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Comment on: “trade and diffusion of embodied technology: An empirical Analysis” by ayerst, ibrahim, mackenzie, and rachapalli

Simone Lenzu

New York University, Stern School of Business, United States

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ABSTRACT

In this paper, I offer some comments on “Trade and Diffusion of Embodied Technology: An Empirical Analysis” by Ayerst, Ibrahim, MacKenzie, and Rachapalli. I emphasize certain aspects of the empirical analysis that are crucial to the message and interpretation of the results. Additionally, I discuss some limitations of the empirical analysis and highlight some interesting stylized facts presented in the paper, which might be worth exploring in future research.

> *The mysteries of the trade become no mysteries;*
>
> *but are as it were in the air, and children learn many of them unconsciously.*
>
> (Marshall 1890: 198)

From the ancient Silk Road to modern global trade networks, trade has played a significant role in diffusing knowledge and technologies throughout history. The exchange of goods and services between different regions and civilizations has facilitated the transfer of ideas, skills, and know-how that have contributed to the advancement of human society. During the ancient Silk Road trade routes, Chinese traders exchanged goods such as silk, porcelain, and gunpowder with Middle Eastern and European traders. This exchange allowed for the spread of Chinese technology, including paper-making, printing, and the compass, which greatly influenced the development of the Western world. The Industrial Revolution of the 18th and 19th centuries is another prominent example. New inventions and processes, such as the steam engine and the spinning jenny, were developed in Europe and then disseminated to other parts of the world through trade. This diffusion of technology facilitated the rapid growth of industry and the rise of modern economies. Globalization has further accelerated the diffusion of knowledge and technologies through trade. Advances in transportation and communication have made it

E-mail address: slenzu@stern.nyu.edu

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easier for people and goods to move around the world, and multinational corporations have created global supply chains that connect different parts of the world.

Given the significance of this topic, it is not surprising that a large body of literature has attempted to establish the theoretical foundations of the link between trade and knowledge diffusion, as well as to document its empirical relevance.[1] However, quantifying the significance of trade as a channel of knowledge diffusion remains an open question in the literature, with measurement and identification challenges that need to be addressed.

Firstly, there is the question of how to define and measure knowledge. As Marshall once remarked, "knowledge is in the air" (1890: 198), suggesting that it is difficult to capture its essence in quantitative terms. Secondly, international trade and the development and adoption of new technologies are equilibrium outcomes that are affected by unobservable demand-side forces. Demand shocks may prompt a country to import more from a technologically advanced country, and, at the same time, increase its investments in innovation. Reverse causality is also a concern, as countries with higher levels of innovation are more likely to import knowledge-intensive goods (such as those produced in the US). If this is the case, the relationship between knowledge embedded in trade and innovation outcomes would not be causal.

In their paper, Ayerst et al. (2023) take up these challenges. The authors conduct an empirical analysis aimed at identifying the causal effect of exposure to knowledge embodied in goods imported from the US, viewed as the technological frontier, on the innovation outcomes of non-US country-sectors.

From a measurement perspective, the linchpin of the empirical analysis is a new measure of the technologies embodied in imported goods. The authors combine cross-country-sector data on international trade flows with data on global patents and citations to construct knowledge input-output (IO) tables. Trade flows measure the connectivity of a given country-sector with the US through trade. The patent citations-based knowledge IO tables measure the relevance of knowledge produced by US sectors for a given sector in a foreign country that trades with the US.

The construction of IO country-sector knowledge tables is one of the contributions of the paper.[2] To gain intuition on the information content of these tables, consider the example of the electronics industry. When countries import electronics from the US, they also import the technologies that are used to produce those electronics, such as microprocessors and software. These technologies can then be adopted by local manufacturers and used in a wide range of applications, possibly leading to the development of new technologies, products, and services. To the extent that both US technologies and foreign technologies end up being patented, it is possible to use patent citations to measure the knowledge embodied in goods traded by the US, as well as the knowledge produced by the importing countries.

To address the identification concerns due to endogeneity and reverse causality, the authors develop an instrumental variable strategy that identifies the elasticity of interest using variation in technologies embodied in traded goods that is driven by country-sector US export shocks (supply socks) that are plausibly orthogonal to changes in the foreign demand of US goods.

The authors find that knowledge flows embodied in traded goods generate positive spillovers on the country-sectors that import those goods, both in terms of increased innovation (measured by forward citations) and knowledge diffusion (backward citations). By using supply shock as an instrumental variable, they are able to identify the causal effect of trade-embodied knowledge on innovation outcomes. This is an important contribution to the literature, as it provides more robust evidence on the causal mechanism driving the relationship between trade and knowledge diffusion.

Below are some comments on the paper. I stress some aspects of the empirical analysis that are key for the message and interpretation of the results, discuss some limitations of the empirical analysis, and highlight some interesting stylized facts in the paper that might be worth exploring in future work.

1. The role of trade

After reading an earlier version of this paper, I was concerned that the authors did not provide sufficient evidence that trade is the fundamental driver of their empirical results. Specifically, trade flows (imports from the US) are used as weights of the different entries of the knowledge IO tables in the construction of their measure of trade-embodied knowledge. It was unclear to me how the results would change if their measure used a different set of weights to weight US patent citations instead of trade flows.

The authors addressed this concern in several ways in the final version of the paper. Notably, they conducted a falsification test where they replaced the actual import flows from the US with random import flows. This test showed that the trade weights used in their embodied technology measures are indeed crucial in finding evidence of innovation spillovers from knowledge embodied in goods.

[1] For instance, see the seminal work of Grossman and Helpman (1991), the recent work of Cai et al. (2022), and the literature surveyed by Keller (2021).

[2] A contemporaneous paper, Liu and Ma (2021), also constructs knowledge IO tables that are similar to the ones in Ayerst et al. (2023). Although the approach and some of the features of the tables are similar across the two papers, the most notable distinction is that Ayerst et al. (2023) focus on characterizing the IO tables at the level of aggregation of country-sectors vis–vis the US, whereas Liu and Ma (2021) construct IO tables at the county-level but look at different countries (US and others) as knowledge originators. Section 4.2 inAyerst et al. (2023) discusses the similarities in the two approaches and highlights some of the similarities and differences in the findings.

2. Measuring knowledge diffusion

Both the measure of knowledge embodied in goods and the outcome variables considered in the paper are based on patents citation data. Understandably, in the absence of direct measures of knowledge, patent citation data offer the most intuitive and easily measurable proxy of technology diffusion: a new patent citing an existing patent unequivocally indicates that (i) a technology diffuses and that (ii) the diffusion is linked to the production of new knowledge.

However, there are certain limitations to this measure that are worth mentioning. By construction, citations only measure the diffusion of technologies that are ultimately patented, but they overlook other important forms of diffusion and adoption, such as reverse engineering, imitation, and learning by doing.

When a company imports a product from another country, it can often disassemble the product and study the technologies used to make it. This process can help the company to learn about new technologies and to develop its own products using those technologies, without generating new patents and without citing the patent that protects the original technology.

Another way in which technologies embodied in traded goods can diffuse to other countries and sectors is through the process of imitation. When a company sees a product that is successful in another country, it can often try to imitate the product by using similar technologies. This process can help the company to develop new products that are similar to the products that are being imported.

Finally, technologies embodied in traded goods can also diffuse to other countries and sectors through the process of learning by doing. When a company imports a product from another country, it can often learn about the technologies used to make the product by working with the product. This process can help the company to develop its own products using those technologies.

Notably, these forms of adoption are particularly relevant for countries away from the frontier, which also tend to have weaker enforcement of intellectual property rights. Mindful of these considerations, other studies have tried to broaden the set of outcome variables to include measures of innovations based on R&D expenditures (e.g., Liu and Ma 2021). Another approach would be to look at variables that are affected by innovation. The most natural one is total factor productivity. Productivity measures are already widely available at the country level (see, for example, the KLEMS database and the COMPNET database). Country-sector level productivity is also becoming available as representative firm-level datasets containing information on production become more accessible and comprehensive in terms of coverage (see, for example, the ORBIS and AMADEUS datasets).

3. Some interesting patterns in the knowledge IO tables

The authors deserve credit for the tremendous amount of work required to construct their knowledge IO tables. While a previous draft of the paper solely focused on cross-sectional differences between the US knowledge and production IO tables, the current version of the paper includes additional descriptive statistics comparing IO knowledge tables across countries and over time. I find some of the descriptive patterns that emerge from the knowledge tables interesting and believe they could inspire future research aimed at understanding the nature of knowledge networks, their interrelation, and persistence. I highlight some of them below.

The authors find that knowledge IO linkages of different country-sectors with the US are highly persistent over time, more so than production IO linkages with the US, and also more persistent than the knowledge IO linkages established with countries other than the US. This suggests that connections to the US through mutual technology are more stable, while customer-supplier relationships are more subject to change over time.[3] This finding is consistent with the importance of knowledge diffusion from the technological frontier, as opposed to away from the frontier. The lower persistence of knowledge linkages established with non-US partners may be related to the dominance of the US in certain sectors.

It is also interesting to note that knowledge inputs in non-US sectors are becoming more similar to those of their counterpart sectors in the US. This convergence pattern seems to be driven by country-sectors that initially have relatively lower correlation to the knowledge used by their US counterparts.

4. Knowledge diffusion from countries away from the frontier

The analysis in the paper exclusively focuses on US technologies as the source of trade-embodied knowledge. As the authors mentioned, this choice is justified by the fact that the US is the largest and most radical innovator of the last few decades, and also because detailed patent data is more broadly available for the US. However, it would be interesting to understand the extent to which knowledge embodied in traded goods with countries that are not at the frontier also generates positive innovation spillovers, and how large these spillovers are.

There are reasons to believe that these types of spillovers might be quite important, especially for developing countries. One reason is that countries lagging far away from the frontier might not be able to make good use of the latest technologies. For example, a new IT system may not be very useful for a firm that predominantly uses analog technologies in its

[3] The authors correctly point out that the persistency of knowledge IO networks has also been shown, at the county-level, in a contemporaneous work by Liu and Ma (2021).

production processes. Another reason is that adopting the latest technologies might be too expensive. It is generally true that royalty rates of US patents are higher than the royalty rates of relatively similar non-US patents, and this can be a deterrent for adopting the latest technologies.

Finally, we should keep in mind that the specific metric used to measure knowledge might matter for the purpose of quantifying diffusion form countries away from the frontier. Due to institutional and cultural reasons, firms in many countries rely less on the patent system as a form of protection of their intellectual property rights. In this scenario, relying solely on patent citations to measure knowledge linkages may provide less informative and noisier results for trade partners outside the US. Consequently, the measurement approach used in this paper could potentially lead to a downward bias in the estimates.

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