Estimating cross-industry cross-country interaction models using benchmark industry characteristics

Estimating industry-country interactions

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Abstract: Cross-industry cross-country models are used to address a wide array of questions in economics. They do so by analysing how the economic performance of industries in different countries depends on an interaction effect between industry and country characteristics. As the relevant industry characteristics are unobservable in most countries, they are approximated by industry characteristics in a benchmark country. We show that this approach generally yields biased estimates of the industry-country interaction effect. The sign of the bias depends on whether or not technologically similar countries tend to be similar in other country characteristics. We propose an alternative estimation approach.

Keywords: Industry interactions, cross-country analysis, measurement error, economic growth, comparative advantage, financial development, institutions

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1 Introduction

Cross-industry cross-country (CI/CC) models have proven useful for addressing a broad array of questions in fields ranging from international and growth economics to financial and industrial economics. They examine how the economic performance of industries in different countries depends on the interaction between industry characteristics—reliance on external finance or certain inputs for example—and country characteristics such as endowments, institutions, or economic policies. CI/CC models are used widely because industry-country interaction effects allow testing theoretical mechanisms and because they can account for arbitrary determinants of economic performance at the industry and the country level.

For example, consider Rajan and Zingales' (1998) influential work on financial development and economic growth. They argue that if financial development matters for growth, it should matter especially in industries that rely more on external finance. Rajan and Zingales test this hypothesis using a CI/CC model that relates industry growth to the interaction between industries' reliance on external finance and countries' financial development. This industry-country interaction effect is significantly positive. Hence, industries that rely more on external finance grow relatively faster in more financially developed countries.

Another influential contribution using a CI/CC model is Nunn's (2007) work on institutions and comparative advantage. He relates industry exports to the interaction between industries' reliance on differentiated inputs and countries' institutional quality. Nunn finds this industry-country interaction effect to be significantly positive. Hence, industries that rely more on differentiated inputs export relatively more in countries with better institutions.

A challenge in the literature employing CI/CC models is that the theoretically relevant industry characteristics are generally unobservable in almost all countries. These are therefore approximated by the corresponding industry characteristics in a benchmark country. For example, both Rajan and Zingales (1998) and Nunn (2007) approximate the theoretically relevant industry characteristics in all countries using US industry characteristics.

We make two contributions to the literature. First, we examine the consequences of using benchmark industry characteristics for estimation of the industry-country interaction effect in CI/CC models. We do so in a framework that allows for cross-country heterogeneity in industry technology. Such heterogeneity is well documented—see, for example, Bernard and Jones (1996), Acemoglu and Zilibotti (2001), Schott (2004), and Caselli (2005). As we find that the benchmarking estimator generally yields biased results, we propose an alternative estimation approach. Our approach draws on insights from the generalized least squares literature to estimate how the technological similarity of countries correlates with other country characteristics. We illustrate the approach by applying it to Nunn (2007).[1]

The bias of the benchmarking estimator used in the CI/CC literature depends on how the technological similarity of countries varies with other country characteristics. Suppose that technologically more similar countries *are not more* similar in other characteristics. In this case, using industry characteristics in a benchmark country as a proxy for the technological industry characteristics of all other countries gives rise to classical measurement error bias. As a result, the benchmarking estimator yields attenuated estimates of the industry-country interaction effect. This possibility is recognised in the literature since Rajan and Zingales (1998), who also point out that attenuated estimates imply a bias against the hypothesis

[1] We have chosen Nunn because the number of industries is relatively large compared to earlier applications of CI/CC models.

being tested. We show that there is another possibility. If technologically more similar countries *are more* similar in other dimensions, the benchmarking estimator can yield amplified or entirely spurious estimates of the industry-country interaction effect.

To understand the benchmarking estimator used in the CI/CC literature, it is useful to break down estimation of the industry-country interaction effect into two steps. The first step is a cross-industry regression: economic outcomes across industries in a country are regressed on the industry characteristics in the benchmark country. This yields a country-specific regression slope that reflects the relationship between industry outcomes in the country and the benchmark industry characteristics. The second step is a cross-country regression: the country-specific slopes from the first step are regressed on the country characteristic of interest. The regression slope of this second step is the benchmarking estimator.

Consider Nunn's analysis of the effect of institutional quality on exports in industries that rely on differentiated inputs. The first step is to regress industry exports in a country on the differentiated-input intensity of the industry in the US. The second step is to regress the country-specific slopes from the first step on the institutional quality of countries. The regression slope of the second step is positive if the country-specific slopes from the first step are larger for countries with greater institutional quality. This, in turn, is the case if the relationship between industry exports in a country and the reliance on differentiated inputs of the industry in the US is stronger for countries with better institutions. In this case, the conclusion using the benchmarking estimator would be that better institutions promote comparative advantage in more differentiated-input intensive industries.

To see that this conclusion may be misleading, consider the following example. The technology used in an industry depends on the country's human capital. In high-human-capital countries, industries use the same technologies as in the US. Hence, the relationship between industry exports and the differentiated-input intensity of the industry in these countries is the same as in the US. Suppose the relationship is positive. In low-human-capital countries, industries use different technologies than in the US. As a result, industry exports in low-human-capital countries are less closely related to the differentiated-input intensity of US industries than industry exports in high-human-capital countries. Now suppose that countries with more human capital have better institutions. The benchmarking estimator would then lead to the conclusion that better institutions promote comparative advantage in differentiated-input intensive industries. This would be misleading as institutions do not play a role for comparative advantage in this example. In particular, it is not because of institutional quality that the differentiated-input intensity of US industries is more closely related to industry exports in countries with good institutions than in countries with bad institutions. Instead, countries with better institutions have more human capital and this leads to them using technologies that are more similar to US technologies.

Our analysis of the benchmarking estimator in the CI/CC literature can be seen as reevaluating the bias introduced by using US (benchmark) industry characteristics as a proxy for industry characteristics elsewhere. The literature implicitly assumes that this proxy introduces measurement error that is independent of all country characteristics (classical measurement error) and that industry-country interaction effects are therefore biased towards zero. That is, using US industry characteristics as a proxy for industry characteristics elsewhere leads to an attenuation bias and hence a bias against the hypothesis being tested.

We add that—because technology is endogenous—US industry characteristics are likely to be a relatively worse proxy for countries that differ from the US in various dimensions. This heterogeneity in the measurement error counteracts the attenuation bias considered in the CI/CC literature and can flip the sign of the bias of the benchmarking estimator. Therefore, using US industry characteristics as a proxy for industry characteristics elsewhere can lead to amplified or entirely spurious industry-country interaction effects.

As the benchmarking estimator used in the CI/CC literature generally yields biased results for the industry-country interaction effects of interest, we propose an alternative. Our approach builds on the assumption in the literature that each industry has some (global) technological characteristics that do not depend on the country where it is located. But we also allow industries to have country-specific technological characteristics. We show how these can be used to capture that industry technologies are more similar for some country pairs than others. We first examine the estimation of the industry-country interaction effect for an arbitrary but known pattern of technological similarity across country pairs. Then we discuss estimation when the pattern is unknown and show that this requires restrictions on technological similarity across country pairs. The restriction we impose is that the technological similarity of countries is unrelated to other country characteristics for countries that are sufficiently apart in terms of the theoretically relevant country characteristic. On the other hand, if countries are sufficiently close in terms of the theoretically relevant country characteristic, their technological similarity is completely unrestricted. This approach allows us to relax the implicit restriction in the CI/CC literature step by step.

The rest of the paper is structured as follows. Section 2 discusses some applications of CI/CC models in the literature. Supplementary Appendix A contains a longer list of almost 90 applications. Section 3 examines the benchmarking estimator used in the CI/CC literature. Sections 4 and 5 introduce our estimation approach and apply it to Nunn (2007). Section 6 concludes. The proofs of our results are in Supplementary Appendix B.

2 Economic Applications of CI/CC Models

We now discuss some economic applications of CI/CC models in the literature. We provide a more exhaustive list of almost 90 applications in Supplementary Appendix A.

The Economic Effects of Financial Markets. Starting with the work of Rajan and Zingales (1998), CI/CC models have been applied extensively to investigate the effects of financial markets on economic growth, firm entry and exit, investment, and innovation. Fisman and Love (2003) document that financial underdevelopment benefits industries that rely more on trade credit and Fisman and Love (2007) show that financial development allows industries to react more rapidly to global growth opportunities. Claessens and Laeven (2003) and Braun and Larrain (2005) examine how financial development interacts with the share of intangible assets of industries, while Acharya and Xu (2017) and Moshirian *et al.* (2021) look at the interplay between financial development and the R&D intensity of industries. The empirical finance literature employs CI/CC models to examine the impact of specific financial market policies and institutions, such as bank recapitalizations (Laeven and Valencia, 2013), insider trading legislation (Edmans *et al.*, 2017), stock market concentration (Bae *et al.*, 2021), and collateral laws (Calomiris *et al.*, 2017). CI/CC models are also used to study financial crises (e.g., Dell'Ariccia *et al.*, 2008; Larrain and Stumpner, 2017; Iacovone *et al.*, 2019).

International Specialization and Trade. Research in international economics employs CI/CC models to examine the impact of institutional quality (e.g., Levchenko, 2007; Nunn, 2007), human and physical capital (e.g., Romalis, 2004; Ciccone and Papaioannou, 2009), and natural resources (Debaere, 2014) on international specialization. Manova (2008) links financial development to the patterns of international trade. Cuñat and Melitz (2012), Mueller and Philippon (2011), Tang (2012), and Cingano and Pinotti (2016) use CI/CC models to examine the effect of cross-country differences in labour market and employment regulation as well as levels of trust in others on comparative advantage.

CI/CC models have proven useful for examining a wide variety of additional economic questions. For example, Alfaro and Charlton (2009), Basco (2013), Blyde and Molina (2015), Paunov (2016), and Fort (2017) analyse the determinants of outsourcing, foreign investment, and the fragmentation of production. Pagano and Schivardi (2003), Klapper *et al.* (2006), Acemoglu *et al.* (2009), Cingano *et al.* (2010), Michelacci and Schivardi (2013), and Aghion *et al.* (2015) examine the economic consequences of cross-country differences in firm size distributions, entry and employment regulation, transaction costs, risk sharing possibilities, and skill dispersion. Rajan and Subramanian (2011) and Chauvet and Ehrhart (2018) use CI/CC models to understand the economic effects of foreign aid and Pierce and Snyder (2018) to examine the legacy of slave trade. Cecchetti and Kharroubi (2018) and Avdjiev *et al.* (2019) analyze economic consequences of fiscal and monetary policy as well as exchange rate volatility, and Erman and te Kaat (2019) the effect of inequality on growth.

3 The Benchmarking Estimator

3.1 The Model

The basis of CI/CC models are theories linking industry outcomes in different countries to an interaction between country characteristics and technological industry characteristics. For example, in Rajan and Zingales (1998), the outcome variable is industry growth and the interaction is between financial development and the external-finance dependence of industries. In Nunn (2007), the outcome is industry exports and the interaction is between institutional quality and the intensity with which industries use differentiated inputs. As the main hypothesis concerns the effect of the interaction between country and industry characteristics, CI/CC models allow controlling for country and industry fixed effects. An empirical framework that encompasses the models in the literature is

$$y_{in} = (\alpha + \beta x_n) z_{in} + \nu_{in} \tag{1}$$

where y_{in} is the outcome in I industries indexed by i and N countries indexed by n; x_n is the relevant country characteristic; z_{in} denotes the relevant industry technological characteristic in different countries; and ν_{in} captures country and industry fixed effects as well as any unobserved determinants of industry outcomes that are independent of z_{in}. The parameter of interest is β. The parameter α captures direct effects of industry characteristics on outcomes.[2] We take the relevant country characteristic x_n to be non-stochastic.

[2]For example, Rajan and Zingales use the external-finance dependence of industries to capture the extent to which technological shocks raise an industry's investment opportunities beyond what internal funds can support. In this application, the parameter β in (1) allows testing RZ's hypothesis that financial development fosters growth disproportionally in industries with greater demand for external finance. The parameter α allows to capture direct effects of the technological shocks raising an industry's investment opportunities on

Estimation of β in (1) would be straightforward if there was data on the relevant technological industry characteristics z_{in} for all countries. However, there is little industry data for most countries. As a result, the CI/CC literature approximates the relevant technological industry characteristics of all countries with the industry characteristics from a highly-developed benchmark country with relatively undistorted markets, usually the USA.

We want to understand the implications of the benchmarking approach in the CI/CC literature when the optimal technology in an industry depends on a range of country characteristics. For example, suppose that—in addition to the country characteristic x_n in (1)—there is a second country characteristic h_n. Suppose also that this second country characteristic enters the model in (1) solely through its effect on the optimal technology used in industry i in country n. A straightforward way to capture this dependence is to assume that the technological industry characteristic z_{in} in industry i and country n is given by $z_{in} = z_i + g(i, h_n)$ for some $g(\cdot)$. z_i capture technological industry characteristics that are independent of the characteristics of the country where the industry is located. We refer to z_i as global technological industry characteristics. The function $g(i, h_n)$ captures that the optimal technology in industry i in country n depends on h_n.

Clearly, in this case, the technological industry characteristics in the benchmark country z_{ib} will generally constitute an imperfect proxy for the technological industry characteristics z_{in} in other countries. This possibility is acknowledged in the CI/CC literature since Rajan and Zingales (1998). They argue that this generates an attenuation bias and therefore a bias against finding the industry-country interaction effect that they focus on (p.567). Our point is that the technological industry characteristics in the benchmark country will generally

industry growth. Technological shocks may affect industry growth directly in several ways, for example by changing the marginal productivity of labour, and hence equilibrium employment, across industries.

be a better proxy for the technological industry characteristics of countries that are more similar to the benchmark country. For example, if $z_{in} = z_i + g(i, h_n)$, the technological industry characteristics in the benchmark country will be a better proxy for the industry characteristics in countries with a level of h_n that is similar to h_b. This may yield upward biased estimates of the industry-country interaction effect.

Consider the study of Nunn (2007). The relevant technological industry characteristic is the reliance on differentiated inputs and the relevant country characteristic is institutional quality. Nunn points out that differentiated inputs are often customised and that this requires relationship-specific investments. Such investments are less profitable when intermediate-input suppliers operate in a country with low institutional quality. Hence, suppliers will invest less in customising differentiated inputs in countries with worse institutions and the limited supply of customised inputs lowers the productivity of the industry. Nunn approximates the technological differentiated-input intensity of industries in all countries by the differentiated-input intensity of industries in the US. This is the natural starting point.

However, the approach could result in amplified or spurious industry-country interaction effects. This may be the case if the differentiated-input intensity of industries in the US is a better proxy for the technological differentiated-input intensity of industries in similar countries. Nunn's study illustrates why this could be the case. He documents that differentiated-input intensive industries also use human capital more intensively. Hence, the level of human capital of a country may affect the optimal technology—and hence the technological differentiated-input intensity—of industries producing in the country. As a result, the differentiated-input intensity of industries in the US could be similar to the technological differentiated-input intensity of industries in countries with high human capital but different from the technological differentiated-input intensity in countries with low human capital.

We want a framework that allows us to capture the possibility that technological industry characteristics may be more similar for some country pairs than others. The first step is to take the technological industry characteristics z_{in} in (1) to be the sum of a country-specific component z_n, the global industry-specific component z_i, and a country-specific industry component ε_{in}

$$z_{in} = z_n + z_i + \varepsilon_{in}. \tag{2}$$

z_n captures country-specific factors that shift the distribution of technological industry characteristics. We treat this component as non-stochastic. The global industry component z_i captures technological industry characteristics that do *not* depend on the country where the industry is located. We treat this component as independent draws from a random variable with $Var(z_i) > 0$. For the ε_{in} we choose a model that allows us to capture that some country pairs may be more similar technologically than others.

To do so we take the ε_{in} in (2) to be jointly normally distributed for all i and n. For any pair of countries $n \neq m$, the correlation of the ε_{in} across industries is an arbitrary function of country characteristics

$$Corr(\varepsilon_{in}, \varepsilon_{im}) = \rho_{nm}. \tag{3}$$

As ρ_{nm} can be different for each country pair, (3) yields a flexible model of the relationship between the characteristics of any pair of countries and their technological similarity. Our analysis of the bias of the estimation approach in the CI/CC literature will show that, whether the bias is upwards or downwards is partly determined by how ρ_{nm} changes as country n and country m become more dissimilar in terms of their x-characteristics. Across industries, the ε_{in} are taken to be independent and

$$E(\varepsilon_{in}) = 0 \text{ and } E(\varepsilon_{in}^2) = \sigma^2. \tag{4}$$

The variance across industries of z_{in} is $Var(z_{in}) = Var(z_i) + \sigma^2$. Hence, if $\sigma^2 = 0$, differences in technological industry characteristics within countries are entirely driven by the global component. As (2) allows for a country-specific component, technological industry characteristics could still vary across countries. However, such cross-country differences do not play an important role in our analysis, as they are absorbed by the country fixed effects always present in CI/CC models.

If $\sigma^2 > 0$, differences in technological industry characteristics within countries will be country specific. To understand the implications it is useful to relate the difference between the technological industry characteristic of two industries i and j in a country n, $z_{in} - z_{jn}$, to differences in US industry characteristics, $z_{iUS} - z_{jUS}$, and differences in the global industry component, $z_i - z_j$. This yields

$$z_{in} - z_{jn} = \rho_{nUS}(z_{iUS} - z_{jUS}) + (1 - \rho_{nUS})(z_i - z_j) + u_{ijnUS} \tag{5}$$

where ρ_{nUS} refers to the correlation in (3) between the specific industry characteristics of country n and the US, and u_{ijnUS} is a random variable with zero mean that is independent of z_i and z_{US}.[3] Hence, the difference between the technological characteristics of any two industries in country n can be thought of as a weighted average of industry differences in

[3]This holds for any pair of countries n and m. It follows from (2)–(4) and joint normality of the distribution of ε_{in} for all i and n.

the US and global industry differences plus random noise. The weight on the US industry characteristics is the correlation coefficient ρ_{nUS} between the specific industry characteristics of country n and the US. As the ρ_{nUS} can be arbitrary functions of country characteristics, our model of technological industry characteristics allows for a flexible relationship between the x-characteristics of countries and their technological similarity with the US.

It is useful to see what the model in (2), and its implication in (5), allows us to capture in the context of Rajan and Zingales (1998) and of Nunn (2007). In Nunn, (5) allows us to capture that even if all countries had the US level of institutional quality, the technological differentiated-input intensity of industries may vary with the country's human capital. As a result, industries in countries with high human capital may be more similar to US industries. In this case, ρ_{nUS} would be positive and larger for countries with high human capital than for countries with low human capital.[4] The estimation approach in the CI/CC literature fails to take this possibility into account. As a result, estimates of the effect of institutional quality on industry outcomes could be biased upward or downward. The sign of the bias depends on how ρ_{nUS} changes as country n and the US become more dissimilar in terms of their x-characteristics. In Rajan and Zingales (1998), the key industry characteristic is external-finance intensity. This variable is seen as capturing technological shocks that raise an industry's investment opportunities beyond what internal funds support. The external-finance intensity of industries in all countries is approximated by that of US industries. The model in (2), and its implication in (5), allows us to capture that the technological shocks affecting US industries could be more similar to shocks in countries with high levels of economic development.

[4]As an aside, a country's human capital could also affect industry outcomes through the technological human-capital intensity of industries of course.

It is interesting to note that (5) does not determine whether the difference between the technological characteristics of any two industries in country n increases or decreases relative to the US as ρ_{nUS} increases. This gives the model additional flexibility. For example, consider the effect of a country's human capital on the differentiated-input intensity of its industries discussed above in the context of Nunn (2007). Compared to the US, industries might be less relation-specific-input intensive in countries with low human capital. However, there is no reason to suppose that this effect is stronger in some industries than others. Hence, the difference in the reliance on differentiated inputs between two industries i and j in a country with low human capital may be greater or smaller than in the US.

3.2 Characterizing the Benchmarking Estimator

We now apply the estimation approach used in the CI/CC literature to the model in (1) and (2). This yields what we refer to as the (standard) benchmarking estimator. We then discuss the forces shaping the bias of this estimator.

3.2.1 The Benchmarking Estimator

The estimating equation in the cross-industry cross-country literature is

$$y_{in} = a_i + a_n + bx_n z_{iUS} + residual_{in} \tag{6}$$

where a_i and a_n are industry and country fixed effects, and z_{iUS} denotes the industry characteristics of the benchmark country (we use the subscript US as the benchmark country is usually the US). The effect of interest is captured by the coefficient b on the industry-country interaction, and the method of estimation is least squares.[5]

It is useful to write the least-squares estimator of b in (6) in terms of demeaned variables (e.g. Baltagi, 2008)

$$\widehat{b} = \frac{\frac{1}{N}\frac{1}{I}\sum_{n=1}^{N}\sum_{i=1}^{I}(z_{iUS} - \overline{z}_{US})(x_n - \overline{x})\,(y_{in} - \overline{y}_n - \overline{y}_i + \overline{y})}{\frac{1}{N}\frac{1}{I}\sum_{n=1}^{N}\sum_{i=1}^{I}(z_{iUS} - \overline{z}_{US})^2(x_n - \overline{x})^2} \tag{7}$$

where $\overline{y}$ is the average of y_{in} across industries and countries; $\overline{y}_i$ is the cross-country average of y_{in} for industry i, $\overline{y}_n$ is the cross-industry average of y_{in} for country n, $\overline{z}_{US}$ is the cross-industry average of z_{iUS}, and $\overline{x}$ is the cross-country average of x_n.

To see when the standard benchmarking estimator identifies the main parameter of interest β, we consider the probability limit of $\widehat{b}$ as the number of industries goes to infinity. Substituting (1) in (7) and taking the probability limit—see the Supplementary Appendix for details—yields

$$b = \operatorname*{plim}_{I\to\infty} \widehat{b} = \left(1 - \frac{\sigma^2}{Var(z_{US})}\right)\beta + \left(\frac{\sigma^2}{Var(z_{US})}\right)(\alpha A + \beta B) \tag{8}$$

where σ^2 is the variance of ε_{in} and $Var(z_{US})$ is the variance of the US industry characteristic z_{iUS}, with $\sigma^2/Var(z_{US}) < 1$; α captures direct effects of industry characteristics on industry outcomes; and A and B capture the relationship between the characteristic x_n of

[5] We assume x_n to be exogenous. In some applications in the literature, exogeneity is an issue and x_n is therefore instrumented. In these applications, our analysis applies to the reduced-form equation. We always include the US (benchmark country) as one of the countries in our analysis. The literature sometimes drops the benchmark country but, given the relatively large number of countries included, this generally makes very little difference for the estimates.

country n and how similar the country is technologically to the US (as measured by ρ_{nUS})

$$A = \frac{Cov(x_n, \rho_{nUS})}{Var(x_n)} = \frac{\sum_{n=1}^{N}(x_n - \overline{x})\rho_{nUS}}{\sum_{n=1}^{N}(x_n - \overline{x})^2} \tag{9}$$

and

$$B = \frac{Cov(x_n, \rho_{nUS}x_n)}{Var(x_n)} = \frac{\sum_{n=1}^{N}(x_n - \overline{x})x_n\rho_{nUS}}{\sum_{n=1}^{N}(x_n - \overline{x})^2}. \tag{10}$$

For example, suppose that the US is a high-x country, i.e., the US has a high level of financial development, institutional quality, or human capital. Then A is positive if countries that are similar technologically to the US are also similar in terms of the x-characteristic. In the typical application of CI/CC models in the literature, B would also be positive in this case.[6]

An implication of (8) is that the benchmarking estimator identifies β when there is no cross-country heterogeneity in technological industry characteristics, $\sigma^2 = 0$. In this case, the technological differences between US (benchmark country) industries are identical to the technological differences between industries of all other countries. Using US industry characteristics as a proxy for the technological industry characteristics of all other countries does therefore not involve any measurement error.[7]

When there is cross-country heterogeneity in technological industry characteristics, $\sigma^2 > 0$, the benchmarking estimator in (8) is biased and the bias is shaped by two main forces.

[6]Theoretically, the sign of B could depend on the distribution of the x-characteristics across countries even if A is positive.

[7]As already mentioned, our model for z_{in} in (2) allows for a country-specific component z_n and the levels of technological industry characteristics could therefore vary across countries even if $\sigma^2 = 0$. But such cross-country heterogeneity does not play an important role in our analysis, as it is absorbed by the country fixed effects always present in CI/CC models.

First, how much country-specific heterogeneity there is in technological industry characteristics (captured by $\sigma^2/Var(z_{US})$). Second, how the technological similarity of countries with the US (captured by ρ_{nUS}) covaries with their characteristics x_n (captured by A and B). We now discuss these forces in some interesting special cases and show that the benchmarking estimator may be attenuated, biased away from zero (amplified), or entirely spurious.

3.2.2 The Bias of the Standard Benchmarking Estimator: a First Approach

Attenuation Bias. We start with the case that we see as corresponding to the implicit assumption in the CI/CC literature. In this case, differences between the technological industry characteristics of a country and global technological industry characteristics are assumed to be completely idiosyncratic to the country. Put differently, the technological industry characteristics of different countries are related through global industry characteristics only.

Formally, this assumption amounts to $\rho_{nm} = 0$ for all country pairs $n \neq m$. In this case, (9) and (10) imply $A = B = 0$ and the expression for the standard benchmarking estimator in (8) simplifies to $b = \beta(1 - \sigma^2/Var(z_{US}))$. As $\sigma^2/Var(z_{US}) < 1$, the benchmarking estimator b has the same sign as the parameter of interest β but is biased towards zero.[8] This possibility is generally understood in the CI/CC literature and explained in terms of a classical measurement error bias due to US (benchmark) industry characteristics measuring the technological industry characteristics of other countries with some error (e.g. Rajan and Zingales, 1998). In fact, the expression for the probability limit of the benchmarking estimator when $\rho_{nm} = 0$ is analogous to that of the least-squares estimator in the presence of

[8] As already mentioned, the assumption $Var(z_i) > 0$ implies $\sigma^2/Var(z_{US}) < 1$ as at least some of the variation in technological industry characteristics in each country, including the US, is due to the global component.

classical measurement error, with $1-\sigma^2/Var(z_{US})$ playing the role of the reliability or signal-to-total-variance ratio (e.g., Wooldridge, 2002). Intuitively, when $\rho_{nm} = 0$, US industry characteristics are an equally imperfect proxy for the technological industry characteristics of all other countries and become a uniformly worse proxy for the technological industry characteristics of all other countries as $\sigma^2/Var(z_{US})$ increases.

Spurious Interaction Effect. When there is cross-country heterogeneity in technological industry characteristics, the standard benchmarking estimator can indicate a positive effect of the country characteristic x_n on industry outcomes even though x_n does not actually enter the true model at all. To see this, suppose that $\beta = 0$, which implies that the country characteristic x_n drops out from the true model in (1). Suppose also that there is cross-country heterogeneity in technological industry characteristics, $\sigma^2 > 0$. In this case, the standard benchmarking estimator in (8) is $b = \alpha A\sigma^2/Var(z_{US})$. Hence, if $\alpha A > 0$, the standard benchmarking estimator indicates a positive effect of the industry-country interaction $x_n z_{iUS}$ on industry outcomes, although the country characteristic is in fact irrelevant for industry outcomes. This is because $\alpha A > 0$ implies that cross-country heterogeneity in technology is such that industry outcomes in high-x countries are more closely correlated with US industry characteristics than industry outcomes in low-x countries.[9] The standard

[9]This could be because the technological industry characteristics of high-x countries are more similar to US industry characteristics and there is a positive direct effect of technological industry characteristics on industry outcomes ($A > 0$ and $\alpha > 0$). Alternatively, technological industry characteristics of high-x countries could be less similar to US industry characteristics and there could be a negative direct effect of technological industry characteristics on industry outcomes ($A < 0$ and $\alpha < 0$).

benchmarking estimator misinterprets this as a positive effect of the industry-country interaction $x_n z_{iUS}$ on industry outcomes, and therefore leads to the erroneous conclusion that the country characteristic x_n has an effect on industry outcomes.[10]

The size of the spurious effect generated by the standard benchmarking estimator depends on A in (9). A is the slope of a least-squares regression of ρ_{nUS}, which measures technological similarity of country n with the US, on the x-characteristic of countries. As a result, the bias of the standard benchmarking estimator could be sizeable although countries that are similar to the US in the x-characteristic are also similar technologically, if there is a drop-off in technological similarity with the US as countries become less similar in the x-characteristic. In fact, if (i) countries similar to the US in the x-characteristic are also similar technologically; (ii) countries are on average similar to the US in the x-characteristic; and (iii) there is a drop-off in technological similarity as countries become less similar to the US in the x-characteristic, then the bias of the standard benchmarking estimator can be sizeable although the average country is technologically quite similar to the US.

Amplification Bias. The benchmarking estimator can also result in an amplification bias. To see this in the simplest case, assume there is no direct effect of industry characteristics on outcomes, $\alpha = 0$. In this case, (8) simplifies to $b = \beta \left[1 + (B-1)\sigma^2/Var(z_{US})\right]$. If $B > 1$ and there is cross-country heterogeneity in technological industry characteristics ($\sigma^2 > 0$), the benchmarking estimator b will be an amplified version of β, $|b| > |\beta|$ and $sign(b) = sign(\beta)$.

[10] More formally, when $\beta = 0$, the benchmarking estimator solely reflects the covariation between the direct effect of country-specific industry characteristics on industry outcomes $\alpha\varepsilon_{in}$ and the interaction $x_n z_{iUS}$. This covariation is $\alpha \frac{1}{N} \sum_{n=1}^{N} (x_n - \overline{x}) E\varepsilon_{in}(z_{iUS} - z_i) = \alpha \frac{1}{N} \sum_{i=1}^{N} (x_n - \overline{x}) \sigma^2 \rho_{nUS} = \alpha\sigma^2 Cov(x_n, \rho_{nUS})$ where we made use of the definition of ρ_{nUS}. Hence, as long as there is cross-country heterogeneity in technological industry characteristics, the covariation is positive if and only if $\alpha Cov(x_n, \rho_{nUS}) > 0$. Using the definition of A, this is equivalent to $\alpha A > 0$.

The amplification bias of the standard benchmarking estimator is the most difficult bias to understand intuitively. At the most general level, for there to be an amplification bias, US industry characteristics must be a better proxy for the technological industry characteristics of countries that have x-characteristics similar to the US. To see the sources of the amplification bias of the standard benchmarking estimator in detail, it is useful to rewrite the model in (1) as

$$y_{in} = \gamma_n z_{in} + \nu_{in} \tag{11}$$

$$\gamma_n = \beta x_n \tag{12}$$

where we continue to assume $\alpha = 0$. We simplify further by treating the disturbance ν_{in} as an independent and identically distributed random variable. The parameters γ_n in (11) capture the effect of industry characteristics on outcomes in different countries. We refer to these parameters as country-specific slopes. The parameter β in (12) captures how these country-specific slopes covary with the country characteristic x_n.

Now imagine estimating the country-specific slopes γ_n in (11) separately for each country. As we only observe the technological industry characteristics of the US, we use US industry characteristics z_{iUS} as a proxy for the technological industry characteristics z_{in} of each country. We denote the least-squares slope estimates of γ_n by $\widehat{g}_n$. Clearly, $\widehat{g}_n$ will generally be biased. To see the factors shaping the bias we take the probability limit of $\widehat{g}_n$ as the number of industries I goes to infinity. This yields

$$g_n = \operatorname*{plim}_{I \to \infty} \widehat{g}_n = \gamma_n \left[\left(1 - \frac{\sigma^2}{Var(z_{US})} \right) + \left(\frac{\sigma^2}{Var(z_{US})} \right) \rho_{nUS} \right] \tag{13}$$

where $\sigma^2/Var(z_{US}) < 1$. The term in square brackets turns out to be the correlation coefficient between the technological industry characteristics of country n and the US, $corr(z_{in}, z_{iUS})$. Hence, the bias of the least-squares slopes, $g_n - \gamma_n$, reflects the technological similarity between country n and the US as captured by $corr(z_{in}, z_{iUS})$. This yields two insights: (i) the more similar a country is technologically to the US (the closer $corr(z_{in}, z_{iUS})$ to 1), the smaller the bias of the least-squares slopes in (13); and (ii) the least-squares slopes in (13) are biased towards zero (attenuated) for all countries n, as long as the technological industry characteristics of all countries are positively correlated with those of the US ($corr(z_{in}, z_{iUS}) \geq 0$ for all n).

Hence, as long as $corr(z_{in}, z_{iUS}) \geq 0$ for all countries n, the term in square brackets in (13) can be thought of as the so-called attenuation factor in the classical measurement error literature. This attenuation factor is larger—and hence the attenuation bias is smaller—for countries that are more similar technologically to the US.

That the country-specific least-squares slope estimates in (13) might be attenuated for all countries is not difficult to understand from the perspective of the classical measurement error literature, as US industry characteristics will generally proxy for industry characteristics of other countries with error. It is harder to see why, if all the slope estimates in (13) are attenuated, the standard benchmarking estimator may be subject to an amplification bias. This is possible because the attenuation bias of the least-squares slope estimates is heterogeneous across countries, with a smaller attenuation bias for countries that are more similar technologically to the US.

To see this, it is useful to express the standard benchmarking estimator in (8) as a slope of slopes. We start from the least-squares slopes g_n in (13) obtained by regressing outcomes across industries on US industry characteristics separately for each country n. These country-specific slopes g_n are then regressed on the country characteristics x_n. The least-squares slope of the second, cross-country regression is the standard benchmarking estimator in (8). To see this, note that

$$\begin{aligned}\frac{\sum_{n=1}^{N} g_n(x_n-\overline{x})}{\sum_{n=1}^{N}(x_n-\overline{x})^2} &= \beta\left(\frac{\sum_{n=1}^{N}\left[\left(1-\frac{\sigma^2}{Var(z_{US})}\right)+\left(\frac{\sigma^2}{Var(z_{US})}\right)\rho_{nUS}\right]\gamma_n(x_n-\overline{x})}{\sum_{n=1}^{N}(x_n-\overline{x})^2}\right) \\ &= \beta\left[\left(1-\frac{\sigma^2}{Var(z_{US})}\right)+\left(\frac{\sigma^2}{Var(z_{US})}\right)B\right]=b.\end{aligned} \tag{14}$$

The left-most expression in (14) is the standard expression for the slope of a least-squares regression, in this case of g_n on x_n. The first equality follows from substituting the least-squares slopes in (13) for g_n. The second equality uses (12) and the definition of B in (10), and the last equality uses the expression for b in (8) for the case $\alpha = 0$. The key message of the slope-of-slopes expression for the standard benchmarking estimator in (14) is that the bias of the estimator reflects how the attenuation factor of the country-specific least-squares slopes in (13) covaries with the country characteristics x_n. The amplification bias can emerge when the attenuation factor (bias) is larger (smaller) for countries with greater x_n.

We now illustrate the amplification bias in the simplest version of our framework.

The Amplification Bias in a Simple Setting. The source of the amplification bias emerges most clearly when there are two groups of countries and countries in the same group are identical. In this two-group setting, the formula for the benchmarking estimator in (14) simplifies to

$$b = \frac{g_S - g_D}{x_S - x_D} \tag{15}$$

where g_S and g_D are the country-specific slope estimates in (13) for countries in group S and group D, and x_S and x_D are the x-characteristics in the two country group.

Suppose that the US is part of group S. As countries in the same group are identical, all countries n in group S are identical technologically to the US, $\rho_{nUS} = 1$. As a result, (13) implies that the estimated and the true country slopes are the same for all countries in group S: $g_S = \gamma_S$. This is unsurprising as using US technological industry characteristics as a proxy for the technological industry characteristics of other countries in group S does not involve any measurement error.

Suppose that countries in group D are technologically somewhat different from the US. The simplest approach is to think of these countries as having specific industry characteristics that are uncorrelated with US-specific industry characteristics, $\rho_{nUS} = 0$ for all n in group D. Then (13) implies that the estimated country slopes for countries in group D are biased towards zero: $g_D = (1 - \sigma^2/Var(z_{US}))\gamma_D$. This is because US industry characteristics are a noisy proxy for the technological industry characteristics of countries in group D.

Substituting the expressions for g_S and g_D into (15) and using (12) yields

$$b = \beta \left[1 + \left(\frac{\sigma^2}{Var(z_{US})} \right) \frac{x_D}{x_S - x_D} \right]. \tag{16}$$

Hence, there will be an amplification bias, $|b| > |\beta|$ and $sign(b) = sign(\beta)$, if $x_S > x_D > 0$. The bias can be large if the two groups of countries have very similar x-characteristics because, in this case, there is a strong positive association between the country characteristic x_n and technological similarity with the US.

Figure 1: The amplification bias in a simple setting.

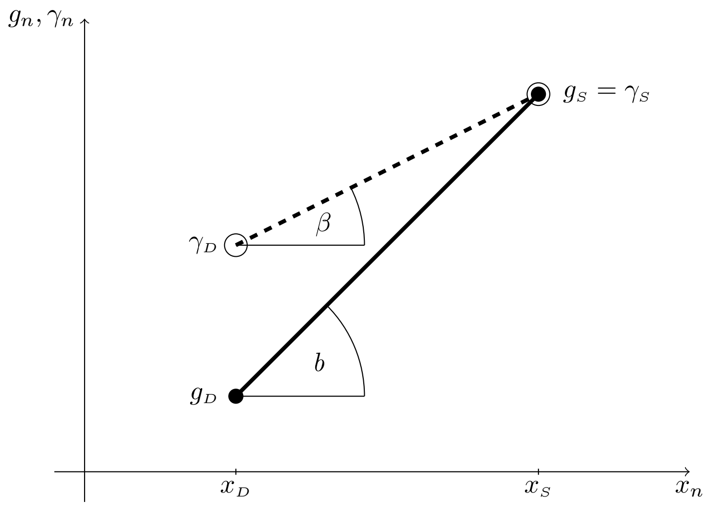


Figure 1 gives a graphical illustration of the amplification bias in the two-group setting for $\beta > 0$. The two circles mark the true country-specific slopes γ_S and γ_D for x_S and x_D respectively. The parameter β is the slope of the dashed line connecting the circles as (12) implies $\beta = (\gamma_S - \gamma_D)/(x_S - x_D)$. The two solid dots mark the least-squares estimates g_S and g_D for x_S and x_D respectively. Equation (15) implies that the benchmarking estimator b is the slope of the solid line connecting the solid dots, $b = (g_S - g_D)/(x_S - x_D)$. The amplification bias $b > \beta > 0$ emerges because:

(i) Countries in group S with high x-values have the same technological industry characteristics as the US. Hence, there is no measurement error when the US is used to proxy for the industry characteristics of these countries. This implies that the least-squares slope estimates for these countries are equal to the true slopes, $g_S = \gamma_S$. That is, the circle and the solid dot lie on top of each other.

(ii) Countries in group D with low x-values have technological industry characteristics that are somewhat different from those of the US, and US industry characteristics therefore proxy for the technological industry characteristics of all low-x countries with some error. Hence, the least-squares slopes estimates g_D for these countries underestimates the true slopes, $g_D < \gamma_D$. That is, the solid dot lies below the circle.

Hence, cross-country heterogeneity in technological industry characteristics implies that using the US industry proxy yields a consistent estimate of γ_S for high-x countries that are technologically identical to the US, but a downwards biased estimate of γ_D for low-x countries that are technologically different from the US. Because the standard benchmarking estimator b is the slope of the solid line connecting the solid dots while the parameter of interest β is the slope of the dashed line connecting the circles, this leads to an amplification bias, $0 < \beta < b$. More generally, the amplification bias of the standard benchmarking estimator arises when greater technological similarity between high-x countries and the US leads to a sufficiently smaller attenuation bias for the country-specific slope estimates of high-x countries.

The size of the amplification bias in the two-group example does not depend on the relative number of countries in the two groups. But the more countries there are in group S with high x-values relative to group D with low x-values, the more similar the average country becomes technologically to the US. Hence, the amplification bias could be sizeable although the average country is quite similar technologically to the US.

3.2.3 The Bias of the Standard Benchmarking Estimator: the General Case

To characterize the bias of the standard benchmarking estimator more generally, it is useful to distinguish between $\beta = 0$ and $\beta \neq 0$.

If $\beta = 0$, (8) simplifies to $b = \alpha A \sigma^2 / Var(z_{US})$ with $\sigma^2 / Var(z_{US}) < 1$. Hence, with cross-country heterogeneity in technological industry characteristics, $\sigma^2 > 0$, the benchmarking estimator is biased upwards if $\alpha A > 0$ and downwards if $\alpha A < 0$.

If $\beta \neq 0$, the benchmarking estimator in (8) can be written as

$$b = \beta \left[\left(1 - \frac{\sigma^2}{Var(z_{US})} \right) + \left(\frac{\sigma^2}{Var(z_{US})} \right) \delta \right] \tag{17}$$

where $\sigma^2 / Var(z_{US}) < 1$ and δ is a function of A and B in (9) and (10)

$$\delta = \theta A + B \tag{18}$$

with

$$\theta = \frac{\alpha}{\beta}. \tag{19}$$

Hence, when there is cross-country heterogeneity in technological industry characteristics, $\sigma^2 > 0$, the bias of the benchmarking estimator depends on δ. If $\delta = 0$, the benchmarking estimator is attenuated. For example, our framework yields $\delta = 0$ when country-specific industry characteristics are uncorrelated across countries. The expression for the probability limit of the benchmarking estimator in (17) with $\delta = 0$ is analogous to that of the least-squares estimator in the presence of classical measurement error, with $1 - \sigma^2 / Var(z_{US})$ playing the role of the reliability or signal-to-total-variance ratio (e.g., Wooldridge, 2002). If

$\delta > 0$, there is a (counteracting) force that weakens the attenuation bias and can result in an amplification bias. If $\delta < 0$, the benchmarking estimates may have the wrong sign.

We now summarise how the bias of the standard benchmarking estimator depends on δ.

PROPOSITION 1 (Bias of standard benchmarking estimator when $\boldsymbol{\beta} \neq \mathbf{0}$).

1. *If $0 \leq \delta \leq 1$, the standard benchmarking estimator is subject to an attenuation bias: b has the same sign as β but is biased towards zero, $sign(b) = sign(\beta)$ and $|b| \leq |\beta|$.*

2. *If $\delta > 1$, the standard benchmarking estimator is subject to an amplification bias: b has the same sign as β but is biased away from zero, $sign(b) = sign(\beta)$ and $|b| > |\beta|$.*

3. *If $\delta < 0$, the standard benchmarking estimator may be subject to an attenuation bias, an amplification bias, or may have a different sign than β, depending on $\sigma^2/Var(z_{US})$.*

4 Identification of β

To get a first idea how the effect of interest might be identified and where the challenges lie, we return to the expression for the benchmarking estimator in (17). Inverting it yields $\beta = b/[1+(\delta-1)\sigma^2/Var(z_{US})]$. The right-hand-side parameter b can be identified using the benchmarking approach in the literature, and the variance of the US industry characteristics $Var(z_{US})$ is observable. If we can identify δ and σ^2, we can therefore identify β. As we will show, δ can be identified from the variances and covariances of industry outcomes for different country pairs. If these variances and covariances would also identify the variance of country-specific industry characteristics σ^2, identification of β would be straightforward. But the variances and covariances of industry outcomes do not identify σ^2.

To see how the variances and covariances of industry outcomes for different country pairs help to identify β, we rewrite the model in (1) as

$$y_{in} = v_i + v_n + \gamma_i x_n + u_{in} \tag{20}$$

where

$$\gamma_i = \beta z_i \tag{21}$$

and

$$u_{in} = (\alpha + \beta x_n)\varepsilon_{in} \tag{22}$$

and v_i and v_n denote industry and country fixed effects.[11] The industry-specific slopes γ_i capture the effect of the country characteristic on outcomes in different industries.

The effect of (unobservable) country-specific technological industry characteristics ε_{in} on industry outcomes is captured by u_{in} in (22). As a result, $E(u_{in}u_{im})$, the variances and covariances of u_{in} for industry i and countries n, m, play a central role for the identification. To see this, note that (3) and (22) imply

$$E(u_{in}u_{im}) = (\alpha\sigma + \beta\sigma x_n)(\alpha\sigma + \beta\sigma x_m)\rho_{nm} = \omega_{nm}. \tag{23}$$

The ω_{nm} are useful for identifing δ in (18) as they reflect the ρ_{nm}, how similar any two countries are technologically, and α/β, the direct effect of technological industry characteristics on industry outcomes relative to the industry-country-interaction effect. However, the ω_{nm} will not allow us to identify the variance of country-specific industry characteristics σ^2.

[11] These industry and country fixed effects capture the industry and country fixed effects in v_{in} and absorb αz_i in the industry fixed effect and z_n in the country fixed effect.

This is because the ω_{nm} solely reflect σ^2 through its effects on outcomes, which is why σ appears multiplied by either α or β. This is what makes the identification of β challenging. To see when and how identification is possible, we proceed in two steps. We first examine the identification of β for known ω_{nm}. Then we discuss how the ω_{nm} can be identified.

4.1 Identification for Known $\mathbf{\Omega}$

It is convenient to collect the variances and covariances ω_{nm} in (23) for all countries n, m in the $N \times N$ variance-covariance matrix $\mathbf{\Omega}$. The straightforward part is determining whether or not $\beta = 0$. The elements on the diagonal of $\mathbf{\Omega}$ are equal to $\omega_{nn} = (\alpha\sigma + \beta\sigma x_n)^2$. As long as there is some cross-country heterogeneity in technological industry characteristics, $\sigma^2 > 0$, the ω_{nn} are independent of country characteristics if and only if $\beta = 0$. Hence, we obtain that $\beta = 0$ if the ω_{nn} are independent of x_n.

The next question is how to identify β if the ω_{nn} depend on the country characteristics x_n. We first explain how $\mathbf{\Omega}$ can be used to obtain two key parameters, δ and $(\beta\sigma)^2$. Then we show how δ and $(\beta\sigma)^2$ can be used to identify β.

We start by determining $\alpha\sigma$ and $\beta\sigma$ from the variances $\omega_{nn} = (\alpha\sigma + \beta\sigma x_n)^2$. This is possible if there are at least two countries with different x-values, so that we have at least two equations in the two unknowns $\alpha\sigma$ and $\beta\sigma$.[12] Then we invert the expression for the covariances ω_{nm} for $n \neq m$ in (23) to get $\rho_{nm} = \omega_{nm}/[(\alpha\sigma + \beta\sigma x_n)(\alpha\sigma + \beta\sigma x_m)]$. This allows us to obtain the ρ_{nm} by combining the ω_{nm} with $\alpha\sigma$ and $\beta\sigma$. Once we have obtained $\alpha\sigma$, $\beta\sigma$, and ρ_{nm}, it is straightforward to obtain A and B in (9)–(10), θ in (19), and δ in (18).

[12] Using more than two ω_{nn} equations leaves results unchanged. When we use our identification results for estimation, we use all ω_{nn} equations.

To see when and how δ and $(\beta\sigma)^2$ allow us to identify β, we start from the expression for the bias of the benchmarking estimator $b-\beta = \beta(\delta-1)\sigma^2/Var(z_{US})$ obtained by rearranging (17). Multiplying both sides by β yields $(b-\beta)\beta = (\delta-1)(\beta\sigma)^2/Var(z_{US})$. The right-hand side parameters δ and $(\beta\sigma)^2$ can be obtained from $\mathbf{\Omega}$ and $Var(z_{US})$ is the observable variance of US industry characteristics. The parameter b is identified by the standard benchmarking approach in the literature. Hence, β is the only unknown of the quadratic equation

$$(b-\beta)\beta = \eta(\delta-1) \tag{24}$$

where we defined

$$\eta = \frac{(\beta\sigma)^2}{Var(z_{US})}. \tag{25}$$

This establishes a key result: β is one of the solutions for q of the quadratic equation

$$(b-q)q = \eta(\delta-1). \tag{26}$$

In addition to the solution $q_1 = \beta$, (26) has a second solution $q_2 = \beta(\delta-1)\sigma^2/Var(z_{US})$. We therefore need to analyze which solution identifies β. We start with the case where δ is positive and smaller than 2. This implies $(\delta-1)\sigma^2/Var(z_{US}) \in (-1,1)$ and hence $|q_1| > |q_2|$. As a result, β can be identified as $\beta = \max(|q_1|, |q_2|)$.

This expression for β does not generalize to other cases where β is exactly identified. An alternative expression that holds for all cases where β is exactly identified is $\beta = \kappa b$, where

b is the benchmarking estimator and κ is a function of the two solutions for q in (26)

$$\kappa = \max\left(\frac{q_1}{q_1+q_2}, \frac{q_2}{q_1+q_2}\right). \tag{27}$$

The next proposition, proven in the Supplementary Appendix, summarizes this result.

PROPOSITION 2 (Identifying β: sufficient condition in terms of identifiable δ). *If $\delta \in [0,2]$, β can be identified as $\beta = \kappa b$ where b is the probability limit of the standard benchmarking estimator and κ is defined in (27).*

The next proposition gives a necessary and sufficient condition for the exact identification of β for known $\mathbf{\Omega}$.

PROPOSITION 3 (Identifying β: necessary and sufficient condition in terms of identifiable δ and κ). *β can be exactly identified if and only if*

$$\begin{array}{llll} \textit{either} & \delta \geq 0 & \textit{and} & \kappa \geq \frac{\delta-1}{\delta} \\ \textit{or} & \delta < 0 & \textit{and} & \kappa \leq \frac{\delta-1}{\delta} \end{array} \tag{28}$$

where δ is defined in (18) and κ is defined in (27). If this condition is not satisfied, β is equal to one of the two solutions for q in (26), but it cannot be determined which.

When β is exactly identified, it can be obtained as

$$\beta = \kappa b \tag{29}$$

where b is the probability limit of the standard benchmarking estimator.

The proposition is proven in the Supplementary Appendix. The idea is the following. The two solutions of the quadratic equation in (26) yield two candidate solutions for β. Each can be combined with the variance of US industry characteristics and the identifiable parameter η in (25) to yield two candidate solutions for the country-specific technological heterogeneity parameter σ^2. As at least some of the variation in technological industry characteristics reflects a global component, it must be that $0 \leq \sigma^2 < Var(z_{US})$. This restriction is only satisfied by one of the two candidate solutions for σ^2 if (28) holds. Hence, only one of the two solutions of (26) is consistent with the model and this solution is $\beta = \kappa b$. On the other hand, if condition (28) fails, both solutions of (26) imply candidate solutions for σ^2 that are consistent with the model and it is impossible to say which identifies β.

The next proposition gives the necessary and sufficient condition for identification in terms of σ^2 and δ.

PROPOSITION 4 (Identifying β: necessary and sufficient condition in terms of model parameters). *β can be exactly identified if and only if*

$$(\delta - 1)^2 \left(\frac{\sigma^2}{Var(z_{US})} \right) \leq 1. \tag{30}$$

If this condition is not satisfied, β is one of the two solutions for q in (26), but it cannot be determined which.

Intuitively, Proposition 4 implies that β can be identified exactly if cross-country heterogeneity in technological industry characteristics is not too large ($\sigma^2/Var(z_{US})$ not too large) and/or if the association between countries' technological similarity with the US and their x-characteristics is not too strong (δ not too large in absolute value).

When exact identification of β is impossible, one could report both solutions for q in (26) as possible values for β. An alternative is to establish bounds on β in terms of the standard benchmarking estimator b. For $\delta > 2$, we have already established upper and lower bounds in Proposition 1. The next proposition establishes somewhat tighter bounds under the condition that $\delta > 2$ and that exact identification of β is impossible. For completeness, the proposition also gives bounds for the case $\delta < 0$ even though these are less useful. The proof of the proposition is in the Supplementary Appendix.

Proposition 5 (Bounds on β). *If the condition in (28) does not hold and exact identification of β is impossible, then*

$$\begin{aligned} &\text{if } \delta > 2 \text{ then } \frac{\beta}{b} \in \left(\frac{1}{\delta}, \frac{\delta-1}{\delta}\right) \\ &\text{if } \delta < 0 \text{ then } \frac{\beta}{b} \notin \left[\frac{1}{\delta}, \frac{\delta-1}{\delta}\right]. \end{aligned} \tag{31}$$

For example, suppose that $\delta = 2.5$, b is positive, and (28) does not hold. Proposition 5 implies that β is between $0.4b$ and $0.6b$. Hence, we can infer the range and the sign of the parameter of interest β from the standard benchmark estimator b. As another example, suppose that $\delta = -2.5$, b is positive, and (28) does not hold. Proposition 5 implies that β is smaller than $-0.4b$ or larger than $0.6b$. Hence, we cannot establish an upper or lower bound for β, nor can we infer the sign of β from the sign of b.

4.2 Identification of $\boldsymbol{\Omega}$

Now we turn to the identification of $\boldsymbol{\Omega}$. Our approach is closely related to the identification of variance-covariance matrices in general least squares theory. The first step consists of least-squares estimation and the second step involves understanding when and how the least-squares residuals can be used to identify $\boldsymbol{\Omega}$.

The starting point to identify $\mathbf{\Omega}$ is least-squares estimation of (20). The residuals $\widehat{u}_{in} = y_{in} - \widehat{\upsilon}_i - \widehat{\upsilon}_n - \widehat{\gamma}_i x_n$, with hats denoting least-squares estimates, allow us to estimate $\frac{1}{I}\sum_{i=1}^{I}\widehat{u}_{in}\widehat{u}_{im}$ for all country pairs n, m. These depend on the ω_{nm} we collected in the variance-covariance matrix $\mathbf{\Omega}$ and can therefore be used to identify $\mathbf{\Omega}$.

Relating $\mathbf{\Omega}$ to the variances and covariances of the residuals across industries. We now derive the relationship between the variances and covariances across industries of the residuals $\widehat{u}_{in}$ for all pairs of countries n, m, $\frac{1}{I}\sum_{i=1}^{I}\widehat{u}_{in}\widehat{u}_{im}$, and the elements ω_{nm} of $\mathbf{\Omega}$.

The first step is to express the least-squares residuals $\widehat{u}_{in}$ in terms of the underlying disturbances u_{in} in (20)

$$\widehat{u}_{in} = \upsilon_{in} - (x_n - \overline{x})\sum_{k=1}^{N}\psi_k \upsilon_{ik} \tag{32}$$

where the υ_{in} are the demeaned versions of u_{in}

$$\upsilon_{in} = u_{in} - \frac{1}{N}\sum_{m=1}^{N} u_{im} - \frac{1}{I}\sum_{j=1}^{I} u_{jn} + \frac{1}{N}\frac{1}{I}\sum_{m=1}^{N}\sum_{j=1}^{I} u_{jm} \tag{33}$$

and the ψ_k are the least-squares regression weights

$$\psi_k = \frac{x_k - \overline{x}}{\sum\limits_{p=1}^{N}(x_p - \overline{x})^2}. \tag{34}$$

The second step is to calculate the probability limit as the number of industries goes to infinity of the variances and covariances of the residuals across industries for all country pairs, which we refer to as π_{nm}

$$\pi_{nm} = \operatorname*{plim}_{I \to \infty} \frac{1}{I} \sum_{i=1}^{I} \widehat{u}_{in} \widehat{u}_{im}. \tag{35}$$

We show in the Supplementary Appendix that using (32)-(33) in (35) yields the following equations linking π_{nm} and the elements ω_{nm} of $\mathbf{\Omega}$

$$\pi_{nm} = \omega_{nm} - \mu_n - \mu_m - (x_n - \overline{x})\lambda_m - (x_m - \overline{x})\lambda_n \tag{36}$$

where μ_n and λ_n are functions of the ω_{nm} and

$$0 = \sum_{n=1}^{N} \lambda_n. \tag{37}$$

These equations are the basis for the identification of the variance-covariance matrix $\mathbf{\Omega}$.

A structure for $\mathbf{\Omega}$. It is well understood that the identification of the variance-covariance matrix $\mathbf{\Omega}$ is impossible for an arbitrary matrix, as (36) and (37) has more unknowns than linearly independent equations (e.g., Amemiya, 1985).[13] For identification to be possible, the empirical framework must put some structure on $\mathbf{\Omega}$. The structures used in the literature depend on the application (e.g., Amemiya, 1985; Wooldridge, 2002; Conley, 2010).

We choose a structure for $\mathbf{\Omega}$ that has the implicit structure in the CI/CC literature as a special case and at the same time allows us to examine the limits of identification. The implicit structure for $\mathbf{\Omega}$ in the cross-industry cross-country literature is that differences between the technological industry characteristics of a country and global technological industry

[13]We show this in the Supplementary Appendix.

characteristics are completely idiosyncratic. This implies that the technological industry characteristics of different countries are related through the global component only. As we have seen above, the benchmarking estimator is attenuated in this case. Our structure for $\mathbf{\Omega}$ follows the CI/CC literature in that the technological industry characteristics of *some country pairs* are related through the global component only. But for all other country pairs, we allow for an entirely arbitrary correlation between the country-specific technological industry characteristics.

Specifically, our structure for $\mathbf{\Omega}$:

(i) Allows for an arbitrary correlation ρ_{nm} with $n \neq m$ between the country-specific technological industry characteristics of two countries if they are sufficiently similar. Two countries are taken to be sufficiently similar if the distance between their x-characteristics is below a threshold τ. When we set large values for the threshold τ, many country pairs satisfy $|x_n - x_m| \leq \tau$, and our structure for $\mathbf{\Omega}$ allows for arbitrary correlations ρ_{nm} between the country-specific technological industry characteristics of many country pairs. Formally, for these country pairs, technological similarity as measured by $corr(z_{in}, z_{im})$ is $[Var(z_i) + \sigma^2 \rho_{nm}]/(Var(z_i) + \sigma^2)$. Hence, the technological industry characteristics of these country pairs *are not* related through the global component only and can be related in arbitrary ways to all country characteristics.

(ii) When the distance between the x-characteristics of a country pair exceeds the threshold τ, their country-specific industry characteristics are taken to be uncorrelated, $\rho_{nm} = 0$.[14] This implies that the technological industry characteristics of these country pairs *are* related through the global technological component only (as implicitly assumed for all

[14] The approach can be thought of as a cross-country analogue of so-called K-dependence in time-series econometrics, which allows for any correlation between random variables at t and T if $|t - T| \leq \tau$ but assumes independence if $|t - T| > \tau$ (e.g., Amemiya, 1985).

country pairs in the CI/CC literature). Formally, technological similarity as measured by $corr(z_{in}, z_{im})$ for country pairs with $\rho_{nm} = 0$ is $Var(z_i)/(Var(z_i)+\sigma^2)$. By increasing τ, we reduce the number of country pairs with $\rho_{nm} = 0$ and therefore deviate substantially from the implicit assumption in the CI/CC literature.

We refer to this structure for the variance-covariance matrix $\mathbf{\Omega}$ as $\mathbf{\Omega}^{\tau}$ to capture that it depends on the threshold τ. $\mathbf{\Omega}^{\tau}$ corresponds to the implicit structure in the CI/CC literature for $\tau = 0$. We can move away from this baseline quite continuously by increasing τ. Moreover, the structure does not impose any functional form on how the technological similarity of country pairs with $|x_n - x_m| \leq \tau$ depends on country characteristics. On the other hand, the number of parameters to be estimated increases very rapidly with τ and this could lead to noisy estimation results.

The threshold τ must be interpreted relative to the distribution of the x-characteristic across countries. It is therefore easier to think about the fraction of unrestricted ρ_{nm} with $n \neq m$ implied by a threshold τ. When τ is very small, the fraction of unrestricted ρ_{nm} will be small as few country pairs will satisfy $|x_n - x_m| \leq \tau$. Hence, the assumed structure for $\mathbf{\Omega}$ will be similar to the implicit structure in the CI/CC literature and relatively few parameters will have to be estimated. On the other hand, when τ is large, the fraction of unrestricted ρ_{nm} will be large and a large number of parameters need to be estimated. (If the threshold τ is so large that all country pairs can have different ρ_{nm}, we are not imposing any structure on $\mathbf{\Omega}$ and identification is impossible.)

As the choice is difficult in practice, we vary the threshold τ over the range that permits identification of $\mathbf{\Omega}$. Put differently, we allow the fraction of unrestricted ρ_{nm} to vary between zero and the maximum that still permits identification of $\mathbf{\Omega}$. As this maximum can be large, our structure for $\mathbf{\Omega}$ can deviate substantially from the implicit structure in the CI/CC. By varying the fraction of the unrestricted ρ_{nm} between zero and the maximum that permits identification, we examine how sensitive the results for β are to the restrictions put on $\mathbf{\Omega}$.

Summarizing, we assume that if countries have sufficiently similar x-characteristics $|x_n - x_m| < \tau$, ρ_{nm} with $n \neq m$ is unrestricted. On the other hand, $\rho_{nm} = 0$ if $|x_n - x_m| \geq \tau$. We present results for the range of τ allowing for the identification of $\mathbf{\Omega}$.

In many economic applications of CI/CC models more parsimonious structures for $\mathbf{\Omega}$ could be chosen. For example, the structures used in spatial econometrics for spatial dependence can be adapted to capture the technological similarity of countries as a function of their x-characteristics and other country characteristics (e.g., Conley, 2010). The advantage of more parsimonious structures is that many fewer parameters need to be estimated.

A condition for identification of $\mathbf{\Omega}$. The structure $\mathbf{\Omega}^\tau$ for the variance-covariance matrix $\mathbf{\Omega}$ assumes $\rho_{nm} = 0$ and hence $\omega_{nm} = 0$ in (23) for all country pairs with relatively different x-characteristics, $|x_n - x_m| \geq \tau$. We denote the number of such country pairs by Q. For these Q country pairs, (36) simplifies to

$$\pi_{nm} = -\mu_n^\tau - \mu_m^\tau - (x_n - \overline{x})\lambda_m^\tau - (x_m - \overline{x})\lambda_n^\tau. \tag{38}$$

These equations are the starting point for the identification of $\mathbf{\Omega}^\tau$ from the π_{nm}. In particular, we use these equations to try and determine the μ_n^τ and λ_n^τ for all n. Then we use (36) to determine the ω_{nm}^τ for all other country pairs.

It is useful write the Q equations in (38) and the restriction in (37) in normal form

$$\boldsymbol{\pi} = \mathbf{G}^{\tau} \begin{pmatrix} \boldsymbol{\mu}^{\tau} \\ \boldsymbol{\lambda}^{\tau} \end{pmatrix} \tag{39}$$

where $\boldsymbol{\mu}^{\tau} = (\mu_1^{\tau}, \ldots, \mu_N^{\tau})'$ and $\boldsymbol{\lambda}^{\tau} = (\lambda_1^{\tau}, \ldots, \lambda_N^{\tau})'$ collect the $2N$ unknowns; $\boldsymbol{\pi}$ is a column vector of length $Q+1$ that collects the values on the left-hand side of equations (37) and (38); and $\mathbf{G}^{\tau}$ is a $(Q+1) \times 2N$ matrix of coefficients implied by the right-hand side of equations (37) and (38). By writing the equations in (37) and (38) in normal form, it becomes clear that $\boldsymbol{\mu}^{\tau}$ and $\boldsymbol{\lambda}^{\tau}$ can be determined if the matrix $\mathbf{G}^{\tau}$ has full rank.

An illustration of the identification condition. We can identify the variance-covariance matrix $\boldsymbol{\Omega}^{\tau}$ if the matrix $\mathbf{G}^{\tau}$ has full rank. This depends on the distance threshold τ and the distribution of the x-values across countries.

Table 1 illustrates this for three types of distributions for the x-values. For each distribution, we draw x-values for 150 countries.[15] We repeat this 50 times. For each draw we calculate the value for the maximum threshold $\tau_{\max}$ such that $\mathbf{G}^{\tau}$ has full rank. As this value is somewhat difficult to interpret, we:

(i) We calculate the average distance $|x_n - x_m|$ across all possible country pairs for each draw. This allows comparing $\tau_{\max}$ with the average distance in the x-characteristics across all country pairs and get a sense whether $\tau_{\max}$ is relatively large or small.

(ii) We calculate the number of countries with unrestricted ρ_{nm} with $n \neq m$ that are implied by $\tau_{\max}$. We then report this number relative to the total number of country pairs.

[15]This is approximately the number of countries in our application of the new benchmarking estimator below. We obtain similar results for 75, 250, and 500 countries.

Table 1: Identification of the variance-covariance matrix.

Distribution	Average distance between x_n across all country pairs	Maximum threshold τ allowing identification ($\tau_{\max}$)	Country pairs $n \neq m$ with unrestricted ρ_{nm} relative to total number of country pairs at $\tau_{\max}$
Uniform on $[0, 1]$	0.33	0.48	0.74
Standard normal	1.13	2.43	0.91
Exp. with $\lambda = 1$	1.00	2.31	0.89

Table 1 presents our results. We start with the case where country characteristics are uniformly distributed between 0 and 1. The distance $|x_n - x_m|$ averaged across all country pairs is 0.33. The maximum value of the distance threshold τ that permits identification ($\tau_{\max}$) is 0.48. The share of country pairs with unrestricted ρ_{nm} with $n \neq m$ at $\tau_{\max}$ is 74%. The statistics in the last two columns remain nearly unchanged when we vary the support of the uniform distribution (not in the table).

Table 1 also shows results when the country characteristics are drawn from a standard normal distribution. The distance $|x_n - x_m|$ averaged across all country pairs is 1.13. $\tau_{\max}$ is 2.43. The share of country pairs with unrestricted ρ_{nm} with $n \neq m$ at $\tau_{\max}$ is 91%. The statistics in the last two columns do not vary with the mean of the normal distribution and remain nearly unchanged when we vary the standard deviation (not in the table). The third case has country characteristics drawn from an exponential distribution and yields results similar to the normal distribution.

5 An Application

We now apply our identification results. We start by explaining how to go from identification to estimation. Then we use the approach to reestimate Nunn (2007).

5.1 From Identification to Estimation

We first explain how our identification results can be used to obtain consistent estimates of q in (26) in five steps.

Step 1: Estimate (20) with least squares and then use the residuals to estimate the variances and covariances across industries of the residuals for all country pairs

$$\widehat{\pi}_{nm} = \frac{1}{I} \sum_{i=1}^{I} \widehat{u}_{in} \widehat{u}_{im}. \tag{40}$$

These variances and covariances are consistent estimators of the π_{nm} in (35) as the number of industries I goes to infinity.

Step 2: Estimate $\boldsymbol{\mu}^{\tau}$ and $\boldsymbol{\lambda}^{\tau}$ on the basis of (39). We start by obtaining the matrix $\mathbf{G}^{\tau}$ for different distance cutoffs τ. We begin with very small values of τ. If all countries have different x-characteristics (as in our application below), the $\rho_{nm} = 0$ condition is imposed for all country pairs $n \neq m$ and that $\boldsymbol{\Omega}$ is a diagonal matrix (as implicitly assumed in the CI/CC literature). The implied matrix $\mathbf{G}^{\tau}$ is of full rank. We then increase τ up to the maximum value still yielding a matrix $\mathbf{G}^{\tau}$ of full rank. To estimate $\boldsymbol{\mu}^{\tau}$ and $\boldsymbol{\lambda}^{\tau}$, we also need an estimator of the column vector $\boldsymbol{\pi}$. We obtain this estimator by replacing the π_{nm} collected in the vector $\boldsymbol{\pi}$ with the estimates $\widehat{\boldsymbol{\pi}}_{nm}$ in (40). Of course, we cannot estimate

$\boldsymbol{\mu}^{\tau}$ and $\boldsymbol{\lambda}^{\tau}$ by simply replacing $\boldsymbol{\pi}$ with $\widehat{\boldsymbol{\pi}}$ in (39). This is because generally $\widehat{\boldsymbol{\pi}} \neq \boldsymbol{\pi}$ due to sampling error and the equation system in (39) would therefore be overdetermined. Instead, $\boldsymbol{\mu}^{\tau}$ and $\boldsymbol{\lambda}^{\tau}$ are estimated by applying least squares to

$$\widehat{\boldsymbol{\pi}} = \mathbf{G}^{\tau} \begin{pmatrix} \boldsymbol{\mu}^{\tau} \\ \boldsymbol{\lambda}^{\tau} \end{pmatrix} + \mathbf{v} \tag{41}$$

where $\mathbf{v}$ is a column vector of length $Q+1$ that captures the sampling error $\widehat{\boldsymbol{\pi}} - \boldsymbol{\pi}$. Because $\widehat{\boldsymbol{\pi}}$ is a consistent estimator of $\boldsymbol{\pi}$ as the number of industries I goes to infinity, the least-squares estimators $\widehat{\boldsymbol{\mu}}^{\tau}$ and $\widehat{\boldsymbol{\lambda}}^{\tau}$ are consistent estimators of $\boldsymbol{\mu}^{\tau}$ and $\boldsymbol{\lambda}^{\tau}$.

Step 3: Estimate the non-zero elements ω_{nm}^{τ} of $\boldsymbol{\Omega}^{\tau}$ by combining (36) with $\widehat{\boldsymbol{\mu}}^{\tau}$, $\widehat{\boldsymbol{\lambda}}^{\tau}$, and $\widehat{\boldsymbol{\pi}}$. This yields

$$\widehat{\omega}_{nm}^{\tau} = \widehat{\mu}_{n}^{\tau} + \widehat{\mu}_{m}^{\tau} + (x_n - \overline{x})\widehat{\lambda}_{m}^{\tau} + (x_m - \overline{x})\widehat{\lambda}_{n}^{\tau} + \widehat{\pi}_{nm}. \tag{42}$$

Consistency of the $\widehat{\omega}_{nm}^{\tau}$ follows from the consistency of $\widehat{\boldsymbol{\mu}}^{\tau}$, $\widehat{\boldsymbol{\lambda}}^{\tau}$, and $\widehat{\boldsymbol{\pi}}$. The estimates of ω_{nm}^{τ} allow us to estimate θ, $\beta\sigma$, and ρ_{nm}. The estimates of θ and $\beta\sigma$ are obtained by combining the expressions for the variances $\omega_{nn} = (\theta + x_n)^2(\beta\sigma)^2$ in (23) with $\widehat{\omega}_{nn}^{\tau}$. This yields

$$\widehat{\omega}_{nn}^{\tau} = (\theta + x_n)^2(\beta\sigma)^2 + \upsilon_{nn} \tag{43}$$

where υ_{nn} captures sampling error. The nonlinear least-squares estimates of θ and $\beta\sigma$ are then combined with ω_{nm}^{τ} and the expression for the covariances in (23) to estimate the nonzero ρ_{nm}^{τ} using that $\rho_{nm}^{\tau} = \omega_{nm}^{\tau}/[(\theta + x_n)(\theta + x_m)(\beta\sigma)^2]$. Moreover, $\beta\sigma$ can be combined with the variance of the industry characteristics in the benchmark country $Var(z_{US})$ to estimate $\widehat{\eta}$ using (25). Consistency follows from the consistency of the $\widehat{\omega}^{\tau}_{nm}$.

Step 4: Use the $\widehat{\rho}^{\tau}_{nm}$ to estimate $\widehat{A}^{\tau}$ and $\widehat{B}^{\tau}$ using (9)-(10) and $\widehat{\delta}^{\tau}$ using (18)

$$\widehat{\delta}^{\tau} = \widehat{\theta}\widehat{A}^{\tau} + \widehat{B}^{\tau}. \tag{44}$$

Step 5: Replace δ and η in (26) by $\widehat{\delta}^{\tau}$ and $\widehat{\eta}$ and obtain estimates of q by solving

$$(\widehat{b} - q)q = \widehat{\eta}^{\tau}(\widehat{\delta}^{\tau} - 1) \tag{45}$$

where $\widehat{b}$ is the standard benchmarking estimator.

The estimates of q based on (45) can be used to estimate β as explained in Proposition 2 and Proposition 3 or to obtain bounds on β as explained in Proposition 5. Confidence bands of all our estimates are obtained by bootstrapping.[16]

5.2 Reestimating Nunn (2007)

Nunn employs export data for up to 222 industries in 146 countries to show that institutional quality has a positive effect on comparative advantage in industries that depend more on differentiated inputs.[17] In terms of the model in (1), the institutional quality of countries

[16] Bootstrapping the confidence intervals of our estimates of δ and β involves reshuffling the u_{in} in (20) across industries for each country 100 times and each time reestimating $\boldsymbol{\pi}$, $\boldsymbol{\mu}$, $\boldsymbol{\lambda}$, ω_{nm}, θ, $\beta\sigma$, A, B, ρ_{nm}, δ, η, q_1, q_2, and β. Confidence intervals are based on the standard deviations of the bootstrapped distributions.

[17] See Levchenko (2007) and Costinot (2009) for related work on institutions and comparative advantage.

takes the place of x_n and log exports in industry i the place of y_{in}. The relevant industry characteristic z_{in} is the differentiated-input intensity of production and the benchmark country is the US. We now apply our estimation approach using Nunn's setting and data.

Figure 2: Estimates of δ for Nunn's baseline specification.

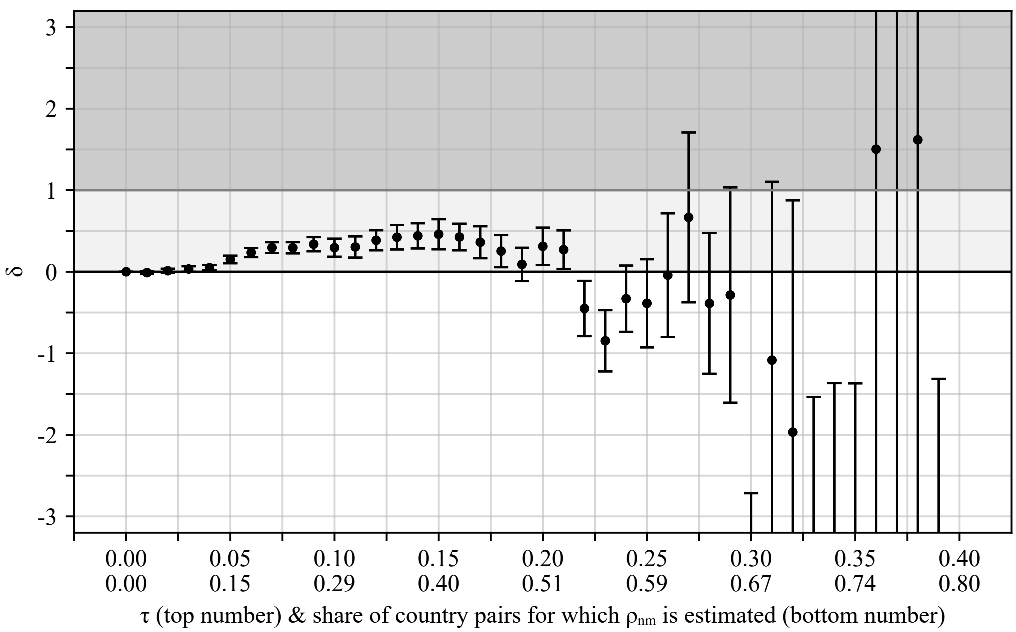
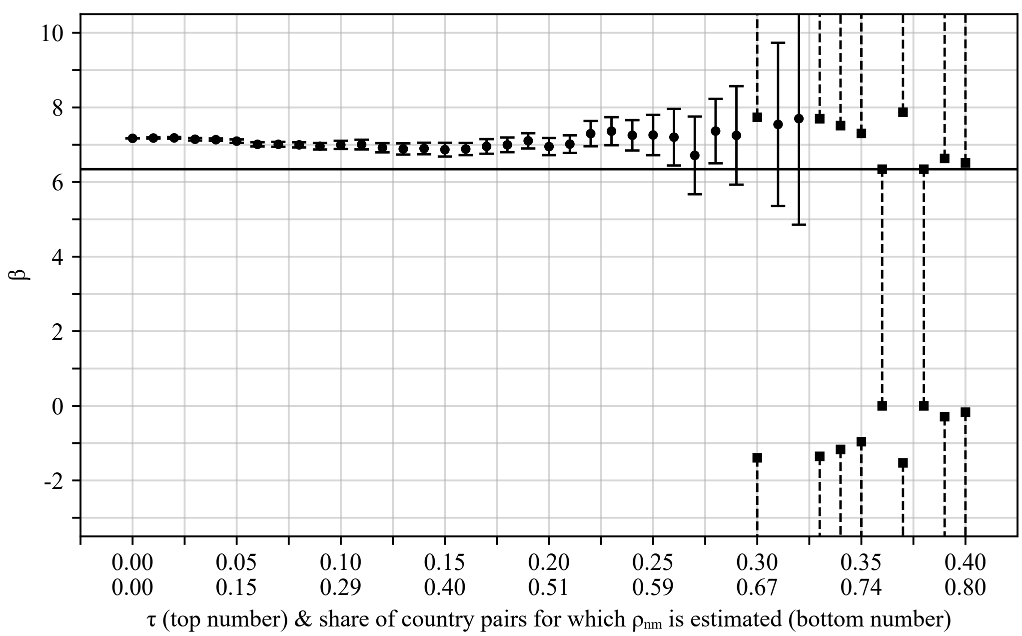


Figure 2 summarises our results for δ for Nunn's baseline specification. Estimates are shown as dots and 95% confidence intervals as bracketed lines. The area shaded in light grey marks values of δ that according to Proposition 1 result in an attenuation bias of the standard benchmarking estimator ($0 \leq \delta < 1$). The area shaded in darker grey marks values of δ that result in an amplification bias of the standard benchmarking estimator ($\delta > 1$). For very small values of τ, we obtain $\delta = 0$. This is unsurprising as the condition $\rho_{nm} = 0$ for $n \neq m$ is assumed for all country pairs in this case. Hence, $A = B = 0$ in (9)–(10) and $\delta = 0$ in (18). Estimates of δ remain very small for values of τ smaller than 0.02. Point estimates are between −0.01 and +0.01 and 95% confidence intervals include 0. Hence, we cannot reject $\delta = 0$. According to Proposition 1, $\delta = 0$ implies that the benchmarking estimator is subject to an attenuation bias. According to Proposition 2, $\delta = 0$ implies that we can estimate β as $\beta = \kappa b$ with κ given in (27). Figure 3 shows our point estimates of β as dots and 95% confidence intervals as bracketed lines. Point estimates are around 7.2, 10% larger than Nunn's estimate of 6.6 obtained with the standard benchmarking estimator (marked by the horizontal black line).[18]

Figure 3: Estimates of β for Nunn's baseline specification.



For values of τ between 0.03 and 0.21, point estimates of δ in Figure 2 are between 0.04 and 0.49. The 95% confidence bands are strictly between 0 and 1, except for $\tau = 0.19$. The data therefore support values of δ greater than 0 but below 1. Proposition 1 implies that

[18]The estimate reported by Nunn differs because it is standardised.

for $0 \leq \delta \leq 1$, the standard benchmarking estimator is subject to an attenuation bias and Proposition 2 implies that we can estimate β as $\beta = \kappa b$. Figure 3 shows our estimates of β. Point estimates are between 7.2 and 6.8. Hence, the difference with Nunn's estimate is smaller than what we obtained for very small τ. This is because very small values for τ imply that the bias of the standard benchmarking estimator is solely shaped by the force generating an attenuation bias. When δ increases, the bias of the standard benchmarking estimator is also shaped by a force counteracting the attenuation bias.

For values of τ between 0.22 and 0.32, estimates of δ in Figure 2 are mostly negative. As a result, we cannot use Proposition 2 to estimate β. However, we can still estimate β as $\beta = \kappa b$ in most cases as our point estimates of κ satisfy the condition for exact identification in Proposition 3.[19] Figure 3 shows our estimates of β, which are up to 25% larger than Nunn's estimate.

For values of τ between 0.33 and 0.4, our estimates of δ in Figure 2 become very noisy. Point estimates are mostly negative. As the necessary and sufficient condition for exact identification of β in Proposition 3 is not satisfied, we can only establish the bounds in Proposition 5. Figure 3 illustrates the values of β consistent with these bounds as dashed lines delimited by squares. For values of τ larger than 0.4, $\mathbf{G}^\tau$ no longer has full rank and $\mathbf{\Omega}^\tau$ cannot be identified.

Building on Romalis (2004), Nunn also presents results controlling for the effect of capital on comparative advantage. He does so by augmenting his baseline specification with an interaction between country-level human capital and the human-capital-intensity of industries

[19] We are evaluating the condition based on the point estimates of δ and κ.

as well as an interaction between country-level physical capital and the physical-capital-intensity of industries. We apply our alternative estimation approach to Nunn's model with controls by following the same steps as above, except that estimation of (20) accounts for the effect of human and physical capital.

Figure 4: Estimates of δ for Nunn's specification with controls for human and physical capital.

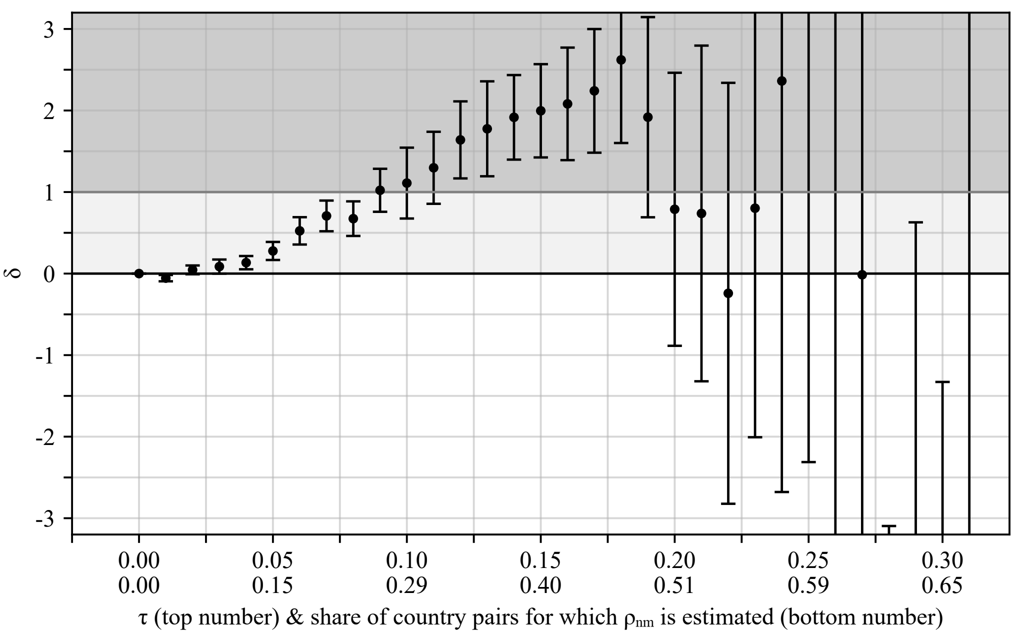
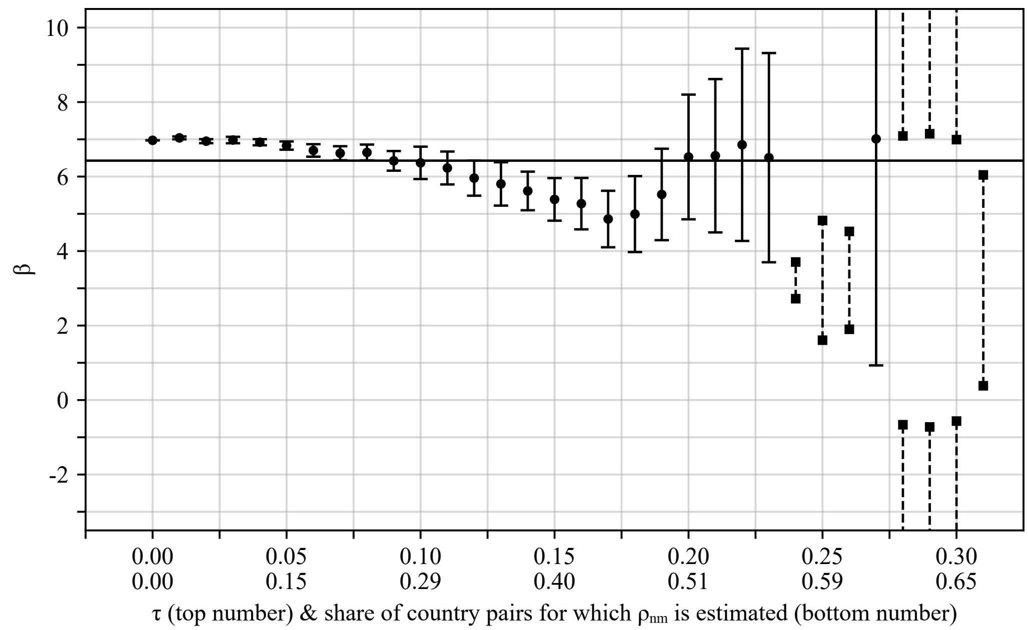


Figure 4 summarises our results for δ. The area shaded in light grey continues to mark values of δ that according to Proposition 1 result in an attenuation bias of the standard benchmarking estimator ($0 \leq \delta < 1$). The area shaded in darker grey marks values of δ that according to Proposition 1 result in an amplification bias of the standard benchmarking estimator ($\delta > 1$). For values of τ smaller than 0.02, point estimates of δ are between -0.01 and $+0.01$ and 95% confidence intervals include 0. According to Proposition 1, $\delta = 0$ implies that the standard benchmarking estimator is attenuated. According to Proposition 2, $\delta = 0$ implies that we can estimate β as $\beta = \kappa b$. This yields estimates of β around 7, see Figure 5. These estimates are about 10% larger than Nunn's point estimate of 6.4 obtained with the standard benchmarking estimator (marked by the horizontal black line).

For values of the threshold distance τ between 0.03 and 0.11, point estimates of δ in Figure 4 are between 0.09 and 1.3. The 95% confidence intervals are between 0 and 2. Hence, the data support values of δ between 0 and 2. According to Proposition 2, $0 \leq \delta \leq 2$ implies that we can estimate β as $\beta = \kappa b$. This yields the estimates of β in Figure 5. These are sometimes above Nunn's estimate of 6.4 and sometimes below. This makes sense as according to Proposition 1, the standard benchmarking estimator is subject to an attenuation bias when δ is between 0 and 1 and subject to an amplification bias when δ is greater than 1.

When τ is between 0.12 and 0.19, estimates of δ in Figure 4 are between 1.6 and 2.3. Hence, the benchmarking estimator is subject to an amplification bias according to Proposition 1. The condition for identification in Proposition 3 is always satisfied and we can estimate β as $\beta = \kappa b$. Estimates of β in Figure 5 are between 5.9 and 4.9, up to 25% smaller than Nunn's estimate. For values of τ between 0.2 and 0.23, estimates of δ in Figure 4 are generally between 0 and 1. According to Proposition 2, we can therefore estimate β as $\beta = \kappa b$. Our point estimates of β in Figure 5 are between 6.5 and 6.7, slightly larger than Nunn's estimate. For values of τ between 0.24 and 0.31, our estimates of δ are very noisy. For values of τ larger than 0.31, $\mathbf{G}^{\tau}$ no longer has full rank and $\mathbf{\Omega}^{\tau}$ cannot be identified.

Figure 5: Estimates of β for Nunn's specification with controls for human and physical capital.



6 Conclusion

Cross-industry cross-country models are used widely because industry-country interaction effects allow testing theoretical mechanisms. We show that the estimation approach in the literature can result in misleading answers to the research questions being asked. The origin of the issue we analyse is straightforward. Cross-industry cross-country models must specify the technological industry characteristics that, according to the theory being tested, should interact with the relevant country characteristic. As these industry characteristics are unobservable for most countries, they are approximated by the industry characteristics in a benchmark country, usually the US. As a result, the technological industry characteristics of all countries except the US are measured with error.

The cross-industry cross-country literature implicitly assumes that this proxy introduces measurement error that is independent of all country characteristics (classical measurement error) and that industry-country interaction effects are therefore biased towards zero. That is, using US industry characteristics as a proxy for industry characteristics elsewhere leads to an attenuation bias and hence a bias against the hypothesis being tested. We add that—because technology is endogenous—US industry characteristics are likely to be a relatively worse proxy for countries that differ from the US in various dimensions. This heterogeneity in the measurement error counteracts the attenuation bias considered in the CI/CC literature and can flip the sign of the bias of the benchmarking estimator. Hence, using US industry characteristics as a proxy for industry characteristics elsewhere can lead to amplified or entirely spurious industry-country interaction effects when using the estimation approach in the literature. We therefore propose an alternative estimation approach and illustrate the approach by applying it to Nunn (2007).

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