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Price overreactions in the commodity futures market: An intraday analysis of the Covid-19 pandemic impact

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The objective of this paper is to examine the overreaction behavior of 20 commodity futures based on intraday data from November 20, 2019 to June 3, 2020 with a focus on the impact of the Covid-19 pandemic. A dynamic and non-parametric approach is applied on intraday data for four different frequencies (from 1 min to 1 h) and two different sub-periods (pre-Covid-19 pandemic and during Covid-19 pandemic) in order to detect overreaction behavior which is defined as a large change of prices followed by proportional price reversals. Our empirical findings show that the overreaction hypothesis is confirmed for the considered commodity futures. Furthermore, both the number and the amplitude of overreactions is higher during the Covid-19 pandemic. Our findings also indicate that soft and metal commodities show much less overreactions than precious metals and especially energy commodities. In particular, crude oil futures exhibit a different overreaction behavior compared to other commodities since it has a higher number of negative than positive overreactions during the Covid-19 pandemic. We also find that the data frequency is independent of the overreacting behavior in both periods as the results continuously improve when having more observations due to higher frequencies. Finally, we find that extreme overreactions during the Covid-19 pandemic provide a great potential for profitable trading returns, which can be exploited by traders.

1. Introduction

Since the pioneer work of De Bondt and Thaler (1985) on the overreaction of stock prices, many academic papers have investigated this hypothesis with various frameworks and methods (e.g. De Bondt and Thaler, 1987; Dissanaike, 1994; Gunaratne and Yonesawa, 1997; Mun et al., 2000; Nam et al., 2001; Choi and Hui, 2014; Miwa, 2019). Most of these studies have focused on stock markets around the world with data frequencies varying from daily to monthly. Very surprisingly, we have found no study investigating the overreaction behavior on commodity futures markets with high-frequency data, meaning intraday data. The present paper aims to fill this gap by analyzing the overreaction behavior for 20 commodity futures over the period from November 20, 2019 to June 3, 2020. We consider various intraday data frequencies (1 min, 5 min, 15 min, 30 min and 1 h) and pay particular attention to the impact of the Covid-19 pandemic by splitting the sample period into two sub-periods, viz. pre-Covid-19 pandemic (20/11/2019-31/01/2020) and Covid-19 pandemic (01/02/2020-03/06/2020).

Examining the impact of the Covid-19 pandemic on the commodity market deserves special attention because the lockdown policy applied by numerous countries to reduce the contagion of the corona virus in the population has changed profoundly the supply chain flow of all goods and services. This tremendous shock to the supply chain has been analyzed by recent academic studies (Belhadi et al., 2020; Nikolopoulos

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et al., 2020; Sharma et al., 2020). Since commodities of all classes (such as energy, agriculture, livestock, precious metals, and industrial) are strongly involved in the supply chain, recent academic studies have also analyzed the impact of the Covid-19 pandemic on the commodity market (Lin and Su, 2020; Adekoya and Ollyide, 2020; Salisu et al., 2020; Ji et al., 2020; Wu, 2020). Overall, these studies show that the Covid-19 pandemic has changed significantly the relationship among the commodities, as well as between commodities and other asset classes. However, to the best of knowledge, no study has investigated the price overreaction behavior of commodities during the Covid-19 pandemic though the World Bank report on the “Commodity Markets Outlook” published in October 2020 shows that there have been significant changes in the price of commodities in 2020 due to the Covid-19 pandemic. However, this change depends on the type of commodities. For example, energy prices decreased while the price of agricultural commodities, precious metals’ prices, and raw materials increased during the Covid-19 pandemic. This commodity price evolution is a direct consequence of lockdown policies which reduce the energy demand for transports while increasing the demand for food and technology related products. Furthermore, according to the statistics of the World Federation of Exchanges in the third quarter of 2020, commodity futures’ volumes have increased by 23.2% compared to the same quarter in 2019, to an amount of 2.3 billion. This volume increase stems from the Asia-Pacific (APAC) region rise while the volume has decreased in American as well as European, Middle-East and African (EMEA) regions.

The commodity price reaction to the Covid-19 pandemic indicates the importance of the commodity market for the global economy and its evolution. Furthermore, the financialization of commodities since 2004 (Adams et al., 2020) further raises the increasing importance of high-frequency trading activities in the commodity market. According to the World Federation of Exchanges (2020), the trading volume of commodity derivatives was 5.64 billion of USD in 2018. Generally, commodities play a crucial role in the real economy as they are important in both the production and the consumption process. With this high importance, commodities have been progressively financialized with trading operations on the stock exchanges and derivative markets (e.g. Kim, 2020; Hu et al., 2020; Nguyen et al., 2020). On the other hand, the Covid-19 pandemic has generated huge impacts on the real economy with a worldwide lockdown over several months. This affects both the supply and the demand of commodities, and it is important to examine how this global shock affects trading behavior on commodity markets. A clear example of overreaction behavior is the negative price of crude oil futures in April 2020 (see Bajaj, 2020, for more information). In addition, while most of the previous studies focusing on the overreaction hypothesis consider monthly (e.g. Guanatne and Yonesawa, 1997; Gaunt, 2000; Nam et al., 2001), weekly (e.g. Bowman and Iverson, 1998; Heyman et al., 2019; Ni et al., 2019), or daily data (e.g. Levy and Lieberman, 2013; Alwathnani et al., 2017; Chevapatrakul and Mascia, 2019), it seems important to consider high-frequency data (or intraday data) due to the possibility for traders, portfolio managers, as well as individual investors to make investment decisions based on high-frequency market data. To the best of our knowledge, only few previous studies have considered intraday data while investigating the overreaction hypothesis (e.g. Fung and Lam, 2004; Levy and Lieberman, 2013; Miwa, 2019; Borgards and Czudaj, 2020) and no study has considered commodity markets.

Another important contribution of our study is related to the use of a dynamic and non-parametric method to detect the overreaction behavior of intraday commodity prices. We indeed follow the method proposed by Borgards and Czudaj (2020) who define an overreaction as a large log price change between two turning points which is followed by a proportional contrary price change so that both price changes are not associated with a change of the fundamental value but with a market anomaly. In doing so, we identify turning points, which define the start and the end of an overreaction, i.e., the price levels at which investor sentiment changes (Sturm, 2016). Identifying overreaction through turning points is an important advantage while studying the overreaction hypothesis because it does not require any constraint about the duration of the overreaction which can vary and does not need to be predefined. For that, we use a moving-average smoothing filter algorithm and different sensitivity parameters to ensure the robustness of our findings. To test the overreaction hypothesis, in the second step, we use the non-parametric Mann-Whitney-U test to check whether the first price change is similarly distributed as the price reversal at different deciles, which correspond to the amplitude of price changes. If this is validated, it can be seen as evidence in favor of the overreaction hypothesis for intraday prices of the 20 considered commodity futures. Another advantage of this method is related to the possibility to quantify the number of overreactions during a given period. This point is important in our study as we aim to compare the intraday overreaction behavior of commodities before and during the Covid-19 pandemic. Finally, we further investigate whether this overreaction behavior can be exploited by investors by implementing a contrarian strategy which consists of entering a short position after a positive price overreaction and a long position after a negative price overreaction. The investor then exits the position at the subsequent price reversal.

Our empirical results show that the overreaction hypothesis is validated for all individual commodity futures among the 20 considered commodities. Furthermore, there is a higher number of overreactions during the Covid-19 pandemic and with a much higher volatility during this period. In line with this result, our findings also show a higher return of the contrarian strategy while exploiting the overreaction behavior. Interestingly, we find that softs and industrial metals have a lower number of overreactions in contrast to precious metals and energy commodities. More importantly, crude oil is found to be a different commodity class as it showed much higher negative than positive overreactions, mostly during the Covid-19 pandemic. These results are found to be robust to different sensitivity parameters. The findings of this study have important implications for investors, portfolio managers as well as policymakers regarding investment strategies and the supervision of the commodity market which can have crucial impacts on the real economy.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on the overreaction hypothesis and on commodity markets. Section 3 presents the data used in the analysis and the methodological framework. Section 4.1 discusses the empirical results on the overreaction hypothesis while Section 4.2 shows the performance of the contrarian trading strategy based on price overreactions. Finally, Section 5 concludes.

2. Review of the literature

In this literature review, we focus on two strands of the literature. The first one refers to the overreaction hypothesis and the second one to commodity markets.

2.1. Price overreaction hypothesis

The pioneer study on the price overreaction hypothesis is undoubtedly that of De Bondt and Thaler (1985), followed by De Bondt and Thaler (1987). These seminal works were inspired by psychological research of Kahneman and Tversky (1982) on biases in intuitive prediction of investors based on past and publicly availability information. Even earlier, Grether (1980) outlined the representative heuristic behavior which violates the Bayes rule. Indeed, Kahneman and Tversky (1982) demonstrate that investors do not behave rationally and tend to react more to new and recent information than to past and well-known information. This behavior is referred to as representativeness heuristic. An implication of this behavior is that investors will continue responding in the same manner to buy stocks of companies associated with good news and to sell stocks of companies associated with bad news. Such a behavior might therefore be responsible for a positive or a negative price
overreaction. However, after recognizing the overreaction, investors will behave in the opposite direction, meaning sell and buy the stocks mentioned above, respectively. This opposite behavior therefore describes the price reversal. Such extreme price movements might thus be due to irrational behavior of investors and not due to fundamental determining factors of prices. This process is referred to as price overreaction defined as an initial large price change (positive or negative) followed by a price reversal in the opposite direction. If such price overreactions exist, it is possible for market participants to forecast future prices and outperform the market. This violates the efficient market hypothesis (EMH) in the weak form, as defined by Fama (1970). This lack of informational efficiency then allows market participants to exploit this price predictability to make profitable arbitrages.

From the work of De Bondt and Thaler (1985), numerous researchers have investigated the price overreaction behavior of stock markets worldwide. Most of them follow the method used by De Bondt and Thaler (1985) by constructing two types of portfolios, loser and winner, based on past information over the last 3-5 years and by examining whether there is a price reversal during the following 3-5 years. If this turns out to be true, then this phenomenon can be explained by price overreactions, and investors can benefit from buying loser portfolios and selling winner portfolios, which is known as the contrarian strategy. Numerous studies have used the same method based on loser and winner portfolios. Gunaratne and Yonesawa (1997) find that extreme losers outperform the extreme winners by 11% per annum in terms of risk-adjusted abnormal returns during the subsequent period. Fung (1999) observes that loser portfolios on average outperform winner portfolios by 9.9% one year after the formation period. Mun et al. (2000) show that the contrarian strategy works in the Canadian US stock market but depends on the time horizon considered (short-term or long-term). Gaunt (2000) provides evidence for price reversal where monthly portfolio rebalancing is employed but the price reversal disappears when a buy-and-hold strategy is used. He also finds that the loser portfolio is dominated by small firms and that any abnormal returns are not exploitable given the lack of liquidity. Boubaker et al. (2015) present evidence for short-term overreaction in the Egyptian Stock Exchange as loser portfolios outperform winner portfolios and investors can earn abnormal returns by selling winners and buying losers. Blackburn and Cakici (2017) provide evidence supporting the global presence of the long-term price reversals. Furthermore, the positive return differential between loser stocks and winner stocks over the past three years is economically and statistically significant. Lerskullawat and Unghpakorn (2019) show that the contrarian strategy is preferred when investing in Thailand, as loser portfolios reveal a reversed performance in the following period. Furthermore, they find that larger stocks appear to overreact compared to small ones. Gang et al. (2019) observe that the contrarian (or reversal) strategy only works for long investment horizons while for short investment horizons, only momentum strategies are profitable. Momentum strategies are contrary to the reversal (or contrarian) strategies as they stipulate that investors follow persisting trends in time, meaning continuing to buy winner stocks and to sell loser stocks. Based on these results, Gang et al. (2019) conclude that the Chinese stock market generally overreact to the company cash flow news while investors in the US market underreact to cash flow news.

All the above-mentioned studies investigate stock markets and only few studies have analyzed the overreaction hypothesis in other markets. For example, Larson and Madura (2001) focus on the foreign exchange market and find that investors overreact most when the Turkish lira, the Brazilian real and the US dollar overreact, while the British pound underreacts. Dao et al. (2016) confirm that the overreaction hypothesis is validated for spot foreign exchange markets. Indeed, after a large price difference between Friday close and subsequent Monday open, most markets are likely to reverse in multiple horizons during the following week. Furthermore, the reversal strategy is profitable even when the transaction cost and interest rate are considered. Zhou (2016) investigates the price overreaction behavior in the housing market in Shanghai and finds that the market tends to overreact to policy changes. Chevapatrakul and Mascia (2019) study the Bitcoin market and find that there is a positive dependence which implies overreacting behavior in the Bitcoin market. Borgards and Czudaj (2020) examine several cryptocurrency markets and find that price overreactions are highly present in the cryptocurrency market for all frequencies, strongly supporting the overreaction hypothesis. Moreover, returns of an overreaction trading strategy are significantly higher for cryptocurrencies than for stocks.

Another observation from our literature review is that most of previous studies were based on low frequency data, meaning daily, weekly, or monthly data, and very few have considered high-frequency data, meaning intraday data. For example, Miwa (2019) study the intraday returns and overnight returns of two Japanese stock futures and find that the overreaction is stronger when the extended-hours session is longer, and the trading activity during the session is higher. Levy and Lieberman (2013) also use intraday prices to study the price formation process of country Exchange-Traded Funds (ETFs). They observe that there is price overreaction in US stock market returns when foreign markets are closed. Fung and Lam (2004) find that overreaction also exists during intraday trading and market closing.

As presented in the above literature review, the price overreaction phenomenon has been widely investigated in the academic literature. Most of the previous studies follow the method used by De Bondt and Thaler (1985) while distinguishing between loser and winner portfolios based on low-frequency data (monthly, weekly, or daily). Furthermore, most of the previous studies confirm the existence of the price overreaction phenomenon and profitability of the contrarian strategy. However, the profitability of the contrarian strategy can vary over the time horizon (short-term, medium-term, or long-term) and over the size of the firm. Our study contributes to this strand of the literature by considering high-frequency data (1 min, 5 min, 15 min, 30 min and 1 h), by relying on a dynamic and non-parametric method to estimate the price reversal phenomenon, by analyzing commodity markets, and by considering a potential effect of the Covid-19 pandemic on the overreaction behavior. To the best of our knowledge, no study has investigated the price overreaction phenomenon of commodity markets while using intraday data and a dynamic method. To our point of view, it is important to consider the commodity market because its fundamental value is totally different from stocks. In this case, the commodity’s supply and demand are the most important determining factors of its fundamental value, while for the stock market, these factors are essentially related to firm factors. More details regarding commodity markets are presented in the next subsection.

2.2. Commodity markets

Regarding commodity markets, most of the recent studies have investigated the financialization phenomenon of commodities. According to Adams et al. (2020), the financialization of commodity markets started in 2004 when inflows into the commodity market increased from $15 billion to more than $450 billion in April 2011 (Bicchetti and Maystre, 2013). According to Kim (2020), trading in commodity derivatives increased massively in the mid-2000s while Adams et al. (2020) underline that financialization indicators for commodities became stronger during the 2008–2009 global financial crisis. On the other hand, Bianchi et al. (2020) state that this financialization is cyclical as they also observe a de-financialization of metals and agricultural markets from 2014 to 2017. Furthermore, Gagnon et al. (2020) demonstrate that the most-financialization period offers new diversification opportunities for commodities in Canada. Adams et al. (2020) show that financial variables become the main driving factors of commodity returns and volatility. Agnello et al. (2020) also find that global macroeconomic conditions affect the commodity price cycle phases. Ahmed and Huo (2020) shows a dynamic relationship among

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the Chinese stock market, commodity markets, and the global crude oil price. In addition, Ali et al. (2020) show that commodities can be beneficial as a safe haven, hedge or portfolio diversifier. Given the important role of commodities in the economic system as an input, Apergis et al. (2020) show that conventional and unconventional monetary policies can affect commodity prices. More importantly, they find that fluctuations in commodity prices are key drivers of economic growth and affect numerous aspects of the economy. Chen and Mu (2020) demonstrate an asymmetric volatility in commodity markets, meaning that the volatility is higher after a positive price shock than a negative price shock.

Regarding predictability, Liu et al. (2020b) find that commodity prices possess a predictive content for exchange rates. On the other hand, Ding and Zhang (2020) indicate that commodity prices can be predicted from cross-market information. Furthermore, Pasanya and Awodimila (2020) show that commodity prices are useful in forecasting inflation. On the other hand, Karabulut et al. (2020) indicate that world trade uncertainty has a predictive power on the price of commodities. The importance of commodities is also demonstrated by Fernandez-Perez et al. (2020) as they show that commodity futures pricing plays an important role in active attention to weather, disease, geopolitical or economic threats or ‘hazard fear’. More importantly, Ge and Tang (2020) find that commodity prices can predict GDP growth rates. Huyub et al. (2020) show that there is a connectedness between commodity spot and future prices. According to Ouyang and Zhang (2020), speculation is also an important driving factor of commodity prices. Based on high-frequency data, Xu et al. (2020) show the presence of intraday return predictability for commodity ETFs. This result is also confirmed by the study of Zhang et al. (2020b) who demonstrate that intraday momentum exists in Chinese commodity futures markets.

Another finding of the existing literature is related to the importance of distinguishing between different commodity families, namely energy, agriculture, livestock, precious metals, and industrial metals (according to the Nasdaq commodity report, 2013). For example, Ali et al. (2020) find that precious and industrial metals are a better hedge and safe haven than other commodities, while considering 21 different commodities. On the other hand, Bakas and Triantafyllou (2020) show that uncertainty related to pandemics have a stronger negative impact on the volatility of crude oil prices than that of gold prices. Chen and Mu (2020) observe that only crude oil exhibits an inverse leverage effect while considering a range of commodities. Ding and Zhang (2020) find that crude oil and industrial metal markets have a long-run price equilibrium relation while it is not the case for agriculture and gold markets. Hu et al. (2020) find that crude oil and gold are more reactive to market sentiment while it is not the case for soybeans. Huang et al. (2020) show that the time-varying impact is greater in agricultural commodity prices than in metals and energy prices. Liu et al. (2020a) indicate that in the short term, metals have the strongest transmission intensity while in the medium term and the long term, the energy sector has the strongest transmission intensity. Nguyen et al. (2020) indicate that although gold futures are typically seen as a hedge against unfavorable fluctuations in the stock market, the majority of commodity futures appear to be treated as a separate asset class in line with their increasing financialization. In addition, Yang et al. (2020) show that the energy futures market plays a leading role in the integration between commodity and stock markets. This heterogeneity among different types of commodities motivates us to consider 20 different commodity futures to be able to examine whether the price overreaction behavior differs among different commodity categories.

Moreover, a high number of previous studies investigate the interaction between commodities and other asset classes. For example, Bouri et al. (2017) study the volatility connectedness between commodities and CDS (credit defaults swaps) and show that commodities can transmit volatility to CDS. However, the strength of this volatility transmission depends on the commodity category, as it is stronger from energy commodities and precious metals. Ji et al. (2018a) examine the relationship between commodities and equities in BRICS countries and in the U.S. The authors find that the network structure among these assets is unstable over time and events can have impacts on the network locally or globally. Regarding energy and agricultural commodities, Ji et al. (2018b) show that there is an asymmetric effect in the volatility spillover between them. Furthermore, there is a significant risk spillover from energy to agricultural commodities. In addition, Rehman et al. (2019) distinguish between energy and non-energy commodities and show that crude oil is a specific commodity which offers higher diversification benefits than other commodities. To explain the dynamics of commodity prices, some authors show that the herding behavior may have a significant impact. For example, Fan and Todorova (2020) find that positive feedback trading, noise trading, and herd mentality are present in 24 Chinese commodities while Kumar et al. (2020) demonstrate that the herding behavior differs across markets and that herding is asymmetric. To summarize, previous studies focusing on commodities show that they have a significant interaction with other asset classes and at some conditions, they can be a hedge and safe haven for other asset classes. It is also important to consider the difference of each commodity category (energy, non-energy, agriculture, precious metals, industrial metals). Furthermore, herding behavior of investors may impact the price of commodities. These previous findings motivate us to consider a large sample of 20 commodities while studying their futures price overreaction behavior.

As we have seen in the literature review, commodity futures play an important role in the financial and economic system. Various behaviors of its prices have been investigated, such as predictability, hedge, safe haven, cycles, etc. However, we have found no study examining the overreaction of commodity futures prices based on intraday data and especially considering the effect of the Covid-19 pandemic. The latter aspect is important as Ge and Tang (2020) show that uncertainty shocks have significant impacts on commodity prices. At the time of this study, some academic studies have been published regarding the impact of the Covid-19 pandemic on the commodity market. However, none of them has analyzed their price overreaction behavior. For example, Kamdem et al. (2020) find that the number of confirmed cases and deaths due to the corona virus has an impact on the volatility of commodity prices. Salisu et al. (2020) construct a global fear index for the Covid-19 pandemic and show that it has predictive power for commodity prices as commodity returns are positively associated with Covid-19 related fear increases. In addition, Maghreyeh and Abdoh (2020) find that investor sentiment has an impact on commodity prices. Furthermore, Adekoya and Oliyide (2020) show a Granger causality from the Covid-19 pandemic (measured by the growth rate of the number of cases and infectious diseases-based equity market volatility) to the volatility connectedness between commodities and financial markets. In the same vein, Ji et al. (2020) indicate that gold and soybean commodity futures are robust safe havens during the Covid-19 pandemic. Moreover, Lin and Su (2020) find that the dependence among energy commodities increases strongly at the outbreak of the Covid-19 pandemic and turns back to the initial level after two months. This research thus shows a potential reversal behavior in the commodity market. In addition, Shruthi and Ramani (2020) find that the risk transmission differs across commodity classes as it is almost zero for agricultural commodities while it is not the case for crude oil. The specific role of oil is also demonstrated by Wu (2020) as it can serve as a hedge for companies in the Chinese commodity sector. Moreover, a number of previous studies indicate that volatility connectedness is broadened in the Covid-19 pandemic. However, none of the recent studies on this topic has investigated the price overreaction behavior of commodities during the Covid-19 pandemic. Therefore, our study extends the existing knowledge regarding commodity futures prices during the Covid-19 pandemic and can help investors and policymakers to better evaluate the investment risks and opportunities of commodities.
3. Data and empirical approach

3.1. Data

The data sample used in this paper is composed of twenty commodity futures. We use the mid price data of the future contracts with the shortest maturity (front contracts), as it has been usually considered in previous studies (e.g., Zhang et al., 2020a). The commodity futures include WTI crude oil (CL), Brent crude oil (CO), heating oil (HO), natural gas (NG), gold (GC), silver (SI), platinum (PL), palladium (PA), copper (HG), aluminium (AA), zinc (LX), nickel (LN), wheat (W), corn (C), soybeans (S), soybean oil (BO), cocoa (CC), coffee (KC), sugar (SB) and cotton (CT). The price data is based on a 1 min (1min) frequency and has been upsamplified to the frequencies of 5 min (5min), 15 min (15min), 30 min (30min) and 1 h (1 h). Data gaps of the underlying bid and ask price time series have been filled with the last available price. Collected from the Bloomberg terminal, the futures data was sourced from the Chicago Mercantile Exchange (CME, https://www.cmegroup.com/) and the Intercontinental Exchange (ICE, https://www.theice.com/). In addition, we calculated five commodity future indices based on the equal-weighted mid price data of four commodity futures respectively, which are energy (CL, CO, HO, NG), precious metals (GC, SI, PL, PA), industrial metals (HG, AA, LX, LN), agricultural (W, C, S, BO) and softs (CC, KC, CT, SB). The period under study runs from 20/11/2019 to 03/06/2020. In order to investigate the impact of the Covid-19 pandemic on commodity markets, we have also separated the full sample period into two sub-periods from 20/11/2019 to 31/01/2020 (pre-Covid-19 period) and from 01/02/2020 to 03/06/2020 (Covid-19 period). Table 1 provides descriptive statistics of the respective mid price log changes for the 1 h frequency. It shows that the majority of the commodities have negative mean returns and that the returns are clearly non-Gaussian due to positive skewness and excess kurtosis observed for most of the commodities.

3.2. Empirical approach

We characterize an overreaction as a large log price change between two turning points. A turning point is particularly suitable to describe the start and the end of an overreaction as it indicates the price level at which the sentiment of the investors changes (Sturm, 2016). This enables us to analyze overreaction behavior with varying durations. To identify turning points we follow Borgards and Czudaj (2020), who proposed a moving-average smoothing filter algorithm depending on a sensitivity parameter \( \kappa \). The latter varies the number of identified turning points. By lowering the sensitivity parameter, more turning points are identified and larger overreactions are ignored. To check for robustness, we calculate turning points with three sensitivity parameters (5, 10, and 20) for each of the four data frequencies. Having determined the turning points, the price change of all pairs of turning points is given by

\[
\Delta p_{i,j} = \log(p_{i,j}^{\text{peak (tough)}}) - \log(p_{i,j}^{\text{tough (peak)}}),
\]

where \( l \) denotes the length of the period from trough (peak) to peak (tough). Therefore, a positive (negative) price change is characterized by the log change of the price from trough (peak) to peak (tough). See Borgards and Czudaj (2020) for details.

As already outlined above, an overreaction is a large price change which is followed by a proportional contrary price change such that both price changes together do not represent a shift of the equilibrium price. We therefore examine both an initial price change and its successive price change, which we define as a potential overreaction and its reversal. As both contradictory price changes can be visualized as a pair of legs, we denote the potential overreaction as the first leg (L1) and the associated reversal as the second leg (L2). From each series of positive and negative price log changes, we extract all L1-L2 pairs and separate the positive and negative initial price changes in order to check whether positive and negative overreactions differ. Afterwards, we sort all positive and negative L1 from largest to smallest and group them into deciles where D1 is the first decile and D10 is the last decile. Then, we compute for every decile the mean L1 and L2 price change which means that D1 (D10) has the largest (smallest) mean for L1. In this way, our dynamic modeling approach enables us to detect overreactions in the lower deciles without the previous definition of external parameters. Equivalent to the proportionality of L1 and L2, we assume that the largest means of the reversals L2 are also in the lowest deciles. Therefore, we compare the L2 distribution in each decile \( l \) with the L2 distribution of all subsequent, higher deciles \( (i + 1 \text{ to } 10) \). For example, a rejection of the null hypothesis (i.e. the D1 reversals come from the same distribution as the D2 to D10 reversals) would mean that the reversal distribution after the largest initial price changes is different from the reversal distribution after lower initial price changes. Consequently, different L2 distributions of both decile groups demonstrate the proportionality of L1 and L2 and indicate overreacting behavior in decile D1. In line with the overreaction hypothesis, we expect to significantly reject the null hypothesis for the lower deciles as they contain the largest initial price changes.

In order to test the null hypothesis described above, we use the non-parametric Mann-Whitney-U test for multiple groups and compute the \( p \)-value as the level of statistical significance which is based on the Gaussian approximation of the distribution of the \( U \)-statistic.

Finally, to show that our empirical findings are exploitable for investors, we design a trading strategy which is described in detail in Borgards and Czudaj (2020). We use a time lag parameter to model the lagged entry and exit of a position after a peak or trough as an investor is not able to perfectly predict its price levels. Therefore, we conservatively assume that an investor who intends to trade the price reversal L2 after a large positive (negative) initial price change L1 is capable of trading at least 20% (i.e. lag parameter of 1/5) of the tradable range of the reversal from the peak (tough) to the trough (peak) turning point. We compute the mean trading return of a position as the lag parameter percentage of the mean price reversal L2. For reasons of simplicity, we abstract from trading fees or slippage as the difference of the expected price of a trade and the price at which the trade is executed. The findings are presented and discussed in the following section.

4. Empirical findings

4.1. Price overreactions in commodity futures markets

Figs. 1 and 2 present the evolution of the subsequent price changes L2 of the first five deciles for all commodities and commodity indices after positive (Fig. 1) and negative (Fig. 2) initial price changes L1 for the period prior to the Covid-19 pandemic. As the mean L1 price changes are sorted across the deciles, we expect that the mean L2 price changes have an equivalent ranking order. This proportionality of L1 and L2 would mean that the largest price changes are followed by the largest price reversals which is the definition of an overreaction. We compare these pre-pandemic results with Figs. 3 and 4 which represent the core period of the Covid-19 pandemic so that we can draw conclusions whether the pandemic has affected the overreacting behavior of the market participants.

First, we analyze the absolute gradient of the L2 curves which measures whether a L2 curve continuously increases (decreases) after positive (negative) initial price changes with higher deciles. In case of a

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1 A D’Agostino-Pearson omnibus test for normality confirmed that the L2 price changes are not normally distributed across all deciles, which requires the use of a non-parametric test. The corresponding findings are available upon request.
lower deciles but weak overreacting behavior in the upper deciles. The commodities without a boundary in the first five deciles gradually improves boundary in the pre-pandemic period after positive (negative) negative initial price changes in all periods. For the 1-h curves in Figs. 1 and 2, commodities have no boundary in the first five deciles for positive and 5 min curve after positive initial price changes in advance of the Covid-19 pandemic. This boundary implies that we observe overreacting behavior in the rates the deciles with or without ascertainable overreacting behavior. does not hold; we define the decile number as a boundary which separates the structural break between two deciles where the L1-L2 proportionality does not hold; we define the decile number as a boundary which separates the deciles with or without ascertainable overreacting behavior. This boundary implies that we observe overreacting behavior in the lower deciles but weak overreacting behavior in the upper deciles. The higher the decile of the boundary, the more prevalent are overreactions or under reactions in the market. For example, the boundary of the cocoa 5 min curve after positive initial price changes in advance of the Covid-19 pandemic lies between its second and third decile which means that 10% of the initial price changes are reverted with an analogous magnitude, con...
Note: The charts show the development of the mean $L_2$ price log return for each frequency over the first five deciles after positive overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 5$.

Fig. 1. Mean $L_2$ price log returns after positive overreactions for the period in advance of the Covid-19 pandemic.

Note: The charts show the development of the mean $L_2$ price log return for each frequency over the first five deciles after positive overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 5$. 
Fig. 2. Mean $L^2$ price log returns after negative overreactions for the period in advance of the Covid-19 pandemic. Note: The charts show the development of the mean $L^2$ price log return for each frequency over the first five deciles after negative overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 5$. 
Fig. 3. Mean $L^2$ price log returns after positive overreactions for the Covid-19 period.

Note: The charts show the development of the mean $L^2$ price log return for each frequency over the first five deciles after positive overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 5$.
Fig. 4. Mean $L_2$ price log returns after negative overreactions for the Covid-19 period.

**Note:** The charts show the development of the mean $L_2$ price log return for each frequency over the first five deciles after negative overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $κ = 5$. 

**Note:** The charts show the development of the mean $L_2$ price log return for each frequency over the first five deciles after negative overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $κ = 5$. 

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Note: The charts show the development of the mean $L_2$ price log return for each frequency over the first five deciles after negative overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $κ = 5$.
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Third, in order to inspect the proportionality of \( L1 \) and \( L2 \) more in detail, we compare the \( L2 \) distribution in each single decile with the \( L2 \) distribution of all subsequent deciles by using the Mann-Whitney-U test described in Section 3.2. Figs. 5 and 6 present the p-values of the Mann-Whitney-U tests for negative \( L2 \) (Fig. 5) and positive \( L2 \) (Fig. 6) in advance of the Covid-19 pandemic while Figs. 7 and 8 illustrate the p-values for negative \( L2 \) (Fig. 7) and positive \( L2 \) (Fig. 8) during the pandemic. A low p-value means that the price reversals in the decile significantly differ from the price reversals in the subsequent deciles. In combination with the previously shown \( L1-L2 \) proportionality, the different \( L2 \) distributions indicate overreacting behavior for the respective decile. As the p-values of all commodities and commodity indices are presented in heatmaps per decile and frequency, we are again able to identify a boundary which separates deciles with prevalent overreacting behavior from the ones without.

Confirming the results of our previous \( L2 \) analysis, we find that the higher the frequency, the lower are the p-values and the more statistically significant are the results. For the lowest frequency of 1 h, 35% (45%) of the first decile \( L2 \) commodities are statistically significant at the 1% level after positive (negative) initial price changes in advance of the Covid-19 pandemic, which improves to 90% (85%) for the 15-min and 100% (100%) for the 1-min frequencies (see Figs. 5 and 6). This again supports our finding that a higher number of observations in the deciles is accompanied with a higher statistical significance. This finding lets us conclude that the frequency is independent of the overreacting behavior. Moreover, the percentage of the commodities that are statistically significant at the 1% level decreases with the number of considered deciles. This result clearly shows that overreactions are exceptional events that do not happen during normal market fluctuations. Defining the 5% statistical significance level as our boundary which separates deciles with prevalent overreaction behavior from the ones without, we find that 75% (65%) of the commodities have their boundary after the first decile for the 1-h frequency before the Covid-19 pandemic for positive (negative) \( L1 \), which further improves to 90% (95%) for the 15-min and 100% (100%) for the 1-min frequencies (see Figs. 5 and 6). These large percentages of commodities that have no boundaries before their 10% largest initial price changes support the overreaction hypothesis before the pandemic. During the Covid-19 pandemic, the boundary even shifts to higher-numbered deciles. Over the price directions and frequencies, the lowest percentage of commodities that have a boundary before the first decile is 90%. Even when considering the first three deciles, more than 60% of the commodities have boundaries in higher-numbered deciles which impressively shows that the pandemic has a tangible impact on the overreacting behavior of the market participants.

Fourth, we compare the overreacting behavior regarding the direction of the initial price changes. Our results, both before and after the Covid-19 pandemic, show that overreactions are similarly prevalent, independent of the initial price change across all frequencies. During the pandemic, the volatility considerably increases throughout nearly all commodity prices. However, their price reversals remain constant regarding the proportionality for both directions. We merely find that the convexity of the lower-frequency \( L2 \) curves increases during the Covid-19 pandemic after negative initial price changes which can be explained by the higher negative price pressure of energy commodities.

Finally, we compare the results of the commodity indices with each other. For the 5% significance level, metals, energy and agricultural commodities have the most p-value boundaries within the first three deciles before the Covid-19 pandemic (see Figs. 5 and 6). For metals, we are mostly unable to find overreacting behavior in the lower frequencies after positive initial price changes before the pandemic which can be attributed to zinc and nickel. For the energy and soft indices, we count the lowest number of p-value boundaries whereas their boundaries are almost always after the first deciles. For frequencies lower than 30 min, only metals have a p-value boundary for positive initial price changes which shows the prevalence of overreactions for most of the commodities. In sum, our pre-pandemic results provide evidence that price overreactions are particularly prevalent for precious metals while showing mixed results for the other commodities. Since in particular precious metal markets respond significantly to external price shocks (Batten et al., 2017), we assume that their higher volatility leads to overreacting behavior also under supposedly normal market conditions. During the Covid-19 pandemic, the p-value results improve for nearly all indices in all price directions and frequencies (see Figs. 7 and 8). Precious metals, energy and agricultural commodities do not have a p-value boundary in the first three deciles at all, while metals and soft commodities have a boundary only in the 1-h frequency. We attribute these results to the considerably increased volatility during the pandemic which was pronounced for crude oil, silver, and platinum.

They confirm our findings described above that the Covid-19 pandemic impacted the overreacting behavior in the way that even high initial price changes are followed by equivalent large price reversals.

Overall, our results show that the price overreaction behavior exists in the commodity market. However, the level of the price overreaction depends on the type of commodities, confirming previous studies about the importance to distinguish among different commodity classes (e.g. Gagnon et al., 2020; Huynh et al., 2020; Maghyereh and Abdoh, 2020). Concretely, our results show that metals, energy and agricultural commodities have the highest level of price overreactions. However, the level of price overreactions is much lower for zinc and nickel. These results imply that price overreactions exist in the commodity market. However, the frequency and magnitude of the price overreaction can change depending on the type of commodity and the investment frequency. Referring to the latter aspect, our results indeed show that for metals and soft commodities the price overreaction is significant only for the 1-h frequency. This finding implies that high-frequency investors and portfolio managers should pay attention on the difference among the data frequencies considered regarding the price overreaction behavior of commodities.

Another important finding is related to the increase of the magnitude and frequency of price overreactions of commodities during the first wave of the Covid-19 pandemic in early 2020. During this period, precious metals, energy, and agricultural commodities seem to experience the most price overreactions. These results confirm recent studies on the impact of the Covid-19 pandemic on the commodity market. For example, Salisu et al. (2020) find that the fear sentiment raised by the Covid-19 pandemic is positively correlated with the price of commodities. In addition, Adekoya and Olyide (2020) show that the volatility of commodity returns increases strongly during the first wave of the Covid-19 pandemic in early 2020. The Commodity Markets Outlook published by the World Bank in October 2020 shows that this increasing volatility of commodities’ returns are due to profound changes in the supply and demand of each type of commodity. For example, the energy demand decreased tremendously during the lockdown period in spring 2020 while the demand for agricultural commodities increased strongly during the same period. Therefore, the price of energy decreased strongly while the price for agricultural commodities gained 6 percent in Q3/2020, compared to Q3/2019. Thus, the Covid-19 pandemic
Fig. 5. P-values of the Mann-Whitney-U test for positive overreactions for the period in advance of the Covid-19 pandemic.

**Note:** The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 5$. 

Fig. 5. P-values of the Mann-Whitney-U test for positive overreactions for the period in advance of the Covid-19 pandemic.

**Note:** The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 5$. 

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Fig. 6. P-values of the Mann-Whitney-U test for negative overreactions for the period in advance of the Covid-19 pandemic.

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for negative overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 5$.

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### Table: P-values of the Mann-Whitney-U test for negative overreactions for the period in advance of the Covid-19 pandemic

| Commodity | WTI Crude oil | Brent oil | Heating oil | Natural gas | Energy |
|-----------|--------------|-----------|-------------|------------|--------|
| 1st decile | 0.01 0.00 0.00 0.00 0.00 | 0.05 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 |
| 2nd decile | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 |
| 3rd decile | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 |
| 4th decile | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 |
| 5th decile | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 | 0.00 0.00 0.00 0.00 0.00 |
| All frequencies | 0.13 0.00 0.00 0.00 0.00 | 0.04 0.01 0.00 0.00 0.00 | 0.05 0.01 0.00 0.00 0.00 | 0.20 0.15 0.00 0.00 0.00 | 0.05 0.03 0.00 0.00 0.00 |

**Note:** The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for negative overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 5$. 
Fig. 7. P-values of the Mann-Whitney-U test for positive overreactions for the Covid-19 period. 

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 5$. 

\[ \begin{array}{cccccccc}
\text{Commodity} & \text{WTI-Crude oil} & \text{Brent oil} & \text{Heating oil} & \text{Natural gas} & \text{Others} \\
\hline
\text{Crude oil} & -0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\text{Brent oil} & 0.00 & -0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\text{Heating oil} & 0.00 & 0.00 & -0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\text{Natural gas} & 0.00 & 0.00 & 0.00 & -0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\
\text{Others} & 0.00 & 0.00 & 0.00 & 0.00 & -0.00 & 0.00 & 0.00 & 0.00 \\
\end{array} \] 

\[ \begin{array}{cccccccc}
\text{Note:} & \text{The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter } \kappa = 5. \] 

**Fig. 7. P-values of the Mann-Whitney-U test for positive overreactions for the Covid-19 period.**

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 5$. 

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Fig. 8. P-values of the Mann-Whitney-U test for negative overreactions for the Covid-19 period. 

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for negative overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 5$. 

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increases the volatility of commodities in different manners, depending on their supply and demand changes during the pandemic.

Our findings further show that the efficient market hypothesis (EMH) is not validated for the commodity futures market over the 2019–2020 period. Indeed, the EMH stipulates that in an efficient market, it is not possible to predict future prices because all existing and anticipated information are already included in the present price. However, our results validate the price overreaction behavior of commodities which means that it is possible to predict future prices due to the reversal mechanism, as explained in Section 2. This finding is in contrast with the EMH but confirms previous studies. For example, Hoang et al. (2020) show that the Chinese gold market is not efficient due to seasonal behavior in its prices. Pradhan et al. (2020) find a lead-lag relation in commodity prices in India. Mohanty and Mishra (2020) show that regulatory reforms do not allow to improve the efficiency of the commodity market in India, which is in line with the results by Gallais-Hammonno et al. (2019) regarding the gold market in France. To further confirm the inefficiency of the commodity market, Ding and Zhang (2020) find evidence that commodity prices can be predicted based on cross-market information.

If such price overreactions exist, it is possible for market participants to forecast future prices and outperform the market. This violates the efficient market hypothesis (EMH) in the weak form, as defined by Fama (1970). This lack of informational efficiency then allows market participants to exploit this price predictability to make profitable arbitrages, which is studied in the next subsection.

In order to confirm the robustness of our findings, we have also computed turning points with alternative sensitivity parameters k and have calculated the corresponding L2 curves and p-value heatmaps which are provided in Appendix A.1. When increasing the sensitivity parameter, the smoothing filter algorithm selects more relevant turning points and disregards smaller turning points which also decreases the number of observations. All findings discussed above that overreactions are generally prevalent in the commodity markets and that the Covid-19 pandemic has a measurable influence on the overreacting behavior are clearly confirmed in additional calculations.

4.2. Commodity futures trading exercise

As illustrated in Borgards and Crzudaj (2020), the profitability of our trading strategy depends on three factors, (1) the proportionality of the price changes, in particular for the lowest deciles, (2) the magnitude of the price changes between the turning points and (3) the timely identification of the turning points. We modeled the timely turning point identification with a conservative time lag parameter of 1/5. As the proportionality of the price changes is one of our key findings described above and the price change magnitude is a function of the commodity’s volatility, we expect higher trading returns during the Covid-19 pandemic where both factors are more pronounced than before. Tables 2 and 3 present the results of our trading strategy for the 1-h frequency prior to the Covid-19 pandemic while Tables 4 and 5 show them during the pandemic. Each figure shows the mean trading return of a short (long) commodity position after positive (negative) initial price changes that are higher (lower) than the respective decile. The probably most spectacular case of a commodity overreaction during the pandemic occurred for crude oil when its front contracts future price temporarily became negative. An investor who would have traded all crude oil long positions after the 10% highest negative price changes, would have also traded this price reversal and consequently would have realized a 4.0% (5.0%) compounded return over the pandemic period against the rising volatility.

Our findings offer possibilities for investors and portfolio managers to exploit price overreaction behavior of commodities to improve their profitability. This also implies that they should control for the existence of price overreaction regularly while considering different investment frequencies. If such price overreaction behavior is detected, then investors and portfolio managers should deploy corresponding investment strategies to exploit such price changes. For example, if they detect a negative price overreaction, then investors and portfolio managers should take a long position and close the position at the price reversal.

On the other hand, if investors and portfolio managers detect a positive price overreaction, then they should take a short position and close it at the price reversal. However, to be able to apply such strategies, investors and portfolio managers need to monitor the price dynamics of commodities efficiently to be able to detect price overreaction behaviors and adopt appropriate investment strategies, which can be done following the approach outlined in Section 3.2. This recommendation is in line with previous studies about investment strategies with commodities. For example, Sakkas and Thessaromatis (2020) find that a variance timing strategy applied to commodities helps to generate timing gains only for the momentum factor. In addition, Cassassus et al. (2018) find that the optimal investment in new oil reserves is periodic and lumpy. Interestingly, Yang et al. (2018) indicate that momentum and reversal strategies are profitable for commodities.

5. Conclusion

The present paper studies the overreaction behavior of 20 commodity futures based on intraday data with a focus on the impact of the Covid-19 pandemic. In doing so, we rely on a dynamic and non-

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2 See https://www.interactivebrokers.com for a detailed overview of futures trading fees.
parametric approach and use four different data frequencies (from 1 min to 1 h) for two different sub-periods (pre-Covid-19 pandemic and during Covid-19 pandemic). Our main findings are as follows. First, we show that the overreaction hypothesis is confirmed for the considered commodities. Second, both the number and the amplitude of overreactions is higher during the Covid-19 pandemic. Third, we also observe that soft and metal commodities have much less overreactions than precious metals and energy commodities. Fourth, crude oil can be considered as a special case as it shows a different overreaction behavior compared to other commodities since it has a higher number of negative overreactions than positive overreactions during the Covid-19 pandemic. Fifth, we also find that the data frequency is independent of the overreacting behavior in both periods as the results continuously improve when having more observations due to higher frequencies. Finally, we find that extreme overreactions during the Covid-19 pandemic can be exploited by traders.

The findings of this paper have implications for investors, portfolio managers, and policymakers. For investors and portfolio managers, the presence of price overreactions implies that the commodity market is not efficient, and it is thus possible to exploit price overreactions to design appropriate investment strategies and to improve the investment performance. In addition, the presence of price overreaction behavior in the commodity market also implies that investors and portfolio managers need to monitor its price dynamics regularly, and at high frequency, to be able to adapt the investment strategies accordingly. Thus, an efficient mechanism should be put in place by investors and portfolio managers regarding commodities. Another result that can be insightful to investors is related to specific behavior of crude oil futures which have

Table 2
Mean trading return of a short position after positive price overreactions (L1) for the period in advance of the Covid-19 pandemic.

| Decile | CL  | CO  | HO  | NG  | GC  | SI  | PL  | PA  | HG  | AA  |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1      | 0.51| 0.44| 0.47| 0.53| 0.15| 0.15| 0.26| 0.38| 0.30| 0.18|
| 2      | 0.25| 0.20| 0.27| 0.43| 0.12| 0.23| 0.28| 0.29| 0.29| 0.19|
| 3      | 0.19| 0.17| 0.19| 0.44| 0.12| 0.20| 0.20| 0.55| 0.52| 0.08|
| 4      | 0.22| 0.21| 0.17| 0.45| 0.15| 0.28| 0.27| 0.33| 0.18| 0.09|
| 5      | 0.21| 0.26| 0.19| 0.43| 0.10| 0.23| 0.29| 0.39| 0.14| 0.25|

| Decile | LX  | LN  | W   | C   | S   | BO  | CC  | KC  | SB  | CT  |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1      | 0.28| 3.61| 0.58| 0.29| 0.16| 0.91| 0.33| 1.01| 0.43| 0.19|
| 2      | 0.24| 2.59| 0.49| 0.27| 0.12| 0.57| 0.49| 0.57| 0.31| 0.22|
| 3      | 0.14| 0.34| 0.28| 0.11| 0.17| 0.21| 0.49| 0.42| 0.26| 0.20|
| 4      | 0.45| 0.45| 0.29| 0.16| 0.11| 0.22| 0.39| 0.67| 0.28| 0.19|
| 5      | 0.15| 0.27| 0.25| 0.16| 0.10| 0.43| 0.62| 0.70| 0.25| 0.28|

Note: The table reports the mean trading return as the mean price log change of a short position after a positive price overreaction grouped into the first five deciles for a sensitivity parameter of 5, a lag parameter of 1/5 and a frequency of 1 h for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets.

Table 3
Mean trading return of a long position after negative price overreactions (L1) for the period in advance of the Covid-19 pandemic.

| Decile | CL  | CO  | HO  | NG  | GC  | SI  | PL  | PA  | HG  | AA  |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1      | 0.31| 0.29| 0.54| 0.48| 0.19| 0.42| 0.47| 0.19| 0.19| 0.26|
| 2      | 0.33| 0.33| 0.24| 0.36| 0.12| 0.17| 0.37| 0.70| 0.17| 0.14|
| 3      | 0.34| 0.30| 0.26| 0.33| 0.13| 0.20| 0.27| 0.34| 0.22| 0.16|
| 4      | 0.25| 0.22| 0.27| 0.52| 0.10| 0.19| 0.22| 0.37| 0.09| 0.14|
| 5      | 0.26| 0.29| 0.27| 0.34| 0.19| 0.22| 0.23| 0.30| 0.20| 0.15|

| Decile | LX  | LN  | W   | C   | S   | BO  | CC  | KC  | SB  | CT  |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1      | 0.34| 1.15| 0.62| 0.32| 0.14| 1.10| 0.21| 0.58| 0.32| 0.23|
| 2      | 0.24| 0.53| 0.33| 0.16| 0.14| 0.52| 0.58| 0.43| 0.50| 0.23|
| 3      | 0.26| 0.63| 0.24| 0.18| 0.11| 0.21| 0.53| 0.66| 0.47| 0.30|
| 4      | 0.19| 0.52| 0.27| 0.12| 0.13| 0.35| 0.42| 0.86| 0.51| 0.25|
| 5      | 0.23| 1.37| 0.23| 0.12| 0.14| 0.21| 0.76| 0.55| 0.22| 0.20|

Note: The table reports the mean trading return as the mean price log change of a long position after a negative price overreaction grouped into the first five deciles for a sensitivity parameter of 5, a lag parameter of 1/5 and a frequency of 1 h for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets.
a higher number of negative price overreactions than the number of positive price overreactions during the first wave of the Covid-19 pandemic. This finding might help investors and portfolio managers to better anticipate the behavior of crude oil prices in potential future lockdown or crisis periods. For policymakers, this result suggests that governments should anticipate such shocks related to oil demand in the future while taking into account social and environmental risks (see for example the guide for climate-related and environmental risks published by the European Central Bank in May 2020). The results of this study on the difference of commodity classes (energy, metals, agriculture, livestock) in price overreaction also suggest that policymakers should anticipate environmental and climate risks to efficiently monitor the supply and demand of commodities, particularly agricultural and livestock commodities which are primary needs of the population. A promising avenue for future research is to study if overreactions in commodity futures markets can be explained by herding behavior.

**Author statement**

Oliver Borgards: Formal analysis; Methodology; Software; Visualization; Writing - review & editing. Robert L. Czudaj: Conceptualization; Formal analysis; Methodology; Software; Visualization; Validation; Writing - review & editing. T.H.V. Hoang: Conceptualization; Data curation; Resources; Writing - review & editing.

**Appendix**
Fig. A.1. Mean $L^2$ price log returns after positive overreactions for the period in advance of the Covid-19 pandemic.

Note: The charts show the development of the mean $L^2$ price log return for each frequency over the first five deciles after positive overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$.

Fig. A.1. Mean $L^2$ price log returns after positive overreactions for the period in advance of the Covid-19 pandemic.

Note: The charts show the development of the mean $L^2$ price log return for each frequency over the first five deciles after positive overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $x 10$. 
Fig. A.2. Mean $L^2$ price log returns after negative overreactions for the period in advance of the Covid-19 pandemic.

Note: The charts show the development of the mean $L^2$ price log return for each frequency over the first five deciles after negative overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$. 

Fig. A.2. Mean $L^2$ price log returns after negative overreactions for the period in advance of the Covid-19 pandemic.

Note: The charts show the development of the mean $L^2$ price log return for each frequency over the first five deciles after negative overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$. 

Fig. A.3. Mean $L_2$ price log returns after positive overreactions for the Covid-19 period.

Note: The charts show the development of the mean $L_2$ price log return for each frequency over the first five deciles after positive overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$. 

Note: The charts show the development of the mean $L_2$ price log return for each frequency over the first five deciles after positive overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$. 


Fig. A.4. Mean $L_2$ price log returns after negative overreactions for the Covid-19 period.

Note: The charts show the development of the mean $L_2$ price log return for each frequency over the first five deciles after negative overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$.

Fig. A.4. Mean $L_2$ price log returns after negative overreactions for the Covid-19 period.

Note: The charts show the development of the mean $L_2$ price log return for each frequency over the first five deciles after negative overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$. 
Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$.

**Fig. A.5. P-values of the Mann-Whitney-U test for positive overreactions for the period in advance of the Covid-19 pandemic.**

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$. 
Fig. A.6. P-values of the Mann-Whitney-U test for negative overreactions for the period in advance of the Covid-19 pandemic.

|                | WTI Crude oil | Brent oil | Heating oil | Natural gas | Energy |
|----------------|---------------|-----------|-------------|-------------|--------|
| 0.00           | 0.00          | 0.00      | 0.01        | 0.18        | 0.00   |
| 0.17           | 0.05          | 0.00      | 0.00        | 0.00        | 0.14   |
| 0.05           | 0.00          | 0.00      | 0.00        | 0.00        | 0.00   |
| 0.06           | 0.11          | 0.10      | 0.10        | 0.00        | 0.00   |
| 0.15           | 0.14          | 0.25      | 0.25        | 0.00        | 0.00   |

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for negative overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$.

See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$.
Fig. A.7. P-values of the Mann-Whitney-U test for positive overreactions for the Covid-19 period.

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$.

Fig. A.7. P-values of the Mann-Whitney-U test for positive overreactions for the Covid-19 period.

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$.
Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for negative overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$.

**Fig. A.8. P-values of the Mann-Whitney-U test for negative overreactions for the Covid-19 period.**

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for negative overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 10$. 

| Commodity          | P-value | P-value | P-value | P-value | P-value |
|--------------------|---------|---------|---------|---------|---------|
| WTI Crude Oil      |         |         |         |         |         |
| Brent Crude Oil    |         |         |         |         |         |
| Heating oil        |         |         |         |         |         |
| Natural gas        |         |         |         |         |         |
| Energy             |         |         |         |         |         |

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Note: The charts show the development of the mean $L^2$ price log return for each frequency over the first five deciles after positive overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$.

Fig. A.9. Mean $L^2$ price log returns after positive overreactions for the period in advance of the Covid-19 pandemic.

Note: The charts show the development of the mean $L^2$ price log return for each frequency over the first five deciles after positive overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$. 
Fig. A.10. Mean $L_2$ price log returns after negative overreactions for the period in advance of the Covid-19 pandemic.

Note: The charts show the development of the mean $L_2$ price log return for each frequency over the first five deciles after negative overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$. 
Note: The charts show the development of the mean $L^2$ price log return for each frequency over the first five deciles after positive overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$.

**Fig. A.11. Mean $L^2$ price log returns after positive overreactions for the Covid-19 period.**

Note: The charts show the development of the mean $L^2$ price log return for each frequency over the first five deciles after positive overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$. 
Fig. A.12. Mean $L_2$ price log returns after negative overreactions for the Covid-19 period.

Note: The charts show the development of the mean $L_2$ price log return for each frequency over the first five deciles after negative overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$.

Fig. A.12. Mean $L_2$ price log returns after negative overreactions for the Covid-19 period.

Note: The charts show the development of the mean $L_2$ price log return for each frequency over the first five deciles after negative overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$. 
Fig. A.13. P-values of the Mann-Whitney-U test for positive overreactions for the period in advance of the Covid-19 pandemic.

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$.

Fig. A.13. P-values of the Mann-Whitney-U test for positive overreactions for the period in advance of the Covid-19 pandemic.

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$. 
Fig. A.14. P-values of the Mann-Whitney-U test for negative overreactions for the period in advance of the Covid-19 pandemic.

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for negative overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$.

Table: P-values of the Mann-Whitney-U test for negative overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020.

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for negative overreactions per commodity or commodity index for the period in advance of the Covid-19 pandemic from November 20, 2019 to January 31, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$. 
Fig. A.15. P-values of the Mann-Whitney-U test for positive overreactions for the Covid-19 period.

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$.

Fig. A.15. P-values of the Mann-Whitney-U test for positive overreactions for the Covid-19 period.

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for positive overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$. 
Fig. A.16. P-values of the Mann-Whitney-U test for negative overreactions for the Covid-19 period.

Note: The figure shows heatmaps providing the p-values of the Mann-Whitney-U test for the first five deciles and all frequencies for negative overreactions per commodity or commodity index for the Covid-19 period from February 1, 2020 to June 3, 2020. See Section 3.1 for the abbreviations of the commodity markets. Turning points are calculated with a sensitivity parameter $\kappa = 20$.
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