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R&D and wholesale trade are critical to the economy: Identifying dominant sectors from economic networks[☆]

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HIGHLIGHTS

- We use network techniques to identify critical sectors of 49 OECD economies.
- Using input–output tables we track changes in these sectors from 1996 to 2011.
- Over half of countries have a dominant wholesale trade sector.
- Over time, and with development stage, countries also have a dominant R&D sector.

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ABSTRACT

Using a network approach we identify critical sectors for 49 economies. Wholesale trade is dominant for over half the countries, but increasingly R&D activities have an equivalent importance. Recognizing R&D as critical urges caution against disinvesting in this sector.

1. Introduction

Sectoral shocks have been established as a significant source of business cycle variation in the US economy, Gabaix (2011). While large sectors and/or firms can have large effects due to their size, Foerster et al. (2011) show that it is the networks of connections between the firms and sectors, represented by the covariation between the sectors, which have critical effects. These economy-wide sectoral networks are formally modeled in Acemoglu et al. (2012).[1]

Using network theory to develop a formal test to determine the most critical sectors in the economy Pesaran and Yang (2017) establish the dominance of the wholesale trade and transport sector in the US economy. (Dominance is a formally defined term for sectors which pass the threshold value for critical importance in the network.) Ultimately, if stores cannot source or transport goods they cannot be distributed to their consumers. If manufacturers cannot transport products then they cannot sell their output and hence remain in business. This is a primary reason that modern conflict and war almost always pinpoint key transport linkages (roads, ports, trains, energy supplies) as primary targets to maximize disruption to opponents. Nordhaus (2002) highlights strong productivity growth in the wholesale trade sector as a major contributor to overall productivity growth in the 1990s.

We apply the dominant sector detection methodology of Pesaran and Yang (2017) to input–output tables for 49 economies and determine that in many of the more developed markets *both* R&D and wholesale trade are critical. For a substantial number of countries, including the US, the most recent data indicates a shift

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1 Ando (2014) confirms that US sectoral shocks contribute significantly to the US aggregate output fluctuation and demonstrates the importance of including all relevant sectors in order to avoid bias from excluded nodes.

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towards R&D as the dominant sector. The empirical work on sector dominance has not previously considered the importance of the R&D activities as a key industry in sustaining the economy despite its long-established importance as key in the endogenous growth literature; Coe and Helpman (1995) and Perez-Sebastian (2015).

These results should give rise to cautionary thought amongst countries which are considering reducing their investment in research and development in favor of perhaps more politically appealing infrastructure such as roads and trains. These are not unimportant, but running down public and private incentives to invest in R&D will be as equivalently misguided as neglecting more physically obvious networks for developed economies.

2. Approach

To characterize the effect of unit specific shocks on aggregate output consider the production network model of Acemoglu et al. (2012) in which production of sector i at time t, q_{it}, is determined by the following Cobb–Douglas production function subject to constant returns to scale

$$q_{it} = \exp(\alpha u_{it}) l_{it}^{\alpha} \prod_{j=1}^{N} q_{ij,t}^{\rho w_{ij}}, \quad \text{for } i = 1, \ldots, N; \quad t = 1, 2, \ldots, T, \tag{1}$$

where productivity shocks, $u_{it} = \varepsilon_{it} + \gamma_i f_t$, are determined by a sector-specific shock, ε_{it}, and a common technological factor, f_t; labor input is denoted l_{it}, with the share of labor given by $\alpha = 1-\rho$, and ρw_{ij} is the share of output j in the sector i. Following Pesaran and Yang (2017), the cross section exponent of the factor loadings δ_γ is defined to ensure that

$$\lim_{N\to\infty} N^{-\delta_\gamma} \sum_{i=1}^{N} |\gamma_i| = c_\gamma > 0,$$

where c_γ is a finite constant.[2] Moreover, the sector specific shocks are assumed to be independent with zero means and finite variances.

The amount of final goods, $c_{it} = q_{it} - \sum_{j=1}^{N} q_{ji,t}$, is characterized by the amount of output of sector j used in production of sector i, $q_{ji,t}$, and consumed by a representative households with the Cobb–Douglas preferences $u(c_{1t}, \ldots, c_{Nt}) = A\prod_{i=1}^{N} c_{it}^{1/N}, A > 0$. We assume that the aggregate labor supply, l_t, is fixed and labor markets clear, $l_t = \sum_{i=1}^{N} l_{it}$.

A price network is dual to the production network and the former is derived from the sectoral equilibrium prices $p_{it} = \log(P_{it})$ and the equilibrium wage rates $\omega_t = \log(Wage_t)$. Solving sector i's problem leads to

$$q_{ij,t} = \frac{\rho w_{ij} P_{it} q_{it}}{P_{jt}}, \tag{2}$$

$$l_{it} = \frac{\alpha P_{it} q_{it}}{Wage_t}. \tag{3}$$

Substituting Eqs. (2) and (3) in (1) yields the price network[3]

$$\mathbf{p}_t = \rho \mathbf{W} \mathbf{p}_t + \alpha \omega_t \tau_N - (\mathbf{b} + \alpha \gamma f_t + \alpha \varepsilon_t), \tag{4}$$

in which $\mathbf{b} = (b_1, \ldots, b_N)'$ is a vector of price-specific intercepts, $\mathbf{p}_t = (p_{1t}, \ldots, p_{Nt})'$, $\mathbf{W} = (w_{ij})$ is a $N \times N$ matrix, τ_N is an N dimensional vector of ones, $\gamma = (\gamma_1, \ldots, \gamma_N)'$, and $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{Nt})'$. Eqs. (2) and (4) can be used to obtain the sales equation

$$\mathbf{S}_t = \rho \mathbf{W}' \mathbf{S}_t + \mathbf{C}_t = (\mathbf{I}_N - \rho \mathbf{W}')^{-1} \mathbf{C}_t, \tag{5}$$

where $\mathbf{S}_t = (S_{1t}, \ldots, S_{Nt})'$, $\mathbf{C}_t = (C_{1t}, \ldots, C_{Nt})'$, $C_{it} = P_{it} c_{it}$, and $S_{it} = P_{it} q_{it}$. The right-hand side of Eq. (5) shows that the Leontief inverse captures network effects in the sales equation. These network effects, characterized by matrix $\mathbf{W}$, are the main object of interest.

Now consider a network represented by the adjacency matrix $\mathbf{W} = (w_{ij})$ with non-negative elements for all i and j which is row-normalized[4] such that $\sum_{j=1}^{N} w_{ij} = 1$, for all j. To assess the effects of idiosyncratic shocks on some aggregate measure of the network we use out degree as a measure of centrality. In particular, the outdegree of the jth unit, $d_j = \tau_N' \mathbf{w}^j$, counts the number of ties the unit directs to others[5] where $\mathbf{w}^j$ is assigned to the jth column of $\mathbf{W}$. Pesaran and Yang (2017) showed that the network, represented by $\mathbf{W}$ with

$$d_j = \kappa_j N^{\delta_j}, \tag{6}$$

where κ_j is a fixed positive constant and $d_j > 0$, contains a finite number of dominant units with δ_j being the degree of dominance of unit j. For unit-specific shocks to dominate the macro or common factor shocks we require $\delta_i > \delta_\gamma > 0.5$. No network effects of unit-specific shocks can be identified[6] when $\delta_i \leq 0.5$.

Under the exponent specification

$$d_{it} = \kappa N^{\delta_i} \exp(\upsilon_{it}), \quad i = 1, \ldots, N; \quad t = 1, \ldots, T, \tag{7}$$

in which constant $\kappa > 0$, d_{it} represent observations on outdegrees at time t, $\upsilon_{it} \sim i.i.d.(0, \sigma_\upsilon^2)$ over i and t, a consistent estimator of the degree of pervasiveness of the dominant unit δ_i in the network where T is finite and N is large is defined as

$$\hat{\delta}_i = \frac{T^{-1}\sum_{t=1}^{T} \ln(d_{it}) - (TN)^{-1} \sum_{t=1}^{T} \sum_{j=1}^{N} \ln(d_{jt})}{\ln(N)}. \tag{8}$$

We estimate $\hat{\delta}_i$ from input–output tables of 49 countries between 1995 and 2011.

3. Data

We source domestic input–output tables for 49 countries over the period 1995 to 2011 from the World Economic Outlook database.[7] The countries are listed in Table 1. Annual data are used to construct 5 year panels (improving our estimation power over annual samples). We analyze the 36 sectors listed in Table 1 for each economy. Differing level of aggregation for sectors across applications will directly affect the estimated value $\hat{\delta}_i$. The assumption that each sector applies Cobb–Douglas technology, as in Eq. (1), implies that there is no strict additivity from lower to higher aggregation levels. The degree of aggregation in the OECD data means the results are not directly comparable with Pesaran and Yang (2017), who include over 400 sectors for the domestic US economy (R&D is not separately identified), but are comparable across the different economies.

4. Results

Table 1 reports the sectors across 49 countries with the values of $\hat{\delta}_i$ for dominant sectors over the past 20 years from 5 year panels.

[2] This set up is different from the standard factor model as we allow the factor loadings to be random and do not assume $\delta_\gamma = 1$.

[3] This form is clearly related to the spatial econometrics literature.

[4] The assumption that weights are normalized is standard in the network literature. See e.g. Diebold and Yılmaz (2014).

[5] This approach also shows that d_j is a weighted measure of centrality.

[6] see Remark 3 of Pesaran and Yang (2017).

[7] Domestic input–output tables have been also analyzed by Bartelme and Gorodnichenko (2015), Fadinger et al. (2016) and Miranda-Pinto (2017). The annual data are available for 60 countries but are too sparse to implement this approach in 11 countries.