implications are presented in Section 6.

2. Methods - testing for financial bubbles

We wanted to verify the presence of a negative financial bubble in oil prices at the end of 2014 using a set of tests for financial bubbles. We first employed the test by Phillips, Shi, and Yu (PSY, 2015) which builds on the previous work by Phillips, Wu, and Yu (2011, hereafter PWY) and it is designed to identify periods of statistically significant explosive price behavior. Strictly related to this, we also employed the test by Phillips and Shi (PS, 2014) for detecting a potential bubble implosion and estimating the date of market recovery. We then used the log-periodic power law (LPPL) model by Yan et al. (2012) which is specifically designed for negative financial bubbles. Differently from the approach by PSY and PS, the LPPL model does not require the formation of a bubble as a pre-requisite for a price crash.

2.1. Econometric tests for explosive behavior

The generalized-supremum ADF test (GSADF) proposed by Phillips et al. (2015) builds upon the work by Phillips and Yu (2011) and Phillips et al. (2011). This is a test procedure based on ADF-type regressions using rolling estimation windows of different size, which is able to consistently identify and date-stamp multiple bubble episodes even in small sample sizes. It was recently used by Caspi et al. (2015) to date stamp historical periods of oil price explosivity using a sample of yearly data ranging between 1876 and 2014.

The first step is to consider an ADF regression for a rolling sample, where the starting point is given by the fraction r_1 of the total number of observations, the ending point by the fraction r_2, while the window size by $r_w = r_2 - r_1$. The ADF regression is given by

$$x_t = \mu + \rho x_{t-1} + \sum_{i=1}^{p} \phi_{r_w}^{i} \Delta x_{t-i} + \varepsilon_t \tag{1}$$

where μ, ρ, and $\phi_{r_w}^{i}$ are estimated by OLS, and the null hypothesis is of a unit root $\rho = 1$ vs an alternative of a mildly explosive autoregressive coefficient $\rho > 1$.[1] Then, PSY (2015) proposed a backward sup ADF test where the endpoint is fixed at r_2 and the window size is expanded from an initial fraction r_0 to r_2. The test statistic is then given by:

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2} \tag{2}$$

We remark that the PWY (2011) procedure for bubble identification is a special case of the backward sup ADF test where $r_1 = 0$, so that the sup operation is superfluous.

The generalized sup ADF (GSADF) test is computed by repeatedly performing the BSADF test for each $r_2 \in [r_0, 1]$:

$$GSADF(r_0) = \sup_{r_2 \in [r_0, 1]} BSADF_{r_2}(r_0) \tag{3}$$

PSY (2015, Theorem 1) provides the limiting distribution of (3) under the null of a random walk with asymptotically negligible

[1] A detailed analysis of model specification sensitivity in right-tailed unit root testing for explosive behavior was performed by Phillips et al. (2014).