Hedging commodities in times of distress: The case of COVID-19

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Abstract
This study examines the relation between the COVID-19 pandemic and hedge efficiency in commodities futures markets. In particular, we first evaluate the informational content of commodity futures by investigating whether futures prices are accurate and unbiased predictors of future–spot prices, and then we identify key financial and real economy transmission channels associated with the pandemic. We use data of all contracts from all commodities traded at Brazilian futures markets from 2018 to 2020. We document market inefficiency and bias for all commodities. We also find that COVID-19 has a negative correlation with hedge efficiency, and that liquidity, economic activity, export, and agriculture's employment share are transmission channels to hedge efficiency.

KEYWORDS
COVID-19, econometrics, futures markets, futures-spot basis, market efficiency, transmission channels

1 | INTRODUCTION

The emergence of the novel coronavirus (COVID-19) has generated an unprecedented challenge to authorities worldwide. The outbreak initiated in central China in late December 2019 and spread to 216 countries between 2020 and 2021, resulting in millions of deaths around the globe. Given the widespread and ongoing transmission of the novel coronavirus, governments announced social distancing, quarantine, and lockdown measures to mitigate the effects of the virus.¹ These measures provoked economic downturns all over the world as countries experienced recessions, rising inflation, and unemployment.²

Along with the sanitary and economic turmoil, financial markets also took a tumble. Ali et al. (2020) evidence that exchanges worldwide lost nearly 30% of the wealth in a 100-day time window during the COVID-19 pandemic, as global financial markets experienced a meltdown in returns even for safer commodities. D. Zhang et al. (2020) reach a similar conclusion and remark that COVID-19 has a negative correlation with hedge efficiency, and that liquidity, economic activity, export, and agriculture’s employment share are transmission channels to hedge efficiency.

¹For additional information and data on the epidemic aspects of COVID-19, refer to Sohrabi et al. (2020), Nicola et al. (2020), and Goodell (2020).
²A detailed set of information can be mainly found in periodic economic reports done by international economic agencies, regional central banks, and fiscal authorities, such as del Río-Chanona et al. (2020), Long and Ascent (2020), Cantú et al. (2021), and International Monetary Fund (2021).
with the United States, Europe, and other Asian markets. Haroon and Rizvi (2020) find that even the sentiment generated by coronavirus-related news is associated with the volatility of equity markets. They show that sectors most impacted by COVID-19—such as Travel and Leisure industries, Automobiles and Components, Energy, and Transportation—experienced increased volatility in equity markets. Moreover, the investigation of Albulescu (2021) shows that official announcements regarding the COVID-19 new cases of infection and fatality ratios and the prolongation of the pandemic affected the US financial market volatility. Another relevant feature is volatility transmission during COVID-19. Adekoya and Oliyide (2021) find that the pandemic was a period of increased risk transmission across a variety of commodity and financial markets. Given the recent body of evidence on the relationship between the COVID-19 pandemic and financial markets, it is relevant to understand to what extent individual countries, sectors, and economic agents are exposed to the set of contagion contention measures. A body of evidence about energy, stock markets, gold, and Bitcoin shows that the pandemic might have generated some negative effects on futures markets (Akhtaruzzaman et al., 2021; Chemkha et al., 2021; Jiang et al., 2021; H. Zhang et al., 2021), which are used, among other functionalities, to hedge against future positions. We define as hedge efficiency the amount of price risk of a spot position that hedgers can offset by purchasing a futures contract. This paper empirically examines whether hedge efficiency changed during COVID-19 among different asset classes.

As a contribution to the debate, this paper studies one component that, to the best of our knowledge, is still an understudied portion of the financial system during COVID-19: commodity futures markets. Specifically, we investigate if hedge efficiency in Brazil’s agricultural and energy commodities market changed when the COVID-19 was declared a worldwide sanitary issue. The Brazilian futures market provides an adequate setting for this analysis because these commodities are not as liquid as others from developed economies, like the North American and European markets. Therefore, our study expands the scope of analysis to countries other than developed ones. Also, we investigate both the commodity market as a whole and individual commodities rather than market indexes, which contributes to the understanding of COVID-19 on specific assets. Our empirical results can provide insights to support policy making, such as in the design of countercyclical policies to protect the economy against adverse shocks. Additionally, our methodology can also provide more comprehensive information to potential investors about a country’s financial conditions and how hedging conditions can deteriorate during adverse events to commodity producers.

In this paper, we are particularly interested in examining three empirical questions: Is new information readily incorporated into the Brazilian commodity futures markets, and are futures prices unbiased estimators of future–spot prices? What forces in the real economy are associated with the hedge efficiency during the pandemic, and do these forces comove the same way same among different commodities? Is there evidence that liquidity improves hedge efficiency during times of distress, such as the COVID-19 pandemic? We investigate these questions considering three main hypotheses. The first is that market efficiency is less likely to occur in emerging commodities futures markets. In the course of the COVID-19 pandemic, governments worldwide used interpersonal distancing and lockdown as the primary spreading contention mechanisms, which negatively affected global economic activity in ways similar to an economic crisis. Since commodities markets prices are formed globally based on global inventories (Geman & Nguyen, 2005; Geman & Smith, 2013), they are very susceptible to the world’s economic performance. Considering that the COVID-19 pandemic hit all continents, it is feasible to conjecture that they suffered significant impacts from these sanitary measures. Moreover, considering that most emerging markets have a large share of their production on commodities, which are traded through spot and futures markets, economic shocks can come from both the real and financial sides of the economy. This may result in market inefficiencies which, in the case of futures contracts, are captured by the difference between contemporaneous futures and spot prices, called the basis, and by the capacity of the basis to produce unbiased information about spot price in the future.

Second, liquidity is a key component in commodities futures markets. COVID-19 may have affected markets with distinct liquidity provision levels differently. Evidence suggests that liquidity risk affects both commodity returns and volatility shocks, and it can also generate a comovement across different commodity classes, thereby resulting in price aggregation shocks and inflation volatility amplification (Haugom & Ray, 2017; Y. Zhang & Ding, 2018; Y. Zhang et al., 2019). Thus, our rationale is that when an economic crisis like the COVID-19 pandemic occurs, arbitrageurs and

3Evidence suggests that the Brazilian stock market is weakly efficient, meaning that the predictive power is very limited and that systematic excess returns are improbable (Chen & Metghalchi, 2012; Ely, 2011; Urrutia, 1995). Our hypothesis is that these results cannot be readily inferred for commodities futures because the number of international investors trading and providing liquidity in the stock market is much more significant than that of futures markets in Brazil.
speculators start to reallocate their portfolios aiming at less risky markets. Considering that Brazilian commodities futures markets are perceived as more volatile, liquidity shocks may happen to a more considerable extent and may affect the hedge efficiency through increases in futures market volatility.4

Third, contagion contention measures hit commodities futures markets through the real economy by means of both national and international factors. The relationship between commodity prices and inflation is widely documented (Browne & Cronin, 2010; Ciner, 2011; Furlong & Ingenito, 1996; Y. Zhang et al., 2019), and it implies that variables, such as exchange rates and economic activity level, are relevant to determine the price level are also important features in our investigation. Also, commodities are undifferentiated tradeable goods, which means that global supply and demand are jointly relevant for price-setting, and variables that influence foreign market participants' decision-making process, such as exchange rates and exports, are relevant for basis determination and hedge efficiency. Moreover, COVID-19 contention measures consisted mainly of partial to total social distancing, which withdrew a substantial part of the labor force from the workplace worldwide, thereby dropping international income and making demand for goods and services shrink globally, reducing countries' exports. Also, considering that diminishing external demand reduces the purchase of international currency, exchange rates may increase, thus altering the cost of commodities overseas. Therefore, these events caused by the COVID-19 pandemic might be associated with an increase in spot and futures prices volatility. We also test if these real economy drivers are related differently to specific commodities. Aspects such as domestic—international demand prevalence, usage of foreign inputs, and the number of yearly crops may be relevant in determining the relationship between the pandemic and each commodity.

We choose Brazil as a case study because, despite being a major player in commodities production and exports, its futures markets are marginal when compared with developed countries (Adams et al., 1979; Cavalcanti et al., 2015; Cuddington, 1989; Love, 1992). Also, commodities futures are relevant for understanding economic growth. Kang and Kwon (2020) argue that, especially for long horizons, the basis, the change in slope, and the term premium on the basis-momentum are robust predictors for future economic growth. Following a similar path, Ge and Tang (2020) document that commodity returns in spot markets worldwide can predict gross domestic product growth one quarter ahead. Therefore, commodities are also relevant in a broader economic context. From that evidence, we hypothesize that the impact of an economic crisis generated by pandemic mitigation measures causes investors (especially foreign) to withdraw massive amounts of capital from emerging countries to reallocate their portfolios with less risky assets. As a consequence, the probability of not having counterparts to offset Brazilian hedgers (in this case, mainly commodity producers) positions, may result in an increase in futures price volatility, thereby reducing hedge efficiency. Thus, we use Brazil to address this particular feature of emerging economies' financial markets. Considering all commodities futures contracts traded in Brazil (livestock cattle, corn, coffee, soybean, and ethanol) and using a sample from January 2018 to December 2020, we test hypotheses on market efficiency, futures prices estimation unbiasedness, and transmission channels concerning COVID-19.

To perform our investigation we consider all commodities prices traded in Brazilian futures markets up to the current date, which can be grouped into two different types: agricultural and energy. For agricultural, we include livestock cattle, corn, coffee (arabica), and soybeans. Ethanol is the only energy commodity in our sample. We focus on all contracts available for a particular date. For every one of these commodities, we use data from January 2018 to December 2020 which includes all maturity dates for each trading day. To perform market unbiasedness and futures prices as accurate predictors of future–spot prices hypotheses testing we compute individual time-series database from the broader panel for each commodity and estimate a theory-based model used by Chinn and Coibion (2014). About the transmission channels, we use the original panel data to test our set of hypotheses, and we estimate a model with a quarter fixed effect and an asset-month-to-expiration crossed fixed effects to account for time-constant heterogeneity among, respectively, assets and among contracts within the same asset, such as units of measurement and seasonality.

We found that commodities futures markets in Brazil are neither efficient nor futures prices are unbiased and/or accurate predictors of subsequent spot prices. In addition, hedge efficiency in Brazilian commodities futures, on average, reduces during the COVID-19 outbreak. This reduction is commodity specific. We find that economic activity and exports are correlated with hedge efficiency during normal times and, altogether with agriculture's employment share, tend to relate as amplifying or mitigating factors during the pandemic. We also found evidence that liquidity during the COVID-19 pandemic is correlated with higher hedge efficiency. Therefore, we conclude that Brazilian

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4In a related work, Haugom and Ullrich (2012) examine the time-varying relationship from 2000 to 2010 between spot and short-term forward prices in the Pennsylvania-New Jersey-Maryland wholesale electricity market. They find that short-term forward prices converged towards unbiased predictors of the subsequent spot prices during the analyzed period.
futures markets are not efficient and new information is not immediately incorporated into prices, making room for COVID-19-related issues to affect hedge efficiency.

2 | RELATED LITERATURE

Since the COVID-19 outbreak, many studies have been trying to address the impact of contagion contention measures on financial markets. In broader terms, COVID-19 had a negative impact on stock markets worldwide (Ashraf, 2020; Harjoto et al., 2021; He et al., 2020). More specifically, Harjoto et al. (2021) found that these negative shocks affected mainly emerging markets and small firms, and that stimulus from the Federal Reserve made the US stock market experience positive abnormal returns when compared with emerging markets and other developed countries. Similarly, Topcu and Gulal (2020) show that Asian emerging markets suffer higher impacts than European emerging markets, and that the effects of the pandemic can be offset by the size of stimulus package and response time done by governments. Another relevant idea is that the stock market reacts more proactively to the growth in the number of confirmed cases than that to the number of deaths (Ashraf, 2020). Our main goal in this study is to contribute to this body of literature that addresses the impact of COVID-19 on financial markets, and since, to the best of our knowledge, most papers focus on stocks, bonds, and other popular segments, we aim at broadening this discussion to derivatives.

Recently, some studies have addressed the relation between COVID-19 and futures markets. Huang and Zheng (2020) study the long-run relationship between investor sentiment and the West Texas Intermediate oil futures price index and found that there was a structural change in this relationship due to COVID-19. Another finding is that Banerjee (2021) verified that during the COVID-19 pandemic there was futures markets contagion between China and its trading partners. Since these papers discuss more general contagion effects, our research dialogues with them by detailing the correlation between the COVID-19 outbreak and futures markets, by focusing on commodities and by analyzing an emerging market.

A relevant issue on the well function of futures markets is the analysis of the difference between current futures and spot prices, called the basis. Recently, futures-spot basis has been subject to several hypotheses testing by academic research to diagnose the lack or presence of futures market efficiency (Fama & French, 2016; Han & Pan, 2017; Roll et al., 2007; Wu & Zeng, 2019). The efficiency matter relies on the law of one price, which is the idea that two traded or synthesized instruments with the same future cash flows should trade at the same price, therefore, in a frictionless world, the basis should be zero and hedge efficiency should be as high as possible. However, evidence suggests that the occurrence of no-arbitrage between spot and futures markets may depend on arbitrageurs trading in markets with sufficient volume (Kumar & Seppi, 1994), and in the case of commodities futures, on the constraints imposed on speculators’ ability to deploy capital (Acharya et al., 2013), suggesting that liquidity plays a key role in the spot–futures price relationship and in the capacity of investors to hedge their positions efficiently. In addition, periods of economic crisis tend to alter investors’ portfolio allocation by prioritizing less risky assets, thus making liquidity shrink in riskier markets (Caballero & Krishnamurthy, 2008; Marsh & Pfeifferer, 2013; Rösch & Kaserer, 2014), making it harder for investors to hedge their position in futures markets. Such a body of evidence suggests that deepening the understanding of the law of one price is relevant for commodities futures markets. Our investigation contributes to these discussions by empirically testing if Brazilian futures markets can be considered frictionless in times of a major negative economic shock happening in the world’s economy.

Finally, recently emerged some evidence that COVID-19 impacted hedge efficiency. H. Zhang et al. (2021) studied energy and stock markets before and after the COVID-19 outbreak in terms of static, total, and net spillover effects for several countries and found that changes in hedging ratio, optimal portfolio weights, and hedge effectiveness after the COVID-19 outbreak required investors to adjust their portfolio strategies. Moreover, Chemkha et al. (2021) analyze if Bitcoin and gold had consistent hedge and safe haven properties during COVID-19 for major world stock indices and currencies, and evidenced that they are effective as hedge to minimize the risk of international portfolios, but also that Bitcoin cannot provide shelter due to its increased variability and gold is a weak safe haven. Similar to Chemkha et al. (2021), Akhtaruzzaman et al. (2021) also study gold’s hedge and safe haven properties for stock markets worldwide.

5They analyzed S&P 500 (US), DAX (Germany), FTSE 100 (UK), CAC 40 (France), Nikkei 225 (Japan), HSI (Hong Kong), SSE (China), KOSPI 200 (Korea), Ibovespa (Brazil), and RTS (Russia) from January 4, 2011, to August 11, 2020.
6Other important results they found were that COVID-19 outbreak increased the extent of risk acceptance in the energy market and that the COVID-19 pandemic had a significant impact on spillover effects.
and reported that its status as a safe haven is conditional to the time period considered.\textsuperscript{7} We contribute to this literature by identifying other possible factors related to hedge efficiency during COVID-19.

3 | DATA

We consider all commodities prices traded at Brasil, Bolsa, Balcão (B3) up to December 30, 2020, which can be grouped into two different types: agricultural and energy. For agricultural, we include livestock cattle, corn, coffee (arabica), and soybeans. Ethanol is the only energy commodity in our sample. Thus, our data include four agricultural products and one energy commodity. Having these two sets of commodities is helpful for several reasons. First, since commodities have different financing structures, external demands, and expiration months. In this way, comparisons across commodities provide a more in-depth understanding of any commodity-specific heterogeneity in the hedge efficiency during COVID-19. Second, we can compare the impacts of the COVID-19 shock on each individual, group, and the Brazilian commodities futures markets as a whole.

Many exchanges worldwide have historically been trading commodities futures. In Brazil, the B3 is the only one responsible for trading commodities futures. Data on futures prices, open interest, volume, number of deals, and expiration dates come from B3’s publicly available database. Moreover, data on the spot price for each commodity come from the Centro de Estudos Avançados em Economia Aplicada (Cepea) managed by the Escola Superior de Agricultura Luiz de Queiroz (Esalq) from Universidade de São Paulo (USP), which records such prices for the commodities we study and is also used as a reference for futures contracts technical characteristics, such as physical product conditions and delivery location.

We focus on all contracts available for a particular date. For every one of these commodities, we use data from January 2018 to December 2020, including all maturity dates for each trading day. Excluding the cases of livestock cattle and ethanol, futures contracts are not available for every delivery month. For corn, there are seven delivery months, which are January, March, May, July, August, September, and November; for coffee, there are five that are March, May, July, September, and December; and in the case of soybeans, they are March, April, May, June, July, August, September, and November, a total of eight. Therefore, we build a panel database consisting of each trading day for all commodities and every maturity month available for that day.

To perform market unbiasedness and futures prices as accurate predictors of future–spot prices hypotheses testing, we compute an individual time-series database from the broader panel for each commodity. For a particular trading day, we consider a time-series observation of the value from the closest expiration month past that day. One reason for this choice is that maturity months are not the same among studied commodities, making it inadequate to break into time series of different time horizons for specific periods of the year, which may be missing for a particular month. Moreover, we analyze each commodity by considering three different series: one consisting of the whole period, another including the pre-COVID period, and lastly, only during the pandemic.

About the transmission channels, we use the original panel data to test our set of hypotheses. The number of observations varies among commodities due to the differences in the maturity dates shown above. Livestock cattle and ethanol have the most number of maturities. Thus, the sample size considering the same period is more extensive. Also, since contracts different have units of measurement, we need to use fixed effects to account for this time-constant factor.

To capture these possible correlations we use a series of macroeconomic data publicly available on Brazilian government agencies. To measure inflation we use the \textit{Indice de Preços ao Consumidor Amplo} (IPCA), the interest rate we use is the short-term overnight rate computed by the \textit{Sistema Especial de Liquidação e Custódia} (Selic), domestic economic activity is measured by the \textit{Índice de Atividade Econômica do Banco Central} (IBC-Br), employment data comes from \textit{Cadastro Geral de Empregados e Desempregados} (CAGED),\textsuperscript{8} and we collected exports data from the Brazilian Ministry of Industry, International Trade and Services.

\textsuperscript{7}In their investigation, they considered two phases: Phase I (December 31, 2019–March 16, 2020) and Phase II (March 17, 2020–April 24, 2020), marked by governmental monetary and fiscal stimulus packages. The stock indexes they used were S&P 500, Euro Stoxx 50, Nikkei 225, and China FTSE A50 indices.

\textsuperscript{8}This indicator accounts only for formal employment under the \textit{Consolidação das Leis do Trabalho} (CLT) regime, which is the one that rules employment relation in Brazil.
Table 1 lists the summary statistics of the variables employed in the next section of this paper. We discuss their meaning and rationale as we develop the ideas in that section.

| Statistic                  | N    | Mean  | Standard Deviation | Minimum | Percentile (25) | Percentile (75) | Maximum |
|----------------------------|------|-------|--------------------|---------|-----------------|-----------------|---------|
| **Dependent variables**    |      |       |                    |         |                 |                 |         |
| Hedge efficiency           | 18,437 | -1.388 | 1.640              | -6.202  | -1.847          | -0.223          | 0.000   |
| **Independent variables**  |      |       |                    |         |                 |                 |         |
| Money volume (in million R$) | 18,523 | 5.114  | 7.463              | 0.000   | 0.259           | 7.334           | 27.011  |
| Market depth (in thousand R$ per contract) | 15,571 | 4.707  | 3.205              | 1.592   | 2.498           | 6.835           | 11.946  |
| Basis risk (in thousand R$²) | 18,523 | 0.744  | 1.803              | 0.0001  | 0.001           | 0.114           | 6.653   |
| Volume (in number of deals) | 18,523 | 0.051  | 0.105              | 0.000   | 0.001           | 0.040           | 0.445   |
| Inflation (% monthly)      | 18,523 | 0.288  | 0.329              | -0.210  | 0.100           | 0.450           | 1.150   |
| Interest rate (% annually) | 18,523 | 5.496  | 1.306              | 2.150   | 4.900           | 6.400           | 6.400   |
| Exchange rate (R$ per US$) | 18,523 | 4.132  | 0.508              | 3.669   | 3.791           | 4.173           | 5.426   |
| Economic activity (index)  | 18,523 | 137.009 | 4.232             | 126     | 134.7           | 139.5           | 143     |
| Total employment (in million workers) | 18,523 | 38.951 | 0.406              | 38.120  | 38.684         | 39.284          | 39.591  |
| Agriculture's employment share (%) | 18,523 | 4.070  | 0.090              | 3.953   | 3.980           | 4.138           | 4.242   |
| Exports (in million R$, FOB) | 18,523 | 536.625 | 890.996            | 0.039   | 1.497           | 534.020         | 3303.997 |

Note: We winsorize 2.5% of each side of all distributions of numeric variables. The table reports statistics after this winsorization. Abbreviation: FOB, free on board.

Table 1 lists the summary statistics of the variables employed in the next section of this paper. We discuss their meaning and rationale as we develop the ideas in that section.

4 | EMPIRICAL RESULTS

This section presents the methods and results we found in our empirical investigation. First, we present market efficiency and unbiasedness tests done for all commodities. After that, we show the results by identifying the channels through which the COVID-19 economic slowdown correlates with hedge efficiency.

4.1 | Market efficiency and predictive content of futures markets

This subsection addresses how information is incorporated into Brazilian commodity futures markets. News about adverse shocks just like COVID-19 usually provokes reactions from investors worldwide. Therefore, we first investigate if the information that the novel coronavirus could threaten economies worldwide is immediately incorporated into prices (i.e., if they are efficient) and if the difference between futures and spot prices can reveal any signal about spot prices in the future.

The efficient market hypothesis is a key element in the argument that the futures price is the best forecast of the future-spot price. In general terms, the hypothesis asserts that all new information is reflected instantly in commodity prices, and arbitrage opportunities cannot occur systematically. Thus, price patterns are random, and no trading strategy based on past market behavior can provide sustainable profits. Considering that current futures prices can

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9Haroon and Rizvi (2020) show evidence that news that generated panic is associated with increased volatility in the equity markets.
provide some information about the expected price of the commodity at maturity, the difference between them and the future–spot price can be an estimation of the opportunity gain or loss realized from taking certain positions and the forecast error performed by agents. Moreover, if the forecast error is zero, we can conclude that the market is efficient and that futures prices are unbiased estimators.

In the case of the commodities we study, futures prices are determined by key elements beyond spot prices. Agricultural commodities, which are storable and in most cases perishable, can be used in alternative ways, whether as a consumption good or as a production input, adding value to its owner. This option to use the commodity in alternative ways is called the convenience yield and is included in the futures price. Also, storing the product is costly due to physical inventories, insurance requirements and because products lose their properties that would make them useful, diminishing their value as they spend too much time in storage. Moreover, an agent gives up returns on other asset classes by holding commodity inventories. Thus, the difference between the costs related to storage and the value for holding the commodity plus the interest added by a risk premium is the cost of carry.10

To translate these ideas into an empirically testable form, we use the notation and rationale provided by Chinn and Coibion (2014) based on the work of Brenner and Kroner (1995). They assume that the basis is determined as

\[ f_{t,t-k} - s_{t-k} = d_{t,t-k} + Q_{t,t-k}, \tag{1} \]

in which \( f_{t,t-k} \) is the observed (log) time \( t - k \) futures contract price with maturity date \( t \), \( s_{t-k} \) is the time \( t - k \) spot rate, \( d_{t,t-k} \) is the log cost-of-carry, and \( Q_{t,t-k} \) is a term accounting for the marking-to-market feature of futures.11 Note that the left-hand side of Equation (1) is the basis, which tends to be statistically equal to zero in an efficient market. This relation holds by considering that market participants are able to trade in the spot and futures markets simultaneously, meaning that they can pursue arbitrage trading.

Considering that the right-hand side of Equation (1) is not directly available to obtain the commodities we use, Chinn and Coibion (2014) present another specification that allows for estimation. It starts by assuming that the log spot rate follows a time random walk with drift and expectations are rational, also, the time \( t - k \) expectation of the change in the spot rate will equal the basis and the marking-to-market term. We then obtain

\[ s_t - s_{t-k} = \alpha + \beta (f_{t,t-k} - s_{t-k}) + \epsilon_t, \tag{2} \]

in which \( \alpha \) is equivalent to the right-hand side of Equation (1) and also the parameters defining the time-series process governing the spot rate. Moreover, if the underlying commodity futures market is efficient and futures prices are unbiased estimators of the spot rate, then the log cost-of-carry and the marking-to-market feature of futures should be approximately zero, meaning that storage cost and the value from holding the commodity are similar, and that new information is incorporated so fast that no systematic gains are expected between two trading days up to the maturity of a contract. Also, the basis at a particular point in time \( t \) should determine the movement of the spot rate, in other words, we should have that jointly \( \alpha = 0 \) and \( \beta = 1 \).

Figure 1 plots the time series of the log of the daily futures prices, the log of daily spot prices, the basis also computed in log terms, and the spot rate for each of the five commodities we use, and normalized by their January 31, 2020 value. For the futures and spot prices in panels A and B, livestock cattle had the smoothest trajectory around an upward trend during the whole series, seeming to be just marginally affected by the coronavirus crisis. On the other hand, ethanol had the steepest price drop in both markets just a few days after the COVID-19 outbreak, returning to the prepandemic level only at the end of 2020. Corn was the commodity that reached the highest futures price level after the COVID-19 pandemic started. Coffee futures prices remained at the same level as before the crisis, seeming to not be as impacted by COVID-19. Soybean experienced a high difference between futures and spot prices all along the series. Panel C helps visualize these relationships better, evidencing that coffee and soybean have the largest gap between the two prices, providing a preliminary view that the market for these commodities may not be efficient, while the others may require further investigation. In panel D we find evidence that, perhaps except livestock cattle, spot prices at maturity diverge a lot from spot prices at a certain date, expressing that predictability is quite hard in these markets.

10Despite not being equal to agricultural commodities, ethanol is similar in those aspects.
11In the case of futures contracts, marking-to-market the security implies a real financial gain (loss) if there is a positive (negative) variation of prices considering the position an agent assumes in the market. These results are recorded at margin accounts.
Table 2 shows the results for the regression specified by Equation (2). Among all commodities, livestock cattle is the market that is closer to not rejecting the joint null hypothesis of market efficiency and unbiasedness of the basis, as both $\alpha$ and $\beta$ are significant and close to 0 and 1, respectively, but the formal coefficient Wald test rejected the null hypothesis. The fact that $\alpha$ is near to zero means that the cost of storing livestock cattle in a farm and the financial cost
in the form of the opportunity cost of livestock cattle, or the cost of funding, and perhaps a risk premium plus the result of marking-to-market offset each other, thereby explaining just a small amount of the difference between current and at maturity spot prices. Moreover, being $\beta$ positive and greater than one it means that the basis at a time $t$ overestimates the spot rate when it is greater than zero, and underestimates it when it is less than zero.

For all other commodities the joint hypothesis is rejected even without a more formal coefficient test. For corn, soybeans, and ethanol, only $\alpha$ was significant, meaning that the basis was not relevant to explain the spot rate and futures markets do not carry a significant amount of information to help predict spot prices at maturity. Coffee, just like livestock cattle, had both coefficients significant but with $\beta$ being positive and less than one, and $\alpha$ being less than absolute one and with a negative sign, which means that the basis at time $t$ underestimates the spot rate when it is greater than zero, and overestimates it when it is less than zero. Also, evidence from Table 2 suggests that cost-of-carry and marking-to-market futures had a limited influence on the difference between current and at maturity spot prices, as all $\alpha$ coefficients were close to zero.

In terms of the joint hypothesis of unbiasedness and market efficiency, evidence about the pre-COVID period shown in Table 3 demonstrates results that are similar to the whole period regression. For all commodities the idea of futures markets being unbiased and efficient is rejected. However, the significance and sometimes the signal of some coefficients have changed. Prepandemic estimation suggests that livestock cattle keeps the same logic as the whole period, that the basis is relevant for determining the spot rate of corn and soybean, that ethanol kept the same characteristics compared with the whole period, and, in contrast to the whole period estimation, both $\alpha$ and $\beta$ are not significant for coffee. These differences indicate that Brazilian commodities futures market conditions may have changed during pandemic times.

Considering the COVID-19 pandemic time frame, once again the hypotheses of market efficiency and unbiasedness are rejected, but there are some important differences between the two previous regressions. Table 4 evidences that the significance of the parameters are the same as the pre-COVID times for livestock cattle, corn and ethanol. Also, the both $\alpha$ and $\beta$ turn from insignificant to significant in the case of coffee, and $\alpha$ became insignificant for soybean during the pandemic. It is worth noticing that the basis for livestock cattle turned from bigger than one to less than one, meaning that the relationship between the basis and the spot rate has changed, indicating that the arrival of new information to the futures markets may cause bias in different directions during a negative economic shock. A similar idea is the example of corn, in which the basis is relevant but weakens its influence on the spot rate. Another piece of evidence is that during economic turmoil, the basis may change in relevance for explaining the spot rate just as in the case of coffee, in which the basis turned into significant during the pandemic.

**Note:** This table presents estimated results by ordinary least squares of Equation (2) in the text for different commodities for the pre-COVID-19 time horizon (January 2018–February 2020). We use the individual time series generated from the broader panel data. We apply log for each variable. Column (I) reports results for livestock cattle, Column (II) for corn, Column (III) for coffee, Column (IV) for soybeans, and Column (V) for ethanol. The joint hypothesis we test is that coefficients of the basis and $\alpha$ are, respectively, one and zero. The goal is to test if the market for that specific commodity is both efficient and unbiased. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

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**Table 3** Regressions of ex post price changes on the basis for the pre-COVID period.

| Dependent variable | Livestock cattle (I) | Corn (II) | Coffee (III) | Soybean (IV) | Ethanol (V) |
|--------------------|----------------------|-----------|--------------|--------------|-------------|
| Basis              | 1.627***             | 0.476***  | −0.186       | 0.110***     | −0.156      |
|                    | (0.100)              | (0.167)   | (0.171)      | (0.030)      | (0.165)     |
| $\alpha$           | 0.006***             | 0.086***  | −0.014       | 0.009***     | 0.069***    |
|                    | (0.002)              | (0.004)   | (0.019)      | (0.003)      | (0.005)     |
| Observations       | 492                  | 488       | 488          | 492          | 488         |
| $R^2$              | 0.352                | 0.016     | 0.002        | 0.028        | 0.002       |
| Adjusted $R^2$     | 0.351                | 0.014     | 0.0004       | 0.026        | −0.0002     |

Note: This table presents estimated results by ordinary least squares of Equation (2) in the text for different commodities for the pre-COVID-19 time horizon (January 2018–February 2020). We use the individual time series generated from the broader panel data. We apply log for each variable. Column (I) reports results for livestock cattle, Column (II) for corn, Column (III) for coffee, Column (IV) for soybeans, and Column (V) for ethanol. The joint hypothesis we test is that coefficients of the basis and $\alpha$ are, respectively, one and zero. The goal is to test if the market for that specific commodity is both efficient and unbiased. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

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12Despite the clear evidence against the null hypothesis of market efficiency and unbiasedness, we performed the Wald test for all commodities which confirmed the values presented in Table 2.
Evaluating the results from all previous regressions we can infer that Brazilian commodity futures markets are not efficient nor unbiased predictors of the spot rate. If an investor, whether it is an arbitrageur, speculator, or hedger, is interested in having an unbiased estimator of the spot price at maturity, he must look at other information beyond the difference between futures and spot prices. Moreover, in times where Brazil suffers a macroeconomic exogenous shock, such as COVID-19, the relation between the basis and the spot rate changes when compared with more normal times.

4.2 COVID-19 transmission channels to futures markets

Since we have evidence that neither the basis is not an optimal predictor of the difference on the spot rate for any commodity nor these markets are efficient, new information can generate frictions and influence hedge effectiveness. Moreover, the emergence of COVID-19 can be associated with negative impacts on hedging activity. In this section we investigate how COVID-19 correlates to hedge efficiency in Brazilian commodity futures markets, and through what channels the association is stronger and more likely to happen. We define the basis as

\[ \text{Basis}_{t,T} = S_t - F^T(t), \]  

where \( S_t \) is the current spot price and \( F^T(t) \) is the current futures price of a contract that matures at date \( T \). Considering that basis risk is defined as the variance of the basis, from Equation (3) we can compute it as

\[ \sigma^2(S_t - F^T(t)) = \sigma^2(S_t) + \sigma^2(F^T(t)) - 2\rho\sigma(S_t)\sigma(F^T(t)), \]  

in which \( \rho \) is the correlation between current spot and futures prices. Hence, from Equation (4) we see that basis risk is zero when the correlation coefficient \( \rho \) between futures and spot prices is one and when variances between spot and futures prices are identical.

By assuming that hedgers are trying to cancel price risks coming from a spot market position, we use the following measure of hedge efficiency\(^{13}\)

\[ h = 1 - \frac{\sigma^2(\text{Basis})}{\sigma^2(S_t)}. \]  

\(^{13}\)To compute basis risk as the variance of the basis we generated monthly series for each commodity considering every maturity date.

| Dependent variable | Livestock cattle (I) | Corn (II) | Coffee (III) | Soybean (IV) | Ethanol (V) |
|--------------------|----------------------|-----------|--------------|--------------|-------------|
| **Basis**          | 0.662***             | 0.011**   | 1.856***     | -0.345***    | 0.035       |
|                    | (0.077)              | (0.005)   | (0.189)      | (0.060)      | (0.227)     |
| **\( \alpha \)**   | 0.022***             | 0.043***  | -0.317***    | 0.003        | 0.052***    |
|                    | (0.002)              | (0.007)   | (0.029)      | (0.007)      | (0.006)     |
| Observations       | 249                  | 218       | 240          | 206          | 226         |
| \( R^2 \)          | 0.228                | 0.026     | 0.288        | 0.139        | 0.0001      |
| Adjusted \( R^2 \) | 0.225                | 0.022     | 0.285        | 0.135        | -0.004      |

Note: This table presents estimated results by ordinary least squares of Equation (2) in the text for different commodities for the COVID-19 time horizon (February 2020–December 2020). We use the individual time series generated from the broader panel data. We apply log for each variable. Column (I) reports results for livestock cattle, Column (II) for corn, Column (III) for coffee, Column (IV) for soybeans, and Column (V) for ethanol. The joint hypothesis we test is that coefficients of the basis and \( \alpha \) are, respectively, one and zero. The goal is to test if the market for that specific commodity is both efficient and unbiased. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.
From it we observe that the higher the spot price risk relative to the basis risk the more effective is the hedge, and also, if the basis risk is higher than the spot price risk, the hedger can incur a potential loss. In a hypothetical scenario, if the correlation between futures and spot prices is one and their variance is similar, then basis risk is the lowest, therefore $h$ is close to one and the most effective is the hedge.

From the discussion above, our attention must be directed to factors associated with the variance of futures and spot prices and also drivers of the correlation between them. We separate them into two groups of indicators: financial and real economy. Financial indicators are the ones that are intrinsic to the futures markets of a commodity, while real economies are the ones that are more closely related to spot market conditions.\(^{14}\) We use this grouping to better organize our hypotheses and to better differentiate between intrinsic and extrinsic factors in those markets. In detail, we use both groups as control variables in our main specification and then capture their correlation with the COVID-19 pandemic by interacting them with a COVID-19 dummy variable.

On the financial side, our rationale revolves around the idea that when COVID-19 pandemic lockdown measures were announced and economic activity shrank, arbitrageurs and speculators started to reallocate their portfolios aiming at less risky securities. Since Brazil is an emerging economy perceived to have a riskier financial system, it suffered outflows from nonhedging agents, thereby resulting in liquidity issues. This problem might be captured by some liquidity indicators such as the volume of contracts traded to open-interest ratio, which we call market depth.\(^{15}\)

The real economy indicators we use are mainly macroeconomic variables that tend to capture the effects of major economic exogenous shock on a whole economy. The economic slowdown due to COVID-19 affected almost every country around the world, since a huge number of governments took actions to mitigate the spreading of the virus. Overall, these actions affected most sectors of economies, turning it into a macroeconomic issue. Thus, there is a nonnegligible probability that macroeconomic variables can be related to the shock to futures markets, especially economies that rely relatively more on low-skilled labor which tends to be involved in high-contact activities.

Inflation, interest rates and exchange rates are closely related to each other when we talk about their association with futures markets. COVID-19 contention measures required social distancing, what shrank production in activities that require a relevant amount of physical interactions, thereby reducing supply in many sectors. Moreover, given that governments worldwide also took demand stimulating measures, inflation rose worldwide. As a response to that, monetary authorities started to level up their interest rates intending to tame inflation expectations. After the increase in interest rates, capital flux varied as investors started to reallocate their portfolios according to these new scenarios. Therefore, these variables may be related to Brazilian commodities futures markets hedge efficiency by increasing the variance of futures prices.

We also include economic activity and employment indicators. Domestic economic activity indicators and employment help us control the Brazilian demand, once they can indicate disposable income. About exports, the Brazilian commodities markets we study are closely related to global markets, since domestic prices are highly influenced by world prices and exports are a very relevant destination of the countries’ production. Thus, real economy variables may be related to Brazilian commodities futures markets hedge efficiency by increasing the variance of spot prices. As indicators we use IPCA for inflation, Selic as the short-term overnight rate, the IBC-Br as domestic economic activity is measured, formal employment provided by CAGED, and exports come from the Brazilian Ministry of Industry, International Trade and Services.

Given the structure of the data, we use a specification that aims to control for market and real economy factors while it allows for the investigation related to COVID-19. We use the following empirical specification to analyze whether hedge efficiency changed during the pandemic:

$$\gamma_{m,q,t} = \alpha_q + \alpha_{m} + \beta \text{COVID-19}_{t} + \gamma \text{Controls}_{at} + \eta_{m,q,t},$$  \hspace{1cm} (6)

in which $a$, $m$, $q$, and $t$ index the commodity asset, maturity date, quarter, and time, respectively. COVID-19, is the COVID-19 pandemic dummy variable which is 0 in periods before the COVID-19 pandemic (from January 2018 to December 2019) and 1 during the pandemic (from January 2020 to December 2020), and Controls, is the vector of controls described before, with all of them varying in $t$, and money volume, market depth, basis risk, volume (in a

\(^{14}\) Despite being a handy division, it is not a perfect setting mainly because some variables can be closely related to both groups. For example, short-term interest rate, which is the opportunity cost of capital for both real economy participants and futures markets agents.

\(^{15}\) An in-depth discussion about this indicator is done by Bessembinder and Seguin (1993).
number of deals) and exports also varying accordingly to each asset \( a \).\(^{16}\) We introduce quarter fixed effects \( \alpha_q \) to absorb seasonal patterns in commodity markets. We do not add month–year fixed effects because it would be collinear with our main variable of interest COVID-19. Therefore, it would be dropped in all our regressions, along with the time-variant macroeconomic controls. The term \( \alpha_{a,m} \) represents cross-fixed effects of asset and maturity date. Therefore, we consider as a different unit of analysis commodities that mature at different dates.

Our main goal is to verify if \( \beta \) is significant and to test the idea that, since the COVID-19 pandemic outbreak, hedge efficiency diminished, meaning that \( \beta < 0 \). We cluster errors at the asset level within each expiration period. We also subtract the mean and then divide by the standard deviation of all numeric explanatory variables. Our coefficient of interest is \( \beta \), which measures the difference in the asset-and-expiration-level outcome of contracts with one standard deviation higher exposure to COVID-19 than the average exposure of contracts. Similarly, we run Equation (6) for each commodity.

On the basis of literature review and on the explanation for the choice of controls, we elaborate a set of ex ante hypothesis. First, inflation, interest rates, exports, and total employment have negative coefficients. The correlation between inflation and hedge efficiency is justified by the idea that the rise in price level may decrease the correlation between futures and spot prices due to the rise in inflation expectation one time period to another. Interest rates are related negatively to hedge efficiency because higher rates push investors to government bonds and bills, so that it shrinks the correlation between futures and spot prices from the financial side. Exports may be negatively related to hedge efficiency due to a commodity’s domestic inventory reduction, which increases the volatility of futures prices and basis risk.

Second, we hypothesize that exchange rates, economic activity, and the agriculture’s employment share have positive coefficients. Overall, higher exchange rates imply an increase in a commodity’s export volume, thus reducing demand uncertainty and increasing the correlation between futures and spot prices and hedge efficiency. We expect economic activity to have the same idea as exports, except that it refers to domestic demand. Finally, agriculture’s employment share work as an indicator of the sector’s expansion or contraction, therefore an increase relates with better hedge efficiency.

Table 5 reports our coefficient estimates for the specification in Equation (6). We run our regressions with the following data samples: whole market (Column I), livestock cattle (Column II), corn (Column III), ethanol (Column IV), coffee (Column V), and soybean (Column VI). We find empirical evidence that hedge efficiency decreased during the COVID-19 compared with the prepandemic period in the Brazilian futures markets as a whole, even when we account for a series of real economy and financial controls. Higher volume and economic activity are correlated with higher hedge efficiency. In contrast, higher inflation, total employment, and exports associated with decreased hedge efficiency.

Considering each commodity separately (Columns II–VI in Table 5), we have evidence that the observed changes during the pandemic in hedge efficiency were heterogeneous across commodities. Some controls also relate differently to hedge efficiency depending on the commodity. Hedge efficiency on corn, ethanol decreased during the COVID-19 pandemic, while soybeans experienced an increase in the hedge efficiency during the COVID-19 outbreak. We do not find any statistical significant change in hedge efficiency for livestock cattle and coffee. This heterogeneous result among commodities can be related to the divergent production process. Brazilian livestock cattle and coffee productions are more long-run oriented than soybean and corn (the average cattle fattening is 18 months, and coffee takes about 5 years to be ready for harvesting), thus they are less sensitive to short-term fluctuations. In the case of ethanol, the correlation to COVID-19 is due to the drop in economic activity.

We also analyze potential transmission channels that could amplify or attenuate changes in the hedge efficiency during COVID-19 across commodities. To do so, we interact ex ante financial and economic indicators with our dummy variable COVID-19, in Equation (6), as follows:

\[
y_{a,m,q,t} = \alpha_q + \alpha_{a,m} + \beta_{COVID-19} + \lambda \text{Indicator}_t + \mu_{COVID-19} \cdot \text{Indicator}_t + \gamma \text{Controls}_t + \eta_{a,m,q,t},
\]

in which \( \text{Indicator}_t \) can be any of the following factors: financial indicators (month to expiration, money volume, market depth,\(^{17}\) basis risk, and volume) and economic indicators (inflation, interest rate, exchange rate, economic activity, agriculture’s employment share, and exports). For instance, the interaction between COVID-19, and months to

\(^{16}\)Considering that there are no exports of livestock cattle, we used total exports of cattle meat as a proxy.

\(^{17}\)We compute market depth as the volume to open-interest ratio, as suggested by Chinn and Coibion (2014).
**Table 5** Regression of hedge efficiency on all commodities (entire future market) and on each commodity individually.

| Dependent variable | Hedge efficiency | Whole market (I) | Livestock cattle (II) | Corn (III) | Ethanol (IV) | Coffee (V) | Soybeans (VI) |
|--------------------|------------------|------------------|-----------------------|------------|--------------|------------|--------------|
| COVID-19_t         | -1.236***        | -0.1899          | -3.515***             | -1.219***  | -0.2895      | 2.103***   |
|                    | (0.3020)         | (0.2485)         | (0.3999)              | (0.4754)   | (0.3266)     | (0.3473)   |
| Money volume_at    | -0.0234          | -0.1155          | -0.0761               | -0.6333    | 0.6172       | 0.7380     |
|                    | (0.0406)         | (0.3039)         | (0.1312)              | (1.526)    | (0.9658)     | (0.8222)   |
| Market depth_at    | 0.0543           | -0.0462          | 0.1291                | 0.1610     | -0.0434      | 0.0170     |
|                    | (0.0361)         | (0.0617)         | (0.1337)              | (0.2010)   | (0.0840)     | (0.0384)   |
| Basis risk_at      | 2.430            | -221.3           | 842.6                 | 5.300*     | -102.8       |
|                    | (2.129)          | (204.8)          | (6744.0)              | (2.788)    | (66.74)      |
| Volume_at          | 0.1009***        | 0.3224           | 0.0752                | 14.83      | -1.069       | -0.4155    |
|                    | (0.0489)         | (1.231)          | (0.1100)              | (25.84)    | (1.196)      | (4.243)    |
| Inflation_t        | -0.0867*         | 0.3544***        | -0.1081***            | 0.1596**   | -0.2940***   | -0.3121*** |
|                    | (0.0446)         | (0.0540)         | (0.0176)              | (0.0590)   | (0.0650)     | (0.0792)   |
| Interest rate_t    | -0.1385          | -0.1184          | -0.1836***            | -0.6254*   | -0.6984***   | 1.572***   |
|                    | (0.1406)         | (0.2416)         | (0.0615)              | (0.2983)   | (0.2593)     | (0.3111)   |
| Exchange rate_t    | 0.2441           | -0.6904***       | 1.000***              | 0.0168     | -0.5274***   | 0.8508***  |
|                    | (0.1637)         | (0.2739)         | (0.1344)              | (0.2239)   | (0.2433)     | (0.1830)   |
| Economic activity_t| 0.2169***        | -0.3240***       | 0.2406***             | 0.3989***  | 0.2727***    | 0.5443*    |
|                    | (0.0596)         | (0.0982)         | (0.0454)              | (0.0698)   | (0.1242)     | (0.2611)   |
| Total employment_t | -0.1675***       | 0.0772           | -0.5414***            | 0.2687     | -0.1706***   | -0.1434    |
|                    | (0.0613)         | (0.0710)         | (0.0416)              | (0.2518)   | (0.0726)     | (0.2659)   |
| Agriculture's employment share_t | 0.0539   | 0.2219***       | -0.0229               | 0.2641     | -0.1696      | -0.3207**  |
|                    | (0.0498)         | (0.0667)         | (0.0180)              | (0.2117)   | (0.1090)     | (0.1352)   |
| Exports_at         | -0.1186**        | -93.81           | 0.5842***             | 4.276      | -2.600*      | -0.0624    |
|                    | (0.0586)         | (84.85)          | (10.88)               | (8.152)    | (1.029)      | (0.1268)   |

Fixed effects

| Asset * months-to-expiration | Yes | Yes | Yes | Yes | Yes | Yes |
|------------------------------|-----|-----|-----|-----|-----|-----|
| Quarter                      | Yes | Yes | Yes | Yes | Yes | Yes |

Fit statistics

| Observations | 15,489 | 3594 | 3531 | 2810 | 3464 | 2089 |
|--------------|--------|------|------|------|------|------|
| R²           | 0.26996| 0.47487| 0.65761| 0.37812| 0.30070| 0.56596|
| Within R²    | 0.09770| 0.41824| 0.57705| 0.26679| 0.18188| 0.45641|

Note: This table presents estimated results by ordinary least squares of Equation (6) in the text for the whole Brazilian commodity futures markets (Column I) and for each different commodity (Column II for livestock cattle, Column III for corn, Column IV for ethanol, Column V for coffee, and Column VI for soybean). We use panel data from January 2018 to December 2020 which includes daily observations for each contract negotiated in a particular business day for that commodity at Brasil, Bolsa, Balcão. We compute the monthly value from the daily observations. We also subtract the mean then divide by the standard deviation of all numeric explanatory variables. We use (i) asset fixed effects to absorb asset-specific nonobservables that are time-invariant and (ii) asset-months-to-maturity fixed effects to compare subgroups of assets within the same contract. Therefore, we investigate if COVID-19 is correlated with hedge efficiency and which transmission channels are associated with hedge efficiency for the whole market and for each individual commodity. Standard errors are clustered at the asset-expiration level, and they are presented inside parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and *** respectively.
**TABLE 6** Regression of hedge efficiency on all commodities (entire future market) and on financial indicators during COVID-19.

| Dependent variable | Model | (I) | (II) | (III) | (IV) | (V) |
|--------------------|-------|-----|------|-------|------|-----|
|                    | Hedge efficiency |       |       |       |      |     |
| **COVID-19**       | -1.259** | -0.9329** | -0.9665** | -0.9478** | -0.9319** |
|                    | (0.4847) | (0.4277) | (0.4022) | (0.4251) | (0.4187) |
| **COVID-19** × Months to expiration | -0.6882 |       |       |       |     |     |
|                    | (0.4242) |       |       |       |     |     |
| **COVID-19** × Money volume | -0.1841 | 0.6227*** |       |       |     |
|                    | (0.2328) | (0.1726) |       |       |     |
| **COVID-19** × Market depth |       |       |       |       |     |
|                    |       |       |       |       |     |
| **COVID-19** × Basis risk |       |       |       |       |     |
|                    |       |       |       |       |     |
| **COVID-19** × Volume |       |       |       |       |     |
|                    |       |       |       |       |     |
| **Money volume**   | -0.0103 | -0.0346 | 0.0793 | -0.0435 | -0.0415 |
|                    | (0.0752) | (0.0741) | (0.0640) | (0.0732) | (0.0739) |
| **Market depth**   | 0.0349 | 0.0422 | -0.1331* | 0.0647 | 0.0303 |
|                    | (0.0829) | (0.0816) | (0.0728) | (0.0835) | (0.0805) |
| **Basis risk**     | 0.0201 | 0.0191 | 0.0325 | 0.0227 | 0.0204 |
|                    | (0.0408) | (0.0424) | (0.0507) | (0.0462) | (0.0417) |
| **Volume**         | 0.0817 | 0.1029 | 0.0341 | 0.0814 | 0.1285** |
|                    | (0.0611) | (0.0639) | (0.0638) | (0.0615) | (0.0564) |
| **Inflation**      | -0.2790*** | -0.2788*** | -0.2814*** | -0.2764*** | -0.2882*** |
|                    | (0.1016) | (0.1005) | (0.1022) | (0.1014) | (0.1003) |
| **Interest rate**  | -0.4108 | -0.3872 | -0.3673 | -0.3517 | -0.4024 |
|                    | (0.2624) | (0.2686) | (0.2544) | (0.2676) | (0.2636) |
| **Exchange rate**  | -0.0402 | -0.0307 | -0.0191 | -0.0088 | -0.0641 |
|                    | (0.2864) | (0.2932) | (0.2818) | (0.2891) | (0.2847) |
| **Economic activity** | 0.3244*** | 0.3567*** | 0.3454*** | 0.3633*** | 0.3519*** |
|                    | (0.1177) | (0.1206) | (0.1191) | (0.1194) | (0.1180) |
| **Total employment** | -0.3212*** | -0.3425*** | -0.3535*** | -0.3443*** | -0.3402*** |
|                    | (0.1074) | (0.1084) | (0.1062) | (0.1085) | (0.1082) |
| **Agriculture's employment share** | -0.0751 | -0.0447 | -0.0235 | -0.0448 | -0.0555 |
|                    | (0.1018) | (0.1025) | (0.1035) | (0.1035) | (0.1026) |
| **Exports**        | 0.0107 | 0.0489 | -0.2962** | 0.0428 | 0.0377 |
|                    | (0.1067) | (0.1112) | (0.1475) | (0.1115) | (0.1141) |

**Fixed effects**

|                   | Model |       |       |       |     |
|--------------------|-------|-------|-------|-------|-----|
| **Asset * months-to-expiration** | Yes | Yes | Yes | Yes | Yes |
| **Quarter**        | Yes | Yes | Yes | Yes | Yes |
TABLE 6 (Continued)

| Dependent variable Hedge efficiency |
|-------------------------------------|
| Model (I) (II) (III) (IV) (V)       |
| Fit statistics                      |
| Observations                        | 7263 | 7263 | 7263 | 7263 | 7263 |
| $R^2$                               | 0.32753 | 0.32139 | 0.34162 | 0.31975 | 0.32637 |
| Within $R^2$                        | 0.08352 | 0.07516 | 0.10273 | 0.07293 | 0.08195 |

Note: This table presents estimated results by ordinary least squares of Equation (7) in the text for the whole Brazilian commodity futures markets adding up each different economic indicator interacted with COVID-19 dummy variable (Column I includes months to expiration, Column II includes money volume, Column III includes market depth, Column IV includes basis risk, and Column V includes volume). We use panel data from January 2018 to December 2020 which includes daily observations for each contract negotiated in a particular business day for that commodity at Brasil, Bolsa, Balcao. We compute the monthly value from the daily observations. We also subtract the mean then divide by the standard deviation of all numeric explanatory variables. We use (i) asset fixed effects to absorb asset-specific nonobservables that are time-invariant and (ii) asset-months-to-maturity fixed effects to compare subgroups of assets within the same contract. Therefore, we investigate if COVID-19 is correlated with hedge efficiency, which transmission channels are associated with hedge efficiency, and which financial indicator is related to amplification or mitigation of the pandemic. Standard errors are clustered at the asset-expiration level, and they are presented inside parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

TABLE 7 Regression of hedge efficiency on all commodities (entire future market) and on economic indicators during COVID-19

| Dependent variable Hedge efficiency |
|-------------------------------------|
| Model (I) (II) (III) (IV) (V) (VI) |
| Variables                           |
| COVID-19$_t$                        | $-1.281^{***}$ | $-1.304^{***}$ | $-1.233^{***}$ | $-1.341^{***}$ | $-0.9049^{**}$ | $-1.151^{***}$ |
|                                          | (0.3130)       | (0.3504)       | (0.3008)       | (0.3069)       | (0.3717)       | (0.3024)       |
| COVID-19$_t$ × Inflation$_t$          | $-0.2186$      |                 |                 |                 |                 |                 |
|                                          | (0.1520)       |                 |                 |                 |                 |                 |
| COVID-19$_t$ × Interest rate$_t$      |                 | $-0.1070$       |                 |                 |                 |                 |
|                                          |                 | (0.2349)        |                 |                 |                 |                 |
| COVID-19$_t$ × Exchange rate$_t$      |                 |                 | 0.2315          |                 |                 |                 |
|                                          |                 |                 | (0.2687)        |                 |                 |                 |
| COVID-19$_t$ × Economic activity$_t$  |                 |                 |                 | $-0.2977^{***}$ |                 |                 |
|                                          |                 |                 |                 | (0.0945)        |                 |                 |
| COVID-19$_t$ × Agriculture's employment share$_t$ |                 |                 |                 |                 | 0.2109*$       |                 |
|                                          |                 |                 |                 |                 | (0.1261)        |                 |
| COVID-19$_t$ × Exports$_at$           |                 |                 |                 |                 |                 | 0.2961$^{***}$ |
|                                          |                 |                 |                 |                 |                 | (0.0836)        |
| Money volume$_at$                     | $-0.0257$       | $-0.0232$       | $-0.0228$       | $-0.0307$       | $-0.0255$       | $-0.0305$       |
|                                          | (0.0411)        | (0.0408)        | (0.0414)        | (0.0422)        | (0.0400)        | (0.0397)        |
| Market depth$_at$                     | 0.0498          | 0.0554          | 0.0549          | 0.0499          | 0.0569          | 0.0376          |
|                                          | (0.0359)        | (0.0363)        | (0.0363)        | (0.0357)        | (0.0363)        | (0.0361)        |
| Basis risk$_at$                       | 2.617           | 2.366           | 2.409           | 2.570           | 2.168           | 2.339           |
|                                          | (2.105)         | (2.154)         | (2.120)         | (2.066)         | (2.177)         | (2.121)         |
| Volume$_at$                           | 0.1025$^{**}$   | 0.1018$^{**}$   | 0.1001$^{**}$   | 0.1112$^{**}$   | 0.1107$^{**}$   | 0.1033$^{**}$   |
|                                          | (0.0495)        | (0.0486)        | (0.0495)        | (0.0504)        | (0.0461)        | (0.0481)        |

(Continues)
expiration could indicate any heterogeneity in hedge efficiency across commodities of the same nature but that mature in the short and long term due to different expectations about prices at maturity. We expect that markets with bigger depth are less affected by the pandemic, since higher liquidity correlates with lower basis, that is, increasing the futures–spot prices correlation and increasing hedge efficiency as consequence.

Results shown in Table 6 also confirm the significance of the correlation between COVID-19 pandemic and hedge efficiency. As we included financial indicators interacting with the pandemic dummy variable terms, \( \beta \) remained significant regardless of the indicator included and kept the same negative relation, thereby providing strong evidence that COVID-19 is negatively related to hedge efficiency. These findings are in accordance with H. Zhang et al. (2021) about the possibility that, after the COVID-19 outbreak, investors needed to adjust their portfolio strategies, and in the case of commodities futures, they moved capital away from them. Also, we showed strong evidence that, similar to the findings about the stock market, commodity futures suffered a negative shock during the pandemic.

### Table 7 (Continued)

| Dependent variable | Hedge efficiency |
|--------------------|------------------|
|                    | (I)  | (II) | (III) | (IV) | (V)  | (VI) |
| Inflation\(_t\)    | -0.0662 | -0.0857* | -0.0733* | -0.0585 | -0.0809* | -0.0872* |
|                    | (0.0411) | (0.0449) | (0.0399) | (0.0432) | (0.0456) | (0.0447) |
| Interest rate\(_t\) | -0.1833 | -0.1020 | -0.0927 | -0.1571 | 0.0122 | -0.1380 |
|                    | (0.1458) | (0.1726) | (0.1509) | (0.1396) | (0.1716) | (0.1397) |
| Exchange rate\(_t\) | 0.2006 | 0.2317 | 0.1262 | 0.1905 | 0.2303 | 0.2341 |
|                    | (0.1586) | (0.1614) | (0.1364) | (0.1641) | (0.1648) | (0.1654) |
| Economic activity\(_t\) | 0.2591*** | 0.2071*** | 0.2072*** | 0.3234*** | 0.1912*** | 0.2161*** |
|                    | (0.0700) | (0.0612) | (0.0550) | (0.0697) | (0.0638) | (0.0594) |
| Total employment\(_t\) | -0.1637*** | -0.1492*** | -0.1140 | -0.1407** | -0.0921 | -0.1614*** |
|                    | (0.0610) | (0.0686) | (0.0712) | (0.0628) | (0.0797) | (0.0612) |
| Agriculture’s employment share\(_t\) | 0.0851 | 0.0446 | 0.0464 | 0.0867* | 0.0181 | 0.0543 |
|                    | (0.0528) | (0.0490) | (0.0486) | (0.0504) | (0.0503) | (0.0493) |
| Exports\(_at\) | -0.1199** | -0.1196** | -0.1243** | -0.1200** | -0.1189** | -0.1714*** |
|                    | (0.0588) | (0.0587) | (0.0591) | (0.0569) | (0.0582) | (0.0564) |

### Fixed effects

| Asset * Months-to-expiration | Yes | Yes | Yes | Yes | Yes | Yes |
|-------------------------------|-----|-----|-----|-----|-----|-----|
| Quarter                      | Yes | Yes | Yes | Yes | Yes | Yes |

### Fit statistics

| Observations | 15,489 | 15,489 | 15,489 | 15,489 | 15,489 | 15,489 |
|---------------|-------|-------|-------|-------|-------|-------|
| R\(^2\)       | 0.27259 | 0.27011 | 0.27112 | 0.27717 | 0.27183 | 0.27372 |
| Within R\(^2\) | 0.10095 | 0.09788 | 0.09913 | 0.10661 | 0.10001 | 0.10235 |

Note: This table presents estimated results by ordinary least squares of Equation (7) in the text for the whole Brazilian commodity futures markets adding up each different economic indicator interacted with COVID-19 dummy variable (Column I includes inflation, Column II includes interest rates, Column III includes exchange rate, Column IV economic activity, Column V include agriculture’s employment share, and Column VI includes exports). We use panel data from January 2018 to December 2020 which includes daily observations for each contract negotiated in a particular business day for that commodity at Brasil, Bolsa, Balcão. We compute the monthly value from the daily observations. We also subtract the mean then divide by the standard deviation of all numeric explanatory variables. We use (i) asset fixed effects to absorb asset-specific nonobservables that are time-invariant and (ii) asset-months-to-maturity fixed effects to compare subgroups of assets within the same contract. Therefore, we investigate if COVID-19 is correlated with hedge efficiency, which transmission channels are associated with hedge efficiency, and which economic indicator is related to amplification or mitigation of the pandemic. Standard errors are clustered at the asset-expiration level, and they are presented inside parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.
Also in Table 6 there is evidence that market depth is not associated with hedge efficiency in pre-COVID periods but it becomes significant during the pandemic. The coefficient is positive, what confirms the intuition that higher liquidity is related to high hedge efficiency. Thus, we found support to the theory elaborated by Acharya et al. (2013) in the sense that, during COVID-19, speculators’ capital constraints and commodity producers’ hedging demand may have increased, thereby increasing hedging costs through pressure on futures prices, which causes frictions between futures and spot prices through changes in both producers’ equilibrium hedging and supply decision.

In Table 7, we found that economic activity during the pandemic is related to the amplification of its negative effect on hedge efficiency, and that agriculture’s employment share and exports are correlated with the mitigation of COVID-19 impacts. These findings expand the scope of analysis focused on financial aspects of the crisis (Akhtaruzzaman et al., 2021; Chemkha et al., 2021; H. Zhang et al., 2021) and show that factors other than financial markets are also relevant for understanding hedge efficiency in pandemic times. Moreover, we evidence that commodity prices are not only related to long-run economic performance, as studied by Kang and Kwon (2020), but also to short-term events. Therefore hedge efficiency in emerging market commodity futures markets is closely related to both financial and economic variables.

5 | CONCLUSIONS

The emergence of the novel coronavirus (COVID-19) has generated an unprecedented challenge to authorities worldwide. Given the widespread and ongoing transmission of the novel coronavirus, governments announced social distancing, quarantine, and lockdown measures to mitigate the effects of the virus. These measures provoked economic downturns all over the world as countries experienced recessions, rising inflation, and unemployment. Alongside sanitary and economic turmoil, financial markets also took a tumble, which includes facts such as that exchanges worldwide lost nearly 30% of wealth in a 100-day time window, and an increase in market volatility influenced by sentiment generated by coronavirus-related news.

We consider all commodities prices traded at B3 up to the current date, which can be grouped into two different types: agricultural and energy. We include livestock cattle, corn, coffee (arabica), and soybeans as agricultural, and ethanol as the only energy commodity. To perform market unbiasedness and futures prices as accurate predictors of future–spot prices hypotheses testing we compute individual time-series database from the broader panel for each commodity. About the transmission channels, we use the original panel data to test our set of hypotheses.

Our main findings are that commodities futures markets in Brazil are neither efficient nor futures prices are unbiased and/or accurate predictors of subsequent spot prices. In addition, COVID-19 is negatively related to hedge efficiency in Brazilian commodities futures, and its association is relevant or not depending on the commodity. Some macroeconomic variables are correlated with hedge efficiency during normal times and these same variables tend to relate as amplifying or mitigating factors during the pandemic. We also found evidence that liquidity during the pandemic is correlated with hedge efficiency.

The data we use in this study help shed a preliminary light on this issue, but it would be desirable to use new information about the market microstructure of commodity futures markets. An important task for future research is therefore to include databases which allow for causality empirical investigation. By including, for example, individual decision-making data, randomization and the establishment of control and treatment groups will be much more handy and one will be able to test if these associations have indeed causal status or are only strong correlations.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Figshare (Magalhães et al., 2022) at https://doi.org/10.6084/m9.figshare.19699795.v1.
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