# Estimating Cross-Industry Cross-Country Interaction Models Using Benchmark Industry Characteristics

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## Abstract

Cross-industry cross-country models have proven useful for addressing a wide array of research questions in economics. They do so by analyzing how the economic performance of industries in different countries depends on the interaction between country characteristics and theoretically relevant industry characteristics. A common challenge in the literature is that the theoretically relevant industry characteristics are unobservable for almost all countries and must be proxied by industry characteristics in a benchmark country. We analyze this approach when there is cross-country heterogeneity in technology and make two main contributions. First, we show that the estimation approach in the literature can yield a sizable upward bias or entirely spurious effects when countries that are more similar in terms of the country characteristics of interest are also more similar technologically. Second, drawing on insights from the generalized least squares literature, we propose an alternative estimation approach. We use the approach to reestimate the impact of institutional quality on exports in industries that rely more on relationship-specific inputs.

*Keywords:* Economic Growth, Country-Specific Technology, Financial Development, Institutions, International Specialization and Trade

*JEL classification numbers:* G30, F10, O40

# 1 Introduction

Following the seminal contribution of Rajan and Zingales (1998), empirical cross-industry cross-country models have proven useful for addressing an array of questions in fields ranging from growth and international economics to financial and industrial economics (we review applications below). Cross-industry cross-country models examine how the economic performance of industries across countries depends on the interaction between industry characteristics—dependence on external finance or reliance on certain inputs for example—and country endowments, institutions, or economic policies. These models are popular because they allow testing specific theoretical mechanisms and can account for arbitrary country and industry level determinants of economic performance.

A common challenge in the cross-industry cross-country literature is that the relevant industry characteristics are unobservable in almost all countries. These are therefore treated as latent variables proxied using data from a benchmark country, generally the USA. For example, Levchenko's (2007) and Nunn's (2007) influential work on the effect of institutions on exports proxies industry characteristic in all countries using US input-output data.

We make two contributions to the literature. First, we show that the benchmarking estimator may yield upward or downward biased estimates when there is cross-country heterogeneity in technology. Cross-country differences in technology are well documented, see Bernard and Jones (1996), Acemoglu and Zilibotti (2001), Schott (2004), and Caselli (2005) for example. We demonstrate that if technologically similar countries are also similar in terms of the country characteristics of interest in the cross-industry cross-country literature, the benchmarking estimator can yield an upward biased or entirely spurious interaction effect. Our second contribution is to propose an alternative estimation approach. We use the approach to reexamine Nunn's (2007) finding that institutional quality promotes exports in relationship-specific-input intensive industries,

To understand the benchmarking estimator employed in the cross-industry cross-country literature, it is useful to break the estimator down into two steps. The first step is to calculate the covariances between US industry characteristics—industry characteristics obtained using US data—and the economic performance of industries in any other country. The second step is to regress these covariances on the country characteristics of interest. The slope of this regression is identical to the estimate obtained using the benchmarking estimator. For example, take Nunn's (2007) research question whether countries' institutional quality promotes exports in industries that use relationship-specific inputs more intensively. In this case, the first step is to calculate the covariances between the relationship-specific-input intensity of US industries and industry exports in any other country. The second step is to regress these convariances on the institutional quality of countries. The coefficient is

positive if the covariance between the relationship-specific-input intensity of US industries and industry exports is larger for countries with greater institutional quality. In this case, the conclusion using the benchmarking estimator would be that institutional quality promotes exports in more relationship-specific-inputs intensive industries.

To see that this conclusion may be misleading, consider the following, extremely simplified, scenario. There is cross-country heterogeneity in technology and the optimal technology of firms in a country is determined solely by the country's human capital—the quality of institutions is irrelevant. In this case, industries in countries with high human capital will employ technologies similar to US technologies. By contrast, industries in countries with low human capital will employ technologies that are different from US technologies. This heterogeneity in technology translates into a lower covariance between the relationship-specific-input intensity of US industries and industry exports in countries with lower human capital. If countries with lower institutional quality have lower human capital, the benchmarking estimator would lead to the conclusion that institutional quality raises exports in relationship-specific-input intensive industries. The benchmarking estimator leads to an incorrect conclusion due to a combination of two factors. First, countries with different human capital use different technology. Second, institutional quality and human capital are positively correlated.

This is not a standard omitted variable problem that can be resolved by adding cross-industry cross-country interactions to the empirical framework. A standard omitted variable problem would be that human capital affects industry exports through the human-capital intensity of industries, the relationship-specific-input intensity of industries, or other industry characteristics. The issue highlighted in the example above is that optimal technology is endogenous and a function of country characteristics. Using US data to proxy for technology in other countries therefore gives rise to non-classical measurement error. This can result in a substantial upward or downward bias, depending on how the country characteristics determining optimal technology covary with the country characteristics of interest in the cross-country literature.[1]

As the benchmarking estimator used in the literature generally yields biased results when there is cross-country heterogeneity in technology, we propose an alternative estimation approach. This approach draws on insights from the generalized least squares literature to estimate how technological differences between countries vary with other country characteristics. We illustrate the approach by reestimating the effect of institutional quality on exports in industries that use relationship-specific inputs more intensively in Nunn (2007). Our estimates tend to be similar to Nunn's.

The rest of the paper is structured as follows. Section 2 summarizes numerous applica-

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[1]The issue we highlight is also unrelated to concerns that country characteristics or US industry characteristics may be endogenous. We abstract from these issues by taking both country characteristics and US industry characteristics to be exogenous.

tions of cross-industry cross-country interaction models. Section 3 examines the properties of the estimation approach in the literature in the presence of technological differences across countries. Section 4 introduces our alternative approach to estimation. Section 5 reestimates Nunn (2007). Section 6 concludes.

## 2    Applications in the Literature

Cross-industry cross-country models have been applied extensively in many areas of economics. Our review is only meant to illustrate the range of applications. Appendix Table 1 provides brief summaries of more papers in the literature.

**The Economic Effects of Financial Markets.**    Starting with the influential work of Rajan and Zingales (1998), who showed that financial development exerts a disproportionately large impact on sales growth in industries that depend more on external sources of finance, cross-industry cross-country models have been applied extensively to investigate the effects of financial markets on economic growth, firm entry and exit, investment, and innovation. For example, Fisman and Love (2003) find that in countries with less developed financial markets, industries that rely more on trade credit grow faster, and Fisman and Love (2007) show that better developed financial markets spur growth in industries facing better global growth opportunities. Claessens and Laeven (2003), Braun and Larrain (2005), and Lei, Qiu, and Wan (2018) extend the cross-industry cross-country model of Rajan and Zingales (1998) to account for the role of intangible assets. Brown, Martinson, and Petersen (2013), Hsu, Tian, and Xu (2014), and Acharya and Zu (2017) use cross-industry cross-country models to examine the impact of financial markets on innovation. Pagano and Shivardi (2003), Aghion, Fally, and Scarpetta (2007), and Beck, Demirguüc-Kunt, Laeven, and Levine (2008) analyze how financial markets affect firm entry and exit and the growth of smaller versus larger firms.

Cross-industry cross-country models are also used to examine the economic effects of specific financial market policies or institutions, such as bank recapitalizations (Laeven and Valencia, 2013), insider trading legislation (Edmans, Jayaraman, and Schneemeir, 2017), and collateral laws (Calomiris, Larrain, Liberti, and Sturgess, 2017). A more recent strand of research employs cross-industry cross-country models to assess the effects of financial crises and capital account liberalization on macroeconomic performance (Dell'Ariccia, Detragiache, and Rajan, 2008; Iacovone and Zavacka, 2009; Duchin, Ozbas, and Sensoy, 2010; Claessens, Tong, and Wei, 2012; Larrain and Stumpner, 2018).

**International Specialization and Trade.**    Cross-industry cross-country models are widely used to examine the determinants of international trade and international specialization.

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Levchenko (2007) and Nunn (2007) use cross-industry cross-country models to examine the effect of institutional quality on international specialization (see also Ferguson and Formai, 2013; Nunn and Trefler, 2014). Manova (2008, 2013) uses cross-industry cross-country models to link financial development to the patterns of international trade (see also Chan and Manova, 2015; Manova, Wei, and Zhang, 2015; Claessens, Hassib, and van Horen, 2017; Crinò and Oglirari, 2017). Ciccone and Papaioannou (2009) and Debaere (2015) use cross-industry cross-country models to examine the effects of human capital and natural resources on international specialization. Cingano, Leonardi, Messina and Pica (2010), Mueller and Phillippon (2011), Cuñat and Melitz (2012), Tang (2012), Griffith and Macartney (2014), and Broner, Bustos, and Carvalho, (2016) use cross-industry cross-country models to examine role of labor-market and environmental regulation for international trade.

**Other Applications.** Cross-industry cross-country models have proven useful for examining a surprisingly wide variety of additional economic questions. For example, Alfaro and Charlton (2009), Carluccio and Fally (2012), Basco (2013), Blyde and Danielken (2015), Paunov (2016), and Fort (2017) use cross-industry cross-country models to analyze the determinants of outsourcing, foreign direct investment, and the fragmentation of production. Pagano and Schivardi (2003), Klapper, Laeven, and Rajan (2006), Acemoglu, Johnson, and Mitton (2009), Aizenman and Sushko (2011), Bombardini, Gallipoli, and Pupato (2012), Michelacci and Schivardi (2013), Larrain (2014), and Aghion, Howitt, and Prantl (2014) use cross-industry cross-country models to analyze the economic consequences of cross-country differences in firm size distributions, entry regulation, transaction costs, risk sharing possibilities, and skill dispersion. Rajan and Subramanian (2010) and Chauvet and Ehrhart (2018) use cross-industry cross-country models to understand the economic effects of foreign aid, while Pierce and Snyder (2017) and Levine, Lin, and Xie (2018) use them to study the legacy of slave trade. Aghion, Farhi, and Kharroubi (2015), Aghion, Hemous, and Kharroubi (2014), and Cecchetti and Kharoubi (2018) use cross-industry cross-country models to analyze the economic effects of fiscal and monetary policy over the business cycle and Avdjiev, Bruno, Koch, and Shin (2018) to analyze the economic impact of exchange rates.

# 3 The Standard Benchmarking Estimator

## 3.1 The Model

The basis of cross-industry cross-country 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 relationship-specific inputs. As the main hypothesis concerns the effect of the interaction between country and industry characteristics, cross-industry cross-country 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 characteristic in different countries; and $\nu_{in}$ 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 $\beta$. The parameter $\alpha$ captures direct effects of industry characteristics on outcomes.[2] We take the relevant country characteristic $x_n$ to be non-stochastic.

Estimation of $\beta$ in (1) would be straightforward if there was data on the relevant industry characteristics $z_{in}$ for a broad set of countries. But the necessary data is unavailable for most countries. Moreover, the cross-industry cross-country literature often focuses on technological industry characteristics that must be inferred from observed, endogenous industry behavior. Such inference is challenging in countries where firms have adapted to, for example, low financial development, institutional quality, or human capital. As a result, the cross-industry cross-country literature proceeds by proxying the relevant technological industry characteristics of all countries with industry characteristics from a highly-developed benchmark country with relatively undistorted markets, usually the USA.

To better understand this benchmarking approach, it is useful to distinguish between the relevant technological industry characteristics $z_{in}$ in (1) and observed industry characteristics $\tilde{z}_{in}$. Observed industry characteristics are endogenous and may therefore depend on the country characteristic $x_n$ the model in (1) focuses on, as well as other country characteristics $h_n$, $\tilde{z}_{in} = g(i, x_n, h_n)$. The objective is to determine the economic effects of cross-country differences in $x_n$ through the industry-specific channel captured by $z_{in}$. Because $\tilde{z}_{in}$ is endogenous to the cross-country differences in $x_n$, using $\tilde{z}_{in}$ as right-hand-side industry char-

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[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 $\beta$ in (1) allows testing RZ's hypothesis that financial development fosters growth disproportionally in industries with greater demand for external finance. The parameter $\alpha$ allows to capture direct effects of the technological shocks raising an industry's investment opportunities on industry growth. Technological shocks may affect industry growth directly in several ways, for example by changing the marginal productivity of labor, and hence equilibrium employment, across industries.

acteristics in (1) would generally produce misleading conclusions. A better choice for the right-hand-side industry characteristics would be the hypothetical industry characteristics of countries $n$ if they all had the same country characteristic $x^*$, $\tilde{z}_{in}^* = g(i, x^*, h_n)$ for some function $g(\cdot)$. The industry data to infer these hypothetical industry characteristics is unavailable for most countries. As a result, the cross-industry cross-country literature generally proceeds by proxing the industry characteristics $z_{in}$ in (1) with the industry characteristics of a highly-developed benchmark country with relatively undistorted markets.[3]

It is important to understand if the benchmarking approach used in the cross-industry cross-country literature can identify the effect of interest $\beta$. Clearly, the approach works if the technological industry characteristics $z_{in}$ of all countries were identical, i.e. $z_{in} = z_i$. In this case, using the industry characteristics of a benchmark country as a proxy for the industry characteristics of all other countries would not involve any measurement error.

But as countries differ in a range of characteristics that could be relevant for industry structure and technology adoption, it seems implausible that the relevant technological industry characteristics are identical (e.g., Bernard and Jones, 1996; Acemoglu and Zilibotti, 2001; Schott, 2004; Caselli, 2005).[4] The technological industry characteristics of any benchmark country will therefore be a noisy proxy for the technological industry characteristics of other countries. How good a proxy, can be expected to be country specific.

This point can be illustrated with the study of Nunn (2007). The key industry-level variable is the relationship-specific-input intensity of industries and the country characteristic of interest is institutional quality. Clearly, the observed relationship-specific-input intensity of industries in a country may depend on its institutional quality, as firms might make fewer relationship-specific investments when they operate in an environment with worse institutional quality. For this reason, and because there is little industry data for most countries, Nunn proxies the technological relationship-specific-input intensity of industries of all countries by the observed relationship-specific-input intensity of US industries. However, even if all countries had the US level of institutional quality, the technological relationship-specific-input intensity of industries might still differ across countries, as industry structure and technology may not depend solely on institutional quality. Put differently, the relationship-specific-input intensity of US industries may be a noisy proxy for the technological relationship-specific-input intensity of other countries even if these countries had the institutional quality of the US. How good a proxy, depends on country characteristic other than institutional quality that affect industry structure and the technological relationship-

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[3]In a few cases, $z_{in}$ is proxied using industry data from several highly-developed countries. This does not affect our analysis below at all, except that the place of US industry characteristics would be taken by the industry characteristics of the alternative benchmark country/countries.

[4]In fact, the cross-industry cross-country literature has regarded this assumption as unreasonable since its beginnings, see Rajan and Zingales (1998), p. 563.

specific-input intensity of industries.

For example, Nunn documents that industries that rely more on relationship-specific inputs also use human capital more intensively. Hence, the level of human capital of a country may affect which of the many industries with different technological relationship-specific-input intensities produce in the country. That is, the technological relationship-specific-input intensity of industries may depend on the country's human capital. As a result, the relationship-specific-input intensity of industries in a high human capital country like the US could be similar to the technological relationship-specific-input intensity of countries with similar human capital but substantially different from the technological relationship-specific-input intensity of countries with low human capital.

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

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

The country-specific component $z_n$ captures all country-specific factors that shift the entire distribution of technological industry characteristics. We treat this component as non-stochastic. The global industry component $z_i$ allows us to capture factors that make two industries $i$ and $j$ different from each other independently of the country where they are located.[5] We treat this component as an independent and identically distributed random variable with $Var(z_i) > 0$. For the $\varepsilon_{in}$ we chose a model that allows us to capture that:

(i) How different any two industries are technologically may be country specific.
(ii) Some countries may be more similar technologically than others.

To capture (i) and (ii) we assume that the $\varepsilon_{in}$ in (2) are jointly normally distributed for all $i$ and $n$. For any pair of countries $n \neq m$, the correlation of the $\varepsilon_{in}$ across industries is allowed to be an arbitrary function of country characteristics

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

As $\rho_{nm}$ 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 cross-industry cross-country literature will show that, whether the bias is upwards or downwards is partly determined by

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[5]That there must be such a global component for the estimation approach in the cross-industry cross-country literature to make sense was already pointed out in Rajan and Zingales (1998).

how $\rho_{nm}$ changes as country $n$ and country $m$ become more dissimilar in terms of their $x$-characteristics. Across industries, the $\varepsilon_{in}$ 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 the technological industry characteristics $z_{in}$ in (2) is $Var(z_{in}) = Var(z_i) + \sigma^2$ for all countries $n$. Hence, larger values of $\sigma^2$ imply that more of the heterogeneity in technological industry characteristics is country specific. The assumption that $Var(z_i) > 0$ implies that $\sigma^2$ is strictly smaller than the variance across industries of the technological industry characteristics in each country, $\sigma^2 < Var(z_{in})$ for all $n$. This is because $Var(z_i) > 0$ and (2) imply that at least some of the variance across industries of technological characteristics in each country reflects a global component.

If $\sigma^2 = 0$, the variance across industries of the technological industry characteristics is entirely driven by the global component and there is no cross-country heterogeneity in technological differences between industries. This is because in this case, $\varepsilon_{in} = 0$ for all $i$, $n$ and (2) implies that $z_{in} - z_{jn} = z_i - z_j$. Hence, technological differences between industries $z_{in} - z_{jn}$ do not vary at all across countries $n$. Because our model for $z_{in}$ in (2) allows for a country-specific component $z_n$, the levels of technological industry characteristics could still vary across countries. 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 cross-industry cross-country models.

If $\sigma^2 > 0$, there is cross-country heterogeneity in technological differences between industries. To see this, note that (2) implies $z_{in} - z_{jn} = (z_i - z_j) + (\varepsilon_{in} - \varepsilon_{jn})$ and generically $\varepsilon_{in} - \varepsilon_{jn} \neq \varepsilon_{im} - \varepsilon_{jm}$ for all $n \neq m$. To understand the implications of this heterogeneity, it is useful to relate $z_{in} - z_{jn}$ for country $n$ and any pair of industries $i$ and $j$ 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 $\rho_{nUS}$ 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 $E(u_{ijnUS}) = 0$ that is independent of the $z_i$ and the $z_{iUS}$.[6] Hence, in expectation:

(i) 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 the US and industry differences in the global component.

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

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(ii) The weight on the technological industry characteristics of the US is the correlation coefficient $\rho_{nUS}$ between the specific industry characteristics of country $n$ and the US.

As the coefficients $\rho_{nUS}$ in (5) 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 (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 relationship-specific-input intensity of a high human capital country like the US could be different from countries with low human capital. As the coefficients $\rho_{nUS}$ can be arbitrary functions of country characteristics, they allow us to capture in a flexible way that how similar countries are in terms of the technological relationship-specific-input intensity of their industries may depend on human capital—that is, $\rho_{nUS} = g(h_n, h_{US})$ for some function $g(\cdot)$.[7] The estimation approach in the cross-industry cross-country literature fails to take this into account and estimates of the effect of institutional quality on industry outcomes could therefore be biased upwards or downwards. Our analysis of the bias of the estimation approach in the cross-industry cross-country literature will show that when the US is used as a benchmark country, the bias depends on how $\rho_{nUS}$ changes as country $n$ and the US become more dissimilar in terms of their $x$-characteristics. In the context of Nunn's study, where the $x$-characteristic is institutional quality, the bias would therefore depend how $\rho_{nUS}$ changes as country $n$ and the US become more dissimilar in terms of their institutional quality. If $\rho_{nUS} = g(h_n, h_{US})$, this depends on both the effect of countries' human capital on the technological relationship-specific-input intensity of their industries and on whether countries with more dissimilar institutional quality are also more dissimilar in human capital.

In Rajan and Zingales (1998), the key industry-level variable is external-finance intensity. Rajan and Zingales use this variable to capture technological shocks that raise an industry's investment opportunities beyond what internal funds could support. As the benchmark country in Rajan and Zingales is the US, the external-finance intensity of industries used in their empirical analysis is that of US industries. The technological shocks affecting US industries could be similar to shocks affecting industries in countries with similar human capital, for example, but quite different from shocks in countries with low human capital. As the coefficients $\rho_{nUS}$ in (5) can be arbitrary functions of country characteristics, our framework allows us to capture flexibly that technological shocks in countries with low human capital could be quite different from technological shocks in high human capital countries like the US. The estimation approach in the cross-industry cross-country literature does

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

not take this into account and can therefore yield upwards or downwards biased estimates of the effect of financial development on industry outcomes. If the technological shocks affecting industries vary with the human capital of countries, the bias depends on both the relationship between human capital and technological shocks and on whether countries with more dissimilar financial development are also more dissimilar in human capital.

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 $\rho_{nUS}$ increases. The answer depends on whether the difference between the global component of technological industry characteristics, $z_i - z_j$, is greater or smaller than the difference between the technological industry characteristics of the US, $z_{iUS} - z_{jUS}$. This gives the model additional flexibility. For example, consider the effect of a country's human capital on the relationship-specific-input intensity of its industries discussed above in the context of Nunn's (2007) study. Compared to the US, industries might be less relation-specific-input intensive in countries with low human capital. However, there seems no reason to suppose that this effect is stronger in some industries than others. Hence, the difference in the use of relation-specific inputs between industries $i$ and $j$ in countries with low human capital may be greater or smaller than in the US.

We could also model the endogeneity of US industry characteristics by extending our conceptual framework to include a fictional frictionless (ff) country. This would allow us to write US industry characteristics in terms of industry characteristics in the fictional frictionless country, $z_{iUS} - z_{jUS} = \rho_{USff}(z_{iff} - z_{jff}) + (1 - \rho_{USff})(z_i - z_j) + u_{ijUSff}$ where the derivation and variable definitions are analogous to (5). This results in a flexible model of how US industry characteristics—and, using (5), the characteristics of any other country—differ compared to a frictionless baseline as $\rho_{USff}$ is allowed to be an arbitrary function of US characteristics.

## 3.2 Characterizing the Standard Benchmarking Estimator

We now apply the estimation approach used in the cross-industry cross-country 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 Deriving the Standard 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.[8]

It is useful to write the least-squares estimator of $b$ in (6) in terms of demeaned variables

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

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 $\beta$, 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 Appendix for details—yields

$$b = \plim_{I\to\infty}\widehat{b} = \left(1 - \frac{\sigma^2}{\sigma_{US}^2}\right)\beta + \left(\frac{\sigma^2}{\sigma_{US}^2}\right)(\alpha A + \beta B) \tag{8}$$

where $\sigma^2$ is the variance of $\varepsilon_{in}$ and $\sigma_{US}^2$ is the variance of the US industry characteristic $z_{iUS}$, with $\sigma^2/\sigma_{US}^2 < 1$; $\alpha$ captures direct effects of industry characteristics on industry outcomes; and $A$ and $B$ capture the relationship between the characteristic $x_n$ of country $n$ and how similar the country is technologically to the US (as measured by $\rho_{nUS}$)

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

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[8]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.

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 to the US in terms of the $x$-characteristic. In the typical application of cross-industry cross-country models in the literature, $B$ would also tend to be positive in this case.[9]

An immediate implication of (8) is that the standard benchmarking estimator identifies $\beta$ 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.[10]

When there is cross-country heterogeneity in technological industry characteristics, $\sigma^2 > 0$, the standard benchmarking estimator in (8) is biased and the bias is shaped by two main forces. First, how much country-specific heterogeneity there is in technological industry characteristics (captured by $\sigma^2/\sigma_{US}^2$). Second, how the technological similarity of countries with the US (captured by $\rho_{nUS}$) covaries with their characteristics $x_n$ (captured by $A$ and $B$). We now discuss the forces shaping the bias in some interesting special cases and show that the standard benchmarking estimator may be biased towards zero (attenuated); biased away from zero (amplified); or entirely spurious.

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

The expressions in (8)–(10) allow us to discuss the forces shaping the bias of the standard benchmarking estimator and distinguish three main types of biases.

**Attenuation Bias.**   We start with the case that we see as corresponding to the implicit assumption in the cross-industry cross-country literature. In this case, differences between the technological industry characteristics of a country and global technological industry

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

[10]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 cross-industry cross-country models.

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, i.e. $\rho_{nm} = 0$ 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 $b = \beta(1 - \sigma^2/\sigma_{US}^2)$. As already mentioned, the assumption $Var(z_i) > 0$ implies $\sigma^2/\sigma_{US}^2 < 1$ as at least some of the variation in technological industry characteristics in each country, including the US, is due to the global component. Hence, the standard benchmarking estimator $b$ has the same sign as the parameter of interest $\beta$ but is biased towards zero. This possibility is generally understood in the cross-industry cross-country literature and explained in terms of a classical measurement error bias due to US (benchmark country) industry characteristics measuring the technological industry characteristics of other countries with some error (e.g. Rajan and Zingales, 1998). $\rho_{nm} = 0$ for all $n \neq m$ implies that US industry characteristics are an equally imperfect proxy for the technological industry characteristics of all other countries. US industry characteristics become a uniformly worse proxy for the technological industry characteristics of other countries for larger values of $\sigma^2/\sigma_{US}^2$. As a result, the attenuation bias is stronger the greater the country-specific component of technological industry characteristics.

**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 $b = \alpha A \sigma^2/\sigma_{US}^2$. 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.[11] The standard 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

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[11]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 $\alpha < 0$).

characteristic $x_n$ has an effect on industry outcomes.[12]

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 $\rho_{nUS}$, 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 sizable 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 sizable although the average country is technologically quite similar to the US.

**Amplification Bias.** The standard 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 $b = \beta \left[ 1 + (B-1)\sigma^2/\sigma_{US}^2 \right]$. Hence, if $B > 1$ and there is cross-country heterogeneity in technological industry characteristics ($\sigma^2 > 0$), the standard benchmarking estimator $b$ will be an amplified version of $\beta$, $|b| > |\beta|$ and $sign(b) = sign(\beta)$.

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 some countries than others. Specifically, US industry characteristics must be a better proxy for the technological industry characteristics of countries that have $x$-characteristics similar to the US. In our framework, this is the case if countries that are more similar technologically to the US are also more similar in terms of their $x$-characteristics.

To see the sources of the amplification bias of the standard benchmarking estimator formally, 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 $\nu_{in}$

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[12]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 $\alpha \frac{1}{N} \sum_{n=1}^{N} (x_n - \bar{x}) E\varepsilon_{in}(z_{iUS} - z_i) = \alpha \frac{1}{N} \sum_{i=1}^{N} (x_n - \bar{x})\sigma^2 \rho_{nUS} = \alpha \sigma^2 Cov(x_n, \rho_{nUS})$ where we made use of the definition of $\rho_{nUS}$. 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 $\alpha A > 0$.

as an independent and identically distributed random variable. The parameters $\gamma_n$ in (11) capture the effect of industry characteristics on outcomes in different countries. We refer to these parameters as country-specific slopes. The parameter $\beta$ in (12) captures how these country-specific slopes covary with the country characteristic $x_n$.

Now imagine estimating the country-specific slopes $\gamma_n$ 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 $\gamma_n$ 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

$$g_n = \plim_{I \to \infty} \widehat{g}_n = \gamma_n \left[ \left( 1 - \frac{\sigma^2}{\sigma_{US}^2} \right) + \left( \frac{\sigma^2}{\sigma_{US}^2} \right) \rho_{nUS} \right] \tag{13}$$

where $\sigma^2/\sigma_{US}^2 < 1$. 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

$$\frac{\sum_{n=1}^{N} g_n(x_n - \overline{x})}{\sum_{n=1}^{N}(x_n - \overline{x})^2} = \beta \left( \frac{\sum_{n=1}^{N} \left[ \left(1 - \frac{\sigma^2}{\sigma_{US}^2}\right) + \left(\frac{\sigma^2}{\sigma_{US}^2}\right) \rho_{nUS} \right] \gamma_n(x_n - \overline{x})}{\sum_{n=1}^{N}(x_n - \overline{x})^2} \right) \tag{14}$$

$$= \beta \left[ \left(1 - \frac{\sigma^2}{\sigma_{US}^2}\right) + \left(\frac{\sigma^2}{\sigma_{US}^2}\right) B \right] = b.$$

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 the Simplest 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 of countries in the two groups.

Now suppose that the US is part of group $S$. As countries in the same group are identical, this implies that all countries $n$ in group $S$ are identical technologically to the US, $\rho_{nUS} = 1$. As a result, (13) implies that the estimated country slopes 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.

On the other hand, 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. That is, $\rho_{nUS} = 0$ for all countries $n$ in group $D$. If there is some cross-country heterogeneity in

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technological industry characteristics ($\sigma^2 > 0$), (13) implies that the estimated country slopes for all countries in group $D$ are an attenuated version of the true slopes: $g_D = (1 - \sigma^2/\sigma_{US}^2)\gamma_D$. 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 $g_D$ we just obtained into (15) and using (12) yields

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

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. This is because in this case, there is a strong positive association between the country characteristic $x_n$ and technological similarity with the US.

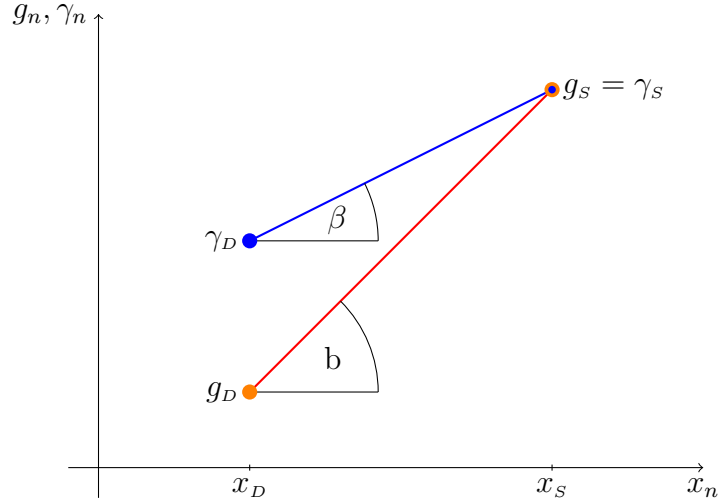Figure 1: The amplification bias in the simplest possible case.



Figure 1 gives a graphical illustration of the amplification bias in the two-group setting for $\beta > 0$. The two blue dots plot the true country-specific slopes $\gamma_S$ and $\gamma_D$ against $x_S$ and $x_D$. The parameter $\beta$ we want to estimate is the slope of the blue line connecting the two blue dots as (12) implies $\beta = (\gamma_S - \gamma_D)/(x_S - x_D)$. The two red dots plot the least-squares slope estimates $g_S$ and $g_D$ against $x_S$ and $x_D$. Equation (15) implies that the benchmarking estimator $b$ is the slope of the red line connecting the two red 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, and US industry characteristics are therefore a perfect proxy for the industry characteristics of all high-$x$ countries. Hence, there is no measurement error when the US is used to proxy for the industry characteristics of these countries. This

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implies that the least-squares slope estimates for these countries are equal to the true slopes, $g_S = \gamma_S$. That is, the blue and the red 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 red dot lies below the blue dot.

Hence, cross-country heterogeneity in technological industry characteristics implies that using the US industry proxy yields a consistent estimate of $\gamma_S$ for high-$x$ countries that are technologically identical to the US, but a downwards biased estimate of $\gamma_D$ for low-$x$ countries that are technologically different from the US. Because the standard benchmarking estimator $b$ is the slope of the red line connecting the red dots while the parameter of interest $\beta$ is the slope of the blue line connecting the blue dots, 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.

It is interesting to note that 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 (the benchmark country). Hence, the amplification bias could be sizable 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 the case $\beta = 0$ and the case $\beta \neq 0$.

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

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

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

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

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

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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 standard benchmarking estimator depends on $\delta$. If $\delta = 0$, the standard benchmarking estimator is attenuated. For example, our framework yields $\delta = 0$ when country-specific industry characteristics are uncorrelated across countries. If $\delta > 0$, there is a countervailing force that can weaken the attenuation bias or result in an amplification bias. If $\delta < 0$, the standard benchmarking estimates may have the wrong sign.

We now summarize how the bias of the standard benchmarking estimator depends on $\delta$.

**Proposition 1. [Bias of standard benchmarking estimator when $\beta \neq 0$]**

1. If $0 \leq \delta \leq 1$, the standard benchmarking estimator is subject to an attenuation bias: $b$ has the same sign as $\beta$ 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 $\beta$ 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 $\beta$, depending on $\sigma^2/\sigma_{US}^2$.

# 4    Identification of $\beta$

We have seen that the standard benchmarking estimator used in the cross-industry cross-country literature does not identify the effect of interest when there is cross-country heterogeneity in technological industry characteristics ($\sigma^2 > 0$). Moreover, the bias cannot be signed if technologically similar countries are similar in terms of other characteristics ($A \neq 0$ or $B \neq 0$). We now examine how the effect of interest can be identified when there is cross-country heterogeneity in technological industry characteristics.

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 $\beta = b/[1 + (\delta - 1)\sigma^2/\sigma_{US}^2]$. The right-hand-side parameter $b$ can be identified using the standard benchmarking approach in the literature, and the variance of the US industry characteristics $\sigma_{US}^2$ is observable. If we can identify $\delta$ and $\sigma^2$, we can therefore identify $\beta$. As we will show, $\delta$ 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 $\sigma^2$, identification of $\beta$ would be straightforward. But the variances and covariances of industry outcomes do not identify $\sigma^2$.

To see how the variances and covariances of industry outcomes for different country pairs help to identify $\beta$, 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.[13] The industry-specific slopes $\gamma_i$ capture the effect of the country characteristic on outcomes in different industries.

The effect of (unobservable) country-specific technological industry characteristics $\varepsilon_{in}$ on industry outcomes is captured by $u_{in}$ in (22). $E(u_{in}u_{im})$, the variances and covariances of $u_{in}$ for industry $i$ and countries $n$, $m$, reflect the effect of cross-country heterogeneity in technological industry characteristics on the variances and covariances of industry outcomes in countries $n$, $m$. As a result, they play a central role for the identification of $\delta$ and $\beta$.

To see this, note that (3) and (22) imply that the variances and covariances $E(u_{in}u_{im})$ are

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

That the $\omega_{nm}$ may allow us to identify $\delta$ is quite straightforward. From (18) and $A$ and $B$ in (9)–(10), it can be seen that $\delta$ depends on the $\rho_{nm}$, which capture how similar any two countries are technologically, and on $\alpha/\beta$, which captures the direct effect of technological industry characteristics on industry outcomes relative to the industry-country-interaction effect. We should be able to infer these parameters entering $\delta$ from the $\omega_{nm}$ under some conditions as according to (23), the $\omega_{nm}$ depend on the $\rho_{nm}$; on $\alpha\sigma$, which captures the direct effect of country-specific heterogeneity in technological industry characteristics on industry outcomes; and on $\beta\sigma$, which captures the industry-country-interaction effect of country-specific heterogeneity in technological industry characteristics on industry outcomes.

However, the $\omega_{nm}$ will not allow us to identify the variance of country-specific industry characteristics $\sigma^2$. This is because the $\omega_{nm}$ solely reflect $\sigma^2$ through its effects on outcomes, which is why $\sigma$ only appears multiplied by either $\alpha$ or $\beta$. This is what makes the identification of $\beta$ challenging.

To see when and how $\beta$ can be identified, we now proceed in two steps. We first examine the identification of $\beta$ for known $\omega_{nm}$. Then we discuss how the $\omega_{nm}$ can be identified.

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[13]These industry and country fixed effects capture the industry and country fixed effects in $v_{in}$ and absorb $\alpha z_i$ in the industry fixed effect and $z_n$ in the country fixed effect.

## 4.1 Identification of $\beta$ for Known $\boldsymbol{\Omega}$

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

The next question is how to identify $\beta$ if the $\omega_{nn}$ depend on the country characteristics $x_n$. We first explain how $\boldsymbol{\Omega}$ can be used to obtain two key parameters for the identification of $\beta$, namely $\delta$ and $(\beta\sigma)^2$. Then we show how $\delta$ and $(\beta\sigma)^2$ can be used to identify $\beta$.

Obtaining $\delta$ and $(\beta\sigma)^2$ from $\boldsymbol{\Omega}$ is simple. We start by determining $\alpha\sigma$ and $\beta\sigma$—and hence $(\beta\sigma)^2$—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 $\beta\sigma$.[14] Then we invert the expression for the covariances $\omega_{nm}$ 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 $\rho_{nm}$ by combining the $\omega_{nm}$ with $\alpha\sigma$ and $\beta\sigma$. Once we have obtained $\alpha\sigma$, $\beta\sigma$, and the $\rho_{nm}$, it is straightforward to obtain $A$ and $B$ in (9)–(10), $\theta$ in (19), and hence $\delta = \theta A + B$ in (18).

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

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

where we defined

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

This establishes a key result: $\beta$ is one of the solutions for $q$ of the quadratic equation

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

Generally, the quadratic equation in (26) has two solutions. In addition to the solution $q_1 = \beta$, there is a second solution $q_2 = \beta(\delta - 1)\sigma^2/\sigma_{US}^2$. We therefore need to analyze when

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[14]There is no gain of using more than two $\omega_{nn}$ equations as additional equations leave results unchanged. When we use our identification results for estimation, we use all $\omega_{nn}$ equations of course.

we can determine which of the two solutions for $q$ in (26) identifies $\beta$.

We start with the simplest case, which is when $\delta$ is positive and smaller than 2. In this case $\sigma^2/\sigma_{US}^2 < 1$ implies $(\delta-1)\sigma^2/\sigma_{US}^2 \in (-1,1)$. As the two solutions for $q$ in (26) are $q_1 = \beta$ and $q_2 = \beta(\delta-1)\sigma^2/\sigma_{US}^2$, this yields that $\beta$ can be identified as the solution for $q$ in (26) with the larger absolute value, $\beta = \max(|q_1|, |q_2|)$.

This is the simplest expression for $\beta$ when $\delta$ is positive and smaller than 2. But the expression does not generalize to other cases where $\beta$ is exactly identified. An alternative expression that holds for all cases where $\beta$ is exactly identified is $\beta = \kappa b$, where $b$ is the standard benchmarking estimator and $\kappa$ 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, which is proven in the Appendix, summarizes this result.

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

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

**Proposition 3. [Identifying $\beta$: necessary and sufficient condition in terms of identifiable $\delta$ and $\kappa$]**
The effect of interest $\beta$ can be exactly identified if and only if

$$
\begin{aligned}
\text{either} \quad & \delta \geq 0 \quad \text{and} \quad \kappa \geq \tfrac{\delta-1}{\delta} \\
\text{or} \quad & \delta < 0 \quad \text{and} \quad \kappa \leq \tfrac{\delta-1}{\delta}
\end{aligned}
\tag{28}
$$

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

When $\beta$ 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 Appendix. The idea is the following. The two solutions for $q$ of the quadratic equation in (26) yield two candidate solutions for $\beta$. Each of these two candidate solutions can be combined with the variance of US industry characteristics and the identifiable parameter $\eta$ in (25) to yield two candidate solutions for the country-specific

technological heterogeneity parameter $\sigma^2$. As at least some of the variation in technological industry characteristics reflects a global component, it must be that $0 \leq \sigma^2 < \sigma_{US}^2$. It turns out that this restriction is only satisfied by one of the two candidate solutions for $\sigma^2$ if the condition in (28) holds. Hence, only one of the two candidate solutions for $\beta$ is consistent with the model and this solution is $\beta = \kappa b$. On the other hand, if the condition in (28) fails, both candidate solutions for $\beta$ imply candidate solutions for $\sigma^2$ that are positive and smaller than $\sigma_{US}^2$. As a result, both candidate solutions are consistent with the model and it is impossible to say which of the two solutions of (26) identifies $\beta$.

The necessary and sufficient condition in Proposition 3 is not easily interpreted in terms of the parameters of the underlying model. The next proposition gives the necessary and sufficient condition for identification in terms of $\sigma^2$ and $\delta$.

**Proposition 4. [Identifying $\beta$: necessary and sufficient condition in terms of model parameters]** $\beta$ can be exactly identified if and only if

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

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

Intuitively, Proposition 4 implies that $\beta$ can be identified exactly if cross-country heterogeneity in technological industry characteristics is not too large ($\sigma^2/\sigma_{US}^2$ not too large) and/or if the association between countries' technological similarity with the US and their $x$-characteristics is not too strong ($\delta$ not too large in absolute value). On the other hand, if there is substantial cross-country heterogeneity in technological industry characteristics and/or countries' technological similarity with the US is strongly associated with their $x$-characteristics, it cannot be established which of the two solutions of (26) identifies $\beta$.

When exact identification of $\beta$ is impossible, one could report both solutions for $q$ in (26) as possible values for $\beta$. An alternative is to establish bounds on $\beta$ 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 $\beta$ 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 Appendix.

**Proposition 5. [Bounds on $\beta$]** If the condition in (28) does not hold and exact identifi-

cation of $\beta$ is impossible, then

$$
\text{if } \delta > 2 \text{ then } \frac{\beta}{b} \in \left( \frac{1}{\delta}, \frac{\delta - 1}{\delta} \right) \tag{31}
$$

$$
\text{if } \delta < 0 \text{ then } \frac{\beta}{b} \notin \left[ \frac{1}{\delta}, \frac{\delta - 1}{\delta} \right].
$$

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

## 4.2 Identification of $\Omega$

Now that we have shown when and how $\beta$ can be identified for known variance-covariance matrix $\Omega$, we turn to the identification of $\Omega$. 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 $\Omega$.[15]

The starting point to identify $\Omega$ is least-squares estimation of the model in (20). The least-squares residuals $\widehat{u}_{in} = y_{in} - \widehat{v}_i - \widehat{v}_n - \widehat{\gamma}_i x_n$, 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 estimated variances and covariances depend on the $\omega_{nm}$ we collected in the variance-covariance matrix $\Omega$ and can therefore be used to identify $\Omega$ under some conditions.

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

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

---

[15]The main difference with GLS analysis is that we are interested in the variance-covariance matrix of the disturbances in (20) but not other model parameters, like the industry slopes for example. GLS analysis is generally interested in variance-covariance matrices because of their role in the efficient estimation of other model parameters. The reason we are not interested in the other model parameters in (20) is that they not help to identify $\beta$.

where the $v_{in}$ are the demeaned versions of $u_{in}$

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

and the $\psi_k$ 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 $\pi_{nm}$

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

We show in the Appendix that using (32)-(33) in (35) yields the following equations linking $\pi_{nm}$ and the elements $\omega_{nm}$ of $\boldsymbol{\Omega}$

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

where $\mu_n$ and $\lambda_n$ are functions of the $\omega_{nm}$ detailed in the Appendix and

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

These equations are the basis for the identification of the variance-covariance matrix $\boldsymbol{\Omega}$ from the least-squares residuals of (20)-(22).

**A structure for $\boldsymbol{\Omega}$.** It is well understood that the identification of the variance-covariance matrix $\boldsymbol{\Omega}$ is impossible for an arbitrary matrix, as (36) and (37) has more unknowns than linearly independent equations (e.g., Amemiya, 1985).[16] For identification to be possible, the empirical framework must put some structure on $\boldsymbol{\Omega}$. The structures used in the literature depend on the application (e.g., Amemiya, 1985; Wooldridge, 2002; Conley, 2010).

We chose a structure for $\boldsymbol{\Omega}$ that has the implicit structure in the cross-industry cross-country literature as a special case but allows for substantial deviations from this baseline. The implicit structure for $\boldsymbol{\Omega}$ in the cross-industry cross-country literature is that differences

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[16]We show this in the Appendix.

between the technological industry characteristics of a country and global technological industry characteristics are completely idiosyncratic to each country. This implies that the technological industry characteristics of different countries are related through the global component only. Put differently, the country-specific technological industry characteristics $\varepsilon_{in}$ in (2) for any pair of countries $n \neq m$ are uncorrelated, i.e. $\rho_{nm} = 0$. As we have seen above, the standard benchmarking estimator is attenuated in this case.

We choose a structure for $\boldsymbol{\Omega}$ that follows the cross-industry cross-country literature in that the technological industry characteristics of *some country pairs* are related through the global component only. I.e. for some country pairs $n \neq m$, $\rho_{nm} = 0$. But for all other country pairs, we allow for an entirely arbitrary correlation $\rho_{nm}$ between the country-specific technological industry characteristics.

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

(i) Allows for an arbitrary correlation $\rho_{nm}$ 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 $\tau$. When we set large values for the threshold $\tau$, many country pairs satisfy $|x_n - x_m| \leq \tau$, and our structure for $\boldsymbol{\Omega}$ therefore allows for arbitrary correlations $\rho_{nm}$ 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* assumed to be 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 $\tau$, their country-specific industry characteristics are taken to be uncorrelated, $\rho_{nm} = 0$.[17] $\rho_{nm} = 0$ implies that the technological industry characteristics of these country pairs *are* related through the global technological component only, as implicitly assumed for all country pairs in the cross-industry cross-country 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 $\tau$, we can reduce the number of country pairs with $\rho_{nm} = 0$ and therefore deviate substantially from the implicit assumption in the cross-industry cross-country literature that $\rho_{nm} = 0$ for all country pairs $n \neq m$.

We refer to this structure for the variance-covariance matrix $\boldsymbol{\Omega}$ as $\boldsymbol{\Omega}^\tau$ to capture that it depends on the threshold $\tau$. What makes this structure for $\boldsymbol{\Omega}$ interesting in our context is that it corresponds to the implicit structure in the cross-industry cross-country literature for $\tau =$

---

[17]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).

0. We can move away from this baseline quite continuously and substantially by increasing $\tau$. 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.

The size of the threshold $\tau$ must be interpreted relative to the distribution of the $x$-characteristic across countries. It is therefore often easier to think about the fraction of unrestricted $\rho_{nm}$ with $n \neq m$ implied by a threshold $\tau$. When $\tau$ is very small, the fraction of unrestricted $\rho_{nm}$ will be small as few country pairs will satisfy $|x_n - x_m| \leq \tau$. As a result, the assumed structure for $\boldsymbol{\Omega}$ will be similar to the implicit structure in the cross-industry cross-country literature. On the other hand, when the threshold $\tau$ is large, the fraction of unrestricted $\rho_{nm}$ will be large as many country pairs will satisfy $|x_n - x_m| \leq \tau$. As a result, the structure for $\boldsymbol{\Omega}$ can deviate quite substantially from the implicit structure in the cross-industry cross-country literature. (If the threshold $\tau$ is chosen so large that all country pairs with $n \neq m$ can have different $\rho_{nm}$, we are not imposing any structure on the variance-covariance matrix $\boldsymbol{\Omega}$ and identification is impossible.)

As the choice is difficult in practice, we vary the threshold $\tau$ over the whole range that permits identification of $\boldsymbol{\Omega}$. Put differently, we allow the fraction of unrestricted $\rho_{nm}$ with $n \neq m$ to vary between zero and the maximum that still permits identification of $\boldsymbol{\Omega}$. As this maximum can be surprisingly large, our structure for $\boldsymbol{\Omega}$ can deviate substantially from the implicit structure in the cross-industry cross-country. In some cases, $\boldsymbol{\Omega}$ can be identified for values of $\tau$ that leave 90% of the $\rho_{nm}$ unrestricted. This amounts to little structure being put on the cross-country heterogeneity in technological industry characteristics. By varying the fraction of the unrestricted $\rho_{nm}$ between zero and the maximum that permits identification, we can examine how sensitive the results for $\beta$ are to the restrictions put on $\boldsymbol{\Omega}$.

Of course, other, more parsimonious structures for $\boldsymbol{\Omega}$ could be chosen (and would generally be simpler to deal with). For example, the structures used in spatial econometrics for spatial dependence could be adapted to capture the technological similarity of countries as a function of their $x$-characteristics and other country characteristics (e.g., Conley, 2010).

Summarizing, we assume that if countries have sufficiently similar $x$-characteristics $|x_n - x_m| < \tau$, $\rho_{nm}$ with $n \neq m$ is unrestricted. On the other hand, $\rho_{nm} = 0$ if $|x_n - x_m| \geq \tau$. The threshold $\tau$ is set by us and we present results for the largest possible range allowing for the identification of $\boldsymbol{\Omega}$. Larger $\tau$ translate into a greater fraction of $\rho_{nm}$ that are unrestricted.

**A condition for identification of $\boldsymbol{\Omega}$.** The structure $\boldsymbol{\Omega}^\tau$ for the variance-covariance matrix $\boldsymbol{\Omega}$ 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

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

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

To take the first step and determine $\mu_n^\tau$ and $\lambda_n^\tau$, 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 $\mathbf{\Omega}^\tau$ if the matrix $\mathbf{G}^\tau$ has full rank. This depends on the distance threshold $\tau$ and the distribution of the $x$-values across countries.

Table 1 illustrates this for three types of distributions for the $x$-values across countries. For each distribution, we draw $x$-values for 150 countries.[18] We repeat this 300 times. For each draw we calculate the value for the maximum threshold $\tau$ such that $\mathbf{G}^\tau$ has full rank for all smaller $\tau$. We refer to this value as $\tau_{\max}$. As this value is somewhat difficult to interpret, we do two things to put it into perspective:

(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 $\rho_{nm}$ with $n \neq m$ that are implied by $\tau_{\max}$. We then report this number relative to the total number of country pairs. For example, if this ratio is 0.8, the $\rho_{nm}$ are unrestricted for 80% of all country pairs.

Table 1 reports these statistics averaged across the 300 draws we take. We first present results for the case where the country characteristics are uniformly distributed between 0

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[18]This is approximately the number of countries in our application of the new benchmarking estimator below. We obtain very 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 $\tau$ allowing identification $(\tau_{\max})$ | Country pairs $n \neq m$ with unrestricted $\rho_{nm}$ relative to total number of country pairs at $\tau_{\max}$ |
|---|---|---|---|
| Uniform on $[0,1]$ | 0.33 | 0.49 | 0.74 |
| Standard normal | 1.13 | 2.58 | 0.93 |
| Exp. with $\lambda = 1$ | 1.01 | 2.55 | 0.91 |

and 1. The distance $|x_n - x_m|$ averaged across all country pairs is 0.33. The maximum value of the distance threshold $\tau$ that still permits identification $(\tau_{\max})$ is 0.49. The number of country pairs with unrestricted $\rho_{nm}$ with $n \neq m$ relative to the total number of country pairs 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).

As a second illustration, Table 1 shows results for the case where the country characteristics are drawn from a normal distribution with mean 0 and a standard deviation of 1. The distance $|x_n - x_m|$ averaged across all country pairs is 1.13. $\tau_{\max}$ is 2.42. The number of country pairs with unrestricted $\rho_{nm}$ with $n \neq m$ relative to the total number of country pairs at $\tau_{\max}$ is 93%. 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 illustration in Table 1 is for the 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. Once we have estimated the solutions for $q$, we estimate $\beta$ using Proposition 2 or Proposition 3, or obtain bounds for $\beta$ using Proposition 5.

**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 $\pi_{nm}$ 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 $\tau$. We begin with very small values of $\tau$. If all countries have different $x$-characteristics (as in our application below), this implies that 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 cross-industry cross-country literature). The implied matrix $\mathbf{G}^\tau$ is of full rank. We then increase $\tau$ up to the maximum value still yielding a matrix $\mathbf{G}^\tau$ of full rank. To estimate $\boldsymbol{\mu}^\tau$ and $\boldsymbol{\lambda}^\tau$ on the basis of (39), we also need an estimator of the column vector $\boldsymbol{\pi}$. We obtain this estimator by replacing the $\pi_{nm}$ collected in the vector $\boldsymbol{\pi}$ with the estimates $\widehat{\pi}_{nm}$ 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 $\omega_{nm}^\tau$ 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 $\omega_{nm}^\tau$ allow us to estimate $\theta$, $\beta\sigma$, and $\rho_{nm}$. The estimates of $\theta$ and $\beta\sigma$ are obtained by combining the expressions for the variances $\omega_{nn} = (\theta + x_n)^2(\beta\sigma)^2$ in (23) with our estimates $\widehat{\omega}_{nn}^\tau$. This yields

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

where $\upsilon_{nn}$ captures sampling error. The nonlinear least-squares estimates of $\theta$ and $\beta\sigma$ are then combined with our estimates of the nonzero $\omega_{nm}^\tau$ with $n \neq m$ and the expression for

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the covariances in (23) to estimate the nonzero $\rho_{nm}^{\tau}$ using that $\rho_{nm}^{\tau} = \omega_{nm}^{\tau}/[(\theta + x_n)(\theta + x_m)(\beta\sigma)^2]$. Moreover, our estimate of $\beta\sigma$ can be combined with the variance of the industry characteristics in the benchmark country $\sigma_{US}^2$ to estimate $\widehat{\eta}$ using (25). Consistency follows from the consistency of the $\widehat{\omega}_{nm}^{\tau}$.

**Step 4:** Use the estimates $\widehat{\rho}_{nm}^{\tau}$ to estimate $\widehat{A}^{\tau}$ using (9) and $\widehat{B}^{\tau}$ using (10). Hence, we have all the elements to estimate $\widehat{\delta}^{\tau}$ using (18)

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

**Step 5:** Replace $\delta$ and $\eta$ in (26) by the consistent estimates $\widehat{\delta}^{\tau}$ and $\widehat{\eta}$. This allows us to obtain consistent 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 $\beta$ as explained in Proposition 2 and Proposition 3 or to obtain bounds on $\beta$ as explained in Proposition 5. Confidence bands of all our estimates are obtained by bootstrapping.[19]

## 5.2  Reestimating Nunn (2007)

Nunn employs data on exports for up to 222 industries in up to 146 countries to show that institutional quality has a positive effect on comparative advantage in industries that depend more on relationship-specific intermediate inputs.[20]  In terms of the model in (1), the institutional quality of countries takes the place of $x_n$ and their log exports in industry $i$ takes the place of $y_{in}$. The theoretically relevant industry characteristic $z_{in}$ is the relationship-specific intermediate-input intensity of production. The benchmark country used to obtain proxies for how intensively industries use relationship-specific inputs is the US.

We apply the approach in the previous section to reestimate Nunn's baseline specification without controls and his specification with controls for human and physical capital. We report our estimates of $\delta$ and $\beta$ as a function of the threshold distance $\tau$ and the share of unrestricted, and hence estimated, correlation coefficients $\rho_{nm}$.

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[19]Bootstrapping the confidence intervals of our estimates of $\delta$ and $\beta$ involves reshuffling the $u_{in}$ in (20) across industries for each country 300 times and each time reestimating $\boldsymbol{\pi}$, $\boldsymbol{\mu}$, $\boldsymbol{\lambda}$, $\omega_{nm}$, $\theta$, $\beta\sigma$, $A$, $B$, $\rho_{nm}$, $\delta$, $\eta$, $q_1$, $q_2$, and $\beta$. The confidence intervals for our point estimates of $\delta$ and $\beta$ are obtained from the distributions of the estimated $\delta$ and $\beta$.

[20]See Levchenko (2007) and Costinot (2009) for related empirical and theoretical findings on the effect of institutional quality on comparative advantage.

### 5.2.1 Results for the Baseline Specification

Figure 2: Share of unrestricted $\rho_{nm}$ with $n \neq m$ as a function of $\tau$ for Nunn's baseline specification.
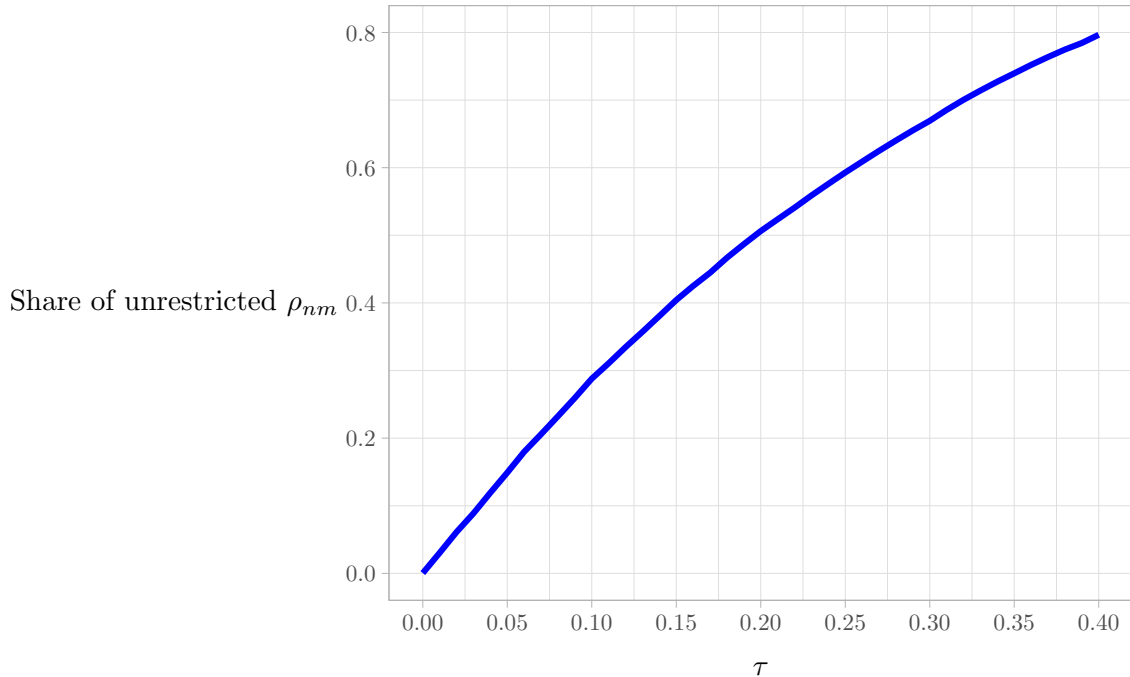


Figure 2 plots the threshold distance $\tau$ on the horizontal axis and the number of unrestricted correlation coefficients $\rho_{nm}$ relative to the total number of country pairs on the vertical axis (there are 10,585 country pairs as Nunn uses data for 146 countries). When $\tau$ is very small, the condition $\rho_{nm} = 0$ is assumed for all country pairs $n \neq m$ (all countries have different institutional quality). Hence, the number of unrestricted $\rho_{nm}$ relative to the total number of country pairs is 0. This corresponds to the implicit assumption in the cross-industry cross-country literature. For $\tau = 0.2$, around half the $\rho_{nm}$ are unrestricted and must therefore be estimated. As $\tau$ goes to 0.4, 80% of the $\rho_{nm}$ must be estimated. For values of $\tau$ larger than 0.4, $\mathbf{G}^\tau$ no longer has full rank and $\boldsymbol{\mu}^\tau$ and $\boldsymbol{\lambda}^\tau$ cannot be determined. In this case, $\boldsymbol{\Omega}^\tau$ cannot be identified.

Figure 3 summarizes our results for $\delta$. Estimates are shown as green dots and 95% confidence intervals are marked as green lines. The area shaded in light grey marks values of $\delta$ that according to Proposition 1 result in an attenuation bias of the standard benchmarking estimator. The area shaded in darker grey marks values of $\delta$ that according to Proposition 1 result in an amplification bias of the standard benchmarking estimator. For very small values of $\tau$, 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 (as implicitly assumed in the cross-industry cross-country literature). Hence, $A = B = 0$ in (9)–(10) and $\delta = 0$ in (18). Estimates of $\delta$ remain very

Figure 3: Estimates of $\delta$ for Nunn's baseline specification.

$\tau$ (top number) & share of country pairs for which $\rho_{nm}$ is estimated (bottom number)
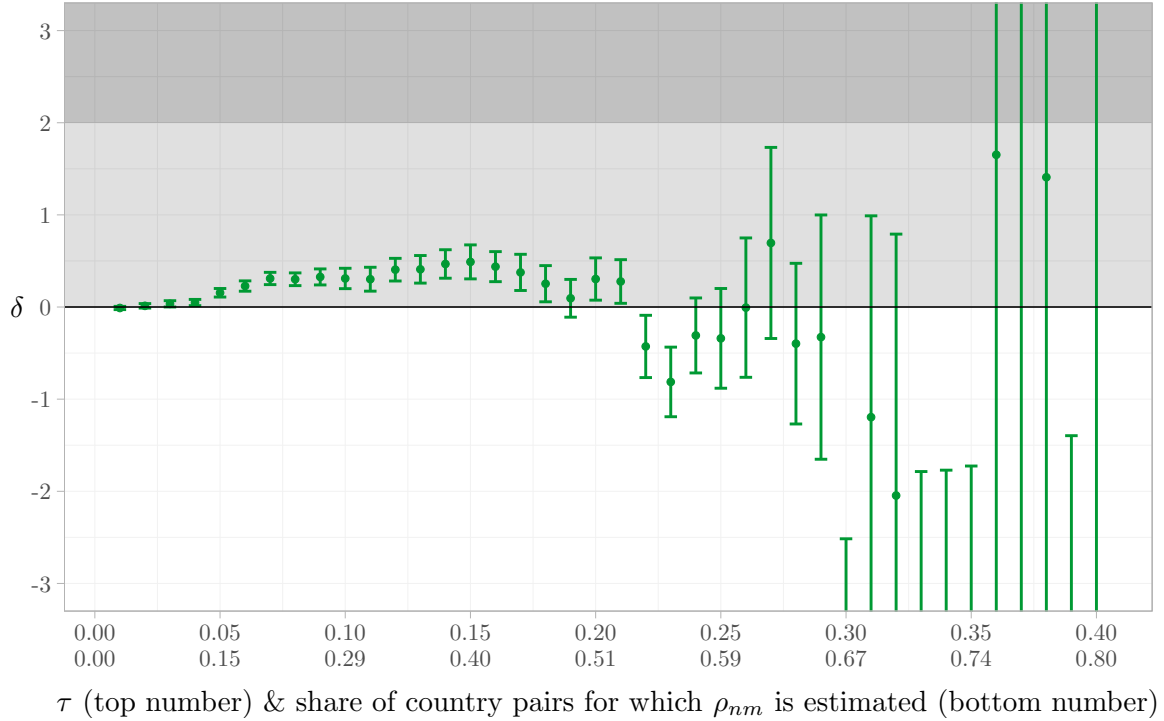
small for values of $\tau$ smaller than 0.02. Point estimates are between $-0.01$ and $+0.01$ and 95% confidence intervals include 0. Hence, we cannot reject $\delta = 0$. According to Proposition 1, $\delta = 0$ implies that the standard benchmarking estimator is subject to an attenuation bias. According to Proposition 2, $\delta = 0$ implies that we can estimate $\beta$ as $\beta = \kappa b$ with $\kappa$ given in (27). Figure 4 shows our point estimates for $\beta$ as orange dots and 95% confidence intervals as orange lines. Point estimates are around 7.2, around 10% larger than Nunn's estimate of 6.6 obtained with the standard benchmarking estimator (marked by the horizontal black line).[21] The 95% confidence intervals of our estimates are between 6.7 and 7.7.

For values of $\tau$ between 0.03 and 0.21, point estimates of $\delta$ in Figure 3 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 $\delta$ greater than 0 but below 1. Proposition 1 implies that for $0 \leq \delta \leq 1$, the standard benchmarking estimator is subject to an attenuation bias. Proposition 2 implies that for $0 \leq \delta \leq 1$, we can estimate $\beta$ as $\beta = \kappa b$. Figure 4 shows our estimates for $\beta$. Point estimates are between 7.2 and 6.8. Hence, the difference with Nunn's benchmarking estimate of 6.6 is smaller than what we obtained for very small $\tau$. This is because very small values for $\tau$ imply $\delta = 0$, and the bias of the standard benchmarking estimator is solely shaped by a force generating attenuation in this case. When $\delta > 0$, the

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[21]The estimate reported by Nunn differs because it is standardized. We report non-standardized estimates throughout.

Figure 4: Estimates of $\beta$ for Nunn's baseline specification.



$\tau$ (top number) & share of country pairs for which $\rho_{nm}$ is estimated (bottom number)
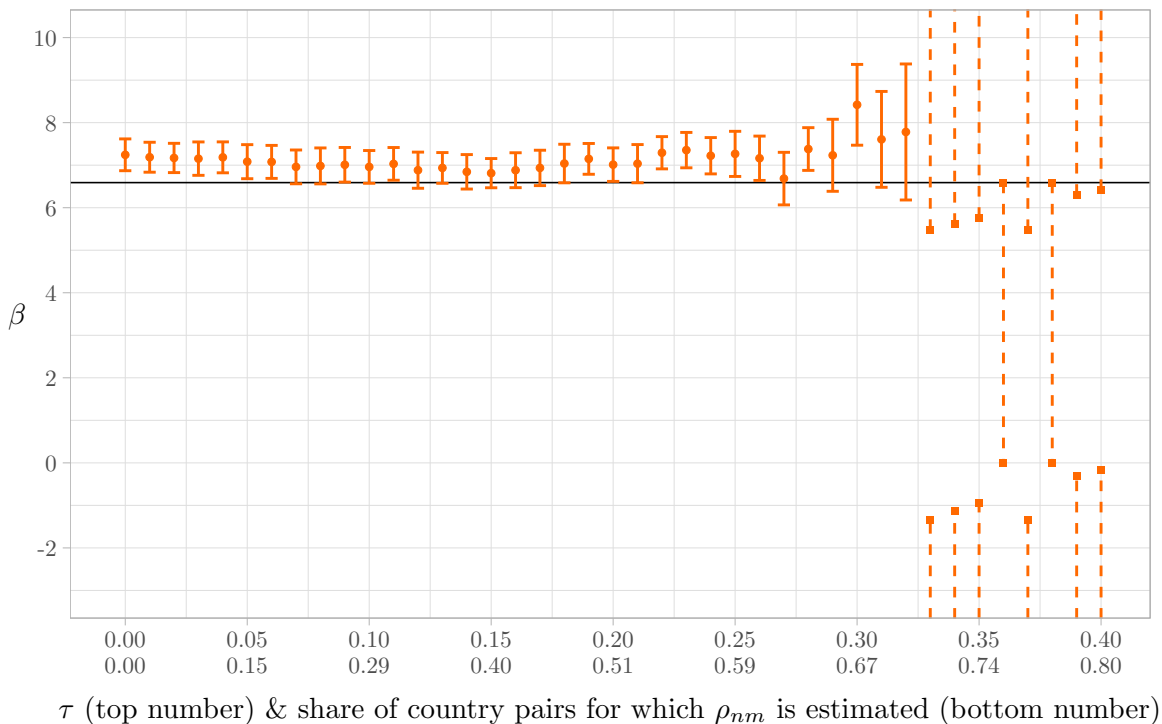
bias of the standard benchmarking estimator is also shaped by a force countervailing the attenuation bias. The 95% confidence intervals of our estimates lie between 6.5 and 7.6.

For values of $\tau$ between 0.22 and 0.32, estimates of $\delta$ in Figure 3 are negative, except for $\tau = 0.27$. As a result, we cannot use Proposition 2 to estimate $\beta$. However, we can still estimate $\beta$ as $\beta = \kappa b$ as our point estimates of $\kappa$ satisfy the condition for exact identification in Proposition 3.[22] Figure 4 shows our estimates for $\beta$. Point estimates are between 6.6 and 8.5 and therefore up to 30% larger than Nunn's standard benchmarking estimate of 6.6 (the horizontal black line). The 95% confidence intervals of our estimates lie between 6 and 9.5.

For values of $\tau$ between 0.33 and 0.4, our estimates of $\delta$ in Figure 3 become very noisy. The range of 95% confidence intervals varies between 6 and 82 (we do not show the full intervals as this would make the figure unreadable). This likely reflects that for $\tau \geq 0.33$, the correlation coefficients $\rho_{nm}$ with $n \neq m$ of at least 70% of the 10,585 country pairs are being estimated. Point estimates of $\delta$ for $\tau$ between 0.33 and 0.4 are mostly negative. As the necessary and sufficient condition for exact identification of $\beta$ in Proposition 3 is not satisfied, we can only establish the bounds in Proposition 5. Figure 4 illustrates the values of $\beta$ consistent with these bounds as dashed lines delimited by squares.

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[22]For simplicity, we are evaluating the condition in (28) based on the point estimates of $\delta$ and $\kappa$. A more complete approach would be to test the condition. To do so, note that the two cases in (28) can be combined in a single condition $\delta(\kappa - 1) + 1 \geq 0$. Bootstrapping the 95% confidence levels of the left-hand side of the inequality would allow testing this condition.

Overall, our estimation approach applied to Nunn's baseline specification yields estimates that are close to Nunn's even when we impose little structure on the cross-country heterogeneity in technological industry characteristics, i.e. as many as 70% of the $\rho_{nm}$ with $n \neq m$ are unrestricted and hence estimated. Sometimes this is because the countervailing forces generating an attenuation and amplification bias of the standard benchmarkiong estimator partly offset each other. Our estimates become very noisy and/or exact identification becomes impossible when more than 70% of the $\rho_{nm}$ are unrestricted (the theoretical limit to identification is when 80% of the $\rho_{nm}$ are unrestricted).

### 5.2.2 Results with Controls for Human and Physical Capital

Building on Romalis (2004) and other studies in international trade, Nunn also presents results controlling for the effect of human and physical 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 as well as an interaction between country-level physical capital and the physical-capital-intensity of industries.

We reestimate Nunn's specification controlling for the effect of human and physical capital on comparative advantage using the new benchmarking estimator. The implementation follows the same steps as for Nunn's baseline specification, except that least-squares estimation of (20) accounts for the effect of human and physical capital following Nunn.

Figure 5: Share of unrestricted $\rho_{nm}$ with $n \neq m$ as a function of $\tau$ for Nunn's specification with controls for human and physical capital.
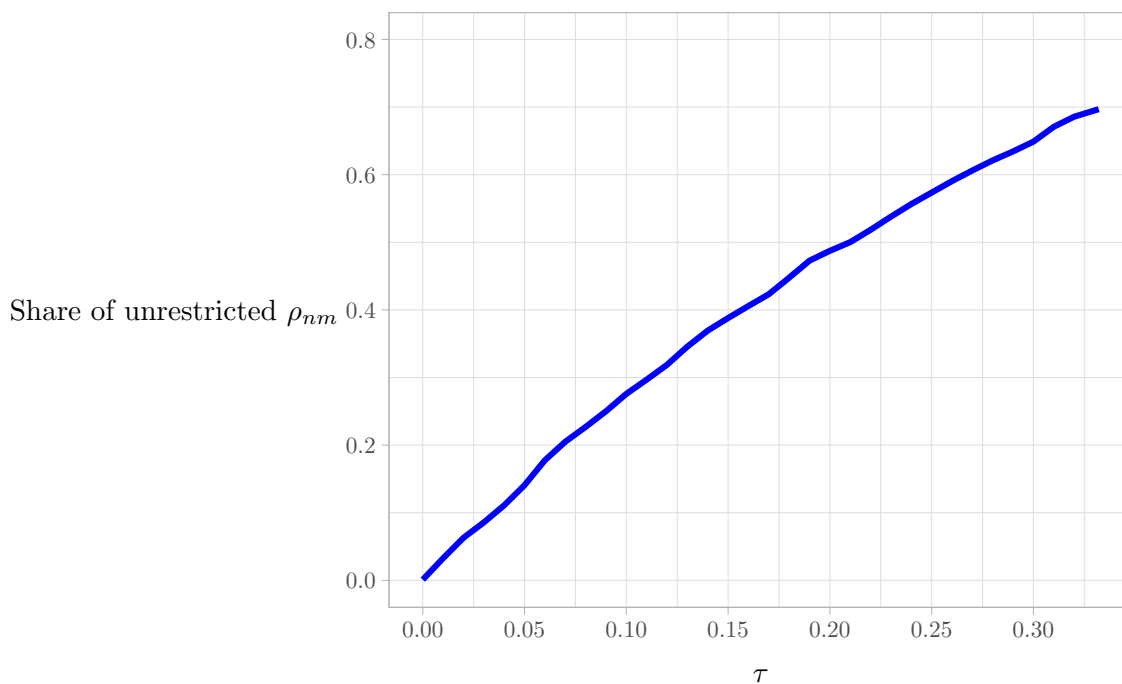
Figure 5 plots the threshold distance $\tau$ on the horizontal axis and the number of unrestricted correlation coefficients $\rho_{nm}$ with $n \neq m$ relative to the total number of country pairs on the vertical axis (there are only 2,415 country pairs in this specification, as Nunn has the necessary data for fewer countries). The ratio starts at 0 when $\tau$ is very small. This corresponds to the implicit assumption in the cross-industry cross-country literature. For $\tau = 0.2$, around half the $\rho_{nm}$ are unrestricted and must therefore be estimated. As $\tau$ goes to 0.31, 70% the $\rho_{nm}$ are unrestricted and must therefore be estimated. For larger values of $\tau$, $\boldsymbol{G}^{\tau}$ no longer has full rank. Hence, $\boldsymbol{\Omega}^{\tau}$ can no longer be identified.

Figure 6: Estimates of $\delta$ for Nunn's specification with controls for human and physical capital.



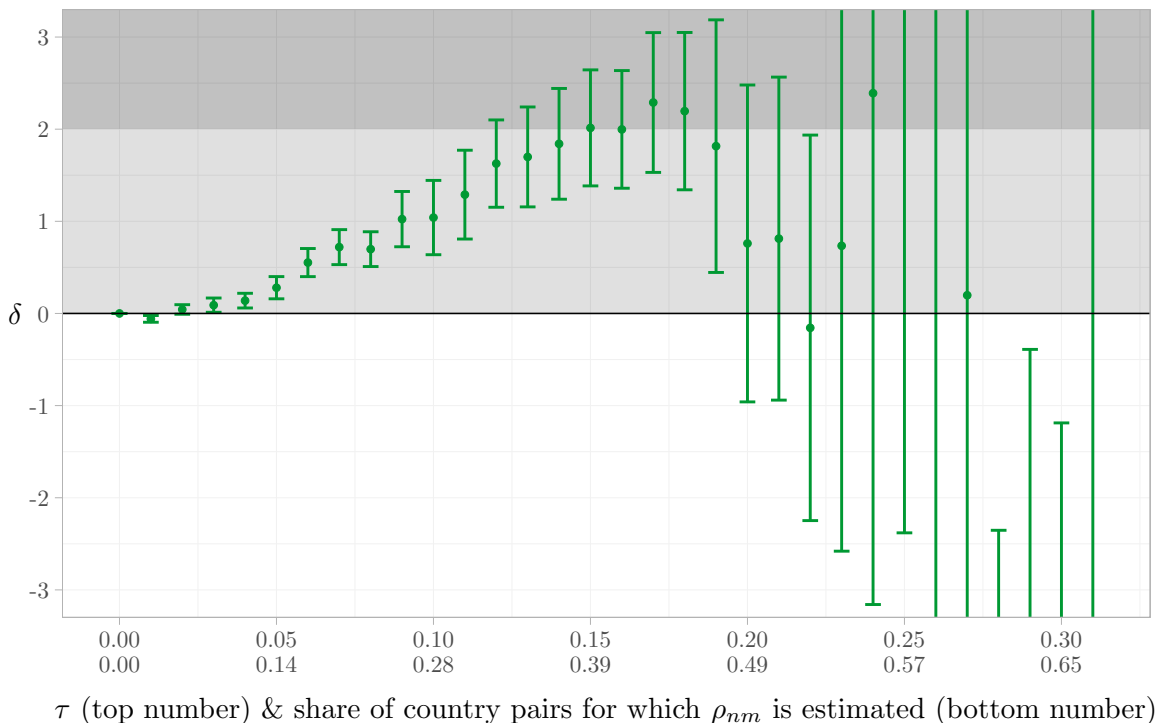$\tau$ (top number) & share of country pairs for which $\rho_{nm}$ is estimated (bottom number)

Figure 6 summarizes our results for $\delta$. The area shaded in light grey continues to mark values of $\delta$ that according to Proposition 1 result in an attenuation bias of the standard benchmarking estimator. The area shaded in darker grey marks values of $\delta$ that according to Proposition 1 result in an amplification bias of the standard benchmarking estimator. For values of $\tau$ smaller than 0.02, point estimates of $\delta$ 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 standard benchmarking estimator is attenuated. According to Proposition 2, $\delta = 0$ implies that we can estimate $\beta$ as $\beta = \kappa b$. This yields estimates of $\beta$ around 7, see Figure 7. 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). The 95% confidence intervals of our estimates for $\beta$ lie between 6.4 and 7.5.

For values of the threshold distance $\tau$ between 0.03 and 0.11, point estimates of $\delta$ in Figure 6 are between 0.09 and 1.3. The 95% confidence intervals are between 0 and 2. Hence, the data support values of $\delta$ between 0 and 2. According to Proposition 2, $0 \leq \delta \leq 2$ implies that we can estimate $\beta$ as $\beta = \kappa b$. This yields the estimates of $\beta$ in Figure 7. 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 $\delta$ is between 0 and 1 and subject to an amplification bias when $\delta$ is greater than 1. The 95% confidence intervals of our estimates of $\beta$ are between 5.7 and 7.5.

Figure 7: Estimates of $\beta$ for Nunn's specification with controls for human and physical capital.



$\tau$ (top number) & share of country pairs for which $\rho_{nm}$ is estimated (bottom number)
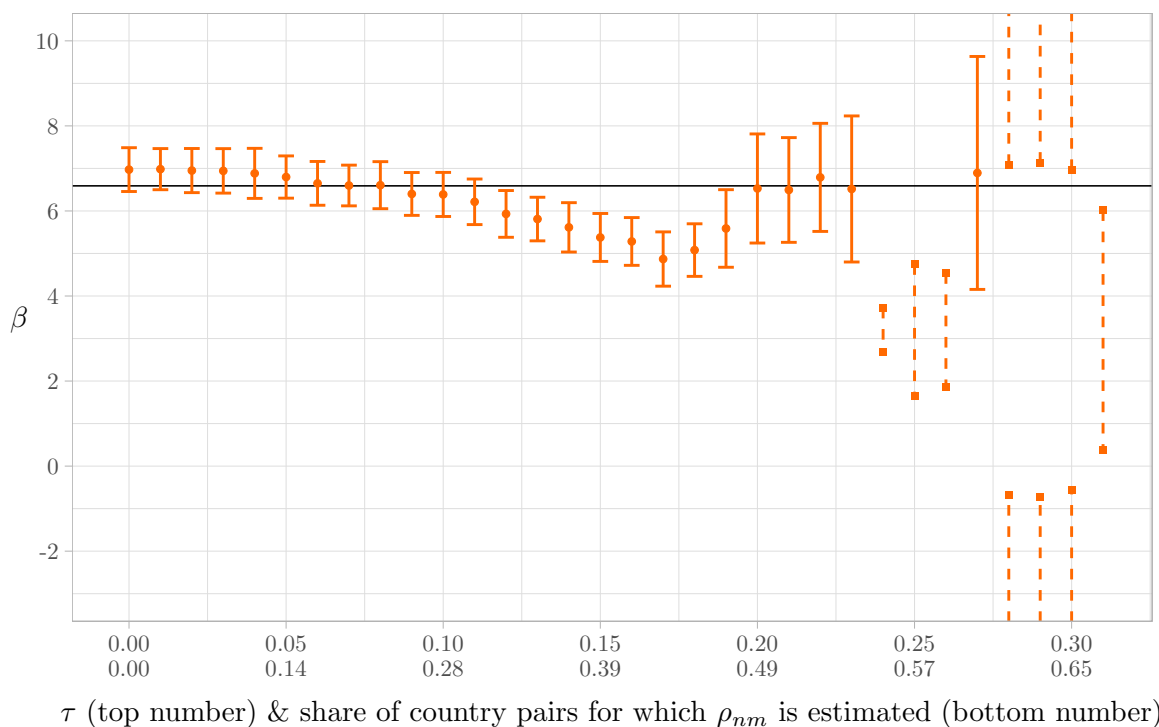
When $\tau$ is between 0.12 and 0.19, estimates of $\delta$ in Figure 6 are between 1.6 and 2.3. Hence, the standard benchmarking estimator is subject to an amplification bias according to Proposition 1. The condition for exact identification in Proposition 3 is always satisfied and we can therefore estimate $\beta$ as $\beta = \kappa b$. Estimates of $\beta$ in Figure 7 are between 5.9 and 4.9, up to 25% smaller than Nunn's estimate of 6.4. The 95% confidence intervals of our estimates lie between 6.5 and 4.2.

For values of $\tau$ between 0.2 and 0.23, estimates of $\delta$ in Figure 6 are generally between 0 and 1. According to Proposition 2, $0 \leq \delta \leq 1$ implies that we can estimate $\beta$ as $\beta = \kappa b$. Our point estimates of $\beta$ in Figure 7 are between 6.5 and 6.7, only slightly larger than Nunn's

estimate of 6.4. The 95% confidence intervals of our estimates lie between 4.8 and 7.8.

For values of $\tau$ between 0.24 and 0.31, our estimates of $\delta$ are very noisy. The range of 95% confidence intervals varies between 11 and 42 (we do not show the full intervals as the figure would become unreadable). This likely reflects that we are approaching the limits of identification as for $\tau \geq 0.24$, the correlation coefficients $\rho_{nm}$ of at least 55% of the 2,415 country pairs are being estimated.

Overall, our estimation approach applied to Nunn's specification with controls for human and physical capital yields results that are similar to Nunn's even when as many as 55% of the $\rho_{nm}$ with $n \neq m$ are unrestricted and hence estimated. When there are larger discrepancies between our estimates and those of Nunn, the forces generating an amplification bias of the standard benchmarking estimator dominate those generating an attenuation bias. As a result, our estimates tend to indicate smaller effects than Nunn's. Our estimates become noisy and/or exact identification becomes impossible when more than 55% of the $\rho_{nm}$ are unrestricted (the theoretical limit to identification is when 70% of the $\rho_{nm}$ are left unrestricted).

# 6    Conclusion

Using data on differences in industry performance across countries to test economic theories is attractive. We argue that the estimation approach in the literature does generally not answer the research questions being asked correctly and therefore propose an alternative.

The source of the problem with the estimation approach in the literature is not difficult to see. Cross-industry cross-country models must specify the technological industry characteristics that according to the economic theory being tested, should interact with the country characteristic being examined. As these industry characteristics are unobservable for most countries, they are proxied by industry characteristics in a benchmark country, usually the US. If optimal technology is endogenous, there is no reason to expect the technology of US firms –and hence the technological industry characteristics of US industries – to be identical to the optimal technology of firms and industries in other, often much less economically and institutionally developed, countries. Moreover, the optimal technology in an industry is likely to be endogenous to a variety of country characteristics. Depending on the correlation among these characteristics, the estimation approach in the literature may yield attenuated, amplified, or entirely spurious results.

Amplified or spurious estimates can arise when countries that are more similar in their optimal industry technologies tend to be more similar in several other characteristics. The size of the amplification bias and of spurious effects depends on how much more similar countries are technologically to the benchmark country as they become more similar in

other characteristics.

As the estimation approach in the literature generally yields biased results when there is cross-country heterogeneity in technological industry characteristics, we propose an alternative estimation approach that draws on insights from the generalized least squares literature. We show how the alternative approach can be implemented by reestimating the effect of institutional quality on exports in industries that rely more on relationship-specific inputs in Nunn (2007). Our estimates tend to be similar to Nunn's even when we impose little structure on cross-country heterogeneity in technological industry characteristics.

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