# How does the financial market update beliefs about the real economy? Evidence from the oil market


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**A Online Appendix** **a.1**

A.1 Dispersed beliefs and inventory announcements . . . . . . . . . . . . . . . . . . . . . . a.1

A.2 Convenience yield . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . a.5

A.3 Dealing with futures contracts: expiration . . . . . . . . . . . . . . . . . . . . . . a.6

A.4 Realized variance . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . a.7

A.5 Time variation in parameters . . . . . . . . . . . . . . . . . . . . . . . . . . . . a.7

A.6 Long term effects . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . a.13

A.7 Oil market during pandemic . . . . . . . . . . . . . . . . . . . . . . . . . . . . a.18

**References** **a.18**

# A Online Appendix

## A.1 Dispersed beliefs and inventory announcements

To clarify the role of inventory announcements and the connection between 'inventory' shocks and underlying demand and supply shocks that hit the economy, we further extend our toy model. Our goal is to parsimoniously introduce dispersion of beliefs to create informational role of inventory announcements. We do that using a simple island framework.

Imagine two regions, A and B. Each region is inhabited by a risk neutral oil producer and unmodelled oil consumers. The two regions are completely separated, meaning that each producer delivers oil to his region only, and consumers only purchase oil locally. The regions are nonetheless subject to a common supply shock (for instance, due to similarities in oil extracting technologies). Therefore, any signals about current or future supply shocks received by one producer are informative to the other.

Let the supply of oil in region $i \in \{A, B\}$ in period $t$ be given by $q_{i,t}^s = 1 + \varepsilon_t + \eta_{i,t}$, where $\varepsilon_t$ denotes a common supply shock that hits both regions simultaneously, while $\eta_{i,t}$ denotes idiosyncratic shock that hits region $i$ only; all shocks are independent both across regions and time, $\varepsilon_t \sim$ iid $N(0, \sigma_\varepsilon^2)$ and $\eta_{i,t} \sim$ iid $N(0, \sigma_\eta^2)$. As before, the demand for oil in each region is given by a simple function $q_{i,t}^d = 2 - p_{i,t}$, where $p_{i,t}$ is the local price of oil. Each producer solves his optimization problem by optimally choosing the level of inventories, $x_i$. Note that our island assumption eliminates all strategic concerns, because actions of one producer have no direct impact on the other.

For the sake of exposition, we introduce an extreme version of dispersion of beliefs. We assume that Producer $A$ receives private information about productivity shocks (current or future), and chooses optimal inventories conditional on that information. In contrast, Producer $B$ does not observe any private signals. We will then allow Producer $B$ to observe optimal inventory decision of Producer $A$. The opportunity for Producer $B$ to observe inventory level $x_A$ before choosing it own inventory level is exactly our reduced-form way to model inventory announcements.

We can now explore how higher or lower than expected level of announced inventories $x_A$ shapes the optimal inventory choice of Producer $B$ and how it affects current and future prices in region $B$.

**Realized shock** First, let us assume that Producer $A$ observes the combined current period supply shock, $\varepsilon_1+\eta_{A,1}$, which is a combination of common and idiosyncratic components. Producer A's problem coincides with the one solved in the main text, thus we know that the optimal level of inventories is to save half of the shock, $x_A = \frac{1}{2}\left(\varepsilon_1 + \eta_{A,1}\right)$.

Now let us solve Producer $B$'s problem. Clearly, when $x_A$ is not observed, Producer $B$ receives no information about any of the shocks. In that case, there is no reason to hold inventories, as the producer expects the same level of productivity in both periods. Thus, $x_B = 0$, and the expected current and future prices in region B are equal to their unconditional means:

$$\begin{aligned} E\left[p_{B,1}\right] &= E\left[1 + x_B - \varepsilon_1 - \eta_{B,1}\right] = 1, \\ E\left[p_{B,2}\right] &= E\left[1 + x_B - \varepsilon_2 - \eta_{B,2}\right] = 1. \end{aligned} \tag{1}$$

In contrast, when $x_A$ is observed, Producer $B$ updates his beliefs about $\varepsilon_1$, as $E\left[\varepsilon_1|x_A\right] \neq 0$, and thus can make more informed inventory decision. Producer $B$'s expected profit becomes

$$\begin{aligned} \pi_B(x_B) = {} & E\left[(1 + x_B - \varepsilon_1 - \eta_{B,1})(1 - x_B + \varepsilon_1 + \eta_{B,1})|x_A\right] \\ & + E\left[\left(1 - x_B - \varepsilon_2 - \eta_{B,2}\right)\left(1 + x_B + \varepsilon_2 + \eta_{B,2}\right)|x_A\right] \\ = {} & 2x_B E\left[\varepsilon_1|x_A\right] - E\left[\varepsilon_1^2|x_A\right] + 2 - 2\sigma_\eta^2 - 2x_B^2 - \sigma_\varepsilon^2, \end{aligned}$$

which attains maximum at $x_B = \frac{1}{2}E\left[\varepsilon_1|x_A\right]$, where $E\left[\varepsilon_1|x_A\right] = \frac{2\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_\eta^2}x_A \equiv \alpha x_A$, with $\alpha > 0$.

Thus, if Producer $B$ observes *higher than initially expected inventories*, $x_A > 0$,[1] then he revises his beliefs upwards, $E\left[\varepsilon_1|x_A\right] > E\left[\varepsilon_1\right] = 0$. Therefore, it is optimal for Producer B to also store a

[1]The unconditional expectation of $x_A$ is zero.

positive amount of oil, $x_B > 0$.

Of course, higher expected oil supply depresses both expected current and future prices in region $B$ (relative to the pre-announcement unconditional level):

$$\begin{aligned} E\left[p_{B,1}|x_A\right] &= 1 - \tfrac{1}{2}E\left[\varepsilon_1|x_A\right] < 1 = E\left[p_{B,1}\right], \\ E\left[p_{B,2}|x_A\right] &= 1 - \tfrac{1}{2}E\left[\varepsilon_1|x_A\right] < 1 = E\left[p_{B,2}\right]. \end{aligned} \tag{2}$$

As usual, availability of storage allows smoothing current period shocks over time and equalization of expected prices across periods.

In sum, *higher than initially expected inventories*, $x_A > 0$, trigger additional oil accumulation and depress both expected current and future prices in region $B$.

**News shock** An arrival of a news shock can be considered similarly. Now we assume that Producer $A$ receives news about future productivity, he perfectly observes $\varepsilon_2 + \eta_{B,2}$. As usual, the optimal decision is to spread out the shock equally across periods, thus $x_A = -\frac{1}{2}\left(\varepsilon_2 + \eta_{A,2}\right)$.

The chosen level of inventories, $x_A$, now contains information about $\varepsilon_2$ which is relevant to Producer $B$. Thus, $E\left[\varepsilon_2|x_A\right] = -\alpha x_A \neq 0$, where $\alpha > 0$ is the same signal-to-noise ratio as before. The expected profit becomes

$$\begin{aligned} \pi_B(x_B) = {} & E\left[(1 + x_B - \varepsilon_1 - \eta_{B,1})(1 - x_B + \varepsilon_1 + \eta_{B,1})|x_A\right] \\ & + E\left[\left(1 - x_B - \varepsilon_2 - \eta_{B,2}\right)\left(1 + x_B + \varepsilon_2 + \eta_{B,2}\right)|x_A\right] \\ = {} & 2 - \sigma_\varepsilon^2 - 2\sigma_\eta^2 - 2x_B^2 - E\left[\varepsilon_2^2|x_A\right] - 2x_B E\left[\varepsilon_2|x_A\right], \end{aligned}$$

which attains maximum at $x_B = -\frac{1}{2}E\left[\varepsilon_2|x_A\right]$.

Thus, if Producer $B$ observes *higher than initially expected inventories*, $x_A > 0$, then he revises his next period productivity expectations downwards, because $E\left[\varepsilon_2|x_A\right] < E\left[\varepsilon_2\right] = 0$. Therefore, it is optimal for Producer $B$ to also store a positive amount of oil, $x_B > 0$.

Naturally, lower future productivity increases prices (relative to the pre-announcement unconditional level):

$$E\left[p_{B,1}|x_A\right] = 1 - \tfrac{1}{2}E\left[\varepsilon_2|x_A\right] > 1 = E\left[p_{B,1}\right],$$
$$E\left[p_{B,2}|x_A\right] = 1 - \tfrac{1}{2}E\left[\varepsilon_2|x_A\right] > 1 = E\left[p_{B,2}\right]. \tag{3}$$

As usual, availability of storage allows to smooth shocks over time and equalizes expected prices.

Overall, in case of news shocks we can see that *higher than initially expected inventories*, $x_A > 0$, trigger additional storage accumulation and increase both expected current and future prices in region $B$.

**Constrained cases** So far we have not imposed any restrictions on the size of oil inventories. Given that we have two regions in the model, in principle, we have to consider 4 different cases, depending on whether the constraint binds in one region or another, or both, or none. The analysis of all these cases is similar, and the results follow the ones in the main text and the ones that we just derived. For example, imagine that Producer $A$ is unconstrained and responds optimally to a realized shock, but after observing $x_A$, Producer $B$ exhausts available inventory capacity, $x_B = x_{B,max}$. Then, as before, both expected current or future prices fall relative to their unconditional levels; however, perfect equalization would not be achieved. In particular, the expected current price would decrease by more.

In cases when Producer $A$ exhausts spare capacity, the inference problem of Producer $B$ changes, because now he has to compute $E\left[\varepsilon_1|x_A = x_{max}\right]$ or $E\left[\varepsilon_2|x_A = x_{max}\right]$. But that is the only change, and the optimal choice of $x_B$ and the corresponding effect on prices in region $B$ remain the same. Intuitively, when, for example, Producer $B$ knows that a realized shock has arrived and observes inventories in region A at the highest possible level, he naturally needs to revise his beliefs about the common current supply shock upwards, thus increasing his own inventories and expecting higher prices both now and tomorrow. Other cases can be considered in a similar way.

## A.2 Convenience yield

In this section we would like to comment on the role of convenience yield in our analysis. In short, we analyze the changes in the real convenience yield following inventory announcement, we just do not use the term itself to avoid confusions.

**Real benefits of holding inventories or the real convenience yield** Inventories bring certain benefits to the owners. This benefits can be modeled in a more or less reduced way. Typically, the structural or microfounded way of modeling would be to assume uncertainty of demand and some convexity of production, which leads to positive inventories being held in equilibrium to meet the demand shocks. See Wen (2005). The benefits of this approach are apparent; however, the models are typically hard to solve.

Instead, many papers choose a less microfounded, reduced form approach. For example, Byun (2017), directly includes inventories into the refinery production function $f(q_t, i_{t-1}) = (1-e^{-i_{t-1}})q_t^{\alpha}$, and the storage costs also include a term proportional to $i_t^2$ to achieve interior solution. By assumption, the refinery has a direct benefit of holding inventories in equilibrium. The assumptions are more ad hoc; however, the models become tractable.

In any case, the convenience yield is an equilibrium object that defines the benefits of having extra barrel of oil in storage (more or less easily derived).

**The difference between the long and short term futures contracts vs the convenience yield** In energy finance literature, however, it became customary to define the 'convenience yield' as the difference between long and short futures prices. Unfortunately, the futures prices are driven by many other factors. Under this approach, the interpretation of the 'convenience yield' becomes convoluted, as it can no longer be interpreted as the benefits of having an extra barrel of oil in storage (which we continue to call the true convenience yield).

In a nutshell, in equilibrium there cannot be arbitrage opportunities of any kind, which means that *all no-arbitrage conditions* must be *jointly satisfied.* This means that the no physical arbitrage condition can be satisfied as a *strict inequality.* In other words, the benefits of buying and holding an extra barrel of oil can be *strictly smaller* than the costs in equilibrium. Formally, let us denote by $b_t$ the benefits of holding an extra barrel of oil (the true convenience yield); $r_t + c_t$ denotes the combined borrowing and storage costs; and, finally, $F_{2,t} - F_{1,t}$ is the futures price difference. In equilibrium, we may observe that $\underbrace{F_{2,t} - F_{1,t} + b_t}_{\text{benefits}} - \underbrace{(r_t + c_t)}_{\text{costs}} < 0$, and it will still be consistent with no arbitrage. Hence, in general, $\tilde{b}_t \equiv -(F_{2,t} - F_{1,t}) + r_t + c_t$ is not equal to the 'true convenience yield', $\tilde{b}_t \neq b_t$. See Hamilton (2009) for further discussion.

**Relation to our approach** In sum, the marginal benefit of storing extra oil is an endogenous object defined in equilibrium. It is fully driven by the real side of the economy, either due to the stock out avoidance motive, or smoothing out of production costs etc. In contrast, the difference between the long and the short term futures contracts is not only driven by the real side of the economy, but also shaped by a number of additional factors, including the risk bearing capacity of the financial traders.

Thus, we do analyze the changes in the true convenience yield in response to various shocks, we just don't use the term itself to avoid confusions.

## A.3 Dealing with futures contracts: expiration

At any moment in time, NYMEX offers a set of contracts that differ by delivery month. The expiry dates range from one month up to nine years in the future, thus constituting more than 100 contracts at any given moment. Trading in the current delivery month ceases on the third business day prior to the twenty-fifth calendar day of the month preceding the delivery month (for example, the last trading day of a February-2018 contract is January 22, 2018).[2]

We follow a standard approach in the literature and rely on a rolling procedure to create continuous futures contracts.[3] In particular, we replace the expiring contract with the next one

[2]See contract specifications at the CME website.

[3]See, for example, Halova et al. (2014) or Gorton et al. (2012).

Table A.1: Maturity of a particular contract at the beginning of the period in months.

| Quarter | $F_1$ | Current December | Next June | Next December |
|---|---|---|---|---|
| Q1 | 1 | 11 | 17 | 23 |
| Q2 | 1 | 8 | 14 | 20 |
| Q3 | 1 | 5 | 11 | 17 |
| Q4 | 1 | 2 | 8 | 14 |

Notes: The table shows that, for example, when we consider the first quarters, 'Q1', we are dealing with contracts that have maturity ranging from 11 months to 9 months (the current December contract), from 17 months to 15 months (the next year June contract), and from 23 months to 21 months (the next December contract).

on the 5th day of each month. Thus, the maturity of what we call the first month contract in our sample ranges from 5 weeks to 2 weeks, when the soon-to-expire contract is replaced with the next one, and a new maturity cycle commences. As long as oil traders follow the same procedure and shift their trading from one market to another at about the same time, stationarity concerns are alleviated.

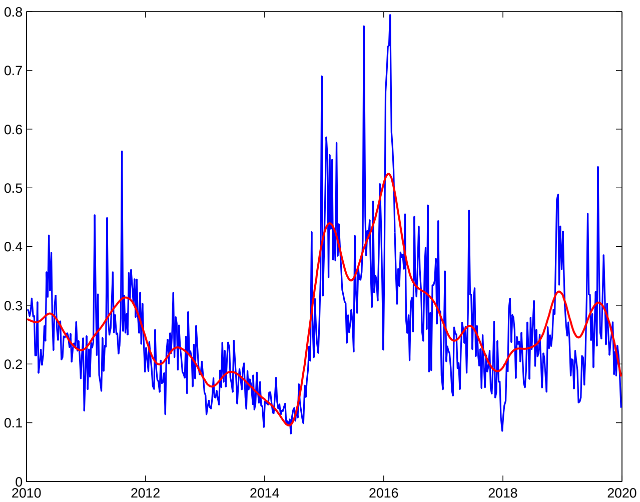
## A.4 Realized variance

We use the high-frequency returns on the front-month futures contract. For each announcement day, we calculate realized variances using a range of sampling frequencies from 5 seconds to 10 minutes, and then take an average. Volatility signature plots for most days are flat in that region of frequencies. Figure A.1 shows the resulting estimates. We can see a distinct shift in the volatility regime at the end of 2014, when volatility increased dramatically and remained high for a long period of time. As was discussed in text, the trading intensity increased at that time as well.

## A.5 Time variation in parameters

To parsimoniously model the evolution of some parameters of our model, we utilize threshold autoregression (TAR, see, e.g., Hansen, 1997) and smooth threshold autoregression (STAR, see, e.g., Teräsvirta, 1994) models, with time as the threshold/transition variable (see also Lin &

Figure A.1: Realized variance, annualized.




Notes: The blue line: daily realized variance of returns on the first futures contract. The red line: a smoothed filtered series using the HP filter with a smoothing parameter of 1600.

Teräsvirta, 1994, for such possibilities).[4]

As before we denote the announcement weeks by $\tau$. The parameter $c_\tau$ varies over time according to

$$c_\tau = c_0 + (c_1 - c_0)G(\tau, \tau^\star, \delta),$$

where time variability is driven by a non decreasing transition function $G(\tau, \tau^\star, \delta)$ that lies between zero and one. The arguments of the transition function, apart from the time index, are the threshold $\tau^\star$ and a vector of parameters $\delta$, which control the timing and speed of adjustment, respectively. The simplest example of the transition is the indicator function: $G(\tau, \tau^\star) = \mathbb{I}_{\tau \geq \tau^\star}$, which assumes a structural break in week $\tau^\star$.

In principle, we could allow all parameters to jump simultaneously and search for the optimal timing of the break. This approach, however, is problematic, as the oil market may be subject to other structural changes at the same time. One potential source of a 'background' change could

[4]An alternative class of models, Markov switching autoregressions, based on dynamic latent state variables, could instead be used; see, in particular, Hamilton (1990) and Chang et al. (2017).

be a dramatic growth of exchange traded funds tracking oil futures prices.[5] An investment flow to ETFs could alter the composition of trading strategies utilized. Thus, as our dynamic model is a direct reflection of oil traders' behavior, any changes in the strategies inevitably lead to changes in model parameters. As a result, this simplistic approach might pick up the wrong transition.

To disentangle changes in parameters related to proliferation of new trading strategies, from the changes in market perception of inventory news, we allow some parameters to follow a more complicated dynamics:

$$c_\tau = c_0 + (c_1 - c_0) G_I(\tau, \tau_I^\star, \delta_I) + (c_1 - c_0) G_H(\tau, \tau_H^\star, \delta_H),$$

where $G_I(\tau, \tau_I^\star, \delta_I)$ and $G_H(\tau, \tau_H^\star, \delta_H)$ define the two separate transition dynamics: *$I$-transition* corresponds to market perception of inventory news and *$H$-transition* corresponds to shifts in the composition of trading strategies. In our notation, the coefficients that govern market reaction to inventory news,$\{c_r^0, c_r^+, c_r^-, c_\sigma^0, c_\sigma^1\}$, follow the $I$-transition only. In contrast, the parameters in the probability equation, $\{\zeta, \xi\}$, the coefficients in the conditional mean equation for returns, $\{\rho, \rho^0\}$ and the coefficients in the conditional variance equation, $\{\psi_2, \psi_3\}$, will all follow $H$-transition only. The constants and certain coefficients in the conditional variance equation follow both transitions, $\{\mu, w, w_h, \phi, \psi_1\}$.

We perform two exercises. The first employs the indicator functions, $G_I(\tau, \tau_I^\star, \delta_I) = \mathbb{I}_{\tau \geq \tau_I^\star}$ and $G_H(\tau, \tau_H^\star, \delta_H) = \mathbb{I}_{\tau \geq \tau_H^\star}$, and we search over all possible combinations of $(\tau_I^\star, \tau_H^\star)$ in the time range we are interested in. In the second exercise, we fix the thresholds, keep the indicator function for $G_H(\tau, \tau_H^\star, \delta_H)$, but replace $G_I(\tau, \tau_I^\star, \delta_I)$ with the following specification

$$G_I(\tau, \tau_I^\star, \delta_I) = \frac{1}{1 + e^{-\delta_1(\tau - \tau_I^\star)}} \mathbb{I}_{\tau < \tau_I^\star} + \frac{1}{1 + e^{-\delta_2(\tau - \tau_I^\star)}} \mathbb{I}_{\tau \geq \tau_I^\star}.$$

[5]Four largest oil ETFs (USO, OIL, UCO, DBO) held approximately 13k first month contracts or only 4% of the open interest at the end of June 2014. Their holdings increased to 58k contracts or 20% of open interest by early January 2015, and to 113k or 32% by early March 2015. At the peak, in March 2016 their holdings reached 196k contracts or 42% of open interest.

This specification allows for different speeds of adjustments before and after the threshold.

Our results also indicate a break in the trading pattern,$\tau_H^\star$, around the first week of December 2014. The time of the change is consistent with observed changes in volatility, see Figure A.1 and intensity of trading as measured by the fraction of intervals with no trading (available on request). We believe that the break in trading patterns can be attributed to immense monetary inflows to exchange traded funds, such as the United States Oil Fund, that track short-term crude oil futures contracts. Similarly, the mid February 2017 was identified for the second transition.

**Identifying moment of transition to constrained inventories, 2014-2015**

We use the period from 2013 to 2016, long enough for informative estimation, but not too long to raise the issue of stationarity.[6]

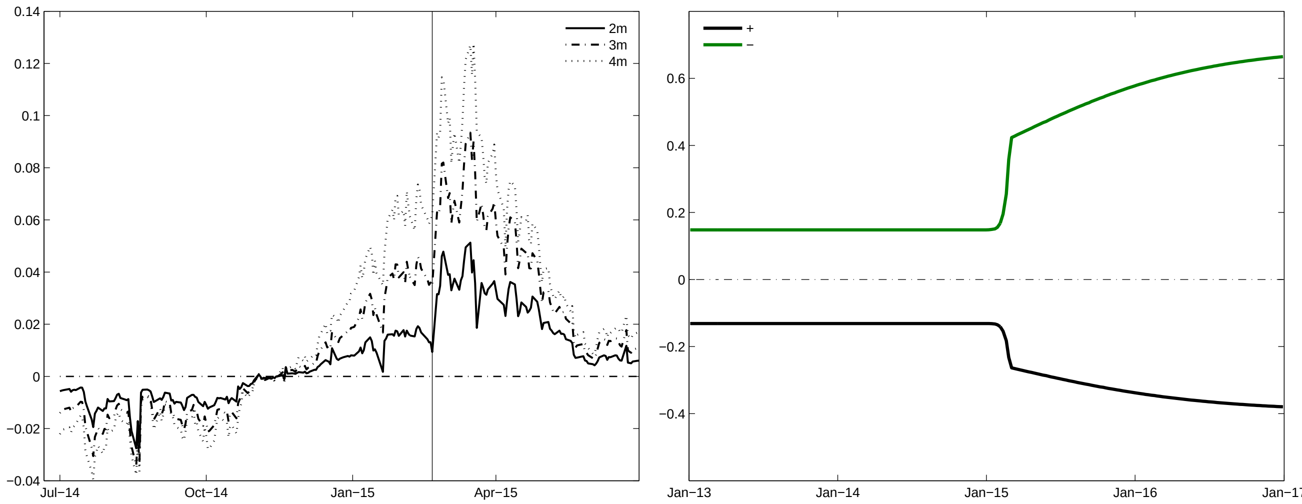
When we use a one time jump specification, our results suggest that the break in the market response to inventory news occurred precisely in the last week of February 2015! This is exactly when the term structure curve spiked, see Figure A.2, where the last week of February is marked by the vertical line; potentially indicating that inventories reached a certain critical level.

Figure A.2 depicts the estimated evolution of returns reactions to inventory surprises when we use the smoothed specification of the transition function. Despite the dramatic fall of oil prices and steepening of the term structure curve since November 2014, the market responded to inventory shocks in 2014 in exactly the same way as before. Only in February 2015 we observe a distinct increase in the market reaction followed by further gradual adjustments afterwards.

To put our findings in perspective, let us briefly describe the chronology of events in the oil market around the end of 2014. By 2014, US oil production exploded, reaching almost 9 mln barrels per day, and it was expected to grow even further. Struggling economies in China and Europe raised doubts that it would be possible to maintain the same pace of demand growth as

[6]For robustness, we repeat the exercise for a shorter sample, from 2014 to 2015; the results are similar and are available upon request.

Figure A.2: The slope of the term structure and evolution of returns responses to inventory news.




Notes: Left panel: The slope of the term structure at the shorter end at the end of 2014 and beginning of 2015 (see Figure 5 for description). The vertical line marks Friday, February 20, 2015. Right panel: Evolution of returns responses to inventory news. The solid line depicts $R_\tau(x_\tau)$ for $x_\tau = 0.01$ in black (1% positive inventory surprise) and $x_\tau = -0.01$ in green (1% negative inventory surprise), $\bar{x} = 0.006$, (see Figure 4 for description).

before, despite the fact that the oil prices remained high. However, in July of 2014, the price of oil started to decline. By November the oil price had fallen by 30%, and the term structure of oil prices became upward sloping. On November 27, 2014, OPEC announced their decision to maintain production levels, and soon afterwards the price of oil crashed even further. By the beginning of 2015, oil inventories reached unprecedented levels and were interpreted as a sign of an immense oil oversupply (see Figure 2).

The surprising behavior of OPEC suppliers represents a shock to expectations of future supply. The growing oil production and potentially weakening demand had been observed long before the November meeting and had been reflected in falling oil prices. But even though overall oil production was expected to grow, the market maintained the belief that OPEC producers would adjust, by cutting production to give way to shale oil producers. However, after the meeting in November, it became clear that OPEC producers were not willing to sacrifice their share of production. Hence, the expectations of the future path of the oil supply were reconsidered. Moreover, the possibility of temporary oversupply in the nearest future became substantial. However, as long as spare capacity in oil storage facilities is available, such a revision of expectations should not lead to any substantial effects on the term structure, especially at the shorter end. Only the level of the curve should be adjusted to reflect higher than expected supply of oil. That is exactly what we find: we do not see any changes in the market reaction to inventory news in 2014. It was not until inventories reach$\tau_H^\star$ ,ed extremely high levels, the market reaction to inventory news intensified! In other words, both the moment and the speed of transition are consistent with observed dynamics of inventories. Thus, we can reject the hypothesis that the financial market was unaware of the constrained state of inventories.

Our transition results further reinforce the term structure puzzle. The spike in the term structure curve coincides with an abrupt intensification of the market response to inventory news. Moreover, the futures curve became upward sloping well before inventories spiked, potentially indicating the transition to constrained regime. However, we find that when oil inventory announcements come, traders do not revise expectations accordingly and do not adjust the term premium.

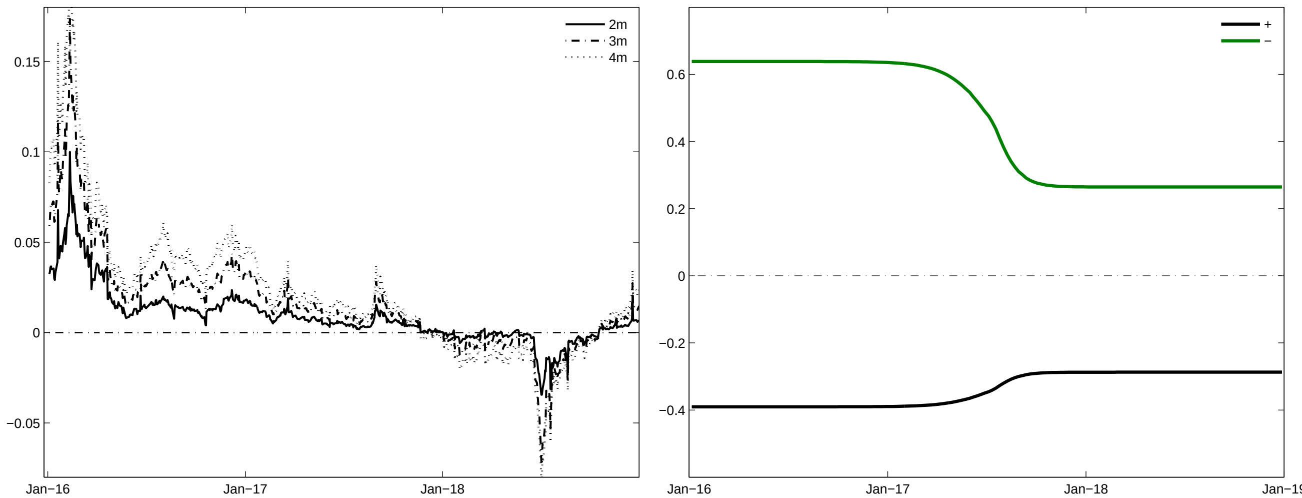
**Identifying moment of transition back to normal, 2017**

We use the sample from 2016 to 2018 to study the second transition. Figure A.3 shows a relatively gradual decline of the term spreads. The oil inventories had been rising until March 2017, but were sharply falling afterwards until the end of the year.

We follow the same approach as described above to characterize the transition process. The results for the smooth specification are presented on Figure A.3. Now we document a relatively gradual transition. The market reaction to shocks was slowly decreasing from March to September of 2017, consistent with the dynamics of the total oil inventories and the spreads.

The gradual transition may reflect the heterogeneity of traders' beliefs and overall uncertainty regardless the state of inventories. As more traders update their beliefs and place higher probability on capacity no longer being maxed out, we observe more and more muted reaction to news.

Figure A.3: The slope of the term structure and evolution of returns responses to inventory news.




Notes: Left panel: The slope of the term structure at the shorter end from 2016 to 2018 (see Figure 5 for description). Right panel: Evolution of returns responses to inventory news. The solid line depicts $R_\tau(x_\tau)$ for $x_\tau = 0.01$ in black (1% positive inventory surprise) and $x_\tau = -0.01$ in green (1% negative inventory surprise), $\bar{x} = 0.006$, (see Figure 4 for description).

## A.6 Long term effects

One potential criticism of our identification approach is that the narrow window around the EIA announcement cannot capture the full market reaction to inventory news. Perhaps it takes longer than half an hour for the market to fully process information and react. To provide further support for our findings, we perform additional estimation but now using daily data and following a standard approach, outlined, for example, in Miao et al. (2018). However, we continue to split the sample into three periods to facilitate the comparison with our benchmark results.

To facilitate comparison of the results, we follow the methodology (and notation) used in Miao et al. (2018). In particular, we do not use API information when calculating market surprises. For most of the announcement days, that would not be a problem, because the API report is released at 4:30 pm on Tuesday when the futures market is already closed. When we calculate the daily return as $R_t = \ln P_t - \ln P_{t-1}$, where $P_t$ is the settlement price as of Wednesday and $P_{t-1}$ is the settlement price as of Tuesday, we automatically capture the cumulative market reaction to both announcements. Hence, we only need to measure market expectations before the market closes on

Table A.2: Estimation results for the 2010-2014 period.

| Panel A: $R_t = \alpha + \sum_{i=1}^{3} \beta_i R_{t-i} + \gamma_0 SSI_t + \varepsilon_t$ | | | | | | |
|---|---|---|---|---|---|---|
| | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | $F_6$ |
| $\alpha$ | $-0.035$ | $-0.035$ | $-0.035$ | $-0.035$ | $-0.034$ | $-0.034$ |
| | (0.047) | (0.046) | (0.045) | (0.044) | (0.043) | (0.042) |
| $R_{t-1}$ | $-0.033$ | $-0.034$ | $-0.035$ | $-0.037$ | $-0.037$ | $-0.038$ |
| | (0.036) | (0.036) | (0.036) | (0.036) | (0.036) | (0.036) |
| $R_{t-2}$ | 0.026 | 0.036 | 0.036 | 0.035 | 0.033 | 0.033 |
| | (0.038) | (0.039) | (0.040) | (0.040) | (0.041) | (0.041) |
| $R_{t-3}$ | 0.002 | $-0.010$ | $-0.015$ | $-0.016$ | $-0.017$ | $-0.018$ |
| | (0.031) | (0.032) | (0.032) | (0.033) | (0.033) | (0.033) |
| $SSI_t$ | $-0.361$ | $-0.345$ | $-0.326$ | $-0.306$ | $-0.290$ | $-0.269$ |
| | (0.109) | (0.108) | (0.105) | (0.103) | (0.100) | (0.098) |
| Adjusted $R^2$ | 0.013 | 0.014 | 0.014 | 0.013 | 0.013 | 0.012 |
| $N$ | 1257 | 1257 | 1257 | 1257 | 1257 | 1257 |

| Panel B: $R_t = \alpha + \sum_{i=1}^{3} \beta_i R_{t-i} + \gamma_+ SSI_t^+ + \gamma_- SSI_t^- + \varepsilon_t$ | | | | | | |
|---|---|---|---|---|---|---|
| | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | $F_6$ |
| $\alpha$ | $-0.032$ | $-0.031$ | $-0.030$ | $-0.029$ | $-0.027$ | $-0.026$ |
| | (0.050) | (0.049) | (0.048) | (0.047) | (0.046) | (0.045) |
| $R_{t-1}$ | $-0.033$ | $-0.034$ | $-0.035$ | $-0.036$ | $-0.037$ | $-0.038$ |
| | (0.036) | (0.036) | (0.036) | (0.036) | (0.036) | (0.036) |
| $R_{t-2}$ | 0.026 | 0.036 | 0.036 | 0.035 | 0.033 | 0.033 |
| | (0.038) | (0.039) | (0.040) | (0.040) | (0.041) | (0.041) |
| $R_{t-3}$ | 0.002 | $-0.010$ | $-0.015$ | $-0.017$ | $-0.017$ | $-0.018$ |
| | (0.031) | (0.032) | (0.032) | (0.033) | (0.033) | (0.033) |
| $SSI_t^+$ | $-0.379$ | $-0.372$ | $-0.359$ | $-0.347$ | $-0.341$ | $-0.325$ |
| | (0.150) | (0.151) | (0.148) | (0.145) | (0.143) | (0.140) |
| $SSI_t^-$ | $-0.345$ | $-0.321$ | $-0.295$ | $-0.270$ | $-0.244$ | $-0.220$ |
| | (0.167) | (0.161) | (0.157) | (0.153) | (0.148) | (0.144) |
| Adjusted $R^2$ | 0.014 | 0.015 | 0.015 | 0.014 | 0.014 | 0.013 |
| P-value | 0.882 | 0.824 | 0.774 | 0.723 | 0.646 | 0.615 |
| $N$ | 1257 | 1257 | 1257 | 1257 | 1257 | 1257 |

Notes: Standard errors in parentheses. P-value is a probability value for the null hypothesis $H_0 : \gamma_+ = \gamma_-$ against $H_A : \gamma_+ \neq \gamma_-$.

Tuesday. However, sometimes the EIA delays the release due to a holiday. So occasionally, there can be more than 24 hours between the announcements, in which case the market surprise will be calculated incorrectly. But for the sake of the comparison of results, we abstract from this issue.

We estimate the following regression:

$$R_t = \alpha + \sum_{i=1}^{3} \beta_i R_{t-i} + \gamma_0 SSI_t + \varepsilon_t,$$

where $R_t$ refers to the daily return on a futures contract, $SSI_t = \frac{A_t - E_t}{\sigma}$ refers to the announcement surprise standardized by its unconditional standard deviation (in our notation, on the day of announcement, the announced value is $A_t = \Delta\text{Inv}_t^{EIA}$ and expected value is the median Bloomberg forecast $E_t = \Delta\text{Inv}_t^{BBG}$). If there is no announcement on day $t$, $SSI_t = 0$. To analyze asymmetry, we repeat the estimation with positive and negative surprises used separately according to $SSI_t^+ = SSI_t \cdot \mathbb{I}_{\{SSI_t>0\}}$ and $SSI_t^- = SSI_t \cdot \mathbb{I}_{\{SSI_t<0\}}$. For our purposes, we again split the sample into the 2010-2014, the 2015-2016, and the 2018-2019 periods. In line with Miao et al. (2018), we focus on the first 6 futures contracts by maturity.

The results are presented in Tables A.2, A.3 and A.4.[7] We see that the results are very similar to ours. Consider the 2010-2014 period. We observe a significant negative link between inventory surprises and returns. We also see that the first four futures contracts by maturity react to news by the same amount. The point estimates show some weakening of the reaction for longer maturity contracts, the coefficient drops from $-0.361$ to $-0.269$, but the difference is small while the standard errors are extremely large (0.109 and 0.098). Moreover, Panel B displays a symmetric market reaction to negative and positive market surprises; the null hypothesis for the equality of coefficients cannot be rejected. The results for the second unconstrained period from 2018 to 2019 are similar.

Now, consider the 2015-2016 period. We clearly observe intensification of the marker reaction to

[7]Our tables should be compared to tables 9 and 11 (panel A) in Miao et al. (2018). The sample in their paper covers the 2003-2011 period.

Table A.3: Estimation results for the 2015-2016 period.

| Panel A: $R_t = \alpha + \sum_{i=1}^{3} \beta_i R_{t-i} + \gamma_0 SSI_t + \varepsilon_t$ | | | | | | |
|---|---|---|---|---|---|---|
| | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | $F_6$ |
| $\alpha$ | $-0.040$ | $-0.042$ | $-0.041$ | $-0.040$ | $-0.038$ | $-0.035$ |
| | (0.131) | (0.124) | (0.119) | (0.115) | (0.112) | (0.109) |
| $R_{t-1}$ | $-0.082$ | $-0.096$ | $-0.105$ | $-0.108$ | $-0.120$ | $-0.121$ |
| | (0.059) | (0.056) | (0.056) | (0.056) | (0.055) | (0.055) |
| $R_{t-2}$ | $-0.003$ | 0.021 | 0.030 | 0.037 | 0.048 | 0.051 |
| | (0.057) | (0.055) | (0.055) | (0.054) | (0.054) | (0.054) |
| $R_{t-3}$ | $-0.041$ | $-0.053$ | $-0.061$ | $-0.067$ | $-0.066$ | $-0.065$ |
| | (0.053) | (0.052) | (0.052) | (0.052) | (0.052) | (0.053) |
| $SSI_t$ | $-0.873$ | $-0.868$ | $-0.843$ | $-0.815$ | $-0.794$ | $-0.762$ |
| | (0.227) | (0.213) | (0.200) | (0.191) | (0.183) | (0.177) |
| Adjusted $R^2$ | 0.044 | 0.052 | 0.056 | 0.059 | 0.063 | 0.063 |
| $N$ | 495 | 495 | 495 | 495 | 495 | 495 |

| Panel B: $R_t = \alpha + \sum_{i=1}^{3} \beta_i R_{t-i} + \gamma_+ SSI_t^+ + \gamma_- SSI_t^- + \varepsilon_t$ | | | | | | |
|---|---|---|---|---|---|---|
| | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | $F_6$ |
| $\alpha$ | 0.002 | 0.002 | 0.000 | $-0.003$ | $-0.005$ | $-0.007$ |
| | (0.131) | (0.130) | (0.125) | (0.121) | (0.118) | (0.115) |
| $R_{t-1}$ | $-0.085$ | $-0.098$ | $-0.107$ | $-0.110$ | $-0.121$ | $-0.123$ |
| | (0.060) | (0.057) | (0.057) | (0.056) | (0.055) | (0.055) |
| $R_{t-2}$ | 0.000 | 0.024 | 0.035 | 0.042 | 0.053 | 0.056 |
| | (0.057) | (0.055) | (0.055) | (0.054) | (0.054) | (0.054) |
| $R_{t-3}$ | $-0.041$ | $-0.053$ | $-0.061$ | $-0.067$ | $-0.066$ | $-0.065$ |
| | (0.053) | (0.052) | (0.052) | (0.052) | (0.052) | (0.053) |
| $SSI_t^+$ | $-0.678$ | $-0.667$ | $-0.630$ | $-0.598$ | $-0.579$ | $-0.548$ |
| | (0.351) | (0.328) | (0.308) | (0.293) | (0.281) | (0.271) |
| $SSI_t^-$ | $-1.072$ | $-1.074$ | $-1.061$ | $-1.039$ | $-1.015$ | $-0.981$ |
| Adjusted $R^2$ | 0.047 | 0.055 | 0.060 | 0.062 | 0.067 | 0.067 |
| P-value | 0.407 | 0.360 | 0.305 | 0.269 | 0.253 | 0.238 |
| $N$ | 495 | 495 | 495 | 495 | 495 | 495 |

Notes: Standard errors in parentheses. P-value is a probability value for the null hypothesis $H_0 : \gamma_+ = \gamma_-$ against $H_A : \gamma_+ \neq \gamma_-$.

Table A.4: Estimation results for the 2018-2019 period.

| Panel A: $R_t = \alpha + \sum_{i=1}^{3} \beta_i R_{t-i} + \gamma_0 SSI_t + \varepsilon_t$ | | | | | | |
|---|---|---|---|---|---|---|
| | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | $F_6$ |
| $\alpha$ | 0.014 | 0.013 | 0.012 | 0.010 | 0.009 | 0.007 |
| | (0.089) | (0.088) | (0.087) | (0.085) | (0.083) | (0.081) |
| $R_{t-1}$ | −0.092 | −0.106 | −0.110 | −0.110 | −0.110 | −0.110 |
| | (0.049) | (0.049) | (0.048) | (0.047) | (0.046) | (0.045) |
| $R_{t-2}$ | −0.033 | −0.028 | −0.029 | −0.029 | −0.028 | -0.026 |
| | (0.050) | (0.052) | (0.053) | (0.053) | (0.054) | (0.054) |
| $R_{t-3}$ | −0.012 | −0.016 | −0.016 | −0.011 | −0.009 | −0.006 |
| | (0.049) | (0.051) | (0.051) | (0.052) | (0.052) | (0.052) |
| $SSI_t$ | −0.479 | −0.471 | −0.457 | −0.439 | −0.423 | −0.409 |
| | (0.147) | (0.144) | (0.141) | (0.140) | (0.139) | (0.137) |
| Adjusted $R^2$ | 0.036 | 0.038 | 0.038 | 0.037 | 0.037 | 0.036 |
| $N$ | 512 | 512 | 512 | 512 | 512 | 512 |

| Panel B: $R_t = \alpha + \sum_{i=1}^{3} \beta_i R_{t-i} + \gamma_+ SSI_t^+ + \gamma_- SSI_t^- + \varepsilon_t$ | | | | | | |
|---|---|---|---|---|---|---|
| | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | $F_6$ |
| $\alpha$ | −0.002 | −0.005 | −0.004 | −0.004 | −0.004 | −0.004 |
| | (0.096) | (0.095) | (0.093) | (0.091) | (0.089) | (0.087) |
| $R_{t-1}$ | −0.093 | −0.107 | −0.111 | −0.111 | −0.110 | −0.111 |
| | (0.048) | (0.049) | (0.048) | (0.047) | (0.046) | (0.045) |
| $R_{t-2}$ | −0.033 | −0.028 | −0.029 | −0.029 | −0.028 | −0.027 |
| | (0.050) | (0.052) | (0.053) | (0.053) | (0.054) | (0.054) |
| $R_{t-3}$ | −0.013 | −0.017 | −0.016 | −0.012 | −0.009 | −0.007 |
| | (0.049) | (0.051) | (0.051) | (0.051) | (0.052) | (0.052) |
| $SSI_t^+$ | −0.414 | −0.400 | −0.393 | −0.384 | −0.374 | −0.364 |
| | (0.175) | (0.172) | (0.170) | (0.170) | (0.169) | (0.168) |
| $SSI_t^-$ | −0.557 | −0.556 | −0.534 | −0.505 | −0.481 | −0.463 |
| | (0.260) | (0.255) | (0.246) | (0.244) | (0.241) | (0.239) |
| Adjusted $R^2$ | 0.038 | 0.040 | 0.040 | 0.040 | 0.039 | 0.039 |
| P-value | 0.659 | 0.622 | 0.648 | 0.695 | 0.724 | 0.743 |
| $N$ | 512 | 512 | 512 | 512 | 512 | 512 |

Notes: Standard errors in parentheses. P-value is a probability value for the null hypothesis $H_0 : \gamma_+ = \gamma_-$ against $H_A : \gamma_+ \neq \gamma_-$.

news, the estimate for the front month contracts now becomes$-0.873$. But even when inventories are constrained, we see that longer maturity contracts react in exactly the same way as the front-month contract: the point estimates for the first and fourth month contracts are $-0.873$ and $-0.762$, an extremely small difference considering the standard errors. Finally, when we split the surprises, we see that negative surprises trigger a larger market reaction. However, the difference is statistically insignificant and symmetry cannot be rejected. However, when we consider only the year of 2016, the asymmetry is rejected for every contract.

Overall, the estimation results of this section confirm our previous findings. The only difference is the precision of the estimates. Standard errors blow up, which is not that surprising, because focusing on daily returns inevitably introduces noise which masks the true market reaction to inventory news. Our approach offers much more precise estimates.

## A.7 Oil market during pandemic

Figure A.4 displays the response of the oil market to coronavirus news in the first quarter of 2020.

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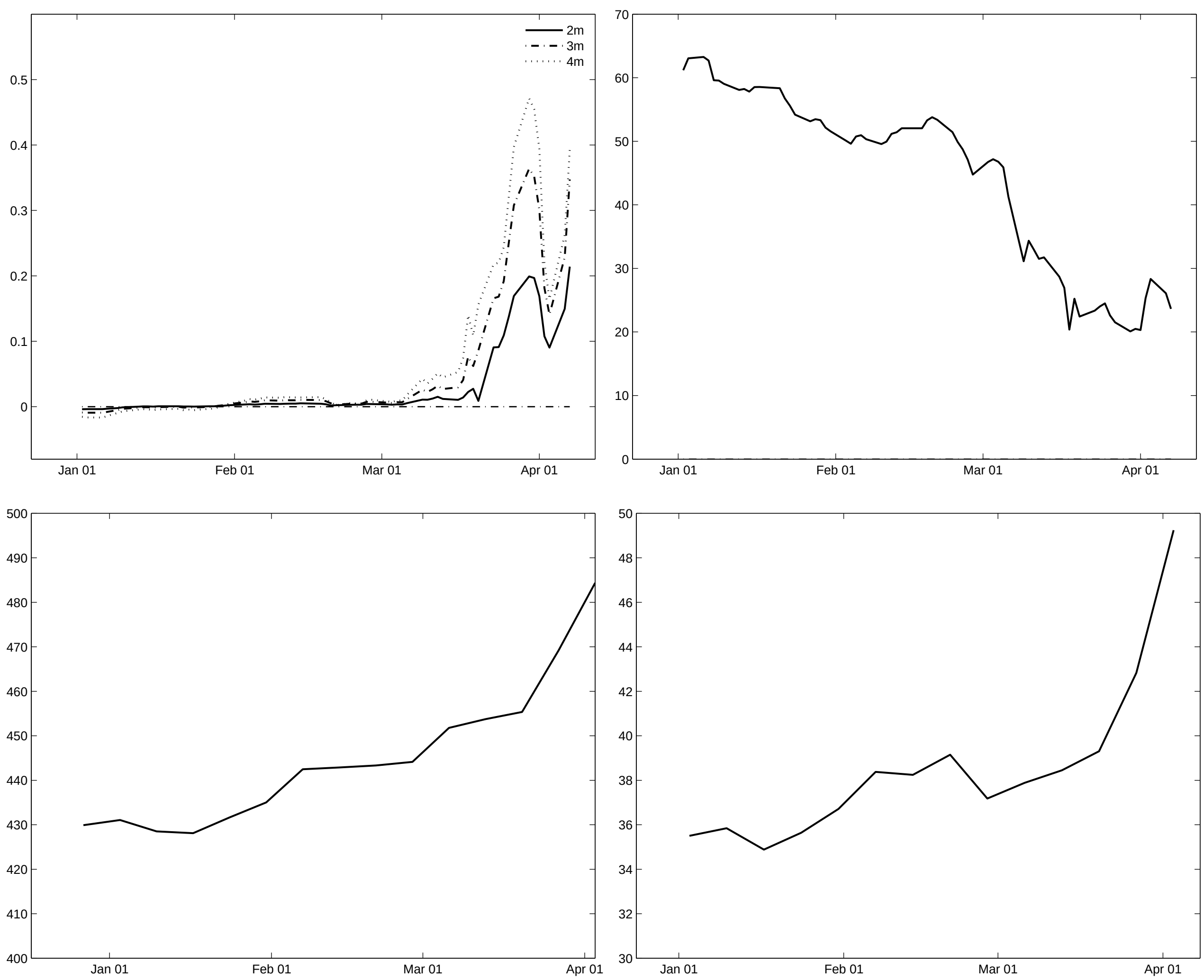
Figure A.4: The term structure and oil inventories dynamics from January to April 2020.




Notes: Top left panel: The term structure of futures prices. The figure displays the daily series of the price difference between the three futures contracts with the shortest maturities and the front month futures contract, normalized by the price of the front month contract, $(F_{n,t} - F_{1,t})/F_{1,t}$, where $n = 2, 3, 4$ months. Top right panel: The front month futures contract price,$F_{1,t}$ (in \$/bbl). Bottom left panel: Weekly U.S. ending stocks of crude oil excluding SPR (mln barrels). Bottom right panel: Weekly Cushing, OK Ending Stocks excluding SPR of Crude Oil (mln barrels).

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