Liquid Prophecy: The Unseen Predictive Power of Oil Futures and Their Role as a Strategic Hedge

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Abstract

This paper investigates the influence of major world event related fears and speculations on oil market prices. Specifically, we examine the relationship between the Efficient Market Hypothesis and the predictive capabilities of front-month oil future prices for imminent, or market perceived imminent, drastic global geopolitical shifts. Through statistical testing and time series analysis of historical data between oil front-month futures and prediction market event contracts, we find that oil futures act as a proxy of prediction markets in times preceding these significant world events. Our results uncover insights for policymakers on assessing the probability of risks during these periods of time. Furthermore, we propose the potential of oil futures and other commodities as a hedging tool against such risks, attributed to their significant correlation with market speculations regarding these events.

Contents

1 Background

1.1 Oil Front Month Futures

In the scope of global energy markets, front-month oil futures contracts stand out as a significant benchmark, instrumental in defining the current economic state of energy commodities. These futures contracts, representing agreements to buy or sell oil at a predetermined price on a specified date in the nearest future month, serve as a barometer for market sentiment and future price expectations. Traded on major futures exchanges, such as the Intercontinental Exchange (ICE) and the New York Mercantile Exchange (NYMEX), these contracts are not merely financial instruments but are foundational to the process of price discovery in oil markets worldwide.

Oil futures are priced based upon both informed and uniformed flow, which can cause some deviations in their pricing - as is true with almost any product in the market. For example, an airline company might buy oil futures due to their natural exposure to the price of oil - if the price of oil skyrockets, the company is at risk of potentially losing billions of dollars. To balance out this risk, the company buys oil futures to provide a safety net in such circumstances. These firms do not necessarily care if the price at which they pay is not hyper-optimal because they need to make the purchase from a pure risk standpoint (this is known as hedging, which we will discuss more later). This is an example of uniformed flow.

Informed flow, such as that from quantitative hedge funds, will take the opportunity to trade oil back to their theoretical fair value and keep markets efficient from the drift as a result of otherwise uniformed flow.

1.2 Prediction Markets

A prediction market, also known as an information market or forecast market, is a platform where individuals can buy and sell contracts based on their predictions about the outcome of future events. These markets leverage the wisdom of the crowd by aggregating diverse opinions and information held by participants, thus producing a collective forecast of possible outcomes. These events encompass general outcomes, for example, prediction markets can allow you to trade contracts on the event of 'Presidential Election Winner 2024'. The underlying principle of prediction markets is based on the Efficient Market Hypothesis, which posits that asset prices fully reflect all available public and private information. As participants trade shares of outcomes, the price of these shares implicitly reflects the probability of the event occurring. Since prediction markets are centered around a specific event, they provide a dynamic, real-time forecast of market sentiment on specific future events.

Prediction markets are incredibly precise. Several factors contribute to the accuracy of prediction markets, which has been shown to be significantly better than traditional polling methods. First, prediction markets incorporate both public and private information held by participants, whereas polls typically measure public opinion at a single point in time without accounting for the depth of knowledge or certainty behind those opinions. Secondly, the financial incentive structure of prediction markets encourages participants to truthfully reveal what they believe will happen, rather than what they hope will happen or what they think others believe. The financial stake in the accuracy of their predictions often leads to more deliberate and informed decision-making. Additionally, prediction markets are dynamic, allowing for continuous updating of predictions as new information becomes available, unlike polls which offer only a snapshot in time.

Research has supported the efficacy of prediction markets in outperforming polls in various contexts, from political elections to economic forecasts. For instance, a study by Berg, Nelson, and Rietz (2008) demonstrated that prediction markets were more accurate than polls in predicting the outcomes of U.S. presidential elections between 1988 and 2004. Similarly, Tziralis and Tatsiopoulos (2007) found that prediction markets could effectively forecast technological innovations, offering more precise predictions than expert opinions or traditional forecasting methods.

1.3 Hedging

Hedging, at its core is a way to prevent, or mitigate, undesirable outcomes. Most people are probably aware of the concept of hedging, even if the name is unfamiliar. Take the case of fire insurance as an example. An individual pays premiums to an insurance company so that in the case of a fire, the individual has mitigated their financial downside.

Hedging almost always comes at a cost - to intuitively see why this is the case, the insurance company that sells individual fire insurance expects to turn a profit from selling such plans; individual policy holders, on the aggregate, lose money from having such plans. Interestingly, this does not mean that the transaction is zero-sum. Even though the insurance company profits from the difference between the premiums paid by individuals and the amount that they need to pay for coverage, the individual who purchased the plan gains value from knowing that they are never at risk of losing the value of the insured hose in the event of a fire. This downside protection provides utility to the individual beyond the loss in expected value that the insurance company gains and therefore makes this a mutually beneficial transaction (if it were not at least perceived to be mutually beneficial then the transaction for the policy would not occur in the first place).

In essence, hedging is a trade-off of expected value and variance and because different market participants have different utilities of these, that allows for trading to occur. (The insurance company is willing to take on the variance of homes burning down in exchange for the positive expected value, and the policyholder is willing to lower their variance for a loss in expected value; the two entities therefore have different views of utility on the same event).

1.3.1 Manifold Markets

Manifold Markets is an online, prediction market exchange that lets users create and and trade contracts that settle with binary outcomes.

1.3.2 PolyMarket

PolyMarket is an online, decentralized prediction market exchange that lets users trade contracts that settle with binary outcomes.

2 Introduction

2.1 Motivation

In 2023, Byrne Hobart gave a speech at Manifest in which he talked about the Efficient Market Hypothesis and how it has caused markets to be extremely efficient in recent times. To illustrate this, he showcased a Manifold question which asked "Will Russia invade Ukrainian territory in 2022?" which showed the traded prices, or percentage chance, that this contract was traded at leading up to the invasion.

Immediately, this figure passes the eye-test. In fact, one might be surprised at how realistically the prediction market seems to assess the probability of Russia Invading Ukraine. However, the market Bryne showcased was later revealed to be edited - this graph is not the price at which the prediction market was traded at, but rather the graph of the front-month Brent Crude Oil futures during the exact same time period. The probability of Russia invading Ukraine was one of the leading driving factors of its price at the time, which is why the picture was so convincingly deceitful - it passes for a prediction market of Russia invading Ukraine.

Due to the fact that oil futures are so actively traded - they are one of the most liquid commodities in the world, selling over 1 million contracts daily - market participants that trade it are therefore forced into being good predictors of world events. This means that if oil futures could be used similarly

Figure 1: Voting on "Will Russia invade Ukrainian territory in 2022"

to a prediction market, the information it represents would be an even better representation of the implied market probability than a less liquid prediction market. Here, when we say implied market probability, we mean the percentage chance the market is giving to the event which corresponds to the dislocation between the current valuation and what the valuation that the contract would have had the market collectively thought there was no chance of an event.

We've seen some brief similarities between prediction markets and oil futures. However, there is a glaring difference between the two: prediction markets are conditioned around a singular event, while oil futures are responsive to a variety of events. So when and how can we frame oil futures as prediction markets?

2.2 Proposed Question

How do the intricacies of oil market dynamics, specifically shifts in pricing, act as precursors to geopolitical conflicts and political destabilization, and what proactive strategies can nations employ to shield their economies and ensure sustainability in the face of such adversities?

2.3 Our Intuition

In the time period preceding world-altering events, for example, war, public opinions of these events will become a major driving factor in the pricing of oil futures. Another way of stating this is that out of all the various factors that influence oil future pricing, the implied market probability - represented through prediction markets - of world-altering events explains a majority of the variance of oil futures pricing. For example, if the market believes strongly that war is imminent, the mass purchasing of oil futures in anticipation of price increases will drive up the current price. Informed flow will pressure futures to move to a fair market price that incorporates all private and public knowledge of the event occurring. The influx of informed flow causes the oil futures price to have similar predictive capabilities to a prediction market for the corresponding event.

3 Russia's Invasion of Ukraine Case Study

3.1 Summary of Exploration

For our first case study, we sought to examine if the market's perceived probability of Russia invading Ukraine is reflected through oil future prices. We took a prediction market traded on Manifold Markets and assessed its relationship with oil futures during the corresponding time period, roughly spanning the month before Russia's invasion of Ukraine. We also explored the relationship between the prediction market and the natural gas spot price as a proxy of its influence in the broader commodity space.

3.2 Expectations

Before initiating our investigation, we hypothesized a strong link between increasing oil prices and the perceived probability of Russia invading Ukraine with a peak price at the time of the invasion. This is because as the market believes more strongly that war is imminent, the response will be to buy oil futures, which will drive up the prices of oil. This represents the influx of informed flow as a result of the increase in implied market probability of Russia invading Ukraine.

3.3 Exploration of Data

For this case study, we used the provided commodities dataset and the prediction market data concerning the event of Russia's invasion of Ukraine. We will briefly discuss each dataset and how they were cleaned.

The commodities dataset has historical data for daily prices. For the purpose of this analysis we looked at the daily close price as a way to reduce prices to a singular value on each given day.

In order to get a single value for every given day on the Manifold Market data, we used a time weighted adjusted price (TWAP). This was to account for the fact that each given price was not available and there was not a 'closing' value as the prediction market was traded 24/7.

$$\text{TWAP} = \frac{\sum_{t=1}^{T} P_t \cdot \Delta t}{\sum_{t=1}^{T} \Delta t} \tag{1}$$

We further smoothed the data by incorporating a five (5) day exponential weighted moving average (EWM) to all values used as this helped to eliminate noise, which can be seen in Figures 2 and 3. The data encompasses the dates from January 3, 2022, to February 24, 2022. February 24, 2022 was the date when Russia officially commenced the invasion of Ukraine. We eliminated weekends from our analysis as we were not provided with after market hours and did not deem it a fair assumption to simply interpolate Friday to Monday. As such, we had 39 dates to analyze in the time prior to February 24, 2022.

$$\begin{aligned} \text{EMA}_t &= \alpha \cdot P_t + (1-\alpha) \cdot \text{EMA}_{t-1} \\ \alpha &= \frac{2}{n+1} \end{aligned} \tag{2}$$

Prices were normalized on a 0 to 1 scale so that different products could be shown with their relative price movements over the time period next to one another.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{3}$$

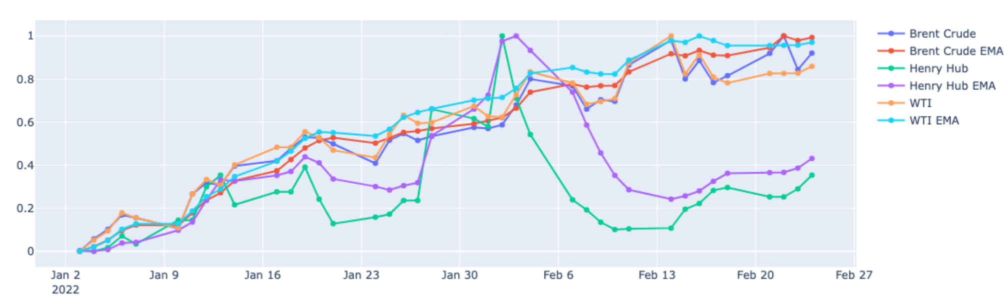

Figure 2: Normalized Oil and Natural Gas Prices from 01/03/2022 to 02/24/2022

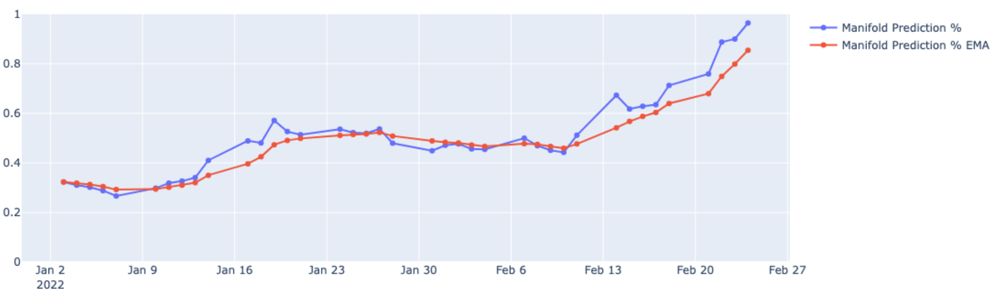

Figure 3: Manifold Markets Prediction of Russian Invasion of Ukraine Before 2023

3.4 Results

3.4.1 Correlation Results

We used the Pearson correlation coefficient to determine a relationship between the prediction market of Russia invading Ukraine and the oil futures/natural gas price data (Figure 4).

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{4}$$

We used a two-tailed t-test to report on the statistical significance of each of the correlation coefficients. These are listed in the table below (Table 1). The t-value is given by:

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \tag{5}$$

where n is the number of data samples. The degrees of freedom is given by $n-2$, which in this case is 37.

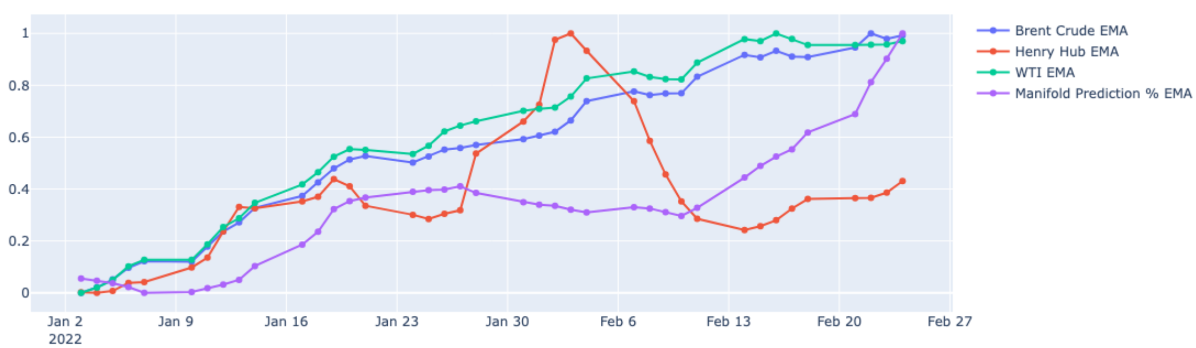

Figure 4: Smoothed Oil, Gas, and Manifold Prediction Values

Table 1: Correlation Coefficients of Commodities vs Russia Invasion of Ukraine Prediction Market

	Pearson Correlation Coefficient	Two-Tailed T Statistic	P-Value
Brent Crude	0.873	10.872	« 1e5
WTI	0.835	9.24	« 1e5
Henry Hub	0.308	1.972	0.056

3.4.2 Distribution Analysis

Next, we performed an analysis on the distribution of the data. Contrary to our expectation of a high Pearson correlation coefficient, we did not expect that the distribution of the oil futures data is the same as the distribution of the prediction market values. This is due to the fundamental difference in the trading of prediction markets and futures, namely that prediction events are related to a single event while stocks have many variables that effect their price. Furthermore, prediction markets lack the abundant liquidity that is seen in commodities so there is less informed flow keeping prices in line. This means that the prediction markets have a higher variance than the oil futures, which is why oil futures seem like a smoothed version of the prediction market values.

Ensuring that these datasets have different underlying distributions is key to ensuring the benefits of using oil futures as a proxy to the prediction markets. Using an indicator with less variance allows users to make more informed decisions.

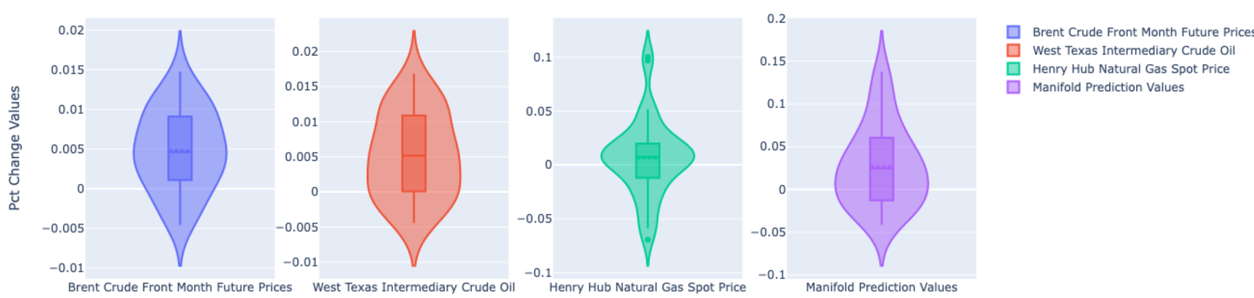

Figure 5: Violin Plot of Percent Change Day-to-Day Values

We first visualize the violin plot to get a general understanding of the shapes and spreads of our data (Figure 5). An important note is that we are using the percent change for each of the variables, which is given by the formula below.

$$PercentageChange = \frac{NewValue - OldValue}{OldValue} \tag{6}$$

We use this to address the problem of non-stationary and auto-correlated nature of the data. Using the percent change reduces the effects by making the data stationary.

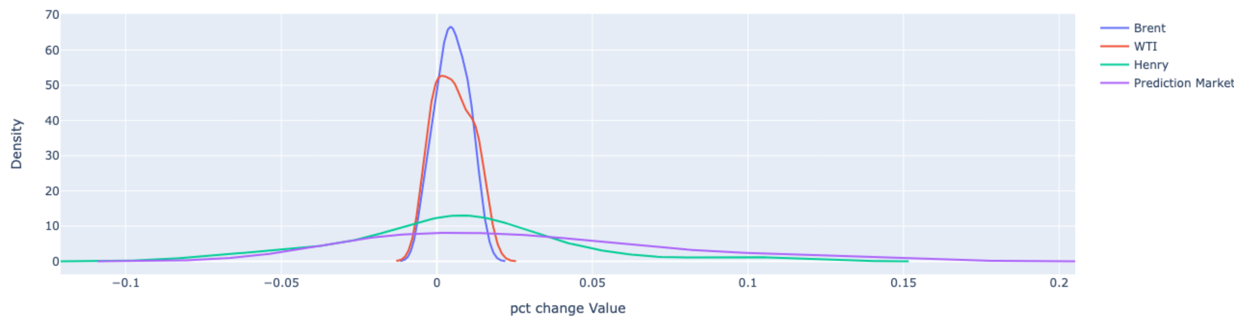

Figure 6: Kernel Density Estimate (KDE) of Commodities and Prediction Market Values

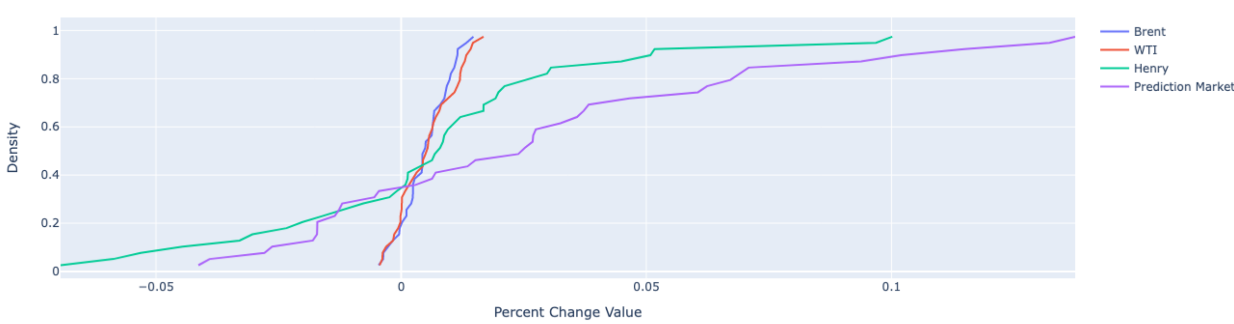

Figure 7: Empirical Cumulative Distribution Function (ECDF) of Commodities and Prediction Market Values

We next analyze the Kernel Density Estimate (KDE) plots and the Empirical Cumulative Distribution Function (ECDF) plots for the values of the commodities and prediction market. These plots give us an estimate of the underlying probability density function (PDF) and cumulative density function (CDF) of the dataset, which are essential to understanding more intricate details of the underlying distributions.

Kernel Density Estimate (KDE) is a non-parametric method of estimating the underlying PDF of a distribution. The essence of the algorithm is placing Gaussians (or any other kernel shape) centered at each data point, summing them up, and normalizing to get a probability density function. It is effectively smoothing out the data while retaining information on the shape and characteristic of the distribution.

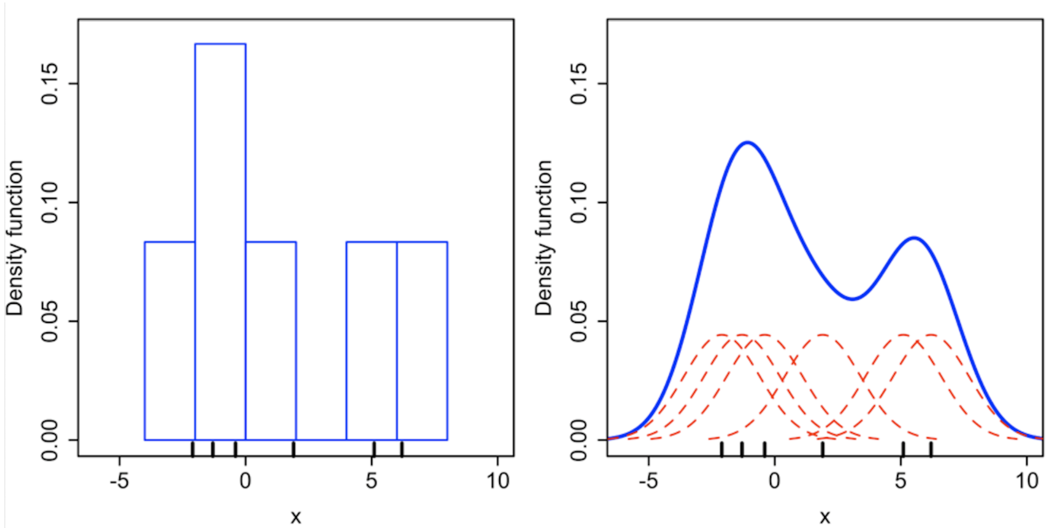

Figure 8: Visualization of KDE

Empirical Cumulative Distribution Function (ECDF) is a non-parametric method of estimating the underlying CDF of a distribution. This algorithm involves sorting the data and assigning probabilities to points based on the proportion of data points less than or equal to it.

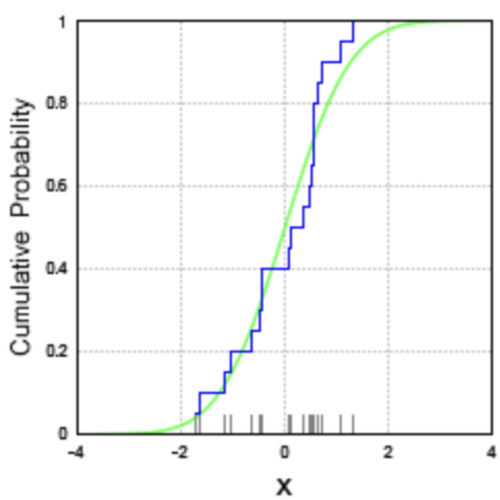

Figure 9: Visualization of ECDF

We can now see clearly that there is a stark difference in the distributions of data. We can see that the Brent futures and the WTI futures have similar PDFs and CDFs, and the Henry Hub natural gas somewhat resembles the Prediction Market values. We are unsure as to why the statistics of the Henry Hub natural gas spot price are more similar to the prediction market values than oil futures, which is something we hope to explore in the future.

To quantitatively assess the similarities of these distributions, we employ a Kolmogorov-Smirnov test (KS test). The null hypothesis that these datasets are from the same distribution. The KS statistic represents the biggest absolute value difference between the datasets, and the p-value probability of observing a KS statistic as extreme as the one observed in the sample data, assuming that the null hypothesis is true. So, a small p-value indicates that the observed data significantly deviates from the null hypothesis, suggesting that the datasets likely come from different distributions. A large p-value, on the other hand, suggests that the observed data is consistent with the null hypothesis, indicating that there is insufficient evidence to reject the null hypothesis.

Table 2: KS test Statistics of the Similarity of Distribution between Commodities and Russia Invasion of Ukraine Prediction Market Values

	KS Test Statistic	**P-value**
Brent Crude	0.538	1.56e-05
WTI	0.513	4.933e-05
Henry Hub	0.308	0.05

3.5 Summary of Results

We find that the Brent Crude futures, WTI futures, and Henry Hub spot prices all have statistically significant results at the $p = 0.1$ level. Thus, we reject the null hypothesis that there is no correlation between these commodities and the prediction market probabilities. We opted for a $p = 0.1$ significance level rather than the standard $p = 0.05$ level due to the fact we have fewer data points, thus warranting a higher level to reject the null hypothesis.

We also find that our KS p-value statistics are statistically significant at the $p = 0.1$ significance level. This provides statistical evidence to reject the null hypothesis for our distribution tests. This means we find evidence to support our hypothesis that the datasets have different underlying distributions.

Combining these results presents an interesting relationship. The oil future data is highly correlated to the prediction market data, but they have different underlying distributions. This relationship can be intuited as follows: when the prediction market values go up, the oil futures prices go up as well. However, the relationship between the amount each value goes up is a more nuanced relationship that is not directly linear. Such a relationship would have to be more deeply explored as it must involve the other pricing components of commodities to more precisely determine the exact relationship.

We note that Russia is one of the world's foremost produces and suppliers in both oil and natural gas, and as such these commodities would be highly effected by Russia's involvement in war. We notice that the correlation coefficient of the Natural Gas is lower than the oil futures prices, which we attribute to the seasonality and use of these commodities. Natural gas is primarily used for heating and electricity applications, which see all time lows in the seasons of fall and spring. Given that spring was approaching, we would actually expect a seasonal decrease in natural gas prices. Despite oil also exhibiting seasonality in its price trends, the extent to which it happens is significantly lesser due to its wider application usage; we would therefore see the Russia conflict contribute more to its price than natural gas.

Such a strong correlation provides evidence for the claim that oil futures acted as a smoothed proxy to a prediction market in the months prior to Russia's invasion of Ukraine.

4 Hamas Ceasefire Case Study

For our second case study, we decided to examine a recent event to determine this strategy's viability to future events. Although neither Israel nor Palestine are leading exporters of oil or gas, we decided to observe the relationship between oil future front month prices and the Israel-Hamas ceasefire prediction market to understand the extent to which oil futures can be viewed as a proxy for prediction markets for world events outside of countries that are major exporters for those specific commodities. We note that it is more likely that commodities that are directly effected by conflict will likely reflect higher correlation with the corresponding prediction market.

4.1 Expectations

For this case study, we hypothesized a strong link between decreasing oil prices and the perceived probability of the Israel and Hamas ceasefire, with a low at the time of a ceasefire. A ceasefire constitutes a lack of conflict, or at a minimum a reduced conflict, hence the relationship would be inverse to the Russia-Ukraine case study that we examined.

4.2 Exploration of Data

We used similar data cleaning and sourcing techniques as for our first study, with the only change being that we used the corresponding prediction market to the Israel-Hamas ceasefire. This prediction market data was similarly smoothed using a five (5) day exponential weighted moving average. We include Figures 7 and 8 to have a visual display of the trends of each of the commodities and the prediction market. The data encompasses the dates from October 27, 2023, to November 24, 2023. The PolyMarket prediction market has data until November 24, 2023, which was the date when Israel and Hamas agreed to a temporary ceasefire. We again eliminated weekends from our analysis for pricing comparison concerns. As such, we had 21 dates to analyze in the time prior to November 25, 2022.

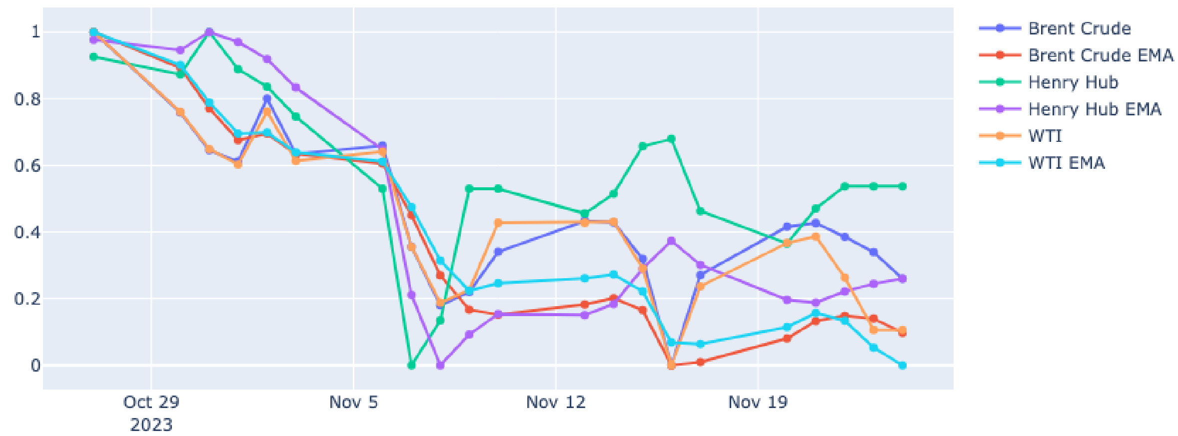

Figure 10: Normalized Oil and Natural Gas Prices from 10/27/2023 to 11/24/2023

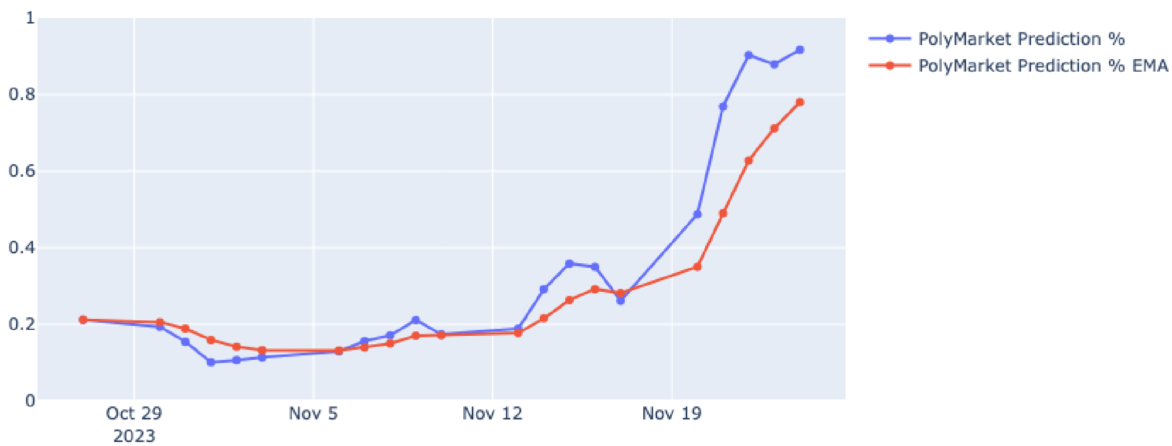

Figure 11: PolyMarket Prediction of Israel and Hamas Ceasefire before November 30

4.3 Results

4.3.1 Correlation Analysis

We use the Pearson correlation coefficient to determine a relationship between the prediction market of Israel-Hamas ceasefire and the oil futures/natural gas price data (Figure 10 and Figure 11). We use a two-tailed t-test with 19 degrees of freedom to report on the statistical significance of each of the correlation coefficients. These are listed in the table below (Table 3).

Table 3: Correlation Coefficients of Commodities vs Israel-Hamas Ceasefire Prediction Market

	Pearson Correlation Coefficient	Two-Tailed T Statistic	P-Value
Brent Crude	-0.471	-2.326	0.031
WTI	-0.588	-3.167	0.005
Henry Hub	-0.332	-1.533	0.142

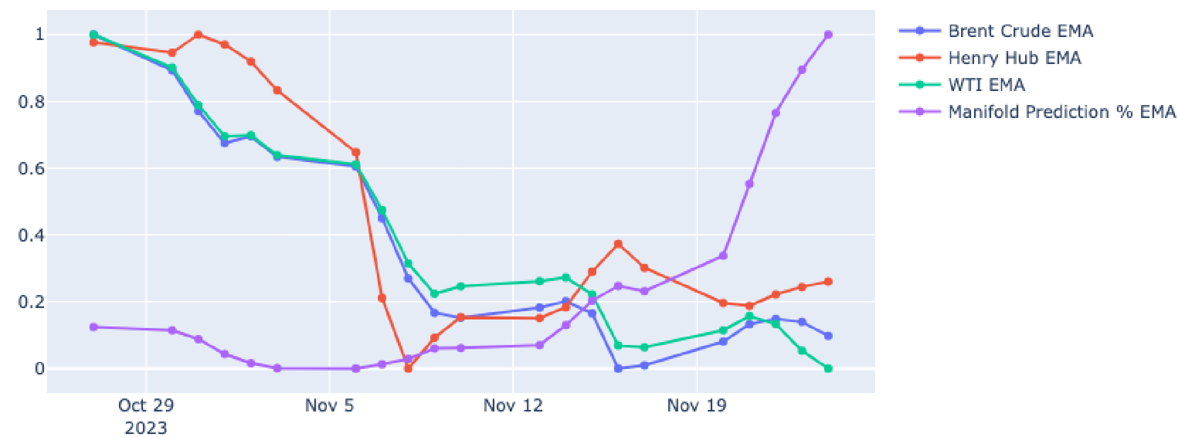

Figure 12: Smoothed Oil, Gas, and Polymarket Prediction Values

4.3.2 Distribution Analysis

Similar to the Russia-Ukraine case study, we now aim to gain an understanding of the latent distribution of the data. Again, we expect to see differences in the distributions of the oil and prediction market values. We again use the percent change of each of the values.

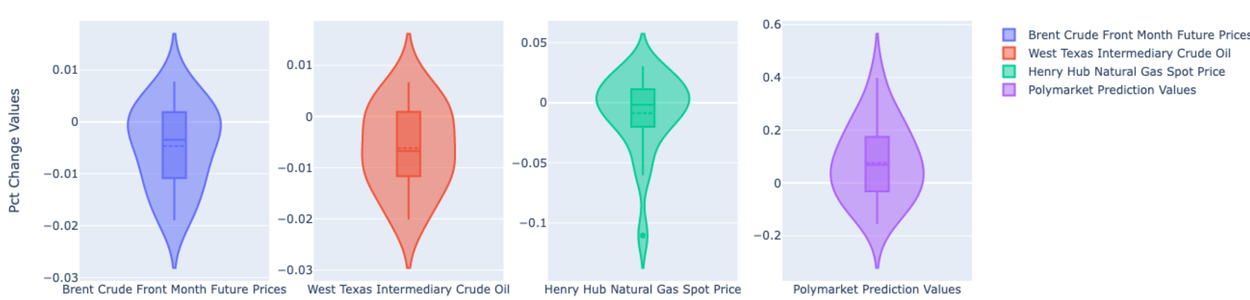

Figure 13: Smoothed Oil, Gas, and Polymarket Prediction Values

We then analyze the KDE and ECDF of the data to gain an understanding of the underlying PDFs and CDFs of the data.

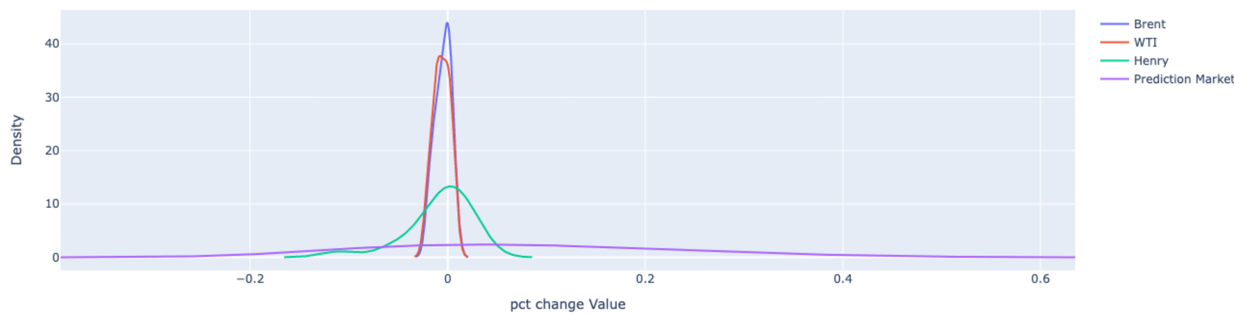

Figure 14: Kernel Density Estimate (KDE) of Commodities and Prediction Market Values

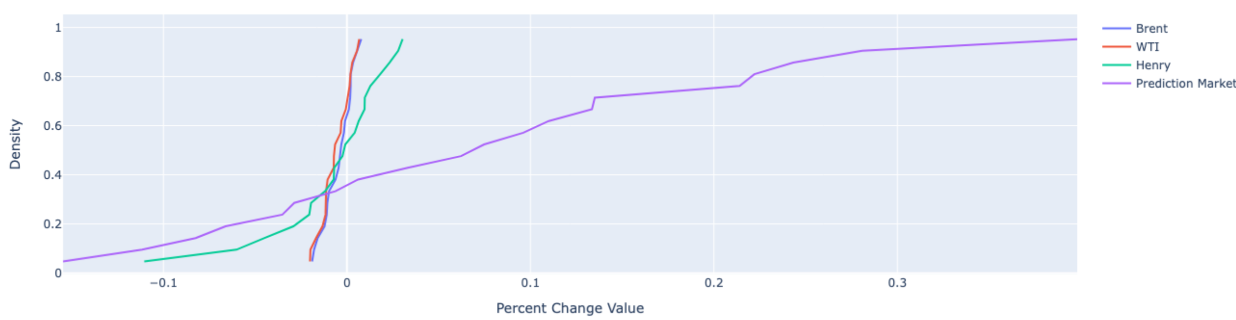

Figure 15: ECDF of Commodities and Prediction Market Values

We observe similar results to the Russia-Ukraine case study, where the pdf and cdf of the Brent Oil futures and the WTI futures are very similar. The PDF and CDF of the Prediction Market values are drastically different than the rest of the commodities.

We formalize the relationships with a Kolmogorov-Smirnov test (KS test), with the null hypothesis that these datasets are from the same distribution.

Table 4: KS test Statistics of the Similarity of Distribution between Commodities and Russia Invasion of Ukraine Prediction Market Values

	KS Test Statistic	**P-value**
Brent Crude	0.572	0.002
WTI	0.572	0.002
Henry Hub	0.572	0.002

4.4 Summary of Results

We find that the Brent Crude futures and WTI futures have statistically significant results at the $p = 0.1$ level, however, the Henry Hub natural gas spot price does not display statistically significant results.

We attribute this to the fact that oil has a larger role in the global economy than natural gas, but also, the location-specific intricacies of Israel. It is located in the Middle East, and is surrounded by many countries who's economic backbone relies upon oil. As such, we expect oil futures to be influenced much more by this conflict as opposed to natural gas. Despite it not being rigorously statistically significant, we still believe that the Henry Hub natural gas spot price visually exhibits a similar, inverse trend to the PolyMarket prediction market values.

We also find statistically significant values at the $p = 0.1$ level. Thus, we reject the null hypothesis for the distribution analysis. As expected, we find that the distribution of these commodities are different. We notice very similar KS-statistics and p-values for each of the three commodities, since these distributions are all significantly different with the respect to the prediction market values.

Again, we are able to establish a strong correlation between the oil futures and the prediction market values, while showing that the oil futures are smoothed proxies of the prediction market values.

5 Implications of Findings

We found such a strong link between oil future prices and world conflicts that we believe the commodity market can act as a proxy to prediction markets in times leading up to world altering. This means that world economies can benchmark commodities pricing to better evaluate probabilities of conflicts and, in turn, adjust actions accordingly.

5.1 Adjustments to Global Polices

In light of the findings between oil future prices and global conflicts, it is imperative for international policymakers to reassess their approach towards geopolitical intelligence and economic preparedness. Recognizing the commodity market's predictive capacity suggests a pathway for preemptive measures: by integrating commodities pricing data into strategic economic and diplomatic decision-making processes, nations can enhance their responsiveness to emerging threats. This could involve the establishment of dedicated analytical units within government economic departments or international bodies, tasked with interpreting market signals and recommending adjustments to foreign policy, trade agreements, and defense readiness in real-time.

5.2 Source of Hedging

Expanding upon the necessity for economic safeguards against the volatility induced by global conflicts, it becomes evident that a more nuanced approach to hedging is required. Just as the airline industry secures its operations against oil price surges by investing in oil futures, national economies must adopt a similar strategy tailored to their unique vulnerabilities. The concept of a 'delta' hedge against geopolitical unrest represents a sophisticated financial mechanism whereby a country's investment in futures adjusts dynamically in response to fluctuating risk levels of conflict. This strategy not only mitigates the immediate economic shocks but also strengthens a nation's capacity to provide humanitarian aid during crises.

Furthermore, while oil futures are a critical component of this hedging strategy, they are not a panacea. The optimal hedging portfolio will vary by country and should consider a diverse range of commodities and financial instruments, particularly those most relevant to the anticipated conflict zones. For instance, countries heavily reliant on agricultural imports from a region prone to unrest may benefit from futures in those specific crops.

By adopting a holistic and flexible approach to hedging against geopolitical risks, world economies can protect themselves against the direst financial repercussions of conflicts and maintain stability in the face of uncertainty.

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