The network of international trade and R&D spillovers

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Abstract

The literature on the channels of international knowledge flows has flourished. Departing from the usual tenets on the proportionality between trade flows and productivity spillovers, this article tests whether particularly intense trade relationships are associated with relatively large international R&D spillovers. By addressing the nuisance parameter problems in a nonlinear two-step estimation nesting the hypothesis that R&D spillovers are trade-unrelated, we show that trade patterns positively influence the transmission of knowledge. Particularly intense exchanges of trade and knowledge are identified on 24 advanced countries over 1971-2004. The results are robust to the adoption of alternative sophisticated measures of trade flows.

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

JEL Classification: C23, F01, O30, O47

1. Introduction

Knowledge has clearly 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 it is directly and indirectly transferred abroad, as shown in several theoretical contributions (e.g. Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991; 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 how domestic and foreign knowledge impact 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 the international transmission of knowledge. To account for this channel, they build import-weighted sums of trade partners' cumulative R&D

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expenditures as measures of foreign knowledge stocks. In addition, in their preferred specification, they include an interaction term between the degree of trade openness (i.e., the country's import/GDP ratio) and the stock of trade-weighted foreign R&D.[1]

Keller (1998) questions the appropriateness of the weighting scheme used by Coe and Helpman 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 than the trade-weighted measures to pick-up the knowledge diffusion process. 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 of the trade flows.[2]

Keller also 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, possibly because the exchanged goods embody the technological know-how of the exporting country.[3] From the theoretical viewpoint, as discussed in Keller (2004) and recognized in passing also 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. While the existence of intense trade relationships is important for the international transmission of knowledge because arm's length market transactions enhance communication between the partners, knowledge transfers and trade flows need not be proportional. Accordingly, this should not be arbitrarily imposed in the estimated models of trade and R&D flows. Moreover, it has been shown that the specific trade-related weights used to aggregate foreign R&D impact on the estimated coefficients of interest since the results vary considerably with the adopted weights (see, for instance, Lichtenberg and van Pottelsberghe de la Potterie, 1998).

Our empirical strategy builds on the straightforward observation that, if spillovers were global and trade-unrelated, all the countries could equally draw from the "common and 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 where trade relations are relatively more intense than usual. We investigate this hypothesis by relaxing the assumption about the existence of a proportional relationship between the size of trade and knowledge flows. In this way, we depart both from Keller (1998), as we take the patterns of the international trade network into account, and from Coe and Helpman (1995), as we neither calculate a trade-weighted measure of foreign R&D stocks nor over-impose a relationship

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[1]Several scholars (e.g. Coe et al., 2009; Engelbrecht, 1997; Lichtenberg and van Pottelsberghe de la Potterie, 1998; Xu and Wang, 1999; Lumenga-Neso et al., 2005; Madsen, 2007) have refined Coe and Helpman's 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. As we shall depart from it, we refer to Keller (2004) and Fracasso and Vittucci Marzetti (2012) for a review of the literature.

[2]The existence of global spillovers is consistent with a theoretical 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, 1991; Rivera-Batiz and Romer, 1991; Eaton and Kortum, 2002).

of 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 model by Keller (1998), thereby allowing to test directly the null hypothesis of global and trade-unrelated R&D spillovers against that of trade-related (yet non-proportional) knowledge spillovers. It is worth noticing that the adoption of a nested nonlinear model and the use of an estimated critical value to identify the relatively intense exchanges raise some nuisance parameter problems in the estimation. We address these issues building on Andrews and Ploberger (1994) and Hansen (1996, 1999).

To anticipate our main findings on a sample of 24 advanced countries over the period 1971-2004, recently studied also by Coe et al. (2009), we reject the null hypothesis of a global pool of knowledge and we identify relatively intense trade relationships associated with large R&D spillovers. Our results support the idea that knowledge spillovers are localized and trade-related, yet non-proportional to the trade flows.

To identify the relatively intense bilateral trade flows associated with relatively large R&D spillovers (which, in what follows, we shall call "strong exchanges" for the sake of brevity), we start by examining the nominal bilateral flows. A "strong exchange" is identified when the bilateral relationship overcomes an estimated threshold, applicable to the entire network of exchanges. Since a nominal trade flow reflects the heterogeneous size of the trading countries, the identification of "strong exchanges" in this way would penalize the smallest countries. Small countries would hardly be found as having intense flows with other small countries because their exchanges, even when remarkable in relative terms, tend to be smaller than those recorded among larger (even when less open) countries.[4] Accordingly, we adjust the nominal bilateral flows for the economic size of the trading countries. To do so, we estimate a gravity model of trade and, using the estimated parameters, calculate the size-adjusted bilateral trade flows.[5] Time-invariant pair-specific factors (geographical distance is a case in point) may in turn affect trade flows and also influence R&D spillovers. Even the size-adjusted trade measures could then appear as associated with intense knowledge spillovers simply because they act as proxies of these pair-specific factors fostering R&D flows. To address this concern, we use the estimates of the gravity model to calculate bilateral trade measures that are adjusted to account for both the size of countries' GDP (as before) and the pair-specific factors (shortly, size- and pair-adjusted trade values). All our results suggest that relevant trade relationships matter for the diffusion of knowledge even once distance and other time-invariant pair-specific factors are taken into account.

This work contributes to the literature in two main ways. First, by nesting Keller's (1998) specification into a more general model accounting for trade patterns, we contribute to discriminate more clearly between the hypotheses of trade-related and trade-unrelated knowledge flows, which are equally plausible at the theoretical level. Adopting nested models is a step forward with respect to previous works using non-nested models to test each hypothesis in turn. In so doing, we address 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"

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[4]For example, in 2004 the Dutch imports from Belgium-Luxembourg amounted to USD 31 billion, while the U.S. imports from Japan—two countries relatively less open than the Netherlands and Belgium—amounted to USD 133 billion.

[5]Taking stock on the recent advancements in the gravity literature to ensure that the estimated coefficients are unbiased, we adopt a specification that acknowledges both time-invariant pair-specific and time-varying country-role-specific unobserved factors (see Baldwin and Taglioni, 2006, 2007).

([2004](), p.1480). Second, we identify the relatively important trade flows associated with R&D spillovers without weighting the R&D stocks for the size of the exchanges, thereby showing that trade patterns matter in the transmission of knowledge even relaxing the assumption of a proportional relationship between the size of trade flows and knowledge spillovers.[6] In so doing, we develop further the preliminary results in Keller ([2000]()), who shows that randomizing the import shares used to build the trade-weighted foreign R&D stocks does not significantly affect the estimated R&D spillovers among the countries that trade relatively little, whereas it tends to underestimate the R&D spillovers among the partners trading more closely: "this is consistent with the idea that trade related-effect of R&D is identified primarily from countries with extreme trade patterns" (Keller, [2000](), p. 29). We test this idea directly by refraining from using trade-weighted R&D stocks and over-imposing an arbitrary threshold to identify the relatively intense exchanges of trade and R&D.[7]

The paper proceeds as follows. In Section 2 we present the baseline empirical analysis of Coe and Helpman ([1995]()) and Keller ([1998]()). In Section 3 we illustrate the model and the analytical strategy, as well as the method to build adjusted trade measures out of an estimated gravity model of trade, adopted to identify the relatively "strong exchanges". The illustration of the data can be found in Section 4. In Section 5 we discuss the main empirical findings, while the networks of "strong exchanges" are plotted and discussed in Section 6. Section 7 concludes.

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

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

$$\log F_{it} = \alpha_i + \beta^d \log S_{it}^d + \beta^f \frac{M_{it}}{Y_{it}} \log S_{it}^f \tag{1}$$

where i is a country index, t is the time index, $\log F$ is the log of TFP, S_{it}^d the domestically produced R&D stock, S_{it}^f an import-weighted sum of the R&D stock produced outside the country i at time t (i.e. $S_{it}^f = \sum_{j \neq i} \frac{M_{ijt}}{\sum_{j \neq i} M_{ijt}} S_{jt}^d$, where M_{ijt} are the imports of country i from country j), and M_{it}/Y_{it} represents the import-GDP ratio of country i at time t.[8],[9]

Trade enters this specification in two distinct ways: i) in the trade-weighted construction of the foreign stocks of R&D; ii) in the interaction term, which allows for cross-country variation in the elasticity of TFP with respect to foreign R&D (i.e., $\beta^f M_{it}/Y_{it}$).

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[6]In addition, we point out in passing that we estimate a gravity model of trade for 24 OECD countries over a very very long period (1971-2004), a time span longer than Wang et al. ([2010]()).

[7]Our approach differs considerably from that in Keller ([2000]()). He estimates importer-specific coefficients while we focus on the traditional form with unique coefficients for all the countries. He also uses import shares to build trade-weighted foreign R&D stocks and then raises doubts on the appropriateness of this procedures for countries that do not trade much, whereas we focus on relatively "strong exchanges" of trade and R&D spillovers without using trade-related weights.

[8]Coe and Helpman ([1995]()) also add 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.

[9]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 exporting country. As shown by Coe et al. ([2009]()), this reasonable modification does neither invalidate nor weakens what found using specification ([1]()).

Coe and Helpman (1995) find significant and relatively large values for β^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 stocks are added to the regressors.

Keller (1998) contends that the simple sum of 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. To show this, he estimates

$$\log F_{it} = \alpha_i + \beta^d \log S_{it}^d + \beta^f \log S_{Kit}^f + \epsilon_{it} \tag{2}$$

where $S_{Kit}^f = \sum_{j \neq i} S_{jt}^d$. He finds estimates for β^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 transmission of knowledge is that the models proposed by Coe and Helpman (1995) and Keller (1998) are non-nested: one cannot use measures of their goodness of fit to discern which is the preferable representation of knowledge spillovers.

In addition, the specification used by Coe and Helpman (1995) implicitly assumes that knowledge transmission follows a local and trade-related diffusion process to the extent that knowledge is embodied in traded goods. In fact, one cannot exclude the existence of different trade-related transmission mechanisms: for instance, knowledge spillovers may be dis-embodied due to the (partially) tacit nature of technology and still related to international trade because the latter facilitates face-to-face interactions. Accordingly, trade patterns may be important even excluding the existence of a proportional relationship between trade and knowledge flows.

To the best of our knowledge, the question of whether the network of trade flows is informative on R&D spillovers once the proportionality of spillovers and trade is relaxed remains to be tackled. Thus, in the next sections, we develop a way to nest Keller's (1998) model into a more general one that also takes into account the actual patterns of the international trade network in a flexible and innovative way.

3. Analytical strategy

In this section we introduce the technical aspects concerning the model specification (Section 3.1) and the identification of the "strong exchanges" for the non-arbitrary binarization of the bilateral trade network. The method employed to adjust the bilateral trade flows for the country size of the trading partners will be presented in Section 3.2.

3.1. Model specification and estimation technique

If knowledge spillovers were trade-unrelated and global, any country could equally draw from the "common and global pool" of world knowledge and the R&D spillovers would be independent from any trade relationships. It would then be impossible to identify relatively intense bilateral trade relationships associated with relatively large knowledge spillovers. On the contrary if spillovers were localized and trade-related, they should be stronger where trade relations are relatively intense.

To test this intuition, we develop a more general nonlinear specification of Keller's (1998) model which we estimate by means of Nonlinear Least Squares (NLS):

$$\log F_{it} = \alpha_i + \beta^h \log H_{it} + \beta^d \log S_{it}^d + \beta^f \log \left(S_{Kit}^f + \iota S_{it}^{fs} \right) + \epsilon_{it} \tag{3}$$

with F_{it}, S_{it}^d and S_{Kit}^f are as specified before, H_{it} stands for the human capital stock of country i at time t, and S_{it}^{fs} is the simple sum of the R&D stocks of the partners of i characterized by "strong exchanges" with country i in the year t. With respect to Keller's specification (2), model (3) includes human capital among the regressors in line with what usually done in most recent works (Engelbrecht, 1997; Coe et al., 2009).

Clearly, model (3) nests (2), as the former becomes the latter when $\iota = 0$. The rejection of the null hypothesis H_0: $\iota = 0$ (i.e. there are no particularly large R&D spillovers among countries engaged in relatively important trade flows) would provide evidence against Keller's (1998) hypothesis of global and trade-unrelated spillovers. Moreover, a positive estimated coefficient ι would support the idea that trade patterns do matter in shaping the international transmission of knowledge.

Clearly, the implementation of this empirical strategy demands to identify the "strong exchanges" so as to generate the variable S_{it}^{fs} for each country i and period t in the sample, that is the unweighted sum of the R&D stocks of the countries engaged in "strong exchanges" with country i.

Endowed with a critical value (i.e., a threshold) φ, we can calculate for each country i and year t the simple sum of the R&D stocks of the partners of country i which are involved in "strong exchanges" with it, that is $S_{it}^{fs} = \sum_{j \in \ominus_i} S_{jt}^d$, where $\ominus_i$ is the set of the trade partners of country i engaged in bilateral "strong exchanges" with i. At this point we can estimate model (3) and explicitly test the null H_0: $\iota = 0$ (more on this in Section 5.1).

It is apparent that the threshold φ is a key determinant of the results. Clearly, we cannot adopt a strategy that revolves around an arbitrarily chosen value of the threshold. Thus, we explore the entire range of plausible values of φ and will let the data indicate what value maximizes the fit of the model. Clearly, the lack of relatively strong flows of knowledge across countries would prevent the identification of any critical value φ.

3.2. Gravity model and size-adjusted trade measures

In Section 5 we shall start by identifying the "strong exchanges" on the basis of a unique metric (i.e., the threshold) for the entire network of nominal bilateral imports (M_{ijt}). In fact, bilateral flows reflect the heterogeneous sizes of the trading countries. This implies that we may systematically fail to detect any relatively "strong exchange" among small countries: even though small economies tend to be very open, their exchanges are limited in absolute size.

To tackle this issue, we develop an empirical strategy so as to adjust the initial trade flows for the size of the trading countries. By doing so, we continue to exploit the information present in the entire network of trade but de-emphasize the importance of the absolute size of the exchanges. Thus, we identify country-size adjusted "strong exchanges".

A straightforward way to adjust the trade measure is calculating the ratio $M_{ijt}/(Y_{it}Y_{jt})$. Though intuitive, this measure is not warranted. It implicitly assumes a unitary elasticity of demand for imports with respect to GDP; moreover, it accounts neither for different patterns in import and GDP price deflators, nor for the trends common to the entire panel of countries.

To adjust properly the trade measures for the countries' size, we resort to the gravity model of trade, which 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, as well as some unobserved pair-, country- and time-specific factors.

To build the country size-adjusted measures of bilateral trade flows, we start by estimating a gravity model for the 24 countries in the sample over the period 1971-2004. Then, using the estimated parameters, we calculate the size-adjusted trade flows as the differences between the actual flows and the amounts of trade due, according to the estimates, to the GDP of the trading countries.

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. Baldwin and Taglioni (2006, 2007) 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), i.e. the factors (such as income and trade barriers) that characterize all the countries.[10] Taking stock on the recent advancements in the literature on gravity models in panel data, we adopt a 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 ($Y_{it}Y_{jt}$), time-invariant pair-specific factors ($\upsilon_{ij.}$), and time-variant country-role factors ($\eta_{i.t}$ and $\eta_{.jt}$, respectively capturing importer-specific time-variant effects and exporter-specific time-variant effects).[11]

Accordingly, the specification of the gravity equation, where the nominal bilateral trade flows and the GDP are in logs ($m_{ijt} = \ln M_{ijt}$, $y_{it} = \ln Y_{it}$, $y_{jt} = \ln Y_{jt}$), reads as follows:

$$m_{ijt} = \theta(y_{it} + y_{jt}) + \upsilon_{ij.} + \eta_{i.t} + \eta_{.jt} + \varepsilon_{ijt} \tag{4}$$

where ε_{ijt} is the error component. The GDP and the trade series are taken in nominal terms because, as observed by Baldwin and Taglioni (2006), the gravity equation reflects a modified expenditure function. In fact, the introduction of the dummies that pick-up the (time-variant and invariant) unobserved effects makes the choice of the denomination of the series almost immaterial.[12] The estimated parameters are reported in Table 1.

The measures we are interested in at this stage, that is the size-adjusted bilateral trade flows (m_{ijt}^{sa}), are calculated using the estimated coefficient θ in Equation (4):

$$m_{ijt}^{sa} = m_{ijt} - \hat{\theta}(y_{it} + y_{jt}) \tag{5}$$

Without loss of generality, we subtract the cross-country annual averages from the series so as to center the adjusted measures around 0.

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[10]In the case of directional trade flows, each observation in the panel 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 estimates in this context it is not sufficient to include in the specification of the gravity model either time-invariant pair-specific effects or time-invariant country-role-specific 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.

[11]When we use . in place of i or j or t, we intend that the unobserved factor is common to, respectively, all the importers from j at time t, all the exports to i at time t, and all the periods for the pair (i, j).

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

Table 1: Estimation results of the gravity model of trade. Fixed-effects estimates (pair-specific effects). Bilateral imports, 1971-2004, 24 countries.

θ	0.772
	(0.020)
R^2	0.576
Obs	18649
Country pairs	552
Average obs per pair	33.78

Unreported importer-specific ($\eta_{i.t}$) and exporter-specific ($\eta_{.jt}$) time-variant dummies. Robust standard error in parenthesis.

We shall discuss in greater detail the features of the network of "strong exchanges" in Section 6. Section 4, that follows, briefly introduces the data employed in the analysis whereas Section 5 will present and discuss the main findings regarding Equation (3).

4. Data

To maintain the comparability of our analysis, 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.

5. Estimation results

Armed with the original trade series and the size-adjusted trade measures (calculated as explained in Section 3.2), we estimate the parameters in Equation (3), that is β^d, β^h, β^f, ι and φ.

It is apparent that the functional form is highly nonlinear: first, the coefficient ι enters the argument of the logarithm, and second, the threshold φ affects the variable $S_{it}^{fs} = \sum_{j \in \ominus_i} S_{jt}^d$, where $\ominus_i$ is the set of countries involved in "strong exchanges" with country i. Notably, while ι could in theory be estimated by nonlinear least squares (NLS) after having chosen some starting values for the parameters, this does not apply to φ.

To address similar estimation problems in panel threshold regressions, several scholars estimate the value of a threshold of interest by: i) running a grid search over a (limited) number of plausible values of φ; ii) choosing the value that minimizes some informational criteria. Unfortunately, the grid search approach may easily lead to local minima in the estimation. To address this drawback, we adopt and implement the Simulated Annealing (SA) algorithm proposed by Corana et al. (1987) (see also Goffe et al., 1994, for an application to M-estimation problems). Although computationally intensive, this technique leads to robust estimates of the parameters of interest.[13]

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[13]Simulated Annealing—named after the process undergone by the atoms in a heated metal when it cools slowly—denotes a class of probabilistic algorithms to locate global minima/maxima of functions in large

Although we do not rely on the SA for the estimation of the coefficient ι (which is subsequently estimated via NLS together with β^d, β^h, and β^f), our SA algorithm maximizes the fit of the model by exploring the space of both ι and φ. While we retain the fit-optimizing value of φ as the estimated threshold, we employ the SA-suggested fit-optimizing value of ι as its starting value in the subsequent NLS estimation. This choice, which admittedly increases the computational intensity of the procedure, is motivated by the sensitivity of the NLS method to the starting values of the nonlinear parameters. Given the ability of the SA to span accurately the space of the parameters under scrutiny, we believe that feeding the SA-suggested value of ι as its starting value in the NLS estimation is a very conservative choice. As expected, indeed, the NLS estimate of ι is nearly identical to that found by the SA procedure.

Table 2 reports the results of the linear estimates of Equation (2) in column (1) and those of the fixed-effect NLS *cum* SA estimation of Equation (3) in columns (2) and (3). Column (2) refers to the nominal trade flows m_{ijt}, while column (3) refers to the size-adjusted trade measures m_{ijt}^{sa}. In both cases, on the basis of $\hat{\varphi}$ we identify the "strong exchanges" to build the series S_{it}^{fs}. We shall come back on columns (4) and (5) in Section 5.2 and 5.3.

According to information criteria (AIC and BIC), the fit of the nonlinear models in columns (2) and (3) is superior to that of the linear model. The improvement of information criteria suggests that our strategy for identifying the "strong exchanges" (i.e., relatively intense bilateral trade flows associated with larger R&D spillovers) is warranted.

The coefficients β^d and β^h are not very different across the three models and fully in line with previous studies. The estimates of the coefficient β^f are also not statistically different and within the range of the estimated values in the literature. More importantly, we find that ι is about 2 for the model with nominal trade flows and slightly smaller than unity (0.855) for the model with size-adjusted trade flows: this implies that the elasticity of the domestic TFP to the stock of R&D in the countries which are engaged in "strong exchanges" is much larger than that in the other trade partners.[14]

This finding provides evidence in favor of the hypothesis that trade patterns matter for the international transmission of knowledge. Even when the proportional relationship between the size of the bilateral exchanges and knowledge flows is not over-imposed in the estimation (as in Coe and Helpman, 1995; Coe et al., 2009), trade relationships appear as important determinants in the process of international diffusion of knowledge.

Table 2 reports the bootstrapped standard errors for all the coefficients. To be conservative, given the adoption of a nonlinear estimation with a generated regressor (i.e., S_{it}^{fs}), we bootstrap the standard errors of the coefficients. To account for the possible heteroskedasticity in the residuals, we adopt a semi-parametric bootstrap procedure, that is the fixed-design wild bootstrap (Gonçalves and Kilian, 2004), which allows for heteroskedasticity of unknown

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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 explore better the entire space of possible solutions. The probability of taking a wrong step decreases if several consecutive iterations lead to no significant improvement in the solution. This is repeated until convergence is achieved. Corana et al.'s (1987) algorithm is just one of the many proposed in the literature. See, for instance, Otten and van Ginneken (1989).

[14]More precisely, given our functional specification, the TFP elasticity in a certain country with respect to the R&D stock of a foreign country is $(1 + \iota)$ times larger in case of partners engaged in "strong exchanges" compared to partners not engaged in such exchanges.

Table 2: Estimation results (Pooled data 1971-2004 for 24 countries: 816 observations)

	(1)	(2)	(3)	(4)	(5)
Trade measure	$-$	m_{ijt}	m_{ijt}^{sa}	m_{ijt}^{spa}	$\hat{\varepsilon}_{ijt}$
β^h	0.523***	0.516***	0.502***	0.546***	0.570***
	(0.054)	(0.050)	(0.050)	(0.056)	(0.053)
β^d	0.046***	0.044***	0.050***	0.045***	0.050***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
β^f	0.158***	0.180***	0.162***	0.158***	0.139***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
ι^a		2.036***	0.855**	0.803**	0.554***
		(0.618)	(0.507)	(0.413)	(0.259)
φ^b		1.6908	0.2755	0.586	0.1766
log-L	832.36	870.25	841.97	840.18	841.83
AIC^c	-1610.74	-1682.50	-1625.95	-1626.36	-1625.66
BIC^d	-1483.72	-1546.07	-1489.53	-1485.94	-1489.24
Linearity test:	SupLM	30.178	10.740	10.537	13.829
H_0: $\iota = 0^e$		(0.000)	(0.049)	(0.020)	(0.003)
	AveLM	13.762	3.716	2.6259	8.079
		(0.000)	(0.001)	(0.037)	(0.004)
	ExpLM	10.435	2.526	2.430	5.134
		(0.000)	(0.020)	(0.024)	(0.003)

[a]Significance as from the largest p-value of the LM-type tests on H_0: $\iota = 0$. Discussion in the main text.

[b]Simulated Annealing over φ and ι. Tolerance: 1e-12. Initial temperature: 50. Function evaluations: 158400 in model (2), 152000 in (3), 149600 in (4) and 156800 in (5).

[c]Akaike Information Criterion calculated, following Akaike's (1974) original formulation, as: AIC $= -2$ log-L $+ 2k$, where k is the number of independently adjusted parameters within the model, i.e. 27 in model (1) and 29 in the others.

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

[e]Bootstrap p-values in parenthesis. Discussion in the main text.

Unreported country dummies. Bootstrapped standard errors in parenthesis (fixed-design wild bootstrap, 1000 replications). Significance levels: ** 5%; *** 1%. Significance of ι and β^f discussed in the main text.

form.[15] We estimate the parameters of Equation 3 for each of 1000 bootstrapped samples (repeating both the SA and the NLS). The standard errors are then derived from the standard deviations of the distributions of the bootstrapped parameters.[16]

Our point estimates corroborate the idea that global knowledge spillovers are related to trade patterns, as suggested by Coe and Helpman (1995) and contrary to Keller (1998). This notwithstanding, the formal test of the null hypothesis of a global and trade-unrelated transmission of knowledge requires more complex inference on the significance of the coefficient ι. It would indeed be incorrect to use the bootstrapped standard errors to test the significance of the coefficient ι. The adoption of bootstrapped standard errors does not deal by itself with an important problem affecting the inference on ι, that is the presence of nuisance parameters under the null. We shall discuss this issue in greater detail in Section 5.1, as testing the null hypothesis $H_0 : \iota = 0$ (i.e. global and trade-unrelated knowledge spillovers) is the core of our analysis. We recall that if trade patterns did not matter and knowledge flows were not stronger where trading links are more intense, then this null hypothesis would never be rejected for any value of the threshold φ.

5.1. Correct inference of the global pool hypothesis

Notwithstanding the calculation of a bootstrapped variance-covariance matrix, a conventional t-test on the significance of $\hat{\iota}$ would not be correct because of a nuisance parameter problem inherent in specification (3) (on this point see, among the others, Davies, 1977, 1987; Hansen, 1996). More precisely, φ is an unidentified nuisance parameter under the null hypothesis $H_0 : \iota = 0$.[17]

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., φ); ii) to calculate a summary statistics of the above mentioned statistics which does not depend on these parameters. Moreover, given that Equation (3) is linear under the null, the most suitable test 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 supremum statistics (SupLM), the average statistics (AveLM), the exponential

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[15]In a nutshell, given a value for each of the linear and nonlinear parameters, a bootstrap sample is generated recursively from the equation:

$$\log F_{it}^* = \hat{\alpha_i} + \hat{\beta}^h \log H_{it} + \hat{\beta}^d \log S_{it}^d + \hat{\beta}^f \log \left(S_{Kit}^f + \hat{\iota} \, S_{it}^{fs} \right) + u_{it}^*$$

where S_{it}^{fs} is calculated on the basis of $\hat{\varphi}$ and the error terms u^* are obtained by resampling the original residuals, each pre-multiplied by either 1 or -1 with 50% probability.

[16]Let us note in passing that these bootstrapped standard errors happen to be always higher than the correspondent robust asymptotic standard errors of the parameters of the NLS estimates.

[17]In principle, a similar issue affects also β^f, because both ι and φ are unidentified nuisance parameters under the null $H_0 : \beta^f = 0$. While theoretically correct, this concern is not very relevant: as revealed both by the rich literature on international R&D spillovers and by the very same distribution of the bootstrapped β^f in our exercise, the parameter β^f is surely larger than 0, fact that makes asymptotic inference with bootstrapped standard errors working fine. Thus, we do not replicate for β^f the exercise which is instead necessary for making correct inference on the (truly unknown) ι.

average statistics (ExpLM).[18]

These statistics have (asymptotically) pivotal but non-standard distributions, which depend on the moments of the distribution of the nonlinear parameter φ. Since the critical values cannot be tabulated, these tests are bootstrapped. We do so by applying the fixed-design wild bootstrapping method used for producing the standard errors in Table 2. Clearly, after having carried out a non-parametric bootstrapped procedure that accounts for heteroskedasticity in the residuals, we adopt a version of the LM-test that is also robust to heteroskedasticity. 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 φ from the set of relevant observed values (i.e. m_{ijt} or m_{ijt}^{sa}) within the 25-75th percentile.[19] For each value, we compute the correspondent heteroskedasticity–robust LM test statistics.[20] Having 1000 test 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[21] and compute the AveLM, ExpLM and wLM statistics for each sample. The bootstrap p-value is than equal to the fraction of bootstrap statistics larger than the correspondent test statistic calculated on the real data.[22]

Notwithstanding the large number of refinements and conservative stances in making

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[18]These statistics are defined as follows:

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

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

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

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).

[19]Throughout the analysis we focus on this range of values to ensure that the correspondent binarized network of "strong exchanges" is not too dense or sparse.

[20]The LM test 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 (3) 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:

$$\log F_{it} = \alpha_i + \beta^h \log H_{it} + \beta^d \log S_{it}^d + \beta^f \log S_{Kit}^f + \epsilon_{it} \tag{6}$$

and take the residuals $\tilde{\epsilon}$; ii) regress $\tilde{\epsilon}$ on $(\alpha, \log H, \log S^d, \log S_K^f, S^{fs}/S_K^f)$; 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_K^f on $(\alpha, \log H, \log S^d, \log S_K^f)$ 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).

[21]A bootstrap sample is generated by taking the fitted values of (6) and randomizing the sign of the residuals.

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

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

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 AveLM_j^* is the correspondent statistic calculated using the j-th bootstrap sample.

inference on ι, we do not fail to reject the null hypothesis $H_0 : \iota = 0$: the p-values are all smaller than 0.05, both for the nominal trade flows and for the size-adjusted ones. 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. Notably, although the absolute size of the trade flows appears to matter in determining the relatively more intense exchanges, our findings hold also when we adjust the series for the size of the trading countries and reduce the weight of the trade relationships of the largest countries. In the following sub-sections, we shall provide evidence that intense trade flows continue to be associated with intense knowledge spillovers even after refining further the measures of trade adopted in the estimation.

5.2. Size- and pair-adjusted trade flows

In the analysis above, the trade series were adjusted for the size of the countries so as to show that R&D spillovers are stronger where commercial links are relatively more intense, not simply relatively larger in absolute value.

It could be argued, however, that some pair-specific factors (such as distance and common language) are simultaneously affecting both bilateral trade and R&D flows. Was this the case, the size-adjusted trade measures could appear significantly associated with intense R&D spillovers simply because they act as proxies of the pair-specific factors that promote R&D flows. To take this possibility into account, we calculate an alternative measure of trade flows (m_{ijt}^{spa}), adjusted both for size and pair-specific factors. We then repeat the same empirical exercise above. Finding that relatively intense commercial exchanges are associated with relatively large R&D spillovers would strengthen our previous findings.

It is worth stressing that this test should be read as complementary to that with the size-adjusted measures: using m_{ijt}^{sa} we entirely attribute the R&D spillover-enhancing effects of any country-pair factors to the relative intensity of their commercial ties, whereas using m_{ijt}^{spa} we exclude by construction that persistently intense commercial ties are associated with larger R&D spillovers. These are both extreme hypotheses: more likely, there are country pair-specific factors that simultaneously facilitate bilateral trade and knowledge flows (e.g., common language) as well as special bilateral commercial ties (such as those determined by trade agreements or immigrants' family networks) that bring about, as a by-product, greater R&D flows.

We use the unbiased estimates of the coefficients of the gravity model (fixed-effects estimates of Equation (4)) to obtain an unbiased estimator of the pair-specific component of trade:

$$\hat{v}_{ij.} = \frac{1}{T} \sum_{t=1}^{T} \left(m_{ijt} - \hat{\theta}(y_{it} + y_{jt}) - \hat{\eta}_{i.t} - \hat{\eta}_{.jt} \right)$$

and we drop it from m_{ijt}^{sa}:

$$m_{ijt}^{spa} = m_{ijt}^{sa} - \hat{v}_{ij.}. \tag{7}$$

If knowledge spillovers were totally unrelated to trade, then the null H_0: $\iota = 0$ in Equation 3 would not be rejected when either of the adjusted trade measures (i.e., m_{ijt}^{sa} and m_{ijt}^{spa}) is used, because no trade-related partition of the countries would be significantly associated with knowledge spillovers. If knowledge spillovers were related to trade patterns only to the extent that close trading partners are in general better connected countries, then the null H_0: $\iota = 0$ would be more difficultly rejected when m_{ijt}^{spa} is used.

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Column (4) in Table 2 reports the results of the estimation with m_{ijt}^{spa}, along with the bootstrap p-values of the linearity tests (SupLM, AveLM and ExpLM). It can be easily seen that the estimated value of ι is similar to that calculated using m^{sa} and smaller than that for m. The p-values of the tests on the null hypothesis $H_0 : \iota = 0$ are smaller than 0.05. These findings confirm that when a relatively intense, however defined, trade relationship exists, then knowledge flows are relatively more intense.

5.3. Unexplained trade flows

We believe that we have offered some evidence on the existence of "strong exchanges", i.e., relatively intense bilateral trade flows associated with larger R&D spillovers. Even so, it could be argued by the skeptical reader that we fall short from showing that trade *per se* facilitates knowledge spillovers. Although country-pair-specific factors are dropped from the measure m_{ijt}^{sa} by using m_{ijt}^{spa}, it cannot be excluded that other country-specific factors influence trade and R&D flows at the same time, yet independently.

To address such kind of concerns we extend the approach adopted above and focus exclusively on the estimated residuals of Equation (4), that is $\hat{\varepsilon}_{ijt}$. These trade residuals are deviations from what a trade model can explain: the greater a residual, the more unusually intense a trade relationship is, and vice versa.[23]

We repeat the previous exercise: rejecting the null hypothesis that knowledge spillovers are trade-unrelated using the residual ε_{ijt} would further strengthen our previous findings. As before, we do not expect the coefficient ι to be as large as that estimated for m_{ijt}, m_{ijt}^{sa} and m_{ijt}^{spa}, because we are discarding a series of potentially "strong exchanges" for the sake of explicitly excluding any factors able to explain simultaneously trade and R&D flows. Yet, as the results in column (5) of Table 2 reveal, the data strongly reject the hypothesis that R&D spillovers are trade-unrelated and find a value of $\hat{\iota}$ close to 0.5. All in all, where trade is unexpectedly intense, knowledge spillovers are stronger.

6. The network of "strong exchanges"

The strategy of adopting an estimated threshold to identify the "strong exchanges" of R&D and trade does not lead to a random network, but a network of relatively intense bilateral trade flows associated with relatively large R&D spillovers. In this section we shall offer some insights on this.

Without the normalization of the trade flows, the network of bilateral trade flows (taking the pair averages over the 34 years in the sample) is graphed in Figure 1, where the position of the nodes reflects the relative strength and composition of the entire set of bilateral flows. It is patent that the United States is at the very center of the graph, and that Canada and Japan are not too far from it. A group of large European countries is not very distant either: these are large and integrated European countries, such as Germany, France, United Kingdom and Italy. Open but relatively small countries, such as Switzerland and Sweden, are far from the center.

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[23]Focusing on the topological properties of the network of the residuals from an estimated gravity model, Fagiolo (2010) shows that the network displays complex trade-interaction patterns, with many small-sized but trade-oriented countries that, independently of their geographical position, play the role of local hubs or attract large and rich countries.
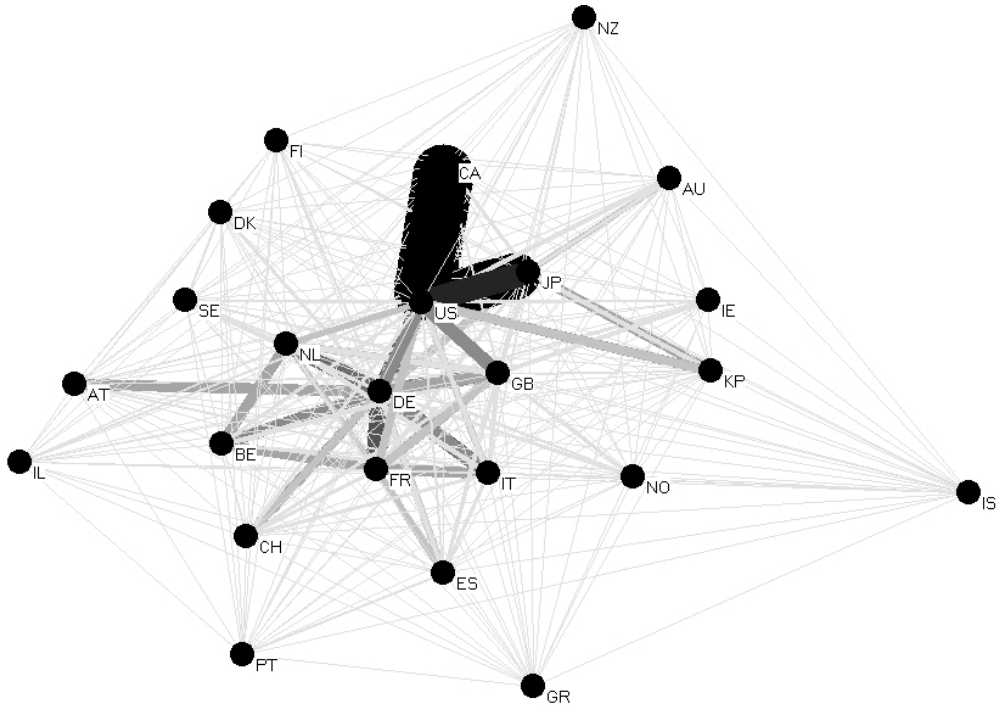
Figure 1: The network of (averaged) trade flows ($m_{ij.}$).

For an estimated threshold $\hat{\varphi}$, the network can be dichotomized and a binary directed network (whose adjacency matrix is made of 0s and 1s) can be calculated for each year t.[24] Figure 2 shows the binary network calculated from the network of nominal bilateral trade flows averaged over the 34 years, where the nodes (i.e. countries) are positioned according to the number and distribution of the "strong exchanges".[25] The first observation is that the G7 countries appear as both sources and destinations of R&D spillovers. On the contrary, a number of countries, such as Denmark, Greece, Iceland, Ireland, New Zealand, and Portugal, appear rather isolated: this is likely due to the fact they are small, distant from or relatively less developed than most of the counterparts. Country size is important, but not the only explanation for the position in the graph: both Belgium and the Netherlands appear much more connected and central than their size would suggest.

To explore the implication of country size, we now focus on the country-size adjusted trade measures. We obtain the dichotomize network of "strong exchanges" (again, for

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[24]In practice, the value the bilateral flows larger than φ are substituted with a 1, whereas the value of the flows smaller than or equal to φ with a 0. The binarization of the network facilitates the construction of the variable S_{it}^{fs} which, for each year t, is obtained pre-multiplying the vector of domestic R&D stocks by the transpose of the adjacency matrix of the binarized network.

[25]The topological properties of the international trade network over time are not of interest in our work. For an analysis, the interested reader can refer to Fagiolo et al. (2010). On these properties see also Chaney (2011).
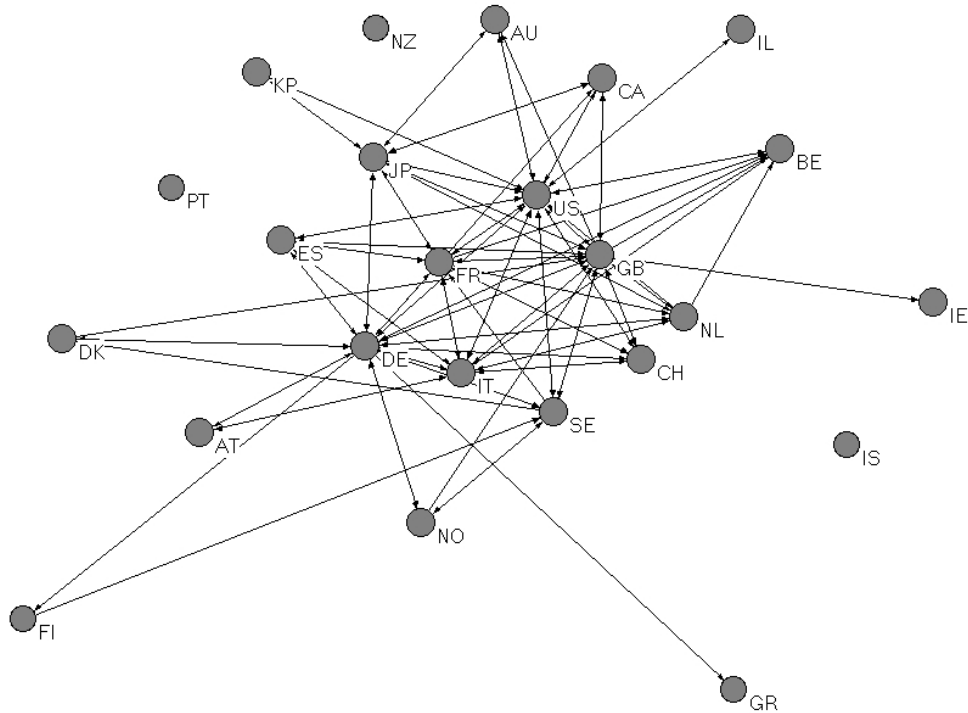
Figure 2: The binarized network of the "strong exchanges" (calculated using $m_{ij.}$).

simplicity, averaged over the 34 years).[26] Figure 3 suggests that the relaxation of the proportionality between trade flows and productivity spillovers we can detect a complex net of (non-proportional) trade-related knowledge spillovers, in line with Keller's (2000) suggestion that trade related-effects of R&D are identified primarily from countries with extreme trade patterns.

We would like to point out only few observations here. First, the network is dense, but far from complete: the network density is 0.4, with an average indegree and outdegree centralities both equal to 9.25. Second, large countries (such as the United States and Japan) are at the periphery of the graph, whereas small countries (e.g., Belgium and the Netherlands) appear very well connected with many partners. This is in line with both: i) the intuition that the United States has quantitatively large, yet not relatively intense exchanges; ii) our previous findings regarding Belgium and the Netherlands. However, other small and isolated countries, such as Greece, Iceland, Israel, and Portugal, remain at the periphery of the graph. Third, the graph shows that the European countries form a "club" of partners connected by "strong exchanges" in terms of R&D and trade. Their separation from the countries in the

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[26]Clearly, we could derive similar graphs for the other measures of trade used in the previous sections. The interpretation of such graphs would however be rather controversial: these trade flows are built under the conservative approach that excludes any pair-specific and country-specific factors which might simultaneously affect trade and R&D flows. While their adoption is meant to show the robustness of the econometric results, we do not claim that these measures are preferable to those for which we present these graphs.
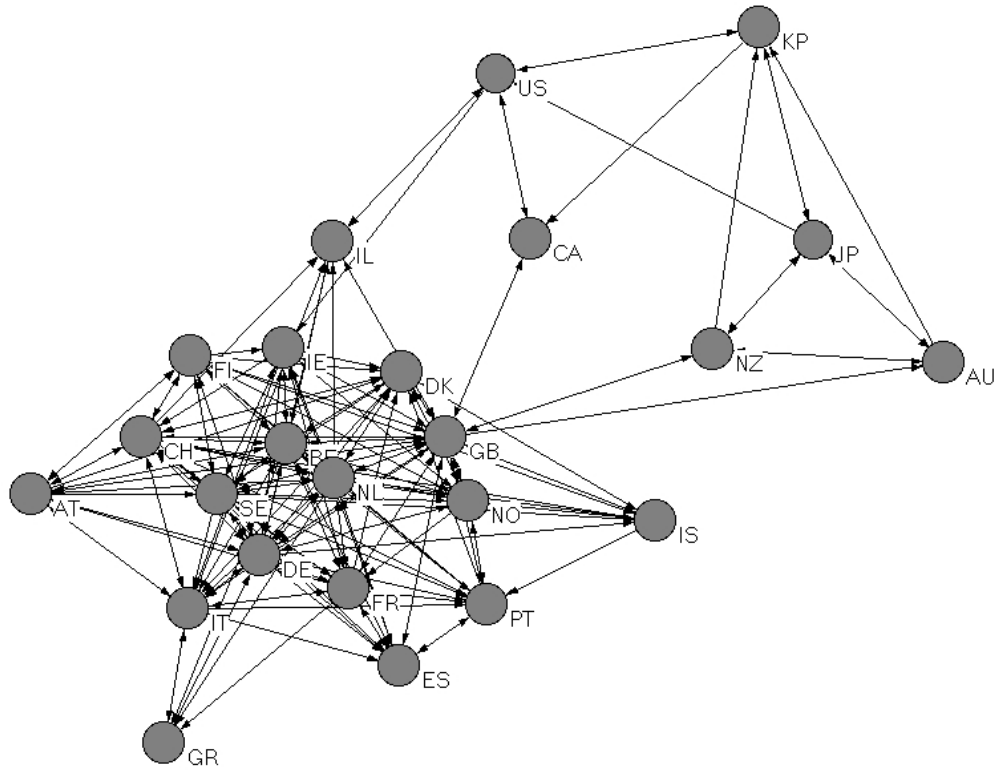
Figure 3: The binarized network of the "strong exchanges" (calculated using $m_{ij.}^{sa}$).

other continents is clear.

7. 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 (e.g. Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991; Eaton and Kortum, 2002) where imported intermediate goods embody foreign technological know-how.

In this work we, too, investigate whether international trade enhances knowledge spillovers, but we introduce some novelties in the analysis. First, we do not assume the existence of a proportional relationship between the size of trade and knowledge flows (as in Coe and Helpman, 1995): rather, we assume that more intense commercial relationships are a favorable precondition for particularly 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) model, according to which knowledge transfers are trade-unrelated, we can directly test the null

hypothesis of trade-unrelated R&D spillovers. Third, we do not calculate trade-weighted measures of foreign R&D stocks; instead, we identify relatively "strong exchanges" of trade and knowledge, and show that the impact of foreign R&D on the domestic TFP is larger the more intense are the trade exchanges.[27] Fourth, we directly explore the intuition of Keller (2000) that trade related-effects of R&D are primarily associated with "extreme" trade patterns.

Besides their intrinsic empirical relevance, our findings bear on the theoretical analysis on the international transmission of knowledge and help discriminate between the theoretical models that, equally plausibly, support the hypotheses of trade-related and trade-unrelated knowledge flows. Our findings suggest that the transmission of knowledge is enhanced by the relative intensity of relationships between the trading countries. In particular, this supports the theoretical models where trade patterns matter in the transmission of knowledge even when intermediate traded goods do not physically embody the knowledge produced abroad.

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[27]In identifying the relatively intense trade flows, we need to address the fact that nominal flows mainly reflect the (heterogeneous) size of the trading countries. Thus, on the basis of the estimates of a gravity model of trade (analyzed for the countries in the sample and over the entire period), we produce adjusted measures of trade, which account for the economic sizes of the trading countries. As a robustness check, we also calculate trade measures adjusted to account for both the size of countries' GDP and other pair-a country-specific factors that might affect simultaneously but independently both trade flows and R&D spillovers.

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