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Measuring US sectoral shocks in the world input–output network

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HIGHLIGHTS

- Three multi-sector general equilibrium models are specified.
- The models are used to measure the US sectoral shocks with the WIOT.
- PC, GPC and MLE are used in factor analysis.
- The estimates are from 10% to 45%.

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ABSTRACT

I measure the importance of sectoral shocks in US aggregate output by using the World Input–Output Table (WIOT). The WIOT allows me to correct potential sub-graph bias in previous literature, caused by using only the US industrial production input–output table. I report results from three closely related models to show how sensitive the analyses are to different specifications. The estimates vary from 10% to 45%.

1. Introduction

What is the structure of the shocks that hit US industries? In particular, how much of common shocks do they share, relative to idiosyncratic sectoral shocks? This paper answers the question quantitatively, by using model-specific filters to extract TFP shocks of each sector, and applying factor analysis to them as in Foerster et al. (2011).

Filters are created by the equilibrium relationship between output growth rate and TFP shocks, derived from models with different specifications on production technologies and inter-linkage structures. Since the extracted TFP shocks are model specific, I will go through three specifications to provide the sense of the robustness of the analysis. The three specifications isolate the effect of including static linkages and dynamic linkages when measuring the importance of sectoral shocks. The obtained TFP shocks then go through factor analysis, so that the common component and the idiosyncratic component are detected systematically.

Foerster et al. (2011) standardize the methodology, but its result is potentially subject to a data-oriented bias. It uses the US industrial production input–output table to report that the sectoral shocks can account from 10% to 50% of the aggregate fluctuation of industrial production. However, their data only reflects a part of the entire network structure among industries. For instance, financial intermediation and services are not in their data. It also ignores the breakdown of import and export, i.e., from/to which industry in which country input comes/output goes. The lack of data for the rest of the network may cause bias in the estimation, which I call "sub-graph bias". For instance, suppose there are three industries, but only two of them are observed. If both of the observed industries purchase inputs from the unobserved sector, the shock to the unobserved sector propagates to the observed two through the network, but is not going to be filtered out because the shock to the observed is observationally equivalent to an aggregate shock, and therefore is counted as such.

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This paper corrects the sub-graph bias by using the WIOT.[1] The WIOT covers US industries which are excluded from Foerster et al. (2011) as well as the breakdown of trades for each industry. Hence, the input–output structure I cover is not only within the US, but also among industries in forty countries that cover 80% of world GDP.

Traditional factor analysis relies on the principal component method (PC), which is known to be inconsistent under heteroskedasticity and fixed T. Hence, I also introduce the maximum likelihood method (MLE) with EM algorithm *a la* Bai and Li (2012). The contribution of US sectoral shocks to US aggregate output varies, depending on which filter is used, from 10% to 45%.

One caveat is that the results in this paper are not necessarily comparable with Foerster et al. (2011). The main reason is the difference in the level of aggregation/disaggregation of the data. Foerster et al. (2011) uses 117 sectors, while this paper uses 35.

2. Models

To extract TFP shocks, I construct three filters implied by three different general equilibrium models. They differ only in assumptions on the production technology. The first model assumes no input–output structure. The second assumes intratemporal, and the third assumes both intra- and intertemporal network propagation mechanisms.

In all models, I assume the CRRA utility function with linear labor disutility

$$\max \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \sum_{j=1}^{N} \left(\frac{C_{jt}^{1-\sigma} - 1}{1-\sigma} - \psi L_{jt} \right), \qquad (1)$$

complete market, and random walk TFP process

$$\ln A_t = \ln A_{t-1} + \epsilon_t,$$

where $A_t = (A_{1t}, \ldots, A_{Nt})'$ is the vector of productivity of each sector. The complete market assumption provides tractability to a general equilibrium model with a large number of sectors. Random walk TFP allows simple differencing to generate an equilibrium relationship between observable growth rates and unobservable TFP shocks.

Although these assumptions look strong, it is not necessarily obvious how restrictive they are. For instance, one may think the complete market cannot capture institutional frictions such as trade barriers or legal maturity. However, the frictions related to trade barriers or geographical cost structure can be thought to be reflected in the production technology of each sector.

All of the derivations are relegated to the online Appendices.

2.1. Identity filter

The first filter corresponds to linear production function. The social planner's problem at each period is to maximize (1) subject to the resource constraint at time t:

$$C_{jt} = A_{jt} L_{jt}, \quad j = 1, \ldots, N.$$

In the competitive equilibrium, $y_t = \mu + a_t$ where y_t is the log of real output, μ is a function of parameters, and $a_t := \ln A_t$ is an $N \times 1$ vector. Given $\ln A_{jt}$ being a random walk, identity filter is defined as identity mapping:

$$\epsilon_t = X_t,$$

where $X_t = \ln Y_t - \ln Y_{t-1}$.

[1] Foerster et al. (2011) are careful to acknowledge, in footnote 4, that they are not identifying "the source of the common factors affecting sectoral productivity", since they only use data from goods-producing industries.

2.2. Static filter

The second filter corresponds to the Cobb–Douglas production function with intermediate inputs. The resource constraint at time t is

$$C_{jt} + \sum_{i=1}^{N} M_{jit} = A_{jt} \left(\prod_{i=1}^{N} M_{ijt}^{\gamma_{ij}} \right) L_{jt}^{1-\sum_{i=1}^{N}\gamma_{ij}}, \quad j = 1, \ldots, N.$$

This is what Shea (2002) and Carvalho (2008) explore. When $\sigma = 1$, the equilibrium relationship is $y_t = \mu + \left(I_N - \Gamma'\right)^{-1} a_t$. Given $\ln A_{jt}$ being a random walk and $\Gamma := \left(\gamma_{ij}\right)_{i,j=1}^{N}$, the static filter is defined as

$$\epsilon_t = \left(I_N - \Gamma'\right) X_t.$$

2.3. Dynamic filter

The third filter corresponds to the Cobb–Douglas production function with both intermediate inputs and capital that connects the current period and the previous period. Social planner's constraint at time t is

$$C_{jt} + \sum_{i=1}^{N} M_{jit} + K_{jt+1} - (1-\delta) K_{jt}$$
$$= A_{jt} K_{jt}^{\alpha_j} \left(\prod_{i=1}^{N} M_{ijt}^{\gamma_{ij}} \right) L_{jt}^{1-\alpha_j-\sum_{i=1}^{N}\gamma_{ij}}, \quad j = 1, \ldots, N.$$

This is the framework of Foerster et al. (2011). When $\sigma = 1$, the equilibrium relationship is $y_{t+1} = \varrho y_t + \Xi a_t + \Pi_a a_{t+1}$, where (ϱ, Ξ, Π_a) is a function of model parameters obtained by solving the rational expectations model. Given $\ln A_{jt}$ being a random walk, the dynamic filter is defined as

$$\epsilon_{t+1} = \Pi_a^{-1} \left(X_{t+1} - \varrho X_t - \Xi \epsilon_t \right)$$

with initial conditions $\epsilon_t = 0$ and $X_0 = 0$.

3. Identification of common shocks

Once I obtain the TFP shocks $(\epsilon_t)_t$ by applying any one of the filters, I estimate the common component and the idiosyncratic component by factor analysis. Let $\left(Y_t^*\right)_t$ denote the demeaned TFP shocks $(\epsilon_t)_t$. The structure imposed in estimation is

$$Y_{it}^* = \lambda_i' f_t + u_{it}, \quad i = 1, \ldots, N, \ t = 1, \ldots, T,$$

or in matrix notation,

$$Y_t^* = \Lambda f_t + u_t, \quad t = 1, \ldots, T,$$

where all variables are *i.i.d.* over t and $f_t \perp u_t$ for each t. Let the first two moments of f and u be

$$Ef_t = 0, \qquad Vf_t = \Sigma_f,$$
$$Eu_t = 0, \qquad Vu_t = \Psi.$$

Following Foerster et al. (2011), the object of interest is $1 - R^2(F)$, or equivalently

$$R^2(F) = \frac{V\left(\bar{w}' s_{US} \Lambda f_t\right)}{V\left(\bar{w}' s_{US} Y_t\right)} = \frac{\bar{w}' s_{US} \Lambda \Sigma_f \Lambda' s_{US}' \bar{w}}{\bar{w}' s_{US} \left(\Lambda \Sigma_f \Lambda' + \Psi\right) s_{US}' \bar{w}},$$

where $\bar{w} = (\bar{w}_i)_{i \in US}$, $\bar{w}_i = \frac{1}{T} \sum_{t=1}^{T} w_{it}$ and s_{US} is the selection matrix that picks up the elements that correspond to the 35 US industries.

Three estimates are considered: the principal component method (PC), the generalized principal component method (GPC), and the maximum likelihood method (MLE). The MLE is conducted by