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Hints of Earlier and Other Creation: Unsupervised Machine Learning in Financial Time-Series Analysis †

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Abstract: This study extends previous work applying unsupervised machine learning to commodity markets. The first article in this sequence examined returns and volatility in commodity markets. The clustering of these time series supported the conventional ontology of commodity markets for precious metals, base metals, agricultural commodities, and crude oil and refined fuels. A second article used temporal clustering to identify critical periods in the trading of crude oil, gasoline, and diesel. This study combines the ontological clustering of financial time series with the temporal clustering of the matrix transpose. Ontological clustering, contingent upon the identification of structural breaks and other critical periods within financial time series, is this study's distinctive contribution. Conditional, time-variant ontological clustering should be applicable to any set of related time series, in finance and beyond.

Keywords: unsupervised machine learning; clustering; financial time series; commodities; energy; fossil fuels

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The sea is the land's edge also, the granite
Into which it reaches, the beaches where it tosses
Its hints of earlier and other creation:
The starfish, the horseshoe crab, the whale's backbone;
The pools where it offers to our curiosity
The more delicate algae and the sea anemone.

T.S. Eliot, "The Dry Salvages", *Four Quartets* (1943) [1] (p. 36)

1. Introduction

This paper extends previous work using unsupervised machine learning to evaluate commodity markets. "Clustering Commodity Markets in Space and Time" examined returns and volatility in commodity markets [2]. That paper supported the conventional ontology of commodity markets for precious metals, base metals, agricultural commodities, and crude oil and refined fuels. These groupings emerged from the application of clustering methods and a nonlinear manifold to the matrices formed by the concatenation of daily logarithmic returns for individual commodities or conditional volatility forecasts based on a GARCH(1, 1, 1) process.

A sequel to [2], "A Pattern New in Every Moment," used temporal clustering to identify critical periods in energy-related commodity markets [3]. That article applied a suite of clustering methods to the transpose of the time-series matrix evaluated in [2]. The temporal clustering of financial markets reveals market events that can be readily interpreted as shifts in volatility, cumulative logarithmic returns, or both. As applied to energy-related commodities trading during the first two decades of the twenty-first century, temporal clustering isolated critical periods associated with wars, terrorist attacks, comprehensive economic crises, and other disruptions in energy supply or demand (Figure 1).

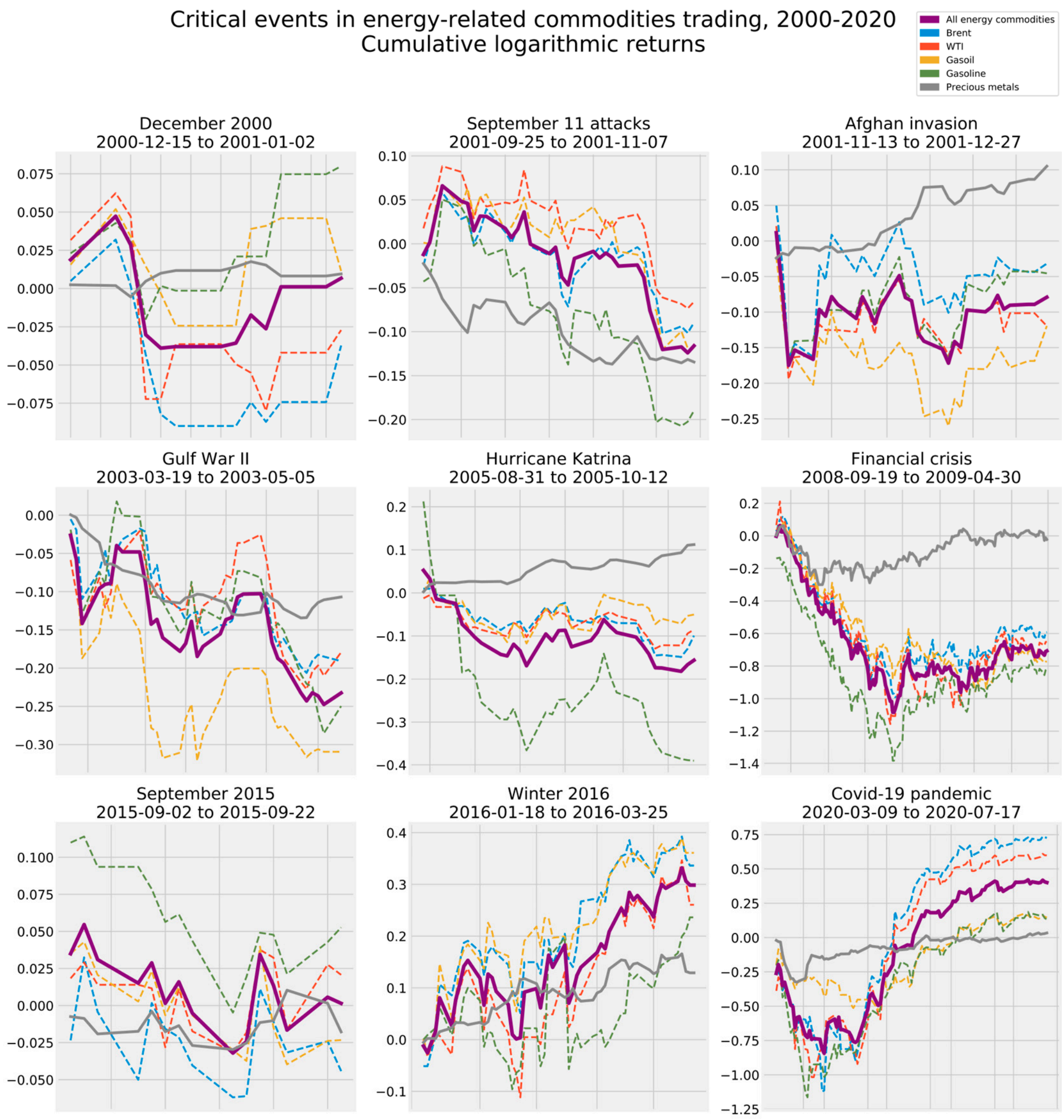

Figure 1. Cumulative logarithmic returns during critical periods for four oil and fuel commodities (dotted colored lines), with cumulative log returns on precious metals (solid gray line) as a benchmark [3] (p. 41).

This study proposes further elaborations in unsupervised machine learning. By combining the ontological (or spatial) approach to clustering of [2] with the temporal approach of [3], this study makes its own distinctive contribution to the application of unsupervised machine learning to financial time series. Ontological clustering, conditioned upon the identification of structural breaks and other critical periods, should reveal information about co-movement among asset classes and discrete assets as markets shift between normal and extraordinary states. By focusing on critical periods identified by temporal clustering, this study's novel hybrid clustering method reveals the extent, if any, to which the unconditional spatial ontology among financial assets changes under economic stress.

Together with its predecessor articles, this study expands the machine-learning toolkit for time-series analysis to three methods: (1) ontological clustering, (2) temporal clustering, and (3) the new hybrid method of conditional, time-variant ontological clustering. In principle, all three methods can be applied to any time series, in finance and beyond. Indeed, future research applying unsupervised machine learning may address forecasting tasks involving meteorology, air quality, and other environmental sciences.

This study contemplates the application of time-variant ontological clustering to markets for crude and refined fossil fuels as well as related commodities. Energy-related commodity markets are affected not only by background macroeconomic events, but also by events specific to energy markets. Shocks to supply should be distinguished from shocks to demand. Co-movement in prices for crude oil and refined fuel is asymmetrical insofar as these markets respond differently to rising and falling prices. Finally, biofuel demand affects markets for agricultural commodities that can provide human food or animal feed in addition to serving as biofuel feedstocks.

2. Materials and Methods

2.1. Materials

This study marshals market data across a variety of commodity markets, ranging from markets for crude oil, natural gas, and refined fuels to agricultural commodities and precious and base metals. Agricultural commodities are both substitutes for and complements to fossil fuels. Precious and base metals track inflation, consumer demand, and other macroeconomic conditions.

- Raw energy commodities: crude oil (Cushing and Brent) and natural gas;
- Refined energy commodities: gasoline, diesel/gasoil, and heating oil;
- Agricultural commodities: corn, soybeans, and sugar;
- Precious metals: gold, silver, platinum, and palladium;
- Base metals: copper, tin, nickel, and aluminum.

These five categories comprise 17 distinct commodity markets. Those 17 markets, in turn, are divided between six energy-specific markets and 11 commodity markets not typically regarded as energy-related. Data used in this study were drawn from Datastream and the United States Energy Information Administration. The data cover the period from 2000 to 2022.

Different combinations among commodity markets advance different research objectives. For instance, their traditional contribution to portfolio hedging and diversification enables precious metals to serve as a control variable for certain macroeconomic conditions, such as inflation or flights to safe havens [4–6]. Perhaps surprisingly, oil itself serves as a hedge, safe haven, and diversifier relative to conventional currencies during periods of turbulence [7]. Base metals indicate industrial demand, especially during declines in demand attributable to events exogenous to the business cycle, such as the COVID-19 pandemic [8].

Hypotheses anticipating asymmetric relationships between crude oil and refined fuels may be evaluated with as few as two individual commodity series, such as Brent or WTI and gasoline. Divergence between crude oil and natural gas prices may prove especially revealing. Finally, agricultural commodity markets may reveal the impact, if any, of renewable energy policies prescribing ethanol additives, E85 fuel, or biodiesel. Soft food commodities, such as corn, cotton, and cocoa, demonstrated safe-haven properties during the COVID-19 pandemic [9]. These crops are intriguingly diverse: whereas corn serves as human food, animal feed, and a biofuel feedstock, cotton is both food and fiber. As a component of sweets and a stimulant in its own right, cocoa serves more as a complement to staple grains and oilseeds than as a substitute for those crops [10].

2.2. Methods

This study applies a broad variety of clustering methods to different subsets of these commodity market time series. The clustering methods deployed in this study include spectral clustering [11–13], mean-shift clustering [14], affinity propagation [15–17], hierarchical agglomerative clustering [18], and k-means clustering [19]. A single method of manifold learning—t-distributed stochastic neighbor embedding (t-SNE)—facilitates the visualization of clusters among commodity markets [20–22]. A comprehensive discussion of those five clustering methods and *t*-SNE appears in [3] (pp. 12–14).

3. Anticipated Results

The application of conditional, time-variant ontological clustering to energy-related commodities should provide deeper insights into a wide range of contestable and controversial propositions about the behavior of these markets. Oil price shocks comprise two distinct components: effects endogenous to the global business cycle and effects specific to markets for energy-related commodities [23]. The endogenous component of oil price volatility reflects cyclical differences in the performance of equity markets in the United States and other advanced economies [24,25].

Industry-specific effects may be usefully divided according to a dichotomy between supply-side and demand-side effects [26,27]. Supply-side disruptions are conventionally ascribed to geographic events, such as storms [28,29], or to or geopolitical events, such as wars or acts of terrorism [30]. Supply-side disruptions have their most pronounced, enduring impacts on poorer countries [31,32]. Disruptions in oil supply leave an especially deep footprint on oil-exporting countries [33–36].

By contrast, many disruptions in demand arise from broader macroeconomic phenomena, such as the financial crisis of 2008–2009 and the ensuing Great Recession. Unsupervised machine learning has suggested that the COVID-19 pandemic should be evaluated as a stochastic "black swan" event in commodity markets rather than an artifact of the business cycle [3]. Demand-side effects are more pronounced in the wealthy, industrialized countries that account for most of the world's consumption of exhaustible and renewable fuels [37–39].

Refined fuel markets, particularly for gasoline, move asymmetrically vis-à-vis crude oil markets [40–43]. According to the "rockets and feathers" hypothesis, increases in crude oil prices are transmitted more quickly to gasoline than decreases [44–46]. Other sources identify Edgeworth price cycles, which are characterized by sawtooth-shaped time series consisting of many price decreases punctuated by occasional upward jumps [47,48]. Since they identify periodicity within otherwise stochastic phenomena, Edgeworth price cycles may be regarded as a special instance of "rockets and feathers" [49]. Edgeworth cycles may arise from consumers who are extremely loyal to a brand and therefore unaware of lower retail gasoline prices, or at least are unwilling to search for bargains [50,51].

Other sources contest the alleged asymmetry of oil and refined fuel markets [52]. Recent crises in energy-related commodity markets have neither exhibited "rocket and feathers" behavior nor followed Edgeworth cycles. The "rockets and feathers" hypothesis may partially explain oil–gasoline asymmetry, but not completely. When oil prices are falling, gasoline prices follow a contrary "boulders and balloons" dynamic by which gasoline more swiftly tracks oil price declines than increases [53]. Reversals in oil–gasoline asymmetry strongly suggest that volatility transmission between crude oil and refined fuels varies over time [54].

Finally, energy commodities move in tandem with agricultural commodities that supply fuel as well as food, feed, or fiber [55–59]. Fuel feedstock crops, such as corn and soybeans, either compete directly against crude oil as renewable substitutes or provide complements to fuels refined from petroleum [60–62]. Although biofuel policies in wealthy countries are suspected of affecting volatility transmission between energy-related and agricultural commodities [63], firm evidence supporting such hypotheses has not emerged [64–68].

4. Discussion

This study advances the understanding of energy-related commodity markets. This study also expands the toolkit for unsupervised machine learning in time-series forecasting. This section discusses each of these contributions.

4.1. Commodity-Specific Insights

Energy-related commodity markets have a disproportionate impact on developmental economics, international trade, and environmental policy. Factors affecting oil prices include wars and other political disturbances, shifts in global supply and demand, and technological and regulatory changes promoting demand for renewable energy. OPEC production decisions and extreme weather events must also be taken into account.

Interactions between fossil fuels and renewable fuel feedstocks attract especially intense security. Crude oil, gasoline, and diesel affect not only energy policy but also demand for agricultural feedstocks for ethanol and biodiesel. Biofuel feedstock demand may be swayed by domestic and international policies responding to global climate change.

Asymmetry, persistence, and cyclicality in volatility must be understood in the context of other financial markets and the macroeconomy. Beyond its impact on public policy, co-movement among all commodity markets and between commodities and other asset classes influences the leadership of energy companies and other forms of private risk management, including portfolio allocation. Fuel taxes, renewable energy policy, and the impact of energy prices on the behavior of industries and households hang in the balance.

4.2. Prelude and Performance: Unsupervised Machine Learning and Time-Series Forecasting

Unsupervised machine learning coexists comfortably alongside conventional methods for time-series forecasting. Indeed, more complete integration of unsupervised machine learning with forecasting forms the basis for future work. Each of the energy market propositions raised in this study—(1) macroeconomic versus industry-specific effects, (2) supply-side versus demand-side shocks, (3) upside versus downside asymmetry in oil and refined fuel prices, and (4) interactions with agricultural commodities—can be described and visualized through clustering and manifold learning.

The unsupervised machine-learning methods in this article exhibit strengths as well as limitations. Unlike traditional forecasting methods or even generalized linear methods for panel data, unsupervised machine learning does not rely on the formal apparatus of null hypothesis significance testing [69]. The statistical community has raised particularly sharp concerns over the rampant misunderstanding and misuse of p-values [70].

Willingness to use unsupervised machine learning does not hinge on a researcher's position on p-values or the growing movement seeking alternatives to statistical conventions based on them [71,72]. Nor should it. Unsupervised machine learning reveals mathematical properties and relationships within the data in ways not restricted by the rigid conventions of null hypothesis significance testing. In the absence of p-values and other conventional indicators of statistical significance, unsupervised learning converts raw data into mathematical outputs that can, in turn, enable more fruitful applications of economic domain knowledge and expert judgment. Other applications of machine learning and artificial intelligence, particularly in natural language processing, readily accommodate a blend of formal mathematics and subjective but mathematically informed analyst judgment [73–75].

The application of unsupervised machine learning to time series provides both prelude and performance in this branch of financial economics. Although unsupervised learning cannot directly forecast time series, unsupervised learning does generate insights beyond those available through descriptive statistics or exploratory data analysis. As the poet T.S. Eliot rendered the sentiment, unsupervised machine learning scours "the beaches where [the sea] tosses / Its hints of earlier and other creation" [1] (p. 36).

Time-variant ontological clustering represents a methodological innovation in its own right. The time-series data of greatest interest to the research questions in this study consist of the transpose of a more conventional matrix whose rows designate trading days and whose columns represent distinct commodity markets. Temporal clustering identifies mathematically distinct periods within the historical record. Transitions between clusters may indicate structural breaks in a trading regime [76]. Successfully locating such events addresses a known weakness of conventional forecasting methods. As the most labor- and data-intensive form of unsupervised machine learning for time series, time-variant ontological clustering can report changes in co-movement among market components—dynamic shifts, as it were, punctuating longer episodes of evanescent equilibrium among assets within a financial ecosystem [77].

Further applications of this study's methods include the investigation of changes in co-movement among asset classes or, more narrowly, among equity or bond market subsectors during shifts in macroeconomic conditions. This study's application of unsupervised machine learning may shed light on jump-diffusion models [78–81], a venerable economic tradition well represented in the literature on commodity markets [82–85]. If jump-diffusion processes can generate random sampling algorithms in pattern theory, computer vision, and medical imaging [86], unsupervised machine learning might facilitate the extraction of previously undetected mixtures within time series.

This study's methods also invite the extension of unsupervised machine learning to forecasting tasks that supervised machine learning methods have begun to tackle. For instance, all three methods of clustering presented in [2,3] and this study can be applied to the immensely popular task of forecasting air pollution in Beijing [87–89]. Unsupervised machine learning holds promise for addressing similar problems in meteorology, pollution control, and other environmental sciences [90].

The application of unsupervised machine learning to time series in finance, meteorology, and ecology should follow a Hegelian dialectic [91,92]. Unconditional ontological clustering as *thesis* stands beside its *antithesis*, temporal clustering of the matrix transpose. As the *synthesis* of space and time, time-variant ontological clustering reveals shifts within these stylized ecosystems during critical periods. What financial economics calls jumps or structural shifts, upon closer inspection, may display the mathematical properties that distinguish recessions from ordinary macroeconomic equilibria [93–95]. Given the common origins of economics and ecology [96], the similarities between these phenomena and punctuated equilibria in biology [77] should come as no surprise. The only difference is the frequency of ticks on the clocks measuring financial and geological time.

5. Conclusions

This study anticipates the completion of a toolkit for applying unsupervised machine learning to financial time series. An initial application of clustering and manifold learning to logarithmic returns and forecast volatility garnered quantitative support for the traditional ontology of commodity markets [2]. Temporal clustering then identified critical periods within energy-related commodity markets [3]. This study combines these methods into a novel hybrid called time-variant ontological clustering.

At a higher level of theoretical abstraction, this study unveils the distinct contributions of machine-learning methodology and data-gathering to time-series analysis. In machine learning, there is no such thing as a free lunch [97,98]. No single method or family of algorithms should be expected to outperform others, with respect to any dataset or even a broad category of problems [99]. The absence of a free lunch counsels the deployment of all plausible methodologies.

Unsupervised machine learning offers a meaningful combination of predictive success and explanatory power. The intrinsic parsimony of mathematics [100], remarkably effective in the natural sciences [101], notoriously fails when applied to economics [102]. By relying on all available data and the mathematical relationships lurking therein, unsupervised machine learning captures the most probable source of "unreasonable effectiveness" in the otherwise dismal science of economics: the data [103]. In that spirit, this study reveals the mechanics underlying energy-related commodity markets through machine-learning methods that neither require nor request human judgment.

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