Is the Belt and Road Initiative a Further Belt on the European Innovation Ecosystem?

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Abstract

This paper asks whether an external trade shock reshapes not only the innovation incentives of individual firms but also the structure of innovation spillovers between them. The shock is China's Belt and Road Initiative (BRI), measured through an ex-ante, country–sector indicator of the expected change in export-market competition induced by BRI-related trade cost reductions. The empirical framework extends the Crépon–Duguet–Mairesse model, in its Mairesse–Mohnen–Kremp variant, by introducing spatial dependence into each block of the R&D–innovation–productivity nexus. Two firm-level weight matrices are constructed: one based on geographical proximity between countries, and one based on economic proximity derived from Eurostat FIGARO inter-country input–output tables. Using three waves of Community Innovation Survey microdata covering twelve EU countries, the results indicate that spatial specifications improve substantially on their non-spatial counterparts, that firm-level innovation responds to the exposure of proximate firms as well as to its own, and that the sign of neighbourhood effects is frequently reversed once BRI exposure is taken into account. The pattern is most visible among firms whose neighbours are internationally oriented, and is consistent with an erosion of intra-European innovation cohesion under external competitive pressure.

Keywords: Belt and Road Initiative; innovation; knowledge spillovers; spatial econometrics; CDM model; Community Innovation Survey

JEL: O31, F14, C21, R12

1. Introduction

The empirical literature on trade shocks and innovation has largely treated firms as independent units. A firm is exposed to foreign competition, and it responds — by innovating more, by innovating less, or by exiting. What this framing omits is that firms are embedded in innovation systems whose value depends on the behaviour of others. A firm benefits from the presence of nearby firms that generate knowledge, from suppliers whose technical standards it shares, and from a regional ecosystem whose coherence is itself a public good. If an external shock alters the incentives of those neighbours, the focal firm is affected even when its own exposure is unchanged.

This paper takes that possibility seriously. It examines whether China's Belt and Road Initiative (BRI) — the largest infrastructure and connectivity programme of the past decade, announced in 2013 — has altered the structure of innovation spillovers among European firms, and not merely the innovation decisions of individually exposed ones. The question is of direct interest to regional science. European innovation policy, from Smart Specialisation Strategies to Horizon programmes, is built on the premise that geographically and economically proximate firms generate mutual benefits which policy can amplify. If an external shock can invert the sign of those benefits, the premise requires qualification.

[*] *The views expressed in this paper are those of the authors and do not necessarily reflect those of the Central Bank of the Republic of Türkiye.*

Three features of the empirical design are worth stating at the outset. First, exposure to the BRI is measured ex ante. The indicator is constructed from the World Bank's simulation of BRI-induced trade cost reductions (de Soyres et al., 2019), which derives from the planned and completed project portfolio, assumed transport speeds, and pre-existing product-level elasticities. It is therefore, by construction, incapable of responding to realised innovation outcomes in Europe. Second, the indicator measures competition rather than access: for each destination market served by a firm's country, the predicted expansion of all suppliers into that market is computed and the firm's own country's component is subtracted, so that a high value denotes rivals' predicted expansion in the firm's export markets. Third, the analysis embeds this exposure measure in the CDM framework, which models R&D engagement, R&D intensity, innovation output and productivity as a recursive system, and extends every block of that framework to admit spatial dependence.

The extension is the paper's methodological contribution. To our knowledge, spatial dependence has not previously been introduced into all blocks of the CDM structure. Doing so requires firm-level weight matrices, and the paper constructs two of them under different definitions of proximity — geographical distance between countries, and economic linkage derived from inter-country input–output tables. The contrast between the two is substantively informative: geographical proximity captures the classical localised-spillover channel, whereas economic proximity captures the transmission of shocks along production networks, which need not respect distance.

The results can be summarised in three statements. Spatial specifications improve on non-spatial ones by likelihood-ratio criteria in the large majority of models, and the dependent variables display significant spatial autocorrelation, particularly under the economic linkage matrix. The direct effect of BRI exposure on R&D expenditure is positive for nationally oriented firms and attenuated or reversed for internationally oriented ones. And the neighbourhood effects — being surrounded by firms of a given market orientation — frequently change sign once BRI exposure is introduced, in both blocks of the nexus and under both definitions of proximity. It is this last finding that we regard as the paper's central empirical claim: the shock appears to operate on the spillover structure itself, not only on individual incentives.

The question sits directly on the theme of this Congress. If regions are to respond to global challenges, the channel through which those challenges reach them matters for the design of the response: a shock operating on individual firms calls for firm-level instruments, whereas a shock operating on the relations between firms calls for something else. The evidence assembled here points towards the second.

The paper proceeds as follows. Section 2 situates the BRI in relation to the European innovation ecosystem. Section 3 reviews the relevant literature. Section 4 describes the data and the construction of the exposure measure and the weight matrices. Section 5 sets out the empirical framework. Section 6 presents the results, Section 7 discusses them, and Section 8 concludes with the limitations of the present specification and the direction of ongoing work.

2. The Belt and Road Initiative and the European Innovation Ecosystem

The BRI was announced in 2013 as a programme of infrastructure investment and connectivity spanning Asia, Africa and Europe. Its economic content, for the purposes of this paper, is a reduction in the cost of moving goods along particular corridors. The World Bank's assessment estimates aggregate trade cost reductions of between roughly one and two per cent worldwide, rising to about ten per cent on the most affected corridors and considerably higher for individual country pairs (de Soyres et al., 2019). These are modest averages concealing highly uneven incidence, which is precisely what makes the programme useful as a source of cross-sectional variation.

For European firms, the relevant consequence is not primarily improved access to Asian markets. It is the improved access of third-country suppliers — China foremost among them — to the destination markets in which European exporters compete. A Bulgarian chemicals producer selling into Germany and Italy is affected by the BRI not because its own shipping costs fall, but because the cost of delivering competing Chinese product into Germany and Italy falls. The exposure measure used here is built to capture exactly this asymmetry.

The timing places the shock in a particular European context. The period covered by the three survey waves — 2012 through 2018 — follows the sovereign debt crisis and coincides with a sustained policy concern about European competitiveness in technology-intensive sectors. It also coincides with the consolidation of Smart Specialisation Strategies as the organising principle of EU regional innovation policy, which makes the question of whether external shocks disturb regional innovation coherence more than academic.

The sample countries are drawn largely from Central and Eastern Europe, together with Germany, Spain, Portugal and Greece. This composition is a consequence of microdata availability rather than design, but it is not unhelpful: Central and Eastern European economies are both more exposed to BRI-related investment flows and more dependent on intra-European production networks, which sharpens the tension between the two channels the paper examines.

3. Related Literature

3.1 The R&D–innovation–productivity nexus

The structural approach to firm-level innovation originates with Crépon, Duguet and Mairesse (1998), who model the decision to engage in R&D, the intensity of R&D conditional on engagement, the transformation of R&D into innovation output, and the effect of innovation output on productivity as a recursive system estimated jointly. The framework addresses two problems simultaneously: selection, since R&D expenditure is observed only for firms that engage in it, and the endogeneity of innovation input in the output equation. Mairesse, Mohnen and Kremp (2005) modify the structure by adding a selection equation before the innovation output block, and it is this variant — referred to here as the MMK framework — that the present paper adopts.

Applications of the framework to European data are numerous. Lööf et al. (2001) and Janz et al. (2003) estimate it for Nordic and German data, Griffith et al. (2006) provide a four-country comparison, and Hashi and Stojčić (2013) apply it to Central and Eastern European countries using CIS microdata. The estimated elasticities of innovation output with respect to R&D vary considerably across these studies, and comparisons with the present results are made in Section 6 with that heterogeneity in mind.

3.2 Trade shocks and innovation

The effect of import competition on innovation is theoretically ambiguous. The escape-competition mechanism predicts that firms close to the technological frontier respond to intensified competition by innovating more, whereas firms far from it are discouraged. The empirical literature on the China shock has produced findings on both sides, and the divergence appears to depend on the margin examined, the measure of exposure, and the institutional setting. What is common to most of this literature is the treatment of firms as independent units of exposure — an assumption this paper relaxes.

A second strand examines infrastructure investment specifically, and here the direction of the effect depends on whether infrastructure primarily improves a firm's own market access or primarily improves that of its competitors. The distinction motivates the construction of the exposure measure in Section 4.2, in which the own-country component is explicitly netted out.

3.3 Spatial dependence and knowledge spillovers

The proposition that innovation activity is spatially correlated is among the most robust findings in regional science, and the econometric apparatus for handling it is well established (Anselin, 1988; LeSage and Pace, 2009; Elhorst, 2014). Neglecting spatial dependence when it is present has known consequences: omitted spatially structured information is absorbed into the error term, generating heteroskedasticity and, where the dependence operates through the dependent variable, inconsistency of the coefficient estimates. Ignoring spatial autocorrelation in the errors alone is less damaging, costing efficiency rather than consistency.

The choice of weight matrix determines what 'proximity' means, and the literature offers a wide menu — contiguity, inverse distance, k-nearest neighbours, input–output linkage, technological similarity, and hybrids. Studies of knowledge spillovers have increasingly moved beyond pure geography, on the argument that technological and input–output relatedness may transmit knowledge more effectively than distance. This paper estimates under both a geographical and an economic linkage matrix rather than choosing between them, and treats the comparison as a result in its own right.

4. Data

4.1 Community Innovation Survey microdata

Firm-level data come from the Community Innovation Survey (CIS) scientific use files for the 2014, 2016 and 2018 waves, covering twelve EU countries: Bulgaria, Czechia, Germany, Estonia, Spain, Greece, Croatia, Hungary, Lithuania, Latvia, Portugal and Slovakia. Each wave references the two preceding years, so that the three waves together span 2012 to 2018 and bracket the 2013 announcement of the BRI.

The CIS scientific use files are repeated cross-sections rather than a panel; firms cannot be linked across waves. The time dimension is therefore introduced by estimating the same model on each wave and comparing results, an approach that identifies changes in the association between exposure and innovation over time but does not permit firm fixed effects. Sectoral information is available at an aggregated NACE Rev. 2 level, and firm location is not disclosed below the country level — a constraint with direct consequences for the construction of the geographical weight matrix, discussed in Section 4.3.

Three variables require comment. Market orientation, denoted largest, records the market from which the firm derives its highest turnover, coded as local/national (the base category), EU–EFTA, or non-EU/non-EFTA. The variable is central to the analysis because exposure to an external trade shock should plausibly operate differently depending on where a firm sells. Firm size is coded in three classes. R&D engagement is a binary indicator used as the dependent variable of the selection equation, and the proportion of employees with tertiary education serves as the exclusion restriction. Because questionnaire structure differs across waves, particularly between 2016 and 2018, the set of explanatory variables in the innovation output block is not fully identical across waves; this is noted where relevant.

4.2 Measuring exposure: the expected export volume change indicator

The exposure measure, denoted EEVC, is constructed in four stages and defined at the country–sector level. It combines three sources: the World Bank's BRI Global Database of predicted sectoral trade cost reductions between country pairs (de Soyres et al., 2019), the BACI bilateral trade database, and product-level trade elasticities from CEPII.

In the first stage, bilateral import values are aggregated by destination and HS-4 product code, and each origin country's share in a destination's imports is computed. These shares are multiplied by the corresponding product elasticity, yielding a term that measures the responsiveness of a destination's import composition to trade cost changes. Since the BRI database is classified in GTAP sectors, the HS-4 terms are converted using UN correspondence tables and aggregated within GTAP sectors.

In the second stage, these share–elasticity terms are multiplied by the predicted trade cost reductions for the corresponding origin–destination–sector combination, producing the expected change in import volume for each such triple.

The third stage performs the operation that gives the measure its interpretation. For each destination and sector, the expected changes are summed across all origin countries, giving the total predicted expansion of that destination's imports in that sector. From this total, the component attributable to the sample country itself is then subtracted. What remains is the predicted expansion of all other suppliers into that destination — that is, the predicted intensification of competition faced by the sample country's exporters. These residual terms are weighted by each destination's share in the sample country's total sectoral exports and summed across destinations.

Two properties follow. The measure is directional: a high value denotes greater predicted competition in the firm's export markets, not greater market access, so the discouragement hypothesis predicts a negative association with innovation and the escape-competition hypothesis a positive one. And the subtraction of the own-country component removes the element of the predicted change most likely to be correlated with the sample country's own conditions, which strengthens the exogeneity of the remainder. In the fourth stage the measure is converted from GTAP to NACE Rev. 2 and merged to the firm data by country and sector.

Because the underlying trade cost predictions derive from announced and completed projects together with assumed transport speeds, the measure is properly described as capturing anticipated rather than realised connectivity. This is a limitation with respect to the eventual realisation of the projects, but an advantage with respect to identification: expectations formed from an announced project portfolio cannot be a response to European firms' subsequent innovation behaviour.

4.3 Weight matrices

Two firm-level weight matrices are constructed.

The geographical matrix is built from great-circle distances between the capital cities of the twelve sample countries, computed from Eurostat GISCO coordinates. Distances are inverted, so that greater distance implies a smaller weight, and the diagonal is zero by construction. The restriction to capital-city distances is imposed by the data: the CIS scientific use files do not disclose firm location below the country level, not even at NUTS 2. The resulting matrix therefore captures between-country proximity and cannot represent within-country agglomeration, which is a material limitation for a regional-science application and is returned to in Section 8.

The economic proximity matrix is built from Eurostat FIGARO inter-country input–output tables for 2011, a year chosen to precede the earliest period covered by the 2014 wave and thereby to limit endogeneity, following the same logic as the vintage choice for the exposure measure. Rows and columns are country–sector combinations, and each cell records the contribution of the column combination to the output of the row combination, expressed as a share of the row's total output in a

Hirschman-type structure. Twelve countries and twenty-four input–output sectors yield an initial 288 × 288 matrix; reconciliation with the dual sectoral classification of the CIS files requires an expansion to 29 sectors and a 348 × 348 matrix. Country–sector rows without a counterpart in the firm data are retained to preserve squareness but are not transmitted to the firm-level matrix.

Both matrices are extended to firms by mapping each firm to its country (geographical matrix) or to its country–sector index (economic matrix), and both are row-standardised so that the weights facing each firm sum to one. The economic linkage matrix is additionally symmetrised by averaging mirrored cells.

Sparsity in the firm-level matrices creates computational difficulties and, as LeSage and Pace (2009) note, imprecision in capturing localised spillovers. Two sparsification procedures are therefore applied. For the geographical matrix, a top-k selection retains the six largest weights in each row, followed by magnitude thresholding at 10^{-6}. For the economic matrix, magnitude thresholding is applied at the mean of the original cell values. The resulting matrices are sparse, row-standardised, and compatible with sparse-matrix estimation algorithms.

5. Empirical Framework

5.1 The MMK structure

The framework comprises three blocks. The first models innovation input: a probit selection equation for the decision to engage in intramural R&D, and an outcome equation for the level of R&D expenditure conditional on engagement, estimated jointly by the Heckman procedure. The proportion of employees with tertiary education enters the selection equation but not the outcome equation, providing the exclusion restriction. The second block models innovation output, measured as turnover from sales of products new to the market, with predicted R&D expenditure from the first block entering as a regressor. The third block models productivity growth as a function of predicted innovation output.

The variables of interest are the exposure measure and market orientation, entered both as level terms and as an interaction. The interaction is the object of primary interest: the hypothesis is not that BRI exposure affects all firms identically, but that its effect depends on where the firm sells, since a shock operating through export-market competition should bind most tightly on firms whose turnover comes from the markets most affected. The exposure measure enters in logarithmic form, following the specification adopted in the underlying study.

5.2 Introducing spatial dependence

Spatial dependence is introduced through the general nesting spatial (GNS) specification, which admits spatial lags in the dependent variable, in selected explanatory variables, and in the error term simultaneously:

$$y = \rho Wy + X\beta + WX\theta + u, \quad u = \lambda Wu + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2 I)$$

where W is the row-standardised firm-level weight matrix, ρ the spatial autoregressive parameter, θ the coefficients on spatially lagged regressors, and λ the spatial error parameter. Both ρ and λ are restricted to the unit interval to ensure invertibility and non-explosiveness. The nested alternatives — SAR, SEM, SDM, SDEM and SARAR — are obtained by restricting subsets of these parameters to zero.

The choice of the most general form is deliberate. Because this is, to our knowledge, the first application of spatial methods to the full CDM structure, the aim is to avoid excluding a channel of spatial dependence by assumption. The cost is efficiency and, in some specifications, difficulty in estimating standard errors for particular coefficients; these cases are marked in the tables. Alternative, more restricted spatial specifications yield broadly consistent results and are available on request.

The spatially lagged regressors are selected in line with the paper's question: the exposure measure, the market orientation indicators, and their interaction. The spatial lag of the interaction term is the coefficient of central interest, since it identifies how a firm's innovation responds to the BRI exposure of its neighbours, differentiated by those neighbours' market orientation. Multicollinearity forces the omission of individual spatially lagged terms in some specifications, and models estimated on the geographical matrix exclude country fixed effects, which are collinear with a weight matrix defined at country level.

5.3 Estimation

Spatial dependence is introduced into the outcome equations only, not into the selection equation. The reason is computational: spatial models with discrete dependent variables are demanding to estimate, and the sparsity of the weight matrices — particularly the economic linkage matrix — produces convergence failures. The Heckman procedure is therefore implemented in two steps, with the inverse Mills ratio computed from a non-spatial probit and entered as a regressor in the spatial outcome equation. This proxies the selection correction while keeping estimation tractable, at the cost of not modelling spatial dependence in the selection process itself.

Models are estimated by maximum likelihood with sparse-matrix methods, and standard errors are obtained from 1,000 bootstrap replications. Spatial autocorrelation in the dependent variables is assessed by Moran's I prior to estimation, and the errors of the fitted spatial models are tested for residual autocorrelation.

6. Results

6.1 Spatial autocorrelation in the dependent variables

Table 1 reports Moran's I for the dependent variables of the first two blocks under both weight matrices. Under the economic linkage matrix, spatial autocorrelation is significant in every wave and for both dependent variables. Under the geographical matrix the evidence is weaker and confined to the 2016 wave. This asymmetry is itself informative: it suggests that the relevant proximity for innovation outcomes in this sample runs through production-network linkage rather than through distance between countries — which is unsurprising given that the geographical matrix, constrained by data disclosure, can only represent proximity at the country level.

Models are nonetheless estimated under both matrices in all waves, for comparability across specifications and because the geographical matrix remains the natural benchmark against which network-based proximity should be assessed.

Table 1. Moran's I statistics for the dependent variables

Wave / dependent variable	Geographical	Economic linkage
2014 log R&D expenditure	0.004	0.20***
2014 log turnover from innovative sales	-0.01	0.01***
2016 log R&D expenditure	0.01***	0.02***
2016 log turnover from innovative sales	0.009*	0.12***
2018 log R&D expenditure	-0.02	0.09***
2018 log turnover from innovative sales	-0.02	0.01***

, **, * denote significance at the 10%, 5% and 1% levels. Rejection indicates the presence of spatial dependence.*

6.2 Innovation input: the first block

Table 2 reports the R&D expenditure equation estimated under geographical proximity. Likelihood-ratio tests indicate that the spatial specification improves on the non-spatial Heckman benchmark in 2014 and 2016. The inverse Mills ratio is significant and negative throughout, confirming that selection into R&D engagement is not ignorable and justifying the Heckman structure.

The conventional determinants behave as expected: R&D expenditure rises with firm size, with public and EU funding, and with orientation towards markets beyond the national one. The direct effect of BRI exposure is positive and significant in 2014 (0.225) and 2016 (0.101), and the interactions with market orientation are negative. Read together, these indicate that exposure is associated with higher R&D expenditure among nationally oriented firms, and that this association is attenuated — and for globally oriented firms in 2014 essentially offset — as the firm's market orientation moves outward. The result is consistent with the interpretation that firms selling into the markets where BRI-induced competition is concentrated respond defensively, while firms insulated in national markets do not face the same pressure.

Table 2. First block: R&D expenditure equation under geographical proximity

	2014	2016	2018
rho	-0.359*** (0.137)	-0.080 (—)	0.016 (0.356)
Constant	12.146*** (0.935)	2.622 (3.077)	10.860*** (3.686)
Cooperation	0.173* (0.089)	-0.102 (0.078)	-0.107 (0.144)
Government funding	0.477*** (0.083)	0.178** (0.071)	0.089 (0.081)
EU funding	0.239*** (0.071)	0.359*** (0.063)	0.060 (0.080)
Local funding	0.427*** (0.085)	-0.133 (0.091)	0.053 (0.112)
Inverse Mills ratio	-0.701*** (0.175)	-1.272*** (0.149)	-0.746*** (0.125)
Orientation: EU–EFTA	0.295** (0.122)	0.355*** (0.088)	0.175 (0.122)
Orientation: non-EU	0.828*** (0.165)	0.836*** (0.177)	0.087 (0.256)
log BRI exposure	0.225*** (0.066)	0.101*** (0.037)	0.114 (0.073)
log BRI × EU–EFTA	-0.128 (0.093)	-0.088* (0.050)	0.117 (0.077)
log BRI × non-EU	-0.153** (0.073)	-0.236** (0.106)	0.238 (0.152)
Size class 2	0.853*** (0.068)	0.859*** (0.060)	0.768*** (0.079)
Size class 3	2.601*** (0.100)	2.328*** (0.078)	1.981*** (0.108)
W · log BRI	1.706*** (0.605)	-3.957 (—)	-0.013 (0.122)
W · EU–EFTA	8.541*** (1.999)	11.127*** (0.180)	-3.429*** (1.300)
W · non-EU	27.507 (19.685)	66.801 (—)	-1.494** (0.643)
W · (log BRI × EU–EFTA)	-7.797*** (1.701)	-1.789*** (0.182)	1.689** (0.659)
W · (log BRI × non-EU)	-14.253 (11.183)	-38.233 (—)	—
lambda	0.054 (—)	0.982*** (0.005)	0.113 (0.352)
R^2	0.491	0.633	0.375
LR test	276.48***	3019.9***	7.48
Observations	3,784	4,157	2,755

*Bootstrap standard errors (1,000 replications) in parentheses. *, **, *** denote significance at 10%, 5% and 1%. (—) indicates that the standard error could not be estimated. W denotes the spatial lag operator. Country fixed effects are excluded under the geographical matrix owing to collinearity.*

The spatially lagged terms carry the paper's distinctive content. In 2014, the coefficient on the spatial lag of exposure is positive and significant: a firm surrounded by exposed, nationally oriented neighbours experiences a positive association with its own R&D expenditure. The spatial lag of EU–EFTA orientation is likewise positive and strongly significant in both 2014 and 2016 — proximity to EU-oriented firms is, in the absence of the shock, beneficial, which is the classical knowledge-spillover result and a reassuring validation of the specification.

The interaction of these two spatial lags reverses that benefit. The coefficient on the spatial lag of exposure interacted with EU–EFTA orientation is negative and significant in both 2014 and 2016. The interpretation is that the advantage of being surrounded by EU-oriented firms is eroded, and at the estimated magnitudes reversed, once those neighbours are themselves exposed to BRI-induced competition. A plausible mechanism is competitive reallocation: as cheaper imports enter European markets, EU-oriented neighbours redirect effort towards defending or expanding market share, and the local knowledge externalities from which the focal firm previously benefited diminish.

Table 3 reports the same equation under economic proximity. The direct effects are qualitatively similar but smaller in magnitude, and the spatial autoregressive parameter is positive and significant in 2014 rather than negative. The contrast with the geographical results is instructive. Under geographical proximity, the sign reversal appears among EU-oriented neighbours; under economic proximity, it appears among neighbours oriented towards markets outside the EU, where the interaction of the spatial lag of exposure with non-EU orientation is negative and strongly significant in both 2014 and 2016.

Table 3. First block: R&D expenditure equation under economic proximity

	2014	2016	2018
rho	0.020** (0.010)	0.024 (0.021)	-0.472** (0.218)
Constant	10.474*** (0.222)	10.284*** (0.141)	15.797*** (2.492)
Cooperation	-0.043 (0.029)	-0.089** (0.037)	0.065 (0.072)
Government funding	0.106** (0.053)	0.159*** (0.058)	0.144** (0.068)
EU funding	0.409*** (0.075)	0.314*** (0.063)	0.133* (0.073)
Local funding	0.087 (0.073)	-0.121 (0.093)	0.014 (—)
Inverse Mills ratio	-0.890*** (0.013)	-1.301*** (0.090)	-0.586*** (0.070)
log BRI exposure	0.176* (0.093)	0.053* (0.027)	-0.016 (—)
Orientation: EU–EFTA	0.644*** (0.134)	0.273*** (0.096)	0.213** (0.109)
Orientation: non-EU	0.410* (0.230)	0.721*** (0.179)	0.119 (0.224)
Size class 2	0.832*** (0.067)	0.891*** (0.061)	0.830*** (0.077)
Size class 3	2.653*** (0.089)	2.341*** (0.079)	2.082*** (0.102)
log BRI × EU–EFTA	-0.196*** (0.073)	-0.053 (0.055)	0.109* (0.060)
log BRI × non-EU	0.062 (0.133)	-0.177* (0.106)	0.230 (0.152)
W · log BRI	0.014 (0.021)	0.021 (—)	0.174 (0.134)
W · EU–EFTA	0.099 (0.189)	1.395*** (0.246)	-0.339 (—)
W · non-EU	1.117* (0.672)	2.906*** (1.028)	1.053 (1.690)
W · (log BRI × EU–EFTA)	-0.261* (0.151)	-0.065 (0.075)	-0.209*** (0.051)
W · (log BRI × non-EU)	-0.935*** (0.332)	-1.333*** (0.497)	0.447 (0.669)
lambda	-0.042 (0.141)	0.060 (—)	0.556*** (0.132)
R^2	0.563	0.638	0.386
LR test	13.947***	29.149**	11.886
Observations	2,942	4,157	2,755

*Bootstrap standard errors (1,000 replications) in parentheses. *, **, *** denote significance at 10%, 5% and 1%. (—) indicates that the standard error could not be estimated. W denotes the spatial lag operator.*

This displacement of the effect from one type of neighbour to another, depending on how proximity is defined, is a substantive finding rather than an inconsistency. Geographical proximity within this sample largely means being in the same country, where the relevant peers are those competing in the same European markets. Economic proximity means being connected through input–output linkages, where the relevant peers are suppliers and customers. That the reversal appears among globally oriented partners in the second case is consistent with a supply-relationship mechanism: when input suppliers oriented towards non-EU markets are themselves exposed to the shock, relational stability and the predictability of input provision may deteriorate, weakening the incentive to commit to long-horizon

R&D. An alternative reading emphasises lock-in: as such suppliers pass through lower input costs from expanded global supply chains, the focal firm's incentive to innovate is reduced.

6.3 Innovation output: the second block

Table 4 reports the innovation output equation under geographical proximity. Likelihood-ratio tests favour the spatial specification in every wave. Turnover from products new to the market rises with firm size, with the auxiliary innovation activities, and with predicted R&D expenditure — the last of these confirming that the recursive structure of the framework operates as intended.

The neighbourhood results again dominate. Absent the shock, being geographically surrounded by globally oriented firms is associated with lower innovative sales in 2014 and 2018, which may indicate limited local knowledge diffusion where neighbours' attention is directed outside the region. Once exposure is accounted for, this effect reverses: the interaction of the spatial lag of exposure with non-EU orientation is positive in 2014 and 2018. As the BRI expands connectivity, globally oriented neighbours may become better integrated into extra-European trade and innovation networks, and their presence then confers access to markets and capabilities that raise the focal firm's innovative sales.

The mirror-image result holds for EU-oriented neighbours. Being surrounded by firms oriented towards EU–EFTA markets is associated with higher innovative sales in all three waves — again the standard spillover result, attributable to shared regulatory standards, technological frameworks and market knowledge. In 2018 this reverses once exposure is introduced, with a large negative coefficient on the interacted spatial lag. The reading we favour is that regional cohesion among EU-oriented firms weakens as the shock matures, with attention and resources diverted towards opportunities opened by lower-cost global connectivity.

The spatial error parameter is positive and significant in 2014 and 2016, indicating that unobserved determinants of innovation output are themselves spatially correlated across country–sector units. Localised shocks or latent factors influencing innovation in one unit propagate to neighbouring ones, which may either amplify or dampen the structural adjustment induced by the shock.

Table 4. Second block: innovative sales equation under geographical proximity

	2014	2016	2018
rho	-0.177 (0.125)	-0.664*** (0.053)	0.000 (0.000)
Constant	11.396*** (1.362)	21.164*** (0.789)	11.799*** (0.143)
Process innovation	—	—	0.277*** (0.068)
Product innovation	0.390*** (0.075)	0.094* (0.052)	—
Organisational innovation	0.430*** (0.078)	0.343*** (0.073)	—
Marketing innovation	0.170** (0.072)	0.022 (—)	—
Inverse Mills ratio	1.216*** (0.182)	-0.588 (—)	0.099 (0.108)
log BRI exposure	0.047 (0.067)	0.088* (0.049)	-0.236*** (0.082)
Orientation: EU–EFTA	0.483*** (0.122)	0.541*** (0.083)	0.328*** (0.091)
Orientation: non-EU	0.520*** (0.116)	0.512 (—)	0.138 (0.234)
Size class 2	1.309*** (0.071)	1.466*** (0.057)	1.366*** (0.070)
Size class 3	3.071*** (0.106)	3.040*** (0.084)	2.897*** (0.104)
Predicted R&D expenditure	0.123*** (0.013)	0.056 (—)	0.057*** (0.010)
log BRI × EU–EFTA	-0.188** (0.076)	-0.014 (0.037)	0.019 (0.038)
log BRI × non-EU	0.013 (0.028)	0.034 (—)	0.323** (0.151)
W · log BRI	1.014*** (0.286)	-1.075 (—)	0.419* (0.224)
W · EU–EFTA	3.622** (1.630)	4.490*** (0.395)	17.767*** (2.670)
W · non-EU	-23.235* (12.147)	133.604*** (13.817)	-9.576* (5.213)
W · (log BRI × EU–EFTA)	2.275 (—)	-1.404 (—)	-12.750*** (2.124)

	2014	2016	2018
W · (log BRI × non-EU)	19.383* (10.746)	-73.899*** (7.427)	6.458* (3.908)
lambda	0.580*** (0.044)	0.519*** (0.041)	0.000 (0.000)
LR test	268.53***	281.86***	86.53***
Observations	2,837	3,167	2,719

*Bootstrap standard errors (1,000 replications) in parentheses. *, **, *** denote significance at 10%, 5% and 1%. (—) indicates that the coefficient was not estimated in that wave or that its standard error could not be estimated. The set of innovation-type controls differs in 2018 owing to questionnaire changes.*

Table 5 reports the corresponding estimates under economic proximity. The spatial specification again improves on the non-spatial benchmark in all waves. The pattern of sign reversal is, if anything, more pronounced: whether the focal firm's input–output partners are oriented towards EU–EFTA or towards markets beyond it, the introduction of exposure reverses the association between their orientation and the focal firm's innovative sales, and it does so in every wave. The direction of the reversal is not uniform, however — it runs from negative to positive in some cases and from positive to negative in others.

Table 5. Second block: innovative sales equation under economic proximity

	2014	2016	2018
rho	-0.067 (0.198)	-0.199 (—)	0.000 (0.000)
Constant	11.749*** (2.495)	13.973*** (0.797)	11.799*** (0.143)
Process innovation	—	—	0.277*** (0.068)
Product innovation	0.080 (0.093)	-0.105 (0.086)	—
Organisational innovation	0.312*** (0.099)	0.302*** (0.081)	—
Marketing innovation	0.118 (0.093)	0.021 (—)	—
Inverse Mills ratio	-0.354* (0.211)	-1.140 (—)	0.099 (0.108)
log BRI exposure	-0.048 (0.086)	-0.014 (0.052)	-0.236*** (0.082)
Orientation: EU–EFTA	0.436*** (0.154)	0.414*** (0.136)	0.328*** (0.091)
Orientation: non-EU	0.522 (—)	0.599 (—)	0.138 (0.234)
Predicted R&D expenditure	0.10*** (0.020)	0.07*** (0.010)	0.057*** (0.010)
Size class 2	1.495*** (0.089)	1.521*** (0.076)	1.366*** (0.070)
Size class 3	3.413*** (0.115)	3.229*** (0.100)	2.897*** (0.104)
log BRI × EU–EFTA	-0.121 (0.089)	0.111 (0.082)	0.019 (0.038)
log BRI × non-EU	0.036 (—)	0.069 (—)	0.323** (0.151)
W · log BRI	0.340 (0.215)	0.487*** (0.184)	0.419* (0.224)
W · EU–EFTA	-0.627 (0.524)	0.912*** (0.174)	17.767*** (2.670)
W · non-EU	2.147** (1.018)	4.226*** (1.580)	-9.576* (5.213)
W · (log BRI × EU–EFTA)	-0.107 (—)	-0.709* (0.406)	-12.750*** (2.124)
W · (log BRI × non-EU)	-0.682 (0.660)	-2.262*** (0.803)	6.458* (3.908)
lambda	-0.308 (0.362)	-0.640*** (0.147)	0.000 (0.000)
R^2	0.527	0.526	0.478
Observations	1,741	2,062	2,719

*Bootstrap standard errors (1,000 replications) in parentheses. *, **, *** denote significance at 10%, 5% and 1%. (—) indicates that the coefficient was not estimated or that its standard error could not be estimated.*

6.4 Productivity: the third block

Estimates for the productivity block are reported in Table 6. Likelihood-ratio statistics again favour the spatial specification, but the coefficients are close to zero throughout and support no substantive inference. The most plausible explanation is the choice of dependent variable: productivity growth rather than the level of labour productivity, which departs from most of the CDM literature and removes much of the cross-sectional variation on which the third block ordinarily relies. The block is reported for completeness of the framework rather than as a source of findings, and any interpretation of the productivity consequences of the shock should await a specification in levels.

Table 6. Third block: productivity growth equation

	Econ. 2014	Econ. 2016	Econ. 2018	Geog. 2014	Geog. 2016	Geog. 2018
Predicted innovative sales	0.00	0.00	0.00	0.00	0.00	0.00
log physical capital exp.	0.00	0.00	0.00	0.00	0.00	0.00
Orientation: EU–EFTA	-0.08	0.03	-0.05	-0.06	0.06	-0.03
Orientation: non-EU	0.05	0.00	-0.006	0.06	0.06	-0.08
log BRI exposure	0.01	0.03*	0.04	0.05**	0.03	0.02
log BRI × local/national	0.06**	-0.01	-0.03	0.05***	0.00	-0.03
log BRI × EU–EFTA	0.07**	-0.02	-0.01	0.06**	-0.01	-0.02
log BRI × non-EU	0.04	-0.01	0.02	0.04	-0.01	0.00
W · log BRI	0.01	0.08*	0.03	0.20**	-0.01	0.001
W · (log BRI × EU–EFTA)	-0.07	0.06	-0.01	0.28*	-0.02	-0.13**
W · (log BRI × non-EU)	0.07	-0.14	0.02	0.14*	0.01	0.01
rho	-0.19	0.37***	-0.25	-0.02	-0.03	-0.17
lambda	-0.76	-2.19***	-0.85	-0.14	-0.07	-0.39**
LR test	21594**	40.89***	31.07***	12.81*	15.87**	34.38***
Observations	1,043	1,661	1,908	1,043	1,661	1,908

*Country and sector dummies included in all specifications. *, **, *** denote significance at 10%, 5% and 1%.*

6.5 Residual spatial dependence

Moran tests on the residuals of the fitted models indicate that, for almost all specifications estimated on the geographical matrix, no significant spatial autocorrelation remains in the errors, which supports the adequacy of the spatial specification under that definition of proximity. Residual dependence persists more often under the economic linkage matrix, suggesting that the network channel carries structure not fully captured even by the general nesting form — a point taken up in Section 8.

7. Discussion

Three claims emerge from the estimates, in ascending order of interest.

First, spatial dependence in firm-level innovation outcomes is present and material. It is detected in the dependent variables, particularly under network-based proximity; the spatial specifications improve on non-spatial benchmarks by likelihood-ratio criteria in the large majority of models; and the spatial error parameter is significant in several innovation-output specifications, indicating that unobserved determinants of innovation are themselves spatially structured. For applied work on the CDM framework, this suggests that the standard non-spatial implementation omits a systematic component.

Second, the direct effect of BRI exposure on innovation input differs by market orientation in the direction the competition interpretation predicts. Nationally oriented firms show a positive association; firms selling into EU–EFTA and global markets show attenuated or reversed associations. If exposure is understood as the predicted expansion of rival suppliers into the destinations a firm serves, then firms that do not serve those destinations should not respond, and firms that do should respond in proportion to their dependence on them.

Third — and this is the finding we would place at the centre of the paper — the shock appears to operate on the spillover structure and not only on individual incentives. In the absence of exposure, proximity to EU-oriented firms is associated with higher R&D expenditure and higher innovative sales, which reproduces the standard knowledge-spillover result and indicates that the specification is capturing something real. Once exposure enters, that association is attenuated and in several specifications reversed. The neighbourhood is still there; what it transmits has changed.

A coherent, if provisional, account runs as follows. Prior to the shock, the European innovation ecosystem exhibits a degree of coherence sustained by common regulatory standards, shared technological frameworks, and coordinated funding instruments. Firms in geographical or economic proximity benefit from this coherence through reduced uncertainty and clearer priorities. As external competitive pressure intensifies, proximate firms — particularly those already oriented towards international markets — redirect attention and resources: towards defending market share, towards new destinations opened at lower cost, or towards inputs sourced through expanded global supply chains. The externalities on which the focal firm relied thin out, and in some specifications turn adverse. The shock, on this reading, is felt less as a direct competitive blow than as an erosion of the collective structure within which firms innovate.

The policy implication is a qualification of a common assumption in European regional innovation policy. Instruments premised on agglomeration and cluster formation take the sign of proximity effects as given and seek to amplify them. These results suggest the sign is contingent on the external environment. Policy designed to strengthen regional innovation ecosystems may therefore need an explicit external dimension — attentive not only to the exposure of individual firms but to whether the cohesion of the ecosystem itself is being eroded — and should differentiate by firms' market orientation rather than treating exposure as uniform across a region or sector.

8. Conclusion, Limitations and Ongoing Work

This paper has extended the CDM framework to admit spatial dependence in each of its blocks, and used it to ask whether China's Belt and Road Initiative has altered the structure of innovation spillovers among European firms. Using an ex-ante, country–sector measure of predicted export-market competition and two firm-level weight matrices representing geographical and economic proximity, the estimates indicate that firms respond to the exposure of their neighbours as well as to their own, and that the sign of neighbourhood effects is frequently reversed once exposure is taken into account.

Several limitations bear on how firmly these results should be read, and are stated here both because they qualify the findings and because they identify where the work is currently being extended.

The most consequential concerns inference. The exposure measure varies at the country–sector level, not at the firm level, whereas standard errors here are bootstrapped over firms. Where a regressor varies at a coarser level than the unit of observation, this understates sampling variability, and the appropriate correction is to cluster at the level at which treatment varies. In this application the number of such clusters is small — of the order of the number of sectors — which places the problem in the few-clusters regime where asymptotic cluster-robust inference is itself unreliable and wild cluster bootstrap procedures are indicated. Re-estimation of the non-spatial specifications under wild cluster bootstrap is currently underway, and preliminary results indicate that some coefficients significant under firm-level inference do not survive it. The corresponding correction for the spatial specifications is not yet implemented, and the significance levels reported above should be read with that qualification in mind. We would particularly welcome discussion of how wild cluster bootstrap procedures should be adapted to the general nesting spatial form.

A second limitation concerns the functional form of the exposure measure. Entering it in logarithms, as here, excludes country–sector cells with zero predicted exposure and rescales the measure so that identification is influenced by observations in the near-zero tail. Specifications in levels and in standardised form are being examined as alternatives.

Third, the geographical weight matrix is constrained by disclosure rules in the CIS scientific use files, which do not report firm location below the country level. Geographical proximity is therefore measured between capital cities, and within-country agglomeration — the object of most interest to regional science — cannot be represented. That the economic linkage matrix performs better on the Moran diagnostics may partly reflect this constraint rather than an intrinsic superiority of network proximity. Access to geocoded innovation microdata would permit a considerably sharper test.

Fourth, spatial dependence is introduced into the outcome equations only, and the selection equation is estimated without it for computational reasons. If selection into R&D engagement is itself spatially dependent, the inverse Mills ratio is imperfectly measured. Fifth, the CIS scientific use files are repeated cross-sections, so that changes across waves conflate time effects with changes in sample composition; country coverage is not identical across waves, and a constant-composition specification is in preparation. Finally, the exposure measure reflects announced rather than realised infrastructure, and is best understood as capturing anticipation.

These qualifications notwithstanding, the substantive proposition the paper advances is one we believe survives them: that the effects of external trade shocks on innovation cannot be adequately assessed firm by firm, because a substantial part of what such shocks do is to alter what proximity is worth.

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