Journal of International Economics 146 (2023) 103753

Contents lists available at ScienceDirect

Journal of International Economics

journal homepage: www.elsevier.com/locate/jie

Utilization-adjusted TFP across countries: Measurement and implications for international comovement☆

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ARTICLE INFO

Article history:
Received 16 August 2022
Received in revised form 15 March 2023
Accepted 16 March 2023
Available online 28 March 2023

Repository link: https://data.mendeley.com/datasets/ps6dntdftk/1

JEL codes:
F41
F44

Keywords:
TFP
Utilization
Solow residual
International Comovement

ABSTRACT

This paper develops estimates of TFP growth adjusted for movements in unobserved factor utilization for a panel of 29 countries and up to 37 years. When factor utilization changes are unobserved, the commonly used Solow residual mismeasures actual changes in TFP. We use a general equilibrium dynamic multi-country multi-sector model to derive a production function estimating equation that corrects for unobserved factor usage. We compare the properties of utilization-adjusted TFP series to the standard Solow residual, and quantify the roles of both TFP and utilization for international business cycle comovement. Utilization-adjusted TFP is virtually uncorrelated across countries, and does not generate much GDP comovement through its propagation. Shocks to factor utilization can more successfully account for international comovement.

1. Introduction

It has long been acknowledged in macroeconomics that the intensity of factor utilization varies over the business cycle. When some dimensions of variable factor utilization are not directly observed, conventional ways of inferring TFP changes, such as the Solow residual, can be misleading as measures of technology shocks. Thus, estimation of TFP shocks must account for variation in unobserved factor usage. Following the seminal work of Basu, Fernald, and Kimball (2006, henceforth BFK), it has become standard to use a utilization-adjusted series as a measure of TFP when studying the US economy. Importantly, BFK show that the utilization-adjusted TFP series have substantially different properties than the traditional Solow residual.

☆ The time series for the utilization-adjusted TFP estimates by country and sector are available for download online. We are grateful to the editor, Linda Tesar, our discussants Jordi Galí and Galina Hale, as well as David Baqaee, Chris Boehm, Lorenzo Caliendo, Yongsung Chang, Gabe Chodorow-Reich, Olivier Coibion, Javier Cravino, Emmanuel Farhi, John Fernald, Jesus Fernandez-Villaverde, Simon Gilchrist, Felipe Saffie, Kang Shi, Alireza Tahbaz-Salehi and seminar participants at various institutions for helpful comments, and to Barthélémy Bonadio and Jaedo Choi for superb research assistance. Email: zhen.huo@yale.edu, alev@umich.edu and npnayar@utexas.edu.
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https://doi.org/10.1016/j.jinteco.2023.103753

However, studies of international business cycles have typically employed the Solow residual as the measure of technology shocks. This approach makes it challenging to study the sources of international business cycle comovement in general, and to isolate the role of technology shocks in particular. Variable factor utilization in a country could respond to TFP shocks originating abroad. Non-technology shocks that produce a utilization response will also appear in the measured Solow residual.

Our first contribution is to develop utilization-adjusted TFP series for a sample of 29 countries, 30 sectors, and up to 37 years. To guide the estimation, we present a theoretical framework in which capital utilization rates, hours per worker, and workers' effort are endogenous and can vary within a period in response to shocks. The model yields an estimating equation that features a correction for unobserved factor utilization. The first main result is that utilization-adjusted TFP is virtually uncorrelated across countries. This is in contrast to the Solow residual, which is modestly positively correlated. Our findings imply that the cross-country correlation in the Solow residual typically found in the literature is in fact due to correlated movements in unobserved factor utilization.

Our second contribution is to quantify the roles of TFP and factor utilization in the international business cycle. A feature of our modeling and estimation approach is that we can explicitly separate the impacts of TFP and utilization on GDP comovement. We use the model structure to extract a utilization shock, that rationalizes movements in utilization conditional on the world vectors of TFP shocks and pre-determined variables, and world general equilibrium. While we do not microfound the utilization shock, it captures the effects of all non-TFP shocks on utilization rates. We then assess how much GDP comovement can be generated with TFP and utilization shocks. Our second main finding is that TFP shocks alone cannot generate much GDP correlation when fed into a multi-country, multi-sector general equilibrium model of production and trade. In the G7 countries, TFP shocks account for less than 10% of the observed GDP correlation on average. In the full 29-country sample, they produce zero GDP correlation on average. By contrast, utilization shocks are correlated, and generate about one-third of observed GDP comovement.

We thus conclude that the common approach in the international business cycle literature of working with TFP-shock-driven fluctuations is not the most promising way to fully understand international comovement. By contrast, non-technology shocks that move factor utilization conditional on TFP are considerably more important as a driver of comovement.

We estimate the production function parameters using a theoretically-founded estimating equation and data on many countries and sectors from the KLEMS database (O'Mahony and Timmer, 2009). The key intuition behind this approach comes from BFK: agents optimize multiple dimensions of factor use intensity simultaneously. Thus, an observed dimension of factor utilization – hours per worker – can serve as a proxy for unobserved dimensions of factor utilization such as worker effort. To account for the endogeneity of inputs to TFP we build instruments that combine oil shocks and military expenditures with the input-output network. Our quantification uses a multi-country, multi-sector model of world production and trade in both intermediate inputs and final goods. We calibrate all the country-sector input and final expenditure shares using the World Input-Output Database (Timmer et al., 2015).

Our paper contributes to the empirical and quantitative literature on international business cycle comovement. A number of papers are dedicated to documenting international correlations in productivity shocks and inputs (e.g. Imbs, 1999; Kose et al., 2003; Ambler et al., 2004). Also related is the body of work that identifies technology and demand shocks in a VAR setting and examines their international propagation (e.g. Canova, 2005; Corsetti et al., 2014; Levchenko and Pandalai-Nayar, 2020). Relative to these papers, we use sector-level data to provide novel estimates of utilization-adjusted TFP shocks, and expand the sample of countries. A large research agenda builds models in which fluctuations are driven by productivity shocks, and asks under what conditions those models can generate observed international comovement (see, among many others, Backus et al., 1992; Heathcote and Perri, 2002). In these analyses, productivity shocks are proxied by the Solow residual, which we show can be misleading. Our quantitative assessment benefits from improved measurement of TFP shocks.[1]

Our estimation belongs to the family of methods that measure factor utilization. Complementing the more model-based approaches such as BFK and Fernald (2014), other work has considered survey-based direct measures of plant capacity utilization (e.g. Shapiro, 1989; Gorodnichenko and Shapiro, 2011; Boehm and Pandalai-Nayar, 2022), or used other observable proxies such as electricity consumption (e.g. Burnside et al., 1995). The alternative methods cannot be straightforwardly applied in our setting, as utilization surveys and electricity usage are not available for the large sample of countries, sectors, and years in our analysis. Our indirect measures of utilization are modestly positively correlated with the survey-based measures in the subset of countries and sectors for which those exist, although caution in such comparisons is important, as the questions on the surveys vary and do not closely correspond to the theoretical margin in our model. A literature in closed-economy macroeconomics going back to Greenwood et al. (1988) studies the implications of variable factor utilization for domestic business cycles (see, among many others, Bils and Cho, 1994; Cooley et al., 1995; Gilchrist and Williams, 2000; Fair, 2018; Chodorow-Reich et al., 2019). Closely related to the focus of BFK, Shapiro (1993) finds that variations in capital's workweek explain much of the cyclicality of TFP, while Galí and van Rens (2020) and Mitra (2022) document the fall in the procylicality of labor productivity over time and attribute it to the changing micro features of the labor market such as hiring frictions and de-unionization. Our paper builds on this literature by assessing the implications of utilization adjustments to TFP for international GDP comovement.

Our approach is also related to the large literature estimating production functions and markups (De Loecker and Warzynski, 2012; Ackerberg et al., 2015, and many others). This literature typically (though not always) uses Cobb-Douglas firm-level production functions featuring a mix of variable and fixed inputs, together with a control function approach which relies on only some inputs responding to contemporaneous productivity shocks to estimate output elasticities and calculate implied markups. The variable inputs are typically materials or investment. Our approach to estimating sectoral production functions is

[1] A vast literature studies the drivers of international comovement more broadly, emphasizing both trade and financial linkages, e.g. Kalemli-Ozcan et al. (2013), Cesa-Bianchi et al. (2019), Huo et al. (2020), among many others.

complementary – we assume a component of the labor input is flexible in a period, and use external instruments to isolate exogenous variation in this input. We do not separately identify markups, as our data are not at the firm level. Since we deflate output by sectoral price indices, our estimates should be interpreted as physical rather than revenue TFP.

The rest of the paper is organized as follows. Section 2 sets out a simple accounting framework that illustrates the potentially confounding role of unobserved factor utilization in studying international comovement due to TFP shocks. Section 3 presents the theory behind our estimation approach. The results of the estimation are in Section 4. We assess the importance of TFP and utilization for international comovement in a general-equilibrium framework in Section 5. Section 6 concludes.

2. TFP and the Solow residual in international comovement

2.1. Factor usage, TFP, and the Solow residual

Let there be J sectors indexed by j and N countries indexed by n. Let gross output Y_{njt} in sector j country n be given by:

$$Y_{njt} = Z_{njt}\left(K_{njt}^{\alpha_j} L_{njt}^{1-\alpha_j}\right)^{\eta_j} X_{njt}^{1-\eta_j}, \tag{2.1}$$

where Z_{njt}, K_{njt}, L_{njt}, and X_{njt} are TFP, capital, labor, and materials inputs, respectively. For simplicity, input elasticities α_j and η_j are assumed to vary by sector in the baseline, but allowed to vary by country, sector and time in Appendix A.2.

When it comes to measurement, it is important that K_{njt} and L_{njt} are utilization-adjusted inputs that may not be directly observable to the econometrician. Let the factor inputs be comprised of:

$$K_{njt} \equiv U_{njt} M_{njt}, \qquad \text{and} \qquad L_{njt} \equiv E_{njt} H_{njt} N_{njt}. \tag{2.2}$$

The capital input is the product of the quantity of installed capital ("machines") M_{njt} that can be measured in the data, and capital utilization U_{njt} that is not directly observable. Similarly, the true labor input is the product of the number of workers N_{njt}, hours per worker H_{njt}, and labor effort E_{njt}. While N_{njt} and H_{njt} can be obtained from existing datasets, E_{njt} is unobservable.

The Solow residual S_{njt} nets out observable factor usage from gross output:

$$d\ln S_{njt} \equiv d\ln Y_{njt} - \alpha_j\eta_j d\ln M_{njt} - \left(1-\alpha_j\right)\eta_j d\ln H_{njt} - \left(1-\alpha_j\right)\eta_j d\ln N_{njt} - \left(1-\eta_j\right) d\ln X_{njt}.$$

The Solow residual thus contains the following components:

$$d\ln S_{njt} \equiv \underbrace{d\ln Z_{njt}}_{\text{True TFP}} + \underbrace{\alpha_j\eta_j d\ln U_{njt} + \left(1-\alpha_j\right)\eta_j d\ln E_{njt}}_{\text{Unobserved utilization}}.$$

This expression makes it transparent that in this setting, the Solow residual can diverge from the true TFP shock due to unobserved utilization of inputs.

2.2. GDP accounting and the aggregates

Following national accounting conventions, real GDP at time t, evaluated at base prices (prices at $t-1$) is defined by:

$$Y_{nt} = \sum_{j=1}^{J}\left(P_{njt-1}Y_{njt} - P_{njt-1}^{X} X_{njt}\right),$$

where P_{njt-1} is the gross output base price, and P_{njt-1}^{X} is the base price of inputs in that sector-country.

Approximating growth rates with log differences, and assuming profits are zero, the real GDP change between $t-1$ and t is then:

$$d\ln Y_{nt} = \sum_{j=1}^{J} D_{njt-1}\left(d\ln Y_{njt} - \left(1-\eta_j\right) d\ln X_{njt}\right), \tag{2.3}$$

where $D_{njt-1} \equiv \frac{P_{njt-1}Y_{njt-1}}{Y_{nt-1}}$ is sector j's base period Domar weight, that is, the sector's gross sales as a fraction of aggregate value added.

Combining (2.1) and (2.3) leads to aggregate TFP:

$$d\ln Z_{nt} = \sum_{j=1}^{J} D_{njt-1} d\ln Z_{njt}. \tag{2.4}$$

The aggregate Solow residual can be written as:

$$d\ \ln S_{nt} = \sum_{j=1}^{J} D_{njt-1} d\ \ln S_{njt} = d\ \ln Z_{nt} + d\ \ln \mathcal{U}_{nt}, \tag{2.5}$$

where in the second equality, $d \ln \mathcal{U}_{nt}$ is the aggregated log change in unobserved utilization:

$$d \ln \mathcal{U}_{nt} \equiv \sum_{j=1}^{J} D_{njt-1} \left\{ \alpha_j \eta_j d \ln U_{njt} + \left(1 - \alpha_j\right) \eta_j d \ln E_{njt} \right\}. \tag{2.6}$$

Appendix B.1 details the derivations behind all the equations in this section.

2.3. Implications for international Comovement

The covariance in the Solow residual between countries n and m is:

$$\sigma(S_n, S_m) = \sigma(Z_n, Z_m) + \sigma(\mathcal{U}_n, \mathcal{U}_m) + \sigma(Z_n, \mathcal{U}_m) + \sigma(Z_m, \mathcal{U}_n),$$

where $\sigma(x,y) \equiv \mathrm{Cov}(d \ln x_t, d \ln y_t)$.

The observed Solow residual can be correlated across countries both due to correlated TFP shocks, and due to correlated unobserved input changes. This leads to two distinct problems with using the Solow residual to study international comovement. The first is that $\mathcal{U}_n$ may be responding endogenously to technology shocks. If input use in country m responds to TFP shocks in country n, Solow residuals in n and m will become correlated even if true TFP is not. Using Solow residuals will then lead the researchers to attribute GDP comovement to correlated productivity shocks rather than shock transmission.

The second problem is shocks to input usage $\mathcal{U}_n$ itself. If the economy is subject to non-technology shocks that affect input usage directly, the Solow residual will reflect the correlation and transmission of non-technology, rather than technology shocks.

It is an empirical question to what degree correlations in the Solow residual reflect true technology shock correlation, as opposed to endogenous transmission or non-technology shocks. It is clear, however, that using the Solow residual as a measure of technology shocks can lead to incorrect assessments both of the relative importance of correlated shocks vs. endogenous transmission, and of the relative importance of technology vs. non-technology shocks for international comovement. To make progress, we need to overcome the measurement challenge of estimating true TFP when utilization-adjusted factor usage is unobserved.

3. Variable factor utilization model

We now set up a multi-country, multi-sector framework with variable factor utilization. The model has two principal uses. The first is to derive an estimating equation that can be used to infer TFP in an environment with unobserved factor utilization. The second is quantification of the roles of TFP and variable utilization in international comovement, that we undertake in Section 5 after estimating the TFP series.

3.1. Households

Each country n is populated by a representative household. The household consumes the final good available in country n and supplies labor and capital to firms. There is a continuum of workers in the household who share the same consumption. The problem of the household is

$$\max_{\substack{\{M_{njt}\},\{N_{njt}\},\\ \{H_{njt}\},\{E_{njt}\},\{U_{njt}\}}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t\ \Psi\left(C_{nt} - \sum_j \xi_{njt} N_{njt} G_j\left(H_{njt}, E_{njt}, U_{njt}\right) - \sum_j N_{njt}^{\psi^n}\right) \tag{3.1}$$

subject to

$$P_{nt}\left(C_{nt} + \sum_j I_{njt}\right) = \sum_j W_{njt} N_{njt} H_{njt} E_{njt} + \sum_j R_{njt} U_{njt} M_{njt}$$
$$M_{njt+1} = \left(1 - \rho_j\right) M_{njt} + I_{njt}$$

where C_{nt} is consumption and I_{njt} is investment, both of which are bundles of goods coming from different countries and sectors. The total efficiency units of labor supplied in a sector is $E_{njt}H_{njt}N_{njt}$, and the total efficiency units of capital supplied is $U_{njt}M_{njt}$. Labor collects a sector-specific wage W_{njt}, and capital is rented for the price R_{njt}. The variable ξ_{njt} captures potential preference shocks that shift factor supplies. We assume financial autarky throughout and assume $\Psi(\cdot)$ is log utility.

We assume the following functional form for $G_j(.)$:

$$G_j(H,E,U) = H^{\psi_j^h} + E^{\psi_j^e} + U^{\psi_j^u}. \tag{3.2}$$

We highlight three features of the household problem. First, labor and capital are differentiated by sector, as the household supplies factors to, and accumulates capital in, each sector separately. In this formulation, labor and capital are neither fixed to each sector nor fully flexible. As $\psi_j^\iota \to 1$, $\iota = h, e, u$, factor supply across sectors becomes more sensitive to factor price differentials. In the limit, households supply variable factors only to the sector offering the highest factor price. At the opposite extreme, as $\psi_j^\iota \to \infty$, the supply of hours, effort, and capital utilization is fixed in each sector by the preference parameters.

Second, we assume that the number of employed workers N_{njt} and machines M_{njt} in a sector is predetermined. This is required in order to have a well-defined notion of variable utilization. While this approach is standard for machines, it is less common for employment, where it is usually assumed that hours and employment move in parallel. Specifically, in our model the number of workers in a particular sector has to be chosen before observing the current shocks as in Burnside et al. (1993), reflecting the fact that it takes time to adjust the labor force.[2] On the other hand, within a period households can choose the hours H_{njt} and effort E_{njt} that change the effective amount of labor supply, and utilization rates U_{njt} that change the effective amount of capital supply. These margins capture the idea that utilization rates of factor inputs typically vary over the business cycle. Our framework thus implies that within a period, labor and capital supply to each sector are upward-sloping (e.g. Christiano et al., 2014).

Third, our formulation of the disutility of the variable factor supply (3.2) is based on the Greenwood, Hercowitz, and Huffman (1988, henceforth GHH) preferences for labor and a similar isoelastic formulation of the utilization cost of capital. The GHH preferences mute the interest rate effects and income effects on the choice of hours, effort, and utilization rates, which helps to study the properties of the static equilibrium where the number of machines and employees are treated as exogenous.

3.2. Firms

To make the estimation more reliable, we follow BFK and allow for potentially non-constant returns to scale in production. Ex post, our estimates show that returns to scale are close to constant, and thus it is not a large force empirically or quantitatively. A representative firm in sector j in country n operates a CRS production function

$$Y_{njt} = Z_{njt}\Theta_{njt}\left(K_{njt}^{\alpha_j}L_{njt}^{1-\alpha_j}\right)^{\eta_j}X_{njt}^{1-\eta_j}, \tag{3.3}$$

where K_{njt} and L_{njt} are the true capital and labor inputs as in (2.2), and the total factor productivity $Z_{njt}\Theta_{njt}$ is taken as given by the firm. The intermediate input bundle X_{njt} is an aggregate of inputs from potentially all countries and sectors.

The total factor productivity consists of two parts: the exogenous shocks Z_{njt} and the endogenous component:

$$\Theta_{njt} = \left(\left(K_{njt}^{\alpha_j}L_{njt}^{1-\alpha_j}\right)^{\eta_j}X_{njt}^{1-\eta_j}\right)^{\gamma_j-1}, \tag{3.4}$$

where γ_j controls possible congestion or agglomeration effects. As a result, the sectoral aggregate production function is:

$$Y_{njt} = Z_{njt}\left[\left(K_{njt}^{\alpha_j}L_{njt}^{1-\alpha_j}\right)^{\eta_j}X_{njt}^{1-\eta_j}\right]^{\gamma_j}. \tag{3.5}$$

3.3. Optimality conditions

The households' intra-temporal optimization problem leads to

$$H_{njt}G_{jh}\left(H_{njt},E_{njt},U_{njt}\right) = E_{njt}G_{je}\left(H_{njt},E_{njt},U_{njt}\right),$$

[2] Our assumption implies that there are frictions that limit the substitutability of employment and the workweek. This assumption can be supported by the data. For instance, in our sample the standard deviations of hours per worker growth and of employment growth are 0.02 and 0.06 respectively, suggesting the two margins should not be treated symmetrically.

where G_{jh} is the partial derivative of $G_j(\cdot)$ with respect to H. Under the functional form adopted for $G_j(\cdot)$, this condition implies that the choice of effort has a log-linear relationship with the choice of hours:

$$d\ \ln E_{njt} = \frac{\psi_j^h}{\psi_j^e} d\ \ln H_{njt}. \tag{3.6}$$

A similar expression can be derived for the relationship between the optimal choice of capital utilization and the optimal choice of hours:

$$\frac{H_{njt} G_{jh}\left(H_{njt}, E_{njt}, U_{njt}\right)}{U_{njt} G_{ju}\left(H_{njt}, E_{njt}, U_{njt}\right)} = \frac{W_{njt} L_{njt}}{R_{njt} K_{njt}}.$$

We know from the firms' problem that the right-hand side of the equation above is equal to the ratio of output elasticities $\alpha_j/(1-\alpha_j)$, which is a constant. As a result, the utilization rate also has a log-linear relationship with hours worked:

$$d\ \ln U_{njt} = \frac{\psi_j^h}{\psi_j^u} d\ \ln H_{njt} \tag{3.7}$$

up to a normalization constant.

The properties (3.6)–(3.7) capture the idea that flexible inputs tend to move jointly in the same direction. The household intra-temporal first-order conditions therefore allow us to express unobserved effort and capital utilization as a log-linear function of observed hours:

$$\alpha_j d\ \ln U_{njt} + \left(1-\alpha_j\right) d\ \ln E_{njt} = \zeta_j d\ \ln H_{njt}, \tag{3.8}$$

where $\zeta_j = \alpha_j \frac{\psi_j^h}{\psi_j^u} + (1-\alpha_j)\frac{\psi_j^h}{\psi_j^e}$.

3.4. Estimating equation

Log-differencing (3.5), and separating the observed and the unobserved components of input usage yields:

$$\begin{aligned} d\ \ln Y_{njt} = \gamma_j & \underbrace{\left(\alpha_j\eta_j d\ \ln M_{njt} + \left(1-\alpha_j\right)\eta_j d\ \ln\left(H_{njt}N_{njt}\right) + \left(1-\eta_j\right) d\ \ln X_{njt}\right)}_{\text{Observed Inputs}} \\ & + \gamma_j \underbrace{\left(\alpha_j\eta_j d\ \ln U_{njt} + \left(1-\alpha_j\right)\eta_j d\ \ln E_{njt}\right)}_{\text{Unobserved Inputs}} + d\ \ln Z_{njt}. \end{aligned} \tag{3.9}$$

This equation makes it plain that measuring TFP innovations is difficult because the intensity with which factors are used in production varies over the business cycle, and cannot be directly observed by the econometrician. As unobserved factor utilization will respond to TFP innovations, it is especially important to account for it in estimation, otherwise factor usage will appear in estimated TFP.

Plugging (3.8) into (3.9) yields the following estimating equation:

$$d\ \ln Y_{njt} = \delta_j^1\left(\alpha_j\eta_j d\ \ln M_{njt} + \left(1-\alpha_j\right)\eta_j d\ \ln\left(H_{njt}N_{njt}\right) + \left(1-\eta_j\right) d\ \ln X_{njt}\right) + \delta_j^2 d\ \ln H_{njt} + \delta_{nj} + d\ \ln Z_{njt}. \tag{3.10}$$

The country × sector fixed effects δ_{nj} allow for country-sector specific trend output growth rates, that can be driven by either trend TFP or trend factor accumulation. We take out these trend differences, since we are interested in comovement of business cycles.

The coefficient δ_j^1 is clearly an estimate of returns to scale γ_j. Eq. (3.8) provides a structural interpretation for the coefficient $\delta_j^2 = \gamma_j\eta_j\zeta_j$. Conditional on the coefficient estimates and the log changes in the observed inputs, we obtain the TFP shocks $d\ \ln Z_{njt}$ as residuals.

Our estimating equation and the factor use optimality condition (3.8) coincide with BFK. The key insight of BFK is that agents' static optimization imposes a relationship between the intensities of observed and unobserved input uses. This insight is more general than the model above. Indeed, BFK derive the same estimating equation in a partial-equilibrium setting without specifying the details of household choices or dynamics. In BFK, the choice between effort, utilization rates, and hours is made by firms facing upward-sloping supply curves of these dimensions of factor inputs. In contrast, we model the trade-off between these margins as being faced by households. Fully articulating a model as we do here has the benefit of showing that the BFK structural equation applies in a fairly general open economy setting that can easily be nested in standard general-equilibrium IRBC models. Our approach thus has the advantage of being simultaneously consistent with the econometric TFP estimation and with model-based quantification in world general equilibrium, allowing us to move seamlessly between the two. Though our framework is less general than BFK in some dimensions, an additional advantage is that we do not have to assume ad hoc convex cost functions for firm choices.

4. Estimation

4.1. Identification

The estimation proceeds to regress real output growth on the growth of the composite observed input bundle and the change in hours per worker. Because input usage will move with TFP shocks $d \ln Z_{njt}$, the regressors in (3.10) are correlated with the residual. To overcome this endogeneity problem, we combine country-level sources of exogenous variation with the input-output network to build a set of instruments that are plausibly orthogonal to true TFP shocks but have predictive power for changes in production.

The first source of country-level variation is oil shocks, constructed using the approach in Hamilton (1996). An oil shock is defined as the difference between the log oil price and the maximum log oil price in the preceding four quarters. This oil price shock is either zero, or is positive when this difference is positive, reflecting the notion that oil prices have an asymmetric effect on output. The annualized oil shock is the sum over the four quarters of the preceding year. The second source of exogenous variation is the growth rate in real government defense spending, lagged by one year.

Our instruments are first- and second-order indices of exposure to these aggregate shocks through the input network, following Acemoglu et al. (2016). Specifically, a sector's first-order exposure to the oil shock is computed as the aggregate oil shock OIL_t times the share of the sector's expenditure on oil as an input: $\mathcal{O}_{njt} = OIL_t \times \sum_{m,i=oil} \pi^x_{mi,nj}$, where $\pi^x_{mi,nj}$ are nj's expenditures on inputs from mi. A sector's first-order exposure to the defense spending shock is $\mathcal{D}_{njt} = DEF_{nt} \times \frac{\mathcal{G}_{nj}}{Y_{nj}}$, where DEF_{nt} is national defense spending and $\frac{\mathcal{G}_{nj}}{Y_{nj}}$ is the fraction of sales to the government in total sectoral sales. The resulting instruments vary at the country-sector-year level.

We next construct second-order network propagation shocks. Sectors purchase inputs from and sell output to potentially all other countries and sectors in the world. Therefore, output in a sector might also respond to the effect of the oil and defense shocks on its suppliers and customers. We can thus build four additional instruments, capturing the second-order upstream and downstream exposure of industries to oil and defense spending shocks. These instruments are constructed by weighting the country-sector oil or defense spending shocks with the sales shares (cost shares) of downstream (upstream) industries for each sector.[3,4]

Following BFK, to reduce the number of parameters to be estimated, we restrict δ^2_j to take only three values, according to a broad grouping of sectors: durable manufacturing, non-durable manufacturing, and all others. We similarly estimate a single returns-to-scale coefficient δ^1_j for each group. Appendix Table A6 shows that allowing for sector-specific returns-to-scale yields estimates that are insignificantly different from the pooled estimate in most cases. Finally, we restrict the production function estimation sample to the G7 countries, for which we have the longest time series. This tends to lead to the strongest instruments and most precisely estimated coefficients.

4.2. Data

The data requirements for estimating eq. (3.10) are growth of real output and real inputs for a panel of countries, sectors, and years. The dataset with the broadest coverage of this information is KLEMS 2009 (O'Mahony and Timmer, 2009).[5] This database contains gross output, value added, labor and capital inputs, as well as output and input deflators. In a limited number of instances, we supplemented the information available in KLEMS with data from the WIOD Socioeconomic Accounts, which contains similar variables. After data quality checking and cleaning, we retain a sample of 29 countries, listed in Appendix Table A1. The database covers all sectors of the economy at a level slightly more aggregated than the 2-digit ISIC revision 3, yielding, after harmonization, 30 sectors listed in Appendix Table A2. In the best cases we have 38 years of data, 1970–2007, although the panel is not balanced and many emerging countries do not appear in the data until the mid-1990s. Appendix Table A3 provides a precise

[3] The upstream instruments for sector j, country n are $\sum_{m,i} \pi^x_{mi,nj} \mathcal{O}_{mit}$ and $\sum_{m,i} \pi^x_{mi,nj} \mathcal{D}_{mit}$. The downstream instruments for sector j, country n are $\sum_m \frac{\pi^f_{mnj} P^f_{mj} \mathcal{F}_{mj}}{P_{nj} Y_{nj}} \mathcal{O}_{mt} + \sum_{mi} \frac{P_{nj,mi} X_{nj,mi}}{P_{nj} Y_{nj}} \mathcal{O}_{mit}$ and $\sum_m \frac{\pi^f_{mnj} P^f_{mj} \mathcal{F}_{mi}}{P_{nj} Y_{nj}} \mathcal{D}_{mt} + \sum_{m,i} \frac{P_{nj,mi} X_{nj,mi}}{P_{nj} Y_{nj}} \mathcal{D}_{mit}$, where $\mathcal{O}_{mt}$ is the oil shock times the share of oil in final expenditure, and $\mathcal{D}_{mt}$ is the defense shock times the share of government in final expenditure. The shares $\pi^x_{mi,nj}$ and π^f_{mnj} and final expenditures $P^f_{mj} \mathcal{F}_{mj}$ are defined in Appendix B.2. Downstream exposure includes exposure through final sales to consumers in all countries.

[4] BFK face a similar identification problem when estimating the utilization-adjusted series for the US. They use an oil price shock, the growth in real defense spending, and a monetary policy shock identified in a VAR. Our instruments build on BFK by taking advantage of subsequent advances in the networks literature. A monetary policy instrument has a poor first stage for the countries in our sample.

[5] This is not the latest vintage of KLEMS, as there is a version released in 2016. Unfortunately, however, the 2016 version has a shorter available time series, as the data start in 1995, and also has many fewer countries. A consistent concordance between the two vintages is not possible without substantial aggregation.

Table 1
Production Function Parameter Estimates.

Industry Group	Returns to Scale	Utilization Adjustment
	(δ_j^1)	(δ_j^2)
Durables	1.049 (0.046)	0.435 (0.172)
Non-durable manufacturing	1.172 (0.119)	1.48 (0.627)
Non-durable non-manufacturing	0.938 (0.209)	1.128 (0.674)

Notes: This table reports the estimates of δ_j^1 and δ_j^2 in the three broad groups of sectors, along with the Driskoll-Kraay standard errors in parentheses. The instruments used are the first- and second-order oil and defense spending shocks, described in the text. The regressions include country-sector fixed effects. First stage diagnostics are reported in Appendix Table A5.

mapping between all the variables we use and their KLEMS counterparts, and lists instances in which WIOD Socioeconomic Accounts were used to supplement KLEMS. Appendix Table A4 provides detailed definitions and underlying sources of the KLEMS data, and lists instances in which the national surveys have missing observations and thus data were imputed in the G7 countries. This is the case for the capital stock in Japan in some years, and for occasionally missing price growth data. O'Mahony and Timmer (2009) contains an exhaustive documentation of the KLEMS data.

The oil price series is the West Texas Intermediate, obtained from the St. Louis Fed's FRED database. Military expenditure comes from the Stockholm International Peace Research Institute (SIPRI). The construction of the upstream and downstream instruments and the quantitative analysis in Section 5 require information on the input linkages at the country-sector-pair level as well as on final goods trade. This information comes from the 2013 WIOD database (Timmer et al., 2015), which contains the global input-output matrix.

4.3. Empirical results

4.3.1. Production function estimates

Table 1 summarizes the results of estimating eq. (3.10). The returns to scale parameters are around 1.05 in durable manufacturing, 1.17 in non-durable manufacturing, and 0.94 in the quite heterogeneous non-manufacturing sector. None are significantly different from constant returns to scale. The coefficient on hours per worker ($d \ln H_{njt}$) is significantly different from zero in two out of three industry groups, indicating that adjusting for unobserved utilization is important in the manufacturing industries.

We have multiple instruments and multiple endogenous variables in our estimation. The appropriate test statistic for diagnosing the weak instruments problem is the Sanderson-Windmeijer *F* (SW-*F*), which is designed for such a setting. Appendix Table A5 reports the first-stage *F* statistics for the baseline and alternative combinations of instruments. The SW-*F* statistics indicate that the instruments are not weak. The SW-*F* statistics are greater than 8 for all coefficients except δ_j^1 in the non-durable manufacturing group, where it suggests the instruments are possibly weak (SW-*F* of 5.8). We therefore assess the sensitivity of the non-durable manufacturing δ_j^1 to alternative subsets of the six instruments. Compared to the baseline estimate of 1.17 for this coefficient, the median point estimate across all combinations of instruments is 1.23, and the median SW-*F* is 9.7, while the instrument combination with highest SW-*F* of 12.16 yields a coefficient estimate of 1.2. This suggests that the relatively low SW-*F* when using all 6 instruments does not have an unduly large influence on the estimated coefficient, compared to instrument combinations for which the SW-*F* is higher.[6] Appendix Table A6 reports the production function estimates in which returns to scale are allowed to vary by sector.

4.3.2. Utilization-adjusted TFP series

Fig. 1 plots the aggregate utilization-adjusted TFP series along with the Solow residual for all the countries in our sample. The data displayed in the Figure are available to download online.[7]

As found by BFK, in the US our utilization-adjusted TFP series is less volatile than the Solow residual. However, it turns out that for the large majority of countries the adjusted TFP series is more volatile. The mean (median) standard deviation of the TFP series is 0.037 (0.033), while for the Solow residual it is 0.019 (0.017). Relatedly, there are occasional large deviations of the TFP series from the Solow residual. The difference between the two series is largely accounted for by the Domar-weighted sectoral hours per worker (as the estimated returns-to-scale coefficients are close to 1). A large negative growth rate of utilization-adjusted TFP without a large negative growth of the Solow residual occurs when utilization increases at the same time as TFP growth falls. So these are instances of low true TFP but high utilization. On the flip side, large positive true TFP but small Solow residuals

[6] As far as we are aware, there is no established weak instrument test for a setting with multiple instruments and multiple endogenous variables that also takes into account heteroscedasticity. Therefore, in addition to the SW-*F* statistics appropriate for multiple instruments/endogenous variables we also report the Kleinbergen-Paap *F* statistics, that account for heteroscedasticity.

[7] Throughout the paper, we report aggregate TFP and other values under constant Domar weights D_{nj}, that correspond to period averages. This is done for ease of comparison with the quantitative model, which is solved in deviations from steady state. None of the results change if we use time-varying Domar weights instead. The data available to the public includes sectoral TFP and both constant and time-varying Domar weights, so that the user can undertake their preferred aggregation.

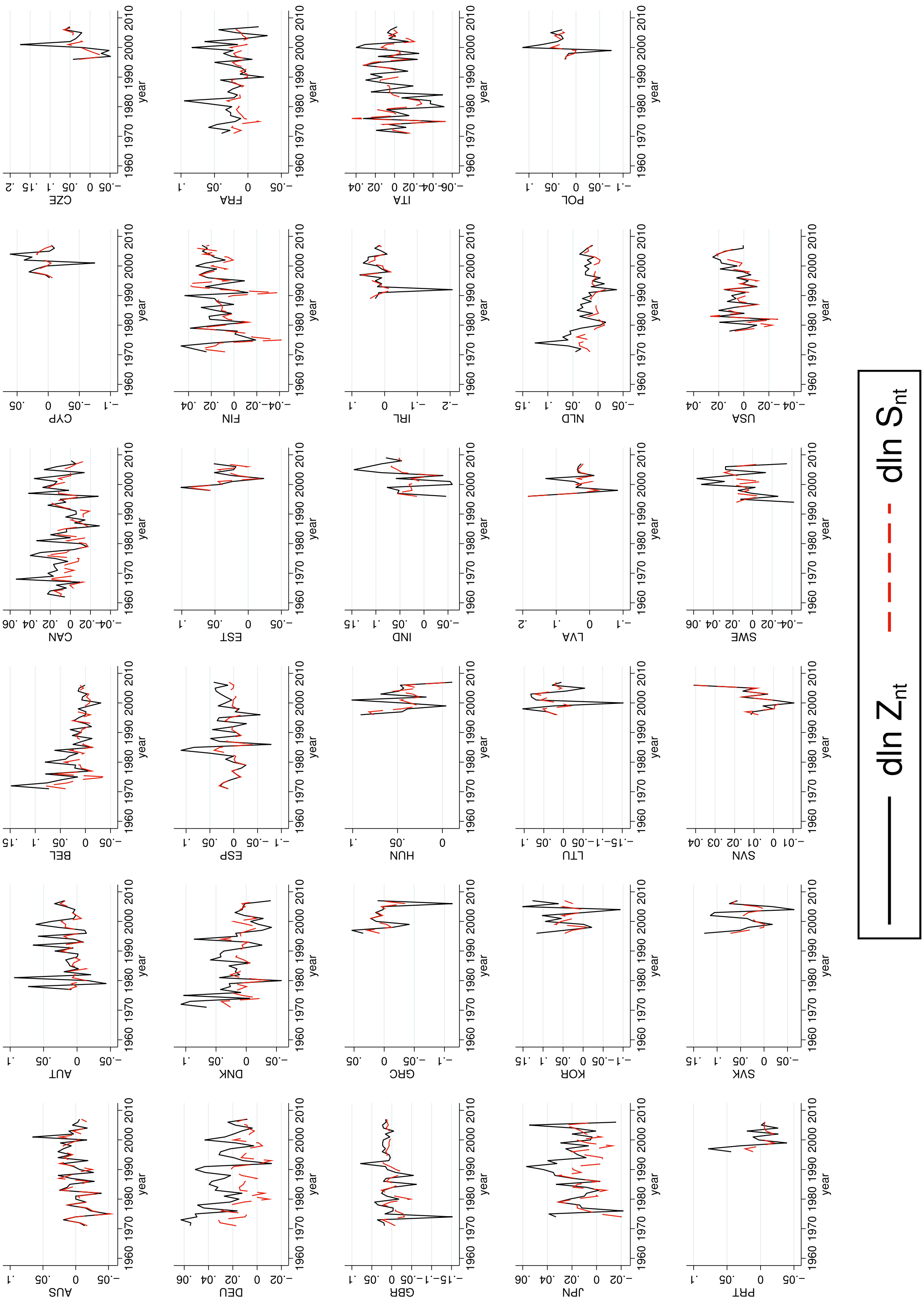

Fig. 1. Utilization-Adjusted TFP and the Solow Residual.
Notes: This figure displays the log changes in the utilization-adjusted TFP series $d \ln Z_{nt}$ and in the Solow residual $d \ln S_{nt}$ for every country in our sample.

correspond to instances of low utilization under high productivity. This is exactly the central finding of the original BFK paper, who also document that technology improvements coincide with utilization reductions and vice versa. So instances of large changes in TFP without large changes in the Solow residual are quite consistent with the original BFK.[8]

We made sure these large deviations are not a sign of poor data quality by checking the underlying KLEMS hours data for documented issues, as well as for any detectable trend breaks or jumps. With the usual caveats applying to any aggregate hours series, data quality does not appear to be the source of large departures of the utilization-adjusted series from the Solow residual. Instead, it seems that the rare, big deviations in some countries and years are due to country-specific circumstances. In the interest of transparency, we make all of the data in Fig. 1 and its sectoral components available publicly without ex post ad hoc adjustments, so that researchers can make their own decisions on which observations are appropriate to use in their application.

4.3.3. Sensitivity

We construct a TFP series applying the original BFK production function coefficient estimates to all countries, and compare the resulting TFP series with ours. While our point estimates will naturally not coincide perfectly with those in BFK, they are not significantly different from the estimates in that paper in many cases. BFK Table 1 reports δ_j^2 coefficients (s.e.'s) of 1.34(0.22), 2.13 (0.38) and 0.64(0.34) for durables, non-durables and non-manufacturing respectively, not far from our estimates in Table 1. The correlation between our TFP series and the series constructed using BFK coefficients is 0.88 (Appendix Table A7).

Next, we repeat the TFP estimation procedure, but allowing sector-specific capital and value added shares α_j and η_j to vary by country, and then by both country and year. The resulting series have correlations with the baseline of 0.97 and 0.96, as reported in Appendix Table A7.

One concern might be institutional differences in labor market flexibility across countries, such that hours per worker cannot adjust to the same extent in different countries. While our estimation approach does not treat all of the labor input as fully flexible, we do require that hours per worker respond within our annual time frame. To assuage this and other concerns about country heterogeneity, we estimate the coefficients excluding each of the G7 countries one by one, and construct TFP series with those alternative coefficients. Appendix Table A7 presents the pairwise correlations between our baseline TFP series, and all TFP series dropping an individual country. Excluding individual G7 countries from production function estimation leads to TFP series with correlations with our baseline between 0.94 and 1.00, suggesting our estimates are not driven by any country in particular.[9]

We also estimate the production function using our full sample of 29 countries. The correlation of the resulting TFP series with the baseline is 0.83. However, the estimated parameters are noisy and the first stage is not as strong, so we prefer our baseline estimates. The TFP series we construct for non-G7 countries thus use the G7 production function estimates. We advise caution when using those, as these production function parameters might be more appropriate for some non-G7 countries than others.

Our TFP estimation procedure also provides us with series for utilization rates by sector. In the US, the Federal Reserve Board (FRB) publishes a series of industry-level utilization. These series are constructed using a number of sources including survey data from the US Census Bureau, by dividing an index of industrial production by an index of estimated industrial capacity. The left panel of Appendix Fig. A1 compares our industry-level estimates to these public series. The two are positively correlated, despite the different underlying data sources and methodologies used for constructing them. The right panel of the figure compares our estimates for the country-level average utilization growth rates against the country-level utilization based on the FRB data for the US, and Eurostat data for some European countries. Again, we find a positive and significant correlation, albeit somewhat low.[10]

[8] The relationship between the variance of the Solow residual and TFP is $\sigma_S^2 = \sigma_Z^2 + \sigma_{\mathcal{U}}^2 + 2\sigma_{Z\mathcal{U}}$. The Solow residual can be less volatile than TFP if the covariance between TFP and utilization is sufficiently negative. The key finding of BFK is indeed that high true TFP tends to coincide with low utilization. While BFK emphasized the central role of this negative covariance for their results, for the US this negative covariance is not large enough to render the Solow residual less volatile than TFP. It turns out that in most other countries that is in fact the case.

[9] To assess whether there are clear first-order differences in the flexibility of hours per worker, we compute standard deviations of actual sectoral hours per worker growth rates. Reassuringly, the standard deviations of hours per worker are not systematically different between the countries with more flexible labor markets (US: 0.010; UK: 0.016; Canada: 0.014), and more inflexible ones (Germany: 0.015; France: 0.014; Italy: 0.014).

[10] Both the US and the European data are available for the manufacturing sector only (the European survey has capacity utilization for services, but it starts in 2010, after the end of our sample in 2007). We stress that there is no strong reason to treat the capacity utilization surveys as closer to the truth than the BFK method. First, as a survey answer it entails some subjectivity. This is exacerbated by the fact that the question being asked differs somewhat between European countries, as detailed in Appendix A.2. By contrast, our measure of utilization intensity is just a transformation of log hours per worker. It has the benefit of being transparent and intuitive: workers working longer hours is a good indication of variable factors being used more intensively. It is concerning for the survey answers when the managers reporting low capacity utilization coincides with high hours per worker. Second, the survey question is about capacity utilization. Conceptually, the closest analog in our model to what the surveys are presumably capturing would be actual output divided by output when factors are utilized so intensively that the marginal costs of increasing utilization rise steeply. This is related, but not the same as our model's notion of variable factor utilization intensity. Third, the history of the development of capacity utilization series suggests caution in using the relatively new EU surveys as a benchmark. In the US, in response to concerns about earlier vintages of these data, the collection methodology was improved to provide managers with a detailed and precise notion of "full production capability," namely that the number of shifts, hours of operation and overtime pay can be sustained under normal conditions and a realistic work schedule in the long run. The EU surveys are more recent, and the mapping between them and theory is even less clear. As far as we are aware, the EU surveys do not provide managers with a precise notion of capacity. So each manager is more free to apply their own definition of "full capacity" output. Finally, one benefit of our approach is that we can produce measures of utilization-adjusted TFP for many more countries and sectors than capacity utilization surveys have available.

Table 2
Correlations Summary Statistics.

	Mean	Median	25th pctile	75th pctile
G7 Countries (N. obs. = 21)				
$d\ \ln Y_{nt}$	0.358	0.337	0.242	0.565
$d\ \ln Z_{nt}$	0.020	−0.007	−0.087	0.140
$d\ \ln \mathcal{I}_{nt}$	0.247	0.231	0.100	0.461
$d\ \ln \mathcal{S}_{nt}$	0.086	0.120	−0.022	0.300
$d\ \ln \mathcal{U}_{nt}$	0.152	0.157	0.082	0.301
$d\ \ln \mathcal{H}_{nt}$	0.175	0.223	0.073	0.314
All countries (N. obs. = 406)				
$d\ \ln Y_{nt}$	0.190	0.231	−0.027	0.437
$d\ \ln Z_{nt}$	−0.007	0.003	−0.214	0.212
$d\ \ln \mathcal{I}_{nt}$	0.111	0.132	−0.089	0.327
$d\ \ln \mathcal{S}_{nt}$	0.052	0.083	−0.150	0.296
$d\ \ln \mathcal{U}_{nt}$	0.047	0.076	−0.172	0.262
$d\ \ln \mathcal{H}_{nt}$	0.054	0.083	−0.132	0.261

Notes: This table presents the summary statistics of the correlations in the sample of G7 countries (top panel) and full sample (bottom panel). Variable definitions and sources are described in detail in the text.

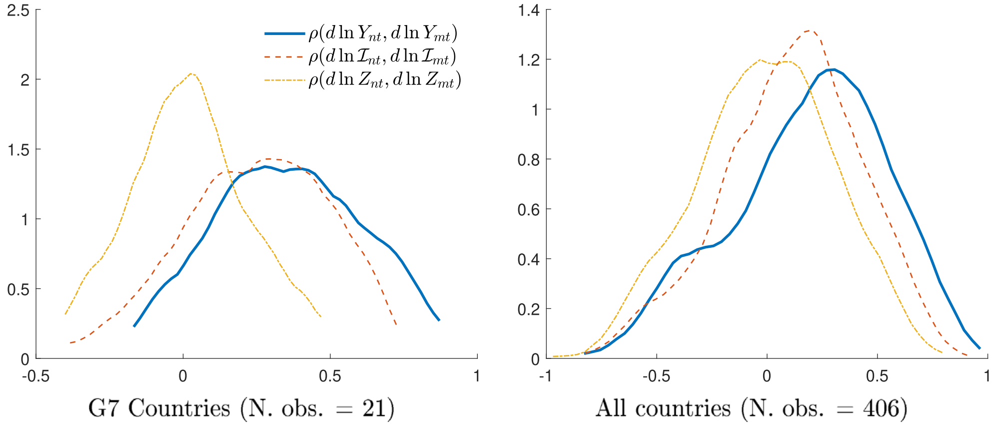

Fig. 2. Correlations: Kernel Densities.
Notes: This figure displays the kernel densities of real GDP growth, the utilization-adjusted TFP, and input correlations in the sample of G7 countries (left panel) and full sample (right panel). Variable definitions and sources are described in detail in the text. Appendix Fig. A2 correlates the TFP series with real GDP growth for the G7 sample.

4.3.4. International correlation decomposition

To highlight the relative importance of TFP in international comovement, combine (2.3) and (3.9) to write real GDP growth as a sum of two components (see Appendix B.1 for the derivation):

$$d\ \ln Y_{nt} = d\ \ln Z_{nt} + d\ \ln \mathcal{I}_{nt}, \tag{4.1}$$

where $d \ln \mathcal{I}_{nt}$ is the component of GDP growth accounted for by changes in inputs, and given by eq. (B.4). Our estimation approach allows us to construct the true (utilization- and scale-adjusted) $d \ln \mathcal{I}_{nt}$.

Table 2 presents the basic summary statistics for the elements of the GDP decomposition (4.1). These results are useful for highlighting the role of the TFP shocks and comparing them to the Solow residual. The top panel reports the correlations among the G7 countries. The average correlation of real GDP growth among these countries is 0.36. The second line summarizes correlations of the TFP shocks. Those are on average close to zero. By contrast, input growth is positively correlated, with a mean of 0.25. The left panel of Fig. 2 depicts the kernel densities of the correlations of real GDP, TFP, and inputs. There is a clear hierarchy, with the real GDP the most correlated, and the TFP the least correlated and centered on zero.

Section 2 shows that the Solow residual can be written as a sum of the aggregate TFP growth and the aggregated variable utilization change $d \ln \mathcal{U}_{nt}$.[11] Thus, it is an empirical question to what degree correlations in the Solow residual reflect true technology shock correlation as opposed to endogenous input adjustments. Table 2 shows that the Solow residual has an average

[11] Now that we augmented the model with variable returns to scale, the difference between TFP and the Solow residual includes a scale adjustment, as in Eq. (B.6). In practice, the scale adjustment plays a minor role relative to unobserved utilization.

correlation of about 0.09 in the G7 countries. If Solow residuals were taken to be a measure of TFP shocks, we would have concluded that TFP is positively correlated in this set of countries. As we can see, this conclusion would be misleading. Indeed, the correlation in the utilization term $\mathcal{U}_{nt}$, which is the difference between the true TFP shock $d \ln Z_{nt}$ and the Solow residual, accounts for all of the correlation in the Solow residual, on average. This indicates that the correlation in the Solow residual is in fact driven by unobserved input utilization and scale adjustments. In our framework, sectoral unobserved utilization is a log-linear transformation of hours per worker. Table 2 shows that indeed the correlation in aggregated hours per worker $d \ln \mathcal{H}_{nt}$ accounts for the correlation in $d \ln \mathcal{U}_{nt}$.[12]

The bottom panel of Table 2 repeats the exercise in the full sample of countries. The basic message is the same as for the G7. It is still the case that $d \ln Z_{nt}$ has a zero average correlation, whereas inputs $d \ln \mathcal{I}_{nt}$ are positively correlated and account on average for about half of the real GDP correlation. The Solow residuals are also more correlated than $d \ln Z_{nt}$, and the difference is accounted for by the fact that the unobserved inputs are positively correlated. The right panel of Fig. 2 displays the kernel densities of the correlations in the full sample.

This is of course only an accounting decomposition. The growth in $\mathcal{I}_{nt}$ is endogenous to both TFP shocks at home and abroad, and to any non-TFP shocks. Though the TFP shocks themselves are uncorrelated, the induced endogenous GDP comovements may still be sizable when TFP shocks are transmitted across borders via production networks and goods trade. We next turn to a quantitative model of international shock propagation to assess the roles of TFP and variable utilization in international comovement.

5. General equilibrium

This section implements the multi-sector IRBC model in Section 3. Appendix B presents a complete characterization of the equilibrium conditions. We proceed in two steps. First, when the adjustments of employment and machines are muted, the model can be viewed as an international version of the network propagation model following Acemoglu et al. (2012). This exercise emphasizes the role of the input-output linkages in amplifying or dampening the underlying contemporaneous sectoral shocks. The advantage of the network model is that it is transparent on the role of input linkages in shock propagation, and can be implemented on a large set of countries and a limited time series like we have in our data. The disadvantage is that it rules out dynamic responses of capital accumulation and intertemporal labor adjustment to the shocks. In the second step, we consider the G7 countries where a longer time series are available, and allow for dynamic responses to shocks, similar to our previous work (Huo et al., 2020). Both the static and dynamic versions of the model are solved by linearizing.

As stressed above, utilization can potentially contribute to international comovement for two distinct reasons: endogenous responses of utilization to TFP shocks, and shocks to utilization itself. To quantify both of these mechanisms, this section introduces a utilization shock that rationalizes the estimated variation in utilization and effort given the global vectors of TFP and predetermined employment and machines. We also subject the model to the standard Solow residual shocks to contrast them with TFP.

5.1. Calibration

5.1.1. Utilization shock

The utilization shock is a shift in the supply of variable factors, ξ_{njt}, in eq. (3.1). Each period, given the observed true TFP and pre-determined machines and employment, we can compute the required utilization shock so that the model-implied unobserved inputs coincide with our estimated unobserved inputs. This shock is essentially the wedge between the estimated utilization and the one implied by the model with only TFP shocks.[13,14] Unlike the TFP shocks, computing the utilization shock requires solving for the global equilibrium of the model, as the unobserved inputs are jointly determined in the world production network. Appendix B.4 describes the details of the procedure.

5.1.2. Elasticities

In implementing the network model, we only need to take a stand on the value of a small number of parameters, and use our data to provide the required quantities. Table 3 summarizes the parameter assumptions for the network model and data sources. The exact functional forms of the final goods and intermediate goods Armington aggregators are given by eqs. (B.7) and (B.9) in Appendix B.2. In Huo et al. (2020) we estimate the substitution elasticities in final and intermediate use. Based on these estimation results, the final goods (consumption and investment) Armington elasticity ρ is set to 2.75, and the intermediate input substitution elasticity ε is set to 1. The scale parameters γ_j come from our own production function estimates reported in Table 1. In practice, returns to scale are close to constant.

The remaining three parameters, ψ_j^h, ψ_j^e, and ψ_j^u, are elasticities of the supply of hours, effort, and capital utilization, respectively. We use a combination of empirical and theoretical restrictions to pin these down. Joint optimization of the different

[12] The reasons the two do not coincide perfectly is scale effects and aggregation across sectors.

[13] This wedge is different from the familiar labor wedge. Our model distinguishes hours from employment, and the utilization shocks help match the observed hours given the predetermined employment and machines. The utilization shock captures all margins of utilization – hours per worker, unobserved effort, and capital utilization rate.

[14] The utilization shock is a shifter in the supply of observed and unobserved variable factors. While providing a deeper microfoundation for these factor supply shocks is beyond the scope of this paper, many “demand” shocks such as sentiments or monetary policy shocks, as well as some forms of financial frictions will appear as exogenous shifts in factor supply in these frameworks. See Huo et al. (2020) for a detailed discussion.

Table 3
Parameter Values.

Param.	Value	Source	Related to
ρ	2.75	Huo et al. (2020)	final substitution elasticity
ε	1	Huo et al. (2020)	intermediate substitution elasticity
γ_j		Table 1	returns to scale
ζ_j		Table 1	joint restriction on variable input elasticities
$\tilde{\psi}_j$	0.5	See Section 5.1	composite variable input elasticity
α_j,η_j		KLEMS	capital shares, intermediate shares
π^f_{mnjt}		WIOD	final use trade shares
$\pi^x_{mi,njt}$		WIOD	intermediate use trade shares
ω_{nj}		WIOD	final consumption shares

Notes: This table summarizes the parameters and data targets used in the quantitative model, and their sources.

margins of utilization implies that to solve for equilibrium in this economy we do not need to know ψ_j^h, ψ_j^e, and ψ_j^u individually. Rather, we only need a single composite utilization supply elasticity. To see this, combine the the optimality conditions for variable factors (B.10)–(B.11) with the production function to get:

$$d\ \ln Y_{njt} = d\ \ln Z_{njt} + \tilde{\psi}_j \gamma_j \eta_j \left(1-\alpha_j\right)\left(d\ \ln W_{njt} + d\ \ln L_{njt} - d\ \ln P_{nt} - d\ \ln \xi_{njt}\right)$$
$$+\gamma_j\left(1-\eta_j\right)d\ \ln X_{njt} + \gamma_j \eta_j\left(\alpha_j d\ \ln M_{njt} + \left(1-\alpha_j\right)d\ \ln N_{njt}\right),$$

where

$$\tilde{\psi}_j \equiv \frac{1}{\psi_j^h} + \frac{1}{\psi_j^e} + \frac{\alpha_j}{1-\alpha_j}\frac{1}{\psi_j^u}$$

is the required composite elasticity.

Our production function estimates yield a restriction on these parameters. Eq. (3.8) implies that the estimated ζ_j corresponds to $\alpha_j \frac{\psi_j^h}{\psi_j^u} + (1-\alpha_j)\frac{\psi_j^h}{\psi_j^e}$. Thus, $\tilde{\psi}_j$ and ζ_j are related by:

$$\tilde{\psi}_j = \frac{1}{\psi_j^h}\left(1 + \frac{\zeta_j}{1-\alpha_j}\right).$$

In the absence of effort and capital utilization margins, only the supply elasticity of hours ψ_j^h is relevant. When variable effort and utilization are present, ζ_j and ψ_j^h jointly govern the combined responsiveness of variable inputs, and our production function estimates put discipline on the value of ζ_j.

The model structure also provides a bound on the choice of ψ_j^h. The steady-state employment level N_{nj} must satisfy

$$\frac{\psi^n N_{nj}^{\psi^n - 1}}{\psi^n N_{nj}^{\psi^n - 1} + G_j\left(H_{nj}, E_{nj}, U_{nj}\right)} = 1 - \tilde{\psi}_j.$$

The constraint that employment must be positive thus imposes a restriction that the composite factor supply elasticity $\tilde{\psi}_j$ is less than one. When effort and capital utilization adjustments are muted, this simply amounts to the restriction that the Frisch labor supply elasticity $(\psi_j^h - 1)^{-1}$ is positive. Given the discussion above, in the baseline parameterization we set the composite elasticity $\tilde{\psi}_j$ to be 0.5 in all sectors, which corresponds to a Frisch elasticity equal to one in the absence of effort and utilization variation. Given our estimates of ζ_j, the sector-specific ψ_j^h can be obtained accordingly. Appendix B.5 assesses sensitivity to alternative elasticities. The main quantitative implications remain valid under the alternative parameterizations.

5.1.3. Shares

All other parameters in the model have close counterparts in basic data and thus we compute them directly. The ratio of value added to gross output corresponds to η_j. The labor share $(1-\alpha_j)$ is computed as labor payments as a fraction of value added. In KLEMS, payments to capital are computed as the difference between measured sectoral value added and payments to labor. This implies that profits are mechanically included in the capital share. Both η_j and $(1-\alpha_j)$ come from KLEMS (see Appendix Table A3), and are averaged in each sector across countries and years in the baseline calibration to minimize noise. As noted above, allowing these parameters to be country-sector-time specific leads to very similar TFP series. Steady state input shares $(\pi^x_{mi,nj})$ and final consumption shares (π^f_{mnj}) are computed from WIOD as time averages.

Table 4
GDP Correlations in the Data and in the Static Model.

	Mean	Median	25th pctile	75th pctile
G-7 countries (N. obs. = 21)				
Data	0.358	0.337	0.242	0.565
Model, TFP shock	0.030	0.015	−0.100	0.153
Model, utilization shock	0.126	0.124	0.008	0.1853
Model, TFP and utilization shocks	0.197	0.244	−0.020	0.401
Model, Solow residual	0.086	0.103	−0.084	0.332
All countries (N. obs. = 406)				
Data	0.190	0.231	−0.027	0.437
Model, TFP shock	0.005	−0.011	−0.201	0.230
Model, utilization shock	0.046	0.057	−0.168	0.277
Model, TFP and utilization shocks	0.096	0.090	−0.151	0.380
Model, Solow residual	0.051	0.032	−0.200	0.313

Notes: This table presents the summary statistics of the correlations of $d \ln Y_{nt}$ in the sample of G7 countries for 1978–2007 (top panel) and full sample for 1995–2007 (bottom panel) in the data and the model with various shocks. Variable definitions and sources are described in detail in the text.

5.2. Model GDP correlations

Table 4 reports GDP correlations in our model with employment and capital being fixed. The model is simulated with the utilization-adjusted TFP shocks, the utilization shocks, and the Solow residuals. As our model can only be implemented on a balanced panel, we report results both for a longer G7-only version of the model spanning years 1978–2007, as well as an all-countries version spanning 1995–2007– the longest timespan for which data are available for all 29 countries. For the G7 group, TFP shocks generate mean GDP correlations of 0.03, less than one-tenth of the level found in the data. For the full sample of countries, TFP shocks produce mean correlations of essentially zero. When TFP shocks are uncorrelated, the model can still exhibit GDP comovement through endogenous propagation of shocks. This propagation would manifest itself as comovements in variable factors of production – hours, effort, and capital utilization. The fact that GDP is at best only weakly correlated when the model is subjected to the TFP shocks suggests that endogenous responses of utilization to TFP shocks do very little to synchronize GDP.

The rows labeled "Model, utilization shock" of Table 4 report GDP correlations under the utilization shock. As primary inputs are more correlated than TFP and the utilization shock rationalizes variable inputs that are tied to hours per worker, it is not surprising that the utilization shock generates significantly higher GDP comovement. The utilization shock alone generates between one-quarter and one-third of the observed GDP correlations in the two samples of countries. The model with both TFP and utilization shocks generates about half of the observed correlations in the data.

Section 4 highlighted that the Solow residual is more correlated than true TFP, and that its properties are quite different from true TFP. We now explore the implications of feeding in the Solow residual as a measure of technology shocks into our model where factor utilization can vary. This exercise helps assess the consequences of mismeasurement: if the true model features unobserved factor utilization, and the Solow residual is mistakenly used as the measure of technology innovations, what would we conclude about the contribution of technology shocks for comovement? The rows labeled "model, Solow residual" of Table 4 report GDP comovement with the Solow residual as the shock. For both country samples, comovement is higher with the Solow residual than true TFP. Solow residuals can generate about 25% of the level of observed GDP correlations. These results suggest that TFP mismeasurement does affect our understanding of the role of technology shocks in international comovement.

Now we turn to the dynamic model where employment and capital are endogenously determined every period. To solve the dynamic model, it is necessary to estimate the shock processes for agents to forecast future aggregate outcomes. We impose a parsimonious structure by allowing the sector-specific TFP and utilization shocks to follow autoregressive processes that depend on their own past values and past values of other sectors within the same country.[15] This estimation can only be conducted for G7 countries where a relatively long panel is available. Additional parameters that are only relevant in the dynamic model are specified as follows. We choose the utility function $\Psi(\cdot) = \log(\cdot)$. The depreciation rates ρ_j are set to match the sector specific depreciation rates obtained from the BEA in 2001. The less standard parameter is ψ^n which controls the employment adjustment costs. In the baseline, we set ψ^n to be 4 and we vary it in Appendix B.5. As can be seen in Table 5, adding dynamics in capital and employment does not significantly modify the overall pattern of GDP comovement. This is mainly due to the fact that GDP growth rates are determined for the most part by the the impact responses, which are already captured in the static model.

5.2.1. Sensitivity

Appendix Tables A9–A10 present the model correlations under a variety of parameter combinations in the static and dynamic cases, respectively. Lower substitution elasticities ρ and ε, or more elastic factor supply (higher $\tilde{\psi}_j$) have the expected effect of

[15] See Appendix B.4. for more details on the shock processes. Given the large number of parameters to be estimated and the available data, we must impose some restrictions on lagged spillovers in the shock processes. Note however we feed in estimated shocks in our model exercises, so our results are based on the full empirical contemporaneous and lagged covariance structure of the observed shocks.

Table 5
GDP Correlations in the Data and in the Dynamic Model.

	Mean	Median	25th pctile	75th pctile
G-7 countries (N. obs. = 21)				
Data	0.358	0.337	0.242	0.565
Model, TFP shock	0.002	−0.005	−0.175	0.178
Model, utilization shock	0.132	0.099	−0.010	0.218
Model, TFP and utilization shocks	0.264	0.305	0.051	0.484
Model, Solow residual	0.065	0.081	−0.128	0.285

Notes: This table presents the summary statistics of the correlations of $d \ln Y_{nt}$ in the sample of G7 countries for 1978–2007 and the model with various shocks.

greater GDP synchronization. The "max transmission" model that combines lower ρ and ε with higher $\tilde{\psi}_j$ generates TFP-driven average GDP correlations of 0.078 and 0.036 in the G7 countries and the full sample, respectively. While this is considerably higher than the baseline (0.03 and 0.005), it is still well short of observed comovement. The bottom panel reports the results of a model that suppresses the input network and leaves only final goods trade. The resulting correlations are lower than the baseline, but not dramatically so. This is consistent with the notion that international transmission forces, while present, are not predominant in this framework.

6. Conclusion

When some margins of factor utilization are unobservable, the Solow residual is a misleading measure of technology innovations. While use of utilization-adjusted TFP is common in the research on the US economy, international macroeconomics has thus far worked with the Solow residual. This paper makes two contributions. First, we provide a new dataset containing utilization-adjusted TFP series for many countries and sectors for use in open-economy macroeconomics. We illustrate that these series have different international correlation properties from the standard Solow residual. Second, we quantify the roles of TFP and variable factor utilization in international comovement. We find that while TFP shocks do not generate substantial correlation in GDP growth rates across countries, shocks to variable utilization are more correlated and thus carry greater potential to synchronize GDP. Future research should focus on non-technology shocks that shift factor supply as candidate drivers of international business cycles.

Disclosure statement

I hereby declare that I have no relevant or material financial interests that relate to the research described in the paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jinteco.2023.103753.

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