CARBON TAX FORECASTS: STRUCTURAL MODELS AND VARS

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Overview

It is widely accepted that carbon taxes are required for a transition to cleaner energy (Nordhaus, 2009). This consensus holds not just for economists, but is growing even for large oil and gas companies like Royal Dutch Shell (Hone, 2014). The standard way to model the effects of a carbon tax is via Integrated Assesment Models (IAMs), based on the work of Nordhaus, Houthakker, and Solow (1973). IAMs depict a complex economy via structural equations, with both endogenous and exogenous variables – the latter required for identifying equations.

One difficulty with the IAM approach has been an 'embarassment of riches' – widely varying estimates for a carbon tax high enough to be effective. The UN *High-Level Commission on Carbon Pricing* (Stiglitz, Stern, *et al.,* 2017) attempts to chart the level of tax needed to keep the rise in global mean temperature below 2º Celsius. The models consulted by the UN study estimate effective tax levels that vary by a factor of 20 for the early phases of taxation, and by even more for the longer term (Guivarch and Rogelj, 2017). Such a range gives little guidance to policy.

There has been surprisingly little work on narrowing this IAM range by harnessing the major competitor to a structural approach: Vector Auto-Regressions (VARs). Unlike structural models, VARs treat all variables as endogenous; exogeneity is provided by their lagged values. VARs usually give more accurate forecasts in the short-to-medium term (Makridakis et al., 2010; Sims, 2011).

But it is the basic complementarity between structural and VAR models that is stressed by Sims (2011) – the theory of the former used to test restrictions on the latter. The resulting hybrid is termed a Structural VAR (SVAR). This complementarity is also noted by Vipin Arora (2013), of the US Energy Information Agency (EIA). Arora urges greater use of SVARs for energy policy and forecasting. Yet we have found few attempts to apply VARs to carbon tax forecasts, and none at all for the three basic fossil fuels – Coal, Oil, and Gas – and their substitution effects.

Methods

Our data are Producer and Consumer *Prices*, plus Producer and Consumer *Quantities* for all three fuels – Coal, Oil, and Gas. This gives 3 fuels and 4 variables for each – 2 prices and 2 quantities –a total of 12 variables. Our basic data are from the US EIA, monthly series over a bit more than 32 years, from 1986 to early 2018. We used 12 monthly lags for each variable, so this means 144 variables in each VAR equation. To account for substitution across time, quantity variables were entered as 12-month moving averages, reducing observations on each variable by 12. Thus our data cover about 31 years, times 12 months, times 12 variables: more than 4,400 observations.

After testing for and rejecting stationarity, we confirm that all variables are cointegrated, thus affording our use of a Vector Error Correction Model (VECM). As a first step toward an SVAR, we impose a co-production constraint on Oil and Gas – commonly co-produced, especially with fracking. A second constraint comes from the fact that the US has been fairly autarchic in coal until recently – low exports or imports. We impose a constraint on our error-correction equations, so that the parameter of adjustment between the cointegrating equation for production and the *changes* in Coal production should be equal to the parameter of adjustment between the cointegrating equation for consumption and the *changes* in Coal consumption.

Results

Interestingly, our two constraints on (i) Oil and Gas co-production and (ii) the autarchic US Coal market, improved the performance of the VECM. This is seen in terms of a higher R^2 for 8 of 12 cointegrating equations, and greater predictive accuracy for forecasts on 10 of our 12 series. (Forecasts were back-dated by 3 years, to yield predictions from February 2015 to February 2018.)

More importantly, reasonable forecasts were generated. With taxes of \$10 to \$20 per metric tonne of CO_2 – at the low end of effective level estimates made by the IAMs in the UN Report. As to effectiveness, a \$20 tax is estimated to cause a drop of almost half a billion tonnes in US CO_2 output. Using US share of world CO_2 output (14.3%), we multiply this reduction in CO_2 output by 7 to reach 100% of world output. Such scaling yields 3.3 billion tonnes (i.e., gigatonnes) of CO_2 reduction from a scaled-up global tax – a crude first estimate.

The UN Energy Programme's *Emissions Gap Report* (2018) estimates that we should reduce global emissions by 10 gigatonnes of CO_2 *equivalent* (*all* green house gases, not just CO_2, and not just from burning fuel). This should be achieved by 2025 to stay on track for a rise in global temperature that is less than 1.5º Celsius. By our scaled-up projection of $20 a tonne getting us a global reduction 3.3 gigatonnes, a $20 global carbon tax gets us one-third of the way there by 2022 – three years early, and by fuel efficiencies alone.

This is a crude gloal estimate, since the US already has well-integrated energy markets. It is also clear that further means of reducing CO_2 *equivalents* will have to be found. But such a step change would be a significant down-payment on global carbon reduction, for a surprisingly low tax.

Our tax simulations are run two different ways – as a sudden increase of $20 per tonne, and as a gradual ramp-up to $20 over two years. The more gradual path shows not only less volatility, but also a larger reduction in total CO_2. This may be an artefact of the VAR forecast ceding larger influence to small but *persistent* changes than it to large and sudden changes. But it could also capture greater economic flexibility, if change is not pushed too fast. The correct interpretation is unclear.

Conclusions

The first and most basic conclusion of this study is that relatively low taxes, if introduced gradually, can promote a greater and more rapid reduction in CO_2 than is generally expected. A second conclusion, following the argument of Sims (2011) and Arora (2013), is to see the reasonableness of these simple VAR estimates as an encouraging first step toward fully specified SVAR models.

SVARs can complement and improve the structural models of the IAM tradition, and *vice versa*. The fact that our low effective tax simulations are quite similar to some of the IAMs is already interesting. What SVAR restrictions do the structural models suggest? And can SVAR models help us improve the accuracy of IAM forecasts? Answers to such questions seem worth pursuing.

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