Measuring productivity and absorptive capacity

A factor-augmented panel data model with time-varying parameters

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Extended abstract

The relative importance of Total Factor Productivity (TFP) vis-à-vis factor accumulation for economic growth has occupied economists not least since Tinbergen (1942), Fabricant (1954), Abramovitz (1956) and Solow (1956). In this paper we build on an established strand of the literature that interprets TFP as successfully assimilated global technology (Parente and Prescott, 1994, 2002). What unites concepts such as 'absorptive capacity' and alternatives used to describe this setup – e.g. Abramovitz (1986) social capability – is the notion that despite the designation of technological knowledge as a public good or being in the public domain (Nelson, 1959; Arrow, 1962) technological catch-up and thus convergence in income per capita is by no means guaranteed, but requires considerable efforts and investments (Aghion and Jaravel, 2015).[1]

We propose a novel and less restrictive approach to analysing cross-country productivity spillovers by making use of the cross-section dimension of panel data to empirically identify the evolution of global TFP and of country-specific absorptive capacity. Ours is to the best of our knowledge the first implementation in productivity analysis to allow for a flexible evolution in absorptive capacity,

[1] For a detailed discussion of the origins of absorptive capacity see the early sections of Fagerberg et al. (2009). Gerschenkron (1962) was among the first to recognise the potentially important role of knowledge spillovers and absorptive capacity for growth and development. In this article we use knowledge spillovers synonymously with 'technology spillovers' or more broadly the assimilation of ideas and innovations developed in other countries. Technology is used interchangeably with productivity, knowledge and TFP.

rather than relying on individual proxies/determinants, such as human capital and R&D investments (e.g. Cohen and Levinthal (1989) in the context of firms; Griffith et al. (2004) in the context of industries),[2] and/or imposing explicit channels for knowledge spillovers, such as international trade (imports *and* exports), FDI, and migration (see Keller, 2004, 2010, for detailed surveys). While *a priori* all of these factors are likely to be relevant to capture the identification, assimilation and exploitation of ideas and innovations developed elsewhere, the current empirical literature fails to appreciate (i) the possible bias in estimates for the included proxies if these are correlated with other, omitted determinants (Corrado et al., 2014; Acharya, 2016); and (ii) the presence of cross-section correlation in the panel induced by either spillovers or common shocks as highlighted in the case of private returns to R&D and knowledge spillovers in a recent paper by Eberhardt et al. (2013). These authors show that private returns to R&D are dramatically lower once knowledge spillovers and common shocks are taken into account. At the same time, they hint that the results in the existing empirical literature on knowledge spillovers following the seminal Coe and Helpmann (1995) paper are likely unreliable due to omitted variable bias induced by the presence of common shocks with heterogeneous impact, as well as due to empirical misspecification. In this paper we provide an 'index' for absorptive capacity which agnostically captures all of the above determinants (as well as those unobserved or unmeasured) but at the same time is robust to the concerns of identification raised by Eberhardt et al. (2013); Acharya (2016) and others. The estimated patterns in the country-specific evolution of absorptive capacity and global TFP we present are of interest in their own right, but our methodological contribution further provides the building blocks to incorporate a much richer empirical specification to jointly determine the respective causal effects of trade, innovation effort, human capital, etc. on economic growth and inter-country knowledge spillovers.

Our empirical specification is based on an aggregate log-linearised Cobb-Douglas production function, with constant returns to scale but diminishing returns to each of the observed factors of production.

[2]Acharya (2016) refers to the role of 'intangible capital' in knowledge spillovers, providing a broader interpretation than R&D investments to include other proxies (ICT capital compensation to gross output). Haskel et al. (2013) and Corrado et al. (2014) report on efforts to quantify non-R&D intangibles so as to capture organsational capital, skills and training, etc. at the macro level – the available time series is however at present still limited (1995 to 2010 for most advanced economies).

For country $i = 1, \ldots, N$ at time $t = 1, \ldots, T$, let real output Y_{it} be given by

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{1-\alpha} e^{\varepsilon_{it}}, \qquad \text{with} \quad 0 < \alpha < 1, \tag{1}$$

and where A_{it} is unobserved TFP, K_{it} is aggregate capital stock, L_{it} is labour input (expressed in hours worked) and ε_{it} is a mean-zero, white noise error term. Dividing by L_{it} and taking logs yields

$$y_{it} = \ln A_{it} + \alpha k_{it} + \varepsilon_{it}, \tag{2}$$

with $y_{it} = ln\,(Y_{it}/L_{it})$ and $k_{it} = ln\,(K_{it}/L_{it})$. Our model is in the neoclassical tradition, in that we do not explain the determinants of TFP, but it captures some of the defining features of 'new growth theory' and its empirical implementations, namely (i) that TFP evolution is not identical across countries, even in the long-run (Lee et al., 1997), and (ii) that TFP is not limited to the innovation efforts of individual countries, but is made up to a significant extent of spillovers of knowledge from elsewhere (Eaton and Kortum, 1994, 1999; Aghion and Howitt, 1998). This paper parameterises the relationship between ('free') global knowledge and a country's ('restricted') capacity to appropriate this knowledge using a common factor framework

$$A_{it} = e^{\eta_{it}} (e^{F_t})^{\lambda_{it}} = e^{\eta_{it} + \lambda_{it} F_t}, \tag{3}$$

where F_t is the global evolution of technology and, λ_{it} and η_{it} capture shifts in a country's endowments, institutions and policies determining how much of this knowledge is successfully appropriated ('absorptive capacity'). Eventually the econometric specification of interest is

$$y_{it} = \eta_{it} + \lambda_{it} F_t + \alpha k_{it} + \varepsilon_{it}. \tag{4}$$

Our approach to productivity analysis is closest to the work of Everaert et al. (2014), who identify worldwide technology evolution from the observed cross-section correlation in a panel of OECD economies using the Pesaran (2006) Common Correlated Effects (CCE) estimator. They extend the CCE methodology to allow for time-varying absorptive capacity, but restrict this time-variation to be a function of observed changes in fiscal policy. Our implementation is more general in that by modelling η_{it} and λ_{it} as random walk processes we allow for relatively unrestricted changes in each country's absorptive capacity over time, which speaks to the wide range of determinants of absorptive capacity detailed above.

Our model can be cast in a state space representation where the production function in equation (4) is the 'observation equation' and the 'state equations' are made up by the processes we assume for the time varying parameters η_{it} and λ_{it} (i.e. random walks) and the common factor F_t (e.g. random walk with drift). This state space model could then, in general, be estimated using the Kalman filter and maximum likelihood. The empirical implementation, however, of the general production function model described above poses a number of challenges. Firstly, the presence of unobserved time-specific global technology (F_t) multiplied with unobserved country- and time-specific loading (λ_{it}) leads to the state space model itself becoming non-linear in the states. To overcome this non-linearity problem we rely on the Bayesian Gibbs-sampling approach which reduces the non-linear state space model into a sequence of smaller blocks within which we can assume linearity conditional on the other blocks.

A second impediment when estimating (4) is that the scale of λ_{it} and F_t is not separately identified, i.e. it is always possible to write

$$\lambda_{it}F_t = a_t\lambda_{it}F_t/a_t. \tag{5}$$

This identification problem can be solved by normalizing the cross-sectional average of the loadings λ_{it} to be one in every period t. In fact, exactly the same normalization is imposed when we follow the Common Correlated Effects (CCE) appoach of Pesaran (2006). More specifically, taking cross-sectional averages of the model in equation (4)

$$\overline{y}_t = \overline{\eta}_t + \overline{\lambda}_t F_t + \alpha\overline{k}_t + \overline{\varepsilon}_t,$$

where $\overline{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{it}$ and similarly for the other variables, solving for F_t

$$F_t = \frac{1}{\overline{\lambda}_t}\left(\overline{y}_t - \overline{\eta}_t - \alpha\overline{k}_t - \overline{\varepsilon}_t\right),$$

and substituting this solution back into equation (4) yields

$$\begin{aligned} y_{it} &= \left(\eta_{it} - \frac{\lambda_{it}}{\overline{\lambda}_t}\overline{\eta}_t\right) + \frac{\lambda_{it}}{\overline{\lambda}_t}\left(\overline{y}_t - \alpha\overline{K}_t\right) + \alpha K_{it} + \varepsilon_{it} - \frac{\lambda_{it}}{\overline{\lambda}_t}\overline{\varepsilon}_t, \\ &= \eta'_{it} + \lambda'_{it}\left(\overline{y}_t - \alpha\overline{k}_t\right) + \alpha k_{it} + \varepsilon'_{it}, \end{aligned} \tag{6}$$

where it holds that $\overline{\eta}'_t = \frac{1}{N}\sum_{i=1}^{N}\eta'_{it} = 0$ and $\overline{\lambda}'_t = \frac{1}{N}\sum_{i=1}^{N}\lambda'_{it} = 1$. Equation (6) can be estimated using the Gibbs sampler where the states η_{it} and λ_{it} are evaluated using the Kalman filter.

Finally, a last challenge is to gauge the relevance of time-variation in absorptive capacity. We start by specifying η_{it} and λ_{it} as random walks for all countries, but then go on and test whether the time variation is actually relevant. To this end, we use the Bayesian stochastic model specification search proposed by Frühwirth-Schnatter and Wagner (2010). Given the outcome we fall back to a more parsimonious model when appropriate. This not only avoids over-parameterization but will also provide us with information on whether and for which countries absorptive capacity varies over time.

We estimate our model using a balanced panel dataset for 31 advanced and emerging economies covering 1953-2014. Our main results can be summarized as follows. First, and most important, the Frühwirth-Schnatter and Wagner (2010) approach shows that absorptive capacity clearly varies over time. From a policy point of view this finding is encouraging, since this implies absorptive capacity can be built up and fostered through targeted policy. Second, allowing for time variation in absorptive capacity is also important for estimating the capital elasticity coefficient α. While Fixed effects and the standard CCE pooled estimator of Pesaran (2006) yield a value for the capital elasticity of respectivily 0.74 and 0.62, our estimate is 0.51. Finally, the growth rate of the global TFP factor shows a substantial decrease over our 62-year sample period, from over 2% up until the late 1960s to negative growth rates in the late 2000s hinting to a 'secular decline' in TFP growth.

JEL Classifications: O33, O47, F43, F60, C23, C21

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