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Evidence of oil market price clustering during the COVID-19 pandemic

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1. Introduction

Asset prices are clustered when some numbers are observed more often than others. The search for price clustering is relevant to financial economists and traders because they have implications for market efficiency. If markets are efficient then prices should not cluster. If prices do cluster, this clustering can be exploited in devising trading strategies. Our goal is to test for price clustering behavior in oil price data. Our intervention is timely given the dramatic collapse of oil prices during the period of the COVID-19 pandemic. Our hypothesis is that, given COVID-19 represents a major and unprecedented shock to the global financial system, the pandemic has accentuated price clustering behavior. We provide the paper’s motivation in Section II.B. While obviously none of the past shocks can be compared to COVID-19,¹ studies on price clustering show that major shocks like political instability contribute to market inefficiency by increasing price clustering behavior (Narayan & Smyth, 2013).

To-date, two gaps in the literature exist. First, none of the studies has tested and documented evidence of price clustering in the oil market in the manner we do; however, there are related studies that explore psychological barrier in the oil market (see Aggarwal & Lucey, 2007; Dowling, Cummins, & Lucey, 2016; Narayan & Narayan, 2014). Section II.B provides a motivation for price clustering behavior in the oil market. This is surprising because oil is one of the most heavily traded assets and constitutes the largest component of commodities traded (Dolatabadi, Narayan, & Nielsen, 2018). Several studies, for instance, show that oil trading is profitable; see Narayan and Smyth (2013) and Dolatabadi et al. (2018). Documenting price clustering is important because it can aid trading strategies, as we show later in Section III. The second gap relates to the role of COVID-19 in contributing to price clustering behavior, if any, in the oil market. We specifically study whether the COVID-19 pandemic has influenced price clustering behavior in the oil market. This is important because the literature shows price clustering to be associated to events, such as shocks that create panic trading; see Mitchell (2001), Brown and Mitchell (2008), and Brown, Chua, and Mitchell (2002).

Our study by been the first to test for price clustering behavior in the oil market contributes to the literature in multiple ways. First, we use intraday (hourly) data for the period July 2019 to June 2020 and document evidence that in the oil market prices tend to cluster on numbers closer to zero. As much as 65% of prices tend to settle on numbers closer to zero. Just over a third of prices attract numbers beyond 5. This evidence is robust to our test of price clustering in multiple oil prices, such as closing price, opening price, opening bid price, closing bid price, opening ask price and closing ask price. This evidence implies that price clustering is a source of oil market inefficiency –and this inefficiency can be exploited in devising trading strategies. Our work connects to studies that show price clustering in the foreign exchange market (Sopranzetti & Datar, 2002), equities and futures markets (ap Gwilym et al. Ap Gwilym, Clare, & Thomas, 1998; Ohta, 2006), IPOs (ap Gwilym and Verousis Ap Gwilym & Verousis, 2010), and index options (Capelle-Blanchard & Chaudhury, 2007; Ni,

1 For a survey of the COVID-19 literature, see Narayan (2021), Sharma and Sha (2020) and Sha and Sharma (2020).
We add to these studies by showing the presence of price clustering in oil prices. From our paper, the message is clear: that price clustering behavior has a broader appeal and commodity markets are not immune to clustering.

Second, we show that while in general the oil market experiences price clustering behavior, COVID-19 contributed to over 8% more price clustering behavior over the January 2020 to June 2020 period compared to the pre-COVID-19 sample (July 2019 to December 2019). We estimate a probit model of the determinants of price clustering behavior and show that each day of the COVID-19 pandemic increased the chances of price clustering behavior by at most 30%. These findings are broadly consistent with evidence obtained by the literature showing that political instability contributes to price clustering behavior. We add by showing that the pandemic has also contributed to price clustering behavior. We conclude that COVID-19 has contributed to oil market inefficiency. In showing this role of COVID-19 in price clustering, our study joins a small group of studies showing how COVID-19 has impacted energy markets in general. Recent studies, for instance, show that COVID-19 has influenced corporate performance of the energy industry (Fu and Shen, 2020; Iyke, 2020); oil price persistency (Gil-Alana & Monge, 2020); oil and stock market relation (Liu, Wang, & Lee, 2020; Prabheesh et al., 2020); and oil price news and/or oil price volatility (Ertugrul, Gungor, & Soytas, 2020; Narayan, 2020; Devpura and Narayan, 2020; Huang and Zheng, 2020; Salisu & Achediran, 2020). We introduce to this literature the price clustering perspective and show how COVID-19 has influenced price clustering in the oil market.

Third, we formally test the effects of market inefficiency by devising a trading strategy. Using evidence of price clustering as a buy and sell signal, we find that price clustering behavior improves gains from trading in the oil market. Through this exercise, while we contribute to studies showing that oil market trading is profitable, we are unique because we show, for the first time in this literature, that the channel of profitability is price clustering resulting from COVID-19.

We organize the rest of the paper as follows. Section II discusses the price clustering theory and sets out the empirical framework. Section III is about the data and results. The final section concludes.

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2 There are several studies on behavioral aspects of the oil market (Deeney, Cummins, Dowling, & Bermingham, 2015; Narayan, 2019, 2020), non-ferrous metal prices (Cummins, Dowling, & Lucey, 2015), gold and silver prices (Lacey & O’Connor, 2016), carbon market (Palao & Pardo, 2018) and bitcoin (Urquhart, 2017).
The price clustering tests are based on hourly data covering the sample July 1, 2019 starting at 01:00 and ending at 17:00 on June 12, 2020. We have two datasets. The first is the six oil price series: namely closing price (CP), opening price (OP), opening ask price (OAP), opening bid price (OBP), closing ask price (CAP), and closing bid price (CBP). There are three additional variables, namely oil price volatility, trading volume, and price (which is computed as \( (OAP + OBP + CAP + CBP)/4 \))—these variables are used as determinants of price clustering in Table 4. The statistics are mean, standard deviation (SD), minimum and maximum values, and the Narayan and Popp (2010) unit root test, whose slope coefficients and resulting t-statistics are reported in parenthesis. The 1% NP critical value is \(-5.287\). The descriptive statistics are reported for the full sample of data in Panel A, and for pre-COVID-19 sample and COVID-19 sample in panels B and C, respectively.

### 2. Price clustering theory and empirical framework

#### 2.1. The theory

In the previous section, we alluded to numerous studies on price clustering in different markets. These studies are motivated by a well-established theoretical foundation that paves the way for price clustering behavior in asset prices. The first is the psychological barrier hypothesis. A view that sees the importance of symbolic numbers (Mitchell, 2001). This behavior is also supported by the price resolution hypothesis—the idea that clustering behavior in a price digit faster. Clustering will be less intense in liquid markets (Ball, Torous, & Tschoegi, 1985) where market information is readily available. Second is the attraction theory—the idea that individuals are attracted to certain integers (Gottlieb & Kalay, 1985). In this integer attractiveness, rounding off is common. Rounding off to 0 and 5, for instance, is perceived to be more attractive compared to other end digits. Third is the cost negotiation hypothesis, which, as Harris (1991) argues, is favored by agents who find less costly to utilize a small set of integers and use this to settle on a price. Lastly, there is the panic trading hypothesis proposed by Narayan and Smyth (2013). The idea of this hypothesis is that due to the existing and impending uncertainty about market performance, investors would settle quickly on a rounded price. The argument is that uncertainty instigates panic trading which contributes to clustering behavior.

#### 2.2. Motivation for price clustering behavior in oil prices

Oil prices have become highly uncertain over the last 12 months. A large part of this uncertainty owes to obviously the COVID-19 pandemic and the Russia-Saudi Arabia price war (Devpura and Narayan, 2020). A 300% drop in the WTI oil price was recorded on April 20, 2020. Oil prices have become at least five times more volatility during the COVID-19 period compared to the pre-COVID-19 period; See Fig. 1. Panel A of the figure shows a comparison of oil price volatility between pre-COVID-19 and COVID-19 periods. The oil market has never been as uncertain and volatile as it finds itself in the COVID-19 period. The implication, as sounded out by Grossman et al., (1997) and Kleidon and Willig (1995), is that when market makers are unable to time the market, price clustering will be higher. This is because amidst uncertainty there is a tendency to round off quotations. With growing price volatility, price clustering in oil prices is likely to be higher because traders see an opportunity to reduce exposure to risk by closing a trade quickly which may come at the expense of less precise valuation. With the behavior in oil prices and its volatility, oil prices offer a prime asset to test for price clustering. (See Table 1.)

### 3. Data and results

#### 3.1. Data

The price clustering tests are based on hourly data covering the sample July 1, 2019 starting at 01:00 and ending at 17:00 on June 12, 2020. We have two datasets. The first is the six oil price series: namely closing price (CP), opening price (OP), opening ask price (OAP), opening bid price (OBP), closing ask price (CAP), and closing bid price (CBP). The motivation for using these measures of volatility in light of the COVID-19 pandemic is presented in Sharma (2020) and we recommend interested readers to this paper. The second dataset consists of three additional variables, namely oil price volatility, trading volume, and price (which is computed as \( (OAP + OBP + CAP + CBP)/4 \)) while oil price volatility is based on German and Klass (1980): \( 0.5 \cdot \ln(HP) - \ln(LP)^2 - 12 \ln(2 - 1) \cdot \ln(\ln(LP)) - \ln(\ln(OP)^2) \), where in addition to the variables already defined, LP is the low price of oil. All hourly oil price series are obtained from “DATASCOPE” database (https://www.refinitiv.com/en).
Evidence of price clustering.

Table 3

| Panel A: OP | Panel B: CP |
|-------------|-------------|
| **Count**   | **Frequency (%)** | **t-stat.** | **Count** | **Frequency (%)** | **t-stat.** |
| x.00-x.05   | 2614        | 61.51       | 82.40     | 2670        | 62.82       | 84.74       |
| x.00         | 428         | 10.07       | 0.15      | 441         | 10.38       | 0.81        |
| x.01         | 415         | 9.77        | -0.51     | 438         | 10.31       | 0.66        |
| x.02         | 496         | 11.67       | 3.62      | 475         | 11.18       | 2.56        |
| x.03         | 482         | 11.34       | 2.91      | 483         | 11.36       | 2.96        |
| x.04         | 420         | 9.88        | -0.26     | 450         | 10.59       | 1.28        |
| x.05         | 373         | 8.78        | -2.66     | 383         | 9.01        | -2.15       |
| x.06         | 429         | 10.09       | 0.20      | 384         | 9.04        | -2.10       |
| x.07         | 371         | 8.73        | -2.76     | 389         | 9.15        | -1.84       |
| x.08         | 396         | 9.32        | -1.48     | 384         | 9.04        | -1.20       |
| x.09         | 440         | 10.35       | 0.77      | 423         | 9.95        | -0.10       |
| **T**        | 2244        |             |           | 2244        |             |           |
| **Mean**     | 52.97       |             |           | 52.96       |             |           |
| **STD**      | 14.38       |             |           | 14.39       |             |           |
| **Max.**     | 71.22       |             |           | 70.59       |             |           |
| **Min.**     | 16.25       |             |           | 16.28       |             |           |

This table has results on price clustering for open price (OP) and closing price (CP) prices, respectively. The number of times (count) and frequency (%) price settles on digits x.00 to x.05 and on specific digits starting with x.00 to x.09 are reported. The associated t-statistics testing the null hypothesis that the price clustering is zero is also reported in the last column of each panel. Finally, * (**) *** denote statistical significance at the 10% (5%) 1% levels.

3.2. Evidence of price clustering

The literature has commonly considered the following types of price clustering behavior: (a) prices that cluster on 0, (b) prices that cluster on 0 and 5, (c) prices that cluster on even numbers including 0, (d) prices that cluster on odd numbers, and (e) prices that cluster on auspicious/inauspicious numbers. When we examine evidence of price clustering behavior with respect to oil price, from Table 2 we see that both OP and CP do not follow clustering in the manner defined by the literature. In other words, across all digits, clustering falls in the range 8.73% to 11.67% and 9.01% to 11.36% for OP and CP, respectively. On this evidence, it is clear that there is no preferred rounding off in oil prices—a finding in sharp contrast to the literature on price clustering in equities, bonds, IPOs, and exchange rates. We, however, observe a different pattern of clustering: we notice that the bulk of the oil prices tend to cluster on numbers closer to zero than closer to 1. In other words, we have a preponderance of prices that cluster on x.00 to x.05 than on x.06 to x.09. To be more precise, we find that 61.51% of OP and 62.82% of CP cluster on x.00 to x.05.

3.3. Determinants of price clustering

In the preceding section, we documented that in the oil market (across the 6 different types of prices we use) prices tend to cluster closer to zero than to one, and this evidence became stronger with as much as 65% of prices clustering on x.00 to x.05 over the COVID-19 period. (See Table 5.) In this section, we explore the determinants of this price clustering, specifically testing the role of COVID-19. Using the evidence over the full-sample of data and denoting the effect of COVID-19 via a dummy variable that takes a value of one from 1 January 2020 to 6/12/2020. In estimating the determinants of price clustering, we follow the literature and estimate a probit model such that the dependent variable is binary—a value one when prices cluster on any digit between 0 and 5 inclusive and a value zero rest of the times. The explanatory variables, as dictated by theory reviewed in Section II, are volume, volatility, and own price. The role of volume is motivated by the price resolution and price negotiation hypotheses of Grossman et al. (1997) and Harris (1991), respectively. In our results, volume has a statistically significant negative effect on price clustering, suggesting that volume in the oil market is proxying for uncertainty. Own price, on the other hand, has a positive effect on price clustering, suggesting that high priced stocks tend to cluster on digits closer to zero, which is preferred because as per the

Table 3

| Panel A: OBP | Panel B: CBP | Panel C: OAP | Panel D: CAP |
|-------------|-------------|-------------|-------------|
| **Count**   | **Freq. (%)** | **t-stat.** | **Count**   | **Freq. (%)** | **t-stat.** | **Count**   | **Freq. (%)** | **t-stat.** |
| x.00-x.05   | 2617        | 62.82       | 82.52      | 2658        | 62.54       | 84.74       | 2680        | 61.18       | 85.16       |
| x.00         | 439         | 10.33       | 0.71      | 441         | 10.54       | 0.66        | 436         | 10.26       | 0.56        |
| x.01         | 436         | 10.26       | 0.56      | 448         | 10.54       | 0.66        | 439         | 10.33       | 0.72        |
| x.02         | 482         | 11.34       | 2.91      | 481         | 11.32       | 2.61        | 474         | 11.15       | 2.51        |
| x.03         | 484         | 11.39       | 3.02      | 476         | 11.20       | 2.61        | 477         | 11.22       | 2.66        |
| x.04         | 412         | 9.69        | -0.66     | 442         | 10.40       | 0.87        | 450         | 10.59       | 1.28        |
| x.05         | 364         | 8.57        | -3.12     | 379         | 8.92       | -2.35        | 404         | 9.51        | -1.07       |
| x.06         | 441         | 10.38       | 0.82      | 403         | 9.48       | -1.13        | 386         | 9.08        | -1.99       |
| x.07         | 366         | 8.61        | -3.07     | 376         | 8.85       | -2.51        | 385         | 9.06        | -2.05       |
| x.08         | 390         | 9.18        | -1.80     | 388         | 9.13       | -1.89        | 378         | 8.89        | -2.40       |
| x.09         | 436         | 10.26       | 0.56      | 425         | 10.09       | 0.00        | 421         | 9.91        | -0.20       |
| **T**        | 2244        |             |           | 2244        |             |           | 2244        |             |           |
| **Mean**     | 52.96       |             |           | 52.95       |             |           | 52.97       |             |           |
| **STD**      | 14.38       |             |           | 14.38       |             |           | 14.38       |             |           |
| **Max.**     | 71.26       |             |           | 70.59       |             |           | 71.44       |             |           |
| **Min.**     | 16.25       |             |           | 16.25       |             |           | 16.25       |             |           |

This table has results on price clustering for opening bid price (OBP), closing bid price (CBP), opening ask price (OAP), and closing ask price (CAP) in panels A, B, C, and D respectively. The number of times (count) and frequency (%) price settles on digits x.00 to x.05 and on specific digits starting with x.00 to x.09 are reported. The associated t-statistics testing the null hypothesis that the price clustering is zero is also reported in the last column of each panel. Finally, * (**) *** denote statistical significance at the 10% (5%) 1% levels.
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This table has results on price clustering for open price (OP), close price (CP), open bid price (OBP), close bid price (CBP), open ask price (OAP) and close ask price (CAP). Given the evidence in Tables 2 and 3, we focus only on clustering on x.00 to x.05 (Panel i) and on specific digits starting with x.00 to x.09 are reported. The results are reported for two sub-samples, namely pre-COVID-19 sample (Panel A) and COVID-19 sample (Panel B). The number of times (count) and frequency (%) price settles on digits x.00 to x.05 (Panel i) and x.06 to x.09 (Panel ii). The results are reported for two sub-samples, namely pre-COVID-19 sample (Panel A) and COVID-19 sample (Panel B). The number of times (count) and frequency (%) price settles on digits x.00 to x.05 (Panel i) and on specific digits starting with x.00 to x.09 are reported. The associated t-statistics testing the null hypothesis that the price clustering is zero is also reported in the last column of each panel. Finally, * (** *) *** denote statistical significance at the 10% (5%) 1% levels.

Table 5
Determinants of price clustering.

| Constant | Volume (–1) | Volatility (–1) | Price (–1) | COVID-19 Dummy |
|----------|-------------|----------------|------------|----------------|
| OP       | –0.1756     | –0.0000**      | –4.859     | 0.0076***      | 0.2424***      |
|          | (–1.433)    | (–0.177)       | (3.955)    | (4.425)        |
| CP       | –0.2824**   | –0.0000        | 79.721     | 0.0992***      | 0.2891***      |
|          | (–2.211)    | (1.084)        | (4.507)    | (5.217)        |
| OAP      | –0.1107     | –0.0000**      | –0.932     | 0.00071**      | 0.2106***      |
|          | (–0.904)    | (–0.035)       | (3.687)    | (3.844)        |
| OBP      | –0.172      | –0.0000**      | –4.5199    | 0.0076***      | 0.2281***      |
|          | (–1.401)    | (–0.163)       | (3.999)    | (4.466)        |
| CAP      | –0.2346*    | –0.0000        | 73.829     | 0.0086**       | 0.2785**       |
|          | (–1.843)    | (1.058)        | (4.317)    | (5.026)        |
| CBP      | –0.3154**   | –0.0000        | 81.681     | 0.0094**       | 0.3055**       |
|          | (–2.467)    | (0.689)        | (1.093)    | (4.685)        |

This table reports estimates of the determinants of price clustering (PC), where the determinants are oil trading volume, oil price volatility and oil price. Trading volume is the volume of oil traded. Oil price is computed as (OAP + OBP + CAP + CBP)/4, where OAP, OBP, CAP and CBP are, respectively, open ask price, open bid price, close ask price and close bid price. Oil price volatility is based on German and Klaas (1980): 0.5 \( \ln (HP) - \ln (LP) \) \(^2\) – [2 ln 2 – 1] \( \ln (CP) - \ln (OP) \) \(^2\), where HP, LP, CP, and OP are high price, low price, close price and open price, respectively. The COVID-19 dummy variable is a binary variable that takes a value one from 1 January 2020 to the end of the sample and zero prior to 1 January 2020. Finally, * (** *) *** denote statistical significance at the 5% (1%) levels.

price negotiation/resolution hypothesis active clustering minimizes negotiation and information costs. Price volatility tends out to be statistically insignificant in our analysis. The COVID-19 pandemic dummy variable is statistically significant and positive, suggesting that for every day of the pandemic there was a 21–30% chance that prices would cluster on digits x.00 to x.05. This idea is consistent with the Narayan and Smyth (2013) hypothesis that traders tend to be in a panic mode faced with a crisis and the idea is to minimize resolution and negotiation costs at a time when the market is already uncertain. Therefore, the tendency to settle on a price faster is the preferred strategy.

3.4. Economic significance of price clustering

A popular technique for estimating economic gains from trading is the moving average (MA) trend determining technique. When two MA of prices (R) cross, this has implications for buying and selling or the trading position (. When the short-run (S) MA is greater than the corresponding long-run (LONG) MA, investors buy; if not, they sell. This relationship is captured as follows:

\[
LONG = 1 \text{ if } S^{–1} \left( \sum_{t=1}^{L} R_{t-1} \right) \geq L^{–1} \left( \sum_{t=1}^{L} R_{t-1} \right) \\
= 0 \text{ otherwise.}
\]

We set \( S = 100 \) and \( L = 1000 \) and 1500 hours and we allow a transaction cost of 0.1% each time a long or short position is established. Net profit, therefore, can be computed as:

\[
P_t = LONG_t \cdot (R_{t-1} – 1) \cdot (R_t - 0.001 \cdot LONG_{t-1} \cdot (R_{t-1} - 1))
\]

The results are summarized in Table 6. We see that regardless of the S and L values in the MA rule, the oil market is profitable. Both over the full sample of data and in the pre-COVID-19 sample, oil market trading is profitable. When using the full sample of data, oil market profits based on MA(150, 1000) hours are 0.73% per month or 7.38% per annum (t-statistics = 8.80). However, we do not find any statistically significant evidence that raw profits or price clustering adjusted profits were economically meaningful in the COVID-19 period. The conclusion is that despite a rise in price clustering activity, over the COVID-19 period oil market has become unprofitable.

4. Concluding remarks

In this paper, we examine evidence of price clustering behavior in the oil market. Using six different types of hourly oil prices (opening price, closing price, opening ask price, opening bid price, closing ask price and closing bid price), we show that while price clustering is evident it does so on numbers closer to zero. We show that across all six-price series, clustering on digits ending with 0 to 5 inclusive is as much as 65%. We
examine the determinants of this price clustering and show that COVID-19 explains as much as 30% of this price clustering behavior. Although evidence of price clustering signifies market inefficiency, using moving average technical trading rules we show that the oil market has become unprofitable over the COVID-19 period. This is not surprising because the COVID-19 period is marked by one of the most dramatic collapses in oil price, reaching a record negative price, and the price has seen volatility rise by up to 900%.

Acknowledgement

An earlier version of this paper was presented at the 6th Asia-Pacific Applied Economics Association and Energy Economic Special issue conference on June 19, 2021. This research was supported by a research grant on COVID-19 pandemic from the Asia-Pacific Applied Economics Association. Helpful comments and suggestions on earlier versions of this paper from conference participants and reviewers of this journal are acknowledged. The usual disclaimer applies.

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