

# Not Just Guns or Butter, but What Came First? Introducing GVAR to International Relations

HÉCTOR BAHAMONDE <sup>\*1</sup>,

HEIKKI KAUPPI <sup>†2</sup>,

IGOR KOVAC <sup>‡3</sup>, and

WILMA NISSLÄ <sup>§4</sup>

<sup>1</sup>Senior Researcher, University of Turku

<sup>2</sup>Associate Professor in Economics, University of Turku

<sup>3</sup>PhD Candidate in Political Science, University of Cincinnati

<sup>4</sup>PhD Candidate in Economics, University of Turku

October 28, 2022

Work in progress. Please don't cite. Download the last version of the paper [here](#).

**Keywords**— time series; international political economy; GVAR; international relations

---

<sup>\*</sup>[hibano@utu.fi](mailto:hibano@utu.fi); [www.HectorBahamonde.com](http://www.HectorBahamonde.com).

<sup>†</sup>[heikki.kauppi@utu.fi](mailto:heikki.kauppi@utu.fi); <https://www.utu.fi/fi/ihmiset/heikki-kauppi>.

<sup>‡</sup>[kovacir@mail.uc.edu](mailto:kovacir@mail.uc.edu); <https://igorkovac.com>.

<sup>§</sup>[wilma.v.nissila@utu.fi](mailto:wilma.v.nissila@utu.fi); <https://www.utu.fi/fi/ihmiset/wilma-nissila>.

Authors named in alphabetical order. All authors contributed equally. We thank Paul Poast, Jonathan Markowitz, Rosella Cappella Zielinski, Tsung-wu Ho and Cristobal Quininao for their suggestions.

## **Abstract**

Power remains a crucial concept in international relations. In recent decades, the prevailing notion in the literature explains that economic power is a prerequisite for all other forms of power (military, political and cultural). Yet, such an assumption has never been properly tested. To test this assumption, the paper introduces a new time-series method to political science—Global Vector Auto-regression (GVAR). While the method is widely used in economics, it has not been employed in political science. The method should be appealing to scholars in political science since it enables big-N and big-T hypotheses tests. We also present Granger-causality tests within the context of GVAR and test if economic power is a prerequisite for military power. Our results suggest that the role of the economy has changed throughout history. Namely, in 19th century it was the military power that drove (Granger-caused) the economy; yet, since 1955 the roles are reversed.

## POWER: ASSUMED BUT UNTESTED

*“Power is the ultimate aphrodisiac”*

---

Kissinger (1973)

Since the dawn of social and political science, “power” has been a key notion in the discipline (Lasswell and Kaplan 1950). In international relations, power is conceptualized as a latent idea (Kennedy 1989; Luttwak 1990; Fukuyama 1992; Nau 1995; Kirshner 1997; Gilpin 2001; Brooks 2005; Ikenberry 2011). The argument is neatly summed by Organski who explains that economic power is a prerequisite for all other forms of power, i.e., without a strong economy a dominant state stagnates and declines (Organski 1958, 299–306). However, this claim has never been properly tested. For instance, Mearsheimer (2001, Ch. 3) dedicates a whole chapter to explain how latent power matters to military power. Thus, does military power causes economic power? Or is it the other way around? We believe that if the literature makes assumptions about the nature of power while proposing causal mechanisms between different power factors—military, economic, political and cultural (Mann 1986)—then it should also provide empirical evidence about those.

Igor: latent sounds too ambiguous.

This paper contributes to the literature by introducing Global Vector Autoregression (GVAR) methods to international relations. While panel-data methods handle well numerous panels (countries) within relatively short time spans, and time-series methods do the same but for longer time spans but for small panels (usually just one), GVAR perform statistically well in both big  $N$  and long  $T$  settings. To motivate the advantages of the GVAR method, we leverage the endogeneity of military and economic powers as an application. In particular, we show how Granger-causality tests (C. W. J. Granger 1969), within the framework of GVAR methods, might help to disentangle endogenous hypotheses testing in international relations and international political economy.

The paper proceeds as follows.

pending

### I. BRIEF CONCEPTUALIZATION OF POWER

Igor's part

## II. INTRODUCING THE GVAR METHODOLOGY

GVAR was introduced in M. Pesaran, Schuermann, and S. M. Weiner (2004). It “was developed in the aftermath of the 1997 Asian financial crisis to quantify the effects of macroeconomic developments on the losses of major financial institutions” (Mauro and Pesaran 2013, 1). The main feature of GVAR is that it “take[s] into account the various interlinkages in the global economy in the context of a truly multicountry setting” (H. Pesaran, Schuermann, and S. Weiner 2004, 139) by incorporating a large number of panels (“big  $N$ ”) for long time-spans (“big  $T$ ”) which are weighted by exogenous factors such as bilateral trade.

While GVAR has been widely used in economics (Favero 2013; Mauro, Filippo, and Pesaran 2013; Chudik and Pesaran 2016; Eickmeier and Ng 2015) its characteristics are also appealing for political scientists. Yet, to our knowledge, the GVAR method has not been used or introduced in political science so far. We do so in this paper and test relations between economic and military power in a truly global setting. In the rest of the paper we rephrase the famous dilemma about whether governments should allocate resources to finance “guns” (military power) or “butter” (economic power or economic development in general).

Global vector auto-regressive models (GVAR) are a special category of vector auto-regressive models (VAR). Following Box-Steffensmeier et al. (2014, 164), define a VAR model as follows,

$$\mathbf{x}_{it} = \boldsymbol{\alpha}_i + \beta_i \mathbf{x}_{i,t-p} + \mathbf{e}_{it} \quad (1)$$

where  $\mathbf{x}_{it}$  is a  $k_i \times 1$  vector of endogenous variables which are lagged  $p$  times, and where  $E(\mathbf{e}_{it}) = 0$ , that is, is a serially uncorrelated and cross-sectionally weakly dependent process (Mauro and Pesaran 2013, 14). Now, following Mauro and Pesaran (2013, p. 16; eq. 2.3) and Chudik and Pesaran (2016, p. 167; eq. 2), define a GVAR model with  $p$  lags for every country  $i$  at time  $t$  as follows,

$$\mathbf{x}_{it} = \boldsymbol{\alpha}_{i0} + \boldsymbol{\alpha}_{i1}t + \beta_{i1}\mathbf{x}_{i,t-1} + \beta_{i2}\mathbf{x}_{i,t-p} + \boldsymbol{\Lambda}_{i0}\mathbf{x}_{it}^* + \boldsymbol{\Lambda}_{i1}\mathbf{x}_{i,t-1}^* + \boldsymbol{\Lambda}_{i2}\mathbf{x}_{i,t-p}^* + \mathbf{e}_{it} \quad (2)$$

where  $\mathbf{x}_{it}$  is a  $k_i \times 1$  vector of domestic (i.e. endogenous) variables,  $\mathbf{x}_t^*$  is a  $k_i \times 1$  vector of weakly-exogenous foreign variables, and  $\mathbf{e}_{it}$  is a serially uncorrelated and cross-sectionally weakly dependent process. Importantly,

$$\mathbf{x}_{it}^* = \mathbf{W}_i' \mathbf{x}_t \quad (3)$$

where  $\mathbf{W}_i'$  is a  $k \times k^*$  matrix of country-specific weights, “typically constructed using data on bilateral foreign trade or capital flows” (Chudik and Pesaran 2016, 167).

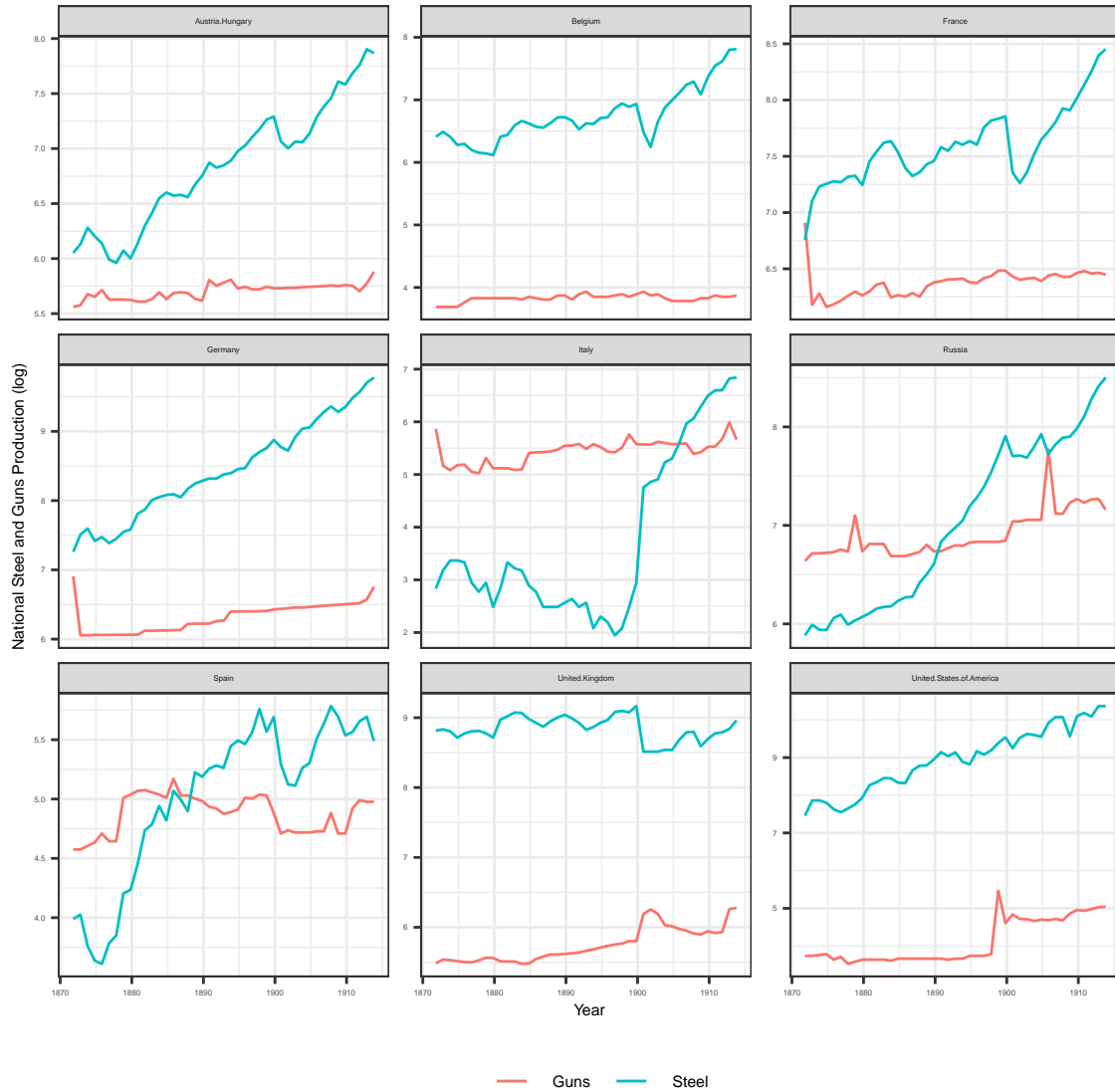
Typically, the choice of the lag orders of every GVAR system is selected according to the Akaike information criterion (Mauro and Pesaran 2013, 19). Also individual country-specific models of the form of Equation 2 “allow for cointegration among domestic variables as well as between domestic and country-specific cross-section averages of foreign variables” (Chudik and Pesaran 2016, 179).

As it becomes apparent, the inclusion of foreign variables  $\mathbf{x}_{it}^*$  in Equation 2 is one of the main characteristics of the GVAR approach, and the main difference with the VAR equation described in Equation 1. As explained by others “[t]hrough the use of foreign variables, the GVAR is able to account for bilateral inter-relationships amongst countries, and therefore control for spillovers on the basis of cross-country exposure.”<sup>1</sup>

We detail in section III that to construct  $\mathbf{W}_t$  we employ bilateral trade—but the particular choice of exogenous variable depends on the empirical application. In simple, the Global vector autoregressive GVAR model in Equation 2 explains  $\mathbf{x}_{i,t}$  as a function of past values  $\mathbf{x}_{i,t-p}$  lagged  $p$  times, at the same time that it weights these dynamics by weakly-exogenous foreign variables  $\mathbf{W}_{t-p}$  (weights which are captured by parameters  $\Lambda_{ni}$ ).

**Granger-causality tests** Since we are substantively interested in whether “guns” (Granger) *cause* “butter” or the other way around, in this paper we estimate country-specific bivariate Granger-causality tests within the GVAR framework.<sup>2</sup> The Granger-causality method was introduced by C. Granger (1969) and seeks to investigate if some variable  $X$  (Granger) “causes” another variable  $Y$ , or the other way around. A variable  $X$  is said to “Granger-cause”  $Y$  if predictions of  $Y$  based on lagged values of  $Y$  and lagged values of  $X$  perform better than explaining  $Y$  just with its own past values.

Since Granger-causality tests are usually estimated via VAR equations (Equation 1) we now derive the Granger-causality test within the GVAR framework. The substantive advantage of GVAR Granger-causality test over regular Granger-causality test is that estimates are weighted by the global economy ( $\mathbf{W}_t$  in Equation 2), situating the domestic dynamics within the global context. More formally, we estimate a GVAR Granger-causality system for every country  $i$  with  $p$  lags as



**Figure 1: National Steel and Guns Production (log), 1871-1913.**

**Note:** Variables are “*milper*” and “*irst.*” Both were obtained from Singer, Bremer, and Stuckey (1972).

shown in Equation 4:

$$\begin{aligned} \mathbf{x}_{it} &= \alpha_i + \Phi_{1i}\mathbf{y}_{i,t-p} + \Phi_{2i}\mathbf{x}_{i,t-p} + \Lambda_{1i}\mathbf{W}_{x,t} + \Lambda_{2i}\mathbf{W}_{x,t-p} + \Lambda_{3i}\mathbf{W}_{y,t} + \Lambda_{4i}\mathbf{W}_{y,t-p} + \mathbf{u}_{it} \\ \mathbf{y}_{it} &= \alpha_i + \Phi_{1i}\mathbf{x}_{i,t-p} + \Phi_{2i}\mathbf{y}_{i,t-p} + \Lambda_{1i}\mathbf{W}_{y,t} + \Lambda_{2i}\mathbf{W}_{y,t-p} + \Lambda_{3i}\mathbf{W}_{x,t} + \Lambda_{4i}\mathbf{W}_{x,t-p} + \mathbf{u}_{it} \end{aligned} \quad (4)$$

where the only added complexity is the introduction of a second variable ( $y$ ), but the lag and weight structure remains the same as in Equation 2.

### III. DATA: THE ART OF POSSIBLE

We operationalize military and economic power using variables from the Correlates of War Project, particularly, the National Material Capabilities dataset (Singer, Bremer, and Stuckey 1972).<sup>3</sup> The dataset covers all countries in the world between 1816-2012. Since we are interested in analyzing the longest  $T$  and the widest  $N$  possible, using the COW dataset seemed the most obvious choice. To proxy military power we use the “military personnel” variable and to proxy economic power we use the “iron and steel production” variable. Let military power be  $\mathbf{x}_{it}$  and economic power be  $\mathbf{y}_{it}$  in Equation 4.

justify both,  
but mostly  
steel

In order to maximize the extension of the dataset, it was necessary to split it in two. Since wars typically not only redraw country borders but also end, merge or split countries, the most efficient way of having the least missing data possible was partitioning the dataset in two. The first period goes between 1871 and 1913 (Figure 1). The second period goes between 1955 and 2012 (Figure 2).

We believe that while GVAR methods offer interesting properties for political scientists and for international relations scholars in particular, there is the inevitable issue of missingness: not all countries remain observed, especially during long periods of times. The biggest concern is that the ones that do remain observed are systematically different from the ones that do not. For instance, it is reasonable to expect that countries that cease to exist were weaker economically, politically and militarily. We believe these issues, while inconvenient, do not threat our statistical inference with selection bias. This paper does not address country survival. In fact, it seeks to shed light on military and economic dynamics of *all* countries who actually survive for the longest timespan possible. Finally, missing data is not a new problem in applied research. There are several ways to cope with this issue, for instance, multiple imputation. However we leave possible solutions for

cite some-  
thing

future research.

Moving forward, there is a considerable gap between 1913 and 1955. At the risk of sounding repetitive, it is worth emphasizing that a country needs to remain available for the *whole* time. Even if just one year is missing then that particular country cannot be considered. While we believe this limitation is an important one, balanced panels are not just a GVAR requirement but rather a general statistical need in most TS-PD models. We encourage analysts to deal with this issue by also finding substantive reasons for splitting the data, as we do next.

While the need for splitting the dataset in two was empirical, the decision was complemented with both theoretical and historical reasons. The hope is to take theoretical advantage of an empirical problem. The first timespan seeks to capture the international dynamics of the German unification and the beginning of World War I. The second time span corresponds to the post World War II international scenario. In order to maximize our analytical leverage respect to the partitioned dataset, we conform the next two working hypotheses:

check

**Hypothesis 1.** *Between 1871 and 1913 military power Granger-causes economic power.*

**Hypothesis 2.** *Between 1955 and 2012 economic power Granger-causes military power.*

The main added value of GVAR methods is the inclusion of a foreign or global variable which acts as a weight  $\mathbf{W}$  in Equation 2 and Equation 4. The idea is to account for shock transmissions across economies. In this application we have opted for dyadic trade data. This variable was constructed by the same project but in the Trade dataset (Barbieri, Keshk, and Pollins 2009; Barbieri and Keshk 2016).<sup>4</sup>

add brief  
justification  
for both H

Foreign variables are by definition (weakly) exogenous (Chudik and Pesaran 2016, 170). However, in many applications, especially in political science and international relations, there might be economic or military superpowers so influential to other countries that cannot be considered exogenous. More on the contrary, it should be quite natural to find that some economies based on asymmetric inter-dependence or post-colonial influence are highly correlated with the economy of the hegemon. For instance, di Mauro and Smith (Mauro and Pesaran 2013, 236) and Chudik and Pesaran (2016) run separate GVAR analyses on the United States. We encounter similar non-exogeneity issues with China, Russia and the United States for the 1955-2012 period. Substantively that means that the role of these three countries is influential in other smaller economies breaking the (weakly) exogeneity assumption. Empirically, due to multicollinearity and matrix non-invertibility issues, the

term cor-  
rect?



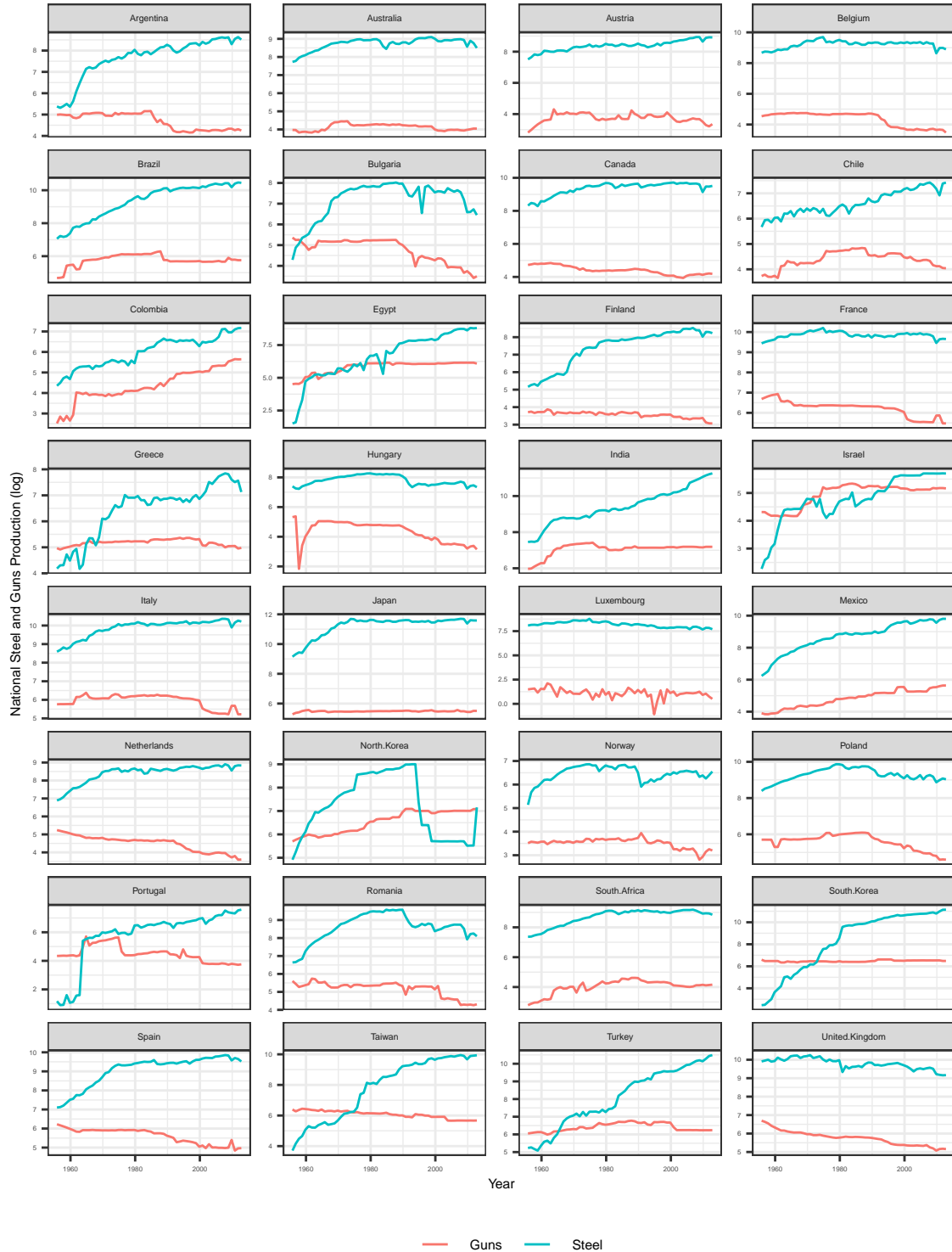


Figure 2: National Steel and Guns Production<sup>7</sup>, 1955-2012.

Note: Variables are “*milper*” and “*irst*.” Both were obtained from Singer, Bremer, and Stuckey (1972).

GVAR models analyzed in this paper were mathematically impossible to perform having China, Russia and the United States along with the rest of the economies. For these reasons these three economic and military superpowers were analyzed separately.

Moving forward, the weight variable  $\mathbf{W}$  is a square matrix which has all  $\mathbf{K}$  countries in both its columns and rows with zeros as diagonal elements. The matrix represents bilateral trade among two countries measured by the *flow1* and the *flow2* variables. The former measures imports from a country (*importer1*) to another country (*importer2*) and the latter measures the reverse dyad, i.e. imports from *importer2* to *importer1*. In addition to that,  $\mathbf{W}$  contains  $\mathbf{T}$  sub-matrices, one sub-matrix per every year  $t$ . Each sub-matrix  $t$  has dimensions  $k \times k$  for a total of  $\mathbf{K}$  countries such that,

$$\mathbf{W}_t = \begin{bmatrix} & \mathbf{i}_1 & \mathbf{i}_2 & \mathbf{i}_3 & \dots & \mathbf{i}_K \\ \mathbf{i}_1 & 0 & f_{21} & f_{31} & \dots & i_{K1} \\ \mathbf{i}_2 & f_{12} & 0 & f_{32} & \dots & i_{K2} \\ \mathbf{i}_3 & f_{13} & f_{23} & 0 & \dots & i_{K3} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{i}_K & f_{1K} & f_{2K} & f_{3K} & \dots & i_{KK} \end{bmatrix}$$

Every  $W_t$  matrix weights all  $\mathbf{K}$  country-specific Granger regressions described in Equation 4. Every  $k$  system is weighted by the other  $\mathbf{K} - 1$  sub-matrices of dyadic trade. As Equation 4 shows, the GVAR methodology also considers  $p$  lags of the  $\mathbf{W}$  matrix.

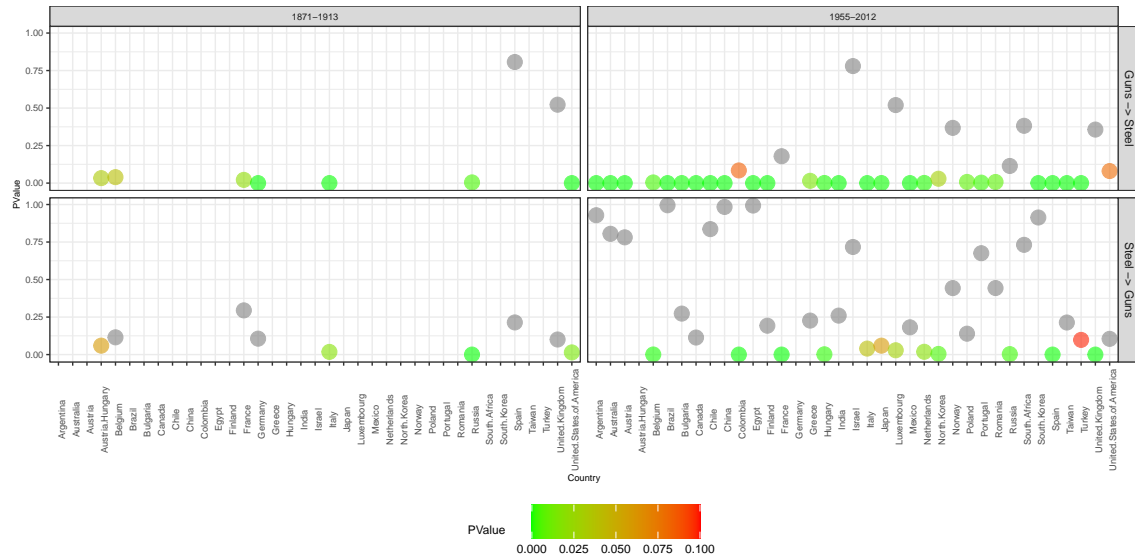
Following the literature on Granger-causality tests we focus our attention model-specific f-tests (one per country) which tests if all variables in the model are jointly significant. Then null is that there is no Granger causality.<sup>5</sup>

#### IV. RESULTS: GVAR GRANGER-CAUSALITY TESTS

The GVAR method handles a large number of panels. While this is an advantage of this approach it imposes restrictions in how to communicate results effectively. We considered that showing a table containing all the  $\mathbf{K} \times 2$  f-tests (one f-test per each country-specific Granger-causality relationship as in Equation 4) would be inefficient. In this application it is more informative getting a general sense of the possible causal mechanisms among all countries rather than analyzing each Granger equation individually. Hence in Figure 3 we show country-specific p-values of all Granger-causality

f-tests obtained when fitting Equation 4.<sup>6</sup> Figure 3 is organized in panels. Columns represent the time period and rows represent the Granger-causality relationship as shown in Equation 4. The figure conveys in colors the statistical significances of every country-specific f-test. In gray are shown the p-values that are larger than .1. While China, Russia and the United States GVAR Granger-causality tests were performed separately, they are shown with the rest of the countries.

From a substantive point of view, Figure 3 shows that during the 1871 – 1913 period, in 44% of the countries economic power Granger-caused military power. Yet, interestingly, this percentage drops to 38% and 33% for the influential economies during the 1955 – 2012 period. On the other hand, in the same second period in 46% of the countries military power Granger-caused economic power.



**Figure 3: P-Values of the Country-specific Granger-causality F-Tests, 1871-2012.**

*Note: Plot shows country-specific p-values of the Granger-causality f-tests obtained when fitting Equation 4 (detailed results shown in Table A1, Table A2 and Table A3). The plot shows that during the 1871-1913 period, in 44% of the countries, steel Granger-caused guns. This percentage changes to 38% and to 33% for the hegemonic countries during the 1955-2012 period.*

## V. SIMULATIONS

In this section we compare different methods for analyzing big-N and big-T datasets. First, we take the VAR example provided by Enders (2014, 286),

briefly an-  
alyze both  
Hypothesis

pending

$$\begin{aligned}
\mathbf{x}_t &= \boldsymbol{\alpha}_{10} + \beta_{11}\mathbf{x}_{t-1} + \beta_{12}\mathbf{y}_{t-1} + \mathbf{u}_{1,t} \\
\mathbf{y}_t &= \boldsymbol{\alpha}_{20} + \beta_{21}\mathbf{y}_{t-1} + \beta_{22}\mathbf{x}_{t-1} + \mathbf{u}_{2,t}
\end{aligned}
\tag{5}$$

and simulate a VAR data-generating process by setting  $\alpha_{10} = \alpha_{20} = 0$ ,  $\beta_{11} = \beta_{22} = \textit{NUMOFPARs}$  and  $\beta_{12} = \beta_{21} = \textit{NUMOFPARs}$ . Next, we derive the panel representation of [Equation 5](#) generating a dataset of 30 countries following the same VAR process.

## VI. DISCUSSION

The present research project makes two contributions to the broader International Relations literature. First, we test the general assumption that the economic power is the prerequisite for all other power factors. Second, we introduce to Political Science a new time series method—GVAR.

Our preliminary results indicate that the assumption of economic power dominance, which is so often and with ease made by scholars, is at least dubious, and flawed at best. In fact, the military power Granger-causes economic power in both periods—19th and 20th century.

However, future iterations of this project are necessary to be fully confident in such a result and conclusion. First, we need to enhance our model to also include military expenditures and energy consumption. Second, robustness checks using different time frames and imputation needs to be performed as well. Third, a comparison of results using GVAR with PVAR method would be beneficial. Namely, the amount of countries whose data is available for 19th century would still be classified as a small N. Thus, PVAR would also be appropriate method to be used for this period with small N. Consequently, we would expect that for 19th century conclusions from PVAR and GVAR would be the same, whereas for 20th century the conclusions would differ due to the big N in that period.

## REFERENCES

- Barbieri, Katherine, and Omar Keshk. 2016. "Correlates of War Project Trade Data Set Codebook, Version 4.0." <http://correlatesofwar.org>.
- Barbieri, Katherine, Omar Keshk, and Brian Pollins. 2009. "TRADING DATA: Evaluating our Assumptions and Coding Rules." *Conflict Management and Peace Science* 26 (5): 471–491.
- Box-Steffensmeier, Janet, John Freeman, Matthew Hitt, and Jon Pevehouse. 2014. *Time Series Analysis for the Social Sciences*. Cambridge University Press.
- Brooks, Stephen G. 2005. *Producing security: Multinational corporations, globalization, and the changing calculus of conflict*. Princeton: Princeton University Press.
- Chudik, Alexander, and Hashem Pesaran. 2016. "Theory and Practice of GVAR Modelling." *Journal of Economic Surveys* 30 (1): 165–197.
- Dees, Stephane, Filippo di Mauro, Hashem Pesaran, and Vanessa Smith. 2007. "Exploring the International Linkages of the Euro Area: A Global VAR Analysis." *Journal of Applied Econometrics* 22 (1): 1–38.
- Eickmeier, Sandra, and Tim Ng. 2015. "How do US Credit Supply Shocks Propagate Internationally? A GVAR Approach." *European Economic Review* 74:128–145.
- Enders, Walter. 2014. *Applied Econometric Time Series*. 4th. 496. Wiley.
- Favero, Carlo. 2013. "Modelling and Forecasting Government Bond Spreads in the Euro Area: A GVAR Model." *Journal of Econometrics* 177 (2): 343–356.
- Fukuyama, Francis. 1992. *The End of History and the Last Man*. New York: Free Press.
- Gilpin, Robert. 2001. *Global Political Economy Understanding the International Economic Order*. Princeton: Princeton University Press.
- Granger, Clive. 1969. "Investigating Causal Relations by Econometric Models and Cross-spectral Methods." *Econometrica* 37 (3): 424.
- Granger, Clive W. J. 1969. "Investigating causal relations by econometric models and cross-spectral methods." *Econometrica* 37 (3): 424–38.

- Ikenberry, G. John. 2011. *Liberal Leviathan: The origins, crisis, and transformation of the American world order*. Princeton: Princeton University Press.
- International Monetary Fund. 2016. "Cross-Country Report on Spillovers: Selected Issues."
- Kennedy, Paul. 1989. *The Rise and Fall of the Great Powers: Economic Change and Military Conflict from 1500 to 2000*. New York: Vintage Books.
- Kirshner, Jonathan. 1997. *Currency and coercion: the political economy of international monetary power*. Princeton: Princeton University Press.
- Kissinger, Henry. 1973. "The Sayings of Secretary Henry." <http://query.nytimes.com/gst/abstract.html?res=9F07E4DF1439E73ABC4051DFB6678388669EDE>.
- Lasswell, Harold D., and Abraham Kaplan. 1950. *Power and Society A Framework for Political Inquiry*. New Haven: Yale University Press.
- Luttwak, Edward N. 1990. "From Geopolitics to Geo-Economics: Logic of Conflict, Grammar of Commerce." *The National Interest* 20:17–23.
- Mann, Michael. 1986. *The sources of social power*. Vol. 1. Cambridge: Cambridge University Press.
- Mauro, Di, Filippo, and M.Hashem Pesaran, eds. 2013. *The GVAR handbook: Structure and applications of a macro model of the global economy for policy analysis*. Oxford: Oxford University Press Oxford.
- Mauro, Filippo di, and Hashem Pesaran. 2013. *The GVAR Handbook: Structure and Applications of a Macro Model of the Global Economy for Policy Analysis*. 1st, edited by Filippo di Mauro and Hashem Pesaran. Oxford University Press.
- Mearsheimer, John J. 2001. *The tragedy of great power politics*. New York: WW Norton & Company.
- Nau, Henry R. 1995. *Trade and security: U.S. policies at cross-purposes*. Washington: American Enterprise Institute.
- Organski, Abramo F. K. 1958. *World politics*. New York: Knopf.
- Pesaran, Hashem, Til Schuermann, and Scott Weiner. 2004. "Modeling Regional Interdependencies Using a Global Error-Correcting Macroeconometric Model." *Journal of Business & Economic Statistics* 22 (2): 129–162.

- Pesaran, M.Hashem, Til Schuermann, and Scott M. Weiner. 2004. “Modeling regional interdependencies using a global error-correcting macroeconometric model.” *Journal of Business & Economic Statistics* 22 (2): 129–62.
- Singer, David, Stuart Bremer, and John Stuckey. 1972. *Capability Distribution, Uncertainty, and Major Power War, 1820-1965*, edited by Bruce Russett, 19–48. Sage.
- Tsung-wu, Ho. 2020. *GVARX: Perform Global Vector Autoregression Estimation and Inference*. R PACKAGE VERSION 1.3.

..... **Word count: 2,922** .....



## VII. APPENDIX

### I. Appendix

**Table A1:** *Bivariate Global Granger Causality Tests of the World Political Economy, 1871-1913*

	Granger Relationship	F-Test	P-Value	DF	Adjusted R-sq	Lags
Austria-Hungary	butter $\rightarrow$ guns	2.16	0.06	8,31	0.192	1
	guns $\rightarrow$ butter	2.48	0.03	8,31	0.233	
Belgium	butter $\rightarrow$ guns	1.781	0.11	16,19	0.263	5
	guns $\rightarrow$ butter	2.339	0.04	16,19	0.38	
France	butter $\rightarrow$ guns	1.27	0.29	8,31	0.052	1
	guns $\rightarrow$ butter	2.72	0.02	8,31	0.261	
Germany	butter $\rightarrow$ guns	1.844	0.11	8,31	0.148	1
	guns $\rightarrow$ butter	7.891	0	8,31	0.586	
Italy	butter $\rightarrow$ guns	2.777	0.02	16,19	0.448	5
	guns $\rightarrow$ butter	6.801	0	16,19	0.726	
Russia	butter $\rightarrow$ guns	8.725	0	16,19	0.779	5
	guns $\rightarrow$ butter	3.595	0	16,19	0.543	
Spain	butter $\rightarrow$ guns	1.454	0.21	8,31	0.085	1
	guns $\rightarrow$ butter	0.554	0.81	8,31	-0.101	
United Kingdom	butter $\rightarrow$ guns	1.85	0.1	16,19	0.28	5
	guns $\rightarrow$ butter	0.966	0.52	16,19	-0.016	
United States	butter $\rightarrow$ guns	2.942	0.01	8,31	0.285	1
	guns $\rightarrow$ butter	8.608	0	8,31	0.609	

Table shows country-specific Granger-causality F-tests. Last column shows number of domestic lags used per every country-specific Granger model. Number of lags for endogenous variables = 2. Number of lags for foreign variables = 2. Max number of lags for estimating the country-specific VAR model = 5. Information criteria for optimal lag length = AIC. Deterministic variables: Trend and constant.

**Table A2:** *Bivariate Global Granger Causality Tests of the World Political Economy, 1955-2012*

	Granger Relationship	F-Test	P-Value	DF	Adjusted R-sq	Lags
Argentina	butter $\rightarrow$ guns	0.422	0.93	10,44	-0.12	1
	guns $\rightarrow$ butter	7.765	0	10,44	0.556	
Australia	butter $\rightarrow$ guns	0.629	0.8	12,41	-0.092	2
	guns $\rightarrow$ butter	5.618	0	12,41	0.511	
Austria	butter $\rightarrow$ guns	0.656	0.78	12,41	-0.084	2
	guns $\rightarrow$ butter	7.305	0	12,41	0.588	
Belgium	butter $\rightarrow$ guns	3.842	0	12,41	0.392	2
	guns $\rightarrow$ butter	3.001	0	12,41	0.312	
Brazil	butter $\rightarrow$ guns	0.237	0.99	12,41	-0.209	2
	guns $\rightarrow$ butter	9.498	0	12,41	0.658	
Bulgaria	butter $\rightarrow$ guns	1.269	0.27	12,41	0.057	2
	guns $\rightarrow$ butter	4.286	0	12,41	0.427	
Canada	butter $\rightarrow$ guns	1.69	0.11	10,44	0.113	1
	guns $\rightarrow$ butter	5.055	0	10,44	0.429	
Chile	butter $\rightarrow$ guns	0.561	0.84	10,44	-0.088	1
	guns $\rightarrow$ butter	7.313	0	10,44	0.539	
Colombia	butter $\rightarrow$ guns	4.855	0	18,32	0.581	5
	guns $\rightarrow$ butter	1.737	0.08	18,32	0.21	
Egypt	butter $\rightarrow$ guns	0.219	0.99	10,44	-0.169	1
	guns $\rightarrow$ butter	5.471	0	10,44	0.453	
Finland	butter $\rightarrow$ guns	1.428	0.19	12,41	0.088	2
	guns $\rightarrow$ butter	5.041	0	12,41	0.478	
France	butter $\rightarrow$ guns	8.235	0	16,35	0.694	4
	guns $\rightarrow$ butter	1.442	0.18	16,35	0.122	
Greece	butter $\rightarrow$ guns	1.344	0.23	18,32	0.11	5
	guns $\rightarrow$ butter	2.39	0.02	18,32	0.334	
Hungary	butter $\rightarrow$ guns	3.363	0	12,41	0.349	2
	guns $\rightarrow$ butter	3.711	0	12,41	0.38	
India	butter $\rightarrow$ guns	1.287	0.26	14,38	0.072	3
	guns $\rightarrow$ butter	6.048	0	14,38	0.576	
Israel	butter $\rightarrow$ guns	0.702	0.72	10,44	-0.058	1
	guns $\rightarrow$ butter	0.63	0.78	10,44	-0.073	
Italy	butter $\rightarrow$ guns	2.151	0.04	10,44	0.176	1
	guns $\rightarrow$ butter	11.365	0	10,44	0.657	
Japan	butter $\rightarrow$ guns	1.876	0.06	16,35	0.216	4
	guns $\rightarrow$ butter	4.079	0	16,35	0.491	
Luxembourg	butter $\rightarrow$ guns	2.296	0.03	10,44	0.194	1
	guns $\rightarrow$ butter	0.925	0.52	10,44	-0.014	
Mexico	butter $\rightarrow$ guns	1.436	0.18	16,35	0.12	4
	guns $\rightarrow$ butter	8.525	0	16,35	0.702	
Netherlands	butter $\rightarrow$ guns	2.483	0.02	10,44	0.216	1
	guns $\rightarrow$ butter	3.73	0	10,44	0.336	
North Korea	butter $\rightarrow$ guns	2.875	0	18,32	0.403	5
	guns $\rightarrow$ butter	2.143	0.03	18,32	0.292	
Norway	butter $\rightarrow$ guns	1.02	0.44	10,44	0.004	1
	guns $\rightarrow$ butter	1.122	0.37	10,44	0.022	
Poland	butter $\rightarrow$ guns	1.57	0.14	12,41	0.114	2
	guns $\rightarrow$ butter	2.745	0.01	12,41	0.283	
Portugal	butter $\rightarrow$ guns	0.749	0.68	10,44	-0.049	1
	guns $\rightarrow$ butter	3.265	0	10,44	0.296	
Romania	butter $\rightarrow$ guns	1.019	0.44	10,44	0.004	1
	guns $\rightarrow$ butter	2.878	0.01	10,44	0.258	
South Africa	butter $\rightarrow$ guns	0.686	0.73	10,44	-0.062	1
	guns $\rightarrow$ butter	1.102	0.38	10,44	0.019	
South Korea	butter $\rightarrow$ guns	0.448	0.91	10,44	-0.114	1
	guns $\rightarrow$ butter	9.019	0	10,44	0.598	
Spain	butter $\rightarrow$ guns	4.66	0	10,44	0.404	1
	guns $\rightarrow$ butter	4.92	0	10,44	0.421	
Taiwan	butter $\rightarrow$ guns	1.382	0.21	12,41	0.08	2
	guns $\rightarrow$ butter	5.667	0	12,41	0.514	
Turkey	butter $\rightarrow$ guns	1.696	0.1	14,38	0.158	3
	guns $\rightarrow$ butter	25.426	0	14,38	0.868	
United Kingdom	butter $\rightarrow$ guns	9.085	0	10,44	0.6	1
	guns $\rightarrow$ butter	1.139	0.36	10,44	0.025	

Table shows country-specific Granger-causality F-tests. Last column shows number of domestic lags used per every country-specific Granger model. Number of lags for endogenous variables = 3. Number of lags for foreign variables = 3. Max number of lags for estimating the country-specific VAR model = 5. Information criteria for optimal lag length = AIC. Deterministic variables: Trend.

**Table A3:** *Bivariate Global Granger Causality Tests of Influential Economies, 1955-2012*

	<b>Granger Relationship</b>	<b>F-Test</b>	<b>P-Value</b>	<b>DF</b>	<b>Adjusted R-sq</b>	<b>Lags</b>
China	butter $\rightarrow$ guns	0.252	0.98	9,45	-0.142	2
	guns $\rightarrow$ butter	83.191	0	9,45	0.932	
Russia	butter $\rightarrow$ guns	3.663	0	7,48	0.253	1
	guns $\rightarrow$ butter	1.775	0.11	7,48	0.09	
United States	butter $\rightarrow$ guns	1.821	0.1	7,48	0.095	1
	guns $\rightarrow$ butter	1.961	0.08	7,48	0.109	

Table shows country-specific Granger-causality F-tests. Last column shows number of domestic lags used per every country-specific Granger model. Number of lags for endogenous variables = 2. Number of lags for foreign variables = 2. Max number of lags for estimating the country-specific VAR model = 5. Information criteria for optimal lag length = AIC. Deterministic variables: NA.

## NOTES

1. International Monetary Fund (2016, 17).
2. We acknowledge that without proper experimentation and randomization there cannot be proper causation. Consequently, and following the Granger methodology, we employ a rather loose definition of “causation” and explore if lagged values of a variable *forecast* another variable.
3. Version 5.0.
4. Version 4.0.
5. All GVAR Granger-causality tests were done using the **GVARX R** package, version 1.3 and implemented by Tsung-wu (2020). The package performs estimations and inferences of Global Vector Autoregression models based on H. Pesaran, Schuermann, and S. Weiner (2004) and Dees et al. (2007).
6. We owe this point to Tsung-wu Ho. Country-specific results are shown in the Appendix section, particularly Table A1, Table A2 and Table A3.