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Granger causality, exogeneity, cointegration, and economic policy analysis

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ABSTRACT

Policy analysis had long been a main interest of Clive Granger's. Here, we present a framework for economic policy analysis that provides a novel integration of several fundamental concepts at the heart of Granger's contributions to time-series analysis. We work with a dynamic structural system analyzed by White and Lu (2010) with well defined causal meaning; under suitable conditional exogeneity restrictions, Granger causality coincides with this structural notion. The system contains target and control subsystems, with possibly integrated or cointegrated behavior. We ensure the invariance of the target subsystem to policy interventions using an explicitly causal partial equilibrium recursivity condition. Policy effectiveness is ensured by another explicit causality condition. These properties only involve the data generating process; models play a subsidiary role. Our framework thus complements that of Ericsson et al. (1998) (EHM) by providing conditions for policy analysis alternative to weak, strong, and superexogeneity. This makes possible policy analysis for systems that may fail EHM's conditions. It also facilitates analysis of the cointegrating properties of systems subject to policymaker control. We discuss a variety of practical procedures useful for analyzing such systems and illustrate with an application to a simple model of the US macroeconomy.

1. Introduction

Although just three of Clive Granger's many papers explicitly focus on aspects of policy analysis (Granger, 1973, 1988; Granger and Deutsch, 1992), a central and long-standing concern evident throughout his work is that econometric theory and practice should be informative and useful to policymakers. In this paper, we further this objective by providing a novel framework for economic policy analysis that blends together a number of concepts at the heart of Granger's contributions to time-series econometrics: causality, exogeneity, cointegration, and model specification.

We study a dynamic structural system with potentially cointegrated variables analyzed by White and Lu (2010) (WL) within which causal meanings are well defined. This system contains target and control subsystems, with possibly integrated or cointegrated behavior. We ensure the invariance of the target subsystem to policy interventions, obviating the Lucas critique, using an explicitly causal partial equilibrium recursivity condition. Another causality requirement ensures policy effectiveness. Causal effects are identified by a conditional form of exogeneity. These effects can be consistently estimated with a correctly specified model.

Following WL, we show that, given conditional exogeneity, Granger causality is equivalent to structural causality. On the other hand, given structural *non*-causality, Granger causality is equivalent to *failure* of conditional exogeneity. In this sense, Granger causality is not a fundamental system property requisite for reliable policy analysis, but an important consequence of necessary underlying structural properties.

By relying only on correct model specification and not weak exogeneity or its extensions (strong and superexogeneity), our framework complements the policy analytic framework of Ericsson et al. (1998) (EHM). Although giving up weak exogeneity may lead to loss of estimator efficiency, it also makes possible policy analysis for systems that may fail EHM's conditions (see Fisher, 1993). As we also show, our approach readily lends itself to analysis of the structural consequences of a variety of control rules that the policymaker may employ. Among other things, we find that proportional (P) control cannot modify the cointegrating properties of a target system, whereas proportional–integral (PI) control can. In fact, PI control can introduce, eliminate, or broadly modify the cointegrating properties of the uncontrolled target system. Whereas cointegration between target variables and policy instruments is possible but unusual with P control, PI control can easily

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induce causal cointegration between the target variables (Y_t) and the policy instruments (ΔZ_t).

The control mode also has interesting implications for estimation, inference, and specification testing in controlled systems. P control or a certain mode of PI control yields $\Delta Z_t \sim I(0)$, resulting in standard inference. Other modes of PI control yield $\Delta Z_t \sim I(1)$; the theory of Park and Phillips (1988, 1989) may be applied to these cases.

The plan of the paper is as follows. In Section 2, we introduce the data generating process (DGP) for the controlled system we study here, together with notions of structural causality and policy interventions natural in these systems. These enable us to formulate causal restrictions, essential for reliable policy analysis, obviating the Lucas critique and ensuring policy effectiveness. Section 3 discusses a conditional form of exogeneity that identifies causal effects of interest and forges links between structural and Granger causality. Section 4 reviews properties of relevant cointegrated systems, with particular attention to their structural content.

In Section 5, we give an explicit comparison of our framework with that of EHM, summarizing their similarities and differences and commenting on their relative merits. Section 6 analyzes the structural consequences of various rules that may be employed by policymakers to control potentially cointegrated systems. We pay particular attention there to how the policy rules may introduce, modify, or eliminate cointegration within the target system and to the possible cointegrating relations that may hold between policy instruments and target variables, or among the policy instruments. Section 7 illustrates these methods with an application to a simple model of the US macroeconomy, and Section 8 contains a summary and concluding remarks.

In what follows, we often refer to processes "integrated of order d", $I(d)$ processes for short. By this we mean a stochastic process that becomes $I(0)$ when differenced d times, where an $I(0)$ process is one that obeys the functional central limit theorem.

2. The DGP, structural causality, policy interventions, and recursivity

In this section we present the key elements of our policy analysis framework. Our starting point is a dynamic structural system with potentially cointegrated variables, as analyzed in WL (2010). This setting allows for a clear definition of the structural links between the elements of the system, and allows us to introduce in Section 2.1 the concepts of *intervention* and *structural causality*. These concepts are instrumental to showing how the structural system introduced in Section 2.1 can serve for economic policy analysis. We next define in Section 2.2 the concept of *policy intervention*, and introduce the causal property of *partial equilibrium recursivity*. This property defines a precise link between the structural reduced form parameters and the underlying "deep" parameters, and allows the structural system of Section 2.1 to be an effective framework for policy analysis. As we will show, this approach permits study of the effectiveness of policy interventions for a broad class of cointegrated structural VAR systems.

2.1. The DGP and structural causality

We begin by specifying the data generating process (DGP). For concreteness, clarity, and to afford maximum comparability to EHM, we mainly work with a linear N-variate structural vector autoregression (VAR) with two lags:

$$X_t \equiv \begin{bmatrix} Y_t \\ Z_t \end{bmatrix} = \delta_0 + A_1 X_{t-1} + A_2 X_{t-2} + \varepsilon_t, \quad t = 1, 2, \ldots, \tag{1}$$

where Y_t represents observable "target" or "non-policy" variables[2] and Z_t represents observable "policy instruments" or "control variables" that may be useful for controlling Y_t. Both Y_t and Z_t are vectors, $N_1 \times 1$ and $N_2 \times 1$ respectively. Thus, $N = N_1 + N_2$. As a practical example, we might be interested in analyzing the effectiveness of the Fed's monetary policy, through open market operations, on some key macroeconomic variables. In that case, the policy instrument Z_t would be the effective Federal Funds rate, while the target variables Y_t could represent a variety of key macroeconomic indicators. We will study this particular example in Section 7.

The vector $\delta_0 \equiv (\delta_{10}', \delta_{20}')'$ includes intercepts and any deterministic trend components. (See EHM, Eq. (4).) We partition the nonrandom coefficient matrices A_1 and A_2 as

$$A_1 = \begin{bmatrix} A_{11} \\ A_{21} \end{bmatrix} = \begin{bmatrix} A_{111} & A_{112} \\ A_{211} & A_{212} \end{bmatrix} \quad \text{and}$$

$$A_2 = \begin{bmatrix} A_{12} \\ A_{22} \end{bmatrix} = \begin{bmatrix} A_{121} & A_{122} \\ A_{221} & A_{222} \end{bmatrix}.$$

As econometricians, we do not know the A's, nor do we observe the random "shocks" $\varepsilon_t = (\varepsilon_{1t}', \varepsilon_{2t}')'$. Although δ_0, A_1, and A_2 may depend deterministically on t, we leave this implicit to avoid further complicating the notation. We allow δ_0, A_1, and A_2 to generate unit root or other nonstationary processes, with or without cointegration. It is convenient to think of $\{X_t\}$ being (at most) $I(1)$ as EHM do, but this is not essential.

By specifying that this is a structural system, we mean that it causally relates variables on the right to variables on the left. For example, consider an *intervention to* X_{t-1}, denoted $x_{t-1} \to x_{t-1}^*$ and defined as the pair (x_{t-1}, x_{t-1}^*). Then the *direct effect on* the key macroeconomic aggregates Y_t of the intervention $x_{t-1} \to x_{t-1}^*$ at (x_{t-1}, x_{t-2}, e_t) is defined as the difference

$$\begin{aligned} y_t^* - y_t &= (\delta_{10} + A_{11} x_{t-1}^* + A_{12} x_{t-2} + e_t) \\ &\quad - (\delta_{10} + A_{11} x_{t-1} + A_{12} x_{t-2} + e_t) \\ &= A_{11}(x_{t-1}^* - x_{t-1}). \end{aligned}$$

We see that A_{11} fully determines the direct effects on Y_t of interventions to X_{t-1}. Indeed, its elements represent the direct effects of a one unit intervention to any given element of X_{t-1}, say $x_{jt-1} \to x_{jt-1} + 1$. Similarly, A_{12} fully determines the direct effects of interventions to X_{t-2}. We may therefore call A_{11} and A_{12} "matrices of effects". These concepts accord well with intuition, and they are especially straightforward because of the linear structure. Similar notions hold generally. See White and Chalak (2009) and WL for discussion of *settable systems*, which provide causal foundations, relied on here, for the general case.

Although A_1 and A_2 are reduced form coefficients, they nevertheless contain structural information and are directly relevant for policy analysis. Specifically, using the notion of causality just given, we can say that if $A_{112} = 0$, then Z_{t-1} *does not (directly) structurally cause* Y_t. Otherwise, Z_{t-1} *structurally causes* Y_t. If $A_{112} = 0$ and $A_{122} = 0$ then $Z_{t-2}^{t-1} \equiv (Z_{t-2}, Z_{t-1})$ does not structurally cause Y_t. Without structural causality from policy variables to target variables (i.e., without $A_{112} \neq 0$ or $A_{122} \neq 0$), policy cannot be effective. EHM (p. 375) make a parallel observation, but stated in terms of Granger causality. We provide further discussion below, when we relate structural causality to Granger causality, using the framework of WL. The next section provides further motivation for examining reduced form parameters, "deep" parameters, and their relationship in studying policy analysis.

[2] We follow EHM in referring to Y_t as "target" variables. This should not be confused with similar nomenclature appearing elsewhere in the literature, where "target *series*" means a sequence of desired values Y_t^* for Y_t or "*policy* target" means a desired value for $E(Y_t)$ or some other aspect of Y_t or its distribution. When, for convenience, we refer simply to "targets" we always mean "target variables".