Technology and Non-Technology Shocks: Measurement and Implications for International Comovement*

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Abstract

This paper examines the role of both technology and non-technology shocks in international business cycle comovement. Using industry-level data on 30 countries and up to 28 years, we first provide estimates of utilization-adjusted TFP shocks, and an approach to infer non-technology shocks. We then set up a quantitative model calibrated to the observed international input-output and final goods trade, and use it to assess the contribution of both technology and non-technology shocks to international comovement. We show that unlike the traditional Solow residual, the utilization-adjusted TFP shocks are virtually uncorrelated across countries. Transmission of TFP shocks across countries also cannot generate noticeable comovement in GDP in our sample of countries. By contrast, non-technology shocks are highly correlated across countries, and the model simulation with only non-technology shocks generates substantial GDP correlations. We conclude that in order to understand international comovement, it is essential to both model and measure non-TFP shocks.

Keywords: TFP shocks, non-technology shocks, international comovement, input linkages
JEL Codes: F41, F44

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1 Introduction

Real GDP growth is positively correlated across countries. In spite of a large amount of research into the causes of international comovement, we still lack a comprehensive account of this phenomenon. Two related themes cut through the literature. First, is international comovement driven predominantly by technology (Backus, Kehoe, and Kydland, 1992) or non-technology (Stockman and Tesar, 1995) shocks? Second, does comovement occur because shocks are transmitted across countries (e.g. Frankel and Rose, 1998; di Giovanni and Levchenko, 2010; di Giovanni, Levchenko, and Mejean, 2018), or because the shocks themselves are correlated across countries (Imbs, 2004)?

This paper uses sector-level data for 30 countries and up to 28 years years to provide a forensic account of the sources of international comovement. The first step in our exercise is measurement of both technology and non-technology shocks. On the technology side, we provide estimates of utilization-adjusted TFP growth rates in our sample of countries, sectors, and years. Basu, Fernald, and Kimball (2006, henceforth BFK) develop a methodology to estimate TFP shocks for the United States controlling for unobserved input utilization and industry-level variable returns to scale. Importantly, BFK show that doing so produces a TFP series with dramatically different properties than the traditional Solow residual. We bring this insight into the international context by estimating the BFK TFP series for a large sample of countries, and analyzing the international correlations in these series.

Having measured the TFP shocks at the country-sector level, we develop a method to infer non-technology shocks. The objective is to obtain a shock that rationalizes the change in primary factor inputs conditional on the technology shock. In our model, sectors use capital, labor, and intermediate inputs from potentially all countries and sectors in the world. For each sector, real output growth is therefore moved by (i) its TFP shock; (ii) the change in the use of its intermediate inputs; and (iii) the non-technology shock to the supply of the primary factors – capital and labor – to this sector. It is this non-technology shock that we are interested in measuring. Using data on productivity shocks, sectoral prices, and the world input-output matrix, we back out the non-technology shock that rationalizes the data on output and input growth in each country, sector, and year.

Using these technology and non-technology shocks in our sample of countries and sectors, we assess the role of both the shocks and the international goods market linkages for cross-country business cycle comovement. We do this by means of two exercises: an accounting decomposition and model-based counterfactuals. The accounting decomposition writes real GDP growth as a sum of two components, the TFP growth and the input growth. Thus, the GDP covariance between any two countries is the sum of the covariance of TFP, covariance of inputs, and the TFP-input cross-covariance terms. We show that TFP growth is virtually uncorrelated across countries, implying that TFP covariance has a small direct contribution to observed comovement in our sample of countries. By contrast, input growth is significantly more correlated across countries, with a correlation coefficient nearly half of the correlation of GDP.

Of course, input growth is endogenous as inputs respond to both domestic and foreign TFP shocks. Thus, the finding that TFP growth is uncorrelated does not necessarily imply TFP shocks do not contribute to international comovement. It could be that correlated observed input growth is driven by the propagation of TFP shocks. We must instead examine the properties of the non-technology shocks, that are constructed after netting out TFP. We show that in contrast to TFP, the aggregated non-technology shocks are quite correlated across countries, with the correlation coefficients about half of the correlation in real GDPs. To develop the full picture of the role of different types of shocks, correlated shocks, and international transmission, we perform model-based counterfactuals.

Our quantitative framework features multiple countries and sectors, and trade in both final and intermediate goods. It is implemented on the data from the World Input-Output Database (WIOD). Final consumption in each country and sector is an Armington aggregate of the goods coming from different source countries. Each sector uses labor, capital, and intermediate inputs in production. The intermediate inputs can come from any sector and country in the world, and we take the information on input usage directly from WIOD. Labor and capital supply to each sector and country are upward-sloping in the real prices of labor and capital, respectively, and subject to shocks. It is these shocks to factor supply that we back out from the data and label as non-technology shocks. We simulate the world economy's responses to shocks using the approach of Dekle, Eaton, and Kortum (2008).

The model features standard international transmission mechanisms. A positive foreign shock lowers the prices of intermediate inputs coming from that country, stimulating demand in countries and sectors that use those inputs in production. At the same time, a positive shock in a foreign country makes final goods supplied by that country cheaper, reducing demand for final goods produced by countries competing with it in final goods markets. Prior to simulating the model, we first structurally estimate two key elasticities – the final demand elasticity and the elasticity of substitution between intermediate inputs. Estimates of these elasticities vary substantially in the literature, and any assessment of the role of transmission vs. correlated shocks will be influenced by these parameters. Our estimates imply an elasticity of substitution between intermediate inputs that is not statistically different from 1. On the other hand, we obtain a range of estimates for the elasticity of substitution in final demand. Given the uncertainty in the appropriate value of this elasticity, our quantitative analysis uses two values, 1 and 2.75, reflecting our range of estimates.

To focus on the distinction between technology and non-technology shocks, we simulate the model with only one type of shock at a time. It turns out that a model with only TFP shocks cannot generate almost any international comovement, whereas the model with only non-technology shocks can produce a correlation that is 60% of the correlation under both types of shocks. Thus, non-technology shocks are much more successful at generating the observed comovement than technology shocks, a result that is insensitive to the choice of elasticities.

To assess the role of trade linkages in the transmission of shocks, we perform two related exercises. First, we compute impulse responses to a hypothetical shock abroad on each country's GDP. We simulate two kinds of shocks: a 1% increase in U.S. productivity and the non-technology shocks, and a 1% increase in those parameters in every other country in the world (rest of the world or ROW shock). The impulse responses point to positive comovement in response to shocks: real GDP in most countries increases following a shock to the U.S., though the effect is much more pronounced under a low substitution elasticity. In response to a 1% ROW shock, the real GDP in the mean country increases by 0.5% under the low elasticity of substitution, and by 0.2% under the high one, suggesting substantial responsiveness of countries to developments in the world economy.

We then simulate the model under the observed shocks, but in which every country is in autarky. This counterfactual reveals how much comovement would occur purely due to correlated shocks, and without any transmission of shocks through trade linkages. On average, the autarky correlations are similar to the baseline under the high elasticity of substitution, and slightly lower than baseline under the low elasticity. However, these averages conceal a great deal of heterogeneity and compositional patterns. There is a part of the country sample that displays higher GDP correlations in autarky than under trade. However, most countries experience higher correlations under trade. Under the low elasticity of substitution, 24 out of 29 countries have higher correlations with international trade compared to autarky with the majority of the countries in the sample, suggesting that trade linkages do increase correlations in most of the country pairs. In addition, correlations under trade are disproportionately more likely to be higher with larger countries. All in all, when it comes to quantifying the role of transmission the results are somewhat more heterogeneous across countries and elasticity-dependent. However, evidence supportive of the transmission of shocks through trade linkages is clear-cut in much of the world economy.

Our paper contributes to the literature on international comovement. There is a small number of papers dedicated to documenting international correlations in productivity shocks and inputs (Imbs, 1999; Ambler, Cardia, and Zimmermann, 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, Dedola, and Leduc, 2014; Levchenko and Pandalai-Nayar, 2017). Relative to these papers, we use sector-level data to provide novel estimates of both utilization-adjusted TFP and non-technology shocks, and expand the sample of countries. A large literature 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, Kehoe, and Kydland, 1992; Kose and Yi, 2006; Johnson, 2014). A smaller set of contributions adds non-technology shocks (Stockman and Tesar, 1995; Wen, 2007). In these analyses, productivity shocks are proxied by the Solow residual, and non-technology shocks are not typically measured based on data. Our quantitative assessment benefits from improved measurement of both types of shocks.

The rest of the paper is organized as follows. Section 2 lays out a basic GDP accounting framework and presents the results of estimating utilization-adjusted TFP. Section 3 introduces the multi-country, multi-sector model of production and trade necessary to back out non-technology shocks, estimates key elasticities and uses that model to perform counterfactuals. Section 4 concludes.

2 Accounting Framework

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

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

where K_{njt}, L_{njt}, and X_{njt} are the capital, labor, and materials inputs, respectively, and Z_{njt} is TFP. Total output is a Cobb-Douglas aggregate of primary factor inputs K_{njt} and L_{njt} and materials inputs X_{njt}, with possibly non-constant returns to scale ($\gamma_j \neq 1$). When it comes to measurement, it will be important that K_{njt} and L_{njt} are true, utilization-adjusted inputs that may not be directly observable.

Define real GDP at time t, evaluated at base prices (prices at $t-1$) 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. The change in real GDP between $t-1$ and t is then:

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

and the proportional change:

$$\begin{aligned}
\frac{\Delta Y_{nt}}{Y_{nt-1}} &= \frac{\sum_{j=1}^{J}\left(P_{njt-1}\Delta Y_{njt} - P_{njt-1}^{X}\Delta X_{njt}\right)}{Y_{nt-1}} \\
&= \sum_{j=1}^{J} w_{njt-1}^{D}\left(\frac{\Delta Y_{njt}}{Y_{njt-1}} - \frac{\Delta X_{njt}}{X_{njt-1}}\frac{P_{njt-1}^{X}X_{njt-1}}{P_{njt-1}Y_{njt-1}}\right),
\end{aligned}$$

where $w_{njt-1}^{D} \equiv \frac{P_{njt-1}Y_{njt-1}}{RGDP_{nt-1}}$ is the Domar weight of sector j in country n, that is, the weight of the sector's gross sales in aggregate value added. Approximate the growth rate with log difference:

$$\begin{aligned} dlogY_{nt} &\approx \sum_{j=1}^{J} w^{D}_{njt-1}\left(dlogY_{njt} - dlogX_{njt}\frac{P^{X}_{njt-1}X_{njt-1}}{P_{njt-1}Y_{njt-1}}\right) \\ &= \sum_{j=1}^{J} w^{D}_{njt-1}\Big(dlogZ_{njt} + \gamma_j\alpha_j\eta_j dlogK_{njt} + \gamma_j(1-\alpha_j)\eta_j dlogL_{njt} \\ &\quad +\gamma_j\left(1-\eta_j\right)dlogX_{njt} - dlogX_{njt}\frac{P^{X}_{njt-1}X_{njt-1}}{P_{njt-1}Y_{njt-1}}\Big). \end{aligned} \tag{2}$$

All of the terms in this expression are either observable or will be estimated, except for α_j and η_j. Thus, in order to proceed we need to take a stand on how to measure these. Regardless of the nature of variable returns to scale or market structure, under cost minimization $\alpha_j\eta_j$ is the share of payments to capital in the total costs, while $(1-\alpha_j)\eta_j$ is the share of payments to labor. We do not observe total costs, only total revenues. We will assume that $\alpha_j\eta_j$ also reflects the share of payments to capital in total revenues. This assumption is satisfied if either (i) sector j is competitive and the variable returns to scale are external to the firm; or (ii) profits are distributed among the inputs in proportion to their share in total costs, as in BFK or Hsieh and Klenow (2009). In either of those cases, these can be taken directly from the data as $\alpha_j\eta_j = r_{njt}K_{njt}/P_{njt}Y_{njt}$ and $(1-\alpha_j)\eta_j = w_{njt}L_{njt}/P_{njt}Y_{njt}$, where $P_{njt}Y_{njt}$ is total revenue, r_{njt} is the price of capital, and w_{njt} is the wage rate. The growth in real GDP then can be written as:

$$\begin{aligned} dlogY_{nt} \approx \sum_{j=1}^{J} w^{D}_{njt-1}\Bigg\{&\underbrace{dlogZ_{njt}}_{True\,TFP} + \underbrace{(\gamma_j-1)dlog\left[\left(K^{\alpha_j}_{njt}L^{1-\alpha_j}_{njt}\right)^{\eta_j}X^{1-\eta_j}_{njt}\right]}_{Scale\,effect} \\ &+\underbrace{\alpha_j\eta_j dlogK_{njt} + (1-\alpha_j)\eta_j dlogL_{njt}}_{Primary\ inputs}\Bigg\}. \end{aligned} \tag{3}$$

In the first instance, we are interested in the proximate drivers of comovement between countries, and in particular whether aggregate comovement occurs because of correlated TFP or inputs. Write real GDP growth as a sum of two components:

$$dlogY_{nt} \approx dlogZ_{nt} + dlogI_{nt}, \tag{4}$$

where aggregate TFP is denoted by:

$$dlogZ_{nt} = \sum_{j=1}^{J} w^{D}_{njt-1}dlogZ_{njt}, \tag{5}$$

and the input-driven component of GDP growth is defined as:

$$dlogI_{nt} \equiv \sum_{j=1}^{J} w^{D}_{njt-1} \Bigg\{ \underbrace{(\gamma_j - 1)dlog\left[\left(K^{\alpha_j}_{njt} L^{1-\alpha_j}_{njt}\right)^{\eta_j} X^{1-\eta_j}_{njt}\right]}_{Scale\, effect} + \underbrace{\alpha_j \eta_j dlogK_{njt} + (1-\alpha_j)\eta_j dlogL_{njt}}_{Primary\, inputs} \Bigg\}. \tag{6}$$

Then the covariance of real GDP between two countries is:

$$\begin{aligned} Cov(dlogY_{nt}, dlogY_{n\prime t}) &= Cov(dlogZ_{nt}, dlogZ_{n\prime t}) + Cov(dlogI_{nt}, dlogI_{n\prime t}) \\ &\quad + Cov(dlogZ_{nt}, dlogI_{n\prime t}) + Cov(dlogI_{nt}, dlogZ_{n\prime t}). \end{aligned} \tag{7}$$

This expression can be converted into correlations, as those have a more natural scale and are most commonly found in business cycle analyses:

$$\begin{aligned} \rho(dlogY_{nt}, dlogY_{n\prime t}) &= \frac{\sigma_{Z_n}\sigma_{Z_{n\prime}}}{\sigma_n \sigma_{n'}} \rho(dlogZ_{nt}, dlogZ_{n\prime t}) + \frac{\sigma_{I_n}\sigma_{I_{n\prime}}}{\sigma_n \sigma_{n'}} \rho(dlogI_{nt}, dlogI_{n\prime t}) \\ &\quad + \frac{\sigma_{Z_n}\sigma_{I_{n\prime}}}{\sigma_n \sigma_{n'}} \rho(dlogZ_{nt}, dlogI_{n\prime t}) + \frac{\sigma_{Z_I}\sigma_{Z_{n\prime}}}{\sigma_n \sigma_{n'}} \rho(dlogI_{nt}, dlogZ_{n\prime t}), \end{aligned} \tag{8}$$

where $\rho(.,.)$ denotes correlation, σ_n is the standard deviation of $dlogY_{nt}$, and σ_{Z_n} and σ_{I_n} are standard deviations of $dlogZ_{nt}$ and $dlogI_{nt}$, respectively. Equations (7)-(8) convey that in the proximate sense, comovement in real GDP between two countries can be driven by correlated TFP shocks $\rho(dlogZ_{nt}, dlogZ_{n\prime t})$, correlated inputs $\rho(dlogI_{nt}, dlogI_{n\prime t})$, or the cross-correlations between them.

We will first establish stylized facts on the TFP and input cross-country correlations. To do this, we need to overcome the measurement challenge of estimating the TFP processes when utilization-adjusted factor usage is unobserved. Since inputs are clearly endogenous, and will respond to both domestic and potentially foreign GDP, we will then impose some additional theoretical structure to extract non-technology shocks that rationalize the observed movements in sector-level quantities and prices.

2.1 Unobserved Factor Utilization

As emphasized by BFK, 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 control for it in estimation, otherwise factor usage will appear in estimated TFP. BFK show that controlling for unobserved factor utilization leads to a TFP series in the United States that has very different properties than the Solow residual.

Let the true factor inputs be comprised of:

$$K_{njt} \equiv A_{njt} M_{njt}$$

and

$$L_{njt} \equiv E_{njt} H_{njt} N_{njt}.$$

The true capital input is the product of the quantity of capital input ("machines") M_{njt} that can be measured in the data, and capital utilization A_{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.

Relationship to Solow residual The Solow residual takes factor shares and nets out the observable factor uses. Denote by S_{njt} the Solow residual. It has the following relationship to gross output and observed inputs:

$$dlogY_{njt} = dlogS_{njt} + \alpha_j \eta_j dlogM_{njt} + (1-\alpha_j)\eta_j dlogH_{njt} + (1-\alpha_j)\eta_j dlogN_{njt} + (1-\eta_j)\, dlogX_{njt}.$$

Plugging this way of writing output growth into the real GDP growth equation (2), we get the following expression:

$$\begin{aligned} dlogY_{nt} \quad &\approx \quad \sum_{j=1}^{J} w^D_{njt-1} \left(dlogS_{njt} + \alpha_j \eta_j dlogM_{njt} + (1-\alpha_j)\eta_j dlogH_{njt} + (1-\alpha_j)\eta_j dlogN_{njt} \right. \\ &\qquad \left. + (1-\eta_j)\, dlogX_{njt} - dlogX_{njt} \frac{p^X_{njt-1} X_{njt-1}}{p_{njt-1} Y_{njt-1}} \right) \\ &= \quad \sum_{j=1}^{J} w^D_{njt-1} \left(dlogS_{njt} + \alpha_j \eta_j dlogM_{njt} + (1-\alpha_j)\eta_j dlogH_{njt} + (1-\alpha_j)\eta_j dlogN_{njt} \right) \end{aligned} \tag{9}$$

Comparing (3) to (9), the Solow residual contains the following components:

$$\begin{aligned} dlogS_{njt} \quad &= \quad \underbrace{dlogZ_{njt}}_{True\,TFP} + \underbrace{(\gamma_j - 1) dlog \left[\left(K^{\alpha_j}_{njt} L^{1-\alpha_j}_{njt} \right)^{\eta_j} X^{1-\eta_j}_{njt} \right]}_{Scale\, effect} \\ &\quad + \underbrace{\alpha_j \eta_j dlogA_{njt} + (1-\alpha_j)\eta_j dlogE_{njt}}_{Unobserved\, utilization}. \end{aligned}$$

This expression makes it transparent that in this setting, the Solow residual can diverge from the true TFP shock for two reasons: departures from constant returns to scale at the industry level, and unobserved utilization of inputs.

Let aggregate Solow residual be denoted by:

$$\begin{aligned} dlogS_{nt} &= \sum_{j=1}^{J} w_{njt-1}^{D} dlogS_{njt} \\ &= dlogZ_{nt} + dlogU_{nt}, \end{aligned}$$

where in the second equality, $dlogU_{nt}$ is the aggregate utilization adjustment:

$$\begin{aligned} dlogU_{nt} \equiv & \sum_{j=1}^{J} w_{njt-1}^{D} \left\{ (\gamma_j - 1) dlog \left[\left(K_{njt}^{\alpha_j} L_{njt}^{1-\alpha_j} \right)^{\eta_j} X_{njt}^{1-\eta_j} \right] \right. \\ & \left. + \alpha_j \eta_j dlogA_{njt} + (1-\alpha_j)\eta_j dlogE_{njt} \right\}. \end{aligned}$$

It is immediate that the observed Solow residual can be correlated across countries both due to correlated shocks to true TFP, and due to correlated unobserved input adjustments:

$$\begin{aligned} \rho(dlogS_{nt}, dlogS_{n\prime t}) = & \frac{\sigma_{Z_n}\sigma_{Z_{n\prime}}}{\sigma_{S_n}\sigma_{S_{n\prime}}} \rho(dlogZ_{nt}, dlogZ_{n\prime t}) + \frac{\sigma_{U_n}\sigma_{U_{n\prime}}}{\sigma_{S_n}\sigma_{S_{n\prime}}} \rho(dlogU_{nt}, dlogU_{n\prime t}) \\ & + \frac{\sigma_{Z_n}\sigma_{U_{n\prime}}}{\sigma_{S_n}\sigma_{S_{n\prime}}} \rho(dlogZ_{nt}, dlogU_{n\prime t}) + \frac{\sigma_{U_n}\sigma_{Z_{n\prime}}}{\sigma_{S_n}\sigma_{S_{n\prime}}} \rho(dlogU_{nt}, dlogZ_{n\prime t}), \end{aligned}$$

where σ_{S_n} and σ_{U_n} are standard deviations of $dlogS_{nt}$ and $dlogU_{nt}$, respectively. 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.

2.2 Estimation

Note that $dlogK_{njt}$ and $dlogL_{njt}$ are true, utilization-adjusted primary input growth rates. Log-differencing (1), and writing input usage breaking up the observed and the unobserved components yields:

$$\begin{aligned} dlogY_{njt} = & \gamma_j \left(\underbrace{\alpha_j \eta_j dlogM_{njt} + (1-\alpha_j)\eta_j dlog\left(H_{njt} N_{njt}\right) + (1-\eta_j) dlogX_{njt}}_{Observed \quad inputs} \right) \\ & + \gamma_j \underbrace{\left(\alpha_j \eta_j dlogA_{njt} + (1-\alpha_j)\eta_j dlogE_{njt}\right) + dlogZ_{njt}}_{Unobserved \quad inputs}. \end{aligned} \tag{10}$$

The key insight of BFK is that the firms' static optimization implies that the intensity of usage of observed and unobserved input usages are related. In particular, they provide a set of conditions under which the change in the unobserved inputs are proportional to the (observed) change in hours per worker, with the constant of proportionality that can be estimated:

$$\alpha_j \eta_j dlogA_{njt} + (1-\alpha_j)\eta_j dlogE_{njt} = \xi_j dlogH_{njt}. \tag{11}$$

The intuition is that firms optimize multiple dimensions of factor use intensity simultaneously to minimize costs. Thus, subject to technological constraints embodied in the composite parameter ξ_j, firms will set the shadow value of the unobserved dimensions of factor usage equal to shadow value of the observed dimensions. Plugging (11) into (10) yields the following estimating equation:

$$\begin{aligned} dlogY_{njt} \quad = \quad & \delta_j^1 \left(\alpha_j \eta_j dlogM_{njt} + (1-\alpha_j)\eta_j dlog\left(H_{njt}N_{njt}\right) + (1-\eta_j) dlogX_{njt}\right) \\ & + \delta_j^2 dlogH_{njt} + \delta_{nj} + dlogZ_{njt}, \end{aligned} \tag{12}$$

where we also added country×sector fixed effects to allow for country-sector specific trend output growth rates. The estimation proceeds to regress real output growth on the growth of the composite observed input bundle and the change in hours.

We follow BFK's implementation approach as closely as possible. First, input usage will move with TFP shocks $dlogZ_{njt}$, and thus the regressors in this equation are correlated with the residual. To overcome this endogeneity problem, we use potentially three instruments. The first is oil shocks, 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 instrument is the growth rate in real government defense spending, lagged by one year. Finally, the third instrument is the foreign monetary policy shock interacted with the exchange rate regime. This instrument follows di Giovanni and Shambaugh (2008) and di Giovanni, McCrary, and von Wachter (2009), who show that major country interest rates have a significant effect on countries' output when they peg their currency to that major country. The assumption in specifications that use this instrument is that for many countries, interest rates in the US, Germany, or the UK are exogenous.

In practice, we estimate two separate sets of regressions. The first is confined to only the G7 countries, and uses only the first two instruments (oil and military spending). This tends to lead to the strongest instruments and most precisely estimated coefficients. Since these are the major world economies, the foreign interest rate instrument is not appropriate here. Second, we estimate this equation on the full sample of countries excluding the "base" countries of US, Germany, and the UK, in which case we use all three instruments.

Finally, following BFK, to reduce the number of parameters to be estimated, we restrict δ_j^2 to take only three values, according to a broad grouping of sectors: durable manufacturing, non-durable manufacturing, and all others.

Estimating equation (12) provides estimates of the two unknown parameters: $\widehat{\delta}_j^1$ corresponds to

γ_j, and $\widehat{\delta}_j^2$ to $\gamma_j\xi_j$. In addition, conditional on these estimates and the log changes in the observed inputs, we obtain the TFP shocks $dlogZ_{njt}$ as residuals. We use the estimate of ξ_j in two places, as we need it to construct the $dlog\left[\left(K_{njt}^{\alpha_j}L_{njt}^{1-\alpha_j}\right)^{\eta_j}X_{njt}^{1-\eta_j}\right]$ term:

$$dlog\left[\left(K_{njt}^{\alpha_j}L_{njt}^{1-\alpha_j}\right)^{\eta_j}X_{njt}^{1-\eta_j}\right] \quad = \quad dlog\left(M_{njt}^{\alpha_j\eta_j}N_{njt}^{(1-\alpha_j)\eta_j}H_{njt}^{(1-\alpha_j)\eta_j+\xi_j}X_{njt}^{1-\eta_j}\right),$$

where we substituted for unobserved inputs using (11). Then, the growth rate of GDP can be expressed in terms of observable and estimated values:

$$\begin{aligned} dlogY_{nt} \quad \approx \quad & \sum_{j=1}^{J} w_{njt-1}^{D}\left\{\underbrace{dlogZ_{njt}}_{True\,TFP} + \underbrace{(\gamma_j-1)\left[dlog\left(M_{njt}^{\alpha_j\eta_j}N_{njt}^{(1-\alpha_j)\eta_j}H_{njt}^{(1-\alpha_j)\eta_j+\xi_j}X_{njt}^{1-\eta_j}\right)\right]}_{Scale\,effect}\right. \\ & \left. + \underbrace{(\alpha_j\eta_j dlogM_{njt} + (1-\alpha_j)\eta_j dlogH_{njt} + (1-\alpha_j)\eta_j dlogN_{njt}) + \xi_j dlogH_{njt}}_{Utilization-adjusted\,primary\,inputs}\right\}. \end{aligned} \quad (13)$$

With this expression in hand, we can implement the decomposition of real GDP growth into TFP and input growth (4), and the covariance/correlation decompositions (7)-(8).

2.3 Data

The data requirements for estimating equation (12) is 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).[1] 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 30 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 28 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.

The oil price series is the West Texas Intermediate, obtained from the St. Louis Fed's FRED database. We have also alternatively used the Brent Crude oil price, obtained from the same source. Military expenditure comes from the Stockholm International Peace Research Institute (SIPRI). The exchange rate regime classification along with information on the base country comes

[1] 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 challenging without substantial aggregation.

from Shambaugh (2004), updated in 2015. Finally, base country interest rates are proxied by the Money Market interest rates in these economies, and obtained from the IMF International Financial Statistics.

The extraction of the non-technology shocks and the quantitative analysis below require additional 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.

2.4 Empirical Results

Appendix Table A3 reports the results of estimating equation (12). The returns to scale parameters vary from about 0.7 to 0.9 in durable manufacturing, from 0.3 to 1 in non-durable manufacturing, and from 0.1 to nearly 2 in the quite heterogeneous non-manufacturing sector. Thus, the estimates show departures from constant returns to scale in a number of industries, consistent with existing evidence. The coefficient on hours per worker ($dlogH_{njt}$) is significantly different from zero in two out of three industry groups, indicating that adjusting for unobserved utilization is important in the manufacturing industries.

Having estimated these production function parameters and TFP shocks, we are ready to examine cross-country correlations. We present results for two subsamples: the G7 countries and the full sample. The G7 countries have less variation among them, making patterns easier to detect. In addition, the production function coefficient estimates are most reliable for the G7 sample, and we use them as the baseline coefficients to be applied to all other countries, implying that TFP and inputs in other countries are likely measured with greater error.

Table 1 reports the basic summary statistics for the main variables of interest. The top panel reports the correlations among the G7 countries. The average correlation of real GDP growth among these countries is 0.38. The second line summarizes correlations of the TFP shocks. Those are on average zero, if not negative. By contrast, input growth is positively correlated, with a 0.21-0.22 average. We then correlate the components of $dlogI_{nt}$ in equation (6) separately. The primary inputs and the scale effect term are both positively correlated across countries, with an order of magnitude that is similar to the correlation in the overall $dlogI_{nt}$. Finally, the Solow residual has an average correlation of 0.16-0.18 in this sample of countries. If Solow residual was 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 utilization term U_{nt}, which is the difference between the TFP shock $dlogZ_{nt}$ and the Solow residual, has a correlation that is more than two-thirds of the correlation of the Solow residual. This indicates that the correlation in the Solow residual is in fact driven by unobserved input utilization and scale adjustments. The top panel of Figure 1 depicts the kernel densities of the correlations of real GDP, TFP, and inputs. There is a clear hierarchy, with the real GDP being most correlated, and the

Table 1: Correlations summary statistics

	Mean	Median	25th pctile	75th pctile
	G7 Countries (N. obs. = 21)			
$dlogY_{nt}$	0.380	0.378	0.265	0.533
$dlogZ_{nt}$	-0.024	-0.014	-0.150	0.164
$dlogI_{nt}$	0.210	0.216	0.061	0.371
$Primary\,inputs$	0.245	0.260	0.151	0.343
$Scale\,effect$	0.185	0.158	0.091	0.352
$dlogS_{nt}$	0.155	0.180	0.067	0.305
$dlogU_{nt}$	0.126	0.124	-0.080	0.298
	All countries (N. obs. = 406)			
$dlogY_{nt}$	0.171	0.205	-0.078	0.428
$dlogZ_{nt}$	0.019	0.043	-0.184	0.240
$dlogI_{nt}$	0.091	0.106	-0.130	0.325
$Primary\,inputs$	0.114	0.142	-0.079	0.339
$Scale\,effect$	0.074	0.085	-0.125	0.295
$dlogS_{nt}$	0.057	0.078	-0.150	0.292
$dlogU_{nt}$	0.041	0.064	-0.152	0.247

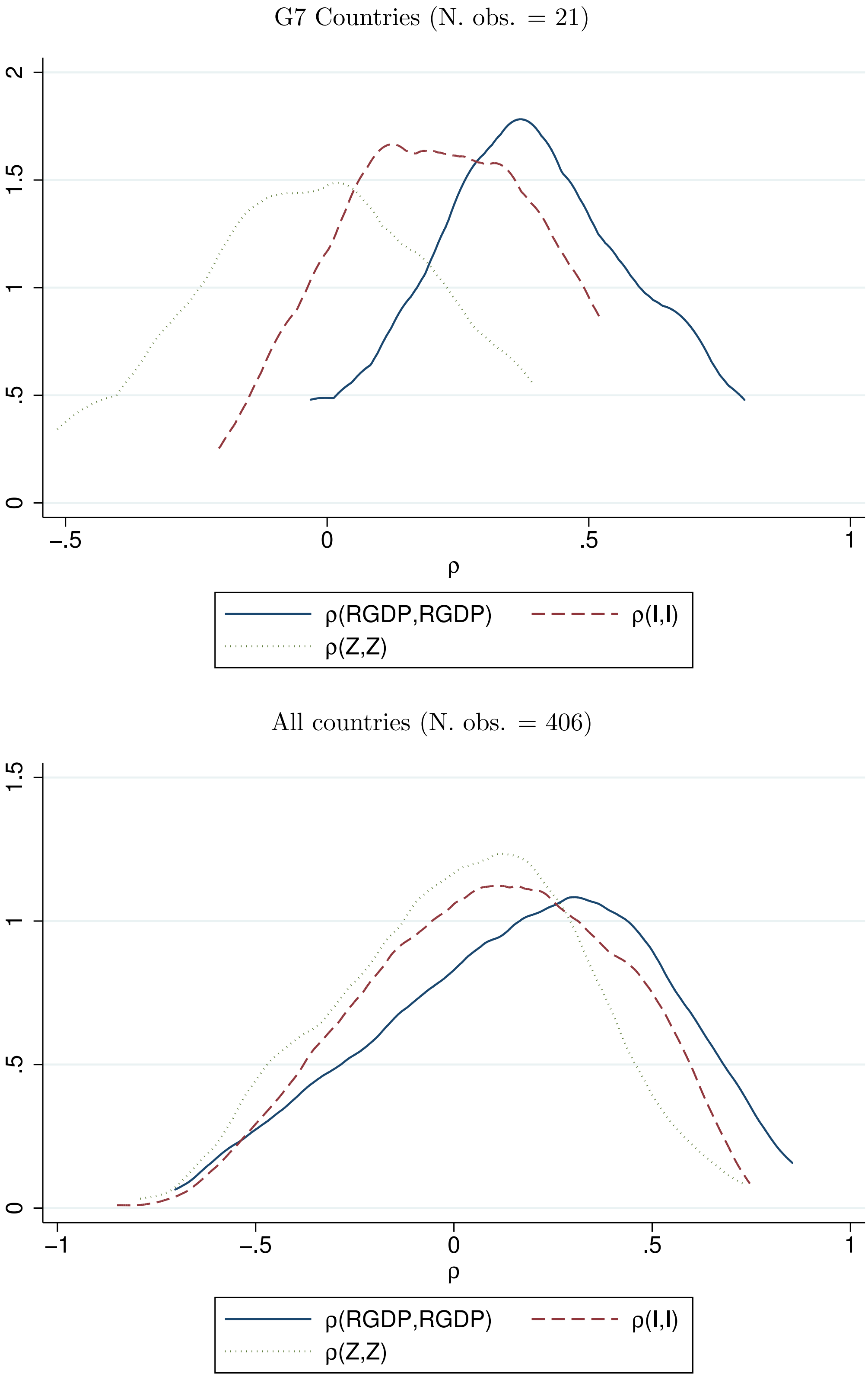
Notes: This table presents the summary statistics of the correlations in the sample of G7 countries (top panel) and full sample (bottom panel). Variable definitions and sources are described in detail in the text.

TFP being least correlated and centered on zero.

The bottom panel of Table 1 repeats the exercise in the full sample of countries. The basic message is the same as for the G7 but quantitatively the picture is not as stark and the variation is greater. It is still the case that $dlogZ_{nt}$ has a very low average correlation, with the mean and median of 0.014 and 0.043, respectively. It is also still the case that the inputs $dlogI_{nt}$ have greater correlation, and that their correlation is on average about half of the average real GDP correlation. The Solow residuals are also more correlated than $dlogZ_{nt}$, and part of the difference is accounted for by the fact that the unobserved inputs are positively correlated. The bottom panel of Figure 1 displays the kernel densities of the correlations in the full sample.

We next implement a covariance decomposition as in (7). We would like to see what share of the covariance in real GDP is due to TFP, input, and TFP-input covariances. One problem with this exercise is that covariances are quite low (most of them are below 0.01), and thus a covariance so close to zero in the denominator produces shares that can be very far away from 1. These

Figure 1: 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 (top panel) and full sample (bottom panel). Variable definitions and sources are described in detail in the text.

Table 2: Covariance Decompositions, $\rho > 0.2$

	Mean	Median	25th pctile	75th pctile
	G7 Countries (N. obs. = 18)			
Share of $Cov(dlogY_{nt}, dlogY_{n\prime t})$				
$Cov(dlogZ_{nt}, dlogZ_{n\prime t})$	-0.215	0.006	-0.466	0.322
$Cov(dlogI_{nt}, dlogI_{n\prime t})$	0.616	0.675	0.249	1.208
$Cov(dlogZ_{nt}, dlogI_{n\prime t})+Cov(dlogI_{nt}, dlogZ_{n\prime t})$	0.599	0.496	-0.049	0.792
	All countries (N. obs. = 203)			
Share of $Cov(dlogY_{nt}, dlogY_{n\prime t})$				
$Cov(dlogZ_{nt}, dlogZ_{n\prime t})$	0.166	0.293	-0.512	1.154
$Cov(dlogI_{nt}, dlogI_{n\prime t})$	0.481	0.574	-0.192	1.407
$Cov(dlogZ_{nt}, dlogI_{n\prime t})+Cov(dlogI_{nt}, dlogZ_{n\prime t})$	0.353	0.203	-1.240	1.410

Notes: This table presents summary statistics for the covariance decomposition in equation (7) in the sample of G7 countries (top panel) and full sample (bottom panel). Variable definitions and sources are described in detail in the text.

outliers are large enough to affect the means. To reduce the impact of dividing by near-zero on the reported shares, we restrict the sample to country pairs with correlation coefficients above the median. Table 2 reports the results. In the G7, the share of GDP covariance accounted for by the covariance of TFP shocks $Cov(dlogZ_{nt}, dlogZ_{n\prime t})$ is zero if not negative on average (the mean is -0.215, but it is clearly affected by an outlier as the median is zero). By contrast, the covariance of inputs accounts for about two-thirds of the observed GDP covariance on average. In the full sample, the contribution of $Cov(dlogZ_{nt}, dlogZ_{n\prime t})$ is clearly larger at about 0.20-0.27 on average. Nonetheless, input covariance contributes about twice as much, about 0.55.

To summarize, real GDP growth is significantly positively correlated in our sample of countries, especially in the G7. TFP growth adjusted for utilization has an order of magnitude lower average correlation than GDP growth. Indeed, average TFP correlation is essentially zero. By contrast, correlations in input growth have the same order of magnitude as real GDP correlations. Covariance decompositions indicate that the contribution of covariance in input growth to covariance in real GDP growth is far larger than the contribution of TFP growth. Finally, using Solow residuals as a proxy for TFP growth can be quite misleading. In our sample of countries, it would lead us to conclude that productivity growth is strongly positively correlated across countries, whereas in fact correlation in the Solow residuals appear to be driven mostly by correlation in the unobserved inputs.

This is of course only an accounting decomposition. Input usage will respond to TFP shocks at home and abroad. Since the growth in inputs has not been cleaned of the impact of technology shocks, it cannot be thought of as driven exclusively by non-technology shocks. At the next step, we combine the data above with information on global input-output linkages and a model of world production and trade to extract non-technology shocks in each country and sector. We will then assess the correlation of non-technology shocks across countries as we did for TFP shocks. Finally, extracting both kinds of shocks allows us to perform counterfactuals to determine which of these shocks are responsible for cross-country comovement.

3 Quantitative Framework

Preliminaries Let there be J sectors indexed by j and i, and N countries indexed by n, m, and k. Time is indexed by t. Each country n is populated by $\overline{L}_n$ households. Each household consumes the final consumption good available in country n and supplies labor and capital to firms. Trade is subject to iceberg costs τ_{mnj} to ship good j from country m to country n (throughout, we adopt the convention that the first subscript denotes source, and the second destination).

Households Household utility is given by:

$$u\left(c_{nt}, \{l_{njt}\}_{j=1}^{J}\right) = \sum_t \beta^t \nu \left(c_{n,t} - \sum_j \frac{\psi_{njt}^0}{\bar{\psi}} \left(\frac{l_{njt}}{\psi_{njt}^0} \right)^{\bar{\psi}} \right),$$

where c_{nt} is per-capita consumption, l_{njt} the utilization-adjusted per-capita labor supply to sector j, and the function ν is increasing and concave.

Households rent capital to firms. Let k_{njt} denote the utilization-adjusted per-capita capital supply to sector j. The household earns r_{njt} per unit of capital rented to sector j. To supply k_{njt} units to sector j, the household incurs a utilization cost of $\frac{\varphi_{njt}^0}{\bar{\varphi}} \left(\frac{k_{njt}}{\varphi_{njt}^0} \right)^{\bar{\varphi}}$ denominated in units of consumption.

Both labor and capital supply are upward-sloping. We capture this with GHH preferences in case of labor (Greenwood, Hercowitz, and Huffman, 1988), and with a similar isoelastic formulation of the utilization cost of capital (e.g. Christiano, Motto, and Rostagno, 2014). Importantly, capital and labor are supplied to individual sectors, and these factor supplies are subject to sector-specific shocks. We will treat the labor and capital supply shocks ψ_{njt}^0 and φ_{njt}^0 as time-varying and back them out from the data. These can have either a literal interpretation as exogenous shifts in factor supply curves, or more broadly as business cycle shocks that are unrelated to contemporaneous productivity, such as news shocks (e.g. Beaudry and Portier, 2006), or sentiment shocks (e.g. Angeletos and La'O, 2013).

Final consumption is the Cobb-Douglas aggregate across sectors:

$$c_{nt} = \prod_j c_{njt}^{\omega_{jn}},$$

where c_{njt} is the consumption of sector j in country n. The associated final consumption price index is:

$$P_{nt} = \prod_j \left(\frac{P^c_{njt}}{\omega_{jn}}\right)^{\omega_{jn}},$$

where P^c_{njt} is the consumption price index in sector j and country n. Within each sector, aggregation across source countries is Armington:

$$c_{njt} = \left[\sum_m \vartheta_{mnj}^{\frac{1}{\rho}} c_{mnjt}^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}},$$

where c_{mnjt} is consumption in n of sector j goods coming from country m. Thus, the consumption price index in sector j, country n is:

$$P^c_{njt} = \left[\sum_m \vartheta_{mnj} {P^c_{mnjt}}^{1-\rho}\right]^{\frac{1}{1-\rho}},$$

where P^c_{mnjt} is the price of c_{mnjt}. Denote by the capital letters $C_{njt} = c_{njt}\overline{L}_n$ and $C_{mnjt} = c_{mnjt}\overline{L}_n$ the aggregate consumption values.

Household optimization yields the following labor and capital supply curves:

$$L_{njt} = \psi^0_{njt} \left(\frac{w_{njt}}{P_{nt}}\right)^{\frac{1}{\overline{\psi}-1}} \overline{L}_n \ \forall j \tag{14}$$

$$K_{njt} = \varphi^0_{njt} \left(\frac{r_{njt}}{P_{nt}}\right)^{\frac{1}{\overline{\varphi}-1}} \overline{L}_n \ \forall j. \tag{15}$$

In this formulation, labor and capital are neither fixed to each sector nor fully flexible. As $\overline{\psi} \to 1$, labor supply across sectors becomes more sensitive to wage differentials, in the limit households supplying labor only to the sector offering the highest wage. At the opposite extreme, as $\overline{\psi} \to \infty$, labor supply is fixed in each sector by the preference parameters ψ^0_{njt}.

Firms Gross output in sector j country n is given by (1). Intermediate input usage X_{njt} is an aggregate of inputs from potentially all countries and sectors:

$$X_{njt} \equiv \left(\sum_{m,i} \mu_{mi,nj}^{\frac{1}{\varepsilon}} X_{mi,njt}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}.$$

where $X_{mi,njt}$ is the usage of inputs coming from sector i in country m in production of sector j in country n, and $\mu_{mi,nj}$ is the input coefficient.

Let P_{njt} denote the price of output produced by sector j in country n (note this is not the same as the ideal price index P^c_{njt} of sector j final consumption in n, which aggregates imports from the other countries). We make the assumption that the price is proportional to the unit cost function:

$$P_{njt} \propto Z_{njt}^{-\frac{1}{\gamma_j}} Y_{njt}^{\frac{1-\gamma_j}{\gamma_j}} \left(\frac{r_{njt}}{\alpha_j \eta_j}\right)^{\alpha_j \eta_j} \left(\frac{w_{njt}}{(1-\alpha_j)\eta_j}\right)^{(1-\alpha_j)\eta_j} \left(\frac{\sum_{m,i} \mu_{mi,nj} p_{mi,njt}^{1-\varepsilon}}{1-\eta_j}\right)^{\frac{1-\eta_j}{1-\varepsilon}},$$

where $p_{mi,njt}$ is the price paid in sector n, j for inputs from m, i. This would be the case, for instance, if firms priced at marginal cost or at a constant markup.

The Armington final consumption aggregation technology and international trade technology are competitive, and thus the prices "at the factory gate" and the price at the time of consumption or intermediate usage are related by:

$$p_{mi,njt} = P^c_{mnit} = \tau_{mni} P_{mit},$$

and therefore the final consumption price index in sector j country n is:

$$P^c_{njt} = \left[\sum_m \vartheta_{mnj} \left(\tau_{mnj} P_{mjt}\right)^{1-\rho}\right]^{\frac{1}{1-\rho}}.$$

We adopt the assumption that the primary factors and inputs receive compensation proportional to their share in total input spending. This would be true when firms are competitive, or when profits are shared among the factors and inputs in proportion to their cost share (BFK, Hsieh and Klenow, 2009). This implies:

$$\begin{aligned} r_{njt} K_{njt} &= \alpha_j \eta_j P_{njt} Y_{njt} \\ w_{njt} L_{njt} &= (1-\alpha_j)\eta_j P_{njt} Y_{njt} \\ p_{mi,njt} X_{mi,njt} &= \pi^x_{mi,njt} (1-\eta_j) P_{njt} Y_{njt}, \end{aligned} \tag{16}$$

where $\pi^x_{mi,njt}$ is the share of intermediates from country m sector i in total intermediate spending by n, j, given by:

$$\pi^x_{mi,njt} = \frac{\mu_{mi,nj} \left(\tau_{mni} P_{mit}\right)^{1-\varepsilon}}{\sum_{k,l} \mu_{kl,nj} \left(\tau_{knl} P_{klt}\right)^{1-\varepsilon}}.$$

Equilibrium An intra-temporal equilibrium at time t in this economy is a set of goods and factor prices $\{P_{njt}, w_{njt}, r_{njt}\}_{n=1,\ldots,N}^{j=1,\ldots,J}$, factor allocations $\{L_{njt}, K_{njt}\}_{n=1,\ldots,N}^{j=1,\ldots,J}$, and goods allocations $\{Y_{njt}\}_{n=1,\ldots,N}^{j=1,\ldots,J}$, $\{C_{mnjt}\}_{n,m=1,\ldots,N}^{j=1,\ldots,J}$, and $\{X_{mi,njt}\}_{n,m=1,\ldots,N}^{i,j=1,\ldots,J}$ such that (i) households maximize utility; (ii) firms maximize profits; and (iii) all markets clear.

Total expenditure on exports from n to m in sector j is the sum of final consumption expenditure and expenditure on intermediates by all sectors i in m:

$$EX_{nmjt} \quad = \quad \pi^c_{nmjt}\omega_{jm}P_{mt}C_{mt} + \sum_i \pi^x_{nj,mit}\left(1-\eta_j\right)P_{mit}Y_{mit},$$

where $\pi^c_{nmjt} \equiv \frac{\vartheta_{nmj}(\tau_{nmj}P_{njt})^{1-\rho}}{\left(P^c_{mjt}\right)^{1-\rho}}$ is the share of country n in the total final consumption expenditure of sector j, country m, and thus $\pi^c_{nmjt}\omega_{jm}P_{mt}C_{mt}$ is the total final consumption expenditure in m on j sector goods from n, and $\sum_i \pi^x_{nj,mit}\left(1-\eta_j\right)P_{mit}Y_{mit}$ is the intermediate spending. Then, total spending on output produced by country n, sector j is:

$$\Upsilon_{njt} \quad = \quad \sum_m \left[\pi^c_{nmjt}\omega_{jm}P_{mt}C_{mt} + \sum_i \pi^x_{nj,mit}\left(1-\eta_j\right)\Upsilon_{mit}\right],$$

where we defined $\Upsilon_{njt} \equiv P_{njt}Y_{njt}$ as the total revenue in sector j, country m, which will be expositionally convenient.

Factor market clearing ensures labor supply equals labor demand:

$$w_{njt}\psi^0_{njt}\left(\frac{w_{njt}}{P_{nt}}\right)^{\frac{1}{\overline{\psi}-1}}\overline{L}_n \quad = \quad (1-\alpha_j)\eta_j\Upsilon_{njt} \tag{17}$$

$$r_{njt}\varphi^0_{njt}\left(\frac{r_{njt}}{P_{nt}}\right)^{\frac{1}{\overline{\varphi}-1}}\overline{L}_n \quad = \quad \alpha_j\eta_j\Upsilon_{njt}. \tag{18}$$

Finally, total primary factor income in country n must equal total final consumption expenditure. Allow for a trade imbalance D_{nt}. Then:

$$P_{nt}C_{nt} \quad = \quad \left(\sum_j w_{njt}l_{njt} + \sum_j r_{njt}k_{njt}\right)\overline{L}_n + D_{nt}.$$

3.1 Extracting Non-Technology Shocks

We have data on gross revenue Υ_{njt} and its deflators P_{njt}, and thus we have estimates of real output Y_{njt} (indeed, we use those data to estimate TFP). Denote by a "$\widehat{\ }$" the gross change in a variable: $\widehat{x}_{t+1} \equiv x_{t+1}/x_t$. Then we can write the growth in real output as:

$$\widehat{Y}_{njt+1} \quad = \quad \widehat{Z}_{njt+1}\left(\left(\widehat{K}^{\alpha_j}_{njt}\widehat{L}^{1-\alpha_j}_{njt}\right)^{\eta_j}\widehat{X}^{1-\eta_j}_{njt+1}\right)^{\gamma_j}.$$

Plugging the gross proportional change versions of (14)-(15) and (17)-(18), we obtain the following expression:

$$\widehat{Y}_{njt+1} = \widehat{Z}_{njt+1}\left(\left(\left(\widehat{Y}_{njt+1}\frac{\widehat{P}_{njt+1}}{\widehat{P}_{nt+1}}\right)^{\frac{1-\alpha_j}{\overline{\psi}}+\frac{\alpha_j}{\overline{\varphi}}}\widehat{\Psi}_{njt+1}\right)^{\eta_j}\widehat{X}_{njt+1}^{1-\eta_j}\right)^{\gamma_j}, \tag{19}$$

where $\widehat{\Psi}_{njt+1} \equiv \left(\widehat{\varphi}^0_{njt+1}\right)^{\alpha_j\frac{\overline{\varphi}-1}{\overline{\varphi}}}\left(\widehat{\psi}^0_{njt+1}\right)^{(1-\alpha_j)\frac{\overline{\psi}-1}{\overline{\psi}}}$ is the composite factor supply shock.

The KLEMS and WIOD data have information on all the elements of equation (19) required to back out the composite factor supply shock $\widehat{\Psi}_{njt+1}$ except for the consumption price index $\widehat{P}_{n,t+1}$. That is, we know real output growth $\widehat{Y}_{njt+1}$, real input growth $\widehat{X}_{njt+1}$, TFP growth $\widehat{Z}_{njt+1}$, as well as the changes in the price indices $\widehat{P}_{njt+1}$. If we knew $\widehat{P}_{nt+1}$, we could back out $\widehat{\Psi}_{njt+1}$.

We rely on the model structure and the observed final expenditure shares to compute the model-implied $\widehat{P}_{nt+1}$. Standard steps yield the following expressions for the changes in price indices:

$$\widehat{P}_{nt+1} = \prod_j\left(\widehat{P}^c_{njt+1}\right)^{\omega_{jn}} \tag{20}$$

$$\widehat{P}^c_{njt+1} = \left[\sum_m \widehat{P}^{1-\rho}_{mjt+1}\pi^c_{mnjt}\right]^{\frac{1}{1-\rho}}. \tag{21}$$

Since we know the gross output price indices for each country and sector $\widehat{P}_{mjt+1}$, and the final consumption shares of each source country in each destination and sector π^c_{mnjt} and ω_{jn}, we can simply construct $\widehat{P}_{nt+1}$ directly.

3.2 Counterfactuals

Having recovered both technology and non-technology shocks in each sector and country, we would like to simulate output growth rates in the counterfactuals in which one of these shocks is turned off. In response to counterfactual shocks, the price in sector j, country n experiences the change:

$$\begin{aligned}\widehat{P}_{njt+1} = {} & \widehat{Z}^{-1}_{njt+1}\widehat{\Upsilon}^{1-\gamma_j}_{njt+1}\Bigg[\left(\widehat{\Upsilon}_{njt+1}^{\alpha_j\frac{\overline{\varphi}-1}{\overline{\varphi}}+(1-\alpha_j)\frac{\overline{\psi}-1}{\overline{\psi}}}\widehat{P}_{nt+1}^{\frac{\alpha_j}{\overline{\varphi}}+\frac{1-\alpha_j}{\overline{\psi}}}\widehat{\Psi}^{-1}_{njt+1}\right)^{\eta_j} \\ & \left(\sum_{m,i}\widehat{P}^{1-\varepsilon}_{mit+1}\pi^x_{mi,njt}\right)^{\frac{1-\eta_j}{1-\varepsilon}}\Bigg]^{\gamma_j}.\end{aligned} \tag{22}$$

This, together with the dependence of $\widehat{P}_{nt+1}$ on the constituent $\widehat{P}_{njt+1}$'s stated in (20)-(21) defines a system of $J \times N$ equations in prices, conditional on known initial-period data quantities (such as

π^c_{mnjt}) and a vector of $\widehat{\Upsilon}_{njt+1}$'s. The price changes in turn determine next period's shares:

$$\pi^c_{nmjt+1} = \frac{\widehat{P}^{1-\rho}_{njt+1}\pi^c_{nmjt}}{\sum_k \widehat{P}^{1-\rho}_{kjt+1}\pi^c_{kmjt}}, \tag{23}$$

$$\pi^x_{nj,mit+1} = \frac{\widehat{P}^{1-\varepsilon}_{njt}\pi^x_{nj,mit}}{\sum_{k,l} \widehat{P}^{1-\varepsilon}_{klt}\pi^x_{kl,mit}}. \tag{24}$$

These trade shares have to be consistent with market clearing at the counterfactual $t+1$, expressed using proportional changes as:

$$\begin{aligned}\widehat{\Upsilon}_{njt+1}\Upsilon_{njt} &= \sum_m \left[\pi^c_{nmjt+1}\omega_{jm}\left(\sum_i \eta_j \widehat{\Upsilon}_{mit+1}\Upsilon_{mit} + \widehat{D}_{mt+1}D_{mt}\right)\right. \\ &\left. + \sum_i \pi^x_{nj,mit+1}\left(1-\eta_j\right)\widehat{\Upsilon}_{mit+1}\Upsilon_{mit}\right].\end{aligned} \tag{25}$$

The sets of equations (22)-(25) represent a system of $2\times N\times J + N^2\times J + N^2\times J^2$ unknowns, $\widehat{P}_{njt+1}$ $\forall n,j$, $\widehat{\Upsilon}_{njt+1}$ $\forall n,j$, π^c_{nmjt+1} $\forall n,m,j$, and $\pi^x_{nj,mit+1}$ $\forall n,j,m,i$ that is solved under given parameter values and under a set of shocks $\widehat{Z}_{njt+1}$ and $\widehat{\Psi}_{njt+1}$.

3.3 Estimating Model Elasticities

Our framework offers a straightforward approach to estimating ρ and ε. To introduce an error term in the estimating equations, assume that iceberg trade costs, final consumer taste shocks, and input share shocks have a stochastic element, and denote their gross proportional changes by $\widehat{\tau}_{mnjt+1}$, $\widehat{\vartheta}_{mnjt+1}$, and $\widehat{\mu}_{mj,ni,t+1}$, respectively. Straightforward manipulation of CES consumption shares yields the following relationships between shares and prices:

$$log\left(\frac{\widehat{\pi}^c_{mnj,t+1}}{\widehat{\pi}^c_{m'nj,t+1}}\right) = (1-\rho)\,log\left(\frac{\widehat{P}_{mj,t+1}}{\widehat{P}_{m'j,t+1}}\right) + log\left(\frac{\widehat{\vartheta}_{mnjt+1}\widehat{\tau}^{1-\rho}_{mnjt+1}}{\widehat{\vartheta}_{m'njt+1}\widehat{\tau}^{1-\rho}_{m'njt+1}}\right) \tag{26}$$

and

$$log\left(\frac{\widehat{\pi}^x_{mj,nit+1}}{\widehat{\pi}^x_{m'j,nit+1}}\right) = (1-\varepsilon)log\left(\frac{\widehat{P}_{mjt+1}}{\widehat{P}_{m'jt+1}}\right) + log\left(\frac{\widehat{\mu}_{mj,ni,t+1}\widehat{\tau}^{1-\varepsilon}_{mnjt+1}}{\widehat{\mu}_{m'j,ni,t+1}\widehat{\tau}^{1-\varepsilon}_{m'njt+1}}\right). \tag{27}$$

We express the final consumption share change $\widehat{\pi}^c_{mnj,t+1}$ relative to the final consumption share change in a reference country m'. This reference country is chosen separately for each importing country-sector n,j as the country with the largest average expenditure share in that country-sector. (Thus, strictly speaking, the identity of the reference country m' is distinct for each importing country-sector, but we suppress the dependence of m' on n,j to streamline notation.) Furthermore, we drop the own expenditure shares $\widehat{\pi}^c_{nnj,t+1}$ from the estimation sample, as those are computed as residuals in WIOD, whereas final import shares from other countries are taken directly from the international trade data. Dropping the own expenditure shares has the added benefit of making the regressions less endogenous, as the domestic taste shocks are much more likely to affect domestic prices.

We use two estimation approaches for (26)-(27). We first show the results with OLS. To absorb as much of the error term as possible, we include source-destination-reference country-time ($n \times m \times m' \times t$) fixed effects. These absorb any common components occurring at the country 3-tuple-time level, such as exchange rate changes and other taste and transport cost changes, and thus the coefficient is estimated from the variation in the relative sectoral price indices and relative sectoral share movements within that cell. The identifying assumption is then that price change ratio $\widehat{P}_{mj,t+1}/\widehat{P}_{m'j,t+1}$ is uncorrelated with the residual net of the $n \times m \times m' \times t$ fixed effects. The remaining errors would be largely measurement error. If this measurement error is uncorrelated with the price change ratios, then the OLS estimates are unbiased, and if not, we would expect a bias towards zero. In the latter case, the IV estimates (described below) should be larger than the OLS estimates, assuming the measurement error in (26) and (27) is independent of the measurement error in the technology shock ratios.

The estimation amounts to regressing relative share changes on relative price changes. A threat to identification would be that relative price changes are affected by demand shocks (e.g. $\widehat{\vartheta}_{mnjt+1}$), and thus correlated with the residual. As a way to mitigate this concern, we also report estimates based on the subsample in which destination countries are all non-G7, and the source and reference countries are all G7 countries. In this sample it is less likely that taste shocks in the (smaller) destination countries will affect relative price changes in the larger G7 source countries. Finally, to reduce the impact of small shares on the estimates, we report results weighting by the size of the initial shares ($\pi^c_{mnj,t}$ and $\pi^x_{mj,ni,t}$).

We also implement IV estimation. We use the TFP shocks $\widehat{Z}_{mjt+1}/\widehat{Z}_{m'jt+1}$ as instruments for changes in relative prices. The exclusion restriction is that the technology shocks are uncorrelated with taste and trade cost shocks, and thus only affect the share ratios through changing the prices. Even if the shock ratio $\widehat{Z}_{mjt+1}/\widehat{Z}_{m'jt+1}$ is a valid instrument for observed prices, it does not include the general-equilibrium effects on prices in the model. To use all of the information –both the direct and indirect GE effects –incorporated in the model, we also use the model-optimal IV approach to construct the instrument. In our context this simply involves computing the model using only the estimated technology shocks, and solving for the sequence of equilibrium prices in all countries and sectors. The model-implied prices are then the optimal instrument for the prices observed in the data. See Chamberlain (1987) for a discussion of optimal instruments, and Adao, Arkolakis, and Esposito (2017) and Bartelme et al. (2017) for two recent applications of this approach. The results from the model-optimal IV are very similar to simply instrumenting with the TFP shock ratio, and we do not report them to conserve space.

Table 3: Elasticity Estimates

	(1) OLS	(2) OLS (G7 m, m', non-G7 n)	(3) OLS (weighted)	(4) IV	(5) IV (G7 m, m', non-G7 n)	(6) IV (weighted)
ρ	0.775	0.730	1.051	2.881	2.273	3.037
SE	(0.055)	(0.146)	(0.082)	(0.584)	(0.966)	(0.470)
First stage K-P F				92.117	30.539	89.669
FE	Yes	Yes	Yes	Yes	Yes	Yes
ε	0.698	0.686	0.682	2.838	0.382	1.322
SE	(0.051)	(0.120)	(0.143)	(0.578)	(0.872)	(0.856)
First stage K-P F				94.863	16.188	86.631
FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the destination-source-reference country level in parentheses. This table presents results from the OLS and IV estimation of 26 and 27. The fixed effects used in each regression are $n \times m \times m' \times t$. The instruments are the relative productivity shocks $\widehat{Z}_{mjt+1}/\widehat{Z}_{m'jt+1}$, with the Kleibergen-Papp first stage F-statistic reported. The weights in columns 3 and 6 are lagged share ratios $\pi^{c}_{mnj,t}$ and $\pi^{x}_{mj,ni,t}$.

Table 3 presents the results. Columns 1-3 report the OLS estimates of ρ (top panel) and ε (bottom panel). The OLS estimates of ρ are all significantly larger than zero, and we cannot rule out a Cobb-Douglas final demand elasticity. The OLS estimates for ρ are also not very sensitive to restricting the sample to non-G7 destinations and G7 sources, or to weighting by the initial share. The IV estimates in columns 4-6 are substantially larger than the OLS coefficients, ranging from 2.27 to 3.04, and significantly different from 1 in most cases. This difference between OLS and IV could suggest either measurement error in (26), or greater noise in the IV estimator (Young, 2017). Given the substantial disagreement between OLS and IV estimates of ρ, we report the results under two values, $\rho = 1$, corresponding to the OLS estimates, and $\rho = 2.75$ based on the IV.

The OLS and IV estimates of ε display somewhat greater consensus. The OLS point estimates are in the range 0.68, and not sensitive to the sample restriction or weighting. The IV estimates are less stable. While the full sample (column 4) yields an elasticity of 2.8, either restricting to the non-G7 destinations/G7 sources, or weighting by size reduces the coefficient dramatically and renders it not statistically different from 1. Such evidence for the low substitutability of intermediate inputs is consistent with the recent estimates by Atalay (2017) and Boehm, Flaaen, and Pandalai-Nayar (2017), who find even stronger complementarity. We therefore set $\varepsilon = 1$ for all implementations of the model.

Table 4: Parameter values

Param.	Value	Source	Related to
ρ	2.75 or 1	Our estimates	final substitution elasticity
ε	1	Our estimates	intermediate substitution elasticity
$\overline{\psi}$	3	Chetty et al. (2013)	Frisch elasticity
$\overline{\varphi}$	3		capital supply elasticity
α_j, β_j		KLEMS	labor and capital shares
γ_j		own estimates	returns to scale
π^c_{mnjt}		WIOD	final use trade shares
π^x_{mnjt}		WIOD	intermediate use trade shares

3.4 Calibration

In implementing this model, we must take a stand on the value of a small number of parameters, and use our data to provide the required quantities. Table 4 summarizes the assumptions and data sources. The final consumption Armington elasticity ρ is set to either 2.75 or 1 from our estimation procedure. The labor supply parameter $\overline{\psi}$ is set to 3, implying the Frisch labor supply elasticity of 0.5 as advocated by Chetty et al. (2013). We have less guidance to set the capital supply parameter, so we set it to 3 as well, implying a similarly inelastic capital supply. Note that our non-technology shock takes the form $\widehat{\Psi}_{njt+1} \equiv \left(\widehat{\varphi}^0_{njt+1}\right)^{\alpha_j \frac{\overline{\varphi}-1}{\overline{\varphi}}} \left(\widehat{\psi}^0_{njt+1}\right)^{(1-\alpha_j)\frac{\overline{\psi}-1}{\overline{\psi}}}$ and is thus already expressed as the primitive shock exponentiated by functions of $\overline{\psi}$ and $\overline{\varphi}$. Nonetheless, we do require these parameters, as they appear separately from $\widehat{\Psi}_{njt+1}$ in (19) and (22). All other parameters have close counterparts in basic data and thus we compute them directly. Capital shares in total output α_j come from KLEMS, and are averaged in each sector across countries and time. The scale parameters γ_j come from our own production function estimates reported in Appendix Table A3. Input shares π^x_{nmjt} and final consumption shares $\pi^c_{mnj,t}$ come from WIOD. Appendix B.1 outlines our algorithm for solving the model and constructing counterfactuals.

3.5 Patterns in Non-Technology Shocks Across Countries

Unlike the decomposition of GDP growth into TFP and inputs in (4), there is no decomposition that isolates the non-technology shocks $\widehat{\Psi}_{njt+1}$ as an additive component in the GDP growth rate. Nonetheless, to provide a simple illustration of the correlations of $\widehat{\Psi}_{njt+1}$ across countries, we construct a Domar-weighted non-technology shock, to parallel the Domar-weighted TFP shock in (5):

$$dlog\Psi_{nt} = \sum_{j=1}^{J} w^D_{njt-1} dlog\Psi_{njt}. \tag{28}$$

Table 5 reports the correlations in $dlog\Psi_{nt}$ among the G7 and in the full sample. We report those correlations under both values of ρ that we consider, 2.75 and 1. The non-technology shocks are positively correlated across countries, unlike TFP. The correlation be non-technology shocks is around 0.170-0.210 on average in the G7 countries, which is well short of the observed GDP correlation, but substantially higher than the average TFP correlation in this set of countries, which is essentially zero. In the full sample, aggregated non-technology shocks have about a 0.08 correlation on average, noticeably higher than TFP correlation. This suggests that non-technology shocks have a better chance of producing positive output correlations observed in the data. The average correlations in $dlog\Psi_{nt}$ are very insensitive to the value of ρ, with the average correlations under the alternative ρ's coinciding to the third digit.

Table 5: Correlations in $dlog\Psi_{nt}$ summary statistics

	Mean	Median	25th pctile	75th pctile
	G7 Countries (N. obs. = 21)			
$\rho = 2.75$	0.170	0.210	0.064	0.272
$\rho = 1$	0.170	0.211	0.063	0.277
	All countries (N. obs. = 406)			
$\rho = 2.75$	0.076	0.086	-0.099	0.291
$\rho = 1$	0.076	0.085	-0.101	0.295

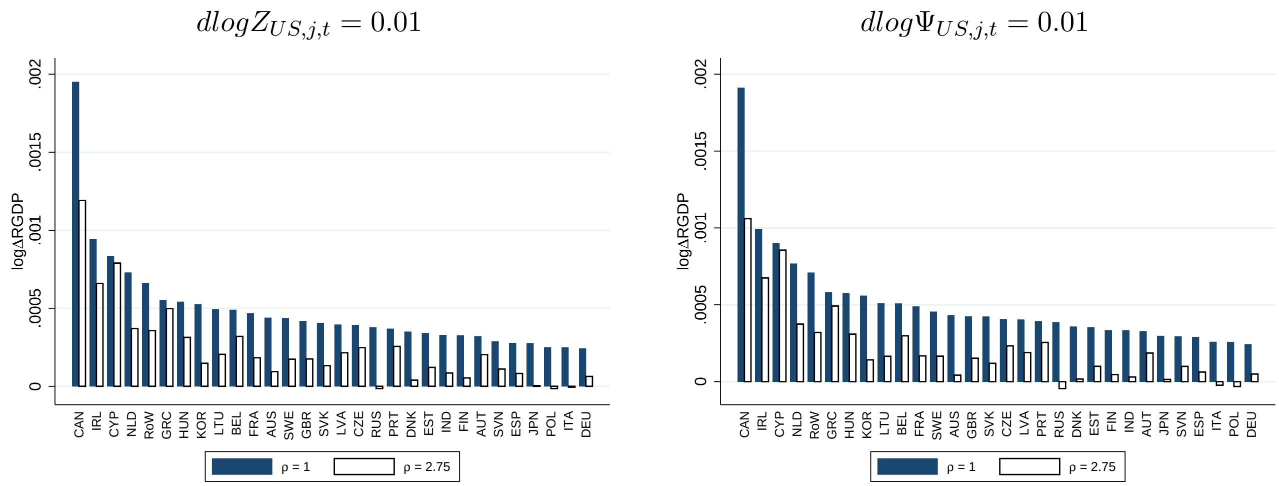
Notes: This table presents the summary statistics of the correlations of $dlog\Psi_{nt}$ defined in (28) in the sample of G7 countries (top panel) and full sample (bottom panel). Variable definitions and sources are described in detail in the text.

3.6 Impulse Responses

Analytical results or intuition about the transmission of shocks in our framework are complicated by the large country and sector dimension of the model. Prior to simulating the model with the observed shocks, we therefore first simulate a hypothetical 1% shock – technology and non-technology. Figure 2 displays the change in real GDP in every other country in the world following a 1% U.S. shock in each sector. The white bars depict the GDP responses under $\rho = 2.75$, while the dark bars depict the response under $\rho = 1$.

The results show that the observed trade linkages do result in transmission of both shocks. Smaller economies with large trade linkages to the U.S., such as Canada, are the most strongly affected by the U.S. shocks. Both the technology and non-technology shocks lead to transmission of a similar magnitude. Under the low elasticity, the mean response of foreign GDP is 0.05%, and

Figure 2: Impulse Responses to US 1% Shocks



Notes: This figure displays the change in log real GDP of every other country in the sample when the United States experiences a productivity shock (left panel) or a non-technology shock (right panel) of 0.01 in every sector.

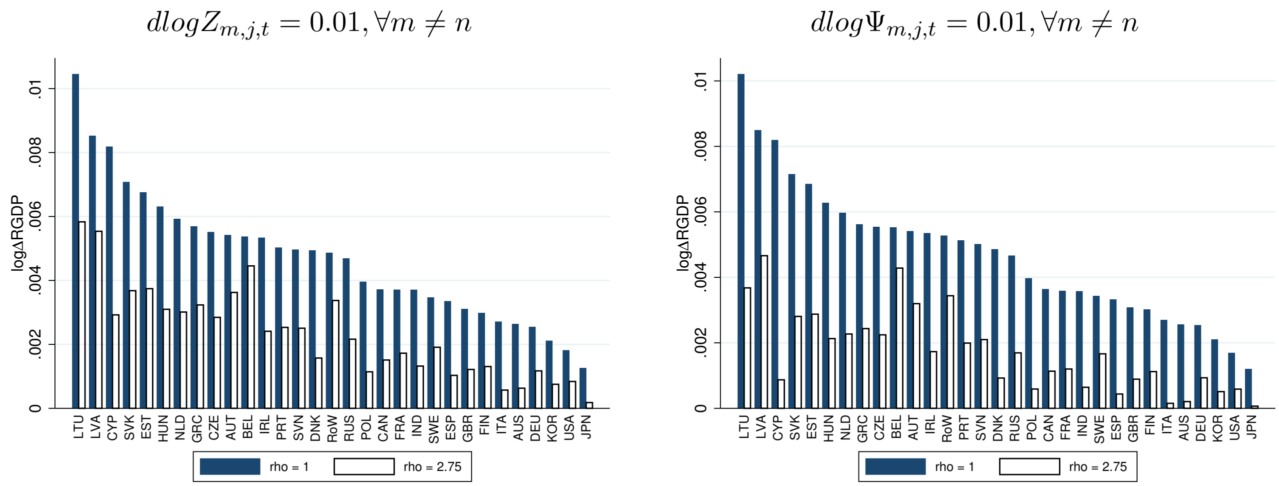
the maximum response – Canada – is about 0.2% for both shocks. On the other hand, the final substitution elasticity matters a great deal for the size of the effects: the response of foreign GDP to the US shocks is about twice as high for $\rho = 1$ than for $\rho = 2.75$. Indeed, under the higher elasticity the positive shock in the US need not raise GDP in every country, though the negative values are negligible.

Next, we simulate the real GDP responses of each country n in the sample when all other countries (excluding n) experience a 1% technology or non-technology shock. The exercise answers the question, if there is a 1% world shock outside of the country, how much of that shock will manifest itself in the country's GDP? Figure 3 displays the results. Again, both non-technology and technology shocks lead to quantitatively similar transmission. In response to a 1% world shock, under the low elasticity of substitution the mean country's GDP increases by 0.5%, with the impact ranging from less than 0.2% in the U.S. and Japan to 0.8-1% in Latvia and Lithuania. Smaller countries are not surprisingly more affected by both the technology and non-technology shocks in their trade partners. The magnitude of transmission is uniformly lower with the higher elasticity. In this case, the mean impact is about 0.2% for both technology and non-technology shocks. All in all, these results suggest that world shocks have a significant impact on most countries.

3.7 Counterfactual Results and Discussion

Tables 6 and 7 report correlations in our model simulated with both technology and non-technology (input) shocks, as well as counterfactual economies featuring only technology or input shocks, under

Figure 3: Impulse Responses to Rest of the World 1% Shocks



Notes: This figure displays the change in log real GDP of every country in the sample when the rest of the world excluding the country experiences a productivity shock (left panel) or a non-technology shock (right panel) of 0.01 in every sector.

$\rho = 2.75$ and $\rho = 1$, respectively. We hold deficits constant at initial (1995) levels.[2] The first two lines report the summary statistics for the real GDP correlations in the data and in the baseline model in which both shocks are as measured in the data. Our model reproduces the average observed data correlations well, for both the G7 and the full sample. The model under $\rho = 1$ generates baseline correlations slightly higher than in the data, whereas the model with $\rho = 2.75$ slightly lower, but in both cases they are close to the data.

Next, we simulate the model under only non-technology and only TFP shocks. It is immediately apparent that the non-technology shocks are responsible for much of the comovement in the model. For the G7 group, the model with only non-technology shocks generates 55-60% of the average correlations implied by the model with both shocks, while the model with only technology shocks generates only 27% of the comovement on average. The results for all countries are even more stark: technology shocks generate 12% of the comovement of the full model on average, while the non-technology shocks generate 60% of the comovement. These relative magnitudes are not sensitive to the two alternative values of ρ.

The lower panels of Tables 6-7 compute all three versions of the model in autarky. On average, the autarky correlations are not lower than the correlations under the observed trade linkages when $\rho = 2.75$. The autarky correlations are modestly lower than the baseline correlations when $\rho = 1$. This difference between the elasticities is consistent with the impulse responses in Figures 2-3, which

[2] Appendix Table A4 reports the fit of the model and counterfactual exercises where deficits are allowed to evolve as in the data.

Table 6: Model Fit and Counterfactuals: Correlations of $dlogY_{nt}$, $\rho = 2.75$

	Mean	Median	25th pctile	75th pctile
Data	0.380	0.378	0.265	0.533
Model	0.312	0.342	0.151	0.538
Non-Technology Shocks Only	0.173	0.156	-0.035	0.403
Technology Shocks Only	0.086	0.049	-0.083	0.317
Autarky: Both Shocks	0.311	0.380	0.167	0.513
Autarky: Non-Technology Shocks Only	0.152	0.111	-0.032	0.370
Autarky: Technology Shocks Only	0.057	0.051	-0.186	0.254
	All countries (N. obs. = 406)			
	Mean	Median	25th pctile	75th pctile
Data	0.171	0.205	-0.078	0.428
Model	0.185	0.232	-0.085	0.508
Non-Technology Shocks Only	0.111	0.139	-0.127	0.346
Technology Shocks Only	0.022	0.033	-0.196	0.224
Autarky: Both Shocks	0.203	0.278	-0.072	0.514
Autarky: Non-Technology Shocks Only	0.126	0.147	-0.110	0.373
Autarky: Technology Shocks Only	0.016	0.034	-0.214	0.252

Notes: This table presents the summary statistics of the correlations of $dlogY_{nt}$ in the sample of G7 countries (top panel) and full sample (bottom panel) under the different assumptions on shocks and trade linkages. Variable definitions and sources are described in detail in the text.

shows that when $\rho = 2.75$ the responses of real GDP to U.S. and world shocks is more muted.

The average correlations reported in Tables 6-7 hide a great deal of heterogeneity and important compositional patterns. To reconcile the results from the counterfactuals with the evidence of positive transmission in the impulse responses, we compare the correlations for each country pair under autarky and trade. Figure 4 reports for each country the number of other countries for which its trade correlation is higher than the autarky correlation (white bars), and the share of world GDP with which the correlation under trade is higher than the autarky correlation (dark bars). Two patterns stand out from these figures. First, trade increases correlation systematically with larger countries. This is evidenced by the fact that the dark bars, displaying the share of world GDP with which correlation increases, are higher in the majority of countries. This is sensible, as larger countries tend to be the more important trading partners. Second, not surprisingly, trade increases correlation relative to autarky to a greater extent when $\rho = 1$ than when $\rho = 2.75$. Under

Table 7: Model Fit and Counterfactuals: Correlations of $dlogY_{nt}$, $\rho = 1$

	Mean	Median	25th pctile	75th pctile
Data	0.380	0.378	0.265	0.533
Model	0.337	0.406	0.179	0.570
Non-Technology Shocks Only	0.206	0.202	-0.031	0.443
Technology Shocks Only	0.091	0.056	-0.131	0.325
Autarky: Both Shocks	0.312	0.379	0.169	0.520
Autarky: Non-Technology Shocks Only	0.153	0.112	-0.034	0.374
Autarky: Technology Shocks Only	0.057	0.051	-0.186	0.254
	All countries (N. obs. = 406)			
	Mean	Median	25th pctile	75th pctile
Data	0.171	0.205	-0.078	0.428
Model	0.218	0.272	-0.069	0.544
Non-Technology Shocks Only	0.127	0.158	-0.108	0.371
Technology Shocks Only	0.027	0.039	-0.194	0.234
Autarky: Both Shocks	0.212	0.291	-0.063	0.524
Autarky: Non-Technology Shocks Only	0.119	0.142	-0.115	0.373
Autarky: Technology Shocks Only	0.016	0.034	-0.214	0.252

Notes: This table presents the summary statistics of the correlations of $dlogY_{nt}$ in the sample of G7 countries (top panel) and full sample (bottom panel) under the different assumptions on shocks and trade linkages. Variable definitions and sources are described in detail in the text.

the low ρ, in 24 out of 29 economies, a greater number of correlations is higher under trade than in autarky. However, even under the high ρ, significant parts of the world economy experience higher correlations under trade compared to autarky. For example, under the high elasticity the U.S. has higher correlations with 70% of the countries and over 80% of world GDP under trade.

All in all, it does appear that observed international trade linkages do result in transmission of shocks in important parts of the world economy, as measured by the difference between trade and autarky correlation. There is enough heterogeneity in the observed trade linkages that unweighted average correlations mask this finding somewhat.

To systematically study whether correlated shocks are the reason for observed comovement, and to assess whether input trade plays a different role from final goods trade in the transmission of shocks, we conduct three additional counterfactuals. In the first, we feed in uncorrelated shocks drawn from a lognormal distribution with the same variance as the true estimated shocks. For this exercise, we simulate the model for 1000 periods to minimize sample correlation in the shocks. We assess comovement with uncorrelated shocks in the model with trade (using 2004 trade linkages) and in autarky. In the second, we assume that all trade is in intermediate inputs, but the country consumes only its own final goods (intermediate input trade only). Finally, we assume that all inputs are sourced domestically, and trade is only in final goods. The results from these exercises are in Tables 8 and 9 for $\rho = 2.75$ and $\rho = 1$, respectively.

Table 8: Additional Counterfactuals: Correlations of $dlogY_{nt}$, $\rho = 2.75$

	Mean	Median	25th pctile	75th pctile
Data	0.380	0.378	0.265	0.533
Model	0.312	0.342	0.151	0.538
Uncorrelated Shocks	0.013	0.020	-0.014	0.037
Autarky: Uncorrelated Shocks	-0.001	-0.003	-0.012	0.010
Input Trade Only	0.326	0.409	0.164	0.566
Final Goods Trade Only	0.302	0.327	0.152	0.523

	All countries (N. obs. = 406)			
	Mean	Median	25th pctile	75th pctile
Data	0.171	0.205	-0.078	0.428
Model	0.185	0.232	-0.085	0.508
Uncorrelated Shocks	0.002	0.001	-0.028	0.033
Autarky: Uncorrelated Shocks	0.000	0.001	-0.012	0.013
Input Trade Only	0.205	0.255	-0.082	0.532
Final Goods Trade Only	0.173	0.211	-0.115	0.501

Uncorrelated shocks do not generate correlated real GDP on average. However, as above, the heterogeneity in the impact of trade links in generating comovement is still evident. With uncorrelated shocks, 2004 trade linkages and $\rho = 1$, the median country-pair experiences a correlation 0.01-0.02 higher than in the model with autarky. The quantitative importance of the comovement due to trade linkages is modest. The mean G7 comovement with uncorrelated shocks is 7% of the comovement in the model with correlated shocks and trade linkages. Finally, we simulate the model with final and intermediate trade only. The implied comovement is somewhat higher in the intermediate-only model compared to the final-only model, but the difference is modest in magnitude.

Table 9: Additional Counterfactuals: Correlations of $dlogY_{nt}$, $\rho = 1$

	Mean	Median	25th pctile	75th pctile
Data	0.380	0.378	0.265	0.533
Model	0.337	0.406	0.179	0.570
Uncorrelated Shocks	0.024	0.020	-0.001	0.047
Autarky: Uncorrelated Shocks	0.000	0.011	-0.015	0.029
Input Trade Only	0.323	0.383	0.172	0.562
Final Goods Trade Only	0.319	0.361	0.179	0.546

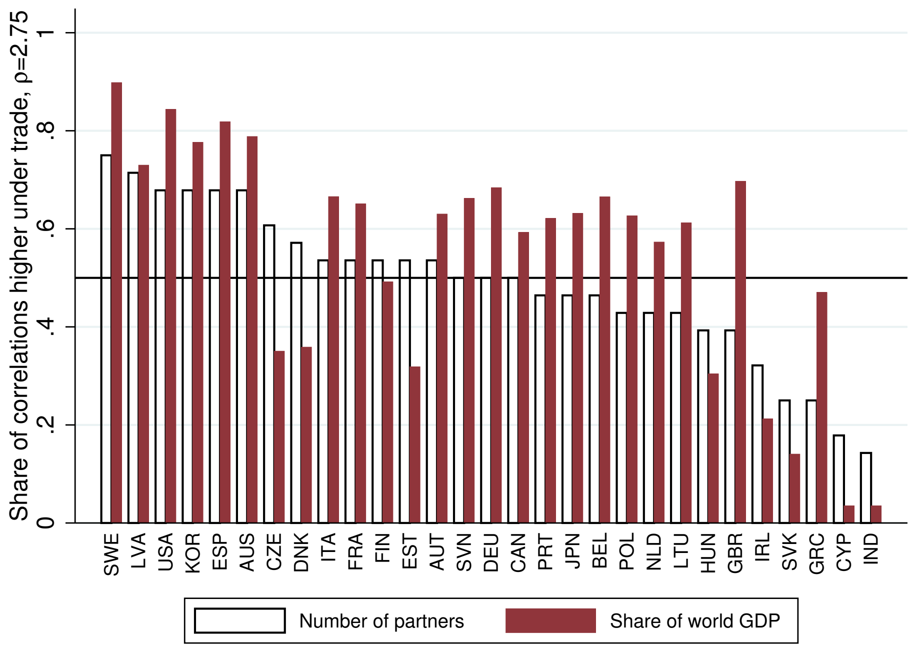
	All countries (N. obs. = 406)			
	Mean	Median	25th pctile	75th pctile
Data	0.171	0.205	-0.078	0.428
Model	0.218	0.272	-0.069	0.544
Uncorrelated Shocks	0.013	0.013	-0.011	0.035
Autarky: Uncorrelated Shocks	0.000	0.001	-0.023	0.023
Input Trade Only	0.205	0.259	-0.080	0.536
Final Goods Trade Only	0.198	0.246	-0.093	0.531

4 Conclusion

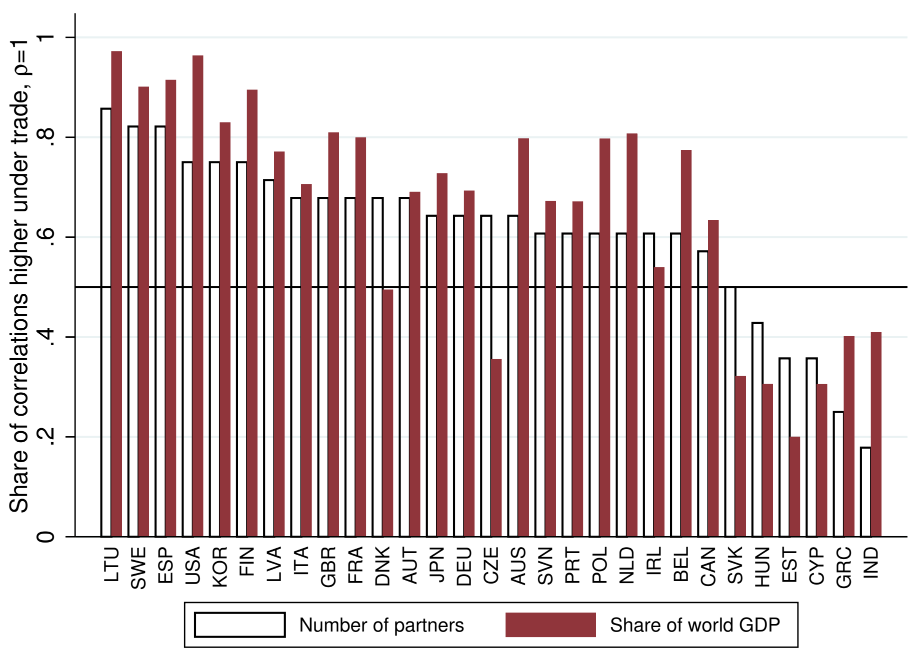
We set out to provide a comprehensive account of international comovement in real GDP. At the heart of our exercise is measurement of both technology and non-technology shocks for a large sample of countries, sectors, and years. Having measured these two types of shocks, we answer two questions. First, is comovement primarily due to TFP or non-technology shocks? The answer here is quite clear: non-technology shocks generate most of the observed international comovement. Second, to what extent do countries comove due to correlated shocks vs. transmission of shocks across countries? One clear answer is that correlated (non-technology) shocks are responsible for the bulk of observed comovement. However, there is also some evidence of transmission, especially under low substitution elasticities. In that case, the large majority of country pairs do experience higher comovement under the observed levels of international trade than in the counterfactual autarky scenario.

Figure 4: Correlations: Comparison between Autarky and Trade

$\rho = 2.75$



$\rho = 1$



Notes: This figure displays the share of pairwise correlations for each country that increase with trade (light bars) compared to autarky for $\rho = 2.75$ (top panel) and $\rho = 1$ (bottom panel). The dark bars depict the GDP shares of the partner countries with whom correlations increase with trade. The horizontal line is placed at 0.5. Sources are described in detail in the text.

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Appendix A Data Appendix

Table A1: Countries in Estimation Sample

Australia	Germany	Netherlands
Austria	Greece	Poland
Belgium	Hungary	Portugal
Canada	India	Russian Federation
Cyprus	Ireland	Slovak Republic
Czech Republic	Italy	Slovenia
Denmark Republic	Japan	Spain
Estonia	Republic of Korea	Sweden
Finland	Latvia	U.K.
France	Lithuania	U.S.A.

Table A2: Sectors in Estimation Sample

agriculture hunting forestry and fishing	basic metals and fabricated metal	financial intermediation
mining and quarrying	machinery nec	real estate activities
food beverages and tobacco	electrical and optical equipment	renting of m&eq and other business activities
textiles textile leather and footwear	transport equipment	public admin and defence; compulsory social security
wood and of wood and cork	manufacturing nec; recycling	education
pulp paper paper printing and publishing	electricity gas and water supply	health and social work
coke refined petroleum and nuclear fuel	construction	other community social and personal services
chemicals and chemical products	hotels and restaurants	sale maintenance and repair of motor vehicles
rubber and plastics	transport and storage	wholesale trade and commission trade
other nonmetallic mineral	post and telecommunications	retail trade except of motor vehicles

Table A3: Estimation Results

Industry	Returns to Scale $(\widehat{\eta}_j^1)$	Utilization $(\widehat{\eta}_j^2)$	Industry	Returns to Scale $(\widehat{\eta}_j^1)$	Utilization $(\widehat{\eta}_j^2)$
Durables			**Non-durable non-manufacturing**		
wood and of wood and cork	0.750***		sale maintenance and repair of motor	1.653***	
	(0.133)		vehicles and motorcycles; retail sale of fuel	(0.317)	
basic metals and fabricated metal	0.701**		wholesale trade and commission trade	1.472***	
	(0.329)		except of motor vehicles and motorcycles	(0.168)	
machinery nec	0.791***		retail trade except of motor vehicles	0.873*	
	(0.241)	1.419***	and motorcycles; repair of household goods	(0.454)	
electrical and optical equipment	0.711**	(0.389)	transport and storage	1.081***	
	(0.300)			(0.164)	
transport equipment	0.844***		post and telecommunications	0.632***	
	(0.207)			(0.150)	
manufacturing nec; recycling	0.895***		real estate activities	0.456	
	(0.129)			(0.332)	
			renting of m&eq and other business activities	1.221***	
				(0.226)	0.245
			agriculture hunting forestry and fishing	1.787*	(0.649)
				(0.959)	
Non-durable manufacturing			mining and quarrying	0.121	
				(0.757)	
food beverages and tobacco	0.988***		electricity gas and water supply	1.825	
	(0.174)			(1.387)	
textiles textile leather and footwear	0.289		construction	1.041***	
	(0.524)			(0.225)	
pulp paper paper printing and publishing	0.504		hotels and restaurants	1.267***	
	(0.430)			(0.429)	
coke refined petroleum and nuclear fuel	0.894	2.939*	financial intermediation	1.335***	
	(1.088)	(1.767)		(0.368)	
chemicals and chemical products	0.806*		public admin and defence;	1.863	
	(0.426)		compulsory social security	(1.504)	
rubber and plastics	0.925***		education	0.674***	
	(0.279)			(0.246)	
other nonmetallic mineral	0.695		health and social work	1.374	
	(0.487)			(2.173)	
			other community social and personal services	0.752***	
				(0.198)	

Notes: This table contains the results from the production function estimation described in Section XX. Standard errors in parentheses. Significance levels are indicated by *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

† These coefficients are estimated in the specification that includes three instruments.

Table A4: Model Fit and Counterfactuals with Deficits: $dlogY_{nt}$

	Mean	Median	25th pctile	75th pctile
	G7 Countries (N. obs. = 21)			
Data	0.380	0.378	0.265	0.533
Model	0.510	0.562	0.363	0.707
No Technology Shocks	0.359	0 .340	0 .286	0 .511
No Input Shocks	0.064	0.065	-0.152	0 .232
	All countries (N. obs. = 435)			
Data	0.185	0.214	-0.074	0.452
Model	0.217	0.254	-0.043	0.484
No Technology Shocks	0.134	0.154	- 0.108	0.376
No Input Shocks	0.027	0.014	-0.182	0.237

Appendix B Model Appendix

B.1 Algorithm for solving the model

To solve the model, we use an initial guess for $\widehat{\Upsilon_{nj,t+1}}$ together with data on $\pi^c_{mnj,t}$ and $\pi^x_{mjni,t}$. Given these variables, the algorithm is as follows:

- Solve for $\widehat{P_{nj,t+1}}$ given the guess of $\widehat{\Upsilon_{nj,t+1}}$ and the data on $\pi^c_{mnj,t}$ and $\pi^x_{mjni,t}$. This step uses equations (21), (20) and (22).
- Update $\pi^c_{mnj,t+1}$ and $\pi^x_{mj,ni,t+1}$ given the solution to (1) and the guess of $\widehat{\Upsilon_{nj,t+1}}$ using equations (23) and (24).
- Solve for $\widehat{\Upsilon'_{nj,t+1}}$ using equation (25) given the prices $\widehat{P_{nj,t+1}}$ obtained in step (1) and the updated shares $\pi^c_{mnj,t+1}$ and $\pi_{minj,t+1}$ from step (2).
- Check if $\max|(\widehat{\Upsilon'_{nj,t+1}}\text{-}\widehat{\Upsilon_{nj,t+1}})| < \delta$, where δ is a tolerance parameter that is arbitrarily small. If not, update the guess of $\widehat{\Upsilon_{nj,t+1}}$ and repeat steps (1)-(4) until convergence.