Assessing Global Vector Autoregressions for Forecasting

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ABSTRACT
Global vector autoregressions (GVARs) have several attractive features: multiple potential channels for the international transmission of macroeconomic and financial shocks, a standardized economically appealing choice of variables for each country or region examined, systematic treatment of long-run properties through cointegration analysis, and flexible dynamic specification through vector error correction modeling. Pesaran, Schuermann, and Smith (2009) generate and evaluate forecasts from a paradigm GVAR with 26 countries, based on Dées, di Mauro, Pesaran, and Smith (2007). The current paper empirically assesses the GVAR in Dées, di Mauro, Pesaran, and Smith (2007) with impulse indicator saturation (IIS)—a new generic procedure for evaluating parameter constancy, which is a central element in model-based forecasting. The empirical results indicate substantial room for an improved, more robust specification of that GVAR. Some tests are suggestive of how to achieve such improvements.

Keywords: cointegration, error correction, forecasting, GVAR, impulse indicator saturation, model design, model evaluation, model selection, parameter constancy, VAR.

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1. INTRODUCTION

The recent financial crisis and ensuing Great Recession have highlighted the importance and pervasiveness of international linkages in the world economy—and the importance of capturing those linkages in empirical macroeconomic models that are used for economic analysis, forecasting, and policy analysis. Pesaran, Schuermann, and Weiner (2004) propose and implement global vector autoregressions (or GVARs) as an ingenious approach for capturing international linkages between country- or region-specific error correction models. Dées, di Mauro, Pesaran, and Smith (2007) (hereafter DdPS) extend that work to a larger number of countries and regions; and Pesaran, Schuermann, and Smith (2009) assess the forecasting properties of the GVAR implemented in DdPS.

The GVAR methodology has several attractive features:

- a versatile structure for characterizing international macroeconomic and financial linkages though multiple channels,
- a standardized economically appealing choice of variables (both domestic and foreign) for each country or region,
- a systematic treatment of long-run properties through cointegration analysis, and
- flexible dynamic specification through vector error correction modeling.

These features are very appealing, and they balance naturally the roles of data and economic theory in empirical modeling. The GVAR explicitly aims to capture international economic linkages, especially linkages between the macroeconomic and financial sides of economies. Weak exogeneity plays an important role through allowing conditional subsystem analysis on a country-by-country basis. Data aggregation—empirically implemented but based on economic theory—achieves a high degree of parsimony in the estimated models.

The current paper re-examines some of the empirical underpinnings for global vector autoregressions, focusing on parameter constancy because of the intimate connections between it and forecast performance. To test parameter constancy, this paper uses impulse indicator saturation, which is a recent generic approach to evaluating constancy. The empirical results indicate substantial room for an improved, more robust specification of DdPS's GVAR; and some tests are suggestive of how to achieve such improvements. See Clements and Hendry (1998, 1999, 2002) and Hendry (2006) for discussions on the relationships between parameter constancy, forecast performance, and forecast failure.

In related work, Ericsson (2011) discusses the theory of reduction and exogeneity in the context of GVARs, thereby providing the background for tests of parameter constancy, data aggregation, and weak exogeneity in GVARs. Using those tests, Ericsson (2011) then evaluates the equations for the United States, the euro area, the United Kingdom, and China in DdPS's GVAR. Ericsson and Reisman (2011) provide parallel results for equations for all 26 countries in DdPS's GVAR.

This paper is organized as follows. Section 2 describes a prototypical GVAR and, in the context of that prototypical GVAR, summarizes the current approach taken to modeling GVARs, as developed in Pesaran, Schuermann, and Weiner (2004) and DdPS *inter alia*. Section 3 reviews the procedure for testing parameter constancy called impulse indicator saturation, which utilizes the computer-automated model selection algorithm in Autometrics. Section 4 empirically evaluates DdPS's GVAR for parameter constancy, using impulse indicator saturation. Section 5 concludes.

2. THE GVAR

To motivate the use of GVARs in practice, this section describes a prototypical GVAR (Section 2.1) and relates it to the GVAR in DdPS (Section 2.2).

The current approach to modeling GVARs has been developed in Pesaran, Schuermann, and Weiner (2004) and DdPS *inter alia*. For further research on GVARs, see Garratt, Lee, Pesaran, and Shin (2006); Pesaran and Smith (2006); Dées, Holly, Pesaran, and Smith (2007); Pesaran, Smith, and Smith (2007); Hieberta and Vansteenkiste (2009); Pesaran, Schuermann, and Smith (2009); Castrén, Dées, and Zaher (2010); Chudik and Pesaran (2011); and the comments and rejoinders to Pesaran, Schuermann, and Weiner (2004) and Pesaran, Schuermann, and Smith (2009). Juselius (1992) provides a conceptual precursor to GVARs in her sector-by-sector analysis of the Danish economy to obtain multiple long-run feedbacks entering an equation for domestic inflation. Smith and Galesi (2010) have designed and documented an easy-to-use Excel-based interface that accesses Matlab procedures to implement GVARs.

2.1. A Prototypical GVAR

This subsection describes a prototypical GVAR that has three countries, with two variables per country and a single lag on each variable in the underlying vector autoregression (VAR). For ease of exposition, global variables (such as oil prices) and deterministic variables (such as an intercept and trend) are ignored. This prototypical GVAR highlights key features that are important to the remainder of this paper. In the exposition below, this prototypical GVAR is considered first in its generic form, then in its error correction representation, then on a country-by-country basis, and finally on a variable-by-variable basis for each country. While the prototypical GVAR may well be unrealistically simple for empirical use, it conveys important aspects of the GVAR without undue algebraic complication, and it allows (in Section 2.2) a straightforward description of the GVAR in DdPS. Ericsson (2011) provides a more complete description of the structure of GVARs, the notation used, and the underlying assumptions.

The underlying VAR for the prototypical GVAR is:

(1) $x_{it} = A_{1i}x_{it-1} + A_{2i}x_{it}^{*} + A_{3i}x_{it-1}^{*} + u_{it}$,

for $i = 0,1,2$, and $t = 1,2,\dots,T$, where i is the country index, t is the time index, T is the number of observations, x_{it} is the vector of domestic variables for country i at time t, x_{it}^{*} is the vector of corresponding foreign aggregates (i.e., foreign relative to country i) at time t, A_{1i} is the matrix of coefficients on the lagged domestic variables, A_{2i} and A_{3i} are the matrices of coefficients on the contemporaneous and lagged foreign aggregates, and u_{it} is the error term induced by having conditioned on those foreign variables. Empirically, one interesting triplet of countries is as follows: the United States ($i = 0$), the euro area ($i = 1$), and China ($i = 2$). Each subsystem in (1) is also a VARX* model—that is, a VAR model that conditions on a set of (assumed) exogenous variables and their lags.

In error correction representation, the prototypical GVAR in (1) is:

(2) $\Delta x_{it} = \Gamma_i \Delta x_{it}^{*} + \alpha_i \beta_i' (x_{it-1}' : x_{it-1}^{*\prime})' + u_{it}$,

for $i = 0,1,2$, and $t = 1,2,\dots,T$, where Δ is the difference operator, Γ_i is the matrix of coefficients on the change in contemporaneous foreign aggregates, and α_i and β_i are the matrices of adjustment coefficients and cointegrating vectors for country i. The matrices Γ_i, α_i, and β_i in (2) are functions of the matrices A_{1i}, A_{2i}, and A_{3i} in (1).

The explicit country-by-country structure of the GVAR in equation (2) is as follows:

$$
\begin{aligned}
(3)\qquad \Delta x_{0t} &= \Gamma_0 \Delta x_{0t}^* + \alpha_0 \beta_0' (x_{0t-1}' : x_{0t-1}^{*}{}')' + u_{0t} \\
\Delta x_{1t} &= \Gamma_1 \Delta x_{1t}^* + \alpha_1 \beta_1' (x_{1t-1}' : x_{1t-1}^{*}{}')' + u_{1t} \\
\Delta x_{2t} &= \Gamma_2 \Delta x_{2t}^* + \alpha_2 \beta_2' (x_{2t-1}' : x_{2t-1}^{*}{}')' + u_{2t}\ .
\end{aligned}
$$

In equation (3), a country's domestic variables respond to the foreign aggregates and to lagged disequilibria involving the domestic and foreign variables. Country 0's foreign aggregate x_{0t}^* is a weighted sum of x_{1t} and x_{2t}, which are the foreign variables for country 0. Likewise, x_{1t}^* is a weighted sum of x_{0t} and x_{2t}, and x_{2t}^* is a weighted sum of x_{0t} and x_{1t}. The weights might be chosen to reflect the relative economic importance of the foreign countries to the domestic country. So, the weights for one country's foreign aggregates need not (and generally would not) be the same as the weights for another country's foreign aggregates.

To further illuminate the structure of the GVAR, suppose that x_{it} in equation (3) comprises two variables: y_{it} (the log of country i's real GDP), and Δp_{it} (country i's CPI inflation). Because $x_{it} = (y_{it} : \Delta p_{it})'$ and $x_{it}^* = (y_{it}^* : \Delta p_{it}^*)'$, equation (3) can thus be written explicitly in six equations.

$$
\begin{aligned}
(4)\quad \Delta y_{0t} &= \Gamma_{0aa} \Delta y_{0t}^* + \Gamma_{0ab} \Delta^2 p_{0t}^* \\
&\quad + \alpha_{0a} \beta_0' (y_0 : \Delta p_0 : y_0^* : \Delta p_0^*)_{t-1}' + u_{0at} \\
\Delta^2 p_{0t} &= \Gamma_{0ba} \Delta y_{0t}^* + \Gamma_{0bb} \Delta^2 p_{0t}^* \\
&\quad + \alpha_{0b} \beta_0' (y_0 : \Delta p_0 : y_0^* : \Delta p_0^*)_{t-1}' + u_{0bt} \\
\Delta y_{1t} &= \Gamma_{1aa} \Delta y_{1t}^* + \Gamma_{1ab} \Delta^2 p_{1t}^* \\
&\quad + \alpha_{1a} \beta_1' (y_1 : \Delta p_1 : y_1^* : \Delta p_1^*)_{t-1}' + u_{1at} \\
\Delta^2 p_{1t} &= \Gamma_{1ba} \Delta y_{1t}^* + \Gamma_{1bb} \Delta^2 p_{1t}^* \\
&\quad + \alpha_{1b} \beta_1' (y_1 : \Delta p_1 : y_1^* : \Delta p_1^*)_{t-1}' + u_{1bt} \\
\Delta y_{2t} &= \Gamma_{2aa} \Delta y_{2t}^* + \Gamma_{2ab} \Delta^2 p_{2t}^* \\
&\quad + \alpha_{2a} \beta_2' (y_2 : \Delta p_2 : y_2^* : \Delta p_2^*)_{t-1}' + u_{2at} \\
\Delta^2 p_{2t} &= \Gamma_{2ba} \Delta y_{2t}^* + \Gamma_{2bb} \Delta^2 p_{2t}^* \\
&\quad + \alpha_{2b} \beta_2' (y_2 : \Delta p_2 : y_2^* : \Delta p_2^*)_{t-1}' + u_{2bt}
\end{aligned}
$$

The subscripts a and b refer to the two variables y and Δp. The GVAR itself is thus a vector error correction model in which the individual conditional error correction models for all of the countries are stacked, one on top of the other.

Consider the interpretation of (4). In the first equation of (4), the growth of GDP in country 0 depends on the growth of GDP and inflation in countries 1 and 2 through Δy_{0t}^* and $\Delta^2 p_{0t}^*$, and on lagged disequilibria involving both domestic and foreign variables through the cointegrating relationships $\beta_0' (y_0 : \Delta p_0 : y_0^* : \Delta p_0^*)_{t-1}'$. In each remaining equation, the domestic variable likewise depends on the foreign variables through the change in their contemporaneous aggregates and through the error correction term.

Some potential cointegrating vectors include the following, where β denotes a generic cointegrating vector and a diamond ♦ denotes a nonzero coefficient.

i. $\beta = (1 : 0 : \blacklozenge : 0)'$: domestic and foreign GDP are cointegrated.

ii. $\beta = (1 : \blacklozenge : 0 : 0)'$: domestic GDP is cointegrated with domestic inflation.

iii. $\beta = (1 : 0 : 0 : 0)'$: domestic GDP is stationary, or is trend-stationary if a trend is included in the cointegrating space.

iv. $\beta = (0 : 1 : 0 : \blacklozenge)'$: domestic and foreign inflation are cointegrated.

v. $\beta = (0 : 1 : 0 : 0)'$: domestic inflation is stationary.

Even in this simple two-variable example, many long-run relationships are possible. Yet more (and more complicated) long-run relationships may exist in multivariate settings such as the GVAR in DdPS, described in Section 2.2.

While the prototypical GVAR in (4) has a remarkable simplicity of structure, it still shows how domestic and foreign variables may influence each other through multiple channels, and in both the short run and the long run. As (4) illustrates, a GVAR provides a versatile structure for characterizing multiple international linkages for a standardized economically appealing choice of variables with a systematic and flexible treatment of long-run and short-run properties through cointegration analysis and vector error correction modeling.

In practice, GVARs have many potential uses, such as private-firm policy regarding risk, banking supervision and regulation, central bank policy, and forecasting; cf. Pesaran, Schuermann, and Weiner (2004), Dées, di Mauro, Pesaran, and Smith (2007), and Pesaran, Schuermann, and Smith (2009). In some of these situations, strong exogeneity, super exogeneity, or both may be required for valid analysis; see Ericsson, Hendry, and Mizon (1998) and Ericsson (2011).

2.2. The GVAR in DdPS

To provide a sense of the empirical aspects involved in modeling a global vector autoregression, consider the GVAR in DdPS.

The set of domestic variables x_{it} is as follows (with a few exceptions for specific countries, as noted in DdPS):

- Real GDP (y_{it}),
- CPI inflation (Δp_{it}),
- Real equity prices (eq_{it}),
- Real exchange rate (ep_{it}),
- Short-term interest rate (r_{it}), and
- Long-term interest rate (lr_{it}).

DdPS focus on 25 countries plus one region (the euro area); see Table 2 in Section 4.2 for a list of the countries. For convenience, both countries and regions are referred to as "countries" below. The country-specific aggregated foreign variables (x_{it}^*) are constructed from the full set of domestic variables across all countries, using fixed trade weights.

The VARX* for each country initially has two lags on domestic variables and on the foreign aggregates. In some instances, however, shorter lags are selected, based on standard information criteria. Also, the VARX* includes a global variable (oil prices) and deterministic variables (an intercept and trend).

Cointegration in the VARX* is tested, following the procedure in Harbo, Johansen, Nielsen, and Rahbek (1998) and using critical values from MacKinnon, Haug, and Michelis (1999); see also Johansen (1992, 1995) and Juselius (2006). The number of cointegrating vectors may differ from country to country. In the conditional error correction model, the country's cointegrating vectors are written in their reduced form, i.e., with β_i' beginning with an identity matrix.

The data are quarterly, taken from the IMF's *International Financial Statistics* (except for Singapore's data, which are from Datastream). Estimation is typically over 1979Q4–2003Q4 ($T = 97$). This GVAR from DdPS provides the empirical illustration examined in Section 4.

3. IMPULSE INDICATOR SATURATION

This section describes the procedure called impulse indicator saturation, which Section 4 uses to test parameter constancy of the GVAR in DdPS.

Impulse indicator saturation (IIS) uses zero-one impulse indicator dummies to analyze properties of a model. There are T such dummies, one for each observation in the sample. While inclusion of all T dummies in an estimated model is infeasible, blocks of dummies can be included; and that insight provides the basis for IIS. A simple example with two equal-sized blocks motivates the generic approach in IIS. See Hendry, Johansen, and Santos (2008), Johansen and Nielsen (2009), and Hendry and Santos (2010) for further discussion and recent developments.

Imagine estimating a model specification such as the GVAR in (4) in three steps. First, estimate that model, including impulse indicator dummies for the first half of the sample. That estimation is equivalent to estimating the model over the second half of the sample, ignoring the first half. Drop all statistically insignificant impulse indicator dummies and retain the statistically significant dummies. Second, repeat this process, but start by including impulse indicator dummies for the second half of the sample; and retain the statistically significant ones. Third, re-estimate the original model, including all dummies retained in the two block searches; and select the statistically significant dummies from that combined set. Hendry, Johansen, and Santos (2008) and Johansen and Nielsen (2009) have shown that, under the null hypothesis of correct specification, the fraction of impulse indicator dummies retained is roughly αT, where α is the target size. For instance, if $T = 100$ and the target size is 1%, then (on average) only one impulse indicator dummy is retained when the model is correctly specified.

If the model is mis-specified such that its implied coefficients are nonconstant over time, IIS has power to detect that nonconstancy. See Hendry and Santos (2010, Section 4) for an example. Interestingly, the residuals of the estimated model *without* any impulse indicator dummies need not lie outside their estimated 95% confidence region, even with a statistically and economically large break in the underlying parameters of the data generation process. Also, the IIS procedure can have high power to detect the break, even though the nature of the break was not utilized in the procedure itself.

In practice, IIS in the Autometrics routine of Doornik and Hendry's (2009) OxMetrics utilizes many blocks, and the partitioning of the sample into blocks may vary over iterations of searches; see also Hendry and Krolzig (1999, 2001, 2005), Hoover and Perez (1999, 2004), and Krolzig and Hendry (2001). IIS is a statistically valid procedure for integrated, cointegrated data; see Johansen and Nielsen (2009). IIS can also serve as a diagnostic statistic for many forms of mis-specification.

Many existing procedures can be interpreted as "special cases" of IIS in that they represent particular algorithmic implementations of IIS. Such special cases include recursive estimation, rolling regression, the Chow (1960) predictive failure statistic (including the 1-step, breakpoint, and forecast versions implemented in OxMetrics), the Andrews (1993) unknown breakpoint test, the Bai and Perron (1998) multiple breakpoint test, intercept correction (in forecasting), and robust estimation. IIS thus provides a general and generic procedure for analyzing a model's constancy, allowing for an unknown number of structural breaks occurring at unknown times with unknown duration anywhere in the sample.

Algorithmically, IIS also solves the problem of having more regressors than observations by testing and selecting over blocks of variables. That block approach permits testing the aggregation assumption implied by the use of foreign aggregates in the GVAR; see Ericsson (2011) for a discussion of the underlying theory and for implementation in Autometrics.

4. EVALUATION OF DdPS's GVAR WITH IIS

This section implements the parameter constancy test associated with impulse indicator saturation, using the GVAR in DdPS to illustrate. Tests on individual equations and on country-specific subsystems are both feasible. Specifically, the subsystem for a given country is unrestricted (either as an unrestricted VARX*, or as an unrestricted cointegrated VARX* conditional on the subsystem estimate of β_i), so OLS estimation equation by equation is maximum likelihood estimation of the subsystem VARX* model. Valid omitted-variables test statistics can be calculated on either the VARX* as a subsystem, or on the individual equations of the VARX*. These two approaches may imply different alternative hypotheses, even while the null hypothesis is the same. This section discusses these test statistics for the equation-by-equation approach for the cointegrated VARX*; Ericsson (2011) and Ericsson and Reisman (2011) examine *inter alia* the IIS test statistics for the subsystem approach.

Section 4.1 discusses the IIS test results in detail for selected equations for the United States, the euro area, the United Kingdom, and China. Section 4.2 summarizes the results for all countries and equations. Section 4.3 compares these results with those reported in DdPS, and it discusses various implications and extensions.

4.1. Selected Highlights

To illustrate the use of impulse indicator saturation, Table 1 reports results from IIS at the 0.1% target level for four selected equations: for US equity prices, for euro-area inflation, for the UK real exchange rate, and for the Chinese short-term interest rate. The table lists the F-statistics for the significance of the retained impulse indicator dummies, the associated p-values, and the dates of the retained impulse indicator dummies.

Table 1. Impulse indicator saturation at the 0.1% target level for certain equations for the United States, the euro area, the United Kingdom, and China.

Country and Dependent variable	F-statistic [p-value] d.f. Impulse dates
United States Δeq	21.8** [0.0000] $F(1, 81)$ 1987Q4
Euro area $\Delta^2 p$	4.40** [0.0067] $F(3, 73)$ 1981Q1, 1986Q3, 1986Q4
United Kingdom Δep	23.3** [0.0000] $F(1, 80)$ 1992Q4
China Δr	$+\infty$** [0.0000] $F(18, 67)$ 18 dummies

Notes. The four entries within a given block of numbers are (i) the F-statistic for the significance of the retained impulse indicator dummies, (ii) the tail probability associated with that value of the F-statistic (in square brackets), (iii) the degrees of freedom (d.f.) for the F-statistic (in parentheses), and (iv) the dates of the retained impulse indicator dummies or (for China) the number of retained impulse indicator dummies. The two superscript asterisks ** on the F-statistics denote significance at the 1% level.

Parameter constancy is rejected by IIS in all four equations. In the first three equations, the retained impulse indicator dummies reflect known historical events associated with major changes in the behavior of the variable being modeled. In the equation for US equity prices, IIS retains an impulse indicator dummy for 1987Q4, reflecting the fall of US stock prices by over 20% on Black Monday (October 19). In the equation for euro-area inflation, IIS retains impulse indicator dummies for periods when euro-area inflation markedly increased or decreased: 1981Q1, and 1986Q3–1986Q4 respectively. In the equation for the UK real exchange rate, IIS retains an impulse indicator dummy for 1992Q4, which captures the substantial devaluation of the pound sterling near the end of the previous quarter on Black Wednesday (September 16), when the UK government was forced to withdraw the pound sterling from the European Exchange Rate Mechanism (the ERM).

IIS for the fourth equation—of the Chinese short-term interest rate—is particularly revealing. IIS detects 18 dummies, with an *infinite* F-statistic for the significance of those dummies. As seen in Figure 1, the Chinese short-term interest rate r_{CHINA} appears to be an administered rate, with stretches of several quarters when it is constant. Hence, the series for Δr_{CHINA} is a series of zeros, interspersed with (nonzero) impulses whose values reflect the magnitude of the change in the level of the interest rate when that level changes. Because the estimated equation is in its error correction form, the dependent variable is Δr_{CHINA}. IIS detects all of the impulses in the series for Δr_{CHINA}; and IIS sets all other coefficients in the equation for Δr_{CHINA} to zero, giving a perfect fit. It is encouraging that IIS demonstrates the ability to detect this plethora of scattered impulses: IIS favors detecting impulses when the impulses are all within a single block; but no single block in IIS for the equation for Δr_{CHINA} includes all of the time periods for which $\Delta r_{CHINAt} \neq 0$. Economically and statistically, IIS for this equation implies that a VARX* model is inadequate to capture the essential features of the Chinese short-term interest rate.

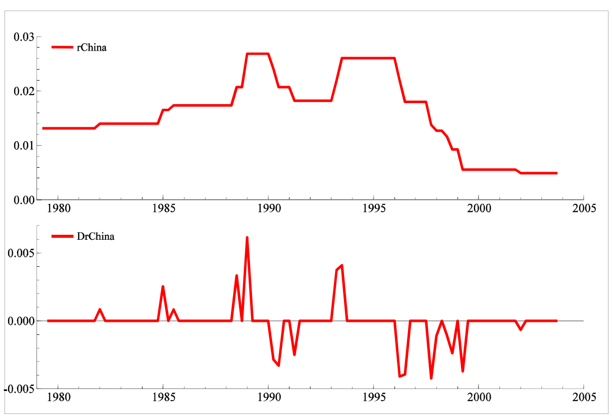

Figure 1. The short-term interest rate for China (r_{CHINA}), and its change (Δr_{CHINA}).

4.2. Results for All Countries and Equations

Table 2 reports the number of impulse indicator dummies found at the 0.1% target level in each equation for each of the 26 countries in DdPS's GVAR. Even at such a stringent target level as 0.1%, statistically and economically significant impulse indicator dummies are detected frequently.

For the short-term interest rate equation, all countries but Switzerland have at least one retained impulse indicator dummy; and five countries have ten or more. That result is particularly impressive because the target level is 0.1% and the sample size is 97, implying an only one-in-ten probability of retaining an impulse indicator dummy in a given equation by chance. IIS of the equations for the short-term interest rate results in the most retained impulse indicator dummies on average for any equation (six impulse indicator dummies per equation, on average), as might be expected for a variable that could be strongly influenced by shifts in monetary policy.

Table 2. The number of retained impulse indicator dummies for IIS at a 0.1% target size, by equation in each country, for DdPS's GVAR.

Country	Δy_{it}	$\Delta^2 p_{it}$	Δeq_{it}	Δep_{it}	Δr_{it}	Δlr_{it}
China	14	4	—	10	18	—
Euro area	None	3	1	None	2	None
Japan	1	None	None	None	9	1
Argentina	1	10	1	14	11	—
Brazil	4	14	—	2	17	—
Chile	1	8	1	3	4	—
Mexico	3	3	—	10	3	—
Peru	5	11	—	13	14	—
Australia	None	None	2	3	8	None
Canada	None	None	3	None	6	3
New Zealand	2	2	4	1	11	6
Indonesia	2	3	—	6	5	—
Korea	1	None	None	5	3	3
Malaysia	None	None	3	2	8	—
Philippines	1	11	1	4	3	—
Singapore	None	4	None	None	1	—
Thailand	5	1	None	11	2	—
India	2	1	None	2	7	—
South Africa	3	1	None	2	2	None
Saudi Arabia	8	2	—	3	—	—
Turkey	1	1	—	None	2	—
Norway	None	1	2	None	3	2
Sweden	2	1	None	1	2	None
Switzerland	None	None	2	None	None	1
UK	None	1	None	1	1	1
US	2	None	1	—	8	3
Fraction	69%	73%	58%	72%	96%	67%

Notes. A dash "—" means that DdPS do not estimate an equation for that country's variable. "None" means that no impulse indicator dummies were found at the 0.1% target level. A number indicates the number of impulse indicator dummies found at the 0.1% target level. "Fraction" means the fraction of equations estimated with at least one retained impulse indicator dummy.

IIS for other types of equation also results in frequently retained impulse indicator dummies. Even the equity price equation—which has the lowest proportion of countries that retain at least one impulse indicator dummy—still rejects parameter constancy for 58% of the countries, suggesting that there is much room for improvement across all variables.

Focusing on properties of IIS *across countries*, the countries with the highest number of impulse indicator dummies are typically emerging market economies, suggesting that equations for these countries are more prone to rejecting parameter constancy. Additionally, the highest numbers of impulse indicator dummies retained in any equation are from emerging market economies: for instance, 14 and 18 (China), 14 (Argentina), 14 and 17 (Brazil), and 13 and 14 (Peru). Conversely, developed countries appear more likely to have equations in which *no* impulse indicator dummies are retained. For example, six countries have at least three equations with no retained impulse indicator dummies: the euro area, Japan, Australia, Canada, Singapore, and Switzerland. All but Singapore are considered developed countries, and Singapore itself has many of the characteristics of a developed country. While parameter constancy is rejected for most equations in most countries at even the 0.1% level, rejections are particularly frequent and compelling in equations for emerging market economies. That said, parameter nonconstancy is detected in at least two equations for every country, regardless of the country.

4.3. Remarks

Several implications follow directly from the rejections in Tables 1 and 2. First, DdPS (Table V) evaluate their GVAR using tests for structural breaks and find little evidence of mis-specification. DdPS's results contrast with the evidence in Tables 1 and 2 above. The explanation of these differences lies in the tests employed. For evaluating parameter constancy, impulse indicator saturation may have more power than the structural break tests in DdPS for the range of relevant alternatives, particularly for breaks near the ends of the sample. Hence, the results in Tables 1 and 2 represent new information about the GVAR's properties and need not be related to other diagnostic tests such as those for residual autocorrelation. Equally, the rejections in Tables 1 and 2 are unsurprising in that IIS was not incorporated as a design criterion in the building of DdPS's GVAR; see Hendry (1987) on the role of design criteria in model construction.

Second, rejection of a given null hypothesis does not imply the alternative hypothesis. For instance, the IIS test of parameter constancy may reject because of omitted-variable bias due to improper data aggregation and changing data moments. More generally, the presence of retained impulse indicator dummies may have any of a number of possible implications for modeling. It may be appropriate to simply include the retained impulse indicator dummies, as in the equation for US equity prices, where the dummy captures information beyond the scope of the model's structure. Or, one might add economic variables that the impulse indicator dummies proxy, as perhaps is the case for the euro-area inflation equation. Or, one might treat the presence of the impulse indicator dummies as evidence for a much more fundamental sort of mis-specification being present in the model, as with the equation for the Chinese short-term interest rate.

Third, while the large number of rejections in Table 2 may be discouraging at first blush, they are also encouraging because they imply substantial potential for model improvement; and they may provide some guidance in finding a better-specified model. Some of the test statistics above indicate clear directions for model redesign, as with impulse indicator saturation of the equation for Δep_{UK} detecting 1992Q4. This modeling approach is consistent with a progressive research strategy; see Hendry (1987), White (1990), and Doornik (2008) *inter alia*.

Fourth, and relatedly, IIS in conjunction with automatic model selection may be used constructively in model building. In particular, Castle, Fawcett, and Hendry (2009), Choi and Varian (2009), and Castle and Hendry (2010) show how automatic model selection among a plethora of variables can improve nowcasting of important economic time series.

Fifth, inclusion of impulse indicator dummies can and does have significant consequences for the rest of the model's coefficients—economically, as well as statistically and numerically; see Ericsson (2011).

Sixth, impulse indicator saturation can be applied to *any* empirical model to assess parameter constancy and model specification of that model. Given the central and substantive roles of invariance and constancy in economic model interpretation, forecasting, and policy analysis, IIS would be of particular interest to apply to dynamic stochastic general equilibrium (DSGE) models, new Keynesian Phillips curve models, Markov switching models, and statistical time series models *inter alia*. For DSGE models in particular, see the analysis in Edge and Gürkaynak (2010); and note Erceg, Guerrieri, and Gust (2006), Smets and Wouters (2007), and Erceg and Lindé (2010).

Finally, discovering test rejections for a given equation has no implications for the properties of a well-specified equation. For instance, the latter may have constant parameters, even though the former does not.

5. CONCLUSIONS

A global vector autoregression is an ingenious structure for capturing international linkages between country- or region-specific error correction models. A GVAR is a versatile structure for characterizing international macroeconomic and financial linkages though multiple channels; it embodies a standardized economically appealing choice of variables for each country or region; it treats long-run properties through cointegration analysis in a systematic fashion; and it permits flexible dynamic specification through vector error correction modeling. The current paper re-examines the empirical underpinnings for GVARs, focusing on tests of parameter constancy that use impulse indicator saturation. Recent developments in computer-automated model selection allow implementation of impulse indicator saturation, even though historically IIS would have been viewed as infeasible. Empirical results from impulse indicator saturation show scope for improving the GVAR in DdPS and suggest directions to pursue for doing so.

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