# International trade and R&D spillovers

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**Abstract**

Departing from the usual tenets of proportionality between cross-border trade flows and knowledge spillovers, we investigate whether relatively intense trade relationships are associated with particularly large international R&D spillovers. A nonlinear specification nesting the hypothesis of global and trade-unrelated R&D spillovers is estimated on a sample of 24 advanced countries over 1971-2004. We find evidence that trade patterns positively affect the international transmission of knowledge, in particular when we consider bilateral trade flows that, thanks to the estimation of an auxiliary gravity model, are normalized for the size and the distance of the trading partners. Finally, we discuss the patterns of the bilateral relationships characterized by both relatively intense trade and large R&D spillovers.

*Key words:* Knowledge spillovers, International R&D spillovers, International trade network, Total Factor Productivity

*JEL Classification*: C23, F01, O30, O47

## 1. Introduction

Knowledge has positive effects on the productivity of the country in which it is produced and accumulated (see, for instance, Aghion and Howitt, 1992; Romer, 1990), but it may also affect foreign productivity to the extent that it is directly and indirectly transferred abroad, as shown in several theoretical contributions (e.g. Grossman and Helpman, 1991a,b; Rivera-Batiz and Romer, 1991;

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Keller, 2004). While this is received wisdom, the channels of the international transmission of knowledge are less clear.

Coe and Helpman (1995) are pioneers in developing an empirical approach to estimate the impact of domestic and foreign knowledge on domestic Total Factor Productivity (TFP). By focusing on a sample of 22 advanced countries over the period 1971-1990, they investigate the specific trade-related channel of international knowledge transmission. To account for this channel, they build import-weighted sums of trade partners' cumulative R&D expenditures as measures of foreign knowledge stocks. In their preferred specification, they also include an interaction term between the degree of trade openness (the country's import/GDP ratio) and the stock of trade-weighted foreign R&D stock.[1]

Keller (1998) questions the appropriateness of the weighting scheme used by Coe and Helpman (1995) in the construction of the foreign stocks of knowledge. According to his empirical findings, the unweighted sum of the foreign R&D stock does an equivalently good job of picking-up the knowledge diffusion process than the trade-weighted sum proposed by Coe and Helpman. Keller concludes that it remains unclear whether the knowledge diffusion process is global and trade-unrelated or not, in contrast with Coe and Helpman's suggestion that knowledge spillovers follow a local diffusion process affected by the size and structure of the trade flows.[2]

Keller (1998, 2004) points out that the empirical studies using trade-weighted foreign R&D stocks and trade-related interacting terms in the specification implicitly assume that the knowledge transferred across countries is proportional to the size of the trade flows, in accordance with the idea that the exchanged goods embody the technological know-how of the exporting countries.[3] From the theoretical viewpoint, as discussed in Keller (2000, 2004) and recognized in passing by Coe et al. (2009, footnote 12), the exchange of technology embodied in the exchanged goods is only one of the various channels through which trade may influence knowledge transmission and thus productivity. Large trade relationships are certainly important for international knowledge transmission, but knowledge

[1]Several scholars have refined Coe and Helpman's (1995) seminal analysis along several directions, ranging from the econometric technique and the data to the level of disaggregation and the composition of the trade flows, while preserving their approach (e.g. Engelbrecht, 1997; Lichtenberg and van Pottelsberghe de la Potterie, 1998; Xu and Wang, 1999; Lumenga-Neso et al., 2005; Madsen, 2007; Coe et al., 2009; Bianco and Niang, 2012; Fracasso and Vittucci Marzetti, 2013). We refer to Keller (2004) for a review of the literature.

[2]At the theoretical level, the existence of global spillovers is consistent with a model of international technology diffusion without trade in intermediate goods, such as the model built by Keller (2004) on the basis of Eaton and Kortum (1999).

[3]More precisely, Keller (1998) argues that Coe and Helpman's (1995) empirical specification implicitly builds on three demanding assumptions: i) output and productivity positively depend on the number of differentiated intermediate inputs used in the production of final products; ii) the number of varieties produced in a country depends on the domestic R&D stock; iii) the larger the aggregate trade flows, the greater the number of imported varieties of intermediate inputs. This setting is consistent with those models where traded goods are used as productive inputs and differentiated goods embody technological know-how (e.g. Grossman and Helpman, 1991b; Rivera-Batiz and Romer, 1991; Eaton and Kortum, 2002).

transfers and trade flows need not be proportional. As arm's length market transactions enhance communication between the partners, relatively intense trade partnerships can favor knowledge transmission even when small in absolute terms. Accordingly, the proportionality between trade and knowledge flows should not be arbitrarily imposed in the empirical specifications to estimate. This is all the more important because it has been shown that the specific trade-related weights used to aggregate foreign R&D stocks impact on the estimated coefficients and that the results vary considerably across the different adopted weights (see, for instance, Lichtenberg and van Pottelsberghe de la Potterie, 1998; Keller, 2000).

Our empirical strategy builds upon the straightforward observation that, if spillovers were global and trade-unrelated, all the countries could equally draw from the "global pool" of knowledge in the world (as in Keller, 1998). On the contrary, if spillovers were localized and trade-related, they should be relatively stronger (though not necessarily in a proportional way) where trade relations are relatively more intense. We investigate this hypothesis by relaxing the assumption about the existence of a proportional relationship between trade and knowledge flows. In so doing, we depart both from Keller (1998), as we account for the patterns of the international trade network, and from Coe and Helpman (1995), as we neither calculate a trade-weighted measure of foreign R&D stocks nor impose proportionality between trade and knowledge flows. Notably, while Coe and Helpman (1995) and Keller (1998) use non-nested specifications, that are not directly comparable, our estimated functional form nests the specification proposed by Keller (1998), thereby allowing to formally test his hypothesis of global and trade-unrelated R&D spillovers against that of trade-related (yet non-proportional) knowledge spillovers.[4]

The adoption of a nonlinear model and the use of an estimated critical value to identify the relatively intense flows of trade and knowledge raise some nuisance parameter problems in the estimation. We address these issues by building on the advances in the threshold regression literature, and in particular on Andrews and Ploberger (1994) and Hansen (1996, 1999).

The aim of our empirical exercise is to establish whether it is possible to identify relatively intense bilateral trade flows associated with relatively large knowledge flows without over-imposing any proportionality between the two. From an operational viewpoint, the method estimates the minimum value of bilateral trade (i.e., a threshold) which maximizes the ability of the specification to account for the actual patterns of international R&D spillovers by identifying a subset of bilateral relationships that exhibit both relatively intense trade and systematically different (expectedly larger, but possibly lower) R&D spillovers. For the sake of brevity, in what follows the bilateral flows which satisfy the joint condition of relatively intense trade and relatively large R&D spillovers will be synthetically called "strong flows": a "strong flow" is therefore a bilateral

[4]See also Keller (1997, 2000), who is the first to include trade-related and trade-unrelated R&D spillovers in the same econometric model.

trade flow overcoming a certain estimated threshold and associated with a relatively large knowledge spillover. As our empirical specification nests both the hypotheses of trade-related and trade-unrelated R&D spillovers, we can discriminate between the two without imposing any implicit restriction on the estimated functional form. Indeed, were R&D spillovers trade-unrelated, no "strong flows" would be detected.

We estimate the specification on a sample of 24 advanced countries over the period 1971-2004, recently studied by Coe et al. (2009).

To anticipate our main findings, we reject the null hypothesis of a "global pool" of knowledge and identify some relatively intense trade flows associated with larger R&D spillovers. Our findings suggest that the international diffusion of knowledge is systematically related to cross-border trade relationships and, therefore, knowledge spillovers are localized. We show that the relaxation of the proportionality between trade and knowledge flows does not prevent from detecting that relatively intense bilateral trade relationships are statistically associated with larger spillovers. We explore various ways to identify relatively intense flows by adopting alternative measures of bilateral trade. Although all the estimates are consistent with the main findings mentioned above, we find that knowledge spillovers are particularly large when bilateral trade flows exceed what is expected on the basis of the partners' size and distance.

This work contributes to the literature in three respects. First, by developing a model that nests both trade-related and trade-unrelated knowledge spillovers, it helps discriminate between the two hypotheses, which are equally plausible from a theoretical perspective. In so doing, this work follows what done by Keller (2000) and addresses Keller's (2004) claim that "the extent to which R&D spillovers are related to the patterns of international trade must be estimated in a model which allows simultaneously for trade-unrelated international technology diffusion" (2004, p.1480).[5] Second, this work addresses the econometric problems due to the presence of nuisance parameters, thereby tackling various issues associated with hypothesis testing in nonlinear specifications. Finally, this paper explores various ways to identify the relatively intense trade flows associated with large R&D spillovers without weighting the R&D stocks for the size of trade, thereby showing that trade matters in international knowledge transmission even relaxing the assumption of proportionality between trade size and knowledge spillovers.

The paper proceeds as follows. In Section 2, we frame the research question in the light of the empirical literature on international knowledge spillovers. Section 3 illustrates the empirical strategy we put forward to assess whether knowledge spillovers are trade-related or not. The results of the estimations using three alternative measures of trade intensity are discussed in Section 4, where we also map and discuss the subsets of "strong flows". In Section 5, we present an alternative analytical strategy that helps appreciate the value added

[5] Although Keller (2000) estimates trade-related and trade-unrelated R&D spillovers in the same model, his specification does not nest Coe and Helpman (1995) and Keller (1998), and imposes the assumption of proportionality between trade flows and knowledge spillovers.

of our threshold-based strategy. Section 6 concludes. The data are discussed in Appendix A, while Appendix B illustrates the details of the method adopted to deal with the nuisance parameter issue affecting statistical inference.

## 2. Trade flows, R&D stocks and international knowledge transmission

In their seminal paper, Coe and Helpman (1995) estimate an intuitive specification to capture the effect of foreign R&D on domestic TFP:

$$\log F_{it} = \alpha_i + \beta^d \log S^d_{it} + \beta^f \log S^f_{it} + \epsilon_{it} \tag{1}$$

where $i$ is the country index, $t$ the time index, $\log F_{it}$ is the log TFP, $S^d_{it}$ the domestically produced R&D stock, $S^f_{it}$ an import-weighted sum of the R&D stock produced outside the country $i$ at time $t$, i.e. $S^f_{it} = S^f_{CHit} \equiv \sum_{j \neq i} \frac{M_{ijt}}{\sum_{j\neq i} M_{ijt}} S^d_{jt}$, where $M_{ijt}$ are the imports of country $i$ from country $j$,[6] and $\epsilon_{it}$ an error term.[7]

Coe and Helpman (1995) find statistically significant and relatively large values for $\beta^f$, and conclude that both domestic and foreign R&D stocks positively impact on TFP, thus corroborating the theoretical works that postulate the impact of international knowledge flows on productivity. These findings are confirmed by Coe et al. (2009), where the analysis is repeated on an extended sample of 24 countries over the period 1971-2004, and human capital and institution-related variables are added to the explanatory variables.

Keller (1998) contends that the simple sum of all the R&D stocks in the rest of the world performs as well as Coe and Helpman's (1995) trade-weighted measures of foreign R&D, and estimates the Equation (1) using $S^f_{it} = S^f_{Kit} \equiv \sum_{j\neq i} S^d_{jt}$. He finds estimates for $\beta^f$ close to those obtained by Coe and Helpman (1995), casting some doubts on the possibility of discriminating between global and localized trade-related spillovers by using specification (1). The problem in adjudicating among the competing claims about the relevance of trade-related knowledge transmission is that the specification with an import-weighted sum of the R&D stocks and that with the simple sum of the R&D stocks are non-nested: one cannot easily implement formal tests to discern which is the preferable representation of knowledge spillovers.

[6] Lichtenberg and van Pottelsberghe de la Potterie (1998) claim that import shares should not be used to weight foreign R&D and suggest to resort to weights equal to the ratios of bilateral imports over the GDP of the exporting country. As shown by Coe et al. (2009), this reasonable modification does neither invalidate nor weakens what found using specification (1).

[7] In fact, Coe and Helpman (1995) estimate also other specifications. In one of them, they add to Equation (1) a term obtained by interacting the domestic R&D stock with a dummy variable for the G7 countries to allow their output elasticities to differ from the others. In another specification, international trade flows enter also as an interaction term, to allow for cross-country variation in the elasticity of TFP with respect to foreign R&D, i.e.:

$$\log F_{it} = \alpha_i + \beta^d \log S^d_{it} + \beta^f \frac{M_{it}}{Y_{it}} \log S^f_{it} + \epsilon_{it}$$

where $M_{it}/Y_{it}$ is the import-GDP ratio of country $i$ at time $t$.

It is worth noticing that the specification adopting the import-weighted sum of the R&D stocks implicitly assumes that knowledge transmission follows a trade-related diffusion process to the extent that knowledge is embodied in the traded goods. In fact, one cannot exclude the existence of different trade-related transmission mechanisms: for instance, knowledge spillovers may be disembodied due to the (partially) tacit nature of technology and they may still be related to international trade because the latter facilitates face-to-face interactions.[8] Accordingly, trade patterns may be important for the transmission of knowledge even excluding the existence of a proportional relationship between trade and knowledge flows.

To the best of our knowledge, the question of whether the international trade network is informative on R&D spillovers once the proportionality of spillovers and trade is relaxed remains to be tackled. In the next sections, we shall develop a way to nest a model with trade-unrelated spillovers into a model with trade-related spillovers and, at the same time, we shall exploit the information available in the entire network of international trade flows in a flexible and innovative way.

## 3. Model specification and estimation technique

If knowledge spillovers were trade-unrelated and global, any country could equally draw from the "global pool" of world knowledge and R&D spillovers would be independent from trade flows. It would then be impossible to identify any relatively intense bilateral trade flow that is systematically associated with relatively large knowledge spillovers. On the contrary, if spillovers were localized and trade-related, they should be stronger where trade flows are relatively more intense. In this case, it could be possible to identify what we defined as "strong flows", that is relatively intense bilateral trade flows associated with relatively large R&D spillovers. In this section, we introduce the technical aspects concerning both the formal testing of the null hypothesis of trade-unrelated and global spillovers and the identification of the "strong flows".

We start from the following nonlinear model that nests Keller's (1998) specification of Equation (1) and that we estimate via Nonlinear Least Squares (NLS):

$$\log F_{it} = \alpha_i + \beta^h \log H_{it} + \beta^d \log S^d_{it} + \beta^f \log\left(S^f_{Kit} + \iota\, S^{fs}_{it}\right) + \epsilon_{it} \qquad (2)$$

where $F_{it}$, $S^d_{it}$ and $S^f_{Kit}$ are as specified above, $H_{it}$ stands for the human capital stock of country $i$ at time $t$ (in line with the most recent papers, e.g. Engelbrecht, 1997; Coe et al., 2009), and $S^{fs}_{it}$ is the simple sum of the R&D stocks of a certain

[8] It is worth noting that, as long as the probability of face-to-face interactions decreases with geographical distance, there could be also trade-unrelated but still localized knowledge spillovers. See Fracasso and Vittucci Marzetti (2013) for an attempt to distinguish trade-related spillovers from trade-unrelated localized spillovers building on Keller (2002a).

subset of the partners of country $i$ that are the source of relatively intense trade flows toward $i$ in the year $t$.

But for the presence of human capital, as in Engelbrecht (1997), model (2) nests Keller's (1998) specification of Equation (1), as the former becomes the latter when $\iota = 0$.[9] The rejection of the null hypothesis $\mathrm{H}_0$: $\iota = 0$ (i.e., no different R&D spillovers among countries engaged in relatively intense trade flows) would provide evidence against Keller's hypothesis of global and trade-unrelated spillovers. Moreover, an estimated coefficient $\iota$ that is statistically greater than zero would support the idea that trade positively impacts on international transmission of knowledge, even without imposing any proportionality between trade and knowledge flows.

The implementation of this empirical strategy demands, first, to identify, in each period in the sample, the relatively intense trade flows so as to generate the variable $S_{it}^{fs}$ and, subsequently, to check whether these flows are associated with relatively large knowledge spillovers. In other words, we need to find a critical value (i.e., a threshold $\varphi$) which the bilateral trade exchanges have to overcome in order to qualify as relatively intense. For a given threshold $\varphi$ we then calculate $S_{it}^{fs}|_{\varphi} = \sum_{j \in \ominus_i|_{\varphi}} S_{jt}^{d}$ for country $i$ and time $t$, where $\ominus_i|_{\varphi}$ is the subset of the country $i$'s trade partners which are the source of bilateral exports above the threshold $\varphi$. After having computed $S_{it}^{fs}|_{\varphi}$, we estimate model (2) and formally test the null $\mathrm{H}_0$: $\iota = 0$ taking into account the presence of nuisance parameters (see Appendix B for details). If we fail to reject the null, we conclude that there is no evidence in favor of the hypothesis that knowledge spillovers are localized and related to the trade flows identified on the basis of the threshold $\varphi$. On the contrary, if we reject the null and the estimated $\iota$ (given $\varphi$) is statistically greater than zero, we can conclude that there is evidence of the existence of "strong flows", i.e. relatively intense trade flows systematically associated with larger knowledge flows.

It is apparent that the threshold $\varphi$ is a key determinant of the results as it is at the basis of the identification of the relatively intense trade flows. Had we adopted a strategy revolving around an arbitrarily chosen threshold, the results would have been conditional on the appropriateness of such initial choice. Instead, we explore the entire range of possible values of $\varphi$ and let the data indicate the value that maximizes model fit. Two considerations regarding this method are worth stressing. First, as Equation (2) explains international R&D spillovers, the threshold that identifies the relatively intense trade flows is chosen on the basis of its contribution to explain R&D spillovers: this ensures that the "strong flows" are the bilateral relationships exhibiting relatively large trade and inducing R&D spillovers that differ systematically from those characterizing the other bilateral relationships. Second, by choosing the fit-maximizing value of $\varphi$, we remain open to the possibility that the best model is the linear one, that is Keller's (1998) specification of Equation (1): if international knowledge flows

[9] Model (2) does not nest Coe and Helpman's (1995) specification of Equation (1), as there is no $\iota$ such that $S_{Kit}^{f} + \iota S_{it}^{fs} = S_{CHit}^{f}$.

were trade-unrelated, we would not identify any critical value $\varphi$ significantly associated with larger R&D spillovers and fail to reject the null of global and trade-unrelated spillovers.

This feature of the empirical strategy ensures that no arbitrary structure of "strong flows" is over-imposed in the estimation. We shall illustrate the importance of this issue in Section 5, where we shall perform an auxiliary estimation to show that over-imposing a plausible structure for the construction of $S_{it}^{fs}$ does not help to account for the actual R&D spillovers.[10] As the subset of "strong flows" is empirically identified and not over-imposed, its structure will be the object of further analysis with a view to casting light on the international transmission of knowledge.

A last feature of the estimation method is worth discussing at this stage, that is the dimension of the threshold $\varphi$. In each of the estimations, we identify the ordered pairs of countries exhibiting "strong flows" on the basis of a unique metric applied to the entire network of bilateral trade-related flows. This implies that, given a measure of trade under investigation, a unique threshold suffices to identify in each period the subnetwork of "strong flows" within the annual network of trade relationships. The threshold could be calculated either in absolute or in relative terms. In the case of the nominal trade flows, for instance, the threshold could be set either as a minimum amount of nominal trade (say, for instance, \$1 bn), or as a minimum percentage above/below the average trade flow in the sample (for instance, 5% above or below the average flow). Since in this study, in order to investigate the implications of various proxies of trade intensity, we shall adopt several measures of trade, it is convenient to adopt a metric that facilitates the comparison across the different measures: while a minimum amount of trade would make the threshold have the same order of magnitude of the series to which it refers, a minimum percentage above/below the average value of the series is a number that is comparable across all the measures of trade we adopt.[11]

The specification (2) is highly nonlinear in the parameters: first, the parameter $\iota$ enters the argument of the log; second, $S_{it}^{fs}|_{\varphi}$ is a function of the threshold $\varphi$. Notably, while $\iota$ can be estimated by NLS, this does not apply to $\varphi$. To address similar problems in threshold regression models, it is common practice to: i) run a grid search over a (limited) number of values of $\varphi$; ii) choose the value that minimizes the sum of squared residuals. The grid search approach, however, may easily lead to local minima in the estimation. To address this issue, we adopt and implement the Simulated Annealing (SA) algorithm proposed by Corana et al. (1987) (see Goffe et al., 1994, for an application to M-estimation problems).[12] Although SA is computationally intensive, it leads to much more

[10]We thank an anonymous reviewer for having suggested this analysis.

[11]It goes without saying that, having found a minimum percentage above/below the average, the threshold can always be rewritten to reflect the magnitude of the series to which it refers. With the exception of the specification with the trade series in absolute terms, however, this transformation would not produce any intuitive insights for the other measures of trade.

[12]Simulated Annealing—named after the process undergone by the atoms in a heated metal

reliable estimates.[13]

Given the presence of a generated regressor (i.e., $S^{fs}_{it}$) in the nonlinear specification, we shall report bootstrap standard errors for all the estimates. To account for the possible heteroskedasticity in the residuals, we shall employ the fixed-design wild bootstrap put forward by Gonçalves and Kilian (2004), which allows for heteroskedasticity of unknown form.[14] We estimate the parameters of Equation (2) for each of 1000 bootstrap samples (repeating both the SA and the NLS). The standard errors are then computed from the standard deviations of the bootstrap distributions of the estimated parameters.

Finally, it is worth noticing that the formal test of the null hypothesis of a global and trade-unrelated transmission of knowledge requires some complex inference on $\iota$, because the inference based on the bootstrap standard errors does not deal by itself with the presence of nuisance parameters under the null (see Appendix B for details).

In the following section, we shall present and discuss the main findings (the data used in the estimation, mostly borrowed from Coe et al. (2009) for comparability, are presented and discussed in Appendix A).[15]

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when it cools slowly—denotes a class of probabilistic algorithms to locate global minima/maxima of functions in large search spaces, when the problem is unmanageable using combinatorial or analytical methods. What makes SA preferable to standard iterative optimization algorithms is the "Metropolis criterion": in searching the parameter space, the algorithm may take some steps in the "wrong direction" with a certain probability, as this helps to better explore the space of possible solutions. The probability of taking a wrong step decreases if several consecutive iterations lead to no significant improvement in the solution. Corana et al.'s (1987) algorithm is just one of the many proposed in the literature (see, for instance, Otten and van Ginneken, 1989).

[13]Although we do not rely on SA for the estimation of the coefficient $\iota$ (which is subsequently estimated via NLS together with $\beta^d$, $\beta^h$, and $\beta^f$), our SA algorithm maximizes the fit of the model by exploring the space of both $\iota$ and $\varphi$. While we retain the fit-maximizing value of $\varphi$ as the estimated threshold, we employ the SA-estimated value of $\iota$ as a starting value in the subsequent NLS estimation. Unsurprisingly, given the ability of SA to span accurately the parameter space, the NLS estimate of $\iota$ is always nearly identical to that found by SA.

[14]In a nutshell, given the estimates of all the parameters, a bootstrap sample is generated recursively from the equation:

$$\log F^*_{it} = \hat{\alpha}_i + \hat{\beta^h} \log H_{it} + \hat{\beta^d} \log S^d_{it} + \hat{\beta^f} \log \left( S^f_{Kit} + \hat{\iota}\, S^{fs}_{it}|_{\hat{\varphi}} \right) + u^*_{it}$$

where the error terms $u^*$ are obtained by resampling the original residuals, each pre-multiplied by either 1 or $-1$ with $1/2$ probability.

[15]Coe et al. (2009) apply up-to-date panel cointegration techniques in their estimations because, as the authors show in the sections 2 and 3 of that article, the series are integrated of order one and co-integrated. As we analyze the very same dataset we do not reproduce here all the integration and the cointegration tests; rather, for the sake of brevity, we refer to their article for the details. In our paper, we do not exploit the improvements that could be derived in terms of inference by adopting a dynamic OLS (DOLS) method. This would increase the computationally intensity of the estimation and would prevent us from accounting for two more important problems: the presence of nuisance parameters (affecting the inference on $\iota$) and the presence of a generated regressor ($S^{fs}_{it}$) in a highly nonlinear model.

## 4. Are international R&D spillovers trade-related? Empirical results

Table 1 reports the results of Keller's (1998) specification of (1) in column I. This serves as a benchmark for the following estimations as it assumes that there is a "global pool" of knowledge in the world which all the countries can draw from at any time. Thus, column I refers to the estimates of Equation (2) under the restriction $\iota = 0$, whereby any trade-related transmission of knowledge is shut by construction. In the other columns of Table 1, we report the estimated parameters of Equation (2), that is $\beta^d$, $\beta^h$, $\beta^f$, $\iota$ and $\varphi$, for various measures of trade (individually explained in the following subsections). For each estimation, we identify and map the bilateral "strong flows" that help account for the observed patterns of international R&D spillovers (Figure 1).

### *4.1. Nominal bilateral trade flows*

The first trade measure we look at to identify "strong flows" is nominal bilateral imports ($M_{ijt}$). The absolute size of import flows represents a straightforward measure: even without a proportional relationship of trade and knowledge flows (which, as we explained, is an untested restriction in specifications *à la* Coe and Helpman, 1995), one could still expect that the larger the size of the trade flows, the larger the trade-related R&D spillovers. Whether this expectation is correct or not is an empirical issue that we endeavor to assess: in principle, as argued in Section 1, international knowledge transmission can be stronger where bilateral trade relationships are relatively intense rather than where they are relatively larger.

Column II in Table 1 reports the estimation of Equation (2) (NLS *cum* SA) where the trade measure is nominal bilateral imports ($M_{ijt}$). All the linear parameters are statistically significant and with the expected sign. The point estimates of the coefficients $\beta^d$, $\beta^h$, and $\beta^f$ are not much different from the linear specification *à la* Keller in Column I and they are also in line with previous studies. More importantly, we find that the estimated $\iota$ is almost equal to 2.4: this implies that the elasticity of the domestic TFP to the foreign R&D stock in case of "strong flows" turns out to be almost three times and a half larger than that for the other flows.[16] As anticipated in Section 3 and explained in details in Appendix B, the formal test of the null hypothesis of a global and trade-unrelated transmission of knowledge requires some complex inference on $\iota$ because of the presence of nuisance parameters under the null. This null hypothesis is strongly rejected by all the linearity tests reported at the bottom of Table 1.

Such finding provides evidence in favor of the hypothesis that trade matters in international knowledge transmission: also when the proportionality relationship between the size of the bilateral trade flows and the flows of knowledge is not over-imposed in the estimation (as instead done in Coe and Helpman, 1995; Coe et al., 2009), trade flows appear important in the process of international

[16] More precisely, given our functional specification, the TFP elasticity to foreign R&D stock is $(1 + \iota)$ times larger in case of "strong flows" than the elasticity for the other flows.

Table 1: Estimation results (Years 1971-2004 for 24 countries: 816 observations)

| | I | II | III | IV | V | VI |
|---|---|---|---|---|---|---|
| Trade measure | | $M_{ijt}$ | $\frac{M_{ijt}}{Y_{it}Y_{jt}}$ | $M_{ijt}^{sda}$ | BTP | $\frac{M_{ijt}}{Y_{it}}$ |
| $\beta^h$ | 0.523 | 0.570 | 0.506 | 0.522 | 0.562 | 0.567 |
| | (0.051) | (0.049) | (0.051) | (0.051) | (0.053) | (0.053) |
| $\beta^d$ | 0.046 | 0.036 | 0.050 | 0.041 | 0.044 | 0.045 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.006) |
| $\beta^f$ | 0.158 | 0.181 | 0.156 | 0.189 | 0.167 | 0.160 |
| | (0.016) | (0.015) | (0.016) | (0.016) | (0.015) | (0.016) |
| $\iota$ | | 2.384 | 0.997 | 3.705 | 1.376 | 2.570 |
| | | (0.793) | (1.245) | (0.893) | (1.013) | (1.735) |
| $\varphi$[a] | | 0.137 | -0.639 | 0.097 | | -0.078 |
| log-L | 832.36 | 877.07 | 838.66 | 895.17 | 841.10 | 849.75 |
| AIC[b] | -1610.74 | -1696.14 | -1619.32 | -1732.34 | -1624.19 | 1641.51 |
| BIC[c] | -1483.72 | -1559.71 | -1482.89 | -1595.91 | -1487.71 | -1505.07 |
| Linearity tests: $H_0\colon \iota = 0$[d] SupLM | | 33.31 | 16.98 | 42.67 | | 34.64 |
| | | [0.000] | [0.001] | [0.000] | | [0.000] |
| AveLM | | 12.89 | 4.40 | 13.30 | | 6.95 |
| | | [0.000] | [0.000] | [0.000] | | [0.000] |
| ExpLM | | 11.65 | 5.18 | 17.09 | | 13.17 |
| | | [0.000] | [0.001] | [0.000] | | [0.000] |

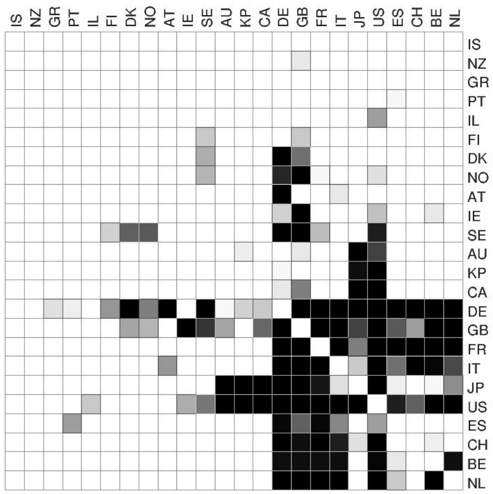
[a] Simulated Annealing over $\varphi$ and $\iota$. Tolerance: 1e-12. Initial temperature: 50. Temperature reduction factor: 0.85. Convergence achieved after on average 150 000 function evaluations.

[b] Akaike Information Criteria calculated, following Akaike's (1974) original formulation, as: AIC $= -2$ log-L $+ 2k$, where $k$ is the number of independently adjusted parameters in the model, i.e. 27 in model I, and 29 in models II, III, IV, V and VI.

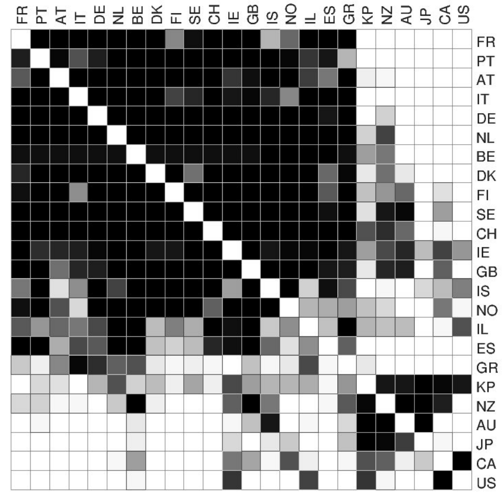
[c] Bayesian Information Criterion (Schwarz, 1978): BIC $= -2$ log-L $+ k \ln n$, where $k$ is the number of independently adjusted parameters and $n$ the number of observations (816).

[d] Bootstrap $p$-values in square brackets (see Appendix B).

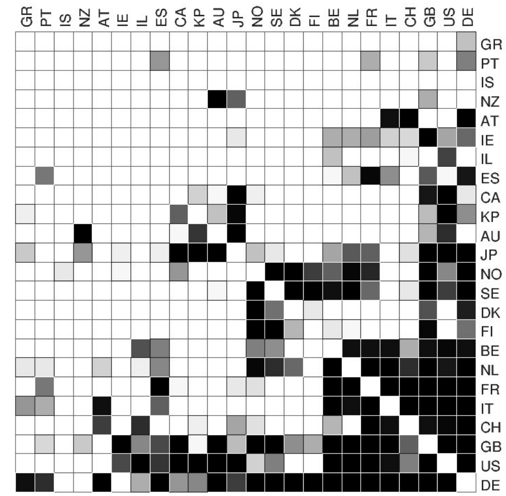
Unreported country dummies. Bootstrap standard errors in parenthesis (fixed-design wild bootstrap, 100 replications).



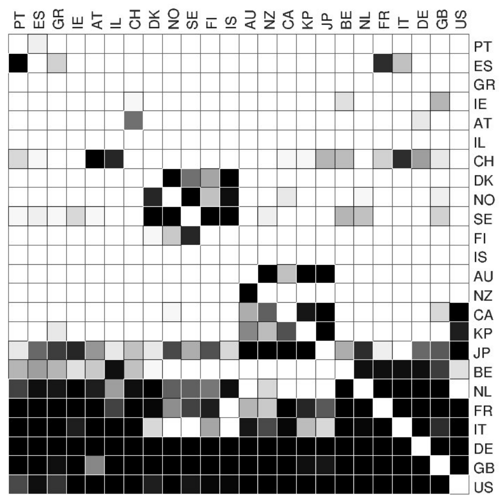

(a) Model II – trade measure: $M_{ijt}$



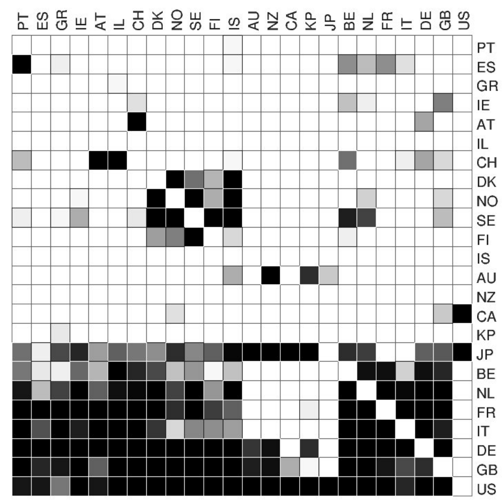

(b) Model III – trade measure: $\frac{M_{ijt}}{Y_{it}Y_{jt}}$




(c) Model IV – trade measure: $M_{ijt}^{sda}$




(d) Model V – 7 Best Trading Partners




(e) Model VI – trade measure: $\frac{M_{ijt}}{Y_{it}}$

Each cell $(i, j)$ refers to the flow from country $i$ to country $j$. Shades of grays are proportional to the fraction of periods in which the bilateral flow is identified as "strong". In all the matrices, except (e), the order of the countries comes from the permutation resulting from hierarchical clustering based on Euclidean dissimilarity indexes. In matrix (e), the order is the same of (d) to facilitate comparison.

Figure 1: Patterns of "strong flows"

transmission of knowledge. In sum, our point estimates corroborate the idea that global knowledge spillovers are related to trade patterns, as suggested by Coe and Helpman (1995), and in line with subsequent works (e.g. Xu and Wang, 1999; Keller, 2002b; Fracasso and Vittucci Marzetti, 2013).

As explained in Section 3, the threshold $\varphi$ is calculated as the relative difference from the annual cross-country average value of the bilateral nominal trade flows in the sample.[17] The estimated threshold in Column II is equal to 0.137 and this implies that bilateral trade flows 13.7% larger than the cross-country average flow in the same year are associated with stronger knowledge spillovers.

Armed with this estimate of $\varphi$, for each and every year we can identify the "strong flows" so as to draw some insights on the features of the bilateral relationships where both trade and knowledge flows are relatively large. Figure 1(a) shows a two-entry table that summarizes the information about the "strong flows". The table is an average of the annual adjacency matrices of the binary directed networks of the relationships identified as "strong". In particular, each cell $(i, j)$ in the table refers to the flow from the row-country $i$ to the column-country $j$, and it is colored according to the fraction of years in which the bilateral relationship between $i$ and $j$ is a "strong" one: dark (light) colored cells indicate fractions close to one (zero). The order of the countries in the matrix (which is identical across columns and rows) is based on the similarity between countries with respect to the profile of their rows and columns in the table, so that countries which are similar in terms of their average patterns of "strong" (in- and out-) flows are placed close to each other.[18]

In the top left corner of the table, one can find New Zealand and Iceland, the smallest and most isolated islands, followed by Greece, Portugal, Israel and Finland, that are the source or the destination of very few (if any) "strong flows". Then there comes a group of countries—Denmark, Norway, Austria, Ireland and Sweden—that exhibit "strong flows" with few partners, but that show persistently strong connections (in- and out-flows) with Germany and Great Britain. In the bottom corner of the table, we have the Netherlands and Belgium, followed by Switzerland and Spain, that i) entertain very persistent "strong" connections with a group of large economies (i.e. Germany, Great Britain, France, Italy, and US), ii) exhibit "strong relationships" among themselves (though in a discontinuous manner), and iii) almost never engage in "strong flows" with the remaining countries. Finally, US, Japan, Italy, France, Great Britain and Germany turn out to entertain "strong flows" among themselves and with the countries in the previously mentioned group in almost all the periods. Intuitively, we would have expected that the largest countries were the source and the

[17] By using relative differences with respect to annual averages we can avoid using real trade flows to account for changes in price levels.

[18] In particular, the order of appearance of the countries is the result of the permutation obtained from hierarchical clustering based on Euclidean dissimilarity indexes computed among country pairs. All the graphs and calculations were made using Pajek 3.15 (see De Nooy et al., 2011, Chapter 12, for details).

destination of several "strong flows" identified on the basis of this measure of trade. This is indeed the case.

These observations suggest that the limited R&D spillovers towards this last group of countries represents a drag on the estimated coefficient $\beta^f$ in a specification of Equation (2) *à la* Keller (1998) because the variable $S^f_{Kit}$ includes the domestic R&D stocks of too many trade partners. This intuition contributes to explain the improvement in ability of our nonlinear model to fit the data with respect to the linear one.

*4.2. Ratio of bilateral trade flows over the importer's and exporter's GDP*

Since nominal bilateral trade flows reflect the heterogeneous size of the trading countries, the identification of "strong flows" on the basis of a unique threshold for all the trade flows in absolute value could penalize the smallest countries. Indeed, despite their size, these countries may be engaged in relatively intense international exchanges of products and knowledge. Consider, for example, a pair of small open economies, such as Belgium and the Netherlands (or, alternatively, Switzerland and Austria). The commercial relationships between two small countries cannot but be limited in absolute terms,[19] and yet their trade may be relatively intense once the size of the countries is taken into account.

If the relatively intense bilateral flows, rather than the relatively large ones, were those conducive to larger R&D spillovers, to capture better the "strong flows" we would need to repeat the previous exercise after having adopted an alternative measure of trade that is able to capture relative intensity. A good candidate is a measure built trough the normalization of the nominal trade flows for the size of the importing and the exporting countries, i.e., $M_{ijt}/(Y_{it}Y_{jt})$. Were international knowledge spillovers stronger where the trade flows are larger in absolute terms, the adoption of such size-adjusted bilateral measure of trade would prevent from identifying any "strong flow" linked with relatively intense commercial ties.

We believe that the specification encompassing a measure of trade normalized for the size of the trading partners can provide additional insights on international knowledge transmission. There are alternative but possibly coexisting channels of trade-related knowledge transmission: one that, even short of a proportionality between trade and knowledge flows, still stems from the sheer dimension of trade; the other that depends on the relative intensity of trade between any two countries, independently from their absolute size. We do not posit that the size-adjusted measure is theoretically preferable to the nominal flows: we let the data speak about these two alternative ways of operationalizing the hypothesis that countries characterized by relatively intense trade flows also enjoy larger knowledge spillovers.

[19]For instance, in 2004 the Dutch imports from Belgium-Luxembourg amounted to USD 31 billion, while the US imports from Japan—two big countries relatively less open than the Netherlands and Belgium—amounted to USD 133 billion.

We identify the "strong flows" by considering the entire network of commercial ties on the basis of a size-adjusted measure of trade obtained by normalizing the nominal flows for the size of both the importer and the exporter. Column III in Table 1 presents the estimates of specification (2) with the size-adjusted trade flows. The estimates of the linear parameters are similar to those in Columns I and II. The estimated $\iota$ is close to unity, implying that the international R&D spillovers among the partners in "strong" partnerships are twice as large than otherwise. The fit of this specification is superior to that of the linear model, which strengthens our previous conclusion that R&D spillovers are trade-related.[20] That said, the overall fit of this specification is inferior to that based on nominal bilateral flows (Column II).

The estimated threshold ($\hat{\varphi}$) is negative and equal to $-0.639$, which implies that only the ratios that are lower than one third of the annual cross-country average ratio are not classified as "strong flows". A better reading of these results, then, would be the following: knowledge spillovers across two countries are limited only when these countries are in particularly bad trading relationships.

This interpretation is confirmed by the structure of "strong flows" summarized by Figure 1(b). Four main observations can be drawn from the table. First, in line with what said above, there is no country that is totally excluded from "strong flows". Second, the US, Canada, and Japan are the source/destination of very few and discontinuous "strong flows". Third, Korea, New Zealand and Australia are also engaged in few "strong flows" but with a larger set of partners: among themselves, with Japan and with a few Northern European nations (Iceland, Norway, Great Britain and Ireland) even though mostly as importers. Finally, all the European countries appear persistently involved in "strong flows" with other European countries, both as importers and exporters of trade and R&D spillovers (with the exception of Greece whose position is mainly that of an importer).

These observations on the structure of "strong flows" hint to a possible role played by distance in the transmission of knowledge. If R&D spillovers were indeed larger when the trade flows are relatively more intense, countries that are very distant could hardly be found as engaged in "strong flows" because adjusting for their size would not help to address the implications of distance on trade. The size-adjusted measure of trade could be an imperfect proxy of relatively intense trade flows: more importantly, ignoring distance would imply to neglect the fact that the latter may simultaneously affect both bilateral trade and knowledge flows. Was this the case, the two trade measures we used so far could simply proxy for distance and fail to capture the relatively intensity of the bilateral commercial ties we are interested in.

To address this concern, with a view to capturing relatively intense trade flows in a more appropriate way, we calculate an alternative measure of bilateral trade that is normalized both for the partners' size and for their geographical

[20] The heteroskedasticity-robust LM-type linearity tests reject the null $H_0$: $\iota = 0$ at the 1% significance level, although the standard error of $\hat{\iota}$ is quite high.

distance. To do so, we shall elaborate an alternative way of normalizing the bilateral trade flows by means of an auxiliary estimation of the gravity model of trade. We shall discuss this in the following section.

*4.3. Gravity model and size-and-distance-adjusted trade measures*

As argued, the normalization of the trade measures for the GDP of the trading partners may not be sufficient to make all bilateral trade flows directly comparable in terms of relative intensity. Both the trade literature and the visual inspection of the patterns of "strong flows" in Figures 1(a) and 1(b) suggest that certain partners tend to exchange limited quantities because of the long distance separating them: was such distance taken into account, we could better appreciate the relatively intense trade relationships they might entertain. It is therefore important to assess whether any interesting pattern of "strong flows" emerges once the bilateral trade flows are normalized both for the size of the partners' GDP (as before) and for the distance between them.

The normalization for the partners' size was conducted in Section 4.2 in an intuitive way, that is calculating the ratio $M_{ijt}/(Y_{it}Y_{jt})$.[21] On the contrary, there is no simple way to normalize the nominal trade flows also for the distance. To do so, in this section we resort to an auxiliary estimation of the gravity model of trade. The gravity model is widely used in international economics to detect the relationship linking actual trade flows and the GDP of the pair of trading countries, while taking into account other observable determinants of trade such as distance and other pair-specific factors, as well as some unobserved fixed effects.[22]

To build the country size-and-distance-adjusted measures of bilateral trade flows ($M_{ijt}^{sda}$), we start by estimating a gravity model of trade for the 24 countries in the sample over the period 1971-2004. Then, using the estimated parameters, we calculate the adjusted trade flows as the difference between the actual flows and the amounts of trade due, according to the estimates, to the GDP of the trading countries plus the "missing trade" due to the distance. For this exercise to be correct, the gravity model needs to be specified in a way that does not produce biased estimates of the coefficients of interest. Baldwin and Taglioni (2006, 2007) and Head and Mayer (2015) discuss the biases arising from measurement errors and from the failure of accounting for the effects of the time-varying "multilateral trade resistance" (Anderson and van Wincoop, 2003).[23] Taking stock on the

[21] This measure is appealing for its simplicity but it has some shortcomings. It implicitly assumes a unitary elasticity of demand for imports with respect to GDP and it does not account for different patterns in import and GDP price deflators. These issues are addressed by the gravity-based trade measure that we use in this section.

[22] Among the many contributions, see, for instance, Anderson and van Wincoop (2003), Feenstra (2003), Santos Silva and Tenreyro (2006), Baier and Bergstrand (2007), Helpman et al. (2008), Baier and Bergstrand (2009a), Anderson (2011), Bergstrand et al. (2013), Costinot and Rodríguez-Clare (2013), Head and Mayer (2015).

[23] In the case of directional trade flows, each observation has three dimensions: a time dimension and two country dimensions, as countries appear as importers and as exporters. As shown by Baldwin and Taglioni (2006), to avoid biased estimators in this context it is not

recent advancements in the literature on the estimation of gravity models in panel data, we adopt a simple specification that relates the imports of country $i$ from country $j$ at time $t$ ($M_{ijt}$) as a function of the product of importer's and exporter's GDP ($Y_{it}Y_{jt}$), a number of variables that characterize each pair of trading partners (borrowed from Head et al., 2010, and presented in Appendix A), and time-variant country-role fixed effects ($\eta_{i.t}$ and $\eta_{.jt}$, respectively capturing importer-specific and exporter-specific time-variant fixed effects).[24]

The introduction of time-variant importer- and exporter-fixed effects helps to capture the constant factors affecting multilateral resistance. This reduces the sources of bias in the estimation at the cost of imposing to drop all country-specific variables (such as GDP) that are subsumed by the time-varying country-role fixed effects. In order to be able to estimate the impact of GDPs of both partners, thus, we need to build a "synthetic" dyadic measure for the pair of trading countries (which cannot be fully captured by the fixed effects). Following both intuition and common practice, we use the product of their GDPs.[25]

Building on the influential work by Head et al. (2010), we estimate a log-specification of the gravity model of trade in which we include the variables of interest for the normalization and additional regressors:

$$\ln M_{ijt} = \theta \ln(Y_{it}Y_{jt}) + \lambda \ln d_{ij.} + \mathbf{x}'_{ij.}\boldsymbol{\gamma} + \eta_{i.t} + \eta_{.jt} + \zeta_{ijt} \tag{3}$$

where the nominal bilateral trade flows, the GDPs and the geographical distance between countries $i$ and $j$ ($d_{ij.}$) are taken in logs, $\mathbf{x}_{ij.}$ is a vector of pair-specific dummies borrowed from Head et al. (2010) (see Appendix A), and $\zeta_{ijt}$ is the error component.[26,27]

The results of the estimation are summarized in Table 2. The estimated parameters are statistically significant and enter with the expected sign.[28]

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sufficient to include in the specification of the gravity model either time-invariant pair-specific fixed effects or time-invariant country-role-specific fixed effects: they are all time-invariant factors which fail to pick the time-varying nature of multilateral resistance factors and, thus, do not remove much of the correlation between the residuals and the regressors.

[24]We use . in place of $i$, $j$ or $t$ to mean that the unobserved factor is common to, respectively, all the importers from $j$ at time $t$, all the exporters to $i$ at time $t$, and all the periods for the pair of countries $(i, j)$.

[25]As pointed out by Head and Mayer (2015), although the identification of these "synthetic" dyadic terms is not always granted, no major problems arise for the "synthetic" dyadic measures of the trading partners' GDP.

[26]GDPs and trade flows are taken in nominal terms following Baldwin and Taglioni (2006). In fact, the introduction of the dummies that pick-up the time-variant unobserved effects makes the choice between nominal and real series almost immaterial.

[27]Since we deal with aggregate import flows for OECD countries—the sample is almost fully balanced with less than 0.1% zero bilateral trade flows—, we do not face the problems that emerge in the presence of many zeros when the series is in logs and the heteroskedasticity of the residuals is not duly accounted for (on this issue, see Santos Silva and Tenreyro, 2006; Baier and Bergstrand, 2009b).

[28]In fact, the coefficient of the common official language dummy variable has a negative sign. We repeated the estimates with an alternative measure used in the literature focusing on whether at least 9% of the population in both countries speaks the same language. The coefficient of this measures is positive, as expected. Since the coefficients of interest in this

Table 2: Gravity model of trade with country-role fixed-effects – Equation (3)

| | |
|---|---|
| $\ln(\text{GDP}_i\,\text{GDP}_j)$ | 0.361 (0.012) |
| ln $\text{Distance}_{ij}$ | -0.249 (0.013) |
| Shared Border | 0.714 (0.021) |
| Shared official language | -0.155 (0.023) |
| Colonial relationship post 1945 | 0.155 (0.059) |
| Ever in colonial relationship | 0.412 (0.024) |
| Shared legal system | 0.482 (0.013) |
| Shared currency | 0.172 (0.039) |
| RTA | 1.285 (0.032) |
| Importer-specific time-variant dummies ($\eta_{i.t}$) | Yes |
| Exporter-specific time-variant dummies ($\eta_{.jt}$) | Yes |
| $R^2$ | 0.68 |
| Obs | 18,649 |
| Country pairs | 552 |
| Average obs per pair | 33.78 |

Dependent variable: log bilateral imports ($\ln M_{ijt}$), 1971-2004, 24 countries. Cluster robust standard errors in parenthesis.

Using the point estimates of the coefficients $\hat{\theta}$ and $\hat{\lambda}$ of Equation (3), we build size-and-distance-adjusted bilateral measures of trade:

$$M_{ijt}^{sda} = \exp(\ln M_{ijt} - \hat{\theta}\ln(Y_{it}Y_{jt}) - \hat{\lambda}\ln d_{ij.}) = \frac{M_{ijt}d_{ij.}^{-\hat{\lambda}}}{(Y_{it}Y_{jt})^{\hat{\theta}}} \tag{4}$$

We repeat the exercise of the previous subsections (4.1 and 4.2) using this size-and-distance-adjusted measure and estimate the coefficients of interest in specification (2). Our expectation is that this adjusted measure of trade will help capture the relative intensity of bilateral flows, thereby facilitating the assessment of the hypothesis that R&D spillovers are relatively large where trade relationships are relatively intense.

One could conjecture that, if it is the sheer size of the bilateral trade flows that positively influences the extent to which knowledge is transmitted across countries, then the patterns of "strong flows" identified by the size-and-distance-adjusted trade flows will explain very little of the international knowledge spillovers. On the contrary, if the relative intensity of trade flows matters for the transmission of knowledge more than the sheer size of the flows, the specification using $M_{ijt}^{sda}$ should outperform those with $M_{ijt}$ and $\frac{M_{ijt}}{Y_{jt}Y_{it}}$ , for it better captures the idea of relative trade intensity.

The estimates are reported in Column IV of Table 1. The linear coefficients

work (i.e, $\theta$ and $\lambda$) are almost identical across the specifications, we do not dwell on the issue.

are statistically significant and again in line with the previous estimates. The estimated $\iota$ indicates that the bilateral flows identified as "strong" are associated to R&D spillovers that are almost five times larger than otherwise. Such relationships are those where the size-and-distance-adjusted trade is 10% higher than the annual cross-country average. The overall fit of this model is higher than any of the previous specifications and this suggests that the idea of looking at the relative intensity of trade flows, rather their sheer size, to identify the channel of international transmission of knowledge is warranted.

The map of the pairs of countries engaged in these "strong flows" (Figure 1(d)) provides some additional insights on the trade-related international transmission of knowledge (let us recall that the ordering of the countries is determined on the basis of the similarity in terms of the patterns of "strong flows"). To start with, Germany, the US and Great Britain show rather similar patterns: these countries are involved in "strong flows" with most of the other countries in most of the years. Switzerland, Italy, France, the Netherlands and Belgium are another group of similar countries: they are closely connected with Germany, the US and Great Britain and among themselves. Belgium, France and the Netherlands are also connected (though more as importers than as exporters) to Japan, Norway, Sweden, Spain and Ireland; Italy (Switzerland) appears as persistently linked by strong ties also with Austria, Ireland and Spain (Austria and Ireland) as importer and with Spain, Austria, Greece and Portugal (Austria, Israel, Japan) as exporter. Norway, Sweden, Denmark and Finland have strong relationships with Germany and Great Britain and among themselves. Canada, South Korea, Australia and Japan exhibit strong patterns among themselves and with Germany, the US and Great Britain. Spain, Israel and Ireland have no strong linkages among themselves but are connected, as exporters and/or importers, with the countries in the first two groups. The same patterns can be found in the remaining countries (Austria, New Zealand, Island, Portugal and Greece), which exhibit however fewer strong linkages.

These patterns suggest that, even after normalizing for the distance and the size, there is a core of countries exporting and importing products and knowledge from all the partners: they are large industrialized countries with heterogeneous degrees of trade openness. Other three groups of highly integrated countries can be distinguished: one consists of the other Central and Southern European industrialized countries; one is made up of the Nordic European countries; the last one includes the Asian-Pacific countries. The normalization for the distance is important as it allows to gather three countries together (the US, Germany and Great Britain) even though they are not concentrated in the same region. Still, a regional component in the other groups seems to emerge: this could be due to cultural and linguistic factors which are likely to affect both trade and knowledge flows.[29]

[29] It could be argued that the nominal trade flows could be normalized also for the cultural and linguistic factors included among the explanatory variables in the empirical specification of the gravity model. However, this would be in contrast with our empirical strategy. The

Although all the specifications confirm that knowledge spillovers are related to trade flows, the results associated with the measure of trade adopted in this section suggest that: i) this measure is a promising way of operationalizing the idea of relatively intense trade relationships associated with relatively large knowledge flows; ii) this allows to capture a very important channel for the international diffusion of knowledge.

## 5. Robustness check

All the previous results indicate that the hypothesis of a "global pool of technology" proposed by Keller (1998) is rejected by the data. Non-trivial patterns of "strong flows", independently from the way in which relatively intense trade relationships are defined, can be identified. However, it is still to be shown that the computationally intensive procedure developed in this work does not produce the same results one could derive by partitioning the network of international trade on the basis of more simple and straightforward criteria. For instance, one could wonder whether the set of partners with which each country entertains its "strong flows" simply consists of a fixed number of its largest trading partners. This alternative definition would have the advantage of simplicity (for no threshold is estimated) and intuitive appeal.

Before discussing the results of this alternative partitioning criterion based on the best trading partners (BTP) of each importer, we would like to clarify the similarities and the differences between this approach and the threshold method adopted in Section 4. As to the similarities, neither of the methods imposes on the empirical specification: i) the assumption of proportionality between trade and knowledge flows (as the foreign R&D stocks are not weighted for any measures of trade); ii) the existence of trade-related R&D spillovers (as the parameter $\iota$ can turn out not to be statistically greater than zero). Moreover, both methods adopt a unique metric for partitioning the network of bilateral trade flows and for distinguishing the "strong flows" from the others: a fixed threshold (calculated for either the original or the normalized series) in Section 4 and a fixed number of largest trading partners for each importer in the BTP approach. The main difference between the two methods, instead, is that the BTP imposes the restriction that a fixed number of trading partners (equal across importers and over time) is involved in "strong flows" with each importer, whereas the threshold method allows each importing country to differ from the

normalization for size and distance is meant to allow the identification of relatively intense trade flows with a unique metric applicable to the entire network of exchanges; more precisely, it serves to prevent that we fail to capture relatively good partnerships only because of the small economic mass or the long distance of the trading countries. On the contrary, there is no reason to normalize for, say, religious affinity (as in Helble, 2007) as long as this latter is one of those factors that make trade and knowledge flows larger than what "mechanically" implied by size and distance. In other words, we do not aim to normalize the bilateral flows for those features that make trade relationships relatively intense, as this is indeed what we are interested to capture.

others in terms of the number of "strong flows" (between 0 and 23) it annually participates in.

What method is to be preferred remains an empirical issue to be decided on the basis of the models' ability to account for international R&D spillovers. To proceed with the BTP method, it is necessary to decide the number of largest trading partners ($\chi$) for each importer to consider. With a view to over-imposing as few restrictions as possible, we explore the results obtained by setting this number equal to each integer between 5 and 15 and then choose the fit-maximizing number of largest trading partners for each importer, i.e. $\chi = 7$.[30]

Thus, we estimate specification (2) by building the variable $S_{it}^{fs}$ as the simple sum of the domestic R&D stocks of the seven BTP of importer $i$ at time $t$, that is $S_{it}^{fs}|_{\chi=7} = \sum_{j \in \otimes_i|_{\chi=7}} S_{jt}^{d}$, where $\otimes_i|_{\chi=7}$ is the set of the seven best trading partners of importer $i$ at time $t$. The results are summed up in Column V of Table 1.

As in the previous specifications, the linear coefficients preserve their dimension and significance. The parameter $\iota$ is positive and larger than 1, implying that R&D spillovers from the seven best trading partners are more than twice as large as those from the remaining partners.[31]

Also this estimation method provides some evidence against the assumption of a "global pool of technology" and, despite relaxing the assumption of proportionality between trade and knowledge flows, in favor of the idea that R&D spillovers are trade related. A comparison between the patterns of "strong flows" identified through the BTP approach and those obtained with the threshold method in Section 4 indicates that these alternative approaches pick up different components of the trade-related R&D spillovers.

At a theoretical level, the "strong flows" found with the BTP method and with the threshold approach developed in Section 4 should not overlap. In Section 4, we consider either the nominal bilateral flows ($M_{ijt}$) or their normalization for the size of the trading partners ($\frac{M_{ijt}}{Y_{jt}Y_{it}}$) and for both the size and the distance between them ($M_{ijt}^{sda}$). The BTP method, instead, implicitly normalizes the bilateral flows for the size of the importing country as the selection of the partners occur for each importer at a time: irrespectively of how large the size of the importer, it is assumed that it receives larger knowledge spillovers from the seven countries from which it imports more. Were one willing to compare the results of the BTP approach with those obtained with an analogous threshold method, she would have to apply the threshold method on a measure of trade that normalizes for the GDP of the importing country. This can be easily done by taking the ratio of the bilateral trade flows on the GDP of the importing

[30] Although here we treat $\chi$ as given in illustrating the features of the BTP method, this parameter is *de facto* estimated. We shall return on this issue later.

[31] Although we do not need to calculate any threshold, NLS is still necessary for the estimation of $\iota$. To feed the NLS with the best starting values, we follow the same approach used in the threshold method and use the SA to find an accurate starting value of $\iota$.

country ($\frac{M_{ijt}}{Y_{it}}$). We undertake this comparison, but for the sake of brevity we do not comment all these estimates (reported in Column VII of Table 1). It suffices to say that the threshold specification using the ratio of the bilateral trade flows over the GDP of the importing country outperforms the BTP estimation with seven partners: the AIC is $-1641.51$ and the BIC $-1505.08$, both (in absolute size) larger than the criteria calculated for the BTP (Column V in Table 1).[32] The main reason why the threshold method fits the data better than the BTP one is that the former does not impose that all importers have the same and fixed number of "strong" partners in each period.

The sets of "strong flows" identified by the BTP method and the threshold method using the ratio of bilateral trade flows over the GDP of the importing country are summarized, respectively, in Figures 1(d) and 1(e). To facilitate the comparison and to visually assess the implications of using either of the two methods, the countries enter in the same order in both the tables, that is the order determined by the similarity indexes obtained with the BTP method. The analogies between the two tables are comforting given that the two methods, though different, refer to bilateral flows normalized for the size of the importer. The main difference in the identified patterns of "strong flows" is represented by those of the US and Japan. With the BTP method we would conclude that they are actively engaged in "strong flows" both as exporters and importers; if we do not over-impose the same number of BTP in all periods, instead, the role that the US and Japan play in the "strong flows" turn out to be mainly that of the exporters of trade and knowledge. This is in line with the results in Section 4.

In the evaluation of the BTP method, two additional remarks are in order. First, the fit-maximizing number of BTP ($\chi = 7$) was chosen after having performed ten auxiliary estimations, each differing in the posited number of BTP. Had we arbitrarily chosen to focus on the first five BTP ($\chi = 5$), for instance, we would have found an almost insignificant $\iota$ and a model that fits the data as well as the linear one. Had we chosen nine BTP ($\chi = 9$), the estimated $\iota$ would have been insignificant and the model would have underperformed the linear one. This implies that one still needs to estimate $\chi$ to make the BTP works properly. If this is so, $\chi$ happens to be a latent (nuisance) parameter as the threshold $\varphi$; this poses the same problems for the estimation of $\varphi$ and the statistical inference on $\iota$ as those discussed in Section 4 and Appendix B. Hence, at the end of the day, when the BTP method is applied taking into account the nuisance parameter problem, it turns out as complex as the threshold method.

Second, it is worth noticing that the BTP method over-imposes the implicit assumption that every importer in each period entertains a "strong" relationship with its seven BTP. This implies that one cannot ascertain whether the failure to reject the null hypothesis stems from having mistakenly imposed the assumption that every importer entertains "strong " relationships with all of its BTP, or it is rather due to existence of global and trade-unrelated knowledge spillovers.

[32] The estimated $\iota$ with the threshold method would be twice as large as the BTP one.

## 6. Closing remarks

The relationship between international trade and knowledge diffusion has been the object of intense research and debate. Starting with Coe and Helpman (1995), most empirical studies have used trade-weighted foreign R&D stocks to measure foreign knowledge and assumed that the internationally transferred knowledge is proportional to the size of the trade flows, in line with the theoretical models where imported intermediate goods embody foreign technological know-how (e.g. Grossman and Helpman, 1991b; Rivera-Batiz and Romer, 1991; Eaton and Kortum, 2002).

In this paper, we investigate whether international trade enhances knowledge spillovers introducing some novelties in the analysis. First, we do not assume the existence of a proportional relationship between trade and knowledge flows (as in the pioneering paper by Coe and Helpman, 1995): rather, we test whether relatively intense commercial ties are a favorable precondition for intense knowledge flows to materialize, as postulated in Keller (2004). Second, we develop and estimate a nonlinear model which allows to detect such trade-related transmission of knowledge: since our model nests Keller's (1998) specification of Coe and Helpman's (1995) model, according to which knowledge transfers are trade-unrelated, we can directly test the null hypothesis of trade-unrelated R&D spillovers. Third, we identify those bilateral relationships that in each year are characterized both by relatively intense trade flows and by relatively large knowledge spillovers (called, in short, "strong flows"). We analyze the main features of the subnetworks of these "strong flows" and cast some light on the actual patterns of international knowledge diffusion.

We explore a number of alternative ways to operationalize the concept of relative trade intensity and derive a set of complementary conclusions for each measure we adopt. We start by looking at the nominal trade flows, so that the larger flows in the world (i.e. those that overcome an estimated threshold) are considered the more intense ones. Subsequently, we address the fact that nominal flows reflect the heterogeneous size of the trading countries as well as the distance between them, because focusing on the absolute value of the trade flows prevents us from identifying those relatively intense trade partnerships that involve a small and/or remote trading country. Thus, we calculate size-adjusted and (on the basis of an estimated gravity model of trade) size-and-distance-adjusted measures of trade, and then test whether trade-related R&D spillovers are primarily associated with relatively intense trade patterns.

The results can be summed up in three main points. First, R&D spillovers are not global and trade-unrelated, since the data always reject the hypothesis of a common "global pool" of knowledge against the alternative of trade-related R&D spillovers. Second, the sheer size of bilateral trade flows appears associated with larger R&D spillovers. This notwithstanding, and this is our third main finding, once the bilateral trade flows are normalized for the size and the geographical distance of the trading partners, so as to discriminate the flows in terms of their relative intensity, the ability of the threshold model to capture the international R&D spillovers greatly increases. This supports the view that particularly intense, and not just large, trade flows are conducive to greater cross-border transmission of knowledge, and it provides some evidence in favor of those theoretical models where trade patterns matter in the transmission of knowledge even though intermediate traded goods do not physically embody all the knowledge produced abroad.


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## A. Data

To maintain the comparability of our analysis with previous works in the literature, we focus on the sample of 24 OECD countries over the period 1971-2004 analyzed by Coe et al. (2009). R&D stocks, human capital (average years of schooling) and TFP indexes are taken from Coe et al. (2009). Bilateral trade imports (in current dollars) come from the historical archive of the IMF Direction of Trade Statistics. GDP (in current dollars) is taken from IMF International Financial Statistics and the UN Statistics Division.

In the estimation of the gravity model of trade, due to the presence of time-varying country-role fixed effects, we focus on dyadic variables. Accordingly, as explanatory variables, we use the geographical distance between the countries' capitals ($d_{ij}$) and a set of dummy variables ($\mathbf{x}_{ij.}$), each taking value 1 if the trading countries: share the same border; adopt the same official language; use the same currency; have same legal system; entertain a colonial relationship post 1945; have been in a colonial relationship; participate in the same Regional Trade Agreement (RTA). All variables are borrowed from Head et al. (2010).

The following country abbreviations are used in Figure 1: Australia (AU), Austria (AT), Belgium-Luxembourg (BE), Canada (CA), Denmark (DK), Finland (FI), France (FR), Germany (DE), Greece (GR), Iceland (IS), Ireland (IE), Israel (IL), Italy (IT), Japan (JP), Korea (KP), the Netherlands (NL), New Zealand (NZ), Norway (NO), Portugal (PT), Spain (ES), Sweden (SE), Switzerland (CH), United Kingdom (UK), United States of America (US).

## B. Testing the "global pool" hypothesis

Notwithstanding the calculation of a bootstrap variance-covariance matrix, a conventional $t$-test on $\hat{\iota}$ would not be correct because of a nuisance parameter problem inherent in specification (2) (on this point see, among the others, Davies, 1977, 1987; Hansen, 1996). More precisely, $\varphi$ is an unidentified nuisance parameter under the null $\mathrm{H}_0$: $\iota = 0$.[33]

To circumvent the identification problem it is nonetheless possible: i) to obtain test statistics for the possible values of the parameters unidentified under the null (i.e., $\varphi$); ii) to calculate a summary statistics of the above mentioned statistics which does not depend on these parameters. Given that Equation (2) is linear under the null, the most suitable statistics is a LM-type test, since it requires only the estimates under the null. Following Andrews (1993) and Andrews and Ploberger (1994), we calculate three alternative summary statistics: the

[33] In principle, a similar issue affects also $\beta^f$, because both $\iota$ and $\varphi$ are unidentified under the null $\mathrm{H}_0$: $\beta^f = 0$. While theoretically correct, this concern is not in practice very relevant: as revealed both by the rich literature on international R&D spillovers and by the very same distribution of the bootstrap $\beta^f$ in our exercise, the parameter $\beta^f$ is surely positive, and this makes asymptotic inference with bootstrap standard errors working fine. Thus, we do not replicate for $\beta^f$ the exercise which is instead necessary for making correct inference on the (truly unknown) $\iota$.

supremum statistics (SupLM), the average statistics (AveLM), the exponential average statistics (ExpLM).[34]

These statistics have (asymptotically) pivotal but non-standard distributions, which depend on the moments of the distribution of the nonlinear parameter $\varphi$. Since the critical values cannot be tabulated, the tests are bootstrapped. We apply the fixed-design wild bootstrap for computing the bootstrap $p$-values of the tests reported in Table 1. Clearly, having carried out a bootstrap procedure that can account for heteroskedasticity, we adopt the heteroskedasticity-robust version of the LM-test. Alas, this is rarely done in applied empirical works.

The complete testing procedure is as follows. We draw uniformly at random 1000 different values of $\varphi$ from the set of relevant observed values in the sample within the 10-90th percentile. For each value, we compute the correspondent heteroskedasticity-robust LM statistic.[35] Having 1000 LM statistics, we compute their supremum (SupLM), their mean (AveLM) and their exponential mean (ExpLM).

To calculate the $p$-values, following Hurn and Becker (2009), we generate 1000 bootstrap samples via fixed-design wild bootstrap under the null[36] and compute the AveLM, ExpLM and wLM statistics for each sample. The bootstrap $p$-value is then equal to the fraction of bootstrap statistics larger than the correspondent test statistic calculated on the real data.[37]

[34] These statistics are defined as follows:

$$\mathrm{SupLM} = \sup_{\varphi\in\Phi} \mathrm{LM}(\varphi)$$

$$\mathrm{AveLM} = \int_{\Phi} \mathrm{LM}(\varphi)\ \mathrm{d}\varphi$$

$$\mathrm{ExpLM} = \ln\left(\int_{\Phi} \exp\left(\frac{1}{2}\,\mathrm{LM}(\varphi)\right) \mathrm{d}\varphi\right)$$

where $\mathrm{LM}(\varphi)$ is the LM statistic given $\varphi$. For applications to linearity testing with unidentified nuisance parameters in the context of threshold regression and smooth transition regression models see, for instance, Hansen (1996, 1999) and González and Teräsvirta (2006).

[35] The LM statistic is equal to $NT$ times the (uncentered) R–squared from the regression of the residuals from the restricted (linear) model on the gradient of (2) with respect to the parameters evaluated at the restricted estimates (see, for instance, Engle (1984, p. 809–811) or Wooldridge (2002, p. 363 e ss.)). In the present case, it amounts to: i) estimate the following specification:

$$\log F_{it} = \alpha_i + \beta^h \log H_{it} + \beta^d \log S^d_{it} + \beta^f \log S^f_{Kit} + \epsilon_{it} \tag{5}$$

and take the residuals $\tilde{\epsilon}$; ii) regress $\tilde{\epsilon}$ on $(\alpha, \log H, \log S^d, \log S^f_K, S^{fs}/S^f_K)$; iii) multiply the R–squared from the latter regression by $24\times 34 = 816$. The heteroskedasticity–robust version of the test can be computed by: i) regressing $S^{fc}/S^f_K$ on $(\alpha, \log H, \log S^d, \log S^f_K)$ and collecting the residuals $\tilde{r}$; ii) subtracting from $NT$ (=816) the sum of squared residuals from the regression of a constant on $\tilde{\epsilon}_{it}\tilde{r}_{it}$ (see Wooldridge, 2002, p. 368, for details).

[36] A bootstrap sample is generated by taking the fitted values of (5) and randomizing the sign of the residuals.

[37] So, for instance, the bootstrap $p$-value for AveLM is:

$$\hat{p} = \frac{1}{1000}\sum_{j=1}^{1000} I(\mathrm{AveLM}^*_j > \mathrm{AveLM})$$

Notwithstanding the large number of refinements and conservative stances in making inference on $\iota$, we do not fail to reject the null hypothesis $\mathrm{H}_0$: $\iota = 0$. The $p$-values are always smaller than 0.01 (see Table 1). This strongly supports our conclusion that knowledge spillovers are not global and trade-unrelated and, rather, they are stronger where trade relationships are relative more intense. This formal test digs further into the suggestive results obtained by Keller (2000): even relaxing the proportionality between trade and knowledge flows, R&D spillovers are significantly stronger when trade flows are relatively intense.

where $I(.)$ is the indicator function, taking value 1 when its argument is true and 0 otherwise, AveLM is the test statistic calculated using the real data, and $\mathrm{AveLM}_j^*$ is the correspondent statistic calculated using the $j$-th bootstrap sample.