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Assessing the Impact of Policy Changes on a Nowcast

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ABSTRACT: Nowcasting enables policymakers to obtain forecasts of key macroeconomic indicators using higher frequency data, resulting in more timely information to guide proposed policy changes. A significant shortcoming of nowcasting estimators is their "reduced-form" nature, which means they cannot be used to assess the impact of policy changes, for example, on the baseline nowcast of real GDP. This paper outlines two separate methodologies to address this problem. The first is a partial equilibrium approach that uses an existing baseline nowcasting regression and single-equation $ARMA(p,q)$ forecasting models for the high-frequency data in that regression. The second approach uses a non-parametric structural VAR estimator recently introduced in Ouliaris and Pagan (2022) that imposes minimal identifying restrictions on the data to estimate the impact of structural shocks. Each approach is illustrated using a country-specific example.

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WORKING PAPERS

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Contents

Figures

Tables

Introduction

Nowcasting is an essential part of a policymaker's toolkit. It enables policymakers to obtain forecasts of low frequency indicators using higher frequency data, resulting in more timely information to guide imminent policy changes. For example, in some countries, annual GDP is available only with a lag of one or two years. In such cases, monthly indicators[1] may help improve the assessment of real GDP relative to potential on a more regular basis and, most importantly, during crisis episodes when data-driven policy adjustments are required urgently.

While standard nowcasting tools are essential for assessing the current state of the macroeconomy, they are "reduced-form" tools and as such cannot be used to assess the impact of proposed policy changes on the baseline forecast/nowcast for real GDP for example, which is a significant shortcoming. This paper proposes two methodologies to address the "reduced-form" problem of standard nowcasting methods. The application of the proposed methods yields estimates of the sensitivity of a nowcast to changes in chosen policy indicators at least *one period ahead*.

Assume a single equation regression model has been formulated to nowcast real GDP. It uses lags of real GDP and at least one high frequency indicator converted to the same lower frequency as real GDP. Policy makers are typically interested in assessing the impact of a proposed policy shock on real GDP. We also assume not enough observations are available to estimate a structural VAR at the frequency of real GDP. Moreover, given the available data, any feasible SVAR involving less variables or lags would be far too simple (i.e., poorly specified) to provide useful information to policy makers.

The first approach to solve this problem uses single-equation $ARMA(p,q)$ models, and in some cases can also be extended to vector autoregressions (VARs). We apply this method to estimate the impact of higher real oil prices and higher US real GDP on the 2022-23 nowcast for real GDP growth of the Commonwealth of Dominica. As expected, an increase in real oil prices reduces the nowcast of real GDP growth for Dominica, though with a small elasticity, while an increase in US real GDP has a large positive effect on Dominica's real GDP. The second approach applies a non-parametric structural estimator recently introduced in Ouliaris and Pagan (2022) to estimate the responsiveness of a nowcast to a structural shock. This estimator is used to assess the impact on the nowcast for the Kingdom of Tonga's real GDP of a positive unit shock in travel receipts. We find that a positive shock to travel receipts has a positive impact on the nowcast for Tonga's real GDP.

[1] All nowcasting exercises are subject to the availability/quantity/quality of high frequency data for analysis.

First Approach

For each high frequency explanatory variable in the baseline model for real GDP, we estimate a single equation $ARMA(p, q)$ model that has an exogenous variable representing the policy instrument (e.g., an interest rate or the nominal exchange rate). The preferred $ARMA(p, q)$ model is then used to generate a conditional forecast for the high frequency variable that is converted to the same frequency as real GDP using an appropriate conversion method (e.g., sum, averaging). The result is a forecast that reflects the impact of the proposed policy change (e.g., the interest rate adjusted by 100bps, or the exchange rate adjusted for a proposed exchange rate shock) on the high-frequency variable. It is valid for more than one period ahead only if there is no feedback from real GDP to the policy instrument.[2]

Each of these high-frequency forecasts is then used in the baseline regression for real GDP, which also has the policy instrument as an exogenous explanatory variable, to obtain a forecast/nowcast for real GDP that reflects the impact of the proposed policy change. The real GDP forecast/nowcast is then compared to the baseline nowcast, which assumes no change in policy, to estimate the one-period impact of the proposed change in policy. Note that the suggested approach is necessarily a one-period ahead exercise because it assumes no feedback effects from, for example, real GDP to the policy instrument or other right-hand side variables in the nowcasting regression.

Of course, one may be able to use a more complex model to forecast the high-frequency indicators used in the baseline regression since the high frequency indicators, by definition, have more observations than the baseline data (in this case, real GDP). This may allow the estimation of multi-equation structural models such as VARs or SVARS for the high frequency indicators as a group. All these models will include a proxy variable (exogenous) for a policy instrument (e.g., interest rates and/or nominal exchange rate target). Forecasts for the high-frequency indicators conditional on a specific policy scenario (e.g., a specific time path for nominal interest rates) can then be converted to the target frequency of real GDP so that the revised nowcast of real GDP accounts for the active scenario. The difference between the baseline nowcast and the revised nowcast of real GDP provides an estimate of the impact of the proposed change in policy. The estimate is valid for only one period ahead because the methodology just described does not capture the feedback effects of the changes in the nowcast on the high frequency estimators.

[2] If used for more than one period, it is important not to re-estimate the $ARMA(p, q)$ model created in the first step, otherwise the impact of the shock will be affected by changes in the estimated parameters of the $ARMA(p, q)$ model.

Feedback effects from the target variable (e.g., real GDP) and the right-hand side variables in the baseline regression are often present and need to be modelled. However, there are situations where feedback effects are not present. For example, consider a small open economy (e.g., Singapore) that is driven primarily by external factors (e.g., world growth, global oil prices, U.S. interest rates) that are not sensitive to changes in the domestic economy. In this case, the baseline regression for real GDP can be considered a structural equation (i.e., the coefficients are not biased as there are no feedback effects) with respect to the external factors. As such, it can provide multi-period estimates of the sensitivity of a nowcast to changes in external factors.

First Example: Limited Data, No Feedback Effects

Our first example is based on data for the Commonwealth of Dominica, an island country in the Caribbean and a member of the Eastern Caribbean Central Bank. It illustrates the case where there are no feedback effects from the domestic economy to its external factors.

The estimated baseline model produces a nowcast for Dominica's annual real GDP using four higher frequency indicators: real domestic imports (**dm_im, monthly**), tourism expenditures (**dm_vis_e, monthly**), the primary balance (**dm_pb**, **monthly**) and the return on average equity (**dm_roe, quarterly**). The baseline regression also includes two exogenous variables, the real GDP of the USA (**rgdp_usa, quarterly**) and the real WTI crude oil price (**r_wti, monthly**), as proxies for the key external factors affecting the Dominican economy.

The baseline (reduced-form) nowcasting regression for real GDP, estimated using annual data for 2001-2021 is:

Table 1: Baseline Nowcasting Regression for the Real GDP of Dominica, 2001-2021(Annual)

Dependent Variable: DLOG(RGDP)
Method: Least Squares
Sample (adjusted): 2001 2021
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.023209	0.010849	-2.139346	0.0505
DLOG(DM_IM)	0.181250	0.046806	3.872325	0.0017
DLOG(DM_VIS_E)	0.051998	0.017337	2.999274	0.0096
D(DM_PB)	0.000422	0.000249	1.694686	0.1123
DM_ROE	0.000749	0.000310	2.419824	0.0297
D(R_WTI)	-0.014054	0.009818	-1.431469	0.1742
D(RGDP_USA)	0.009849	0.003708	2.656161	0.0188

R-squared	0.881552	Mean dependent var	0.007991
Adjusted R-squared	0.830788	S.D. dependent var	0.057046
S.E. of regression	0.023466	Akaike info criterion	-4.405332
Sum squared resid	0.007709	Schwarz criterion	-4.057158
Log likelihood	53.25598	Hannan-Quinn criter.	-4.329769
F-statistic	17.36583	Durbin-Watson stat	2.288516
Prob(F-statistic)	0.000009		

Several preliminary steps were required to estimate the baseline regression at the annual frequency:

a) The monthly data was first converted to quarterly data to match the frequency of the exogenous variable (i.e., the quarterly USA real GDP which influences 2022 outcomes for the high frequency variables). The quarterly data for the high frequency variables in the baseline regression was then extended to 2022Q4 to get an annual forecast for 2022 for each high frequency variable (as they will be used in the baseline regression for Dominican annual real GDP). This step was achieved using an $ARMA(p, q)$ model selected by minimizing the Akaike information criterion (AIC). For example, the preferred quarterly $ARMA(p, q)$ model for expenditure by visitor arrivals (**dm_vis_e)** is an $ARMA(2,1)$ model with a crisis dummy (CRISIS)[3], USA real GDP (RGDP_USA), and real oil prices (R_WTI):

[3] The CRISIS dummy flags the dates of major shocks that have impacted Dominica's economy during 2001-2021.

Table 2: Preferred $ARMA(p, q)$ Model for Tourist Expenditures in Dominica, 2000Q2-2021Q4 (Quarterly)

Dependent Variable: DM_VIS_E
Method: ARMA Maximum Likelihood (BFGS)
Sample: 2000Q2 2021Q4
Included observations: 87

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	51.36789	10.46747	4.907385	0.0000
CRISIS	-7.346555	4.069085	-1.805456	0.0748
DLOG(RGDP_USA)	115.8278	37.74850	3.068408	0.0029
R_WTI	-2.209432	5.524214	-0.399954	0.6903
AR(1)	1.459534	0.487461	2.994153	0.0037
AR(2)	-0.536291	0.447560	-1.198255	0.2344
MA(1)	-0.412037	0.561082	-0.734362	0.4649
SIGMASQ	79.11120	9.889257	7.999711	0.0000

R-squared	0.833063	Mean dependent var	51.28306
Adjusted R-squared	0.818271	S.D. dependent var	21.89543
S.E. of regression	9.333941	Akaike info criterion	7.412926
Sum squared resid	6882.674	Schwarz criterion	7.639676
Log likelihood	-314.4623	Hannan-Quinn criter.	7.504231
F-statistic	56.31906	Durbin-Watson stat	1.994653
Prob(F-statistic)	0.000000		

Inverted AR Roots	.73-.06i	.73+.06i
Inverted MA Roots	.41	

Quarterly **dm_vis_e** is positively affected by the real GDP of the USA but negatively affected by the crisis dummy and by increases in the real oil price (though marginally). Moreover, there is unlikely to be any feedback from visitor expenditures to real USA GDP and real WTI oil prices.

Note that the last data point for estimating the regression is 2021Q4, and the regression is used to generate a quarterly forecast of **dm_vis_e** for 2022Q1-2022Q4. The series is then converted to the annual frequency by averaging the corresponding quarterly observations for each year, yielding an annual series for **dm_vis_e** that includes 2022. This series is used in the baseline regression to produce a nowcast for the annual real GDP of Dominica in 2022, and by construction, it indirectly involves the contribution of the exogenous variables.

b) Similar steps were used to extend the remaining high frequency variables (i.e., **dm_pb**, **dm_im**, **dm_roe**, and **ec_cg_cr**) starting from the quarterly frequency.

These variables were found to be positively associated with USA real GDP, but insensitive to changes in real oil prices.

c) Once the high frequency indicators are forecasted to 2022Q4 and converted to the annual frequency, the data available to estimate the baseline regression is:

Table 3: Annual Data for Baseline Nowcasting Regression for Real GDP, 2001-2022

Year	DLOG(RGDP)	DLOG(DM_IM)	DLOG(DM_VIS_E)	D(DM_PB)	DM_ROE	D(R_WTI)	D(RGDP_USA)
2001	-0.000638651	-0.127272934	0.144325872	-6.73992654	29.59	-1.422112449	0.77125
2002	-0.02868757	-0.114665756	-0.020480765	2.628340017	13.61	-1.270911848	1.384
2003	0.061594853	0.091115565	0.139767796	7.975307484	15.68	-0.314257822	2.32025
2004	0.03005082	0.123505919	0.147892997	-2.56664524	13.2	0.099186885	3.28675
2005	0.006537209	0.135822738	-0.061674359	2.877085416	12.05	0.929705619	3.08575
2006	0.045541612	0.002201998	0.229684871	7.400417574	17.6	0.819212644	2.55125
2007	0.061593305	0.160245464	0.037092186	-6.270298938	19.7	-0.038754082	1.8945
2008	0.068789392	0.23398408	0.173111267	-6.972176529	10.24	-1.526933447	0.11775
2009	-0.011764842	-0.089212693	-0.137343576	-1.424166168	30.25	-0.821274674	-2.5025
2010	0.006703823	0.006653091	0.195406828	-11.93193134	16.02	0.006458141	2.539
2011	-0.002238009	0.033441997	0.124303734	-7.026308988	0.64	-0.035302934	1.4925
2012	-0.010646476	-0.048447422	-0.328627096	-3.286333447	18.52	0.015774458	2.2295
2013	-0.010135409	0.024336903	0.296484769	6.406198543	-1.78	-0.014948342	1.8425
2014	0.046528194	0.039994164	0.214023495	13.94462818	-1.88	-0.008897037	2.3295
2015	-0.027695022	-0.069633069	-0.020590075	2.877757517	2.44	0.018974989	2.81925
2016	0.027261486	-0.03895446	-0.200936718	65.80220183	22.18	0.107375517	1.78425
2017	-0.06848223	-0.077273509	-0.306787465	-55.00014686	-39.09	0.24424816	2.4385
2018	0.034861074	0.416125369	0.082303853	-26.28110361	-14.96	0.321299652	3.27575
2019	0.053564306	0.059920788	0.399845795	-34.76220282	60.43	0.115892472	2.627
2020	-0.181571153	-0.402964783	-1.747786054	49.82300029	23.95	-0.700104651	-3.24175
2021	0.066635222	0.071895046	-0.252937993	-15.25040359	3.03	-0.115989242	6.77175
2022	NA	0.136678244	0.857145508	12.10815161	14.54	0.537959844	3.71884

Because the higher frequency data is complete for 2022 (i.e., there are no missing values in 2022 in the 6 right-most columns), the baseline regression estimated using 2001-2021[4] data can be used to generate a nowcast for 2022 real GDP.

d) The sensitivity of the nowcast for 2022 to changes in USA real GDP and/or real oil prices can be assessed by creating alternative scenarios separately for these external factors. For example, a 10 percent increase in real oil prices relative to the baseline for 2022 can be captured by increasing the annual real oil price for 2022 by 10 percent and then recalculating the nowcast. Note that the forecast for the high frequency variable **dm_vis_e** needs to be recalculated to reflect the impact of the higher real oil price on **dm_vis_e** and hence, indirectly, real GDP. The change in the nowcast relative to the baseline provides an indication of the sensitivity of the domestic economy to changes in real oil prices.

e) For Dominica, the baseline real GDP nowcast for 2022 is 9.55 percent year-on-year growth (or 1217.62 million ECU dollars). Given a 10 percent increase in real oil prices, the baseline real GDP nowcast for 2022 is 9.43 percent (or 1216.35

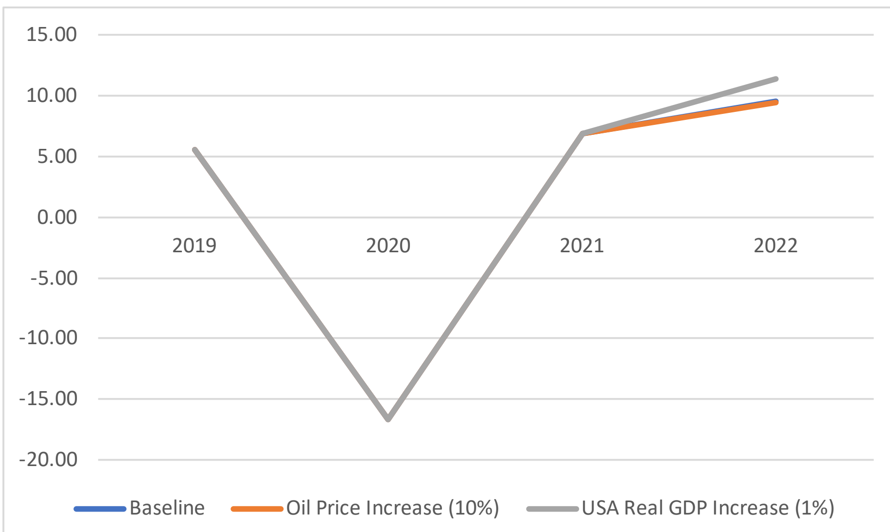
[4] The estimation period is determined by the availability of the published real GDP data, which in this case is 2001-2021.

million ECU dollars), suggesting that the one-period ahead impact of higher oil prices is rather small. Similarly, a 1 percent increase in USA real GDP during 2022 gives rise to a significantly higher nowcast of 11.34 percent year-on-year growth (or 1237.51 ECU dollars) compared to the baseline nowcast of 9.55 percent.

Table 4: Year-On-Year Percentage Change, 2019-2022, Real GDP of Dominica

Year	RGDP	RGDP_BASELINE	RGDP_OIL_10	RGDP_USA_01
2019	5.50	5.50	5.50	5.50
2020	-16.60	-16.60	-16.60	-16.60
2021	6.89	6.89	6.89	6.89
2022		9.55	9.43	11.34

Figure 1: Year-on-Year Percentage Change, 2019-2022, Real GDP of Dominica



f) The baseline regression was not re-estimated after imposing the shocks as these only apply after the end of the estimation period, namely 2021Q4, making re-estimation unnecessary.

g) Because real oil prices and USA real GDP are not affected by the real GDP of Dominica, it is possible to extend the analysis beyond 2022 (i.e., more than one-year ahead). In this case, all the high frequency variables in the baseline regression need to be extended to 2023. The baseline parameter estimates remain relevant (i.e., unbiased) because there are no feedback effects from Dominica to USA real GDP and global real oil prices.[5]

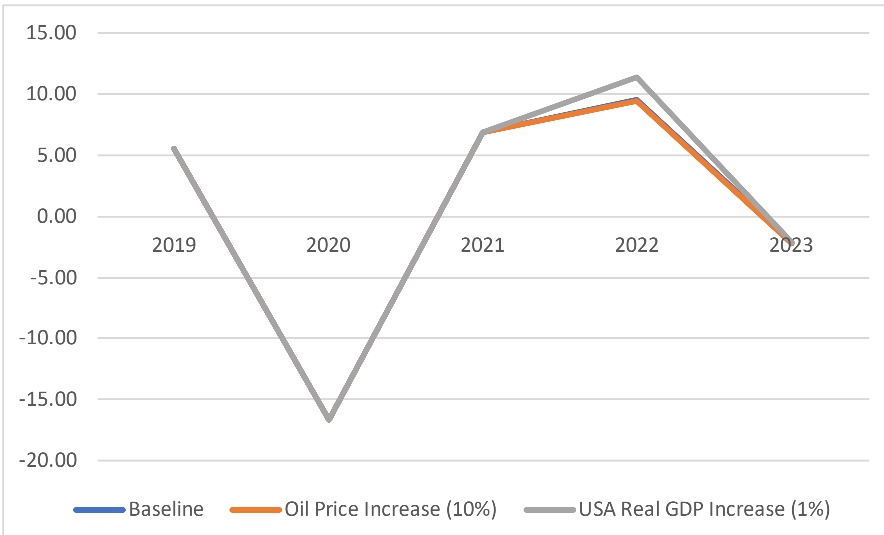
[5] EViews code that fully implements the first example is available from the authors.

h) Extending the nowcast to 2023 yields the following estimates for Dominica's real GDP year-on-year growth for 2023:

Table 5: Year-On-Year Percentage Change, 2019-2023, Real GDP of Dominica

Year	RGDP	RGDP_BASELINE	RGDP_OIL_10	RGDP_USA_01
2019	5.50	5.50	5.50	5.50
2020	-16.60	-16.60	-16.60	-16.60
2021	6.89	6.89	6.89	6.89
2022		9.55	9.43	11.34
2023		-2.10	-2.26	-2.09

Figure 2: Year-on-Year Percentage Change, 2019-2023, Real GDP of Dominica



Second Approach

The second approach involves a non-parametric structural estimator recently introduced in Ouliaris and Pagan (2022) to estimate the responsiveness of a nowcast to a structural shock. It does so without requiring a complete specification of the identifying restrictions. Ouliaris and Pagan (2022) show that once the shock of interest is estimated, the responses of the other variables to the shock can be estimated by regressing these variables on the shock in a single equation from a reduced-form VAR. Based on the sign-restricted approach for estimating structural VARs, this non-parametric method is especially useful in a nowcasting context because (a) the total number of parameters to estimate is low compared to a VAR; (b) by construction, this approach is appropriately agnostic about the identifying restrictions underlying the true impulse response functions in the SVAR.

Consider a standard structural VAR with a triangular identification structure (i.e., the A matrix of the SVAR is triangular, with the “most exogenous” variable in the system ordered first and the most endogenous positioned last). The system we work with is composed of the structural equation(s) of interest and completed by the reduced-form VAR equations for the other variables in the system. The structural equation can, for example, be describing the evolution of a high frequency variable impacted by a structural shock. The shocks in the system are composed of the structural shock of interest, say η_{1t}, and the reduced-form VAR errors, v_{ij}, that are uncorrelated with η_{1t}.

Thus, for a three-variable system involving one high-frequency variable, x_{1t}, the SVAR system would be:

$$x_{1t} = \alpha_{12}x_{2t} + \alpha_{13}y_{3t} + lags + \eta_{1t} \tag{1}$$
$$x_{2t} = lags + \rho_1\eta_{1t} + v_{2t} \tag{2}$$
$$y_{3t} = lags + \rho_2\eta_{1t} + v_{3t} \tag{3}$$

Note that there is only one structural equation in this system, equation (1), and that the v_{jt}, which are reduced-form errors, are linear combinations of the other structural shocks $\eta_{jt}, j = 2, 3$. Hence they are independent of η_{1t}.

Estimation proceeds by simulating α_{12} and α_{13} and generating the residuals of equation (1) to obtain an estimate of η_{1t}, $\hat{\eta}_{1t}$. To enforce the restriction that η_{1t} is uncorrelated with v_{jt} , one regresses x_{2t} and y_{3t} on lags of all endogenous variables and $\hat{\eta}_{1t}$ to obtain unbiased estimates of ρ_1 and ρ_2. It is important to note that simulations of α_{12} and α_{13} that are inconsistent with economic priors are rejected upfront, as failing to do so would yield a structural equation for the high-frequency variable that is difficult to explain. Once the parameters $\alpha_{12}, \alpha_{13,}$ ρ_1 and ρ_2 are determined either by assignment (as in the case of α_{12} and α_{13}) or estimation (i.e., ρ_1 and ρ_2), impulse responses of x_{2t} and y_{3t} to ***positive*** shocks η_{1t} can be obtained easily. Specifically, the response of y_{3t} to a unit shock in the high frequency variable is ρ_2, while that for x_{2t} is ρ_1.

Note that if x_{1t} is an exogenous variable, then α_{12} and α_{13} would equal zero and there would be no lags of x_{2t} and y_{3t} in equation (1). In this case, ρ_1 and ρ_2 can be estimated by replacing η_{1t} in equations (2) and (3) by x_{1t}, which is the methodology we used in the previous section. Note that both US real GDP and global oil prices are exogenous with respect to the real GDP of Dominica. Therefore, the two methodologies coincide in the case of the Dominica example.

Second Example: Limited Data, General Feedback Effects

To illustrate the above method with an empirical example, we consider a nowcasting regression for the real GDP of Tonga, a small island Polynesian country in the South Pacific Ocean. Its economy is subject to frequent and significant weather and geological shocks (hurricanes, and volcanic eruptions). Tonga relies heavily on remittances from its diaspora, especially after natural disasters and large negative external shocks such as COVID. Its main trading partners are Australia, New Zealand, and the United States of America.

Annual estimates of real GDP for Tonga are released with a significant lag of 1-2 years. The following semi-annual nowcasting model for real GDP was estimated to address this problem:

Table 6: Baseline Nowcasting Regression for Tonga, 2011S1-2021S1

Dependent Variable: DLOG(GDPR_CH)
Method: Least Squares
Sample (adjusted): 2011S2 2021S1
Included observations: 20 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000666	0.006342	-0.105059	0.9186
DLOG(GDPR_CH(-1))	0.447579	0.221554	2.020177	0.0741
DLOG(TOTAL_AGR)	0.002912	0.006289	0.462935	0.6544
DLOG(CONST_PERR(-1))	0.015971	0.007837	2.037828	0.0720
DLOG(CONST_PERR(-2))	0.011338	0.008927	1.270036	0.2359
DLOG(REM_R)	0.009365	0.017558	0.533381	0.6067
DLOG(REM_R(-1))	0.004907	0.015061	0.325794	0.7520
CRD_GRW(-1)	0.000128	0.000295	0.433359	0.6750
DLOG(TRV_RECR)	0.005767	0.017392	0.331609	0.7478
DLOG(AUS_GDP(-1))	0.191812	0.424280	0.452088	0.6619
CRISIS	-0.003879	0.010082	-0.384716	0.7094

R-squared	0.728796	Mean dependent var	0.006325
Adjusted R-squared	0.427458	S.D. dependent var	0.011973
S.E. of regression	0.009060	Akaike info criterion	-6.268467
Sum squared resid	0.000739	Schwarz criterion	-5.720815
Log likelihood	73.68467	Hannan-Quinn criter.	-6.161560
F-statistic	2.418531	Durbin-Watson stat	1.325430
Prob(F-statistic)	0.099773		

Tonga's real GDP is assumed to be influenced by the value of total agricultural production (TOTAL_AGR), construction permits (CONST_PERR), remittances (REM_R), credit growth (CRD_GRW), travel receipts (TRV_RECR) and the lagged growth in Australia's real GDP

(AUS_GDP). The baseline regression also has a crisis dummy to capture significant structural events that adversely affected Tonga's real GDP during 2011S2-2021S1. Except for Australia's real GDP, the right-hand side variables have a quarterly (or higher) frequency and are updated by Tonga's Statistics Department more frequently than annual real GDP.

Given the large number of explanatory variables and the limited number of observations (i.e., 20 semi-annual observations), using conventional structural approaches to assess the sensitivity of the nowcast to a shock (such as one to travel receipts) are not feasible.

Assume that we are interested in assessing the impact of an increase in tourism on the nowcast for real GDP. The first step in applying the non-parametric approach suggested by Ouliaris and Pagan (2022) is to specify the structural equation that will yield an estimate of the structural error for travel receipts (i.e., η_{1t} in equation (1)).

The associated structural equation for travel receipts (***trv_recr***) involves current real GDP (***gdpr_ch***), remittances (***rem_r***), and total agricultural production (***total_agr***):

$$dlog(trv\_recr_t) = \alpha_1 + \gamma_1 crisis + \beta_1 dlog(gdpr\_ch_t) + \beta_2 dlog(rem\_r_t) + \beta_3 dlog(total\_agr_t) + lags + \eta_{1t} \quad (4)$$

where η_{1t} is the structural error for travel receipts. Estimates of this structural error can be obtained by simulating $\beta_1,\ \beta_2,\ \beta_3$ according to some random distribution (e.g., uniform) and estimating the residuals in (4) for each draw.

Once η_{1t} is generated as described, an estimate of the impact of a shock to travel receipts on real GDP can be derived from the reduced-form VAR equation for real GDP, namely:

$$dlog(rgdp\_ch_t) = \alpha_2 + \gamma_2 crisis + lags + \rho_2 \hat{\eta}_{1t} + v_{2t} \quad (5)$$

Specifically, the response of the nowcast of real GDP to a positive unit shock in travel receipts is ρ_2. Because $\hat{\eta}_{1t}$ is orthogonal to v_{2t}, ρ_2 can be estimated using Ordinary Least Squares (OLS).

The OLS estimate of ρ_2 is conditional on the current draws for $\beta_1,\ \beta_2,\ \beta_3$. We can obtain a robust estimate of the impact of a shock to travel receipts by searching over the feasible space for $\beta_1,\ \beta_2,\ \beta_3$ and then calculating summary statistics for ρ_2, e.g., its mean, median, maximum, and minimum values. The results can then be used to adjust the baseline nowcast for real GDP given the assumed size of the shock to travel receipts.[6]

[6] Recall that the methodology assumes a unit shock to the high frequency variable.

We now demonstrate the application of the approach to Tonga data for 2011S2-2021S1. The first step is to implement equation (4) using data that is regressed on a constant and the crisis dummy.[7] To avoid imposing unintended constraints on the response of real GDP to a unit shock in travel receipts, we assume a range of $(-\infty, \infty)$ for the three unknown parameters β_1, β_2 β_3.[8] Random values d_i for $\beta_1, \beta_2, \beta_3$, were drawn from a uniform $(-1, 1)$ distribution and transformed to the interval $(-\infty, \infty)$ using $1/(1 - abs(d_i))$. One million estimates of η_{1t} and ρ_2 were generated.

Overall, the estimates for ρ_2 from equation (5) suggest that, on average, there is a positive relationship between the tourism sector and real GDP. The estimates for ρ_2 have a mean of 0.56 percent, a median of 0.24 percent and an interquartile range of [0, 1.12]. These statistics can be used to estimate the sensitivity of the baseline nowcast for real GDP to a unit shock arising from the tourism sector (i.e., travel receipts) one period ahead.

Conclusion

The sensitivity of the baseline nowcast for a low frequency variable from a structural shock to a high frequency explanatory variable is critical information for policymakers. In this paper, we proposed two regression-based methodologies to address this need. The first is a partial equilibrium approach based on an $ARMA(p, q)$ model. The second approach applies a non-parametric structural estimator based on the sign-restricted methodology. Both approaches produce one period estimates of the impact of a policy change and can be shown to be theoretically equivalent when estimating the impact of exogenous variables. Each approach was illustrated using a country-specific example.

References

Ouliaris, Sam and Adrian R. Pagan (2022), “Three Basic Issues that Arise when Using Informational Restrictions in SVARs”, *Oxford Bulletin of Economics and Statistics*, 84(1), pp. 1-20.

[7] In other words, we work with the residuals of $dlog(trv\_recr_t)$ after being regressed on a constant and the crisis dummy. All the required variables in the regression are included with a single lag.

[8] The endpoints of the range (i.e., $-\infty$ and ∞) are excluded.

PUBLICATIONS

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