Chapter 6:

Causality Over Time and Economic Dynamics

6.1 Time and Causality

Economic phenomena unfold in time. While much of causal inference focuses on static comparisons for example, comparing outcomes between treated and untreated units at a point in time, real economic systems are dynamic: the effect of an intervention today may evolve, decay, amplify, or interact with subsequent events. Distinguishing static causal effects from dynamic causal effects is therefore central to understanding temporal causality. The difference between intervention and control in a single point is captured by the static effects, whereas the dynamic effects take into consideration that prior states and shocks affect future outcomes.

The temporal causal reasoning focuses on time sequence: an antecedent has to come before an effect. This ordering in dynamic systems demonstrates the propagation, accumulation or decays of shocks. As an example, an export-led economy can produce an upward-escalating cumulative and compounding growth in output and employment in the long run, which is consequently known as dynamic cumulative causation in the industrial growth literature (Dávila-Fernandez and Oreiro, 2023) [107]. On the same note, structural change and growth can also have the feedback of productivity improvement and investment factor reallocation in medium-term horizons (Cyrek, 2024) [108].

At a methodological level, capturing dynamic causal effects demands causal tools that explicitly incorporate time whether through time-series models, lag structures, or longitudinal panel frameworks, which are taken up in the next sections.

6.2 Time-Series Causal Models

Time-series data are ubiquitous in macroeconomics, finance, and policy analysis. Classical regression approaches ignore temporal structure, but causality in time entails not just association but predictive precedence and temporal sequencing.

Granger Causality

A workhorse of temporal causal analysis is Granger causality, which operationalizes causality in a predictive sense: a variable X Granger-causes a variable Y if past values of X contain information that helps predict future values of Y, beyond past values of Y itself. According to Shojaie and Fox (2022), Granger causality and recent developments in methodology are thoroughly reviewed, which also explains its use in revealing directional effect in multivariate time series and its use in economics and social sciences [103].

Granger causality extensions deal with heterogeneity and cross-sectional dependence between units. Nazlioglu and Karul (2024) create tests permitting to test Granger causal relations in panels in which cross-sectional consequences are not negligible - vital when examining macro panels of nations or industries [105]. There are practical examples: Spectral Granger causality is applied by Alola, Adebayo, and Onifade (2022) to investigate ecological footprint dynamics in China and it is evident that the direction of causality in different frequency domains and the magnitude of disturbances differs [109]. Xu and Zhang (2023) use linear and nonlinear causality tests of the information flows of house prices across Chinese cities and show that causality may differ depending on city pairs and over time [110]; similar studies investigate contemporaneous and dynamic relationships between residential housing markets [112]. Financial markets are not an exception: Elsayed, Gozgor, and Lau (2022) study the dynamic spillovers and causality between cryptocurrencies and currency markets and demonstrate the interaction between financial innovations over time [113]. We can represent it as below

Basic idea: Does X help predict Y?

Two models to compare:

Model 1 (without X):

Y(t) = a0 + a1*Y(t-1) + a2*Y(t-2) + ... + error

Model 2 (with X):

Y(t) = b0 + b1*Y(t-1) + b2*Y(t-2) + ... + c1*X(t-1) + c2*X(t-2) + ... + error

Where:

- Y(t) = value of Y at time t
- X(t-1), X(t-2) = past values of X
- a, b, c = coefficients (numbers to estimate)

Granger causality is fundamentally predictive rather than structural; it does not necessarily reveal underlying economic mechanisms. However, it is a valuable first step in diagnosing temporal dependencies.

Structural Time-Series Models

To embed causality within economic theory and structural interpretation, structural time-series models including structural Vector Autoregressions (VARs) are widely used. These models place theoretical restrictions in order to determine shocks and explain causal mechanisms. Dufour and Wang (2025) present a framework which links Granger causality and structural causal analysis in macroeconomic dynamics, which would bridge the temporal predictive causality and structural economic interpretation [104]. Their methodology assists in disaggregating causal processes and mediation impacts in the dynamic economies.

Reduced form (what we observe):

Y(t) = A1*Y(t-1) + A2*Y(t-2) + ... + error(t)

Where:

- Y(t) = vector of multiple variables at time t (e.g., GDP, inflation, interest rate)
- A1, A2 = coefficient matrices
- error(t) = correlated errors

Structural form (economic interpretation):

B0*Y(t) = B1*Y(t-1) + B2*Y(t-2) + ... + shock(t)

Where:

- B0 = captures how variables affect each other simultaneously
- shock(t) = independent economic shocks (monetary policy, technology, etc.)

Structural time-series models are particularly helpful in policy analysis: by having structural shocks (e.g., monetary policy surprises), scholars can be able to monitor their evolving impacts on output, inflation, and employment across several periods.

6.3 Longitudinal Data Analysis

Not all time-dependent causal questions are addressed solely with univariate or panel time series many involve repeated observations across units over time. Longitudinal or panel data combine cross-sectional and temporal variation, offering richer identification possibilities.

Panel Data Models

The main benefit of using panel data models in causal analysis is that researchers can control the unobserved, time-invariant heterogeneity between the units, which is the main benefit of using this type of data structure. As an example, the fixed characteristics of individuals (ability, culture, quality of management) or firms can be differenced out (or otherwise controlled), which increases the level of causal identification over pure time-series or cross-sectional analysis.

Arkhangelsky and Imbens (2024) offer a broad overview of the causal models of longitudinal and panel data, the issue of identification and methods of its resolution, such as fixed and random effects models and dynamic panels [106]. The effects of a specific unit are averaged in the case of static panel model and lagged outcomes are used as predictors in dynamic panel to explain persistence and feedback.

Fixed and Random Effects

With fixed effects models, each unit is free to have its own intercept which adjusts against time-invariant unobserved confounders. Random effects models assume that unit effects are random samples of a distribution, and are more efficient on the same assumption. In causal studies, fixed effects are frequently used since they make fewer assumptions regarding the independence of confounding factors and randomization of treatments.

Generalized Method of Moments (GMM) estimators including Arellano-Bond and other dynamic panel estimators, extend panel causal estimates further to the case where past outcomes have lagged effects on future outcomes (is endogenous), along with the heterogeneity of units.

Panel and longitudinal methods, combined, bring together both cross-unit and within-unit time-varying variation in a temporal causal analysis.

6.4 Feedback Loops and Policy Dynamics

Economies are recursive and interdependent. The policy shock may create a feedback effect in future policy decisions, consumption, investment, or future expectations, also known as feedback loops.

Economic Shocks

The economy is dynamic in response to macroeconomic shocks like a sudden change in monetary policy, financial crisis, or external trade shock. The propagation patterns can be in most cases lagged responses that take more than one period to unfold. To illustrate, competitiveness shocks, as examined by Dávila-Fernandez and Oreiro (2023), have cumulative dynamic causal impacts in terms of production, export orientation, and factor accumulation [107]. Industrial reallocation and structural changes as witnessed in Poland are another example of the shock and resultant responses being modelled in dynamic causal models (Cyrek, 2024) [108].

Lagged Effects and Feedback

Lagged effects are the main features of the economic process: fluctuations in interest rates today can have an impact on investment and consumption in months or years. Feedback loops occur when the consequences of one period are used to determine the future policy decisions. As an example, in the case of a monetary policy shock, when there is an increase in inflation, the policy can be revised further by the central banks, which forms a feedback mechanism.

The tools to identify lag-lead temporal relationships are offered by the use of the methods based on Granger and structural dynamic models help to understand the identified feedback mechanism in the language of the economic theory.

6.5 Case Study: Monetary Policy and Inflation

The practice of demonstrating that a relationship is causal over time is to look at the dynamic relationship between monetary policy and inflation. Changes in the monetary policy usually done by adjusting the interest rate or the money supply levels are meant to bring stability on the price and output. The assessment of its causal effects needs to consider temporal ordering and dynamic responses and feedback.

The models used in dynamic causal analysis usually start by assuming that inflation and policy variables are simultaneously evolving time series. The tests of Granger causality could show whether the previous policy actions are useful in forecasting inflation. Structural models Structural VARS or time-varying parameters Structural models enable researchers to establish exogenous monetary policy shocks and to monitor their dynamic impacts on inflation and output.

The empirical results indicate that the effects of monetary policy on inflation are not instantaneous or fixed but change over time with lagging effects as well as heterogeneous effects which depend on the economic conditions and the institutional settings. These dynamics are quantifiable using predictive diagnostics (e.g., Granger tests) as well as economically theory-based structural identification.

The case study of the monetary policy can be cited when illustrating the more general themes of this chapter: causal inference over time, the dynamic of response, structural interpretation, and policy feedback.

6.6 Summary

This chapter has highlighted that this aspect of causality over time cannot be well handled by the mere existence of statical frameworks. The temporal aspect of economic dynamics is demanding tools permitting the identification of temporal precedence: predictive causality (e.g., Granger causality) is used to characterize the temporal precedence in economic systems; structural time-series models connect economic theory with causal interpretation; longitudinal panel models are used to exploit the variation across and within units; and feedback loops can be used to emphasize the recursive nature of economic systems.

Key takeaways include:

- Dynamic causal effects acknowledge that prior interventions have an effect on the future.
- Time-series and panel methods offer complementary methods inferring causality of time.
- There are endemic feedback and lagged effects of economic policy.
- Case studies e.g. the effects of monetary policy on inflation show how temporal models of causality have practical applications.

This chapter prepares the reader with the more sophisticated techniques of causal inference that explicitly use time, dynamical processes, and feedback and prepares them to more sophisticated econometric modelling in subsequent chapters by bridging the gap between the foundations of causal statistic and the dynamic aspects of temporal dynamics.