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BITs with a Bite?

EU HOME INVESTMENT EFFECTS OF EU-CHINA BILATERAL INVESTMENT TREATIES

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Abstract

In this paper, we study the impacts of bilateral investment treaties (BITs) between the EU countries and China on EU home investments. We consider BITs as "treatments" that provide further access to global value chains (GVCs). We identify the causal impacts of the BITs on the relationship between home investments and the deepening of GVCs, with identification arising from exogenous, pre-treaty variation in the exposure to the Chinese value chains. We show that strong pre-treaty exposure to the Chinese value chains has led to a further strengthening of the Chinese upstream linkages and a decreasing impact on domestic capital growth in the EU. it seems that the effects of the BITs are strongly felt in growing industries where there have been high capital growth rates, most pronouncedly in the manufacture of computer, electronic, and optical products, and pharmaceuticals. On the other hand, it is also felt in some industries that have had laggard capital growth rates, such as the textile industry. However, it appears that the effect has been heterogeneous, concentrating on countries with low productivity, as relative to the global industry averages. Among the exposed industries with a high pre-treaty fraction of Chinese production, the high-productivity ones tend to increase their relative labor-productivity growth and value-added growth more after the signing of a treaty. The negative link between non-Chinese investments and the pre-treaty exposure also characterizes BITs with China and non-EU countries, but not BITs without China as a partner country.

Tiivistelmä

EU-maiden ja Kiinan investointisopimusten vaikutukset kotimaisiin investointeihin

Tässä raportissa tutkimme EU-maiden ja Kiinan kahdenvälisten investointisopimusten vaikutuksia EU-maiden kotimaisiin investointeihin. Näiden sopimusten seurauksena yritykset saavat paremman pääsyn globaaleihin arvoketjuihin. Tulosten mukaan Kiinan kanssa tehdyt sopimukset ovat johtaneet siihen, että Kiinan rooli arvoketjuissa on noussut. Sen myötä kotimaisen pääoman kasvuvauhti EU-alueella on hidastunut. Vaikutus vaihtelee kuitenkin toimialoittain. Hidastuminen on keskittynyt alhaisen tuottavuuden toimialoihin, kun taas korkean tuottavuuden aloilla vastaavaa vaikutusta ei ollut. Korkean tuottavuuden aloilla työn tuottavuuden ja arvonlisän kasvuvauhti nousivat.

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Contents

Suomenkielinen yhteenveto

Tässä artikkelissa tutkimme EU-maiden ja Kiinan kahdenvälisten investointisopimusten vaikutuksia EU:n kotimaisiin investointeihin. Uusia investointisopimuksia on solmittu laajasti Kiinan ja EU-maiden välillä 2000-luvun alusta alkaen. Sopimukset ovat helpottaneet kansainvälisten arvoketjujen muodostumista. Ne muun muassa sisältävät aikaisempiin sopimuksiin verrattuna laajempia määräyksiä ulkomaisten yritysten yhdenvertaisesta kansallisesta kohtelusta ja sijoittajien ja valtioiden välisistä riitojenratkaisumenettelyistä. Parempaa tietoa sopimusten vaikutuksista tarvitaan sekä uusien sopimusten tarvetta arvioitaessa että EU:n ja Suomen investointikehityksen ymmärtämiseksi.

Tutkimus tarkastelee sopimuksia tilastollisina "käsittelyinä", joiden vaikutuksesta maat saavat laajemman pääsyn globaaleihin arvoketjuihin. Tunnistimme sopimusten syy-seurausvaikutuksia kotimaisiin investointeihin ja globaalien arvoketjujen laajenemiseen hyödyntämällä sopimusta edeltävää vaihtelua kiinalaisiin arvoketjuihin osallistumisessa. Päättely perustuu ajatukseen, että laajempi osallistuminen kiinalaisiin arvoketjuihin ennen sopimusta mahdollistaa arvoketjujen helpomman muuttamisen sopimuksen allekirjoituksen jälkeen.

Sopimuskumppanien välisten arvoketjujen tarkastelu osoittaa, että merkittävä kiinalaisten arvoketjujen hyödyntäminen ennen sopimusta on johtanut niiden käytön laajenemiseen edelleen sopimuksen allekirjoituksen jälkeen. Toisaalta sopimukset ovat merkinneet matalampaa kotimaisen pääoman kasvuvauhtia niillä EU:n teollisuustoimialoilla, jotka ovat jo aikaisemmin käyttäneet runsaasti kiinalaisia arvoketjuja. Vaikuttaa kaiken kaikkiaan siltä, että niillä aloilla, joilla sopimuksia on voitu tehokkaimmin hyödyntää, investointisopimukset ovat merkinneet investointien hidastumista EU:ssa.

Toimialoista voimakkaimmin vaikutukset ovat kohdistuneet moniin kasvaviin aloihin, erityisesti tietokoneiden, elektronisten ja optisten tuotteiden sekä lääkkeiden valmistukseen. Toisaalta vaikutuksia havaitaan myös joillakin taantuvilla toimialoilla, kuten tekstiiliteollisuudessa. Vaikutus nähdään suurempana maissa, joissa alojen tuottavuus jää toimialalle tyypillisen tuottavuuden alapuolelle. Sen sijaan korkean tuottavuuden aloilla sopimukset ovat johtaneet nopeampaan työn tuottavuuden ja arvonlisän kasvuun niillä aloilla, jotka olivat olleet tiiviisti tekemisissä Kiinan kanssa aikaisemmin. Ilmiön vaikutus pääoman kasvuun on ollut keskimäärin pieni, mutta yksittäisissä tapauksissa vaikutus on ollut huomattava.

Suomen kohdalla vaikutukset ovat olleet maltillisia. Analyysi viittaa siihen, että tietokoneiden, elektronisten ja optisten tuotteiden ja kuljetuskaluston valmistuksen heikentynyt pääoman kasvuvauhti voitaisiin jossain määrin selittää sopimusten vaikutuksella.

Tutkimuksessa tarkasteltiin myös laajemmin kahdenvälisten investointisopimusten vaikutuksia. Tulosten mukaan vastaavia investointeja hidastavia vaikutuksia Kiinan sopimuskumppanimaihin on myös Kiinan ja EU:n ulkopuolisten maiden kahdenvälisillä sopimuksilla. Sen sijaan investointivaikutuksia ei ollut sopimuksilla, joissa Kiina ei ole ollut kumppanimaana.

1 Introduction

An increasing volume of products is being produced by global value chains (GVCs), each of which can involve dozens or even hundreds of firms. The geographical dispersion of production stages has affected the composition of international production and the location of investments in many ways.[1] As a result, the foreign content of output has increased while the fraction of domestically created value added (VA) has decreased (Timmer et al., 2014; Johnson and Noguera, 2012). However, surprisingly little is known about how GVCs affect domestic investments. In this paper, we study the impact of GVCs on domestic investments, with a focus on the EU countries and the value chains between the EU and China. As the economic areas are considering of more comprehensive investment agreements that would allow further deepening of their value chains' interactions, the subject is topical. With treaties, the EU hopes to improve its investment environment and overturn its rather nascent, post-2008 investment growth development, while China, on the other hand, expects to further bolster its role as the world's manufacturing powerhouse (see, e.g., Zhang, 2013; Mees, 2016).[2]

It is not obvious what kind of impacts GVC participation has on capital accumulation in the home countries involved in the chain. If a great number of components and other intermediates are produced at a certain location abroad, it might be beneficial to relocate final production to this region in order to avoid transportation or tariff costs (Venables, 1996). As a consequence, making future investments to expand the capacity of final production would be directed overseas instead of to a home country. On the other hand, GVCs potentially lead to a deeper specialization and improved competitiveness that, in turn, may open new positive possibilities and increase investment in the home country.[3] The existing empirical studies often suggest that foreign sourcing complements, rather than substitutes for, domestic activity (Martınez-Galan and Fontoura, 2019; Adarov and Stehrer, 2019). Moreover, domestically, there tends to be a shift towards more non-routine and more interactive tasks, and the use of highly educated workers (Becker et al., 2013; Reijnders and de Vries, 2018), which benefits industries that are intangible intensive (Jona-Lasinio and Meliciani, 2019). However, there are still major identification hurdles. Changes in the access to value chains is hard to isolate from other supply, demand, and technology shocks that govern the global distribution of work.

In this paper, we identify the investment effects by using bilateral investment treaties (BITs) signed between China and the EU countries in the period 2000–2014 as "treatments." The treaties provide us with the most direct evidence of the effects of changes in the access to value chains as they included both national treatment provisions and more comprehensive two-way provisions, allowing investor-to-state dispute settlement (see, e.g., Copenhagen Economics, 2014).

We argue that the treaties provide a natural quasi-experiment in which its treatment effect varies across industries depending on the initial fraction of Chinese production in the value chains (for the general approach, see, e.g., Card, 1992; Angrist and Pischke, 2008). This is because more exposed industries tend to be in a better position to adjust their operations when investment restrictions are lifted. This mechanism, which we verify in our dataset, arises from a combination of natural benefits of specialization, the existence of fixed costs, and increasing returns to scale in the Chinese part of the value chain. We measure the exposure of industries to the Chinese component of value chains by using the industry-level World Input–Output Database (WIOD).[4] Moreover, we use global exposure patterns as instruments for national patterns to avoid the influence of national circumstances on the treaties. Our approach provides an important contribution to the current literature that has, due to the lack of a set of feasible alternative instruments, often merely used lagged values in a generalized method of moments (GMM) setup to control for the endogeneity problems (Cheng and Kwan, 2000; Poncet et al., 2010; Zeng and Lu, 2016).[5]

Our results provide interesting new evidence on the role of GVCs in investment and other economic dynamics. *First*, we show that BITs have been a source of differentiated value chain dynamics: Strong pre-treaty exposure to the Chinese value chains has led into a further strengthening of the China–EU linkage. Therefore, we find that BITs can indeed provide variation in the value chain dynamics. However, the effect is only evident when there is a large pre-treatment fraction of upstream, intermediate production in China (i.e., a strong upstream linkage). In contrast, a similar effect cannot be seen when EU producers provide intermediate goods and services for Chinese final products (downstream linkage).

Second, we find that strong pre-treaty exposure and the resulting increase in the upstream VA fraction of China has a decreasing impact on domestic capital growth. A closer analysis, however, shows that there is a significant variation in the effects across different types of industry. It appears that the negative capital growth effect is concentrated on low-productivity industries, that is, on industries whose productivity is lower than the global median labor productivity of their peers in other countries (within the ISIC Revision 2 industry classification). Similar evidence was also found for industries with low R&D intensity, though the results were somewhat weaker, possibly due to having less data. Overall, we find that our main results are robust to different specifications and extend to extra-EU countries. The results concentrate on a few industries that have been subjected to strong offshoring.

Among the exposed industries with a high pre-treaty fraction of Chinese production, the high-productivity ones tend to also increase their relative labor-productivity growth and VA growth more after the signing of the treaty, while we do not find a statistically significant effect on the exposed low-productivity industries. For industries that have low R&D intensity, the treaties tend to generate a decline in VA and labor-productivity growth rates.

Finally, our results suggest that China has been an exceptional BIT partner country for the EU. When we repeat our analysis for other countries, we find that China is the only country for which the capital growth effect has been negative overall for exposed industries, and the capital growth rate of the industries with low labor productivity is statistically significant. In other countries, the effects are either insignificant or, in some cases, significantly statistically positive, especially for the high-productivity industries.

2 Methodology

2.1 Measuring value chain linkages

In this subsection, we outline our approach to quantifying value chain linkages in GVCs and the participation of EU countries in particular. As our primary measure for the linkages, we consider the *upstream* VA fraction. A large non-EU upstream VA fraction of a country in EU production indicates that an EU country actively uses the non-EU country as the intermediate producer of final products for which final assembly is made in the EU country. On the other hand, a large extra-EU *downstream* fraction in EU production indicates that an EU country actively uses non-EU countries as the final producer of products for which the EU country produces intermediate goods and services.

We estimate these fractions based on the WIOD. It builds on a set of consistent time series of national supply and use tables that are constructed by harmonizing the corresponding national tables and benchmarking them on the national accounts. The national tables are then used to derive international tables after the disaggregation of imports by country of origin and use category by using bilateral trade data. Finally, the national tables are combined to yield corresponding world tables, which are then transformed into a world input–output table (WIOT) (Dietzenbacher et al., 2013; Timmer et al., 2015, 2016).

Let us next formally introduce the building blocks of our analysis. The first element is the input coefficient matrix, $\boldsymbol{A}$, that contains the input coefficients a_{ij}, which give the global value units of intermediate goods from industry i that are required to produce one value unit of gross output in industry j. In A, the numbers of the rows and columns are the same and equal the numbers of total national industries (the number of countries, C, times the number of industries, I). For the final demand block, we similarly define a matrix of final demand flows $\boldsymbol{Y}$, the row elements being different final demand classes (in total: 5 different classes) and columns indicating flows from i to j, with the length $C*I$.

The ratios of VA to gross output in industries in countries are contained in a row vector $\boldsymbol{v}$. The length of this vector equals the numbers of industries, with VA ratios for industries as first elements ($\widetilde{\boldsymbol{v}}$) and zeros elsewhere: $\boldsymbol{v} = [\widetilde{\boldsymbol{v}}\ 0]$. Then, we follow Los et al. (2018) and collect the actual VA distribution in the global value-chain matrix ($\boldsymbol{VA}$), that is

$$(1)\quad \boldsymbol{VA} = \boldsymbol{v}(\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{Y} * \boldsymbol{i},$$

in which $\boldsymbol{i}$ is a column vector where all elements are unity, implying that it sums the elements in each of the rows of the matrix $\boldsymbol{Y}$. The VA matrix has the same dimensions as A, including the contributions of each industry to the overall VA of other industries. The element $(\boldsymbol{I} - \boldsymbol{A})^{-1}$ is the well-known Leontief inverse, in which $\boldsymbol{I}$ is the identity matrix of appropriate dimensions. When multiplied with final demand, the Leontief inverse calculates the gross output in the industries producing the final products and also the output in industries producing the intermediate inputs required for this (Los et al., 2018). In particular, $\boldsymbol{VA}$ can be interpreted as the limiting value of the infinitely long sum of VA contributions, with the number of stages varying from 1 to ∞.

Each column of the value chain matrix shows the VA distribution of the value chains for a given final producer industry. The elements allocate the total VA into the VA contributions of different intermediate good producer industries globally. They provide us with the *upstream* VA fractions of the trade partner countries in each production value chain, as indexed by the final producer industry and country.

Notation for the econometric analysis

We collect the data on value chain linkages for each WIOD country and use them in our econometric analysis as the value chain exposure variables. In particular, the global VA matrices for different years yield the treatment intensities, that is, the fractions of VA of the BIT partner countries in the total VA of a particular final producer in the home country. After denoting the home country producer industry as s and the corresponding BIT trade partner country as p, we denote the total corresponding *upstream VA* fraction of all country p industries in the production of final product of industry s as

$$FVA_{s,t}^{p} = \sum\nolimits_{j \in p} VA_{s,t}^{j} / (\sum\nolimits_{j=all} VA_{s,t}^{j})$$

when the *VA* matrix for year t is used.

In particular, we focus mostly on BITs with China, and we denote the corresponding *VA* fractions of Chinese industries in home industry s as $FVA_{s,t}^{Chn}$ in period t. When we consider the pre-treaty period fractions, we omit the time index and simply use the notation FVA_{s}^{Chn}.[6]

2.2 Measuring the impacts of value chain linkages

Our main aim is to find evidence of the relationship between domestic investments and changes in GVCs. Unlike most of the previous literature, which typically reports correlations between the involvement in value chains and domestic investments, we aim at studying how underlying changes in the access to value chains through changes in bilateral investment conditions have affected domestic investments.

Simple correlations of these variables are problematic above all because the causal relationship between domestic investments and GVC involvement is ambiguous. It could be that value chains are relocated due to changes in demand, supply, or other factors of production technology rather than because of the increased use of GVCs per se. As studies of the broader impacts of China and other countries on local market dynamics through international trade (e.g., Autor et al., 2013, 2016) have acknowledged, the identification requires a valid instrumental variable (IV) or, more broadly, a source of plausibly exogenous variation for regional exposure to value chains.

We follow the related literature (Autor et al., 2013, 2016) in utilizing data on regional industry specialization patterns in the pre-shock period, thus preempting any endogenous adjustment of industry location to contemporaneous trade, demand, and supply shocks other than adjustment through the specialization patterns. To avoid potential problems of the construction of the so-called Bartik instruments that are typically used in the literature (Bartik, 1991; Goldsmith-Pinkham et al., 2020), we combine the approach with an ordinary least squares (OLS) and IV difference-in-differences regression models with treatment intensity differences (see, e.g., Card, 1992; Angrist and Pischke, 2008).

In particular, our strategy builds on the idea that there is variation in the possibilities of industries to operate in the bilateral investment agreement partner countries; there are differences in the impacts of the agreement on the industries that are more or less exposed to the corresponding value chains due to their previous specialization patterns. We measure this exposure by using the global input–output data and the upstream (and downstream) fractions of the investment agreement partners before the signing of the agreement.

In principle, the past high, upstream VA fraction of Chinese producers is a straightforward indicator of the exposure to the further deepened Chinese value chains. However, a well-known challenge is that an identification problem may arise from the connection between trade policy decisions and the importance of individual industries in countries that sign the treaty. As Autor et al. (2016) reminded us, several trade deals involving foreign direct investments have been lobbied hard by multinational companies. Therefore, the timing and content of the agreements may reflect political pressure, thus leading to endogeneity bias in the economic outcomes. Trade policy is driven by the power of individual industries and their economic outcomes, rather than vice versa.

To avoid the caveats of the potential endogeneity problems, we propose using an indicator variable that is independent of the individual country-level idiosyncrasies (which may create endogeneity) and rather reflects a general exposure to the Chinese value chains. Our approach takes stock of the Bartik instruments that are commonly used to isolate, for example, the role of China in labor dynamics in other countries. However, it should be noted that our approach differs from the use of standard Bartik instruments in important ways. Following the treatment-intensity approach (Card, 1992; Angrist and Krueger, 2009), we combine the exposure patterns directly as treatment intensity indicators (of the BITs) in the difference-in-differences equation rather than using the shift-fraction–weighted growth rates of economic variables in the peer countries as IVs for the domestic countries' growth rates, as would be the case if common Bartik instruments were used (Goldsmith-Pinkham et al., 2020). On the other hand, our approach provides an important contribution to the current BIT literature that has, due to the lack of a set of feasible alternative instruments, often merely used lagged values in a GMM setup to control for the endogeneity problems (Zeng and Lu, 2016).

Let us discuss our approach more formally. In our time-series panel of EU countries and industries, we denote the individual industry–country pairs as s, and employ the following model to explain home-country outcome variables, $Y_{s,t}$, primarily capital growth rates:

$$Y_{s,t} = \gamma_s + \lambda_t + \beta(FVA_s^{Chn} * AFTER_t) + AFTER_t + X'_{s,t}\delta + \epsilon_{st}. \quad (2a)$$

In the model, FVA_s^{Chn} denotes the average (upstream) VA fraction of Chinese intermediate production prior to the agreement for industry s, following the notation described in the previous section. For a given country, the treatment indicator variable $AFTER_t$ gives a value of 1 for the BIT signature year and thereafter, while the value is otherwise set at 0. The signing of the BIT is therefore a variable with differing "treatment intensity" across industries, even at the country level, the impact being characterized by $\beta * FVA_s^{Chn}$. In addition to statutory variation in the treatment status, the sectoral importance may thus differ according to the fraction of Chinese VA in the production. Note that we later also analyze the fraction in the post-treaty period, in which case we denote its yearly observation as $FVA_{s,t}^{Chn}$.

In addition, we include fixed effects that are specific to the industry and country (controlling for the pre-treaty effects), γ_s and year-specific fixed effects (controlling for common shocks across countries), λ_t. In the set of additional control variables, we introduce the treatment indicator variable $AFTER_t$ to control for the country-level, average-intensity impacts of the treaty,[7] as well as country-specific linear time trends and other control variables in matrix X. The error terms ε_{st} are allowed to be clustered within each industry–country pair and our estimation is robust to heteroskedasticity. We study the robustness of our key findings to the different specifications of clusterization (see, e.g., Cameron and Miller, 2015) and fixed effects, as well as robustness to potential pre-treaty trends, in a separate robustness analysis detailed in the next section. We also vary the dataset and consider the impacts on the extra-EU countries separately in the next section.

As our key economic outcome variables, we consider the growth rate of EU countries' domestic capital stock at the industry–country level. We also analyze the effects on VA and labor productivity growth.

Let us next discuss the construction of our treatment intensity indicator / IV. An ideal variable should be independent of an agreement country's idiosyncrasies in the industry structure that may affect the political decision-making (the exclusion restriction) and thus the timing and the structure of the BIT, while it should more broadly reflect the exposure of industries in the corresponding value chains (relevance). Our estimation strategy hinges on the variation in the exogenous exposure; the existence of endogeneity may bias our results.

To be more specific, we acknowledge that the endogeneity problem may arise from the fact that in a given BIT between country c and China, the value-chain fractions for individual industries i ($s = i,c$), $FVA_{i,c,t}^{Chn}$, may indicate influence on the treatment outcomes. For example, a large exposure prior to the deal may increase the political pressure to ratify a treaty that benefits a particular industry. Having said this, it is not quite clear what the direction of the bias would be as political lobbying could involve both the support of offshoring and production at home.

We propose the following way to use our extensive data on the typical VA linkages to avoid this problem:

Step 1. We collect direct information concerning the typical covariations of China and its BIT partners by using data on other BITs. That is, we collect data on EU countries' value chain linkages with countries (other than China) that have signed BITs with its members. We then use this information to make predictions of the value-chain patterns between China and the EU members. In the making of the prediction for any EU country, c, we avoid using data in a manner that would violate the exclusion restriction condition. In practice, for any c and for each industry i, individually, we estimate the following model with data from all studied countries excluding country (we indicate this set of other countries by -c) and with i data:

$$(3) \quad FVA_{i,-c,t}^{Chn} = \sum_{oth} \xi^{oth} * FVA_{i,-c,t}^{oth} + \gamma_t + \epsilon_{i,c,t}.$$

That is, the upstream VA fraction of China, $FVA_{i,-c,t}^{Chn}$, is regressed on a set of VA fractions of the EU's other BIT partners, $FVA_{i,-c,t}^{oth}$, yielding a numerical model for the relationship between value-chain fractions for China and other BIT partners, with covariates ξ^{oth}. Furthermore, common year-specific fixed effects, γ_t (estimated with the corresponding data) are included in the model.

In Appendix II, we report a list of roughly 20 countries whose upstream VA fractions we use in Eq. (3) as explanatory variables. The countries have had a BIT with at least one of the current EU countries during the data period. It is notable that the list also includes EU countries that have joined the EU during the period or that have had BITs with applicant countries before they joined the union.

We argue that the model characterizes general patterns of trade relations in a sufficiently rich way to construct relevant indicators while not violating the exclusion restriction condition. For example, due to general orientation towards the Asian value chains, an industry that has strong VA linkages with Korea is more likely to also have stronger linkages with China. In a similar vein, stronger linkages with European countries, such as the Czech Republic, may predict a weaker relationship with Asian countries, including China, and a stronger emphasis on European value chains. During the analysis, we also investigate whether the choice of countries is important for our results.

Step 2. The estimated model from Step 1 allows us to also make a prediction for country c. That is, we can predict the value chain linkage with China by using the observations of linkages with information on all other trading partners $FVA_{i,c,t}^{oth}$ as the explanatory variables. We denote this prediction as $\overline{FVA}_{i,c,t}^{Chn}$.[8]

Step 3. After repeating the procedure for each i, p, and c, we construct panel data from the predictions. In our econometric models, we denote this variable in brief as $\overline{FVA}_{st}^{Chn}$. We combine it with the treaty dummy, yielding our IV, $\overline{FVA}_{s}^{Chn} * AFTER_t$.

Let us elaborate this procedure further with an example where Germany is the home country and we focus on the transportation industry. In Step 1, we collect the industry-specific data from all countries involved in the treaties excluding Germany. Using the data, we then regress the Chinese VA share for the other BIT partner country shares in the same industry to yield a model of the general trade patterns. In Step 2, we then collect the corresponding VA fractions with other BIT partners for the German transportation industry and make a prediction for the VA fraction with China. This prediction serves as the basis of our IV. In Step 3, we collect all the predictions after repeating the procedure for other countries, industries, and years.

We note that this variable is by construction independent of the idiosyncrasies at the level of individual trade deals between China and its treaty partners while it nevertheless reflects the broad exposure patterns of all BIT partner countries. They are likely to reflect geographical distance and broader economic proximity between *p* and *c* while being unlikely to be directly connected to the specificities of the agreement that could bias our results. We discuss these patterns more closely in the next section.

The most straightforward way to use our indicator variable is as a reduced-form model where one replaces the original intensity indicator with our constructed indicator:

$$(2b) \quad Y_{st} = \gamma_s + \lambda_t + \beta(\overline{FVA}_s^{Chn} * AFTER_t) + AFTER_t + X_s^{'}\delta + \epsilon_s.$$

This procedure eradicates the potential endogeneity problem by directly replacing the endogenous component from the intensity variable. When applied in a reduced form in Eq. (2b), the IV is considered as a direct indicator variable for the general exposure of an industry to the value chains based on the trade structure of the country so far, as the structure is not contaminated by the features of trade relations. In many cases, this information is interesting per se and avoids burdening the estimation model with excess structure. While controlling for the average effect of the treaty, $AFTER_t$, $\overline{FVA}_s^{Chn} * AFTER_t$, should not suffer from the potential endogeneity problems due to political influence.

We have also extended the reduced-form approach so that there is more structural IV estimation that allows us to study the interactions between the outcome variables further. We are interested, for example, in analyzing the causal relationship between the post-agreement changes in the GVC linkages and investments. The IV approach allows us to study changes in investments related to trade linkages in investments by using the pre-treaty exposure as an IV for the post-agreement changes in the GVC linkages.

We build on standard two-stage IV estimation techniques and apply two main specifications. In our first specification, we connect our IV and the actual *pre-treaty* fractions as the endogenous variable, dubbed as the *pre-fraction IV*. In Eq. (4), in the first stage we measure the influence of the trade deals on the fraction variable by explaining the pre-exposure variable with the IV:

$$(4) \quad FVA_s^{Chn} * AFTER_t = \gamma_s + \lambda_t + \beta^{1st}(\overline{FVA}_s^{Chn} * AFTER_t) + AFTER_t + X_s^{'}\delta + \epsilon_{st}.$$

In Eq. (4), we only change the reduced-form model in a minor way, by introducing a second step in which we predict the original, Chinese-fraction weighted treatment variable with an augmented variable in which the potentially endogenous component (i.e., the fraction) is replaced with the constructed share while again controlling for the average effect of the treaty, $AFTER_t$. This, allows us, above all, to study the relevance of our instrument while avoiding the potential endogeneity problem.

In the second stage, in Eq. (5) we use the first stage prediction, $\widehat{FVA_s^{Chn} * AFTER_t}$ to provide the IV estimate for the correspondence with the economic outcome variable Y_{st} and the value chain exposure by using:

$$(5) \quad Y_{st} = \gamma_s + \lambda_t + \beta^{iv} * (\widehat{FVA_s^{Chn}} * d_t) + X_s^{'}\delta + \epsilon_{st}.$$

This specification aims at directly correcting the potential bias arising from the use of the pre-treaty exposure variables as an explanatory variable. It is notable that we estimate the model in one step, using the GMM procedure.

Our second specification provides further structure to the model in Eq. (6) by measuring the influence of the trade deals on the contemporaneous VA fractions that also includes fractions at the post-treaty period (*current-fraction IV*):

$$(6) \quad FVA_{st}^{Chn} = \gamma_s + \lambda_t + \beta^{1st}(\overline{FVA}_s^{Chn} * AFTER_t) + X_s^{'}\delta + \epsilon_{st}.$$

Note that, compared with Eq. (4), the only change is to replace the pre-treaty, upstream fraction of Chinese intermediates with the contemporaneous fraction, which allows us to further elaborate the BIT influence on the Chinese part of the value chain. In particular, we can study whether the pre-exposure leads to a higher VA fraction overseas in the post-treaty period and, if so, whether this increase leads to less investments domestically.

Correspondingly, in the second stage (Eq. (7)), we again use the first stage prediction $\widehat{FVA}_{st}$ to provide the IV estimate for the correspondence with economic outcome variable Y_{st} and the value chain exposure:

(7) $Y_{st} = \gamma_s + \lambda_t + \beta^{iv} * \widehat{FVA}_{st}^{\text{Chn}} + X_s'\delta + \epsilon_{st}.$

The second approach allows us to study the structural relationship between our economic outcome variables and the changes in the VA fractions.

Moreover, to provide further insights, we also study the impacts of BITs separately for different kinds of industries. That is, we separately analyze the EU national industries in groups with higher or lower than (global) median labor productivity or R&D intensity within the corresponding industry class. The intensity variables FVA_s and $\overline{FVA}_s$ can be decomposed into corresponding parts by giving them the value 0 if the industry does not belong to a certain group and the actual value if it does. The separation provides us with a straightforward extension of the basic model with two IVs and two endogenous variables, one for each group. Similarly, we make the separation at the industry level. As this approach considerably increases the number of instrumented variables, we focus on the reduced-form estimates and the extension of specification (2b) in particular.

Finally, the procedure above straightforwardly generalizes to any other of the EU's BIT partners and the home production effects of non-EU countries. We will investigate this broader perspective in Section 5.

3 Data and descriptive statistics

3.1 Data sources

As our main data source, we use the 2016 release of the WIOD (Timmer et al., 2015; 2016) and the associated social accounts matrices. The data contains sector-level WIOTs with underlying data for 44 countries and 56 sectors, including services.[9] These countries account for a major part of the world's GDP (at current exchange rates) and almost all developing countries, and therefore, our data represents the overall global economy well. Moreover, the dataset includes comparable measures of productive capital and labor productivity. We complement this data with measures of R&D investments from the OECD STAN database.

Throughout the analysis, we focus on the manufacturing industries where the input–output data has the highest quality. The rest of the economy consists of services and utilities where the measurement of the value chain components is often more difficult, and we omit them from our analysis.

As a particular shock affecting GVCs, we study the impacts of BITs that have been a common tool for promoting overseas investments. BITs are agreements between two countries regarding the promotion and protection of investments made by investors from the respective countries in each other's territory. Typically, the aim of BITs is both to protect investments abroad in countries where investor rights are not already protected through existing agreements and to encourage the adoption of market-oriented domestic policies that treat private investment in an open, transparent, and non-discriminatory way.

To track investment treaties, we use a data set collected by UNCTAD, including data on BITs that were signed globally between 2000 and 2014. The combined dataset that we use in empirical analyses includes all EU countries, as well as many non-EU countries, and covers the period from 2000 to 2014.

Our data period witnesses profound changes in the EU–China BITs as it marks a transition from the first-generation to the second-generation treaties, as discussed by Copenhagen Economics (2012). While the first generation of treaties (signed before 1998) do not include national treatment provisions and only allow investors recourse to international arbitration to adjudicate disputes concerning the amount of compensation for expropriation, the second-period treaties in our data period include both national treatment provisions and more comprehensive provisions, allowing investor-to-state dispute settlements concerning all substantive protections. Overall, the evolution of China's approach toward BITs in favor of a more liberal approach reflects the country's growing international economic interdependence and the rising importance of not only inward foreign direct investments in the Chinese economy but also outward foreign direct investments in the Chinese economy (Zeng and Lu, 2016).

3.2 Data description

In Table 3.1, we describe our data. We report the year of signature for the BITs between the individual EU countries and China.[10] The data consists of these countries, as well as including other EU countries as control group. In total, there are 22 countries, 18 manufacturing industries (for a list, see Table A1.2), and annual data for 2000–2014, yielding 5513 individual observations in our baseline estimations. Of these, 2241 observations are for periods in which the EU country has already signed the treaty, while the rest of the observations are for periods before the treaties. We note that each of the countries already have had a first-generation BIT with China, and our treatment involves a change of generations. In the case of Cyprus and the Netherlands, our data only involves post-treaty observations, and thus they do not contribute to the analysis of our treatment effects. Countries without BITs or pre-treaty periods serve as our control group.

Table 3.1 A summary of the statistics of the variables used in estimations.
The table reports the medians for each EU BIT partner with China in the year of signature and one year before,as well as the total number of EU observations.

		# of OBS, baseline		Pre-treaty median					Difference of median (post-treaty to pre-treaty)				
	Year of signature	Total	Post-treaty	Capital growth rate	China upstream VA share	China down-stream VA share	Labor produc-tivity growth rate	VA growth rate	Capital growth rate	China upstream VA share	China down-stream VA share	Labor produc-tivity growth rate	VA growth rate
AUT		252	0	0.032	0.007	0.013	0.024	0.019					
BEL	2005	252	180	0.012	0.007	0.009	0.033	0.010	-0.019	0.011	0.007	-0.014	-0.005
BGR		252	0	0.078	0.010	0.005	0.099	0.106					
CYP	2001	242	242										
CZE	2005	252	180	0.054	0.004	0.004	0.050	0.054	-0.029	0.008	0.007	-0.030	-0.024
DEU	2003	252	216	-0.004	0.004	0.008	0.012	0.006	0.006	0.007	0.008	0.017	0.019
DNK		252	0	0.008	0.011	0.011	0.030	0.001					
ESP	2005	252	180	0.057	0.004	0.003	0.029	0.043	-0.046	0.008	0.004	-0.002	-0.034
FIN	2004	252	198	0.018	0.003	0.009	0.036	0.009	-0.010	0.010	0.009	-0.012	-0.003
FRA	2007	252	144	0.024	0.006	0.007	0.020	-0.005	-0.017	0.009	0.006	-0.003	0.004
GRC		252	0	-0.013	0.006	0.002	0.004	-0.002					
HRV		252	0	0.037	0.009	0.007	0.055	0.022					
LTU		252	0	0.068	0.009	0.007	0.076	0.084					
LUX	2005	238	170	0.019	0.012	0.010	0.015	0.013	0.000	0.001	0.006	-0.009	-0.033
LVA	2004	245	191	0.011	0.004	0.003	0.070	0.092	0.042	0.010	0.003	0.008	-0.007
MLT	2009	252	108	0.035	0.012	0.006	0.040	0.015	-0.011	0.025	0.004	-0.017	-0.033
NLD	2001	252	252										
PRT	2005	252	180	0.016	0.003	0.002	0.029	0.002	-0.003	0.007	0.005	0.000	0.014
ROU		252	0	0.134	0.008	0.008	0.175	0.152					
SVK		252	0	0.047	0.008	0.006	0.062	0.058					
SVN		252	0	0.030	0.009	0.009	0.061	0.053					
SWE		252	0	0.028	0.010	0.013	0.029	0.013					
ALL	12	5513	2241	0.035	0.007	0.007	0.047	0.037	-0.009	0.010	0.006	-0.006	-0.010
	(total #)	(total #)	(total #)	(average)	(average)	(average)	(average)	(average)	(average)	(average)	(average)	(average)	(average)

Note: The signature years of the BITs are collected from UNCTAD database. In the case where no treaty was signed for a given country, data is collected in the pre-treaty median columns.

As our main explained variable, we consider the capital growth rate (dCAP), expressed in nominal local currency units. The variable is acquired from the WIOD social accounts data. For the EU countries, in almost all cases the capital stock series correspond to fixed assets, as defined in the guidelines of the System of National Accounts 2008 (SNA08). Gross fixed capital formation is measured by the total value of a producer's acquisitions of fixed assets, minus disposals, during the accounting period, plus certain specified expenditures on services that add to the value of non-produced assets.[11]

As other variables, we also analyze VA growth rates (dVA) and labor productivity growth rates, the latter being defined as the growth rate of VA per total employment (VA/L). These series are also from the WIOD social account data. Finally, we also consider R&D investments that we acquire from the STAN database (ANBERD) for the corresponding years. As our R&D intensity variable, we consider the investments related to the total, fixed capital stock (R&D/K). Thus, our variable captures changes in the relative importance of R&D, relative to the other capital, and complements our previous view that focused on fixed assets.

Table 3.1 shows the median capital growth rates prior to the treaties, as well as their changes in the post-treaty period. The table shows that there is, on average, an increase in the upstream and downstream fraction of Chinese production in the post-treaty era. On the other hand, there is a decline in capital growth, labor productivity, and VA growth rates. Our econometric analysis aims at further dissecting the role of Chinese value chain exposure.

4 Results

4.1 Chinese upstream linkages and weaker EU capital growth

In this section, we report our baseline results. Our main approach is to use an exposure research design, where the pre-existing fraction of Chinese VA in production measures differential exposure to the common globalization shocks of value chains. In particular, we study how the differentiated exposure affects the home-country investment behavior in the EU. We focus on the manufacturing industries where the input–output data has the highest quality. Moreover, we study the upstream fraction of the VA that measures how actively an industry uses China as an intermediate producer of their final goods.

Characterizing the investment dynamics

As a first step, we describe the investment dynamics in our data. In Figure 4.1 we show indicative evidence that the growth rate of capital stock in the more pre-exposed industries has fallen more than in less pre-exposed industries after a BIT with China is signed (see panel a in the figure). For illustrative purposes, the low pre-exposure industries are defined as manufacturing industries whose average pre-treaty upstream VA fraction is below or equal to the 25th percentile of the average pre-treaty fractions of all industries in the corresponding country. On the other hand, the high pre-exposure industries are industries whose pre-treaty upstream VA fraction is above or equal to the 75th percentile of the country's pre-treaty fractions.

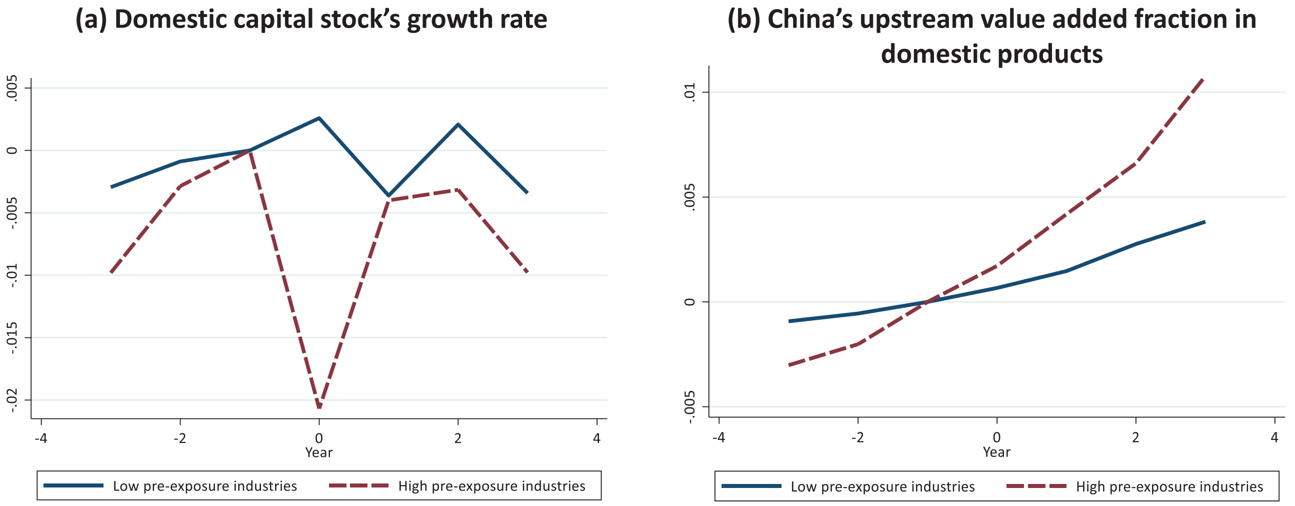
The lines represent the yearly, cross-sectional averages of country-level industry averages. Year 0 is set to mark the year of signature of the BIT. To illustrate changes in the investments, we set the pre-treaty value equal as 0 at year -1.

In the figure, a more than 2 percentage point drop in the capital growth rate is observed at the signing year of the BIT with China. While the effect is somewhat smaller in the following years, it remains persistent. It is notable that the capital growth variable is highly volatile, and the presented difference, even if substantial, is only fraction of the total variation.

In panel b of Figure 4.1, we show that the stronger pre-exposure of an industry provides it with an edge for gaining a bigger fraction of the Chinese VA after the treaty is signed. This finding is well aligned with the underlying logic of our identification strategy. The figure also indicates the possibility of pre-treaty trends that are later addressed in the econometric analysis.

In Figures A1.1 and A1.2 in the Appendix, we show that similar patterns also exist at the country level, and they seem to suggest that systematic impacts have followed the signature of the BITs. In a few cases, there has been a

Figure 4.1 **EU country's domestic capital stock's growth rate (panel a) and China's upstream VA fraction in the value chain (panel b), in percentage points.**
We set year 0 to be equal to the first year of the BIT in force.



Note: *Low pre-exposure industries* are defined as industries whose pre-treaty upstream VA fraction is below or equal to the 25th percentile of the country's distribution corresponding pre-treaty fractions in the manufacturing industries. *High pre-exposure industries* are defined as industries whose pre-treaty upstream VA fraction is above or equal to the 75th percentile of the country's distribution corresponding pre-treaty fractions in the manufacturing industries. The lines represent the cross-sectional average of the country averages for each year.

relative drop in the capital growth rate, while China's VA fraction has increased. In Figure A1.3, we show that the drop in the capital growth rate has coincided with a drop in VA and labor productivity growth rates. However, we also acknowledge that the data shows much heterogeneity in the patterns. In some cases, we see even a reversed pattern with higher capital growth rates in the most exposed industries, or in other cases, the effects do not appear to be persistent. All in all, a detailed econometric analysis is required to confirm the pattern and we study the heterogeneity more closely in the following section.

The IV

To proceed, we then construct an IV that is a prediction of the fraction of Chinese upstream VA (rather than the true one), based on an estimation that regresses the Chinese fraction on the fractions of other BIT trading partners. As discussed in the previous section, the IV is estimated without data from the country of the corresponding unit. Thus, the prediction is independent of the idiosyncrasies in the trade relationship with China in any specific country while reflecting the broader geographical features that the other trade relationships entail.

To further illustrate the characteristics of the constructed IV, we show the industry-specific covariates of the estimated model in Appendix II. Based on the model it is notable that the Chinese fraction is particularly strongly positively correlated with the fractions of other Asian countries (Korea, India, and Indonesia), while the fraction is typically lower when there is stronger dependency on European countries. Overall, the impact of the upstream fractions with other BIT countries predicts a positive impact on the Chinese fraction. Thus, the BIT dependencies tend to be more complements than substitutes.

A central identification concern—raised by, for example, Goldsmith-Pinkham et al. (2020)—is that the industry shares may predict outcomes through channels other than those posited by the research, for example, through responses to common shocks. One way to further study the appropriateness of the IV is to decompose the underlying shares and study the consistency of IVs constructed from the components by means of overidentification testing in the IV setup. As Goldsmith-Pinkham et al. (2020) suggested, one interpretation of the divergence between estimators with different instruments, and the failure of overidentification tests in particular, is that null constant effects is an unreasonable assumption and these tests should be interpreted as pointing to the presence of treatment effect heterogeneity rather than the failure of exogeneity.

Along these lines, we have separately constructed two IVs based on two distinct sets of BIT partner countries: After separating the BIT partner countries into two halves according to an arbitrary criterion (the alphabetical ordering of their names), we separately used Eq. (3) with two distinct sets of explanatory variables $FVA^{oth}_{i,-c,t}$. In both of our baseline models (Eqs. (4) and (6)), we find that the appropriate test for overidentification restrictions fails to invalidate the joint use of the two constructed instruments. This suggests that our instrument does not suffer from major consistency issues, and we still use the full set of BIT countries to construct our actual instruments.[12]

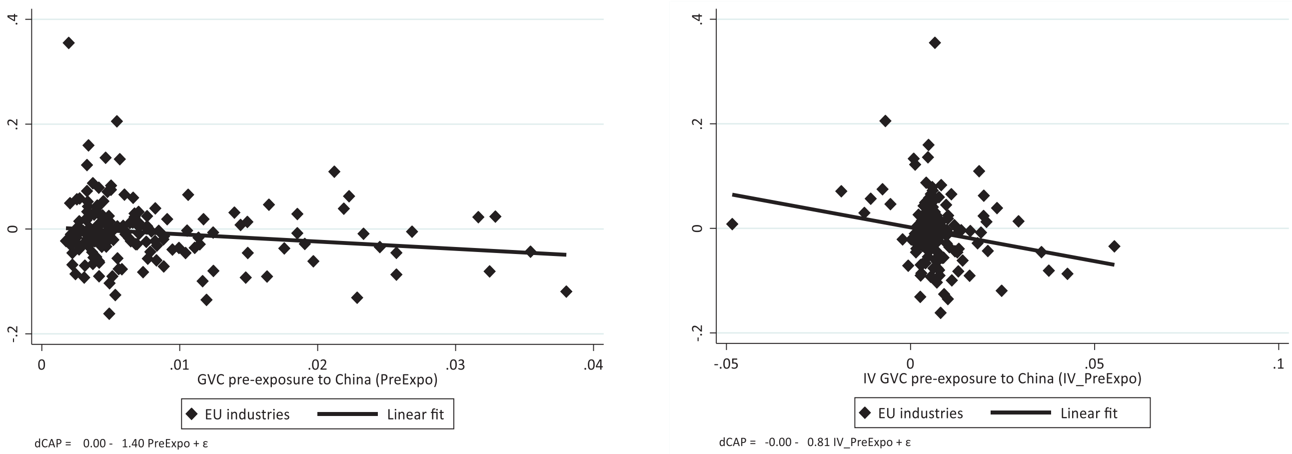
Industry-specific dynamics

After the IV is constructed, we return to analyze the industry-specific dynamics that follow the signing of of a BIT with China. In Figure 4.2, we show scatterplots of the exposure (the actual fraction and our predicted IV) and the pre- versus post-BIT capital growth rates. The capital growth rates are percentage point changes in the capital growth rate for the EU industry–country units.

We find a strong negative correlation. According to the results, there is a significantly lower capital growth rate in industries that are more exposed to China, whether measured in terms of the actual fractions or in terms of our constructed IV. In the case of using the actual fractions, the relationship is moderately stronger (a -1.4 pp decrease in the investment rate for each 1 pp increase in pre-treaty exposure to Chinese value chains). When the IV is considered, the corresponding relationship indicates a slightly weaker effect (a -0.81 pp decrease in the investment rate for each 1 pp increase in pre-treaty China exposure). Both effects are statistically significant at a 5 percent confidence level with heteroskedasticity-robust error terms.

Furthermore, we study what happens to the exposure in the post-treaty period, that is, we study how much the VA fraction of Chinese production in EU industries' final products changes after the treaty is signed (see Figure 4.3). Consistent with our expectation, we find that the fraction increases more strongly for the industries that are more exposed before the treaty, both when the actual pre-exposure or the predicted IV pre-exposure measure is used as the exposure variable. Both relationships are

Figure 4.2 **Change in the capital growth rate (the post-treaty rate vs. pre-treaty rate) (dCAP).**
Compared with the pre-treaty upstream exposure (shown on the left-hand side) and the IV (shown on the right-hand side) for EU industries in individual countries.



Note: Pre-treaty values are measured as the averages of the corresponding variable values up to three years prior to the treaty, depending on the data availability. In the graph, 0.01 denotes a 1 percentage point increase in capital growth rate and pre-treatment upstream fractions. In both cases, coefficients for the variable in the regression equation are statistically significant at a 5% confidence level with heteroskedasticity-robust error terms.

statistically significant, although the impact is moderately stronger in the case of the actual fractions.

This finding, like the quartile dynamics before, provides support for the underlying logic of our identification strategy. The stronger pre-exposure of an industry predicts the more important role of Chinese production in value chains after the treaty is signed. Thus, the treaty generates variation in the post-treaty value chain dynamics that we exploit in our analysis of the links between value chains and the EU's capital growth.

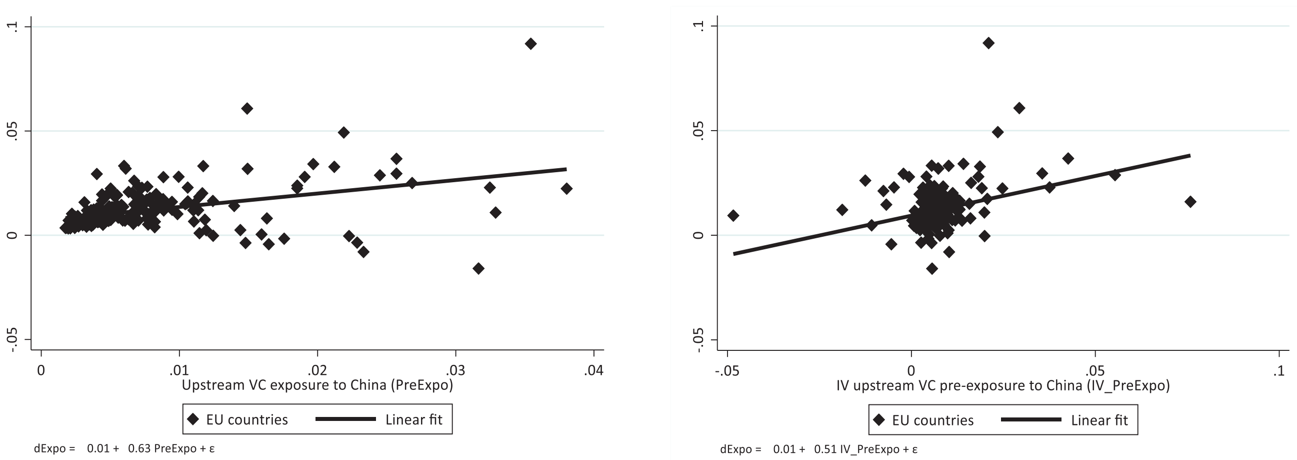
We then proceed to analyze the relationship in the year-level panel data of industries. Table 4.2 shows the baseline results of both the reduced-form and the IV estimation, concentrating on the Chinese BITs. In the table, the first result column shows the reduced-form estimate, β, for the impact of a 1 percentage point increase in the constructed exposure indicator / IV to the capital growth rate. Our result suggests that a 1 percentage point higher indicator of pre-exposure to China tends to lead to a roughly 1 percentage point lower capital growth rate.

Let us next discuss our first IV specification. The second column (in Table 4.1) shows the first stage coefficient, β^{1st}, which indicates the covariance between the (excluded) IV and China's actual pre-treaty upstream VA fraction. The result shows that the IV has strong predictive power for the actual pre-exposure upstream fractions. This again suggests that our IV is relevant. A 1 percentage point higher IV pre-exposure results in a 0.33 percentage point larger actual pre-exposure.

In the second stage, we report the impact of our first stage prediction on the instrumented variable (i.e., the capital growth rate). The result of β^{IV} indicates that changes in the pre-exposure that are due to exogenous variation arising from the IV have a strong negative effect on the capital growth rate.

The second IV specification involves γ^1 as the first-stage coefficient, the covariance between the (excluded) IV, and China's post-treaty upstream VA fraction in the EU countries. The results shows that the IV also has strong predictive power in relation to the actual changes in the upstream fractions during the post-treaty period. A 1 percentage point higher IV pre-exposure results in a 0.42 percentage point larger exposure. These findings suggest that the BITs do indeed result in the reallocation of production across countries within the value chain as the obstacles to cross-country investments are removed, and the effect has been particularly strong when there have been pre-existing, strong chain linkages.

Figure 4.3 Change in the upstream exposure to China (dExpo).
The pre-treaty upstream exposure (shown on the left-hand side), and the IV (shown on the right-hand side) for EU industries (shown in industry–country units).



Note: Pre-treaty values are measured as the averages of the corresponding variable values up to three years prior to the treaty, depending on the data availability. In the graph, 0.01 denotes a 1 percentage point increase in capital growth rate and pre-treatment upstream fractions. In both cases, coefficients for the variable in the regression equation are statistically significant at a 5% confidence level with heteroskedasticity-robust error terms.

Table 4.1 **Baseline estimations concerning the relationship between Chinese upstream value-chain exposure and capital stock's growth rate in the EU countries (dCAP).**

	Equations for change in the capital growth rate		
Explanatory variable	(1) Reduced form	(2) Pre-fraction IV	(3) Current-fraction IV
Fraction of Chinese VA (β)	**-0.97 ****	**-2.56 ****	**-2.13 ***
Standard error	(0.46)	(1.15)	(1.18)
First stage (β^{1st})		0.33 ***	0.42 ***
F-test for weak identification		17.80	7.00
Underidentification test		19.26	7.27
N(obs)	5513	5513	5513
N(industry–country)	395	395	395
Industry–country fixed-effects	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes
Country-level linear trend	Yes	Yes	Yes
Clustered error terms	Industry–Country	Industry–Country	Industry–Country

Note: Error terms are clustered at the industry–country level. Estimation sample countries are LVA, FIN, DEU, HRV, ESP, BEL, BGR, AUT, CZE, SVN, NLD, DNK, SVK, FRA, ROU, GRC, LTU, SWE, LUX, MLT, CYP, and PRT. The data consists of manufacturing industries. Significance levels: *** = 1%, ** = 5%, * = 10%.

Despite its conceptual appeal, the IV method is not without problems. First, underidentification of the instruments may occur, which means that some or all of the instruments are irrelevant as they are not sufficient to identify the relationship between the endogenous regressors and the explained variable. Weak identification arises when the excluded instruments are correlated with the endogenous regressors, but only weakly. Estimators can perform poorly when instruments are weak (see the work of Stock and Yogo [2005] for further discussion). In the estimations and statistical testing, we use the *xtivreg2* module for Stata by Schaffer (2010). The underidentification test is an LM test of whether the rank of the matrix of reduced form coefficients is smaller than the dimensionality of the problem. Under the null condition, the statistic is distributed as chi-squared, and a rejection of the null indicates that the matrix is of full-column rank (i.e., the model is identified, and the rejection is based on the Kleibergen-Paap [2006] rk statistic). In addition, we use the Kleibergen-Paap Wald rk F-statistic with the degrees-of-freedom adjustment for the rk statistic following the standard small-sample adjustment for cluster-robust standard errors. We find that our baseline results are robust to weak identification and underidentification.

We then consider the heterogeneity aspects of our results. We separate the industry observation into two groups, either with higher or lower than (global) median labor productivity or R&D intensity in the corresponding ISIC Revision 2 classification. The separation provides us with a straightforward extension of the basic model with two IVs and two endogenous variables, one for each group, as discussed in the methodology section.

In Table 4.2, we show that the negative effect is particularly strong for types of industry identified as having low labor productivity or low R&D intensity. This holds true both when we use the reduced form estimation or the IV two-stage approach. In the Appendix we show that the disparity remains strong with a wide variety of different specifications of the model. Moreover, the results are robust to weak identification and underidentification.

Further elaboration of our baseline results

Next, we further elaborate the implications of our model for individual countries and their investments, as well as discuss the industry-level aspects further.

First, in Table 4.3 we make predictions for the investment impacts on three representative countries from

Table 4.2 The relationship between Chinese upstream value-chain exposure and capital growth in the EU countries.

Variation in the relationship between Chinese upstream value-chain exposure and capital stock's growth rate in the EU countries (dCAP) in the low- and high-end of labor productivity (VA/L, models 1–3) and the low- and high-end of R&D-intensive (R&D/K, models 4–6) industries.

Explanatory variable	Equations for change in the capital growth rate in different VA/L groups			Equations for change in the capital growth rate in different R&D/K groups		
	(1) Reduced form	(2) Pre-fraction IV	(3) Current-fraction IV	(4) Reduced form	(5) Pre-fraction IV	(6) Current-fraction IV
Fraction of Chinese VA (β), the effect in the low group	**-1.08 ****	**-2.92 ****	**-2.47 ****	**-3.73 ****	**-3.17 ***	-1.54
Standard error	(0.49)	(1.23)	(1.29)	(1.63)	(1.81)	(0.96)
Fraction of Chinese VA (β), the effect in the high group	0.06	-1.41	-1.40	**-0.89 ***	**-2.48 ****	-2.32
Standard error	(1.01)	(1.31)	(1.14)	(0.45)	(1.23)	(1.43)
BIT-in-force dummy	0.01	0.03	0.01	0.01	0.03	0.01
F-test for weak identification		9.06	3.56		9.69	3.79
Underidentification test		19.31	7.24		20.35	7.34
N(obs)	5513	5513	5513	5513	5513	5513
N(industry–country)	395	395	395	395	395	395
Industry–country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-level linear trend	Yes	Yes	Yes	Yes	Yes	Yes
Clustered error terms	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country

Note: The effects in the low and high group indicate the effect of the exposure either according to the grouping based on VA/L or R&D/K. Significance levels: *** = 1%, ** = 5%, * = 10%. Ind.–country = industry-country level clusters.

continental Europe, eastern Europe, and the Nordics: France, the Czech Republic, and Finland respectively. For each country and the EU, we report the (unweighted) average impact of a BIT with China on the capital growth rate separately for each industry. In the calculation, we use Model 2, shown in Table 4.2, where we isolate the BIT's effect by multiplying coefficient with the appropriate Chinese fraction and the BIT treaty dummy. The arising industry-level variation purely reflects the variation in the pre-treaty exposure to the Chinese value chains in a particular industry, and we control for the potential endogeneity problem by resorting to our constructed IV. In line with our modeling structure that controls for all the average effects, we report the effects as differences in the country- or area-level averages across industries. Our measurement period starts from the year of signature and continues until the year 2014, and as a reference, we also report the corresponding total capital growth rates.

Starting from considering the EU as an average, it seems that the effects of the BITs are strongly felt in growing industries where there have been high capital growth rates, most pronouncedly in the manufacture of computer, electronic, and optical products, and pharmaceuticals. On the other hand, it is also felt in some industries that have had laggard capital growth rates, such as the textile industry.

On average, the contribution of the BIT effect to capital growth variation has been modest, though in some special cases, the relative impact has been substantial. For example, according to our point estimates, in France the contribution of the Chinese BITs to the decline in the overall capital growth rate in the textile industry has been over 2 percentage points, and in the Czech Republic, the rate has declined by over 4 percentage points in the computer, electronic, and optical products. In France, the negative impact has added to a deepening investment

Table 4.3 **Predictions for the differences in capital growth rates due to impact (in percentage points [pp]) of the variation in the pre-exposure to the Chinese value chains for the three representative countries and the EU.**

	A China BIT's effect on the capital growth rate (in pp), difference to average				Total capital growth rate (in pp), difference to average			
	France	Czech Rep.	Finland	EU	France	Czech Rep.	Finland	EU
Manufacture of food products, beverages, and tobacco products	0.87	0.44	0.23	0.41	-0.07	-1.46	0.31	0.97
Manufacture of textiles, apparel, and leather products	-2.63	0.16	0.02	-0.40	-2.03	-3.74	-6.31	-3.96
Manufacture of wood and products of wood and cork, except furniture; the manufacture of articles of straw and plaiting materials	0.03	0.52	0.26	0.32	0.42	1.26	-1.38	-0.32
Manufacture of paper and paper products	-0.34	0.44	0.32	0.54	-1.03	-1.09	-2.75	-0.62
Printing and reproduction of recorded media	0.57	0.51	0.30	0.69	-3.46	-0.55	-5.26	-1.44
Manufacture of coke and refined petroleum products	-0.27	0.33	0.08	0.34	2.86	-4.01	4.48	-1.07
Manufacture of chemicals and chemical products	0.39	0.18	0.13	-0.32	2.56	-2.49	0.87	0.85
Manufacture of basic pharmaceutical products and pharmaceutical preparations	0.90	0.35	0.31	-0.45	2.44	0.49	3.59	2.91
Manufacture of rubber and plastic products	0.01	0.04	0.13	-0.13	0.40	1.48	-0.35	1.17
Manufacture of other non-metallic mineral products	0.74	0.45	0.23	0.39	0.87	-2.64	-0.06	0.52
Manufacture of basic metals	-0.26	0.36	0.08	0.07	-3.14	-3.54	0.64	-1.90
Manufacture of fabricated metal products, except machinery and equipment	0.53	0.28	0.13	-0.32	1.18	1.76	1.97	1.55
Manufacture of computer, electronic, and optical products	-0.10	-4.16	-0.72	-1.06	-2.44	6.72	2.12	0.46
Manufacture of electrical equipment	-0.37	-0.26	-0.35	-0.29	2.11	1.78	4.28	0.42
Manufacture of machinery and equipment n.e.c.	-0.03	0.23	-0.05	-0.01	0.58	1.66	3.01	1.54
Manufacture of motor vehicles, trailers, and semi-trailers	-0.28	0.00	-0.58	-0.27	-3.30	0.68	2.24	-0.47
Manufacture of other transport equipment	-0.18	-0.02	-0.73	0.22	2.85	2.29	-2.31	0.36
Manufacture of furniture; other manufacturing	0.42	0.17	0.20	0.26	-0.81	1.40	-5.09	-0.96
SUM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: In the calculation, we use Model 2, shown in Table 4.2, where we isolate the BIT effect by multiplying coefficient β with the appropriate Chinese fraction and the BIT treaty dummy. We report our findings as differences in the country- or area-specific averages that sum up to 0. Czech Rep. = Czech Republic.

decline, and in the Czech Republic, the impact is associated with an otherwise strong capital growth rate. In the case of Finland, the model suggests that the country has not suffered from similar large shocks, albeit the nascent capital growth in computer, electronic, and optical products and the manufacturing of transport equipment can be, to some extent, accounted for by the estimated effect of the BITs.

Overall, these findings emphasize the versatility of the different setups in which the BITs may affect the investment decisions and the difficulty of identifying the impact without a strong identification strategy.

Finally, to elaborate our results further at the industry level, we follow our baseline specification but divide our exposure IV variable into different industry groups in a manner that we discuss in our methodology section more thoroughly. We focus on the reduced-form model and use our IV as an indicator of the general exposure of industries to the Chinese value chains. As noted before, this indicator is highly correlated with the actual exposures, and it does not lead to biases arising from the potential interactions between the trade relations and the specificities of the BITs.

We find that the overall impacts of higher Chinese value-chain exposure are negative across the board.[13] While we acknowledge that the division of our explanatory variable somewhat lowers the power of our statistical inference, we find that there still are three industries that show negative impacts at the 5% significance level. These industries (with the corresponding ISIC code) include the manufacture of chemicals and chemical products (C20), the manufacture of basic pharmaceutical products and pharmaceutical preparations (C21), and the manufacture of computer, electronic, and optical products (C26).

When we further analyze the industry-level effects in the groups of low- and high-productivity industries, we again find that the effects on the capital growth rate are broadly negative for the exposed, low-productivity industries. For individual industry classes, the effects are statistically significant, especially for C20 and C21 but also for the manufacture of wood and products of wood and cork, excepting furniture (C16). It is notable that there is also evidence of negative effects for some high-productivity industry classes at a 10% significance level. These industries include the printing and reproduction of recorded media (C18), the manufacture of rubber and plastic products (C22), the manufacture of computer, electronic, and optical products (C26), and the manufacture of furniture (C31–C32).

Overall, we find that the industry-level findings are well aligned with our baseline results. Most of these industries are considered as the key fields of intensive offshoring to China. On the other hand, it is notable that we do not find any evidence of a positive overall impact on capital growth for any industry.

Table 4.4 The relationship between Chinese upstream value-chain exposure and other variables in the EU countries.

Variation in the relationship between Chinese downstream value-chain exposure and capital stock's growth rate in the EU countries (dCAP) in the low- and high-end of labor productivity (VA/L, models 1–3) and the low- and high-end of R&D-intensive (R&D/K, models 4–6) industries.

	Reduced-form equations in different VA/L groups for			Reduced-form equations in different R&D/K groups for		
Explanatory variable	(1) dVA/L	(2) dVA	(3) R&D/K	(4) dVA/L	(5) dVA	(6) R&D/K
Fraction of Chinese VA (β), the effect in the low group	-1.75	-1.39	0.30	**-7.26 ****	**-4.42 ***	0.01
Standard error	(1.08)	(1.71)	(0.29)	(3.47)	(2.36)	(0.12)
Fraction of Chinese VA (β), the effect in the high group	**6.53 *****	**10.18 *****	0.06	-0.71	-0.06	0.19
Standard error	(2.64)	(3.50)	(0.26)	(0.85)	(1.43)	(0.33)
BIT-in-force dummy	0.00	-0.04	0.00	0.02	-0.02	0.00
N(obs)	5521	5524	3077	5521	5524	3077
N(industry–country)	395	395	273	395	395	273
Industry–country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-level linear trend	Yes	Yes	Yes	Yes	Yes	Yes
Clustered error terms	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country

Note: The effects in the low and high group indicate the effect of the exposure either according to the grouping based on VA/L or R&D/K. The included variables are the labor productivity growth rate (dVA/L) VA growth rate (dVA), and R&D investments relative to the capital stock (R&D/K). Significance levels: *** = 1%, ** = 5%, * = 10%.

4.2 Impacts on VA, productivity, and R&D

It is useful to analyze other outcome variables alongside the capital growth rate. In Table 4.4, we report findings for labor productivity and VA growth, as well as R&D intensity. We find that exposure to Chinese value chains has a positive impact on industries that have above-median labor productivity, whereas the effects on labor productivity and VA growth are negative and statistically insignificant. The weak effect at the lower end of the distribution is consistent with weak investment dynamism. In the absence of productivity or VA gains from the offshoring, there is little incentive for investments. This is especially true for industries that have invested less in R&D investments (relative to their capital stock). In that case, both labor productivity growth rates and VA growth remain weaker when the treaty is signed. In terms of the growth rate of R&D investments, we do not report significant changes.

Our results provide new insights into the literature concerning the increased role of GVCs and offshoring. Overall, the literature finds a positive relationship between firm-level productivity and the outward foreign direct investments (FDI): The best firms tend to self-select outward FDI (Damijan, Polanec, and Prasnikar, 2007; Herzer, 2012). Our results suggest further possibilities for outsourcing leads to further productivity growth in industries that are already at the high-end of productivity distribution.

We also report substantial heterogeneity in the effects. The effects on the home country are already known to vary greatly depending on the characteristics of the investment project and the business environment in the home and host countries (Castellani and Pieri, 2016; Imbriani et al., 2011). To the extent that high productivity corresponds with a higher amount of human capital, the findings are consistent with, for example, the work of Bajo-Rubio and Díaz-Mora (2015) who found that outward FDI showed a positive impact on skilled employment in the case of the EU. The finding is also in line with Simpson (2012) who established a correlation between outward investment in low-wage economies and higher output in complementary high-skill industries at home. Laffineur and Gazaniol (2019) found that outward FDI tends to raise wages for managers and reduces wages for workers performing offshorable tasks.

4.3 Robustness analysis

Despite our set of control variables, it is still possible that some other factors may drive our results. For example, during the time period there may have been time trends or broader globalization shocks that generated our results. To strengthen our case, we thus provide an additional robustness analysis.

We subjected our baseline results to robustness checking of the model specification (see Table 4.5). We mainly focus on the reduced-form relationship between capital growth rate changes and our IV, as its forms our most straightforward, unbiased evidence of the presented investment dynamics. Moreover, we focus on the most detailed evidence that is shown concerning the effect in different groups.

First, we have considered different levels of clusterization. One caveat is that the error terms of our model may be clustered at the industry level as the construction of the IV involves industry-level predictions. Thus, we have repeated the estimations with standard errors that are robust to industry-level clusters (i.e., clusters within observations of a particular industry within all time periods). However, the results remain statistically significant. Another caveat could be that the errors may be clustered due to country-level shocks. We analyze this potential problem by clustering the error terms at country level.

While our estimation results are robust to the alternative clusters of the error terms, we have also tested the use of fixed effects at the year–country level. As our explanatory variable defines pre-existing exposure to the value chains, the causal relationship does not suffer from the omitted variable bias if year-level fixed effects are not included. Nevertheless, this exercise is useful in showing how shocks at the country–year level are related to our results. We find that after introducing the shocks, there is a strong positive impact of the treaties on the high-productivity industries, whereas the effect at the low end is not statistically significant. Meanwhile, the year–country fixed effects for the treaty years indicate an overall decline in the capital growth rates. Jointly, these effects lead to similar outcomes as our baseline results: The low-end industries have experienced low capital growth overall, while the high-end industries with high exposure to Chinese value chains have managed to outperform them.

However, we note that in case of the R&D-intensive industries, the effect is only almost statistically significantly negative for the low-end industries.

Finally, we have also estimated the model while weighting industries with their average VA during the estimation period and also limited our sample to the low-end industries.

A further potential caveat is that there could be pre-treaty time trends in capital growth, and the differentiated capital dynamics could arise from the ongoing trends rather than the treaties per se. This would jeopardize our identification strategy as the capital dynamics would be less closely related to the treaty-related exogenous shock to the value chain access. As a first check, we study the relationship between variations in the exposure and pre-treaty changes in capital growth rate (which could continue during the treaty period). In particular, we correlate the rate *changes* in capital growth from two years before the treaty to one year before the treaty with our exposure variable (the upstream exposure of the Chinese VA in the year of signing the treaty). Our results suggest that there is small and statistically insignificant *positive* relationship between the pre-treaty change in capital growth rate and the pre-treaty upstream exposure. As our baseline result indicates a *negative* relationship after signing the treaty, there does not seems to be any evidence of pre-treaty trends that could continue in the treaty period and thus jeopardize our identification strategy.

To further analyze the possible impact of the pre-trends, we also measure the average growth rate of each industry–country observation up to three years before the treaty. Then, we extrapolate this capital growth rate to the post-treaty period and measure the effect of the treaty as a deviation from this linear trend. Again, this modification results in substantially lower average capital growth while the negative effect is smaller or even positive for high-productivity industries. In particular, the dummy variable indicating the average capital growth change due to the treaty turns substantially negative. Meanwhile, as

Table 4.5 The robustness of the relationship between Chinese upstream value-chain exposure and capital stock's growth rate in the EU countries (dCAP) for various specifications.

	Equations for Change in Capital growth rate in different VA/L groups						Equations for Change in Capital growth rate in different R&D/K groups					
Explanatory variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Fraction of Chinese VA (β), the effect in the low group	**-1.08****	**-1.08****	**-0.50****	2.86	**-1.9****	**-0.96***	**-3.73****	**-3.73***	-1.75	-2.07	-1.97	**-1.44***
Standard error	0.50	0.50	0.60	2.71	0.93	0.49	1.44	1.78	1.14	3.68	1.34	0.82
Fraction of Chinese VA (β), the effect in the high group	0.06	0.06	2.36	**9.3****	-0.65		**-0.89***	**-0.89***	-0.11	3.28	-1.28	
Standard error	1.62	0.87	1.06	4.09	0.70		0.51	0.44	0.54	2.74	0.86	
BIT-in-force dummy	0.01	0.01	0.03	-0.04	-0.01	0.03	0.01	0.01	0.03	-0.02	-0.01	-0.23
N(obs)	5513	5513	5513	2499	5513	3026	5513	5513	5513	2499	5513	396
N(industry–country)	395	395	395	179	395	290	395	395	395	179	395	54
Industry–country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Country-level linear trend	Yes	Yes	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Country–year fixed-effects	No	No	Yes	No	No	No	No	No	Yes	No	No	No
Deviation from previous trend	No	No	No	Yes	No	No	No	No	No	Yes	No	No
Only low-type sample	No	No	No	No	No	Yes	No	No	No	No	No	Yes
VA weights	No	No	No	No	Yes	No	No	No	No	No	Yes	No
Clustered error terms	Country	Industry	Ind.–Count.	Ind.–Count.	Ind.–Count.	Ind.–Count.	Country	Industry	Ind.–Count.	Ind.–Count.	Ind.–Count.	Ind.–Count.

Note: The effects in the low and high group indicate the effect of the exposure either according to the grouping based on VA/L or R&D/K. Significance levels: *** = 1%, ** = 5%, * = 10%.

before, with the introduction of the year–country dummies, the relative performance of the high-productivity industries remains higher.

We also conduct placebo testing. Our dataset includes a few countries that have not signed a BIT during the data period. These non-treaty countries are Austria, Bulgaria, Denmark, Greece, Croatia, Lithuania, Romania, Slovakia, Slovenia, and Sweden. A straightforward way to invalidate our approach would be to show that the "placebo" treatments in non-treaty countries would result in statistically significant results. This finding would strongly indicate that our findings would result from broader globalization shocks and time trends in the data, not from the BITs.

Accordingly, we assign fictional signature dates for BITs to the non-treaty countries and China as placebo treatments. In order to replicate the time distribution of the actual treaties, we randomly draw signature years from the actual distribution of the treaty years for the placebo treaties. Otherwise, we fully replicate our procedure for the construction of instruments and the estimation strategies of our baseline results.

Our findings (see the Appendix, Tables A3.1 and A3.2) show that the placebo group does not have any significant effects for the fictious treaties. Therefore, the test does not invalidate our approach, and thus it appears that general time trends resulting from, for example, general globalization patterns do not explain our results.

Our baseline analysis suggests that there is a meaningful structural relationship between the IV indicator and the actual pre-treaty exposure as well as the post-treaty dynamics. We note that we have also repeated the two-stage IV analysis with the specifications discussed above. Our finding is that the results also remain, by and large, the same for the heterogeneous impacts of BITs, albeit the additional structure somewhat burdens their strength.

When considering the approach that connects our IV and the actual pre-treaty or contemporaneous fractions, we find that our baseline results are robust to industry-level clusters in error terms and pre-treaty trends when introduced in the manner described above. However, we find that allowing clusters of error terms at the country level or including country–year fixed effects overburdens our IV model, and we cannot reject the hypothesis of underidentification. Our results also indicate that the strength of the statistical inference is weaker in the case of differences in the R&D intensity. These results are available from the authors upon request.

Overall, the robustness results indicate that there is indeed strong heterogeneity in the investment outcomes across industries, and after considering the plausibility of the different statistical problems and their possible overall impacts on investment dynamics, we consider our baseline results to be robust to alternative specifications.

5 The broader context of our results

5.1 The impacts of *downstream* China exposure for the EU industries

It is reasonable to ask whether the role of China as a downstream producer has similar impacts. As discussed, a large extra-EU *downstream* fraction indicates that an EU country actively uses extra-EU countries as the final producer of products for which the EU country produces intermediate goods and services.

Our results indicate that such a strong relationship does not exist for the downstream linkages. In Table 5.1, we repeat our baseline analysis for downstream linkages and find that the impact of pre-exposure on the EU investment activity is small, positive, and statistically insignificant. In terms of the heterogeneity of the effect, we repeat the analysis separately for low- and high-productivity/R&D industries in Table 5.2. We find some evidence of a negative impact for the industries with low R&D intensity, while the effect is only statistically significant at a 10% confidence level and for the reduced-form model.

Meanwhile, it is notable that our constructed IV is again statistically highly correlated with the actual downstream fractions, suggesting that our strategy in the construction of the IV provides relevant variation in the exposure variable.

Table 5.1 **Estimations concerning the relationship between Chinese downstream value-chain exposure and capital stock's growth rate in the EU countries (dCAP).**

Explanatory variable	Equations for change in the capital growth rate (1) Reduced form	(2) Pre-fraction IV	(3) Current-fraction IV
Fraction of Chinese VA (β)	0.06	0.07	0.30
Standard error	(0.18)	(0.21)	(0.87)
First stage (β^{1st})		0.79 ***	0.32 *
F-test for weak identification		24.29	90.22
Underidentification test		1.54	2.47
N(obs)	5513	5513	5513
N(industry–country)	395	395	395
Industry–country fixed-effects	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes
Country-level linear trend	Yes	Yes	Yes
Clustered error terms	Industry–Country	Industry–Country	Industry–Country

Note: Significance levels: *** = 1%, ** = 5%, * = 10%.

Table 5.2 **The relationship between Chinese downstream value-chain exposure and capital growth in the EU countries.**
Variation in the relationship between Chinese downstream value-chain exposure and capital stock's growth rate in the EU countries (dCAP) for both the low- and high-end of labor-productivity (VA/L) and for R&D-intensity (R&D/K) industries.

Explanatory variable	Equations for change in the capital growth rate in different VA/L groups (1) Reduced form	(2) Pre-fraction IV	(3) Current-fraction IV	Equations for change in the capital growth rate in different R&D/K groups (4) Reduced form	(5) Pre-fraction IV	(6) Current-fraction IV
Fraction of Chinese VA (β), the effect in the low group	0.06	0.07	0.30	-2.89 *	-4.44	-4.70
Standard error	(0.19)	(0.21)	(0.88)	(1.61)	(2.99)	(3.18)
Fraction of Chinese VA (β), the effect in the high group	0.06	0.09	0.29	0.07	0.08	0.34
Standard error	(0.41)	(0.81)	(1.01)	(0.18)	(0.22)	(0.89)
BIT-in-force dummy	0.01	0.01	0.01	0.01	0.01	0.01
F-test for weak identification		16.02	46.10		16.65	8.91
Underidentification test		22.14	2.33		11.89	8.58
N(obs)	5513	5513	5513	5513	5513	5513
N(industry–country)	395	395	395	395	395	395
Industry–country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-level linear trend	Yes	Yes	Yes	Yes	Yes	Yes
Clustered error terms	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country

Note: Significance levels: *** = 1%, ** = 5%, * = 10%.

5.2 The effects of BITs with China for non-EU countries

We have also analyzed the impacts of the BITs on non-EU countries as a reference point for our analysis. Our data consists of countries that are included in our list of countries that have signed BITs during the data period and therefore we can verify their current treaty status based on the UNCTAD data.[14] Moreover, we focus on countries that are not currently part of the EU, including the UK. In our data, we observe four treaties that have been made with a non-EU country and China during 2000–2014. The partner countries are Switzerland, Korea, Mexico, and Russia.

All in all, we find that the capital dynamics have been very similar to what is seen in the EU (see Table 5.3). There is a notable decline in the low-end of the productivity distribution relative to the high-end of the distribution. However, in terms of the R&D distribution, the dynamics are somewhat different. It appears that industries whose R&D intensity has been below the global median have not suffered from weaker investment growth.

5.3 The effects of EU bilateral investment treaties with other extra-EU countries

We have also repeated our analysis for other BITs that the EU countries have signed with other non-EU countries after the year 2000. In particular, we have repeated the reduced-form analysis in which the capital growth rate in the EU countries is explained with the IV that we have constructed and it is found to be strongly linked with the actual exposure variable.

We find that China has been an exceptional BIT-partner country (see Table 5.4). Namely, it is the only country for which the capital growth effect is negative overall, and the capital growth rate of the industries with low la-

Table 5.3 The relationship between Chinese upstream value-chain exposure and capital growth in the non-EU countries.

Variation in the relationship between Chinese downstream value-chain exposure and capital stock's growth rate in the non-EU countries (dCAP) for both the low- and high-end of labor-productivity (VA/L) and for R&D-intensity (R&D/K) industries.

Explanatory variable	Equations for change in the capital growth rate in different VA/L groups			Equations for change in the capital growth rate in different R&D/K groups		
	(1) Reduced form	(2) Pre-fraction IV	(3) Current-fraction IV	(4) Reduced form	(5) Pre-fraction IV	(6) Current-fraction IV
Fraction of Chinese VA (β), the effect in the low group	**-3.77*****	**-4.98*****	**-9.83*****	**3.04 *****	**2.24 *****	**2.36 ****
Standard error	(0.72)	(0.90)	(1.35)	(1.13)	(0.74)	(1.13)
Fraction of Chinese VA (β), the effect in the high group	**1.08***	**1.26***	**0.93***	0.78	**1.10 ***	0.72
Standard error	(0.61)	(0.69)	(0.54)	(0.51)	(0.64)	(0.50)
BIT-in-force dummy	0.01	0.00	0.01	0.00	-0.01	0.01
F-test for weak identification		180.60	2056.57		55.19	153.72
Underidentification test		3.14	1.13		11.1	2.40
N(obs)	2688	2688	2688	2688	2688	2688
N(industry–country)	192	192	192	192	192	192
Industry–country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-level linear trend	Yes	Yes	Yes	Yes	Yes	Yes
Clustered error terms	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country

Note: The effects in the low and high group indicate the effect of the exposure either according to the grouping based on VA/L or R&D/K. Significance levels: *** = 1%, ** = 5%, * = 10%.

Table 5.4 Estimations concerning the relationship between upstream value-chain exposure of other BIT partners and capital growth in the EU countries

Explanatory variable	BIT partner country	All	Groups based on VA/L		BIT dummy
			Low type	High type	
Fraction of China VA (β)		**-0.96****	**-1.08****	0.06	0.01
Fraction of South Korea VA (β)		1.22	1.08	1.73	-0.02
Fraction of Canada VA (β)		-1.38	-2.13	**12.85****	-0.06
Fraction of Mexico VA (β)		7.32	6.01	**12.86***	-0.03
Fraction of Turkey VA (β)		-0.09	-0.32	**4.6 *****	-0.01
Fraction of Indonesia VA (β)		2.51	-0.09	3.11	0.00
Fraction of India VA (β)		1.53	1.41	24.94	-0.03

Note: Each row corresponds with the capital growth effect of the BIT partner's upstream value chain fraction.
Significance levels: *** = 1%, ** = 5%, * = 10%.

bor productivity is statistically significant. In other countries, the effects are either insignificant or, in some cases, statistically significantly positive, especially for the high-productivity industries.

6 Conclusions and discussion

In this paper, we studied the impacts of deepening GVCs between the EU and China on EU home investments. This subject is topical as China has increased its role in value chains substantially in the last few decades, and the EU has negotiated a new, comprehensive investment treaty with the country.

We employed a quasi-experimental estimation strategy that utilized policy shocks to the economic openness and variation in the exposure of industries to these shocks. We operationalized our approach by focusing on BITs that were signed between the EU and China during 2000–2014. The treaties provide us with direct shocks resulting from access to value chains, and the pre-existing differences in the exposure to the Chinese value chains provided a source of exogenous variation in the intensity of the shock. This quasi-experimental research design allowed us to make causal inferences about the impacts of changes in value chain linkages on EU domestic investment dynamics.

We found that the overall impact of the BITs has been to increase the role of China as an upstream producer of intermediate goods for industries that have already been exposed to China–EU value chains before the treaty. That is, the VA fraction of Chinese intermediate product in the EU final good production has increased.

Meanwhile, this dynamism has coincided with a relative decrease in the EU domestic capital growth rate in the exposed industries. A closer analysis showed that there is significant variation in the effects across different types of industries. When separating the EU national industries into groups with higher or lower than (global) median labor productivity in the corresponding industry, it appears that the negative capital growth effect is concentrated on the low-productivity industries. Similar evidence was also found for low-R&D-intensive industries, while the results were somewhat weaker, possibly due to less data. Meanwhile, the high-productivity industries tend to increase their relative productivity growth and VA growth after the signing of the treaty.

In the broader context, we also find similar evidence for non-EU countries that have signed BITs with China in the period 2000–2014, whereas BITs that are signed with other countries have not resulted in similar dynamism, albeit there is some evidence of heterogeneity in the capital growth responses in their cases.

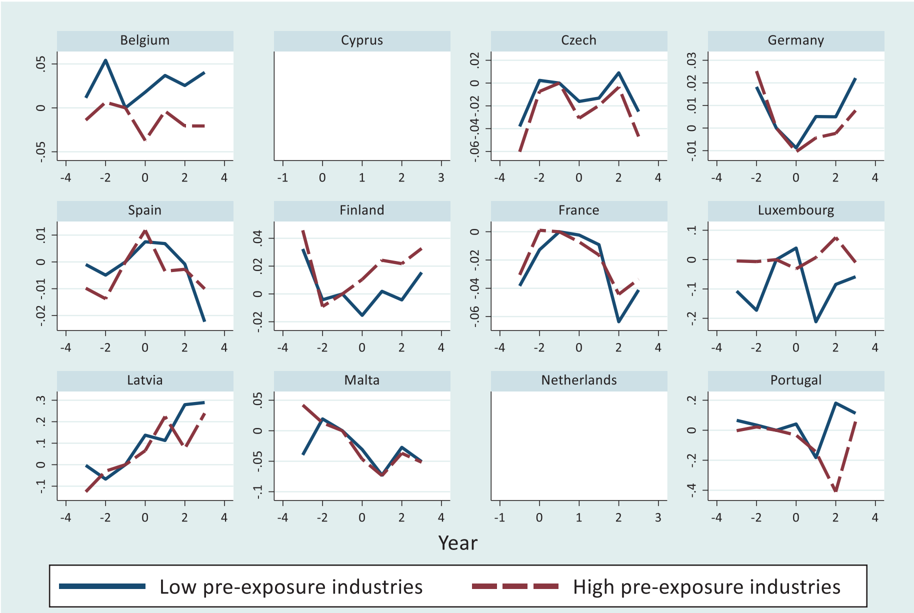
All in all, the arising economic outcomes suggests that the effects of extending GVCs towards China have been profoundly heterogeneous. While productive industries in developed countries have gained through productivity improvements and specialization, the home investments of previously weak industries seem to have gained little from offshoring or have even become depressed.

Whether new investment treaties turn out to increase welfare in the EU and China fundamentally depends on the specification of the new treaties, as well as the underlying market structures and economic policies. While answering this question is beyond the realms of this paper, our results indicate that it may be unrealistic to expect a major, positive EU investment impact from new treaties with China for industries that are tightly linked with China, at least based on the past experiences. Rather, our findings suggest that a likely outcome would be a further increase in the rate of creative destruction. This may turn out to increase welfare, but the impact depends on how efficiently markets operate and the nature and strength of the policy interventions in both the EU and China.

Appendix

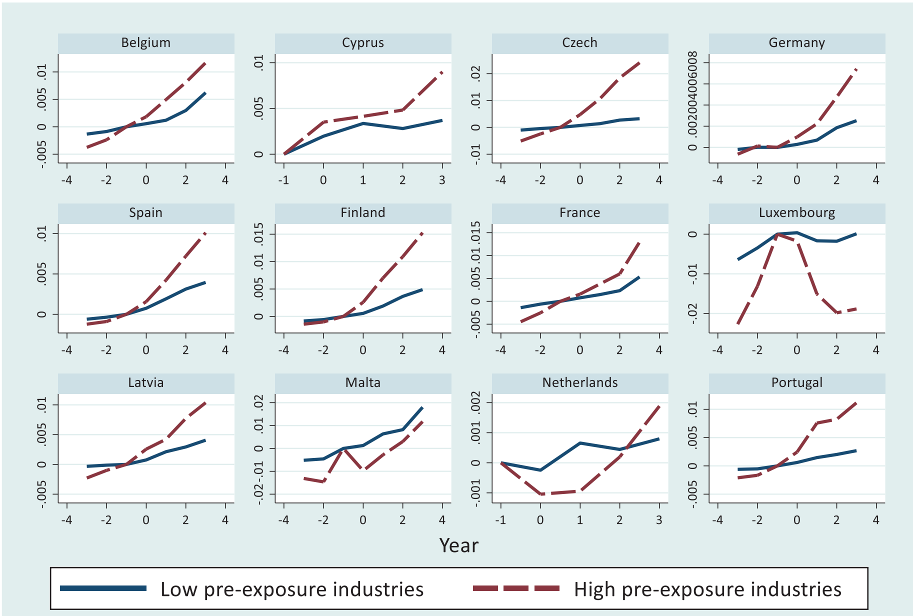
Appendix I. The impacts of BITs with China—descriptive figures at country level

Figure A1.1 **EU countries' average domestic capital stock's growth rate for industry groups in the EU, calculated by country.**
We set year 0 to be equal to the first year of the BIT in force.



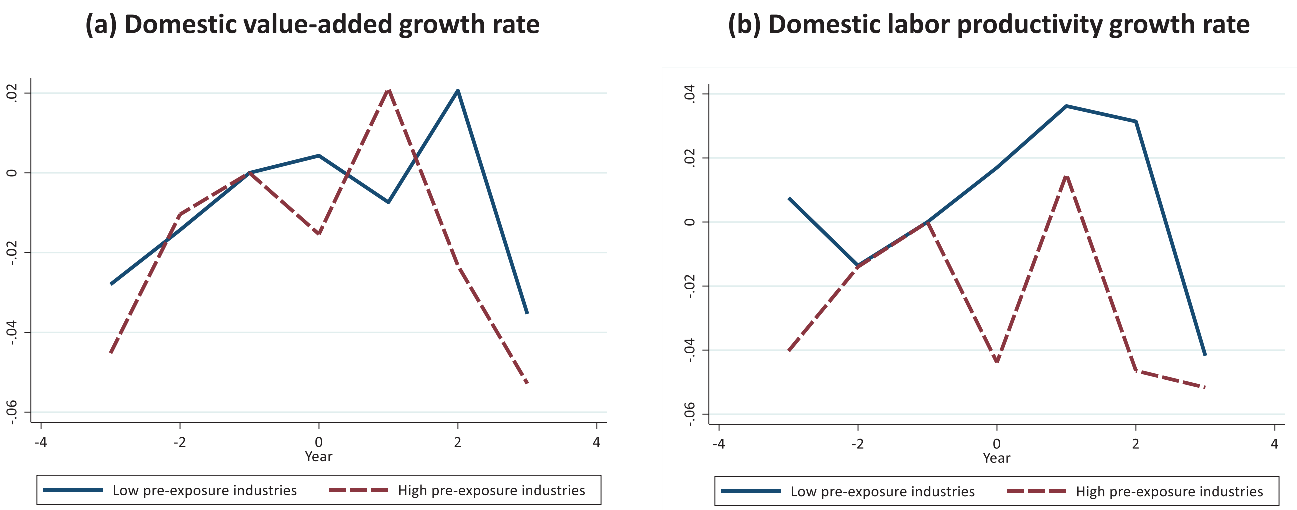
Note: *Low pre-exposure industries* are defined as industries whose pre-treaty upstream VA fraction is below or equal to the 25th percentile of the country's distribution that corresponds to pre-treaty fractions in the manufacturing industries. *High pre-exposure industries* are defined as industries whose pre-treaty upstream VA fraction is above or equal to the 75th percentile of the country's distribution corresponding pre-treaty fractions in the manufacturing industries. The lines represent the cross-sectional average of the country averages for each year.

Figure A1.2 **China's average upstream VA fraction for industry groups in the EU, calculated by country.**
We set year 0 to be equal to the first year of the Chinese BIT in force.



Note: *Low pre-exposure industries* are defined as industries whose pre-treaty upstream VA fraction is below or equal to the 25th percentile of the country's distribution that corresponds to pre-treaty fractions in the manufacturing industries. *High pre-exposure industries* are defined as industries whose pre-treaty upstream VA fraction is above or equal to the 75th percentile of the country's distribution corresponding pre-treaty fractions in the manufacturing industries. The lines represent the cross-sectional average for each year.

Figure A1.3 **Domestic average VA growth rate (panel a) and labor productivity growth rate (panel b) for industry groups in the EU.**
We set year 0 to be- equal to the first year of the Chinese BIT in force.



Note: *Low pre-exposure industries* are defined as industries whose pre-treaty upstream VA fraction is below or equal to the 25th percentile of the country's distribution that corresponds to pre-treaty fractions in the manufacturing industries. *High pre-exposure industries* are defined as industries whose pre-treaty upstream VA fraction is above or equal to the 75th percentile of the country's distribution corresponding pre-treaty fractions in the manufacturing industries. The lines represent the cross-sectional average of the country averages for each year.

Appendix II. Construction of the instruments

In this Appendix, we show a list of roughly 20 countries that have at some stage had a BIT with any of the current EU countries. The list also includes EU countries that have joined the EU during the studied period or have had BITs with applicant countries before they joined the union. We use the VA fractions in EU home production of these countries as variables to predict the corresponding fraction for China.

In the Table A2.1, each row corresponds to the predicted percentage point impact of a 100 percentage point increase of the row partner country´s upstream fraction on the predicted Chinese upstream fraction.[15] The last row shows the overall prediction impact of all the upstream fractions on the Chinese fraction. We note that the estimations are based on all countries, while the actual estimates vary marginally due to the leave-one-out procedure that we use.

Table A2.1 **A table detailing the model that is used to construct the instruments.**
In the Table, each cell corresponds to the predicted effect of a country on the Chinese VA share.

	C13-C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25	C26	C27	C28	C29	C30	C31-C32	C33	Average
MLT	-2.63*	-5.79	-4.87*	-1.85	-1.40	-3.04*	-0.05	-6.29*	-9.67*	-6.31*	-0.31	-6.50	5.53	-2.56	-1.79	-5.23	-12.84*	-1.98	**-3.75**
SVN	0.02	0.11	0.05	0.01	0.00	-0.01	0.17*	0.02	0.12*	0.07	-0.04	0.02	-0.42	-0.34*	-0.28*	-0.09	-0.07	-0.03	**-0.04**
HRV	-0.39*	0.59*	-0.08	-0.07*	-0.10	-0.19*	-0.10	0.05	-0.05	-0.09	-0.07	-0.02	-0.85	-0.56*	-0.81*	-0.29*	-0.66*	-0.29*	**-0.22**
KOR	0.10	0.49*	0.68*	0.46*	0.39*	0.33	0.56*	0.78*	0.44*	-0.45*	0.50*	0.58*	0.60*	0.89*	1.04*	0.32*	0.86*	0.70*	**0.52**
LTU	0.04	0.49*	-0.20*	0.05*	0.07*	-0.09	0.03	0.29*	0.10*	0.00	-0.02	-0.26*	0.32	0.33*	-0.46*	-0.02	0.26*	-0.04	**0.05**
LVA	0.00	1.06*	-0.10*	-0.01	0.06	0.04	0.57*	0.01	-0.12	0.14	0.13*	0.32*	2.43*	0.17	0.66*	0.77*	-0.20	0.06	**0.33**
CZE	0.04	-0.11	-0.01	-0.03	-0.03	-0.03	-0.06*	-0.08*	-0.05	0.02	-0.02	-0.05	-1.23*	-0.25*	-0.19*	-0.06*	-0.19*	-0.13*	**-0.14**
CAN	0.19*	0.30*	-0.05	-0.06	0.04	-0.02	0.00	-0.01	-0.24*	-0.07	-0.01	-0.08	1.20*	-0.25*	-0.17	-0.07*	-0.15*	-0.21*	**0.02**
CYP	0.52*	-0.22	3.57*	0.71*	0.66*	0.48*	-1.43*	0.32	1.18*	1.53*	-0.74	0.39	-2.74	1.16*	-0.84	2.26*	2.06*	2.00*	**0.60**
MEX	-0.19	-0.80*	0.06	0.24*	0.01	0.04*	0.11	0.03	0.66*	0.10	-0.08	0.09	0.79	-0.03	-0.27	0.16*	-0.22	-0.08	**0.03**
TUR	-0.01	0.16*	0.13*	-0.07*	-0.05*	0.04	0.08*	0.24*	0.11*	0.07*	-0.02	0.06*	-0.55*	-0.10*	-0.08*	-0.02	0.04	0.00	**0.00**
IDN	0.59*	0.88*	0.80*	0.61*	0.92*	0.23*	0.96*	1.68*	1.51*	0.62*	0.64*	1.48*	4.66*	1.80*	1.17*	2.26*	2.34*	1.23*	**1.35**
IND	1.80*	1.86*	2.66*	1.97*	2.02*	0.28*	0.86*	1.85*	1.32*	3.10*	2.64*	1.89*	3.24*	2.45*	3.58*	1.82*	2.18*	1.98*	**2.08**
BEL	0.06*	0.18*	0.09*	0.05*	0.09*	0.23*	0.06*	0.34*	-0.04*	0.12*	0.03	0.08*	0.71*	0.10*	0.03	0.26*	0.11	-0.01	**0.14**
DNK	0.12*	-0.26*	0.16*	0.01	0.00	-0.01	-0.08	-0.04	0.12*	0.02	-0.01	0.02	0.12	-0.08	-0.17	-0.15*	0.00	0.02	**-0.01**
LUX	-0.16	-2.58*	0.70*	-0.26*	-0.33*	0.68*	0.00	-0.03	-0.37	-0.72*	-1.02*	0.48	0.64	-0.33	-1.23*	-0.40	-0.02	-1.54*	**-0.36**
SWE	0.00	0.03	0.03	-0.01	0.00	-0.07*	0.00	-0.05	0.00	-0.05*	0.02	0.02	0.07	0.05	0.03	0.03	0.03	0.06*	**0.01**
BGR	-0.24*	-7.17*	-1.19*	-1.28*	-2.42*	0.33	-0.45	-0.65	-1.98*	-1.02*	-0.04	-0.28	1.87	-2.73*	-3.25*	-3.13*	-1.38*	-2.56*	**-1.53**
ROU	-0.02	-1.04*	-0.31*	-0.08	-0.28*	0.31*	-0.46*	-1.02*	-0.56*	-0.33*	-0.18*	-0.38*	2.24*	-0.36*	-0.57*	-0.07	0.10	0.08	**-0.16**
AUT	-0.04	-0.07	0.05*	0.02	0.03	-0.10*	0.04	0.08	0.07	-0.01	-0.02	-0.03	0.35*	0.12*	0.11*	0.07*	0.08	0.12*	**0.05**
Average impact	**0.006**	**0.012**	**0.009**	**0.006**	**0.006**	**0.003**	**0.009**	**0.010**	**0.010**	**0.006**	**0.008**	**0.009**	**0.036**	**0.012**	**0.009**	**0.011**	**0.011**	**0.008**	**0.010**

Note: Industries: C13–C15: Manufacture of textiles, wearing apparel and leather products; C16: Manufacture of wood and of products of wood and cork, except furniture; etc.; C17: Manufacture of paper and paper products; C18: Printing and reproduction of recorded media; C19: Manufacture of coke and refined petroleum products; C20: Manufacture of chemicals and chemical products; C21: Manufacture of basic pharmaceutical products and pharmaceutical preparations; C22: Manufacture of rubber and plastic products; C23: Manufacture of other non-metallic mineral products; C24: Manufacture of basic metals; C25: Manufacture of fabricated metal products, except machinery and equipment; C26: Manufacture of computer, electronic, and optical products; C27: Manufacture of electrical equipment; C28: Manufacture of machinery and equipment n.e.c.; C29: Manufacture of motor vehicles, trailers, and semi-trailers; C30: Manufacture of other transport equipment; C31–C32: Manufacture of furniture; other manufacturing; C33: Repair and installation of machinery and equipment. * = significance level 10% or higher.

Appendix III. The robustness of the baseline estimates to alternative specifications

Table A3.1 Baseline estimations concerning the relationship between Chinese upstream value-chain exposure and capital stock's growth rate in the placebo group (dCAP).

Explanatory variable	Equations for change in the capital growth rate (1) Reduced form	(2) Pre-fraction IV	(3) Current-fraction IV
Fraction of Chinese VA (β)	-0.34	-6.50	-718.02
Standard error	(0.68)	(14.2)	(229475)
First stage (β^{1st})		0.05	0.17
F-test for weak identification		1.27	0.00
Underidentification test		1.75	0.00
N(obs)	2520	2520	2520
N(industry–country)	180	180	180
Industry–country fixed-effects	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes
Country-level linear trend	Yes	Yes	Yes
Clustered error terms	Industry–Country	Industry–Country	Industry–Country

Note: Error terms are clustered at the industry–country level. Estimation sample countries are: LVA, FIN, DEU, HRV, ESP, BEL, BGR, AUT, CZE, SVN, NLD, DNK, SVK, FRA, ROU, GRC, LTU, SWE, LUX, MLT, CYP, and PRT. The data consists of manufacturing industries.
Significance levels: *** = 1%, ** = 5%, *** = 10%.

Table A3.2 Variation in the relationship between Chinese upstream value-chain exposure and capital stock's growth rate in the EU countries (dCAP) in the low- and high-end of labor productivity and R&D-intensive industries in the placebo group.

	Equations for change in the capital growth rate in different VA/L groups			Equations for change in the capital growth rate in different R&D/K groups		
Explanatory variable	(1) Reduced form	(2) Pre-fraction IV	(3) Current-fraction IV	(4) Reduced form	(5) Pre-fraction IV	(6) Current-fraction IV
Fraction of Chinese VA (β), the effect in the low group	-1.37	-10.95	35.12	-1.07	-6.85	-778.30
Standard error	(1.15)	(17.74)	(362.03)	(2.91)	(13.40)	(214468)
Fraction of Chinese VA (β), the effect in the high group	0.51	-4.51	30.49	-0.33	-6.48	-619.37
Standard error	(1.03)	(15.31)	(290.07)	(0.68)	(14.29)	(170844)
BIT-in-force dummy	0.02	0.05	0.01	0.02	0.05	0.20
F-test for weak identification		0.51	0.00		0.63	0.00
Underidentification test		1.35	0.01		1.74	0.00
N(obs)	2520	2520	2520	2520	2520	2520
N(industry–country)	180	180	180	180	180	180
Industry–country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-level linear trend	Yes	Yes	Yes	Yes	Yes	Yes
Clustered error terms	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country	Ind.–Country

Note: Significance levels: *** = 1%, ** = 5%, * = 10%.

Endnotes

1 In addition to arm's-length suppliers, GVCs also include the affiliates of multinational corporations (MNCs) with affiliates in multiple countries. While some of these overseas affiliates might have the same production stages as domestic units, some others focus on different production stages. In the former case, an MNC has made a horizontal foreign direct investment (FDI), and in the latter case, they have made a vertical FDI (Helpman, 1984; Markusen, 1984).

2 Based on the data published by the United Nations Statistics Division, China accounts for almost 30% of global manufacturing output, and the capacity to produce this output has required huge amounts of fixed capital investment in China. In addition to Chinese companies, companies originated from Europe, North America, and Japan have also invested billions of euros in China.

3 Theoretically, the effects of offshoring arise from the interaction of several complex factors (Baldwin and Robert-Nicoud, 2014; Kammritz, 2015). The motivation for trading tasks and offshoring typically lies in differences in the sophistication of technology and wage levels across countries. The investment outcomes depend on the productivity improvements that are akin to technological change caused by lower costs and increased specialization in developed countries, while the developing countries benefit through technology upgrading and the better organization of work. The arising economic outcomes are driven by terms-of-trade effects and technology spillovers with overall impacts that tend to be ambiguous and model dependent.

4 The WIOD dataset (www.wiod.org) includes international input–output data using the ISIC Revision 2 industry classification. Throughout the exercise, we focus on the manufacturing industries where the input–output data has the highest quality.

5 While our approach has similarities to the previous literature that uses the so-called Bartik instruments (Bartik, 1991; Goldsmith-Pinkham et al., 2020) in studying of the exposure to Chinese production (see, e.g., Autor et al., 2013, 2016), we argue that our combination of using the treaties as treatment variables is less prone to the common problems of the approach (see, e.g., Goldsmith-Pinkham et al., 2020).

6 As an alternative perspective, we also consider each row of the ***VA*** matrix that provides us with the contribution of each industry to the final production elsewhere, especially in China. These are the downstream value-added fractions, again indexed by the final producer.

7 By including the average impact, we control for the direct date effect of the treaty, and thus focus on identification through the variation of the treatment intensity differences.

8 It is notable that the linear model may also generate negative predictions of FVA. While not commonly observed, VA may, in some instances, receive negative values, and thus, the fractions may also be negative. Therefore, a choice was made to not restrict our model to have strictly positive values, which could have been achieved, for example, by using a Poisson model. On the other hand, due to the small fractions in the data, the model does not generate VA fractions that exceed 1.

9 The countries were chosen by considering whether there was a sufficient level of data availability and by attempting to cover a major part of the world economy. The selected countries include 27 EU countries and 15 other major countries. Data for the 56 sectors are classified according to the International Standard Industrial Classification Revision 4 (ISIC Rev. 4). The tables adhere to the 2008 version of the System of National Accounts (SNA). The dataset provides WIOTs using current prices, denoted in millions of US dollars (Timmer et al., 2016).

10 We build our identification on a simple dummy variable that indicates that the treaty is *signed* in a given year. However, we acknowledge that the identification could alternatively be built on the year when the treaty *entered into force* or on the individual features of the treaties, as discussed by Zeng and Lu (2016). This would be especially important when the treaties

are heterogenous and their implementation is uncertain. However, as we merely focus on the treaties with EU countries with relative short implementation lags and few implementation problems, we consider our approach to be appropriate.

11 Throughout this paper, we use the following country abbreviations: AUS = Australia, AUT = Austria, BEL = Belgium, BGR = Bulgaria, BRA = Brazil, CAN = Canada, CHE = Switzerland, CHN = China, CYP = Cyprus, CZE = Czechia, DEU = Germany, DNK = Denmark, ESP = Spain, EST = Estonia, FIN = Finland, FRA = France, GBR = United Kingdom, GRC = Greece, HRV = Croatia, HUN = Hungary, IDN = Indonesia, IND = India, IRL = Ireland, ITA = Italy, JPN = Japan, KOR = Republic of Korea, LTU = Lithuania, LUX = Luxembourg, LVA = Latvia, MEX = Mexico, MLT = Malta, NLD = Netherlands, NOR = Norway, POL = Poland, PRT = Portugal, ROU = Romania, RUS = Russian Federation, SVK = Slovakia, SVN = Slovenia, SWE = Sweden, TUR = Turkey, TWN = Taiwan, USA = United States of America.

12 It is notable that the list of countries whose VA fractions are used to construct the instrumental variable in the regression also includes EU countries that have joined the EU during the studied period or EU countries that had BITs with the applicant countries before they were a member of the union. As an additional robustness check, we have also repeated the analysis after constructing the instrumental variable with non-EU country fractions only.

13 Estimation tables are available from the authors upon request.

14 Our panel consists of the following countries: CAN, IND, JPN, CHE, RUS, TUR, AUS, MEX, GBR, KOR, and IDN.

15 For example, the table indicates (row 2, column 2) that 0.1 pps. higher than average share of Malta in final production of a textile industry is on average associated with a 0.26 pps. lower share of China in final production.

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