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► **To cite this version:**

Patrick Owusu, Armelle Brun, Shengrui Wang. Towards Dynamic Structure Changes Detection in Financial Series via Causal Analysis. 2nd Workshop on Large-scale Industrial Time Series Analysis, at International Conference on Data Mining Workshops (ICDMW) 2021, Dec 2021, Auckland/ Online, New Zealand. 10.1109/icdmw53433.2021.00073 . hal-03543760

HAL Id: hal-03543760
https://hal.inria.fr/hal-03543760

Submitted on 26 Jan 2022

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2021 International Conference on Data Mining Workshops (ICDMW) | 978-1-6654-2427-1/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICDMW53433.2021.00073

Towards Dynamic Structure Changes Detection in Financial Series via Causal Analysis

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***Abstract*—This is a preliminary paper describing the concepts and principles for a sequential approach towards causal detection in a financial system presented by large-scale data. In particular, we focus on both the regime-switching and causal discovery detection models. This is to address the problem of heterogeneous conditions when analysing nonlinear characteristics from the financial markets. Thus handling the dynamics of multiple regimes in a series and new data to obtain valid answers to causal queries of interest. The availability of large-scale time series data presents new opportunities in knowledge discovery because the insight that can be gained from a causal perspective in a nonlinear system would be tremendous for asset allocation. However, large-scale series are prone to biases, including sampling selection. For decades, the main ways to study nonlinear time series analysis has been isolated to statistical analysis, largely restricted to parametric models. We here present an approach for handling a nonlinear system, infused with a causal solution in a temporal mining task.**

***Index Terms*—Large-scale time series, Time-series analysis, Causal analysis, Regime-switching, Financial time series**

I. Introduction

For years, time series (TS) analysis applied to temporal data for understanding and uncovering meaningful variations has proven to be challenging, either as a linear or non-linear approach. Time series variables may be influenced by events that arise at various points in time and that changes the underlying data generating process. Notably, these variables are used to first understand the past behaviour and secondly, help predict the future. As experienced in numerous areas including, medicine [1], meteorology [2], economics and finance [3], e.t.c., TS informs on the decision-making process.

However, classical statistical methods are best applied when correlation in the sampling data depend on the assumption that these observations are independent and identically distributed [4]. Wherefore, a series of novel approaches have been developed including machine learning methods: regression trees and clustering models [5], [6], and deep-learning models [7], and a combination of some models for the sole purpose of understanding TS behaviour. In addition, discovering the underlying changes are not enough, as certain characteristics are hard to observe [8].

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An alternate approach to TS analysis is causation - causal discovery or inference [2], [9]. Thus, finding answers to questions that are essential to understanding the mechanisms by which variables are assigned values, especially during data generation process. There are alternative conversations on the approaches in this field of study. For example, [2] showed that novel data-driven causal methods for analysing nonlinear systems are beyond correlation techniques. In another study, [10] the authors combine the approaches of the state-space model and causal discovery for the purpose of forecasting. Heretofore, studies in causal discovery detect causal relations by a single approach, either information theory [11], Granger causality (GC) [12] or structural causal models [13], and others.

The Granger causality approach is widely used in detecting causal relations in time series. This is achieved via a time-lagged test using autoregressive models. Noticeably, GC does not work efficiently in large-scale datasets when using standard regression techniques [2]. Besides, GC applicability is limited to mostly bivariate analyses. Regularized regression techniques are mainly methods that suit large-scale and high-dimensional data in the context of prediction [14]. The majority of TS causality studies predominantly assume linear characteristics and ignore the dynamism of the temporal data to be analysed. As such, the underlying likelihood of the relationship between variables is ignored, especially when structural changes and/or regime shifts. Applying causal models directly to linear TS data leads to the discovery of spurious edges and wrong directions [10].

Additionally, time-series behaviour analysis, which includes volatility and fat tails in financial markets [8] is of interest. The literature simply describe as the continuous transitions/observations of varying regimes over time. Financial market behaviours, especially prices, manifest due to economic uncertainties, government policies, interventions, technological advances, and or globalization [15].

Literature has provided two models that are useful for understanding and identifying sequential dynamic financial behaviours. These are (1) the change point detection model [16]–[18] and (2) the regime-switching (RS) model [8], [15], [19]. The change point model illustrates the specific moment

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DOI 10.1109/ICDMW53433.2021.00073

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that relates to a change in the probability distribution of a stochastic process. This is because the variations in the statistical properties are different. The RS model specifies an ordered region of change with similar statistical properties till another regime starts. Further, the RS model suggests structural breaks lead to regime switch, where a regime expresses some kind of behaviours that explain the market dynamics over time [20].

Empirically, there are several studies on regime-switching, either between single or multiple TS [6], [21]. However, the focus is on the detection of regimes based on statistical tests in statistical properties (mean and variance) in single or multiple regime(s). The choice for modelling TS dynamics via RS models is pervasive but with a noticeable drawback of unobserved regimes due to exogenous variables. Identifying start and endpoints of regimes constitute the basis of the RS model via methods such as state-space [19]. In practice, characteristics of time-series behaviour identified via the RS model across some defined time-series outputs similar structure(s) over time. Nonetheless, an explainable approach for relationship identification between regimes across an entire single or multiple series and regimes' directions is lacking.

To tackle these limits, we propose a novel approach whereby we combine regime-switching and causal models to detect and examine the likelihood of relationships between regimes using large-scale financial TS. This work seeks to shed light on the assertions underlying the causal relationships between regimes via a nonlinear approach. The RS model captures and tracks movement and sudden structural changes from a time series. However, causal discovery models help in identifying structural changes in nonlinear TS by exploiting particular regimes that represent the data generation process.

Reference [22] postulate that nonlinearity contains applicable information essential for causal discovery. Therefore we argue that a combined approach in detecting regimes from a financial TS characterised with variations would benefit from causal knowledge when tackling a forecasting task. We provide a principled approach of how causal discovery help TS behaviour via regime-switching model. Particularly, we formalize causal discovery under regime-switching models as this is our first work. This paper is structured as follows:

- In Section II, we discuss the components of our study and rationale behind our problem and how we intend to tackle it using a combined model.
- Section III details our proposed approach by defining each component, as well as our contributions.
- In Section IV, we present an applicative example that we propose to apply our approach using large-scale nonlinear time series from the financial market.
- Section V is solely for discussion and conclusion of our proposed work alongside future work.

II. Background and Related Works

In this section, we discuss the possibility of a combined model using the regime-switching and causal models to perform TS behaviour analysis. There is emerging interest in detecting and explaining temporal behaviours from financial and economic time series data in various areas of research. This stems from the fact that there are enormous and limited barriers to data accessibility and availability for the purpose of example investments or forecasting prices. Both theoretical and applicative studies on detecting structural changes and causal relationships have been tackled independently. Therefore, with the following sub-sections, we outline the comprising fields of interest to this study.

A. Financial Data

Financial data are a collection of various resources on a business, government, etc. activities that inform on the health of a company and provides the foundation for business analysis and decision-making. Addressing dynamism in financial TS has seen the use of data consisting of price indices (stock price index, exchange-traded fund - ETF, mutual and index funds), nominal exchange rates, commodities price, etc.

The majority of financial data are best classified as historical data that compromises granular detailed data from levels such as daily, weekly, monthly or yearly. To an extent, granular data recorded from transactions with timestamps depict the exact time of recording.

B. Overview of Time Series

A set of observations ordered in time and usually equally spaced; each observation may be related in some way to its predecessors may be regarded as a time series, and denoted as $A(t) = (\alpha_1(t), \alpha_2(t), \ldots, \alpha_n(t))$ where n is the number of variables measured at a discrete time-step $t \in \mathbb{Z}$. Of particular interest are the fields in which observational problems are identified, including; economics, commerce, industry, meteorology, demography, or any fields in which the same measurements are regularly recorded.

With the emergence of big data characterised as somewhat having sequential properties, it is now prudent to analyse temporal behaviours and the financial markets are an ultimate source of time series data. Most time series analysis (TSA) models often assume a linear approach for time series where the premise of correlation is predominant among data points. In contrast, other studied data (longitudinal or cross-sectional) assume that data points are independent of others. One of the best computational approaches to TSA are the concepts of autoregressive (AR) and moving average (MA) [23], [24] models.

1) Autoregressive Model: The AutoRegressive Integrated Moving Average (ARIMA) model assumes three fundamental relationships between TS; autoregressive, moving average and differencing. AR determines the value of a current timestamp $A(t)$ from a finite set of previous timestamps of length k and some error ϵ. The order of autoregression is the number of preceding timestamps used to determine the current timestamp's value, as shown below:

$$AR(k) = \sum_{i=1}^{k} \alpha_i . A(t-i) + c + \epsilon_t \tag{1}$$

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where α_i, k and c are the coefficients, the order of the AR model and a constant term respectively. The MA component models the value of a current timestamp $X(t)$ as a linear combination of the predictor errorϵ_t at the previous timestamp of length q, where q is the order of the moving average, as shown below:

$$MA(q) = \sum_{i=1}^{q} b_i.\epsilon_{t-i} + \mu + \epsilon_t \tag{2}$$

where b_i, μ and q are the coefficients, mean of the series and the order of MA model respectively. The AR and MA components are enough to model a time series in the case the time series data is stationary i.e. the time series have the same values of specific properties (mean, variance) over every time interval.

To understand temporal dynamics in TS, (3) shows that the TS data is differenced with a shifted version of itself to make the data stationary.

$$Y(t) = A(t) - A(t-r) \tag{3}$$

where r is the order of differencing. The primary task of the ARIMA model is estimating the coefficients and orders of each component. Alternatively, the Box and Jenkins model [25] provides a way to estimate ARIMA parameters by essentially verifying the distribution of the residuals or error term. Variations in the model with weighted and exponential smoothing assigned to each observations [26].

2) State-space Model: The state-space model (SSM) is a framework for modelling a dynamic process, i.e. a process where latent variables are connected or linked in time or space, an example is time series. The latent variables are themselves observed with some errors, including either random noise or it can be a process that can change in time or change with observer identity. The latent variables are not independent.

An SSM is denoted by a state-transition equation which describes the transition dynamics $p(b_t \mid b_{t-1})$ of the evolution of the latent state over time. Further, this represents an observational model describing the conditional probability $p(a_t|b_t)$ of observations given the latent state. The widely used state-space methods include: the Kalman filter which is applied to a linear Gaussian model, Hidden Markov Model and Bayesian structural time series [10], [19].

Hence, these help in estimating the underlying state based on observations and inferring tasks such as filtering $(p(b_t|a_1 : t))$, forecasting $(p(a_t|a_{1:t-1}))$ and smoothing $(p(b_t|a_1 : T))$. They differ in their mechanisms in the way each task makes use of present, past and future information in making the best estimate of the state at a given time. To model TS dynamics, SSM allows for modelling the dynamic process and states producing noisy data, thereby allowing for a causality model to be used in explaining what the generating process is.

An advantage of the SSM is the flexibility of changing parameters and coefficients over time, meaning that changes in the underlying behaviour can be modelled or studied. A typical example model of the SSM handling representation is the linear dynamic structure that satisfies the assumption of first-order Markov assumption [27]. The authors approached the dynamics of a nonlinear TS by a nonparametric estimation entailing the examination of conditional moments of the data which corresponded to certain shocks.

Prominent extensions to the components of SSM includes exponential smoothing, kernel Kalman filter, and others [28], [29] to perform various nonlinear time series processing. Recently, the machine learning literature provides an alternative for examining nonlinear TS [30].

C. Regime-Switching

Regime switching (RS) models have been extensively employed in econometric time series analysis. Reference [31] is the widely used RS model characterizing time-series behaviours in either single or multiple regimes. The operative assumption here is that regime switches are governed by unobservable state variables that follow a fixed-order Markov chain process. Drawbacks of this model are stated in [8]. Besides, the RS model has the ability to capture potential structural breaks via latent variables or some underlying patterns. As indicated in [32], RS model is flexible and performs well at capturing correlation asymmetries in TS data.

1) Regime-Switching Behaviour in Financial Time Series: The stock market exemplifies as a source of historic or real-time financial TS data. As already stated, unobserved events do cause several variations in the data generating process. Evidently, regime-switching models capture timely regime shifts as experienced in volatility measures - mean and variance, for example [33]. The Markov-switching model has been applied to investigate the link between exchange rates, stock prices and oil prices [15], [34]. Thus resulting in positive relationship observations between exchange rates and stock prices [35], [36].

However, these studies relied on linear models and ignored the likelihood that the relationship between exchange rates and stock prices may vary due to structural changes and/or regime shifts. Without consideration of time-varying characteristics in the market, shocks and spillovers are experienced. As a result, such events are not captured. Reference [15] employed a nonlinear approach using the RS model to accurately track movement and to capture sudden dramatic changes focusing on frontier stock prices and exchange rates.

Structural changes in the data may have an influence on the relationship that exists between two variables. Nonetheless, relationships between financial markets were described as nonlinear and regime-dependent in [34]. Evidently, RS models have proven to be essential in forecasting tasks and provide evidence that volatilities are not constant, but alternate between regimes [8], [15].

D. Causality

Learning causality with data seeks to solve causal problems which are often identified as associational. There is an increased focus by academicians and practitioners on the explainable causes of events that are often categorized as associations [37]. This is partly due to the unlimited data

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available analyzed and accessibility of new markets. Theoretical arguments such as [38] documented the main goal in applied econometric; however, the data fusion and selection of appropriate data is still mixed. Both theoretical and practical approaches to causal analysis, causal inference or discovery, are faced with challenges of identification and transportability from the underlying structure of the data [39]–[41].

The causal approach proposes that causal studies are inevitable in human intelligence and serve as artificial intelligence's foundation. Considering studies from economics [39], meteorology [2] and medical sciences [1], historically, learning causality focused on two formal approaches: structural causal models [13], [41] and the potential outcome framework [42]. However, as argued by [43] with limited data when using these approaches, a solid prior knowledge is required.

1) Causality for Time Series: Here, we briefly review a number of articles on causal approaches for TS data and the different approaches employed.

Several works have utilized the notion of Granger causality (GC) [44]–[47]. As a probabilistic concept, GC exploits the fact that causes must precede their effects in time. This introduces the challenge of handling spurious causalities, that is, falsely detected relationships, due to neglect of relevant variables.

Existing studies on cause-effect relationships behind the various complex systems such as financial markets or the human brain have mostly been hypothesized on two properties, in particular, the context of TS.

- Temporal precedence: a cause preceding its effects in time.
- Physical influence: manipulation of the cause changes the effects.

The second property raises an additional fact of a continuous change in the causing variable leading to changes in the caused variable. This property has been pioneered by Pearl [22], [40] and other modern facilities like the structural causal model and graphical models.

Since its introduction in 1969, the Granger causilty concept [48] is a prominent feature in detecting causal relationships. Similar to correlation techniques in other TS analysis, the concept of Granger causality is basically probabilistic and can lead to wrongly detected causal relations in the presence of latent variables.

Eichler [49] addresses the approaches for defining causality in multiple time series that includes Granger causality, Sims causality, Structural causality and Interventional causality, I refer to [49]. He goes on though, postulating that "Sims causality corresponds to the total information flow from one variable to another". In contrast, another study using information theory as the basis for identifying causal relationships, making inferences and quantifying information has recently been employed in earth science [2], [50], [51].

E. Limitations

The literature focuses on bivariate, multivariate or multiple time series analysis. Here, we summarize some detailed challenges identified from the literature.

1) Data: At the data-generation process, the data are noisy, exhibit features of heavy tails and extreme values which challenges the assumption of a Gaussian distribution. In addition, these data are collected from high-dimensional temporal data sources. Typically, these data have numerous variables, therefore making extracting relevant variables impossible. Thereby defining a computational challenge where identifying relevant variables that represent either regime or causal sub-process of interest costly. Moreover, the extracted variables should be interpretable and represent some regimes of the system achievable by dimensional reduction methods.

Nonlinear time series analysis via both regime-switching and causal studies are hindered by relevant drivers that are unmeasured. This requires the measurement of unobserved variables for interpretation and estimation. These variables lead to spurious relationship detection and inconclusive analysis. Time series poses a particular challenge regarding time-subsampling which allows for causal dependencies to appear cyclic or contemporaneous. For example, Granger causality is incapable to deal with contemporaneous links, which can be identified using structural causal models.

The quality of financial data is plagued by missing values. Thereby causing a selection bias challenge when defining window size for the regime and causal discoveries. Financial data is either available as continuous or discrete values. The process of quantization can be used to further identify granular levels such as minute, hourly, daily or weekly. For instance, priority is given to an index representing different regimes or a rare event, additionally raising the challenge of data imbalance –many 0 and few 1. Causal inference problems with such data require a suitable choice of methods, for example, conditional independence tests adapted to mixed data types.

2) High dimensionality: The time-dependent nature of data generation gives rise to strong autocorrelation and time delays in both analyses. This requires linear regression frameworks to tackle the issues of nonlinear features of a problem. However, nonlinearity in the form of state-dependence requires careful selection of the estimation method.

3) Computational: From a computational and statistical point of view, scalability is a crucial issue, both regarding sample size and high dimensionality. The more variables are taken into account for explaining a potentially spurious relationship or a regime, the more credible a discovery becomes. However, many variables together with a large time lag account for time delays, leading to high dimensionality which may strongly affect statistical reliability. This compromises statistical power – the probability to detect regime switches and causal relations, therefore, requires a model that deals with nonlinear time series analysis.

III. Contribution

To our knowledge, our work is the first attempt to provide a systematic proposal towards the challenge of nonlinear time series analysis by combining two well-studied analytical models–causal analysis and regime-switching models.

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The overall approach is divided into two main parts that work in sequence. We first employ the strategy from [8], in detecting regimes from a series. Thus we utilise a pattern-based approach that underlies a time series instead of exploiting the dynamics of a latent variable. The second part is the causal detection stage where we intend to employ the results attained from our regime-switch detection stage to answering the identified questions below.

With each regime having unique properties, the causal detection will test for information transfer and in the case of multiple time series, test for synchronization among the data. We intend to apply our soon-to-be approach to primarily, financial series and later adapt to other series in meteorology and neuroscience series.

Our main contributions are fourfold: first, to study by detecting causal discovery in time series by way of underlying causal patterns instead of time lags; second, examine the causal relationship between large-scale multiple financial series; third, rely on behavioral analysis of time series, to identify regimes over the series' size. Finally, identify external factors that cause changes in the underlying relationship between variables.

This new approach contributes to answering the following questions:

- How can we detect general causal interactions among the components of a complex system, for example, include financial system or climate system, including dynamic behavior i.e. regime change or regime-switching?
- How can we quantify the strength and account for the directions of causal interactions within a complex system in an explainable way?
- How do we evaluate the quality of causal models developed, especially in the domain of finance?
- How do we detect and explain (phase) synchronizations within various aspects of a complex system?

By solving the questions, our approach adds to the causal and dynamical understanding of nonlinear systems previously identified. A successful model and implementation should handle the identified issues and have direct implications for portfolio management and optimal investment strategies in terms of fund allocation.

IV. Example applications

Today, no experiment has been conducted about this approach. I think it should be interesting to analyse the impact of a combination: in terms of complexity, and expected accuracy compared to other possible approaches. Some examples of previous applications and the expected contribution of our model.

- Statistical data analysis models are reliant on correlations, associations and regression as they are *de facto* models to analyze and identify relationships. These associations reveal little to no insight into the causal mechanisms that underlie the system.
- The seminal work of Granger [53] in econometrics led to the detection of directional causation between related series variables. Usually, financial series studies focus on limited features to explain phenomena such as volatility in stock prices, ignoring the issue of unobservable variables or possible causal variables.
- Recently, causal discovery via information for discovering interactions mechanisms have been applied in climate science to identify structural changes and as optimal predictors [2], [51], [52].

Our proposed approach focuses on investment allocation serving in the area of asset classes. Thus, answer the question of how patterns improve the selection of values for an asset class. Dynamic structural changes in a financial series are detected through the regime-switching model output patterns by data transformation [8]. The frequency and duration of dips in prices, bond values, or any other event is of interest to make informed decisions in either the short or long run.

An exchange-traded fund (ETF) tracks the various components of asset classes. Thereby, generating large-scale data for analysis. With the prices of assets changing during a trading day, a causal explanation in the data generation process is essential. Our work is differentiated here in our use of a causal approach and that of the traditional regime switching approach used in ETF data. Identifying the dynamic properties of the ETF series provides a firm decision-support when assembling assets for diversification purposes.

V. Conclusion and Future work

Arguably the most relevant to our work is [10], which aims to causally discover and forecast time series by exploiting a particular type of SSM to represent a nonlinear process. Our preliminary paper seeks to identify not only regime-shifts in a series but include casual detection to explain the relationship between these regimes. Despite the importance attributed to the effect of causality in time series analysis, there are few studies on regime changes and that of causality in a nonlinear setting. Our approach is to enable us to address the crucial problem of structural change detection in a financial setting especially when analysing the amount of financial data at our disposal.

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