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Why your neighbor matters: Positions in preferential trade agreement networks and export growth in global value chains*

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Abstract

In rapidly expanding global and regional preferential trade agreements (PTA) networks, policy-makers are keen to situate their countries in a better *position*, believing that a better position in PTA networks will help their economies trade more and grow faster. In this paper, we provide a theory that explains how changes in countries' PTA network positions affect their trade performance. We argue that a dense and deep "neighbor network" provides a country with a wide access to global value chains, better protection to investment, and strong credibility to their policy commitments. To measure trade performance, we compute value-added exports at the country, year, and industry level across 43 countries, 56 industries, and 15 years (2000–14). The estimation of network position effects is done by panel fixed-effects methods and the sample-splitting and cross-fitting double machine-learning method. The findings show that as a country's neighbors have deeper and wider PTA networks, the country's value-added exports grow faster. Also, the industry-level analysis shows that sectors heavily engaging in the fragmentation of production stages exhibit faster growth with the improvement of neighbor networks.

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double machine-learning method, global value chain, hub, neighbor network, positional advantages, preferential trade agreement, value-added exports

1 | INTRODUCTION

Does a better-positioned country in the preferential trade agreement (PTA) network grow faster? While academics have long emphasized the importance of network position in international trade (Baldwin, 2008; Deltas, Desmet, & Facchini, 2012; Hur, Alba, & Park, 2010; Kowalczyk & Wonnacott, 1992; Krugman, 1993b; Mukunoki & Tachi, 2006; Wonnacott, 1975), the proliferation of bilateral or regional PTAs since the 1990s has reignited interest in positional advantages in a growing web of trade agreements. Politicians in industrialized countries have not hesitated to capitalize on this idea to improve the competitive advantages of their countries.

For example, President Roh Moo-Hyun of the Republic of Korea chose PTAs as the "engine of growth" and announced that his government will select PTA partners in a way to transform Korea into "the Northeast Asian economic hub" and "a hub of the global market (Presidential Advisory Policy Committee, 2008, 37)." Similarly, the Canadian Prime Minister Justin Trudeau was advised to pursue the goal of becoming "a global trading hub and a nexus for global supply chains" through PTAs (Advisory Council on Economic Growth, 2017, 2). Also, Japan recently adopted the national strategy of "accelerating the Trans-Pacific Partnership (TPP) and other economic partnership negotiations" to "strengthen the competitiveness of Japan as a business hub" (Government of Japan, 2014, 7).

The spread of the hub-seeking PTA strategy as an international economic policy objective poses several interesting questions. First, what constitutes a "hub" in PTA networks? Second, does hub status, if correctly defined, actually increase the competitive advantage of a country in international trade? The goal of this paper is to answer these two questions.

First, we present the new theoretical concept of node importance in PTA networks, which closely reflects and further clarifies what the policy dialogue and trade literature vaguely call a "hub" in trade relations. The key insight is that a country's value-added exports are heavily dependent not only on the PTA connections they make with others, but also on the PTA connections their PTA partners make with others. The idea that important nodes in a network can be identified by the importance of its partners is well established in the network literature (Bonacich, 1987; Burt, 2010; Katz, 1953). For example, Burt (2010) calls the subset of networks created by the set of actors directly connected to an actor a "neighbor network" and argues that "well-connected neighbors can be a source of opportunity and resource" in social relations (Burt, 2010, 1–6).

There are several channels through which a country's neighbor network in PTAs affects its economy's trade performance in global value chains (GVCs). The first channel is tariffs. According to Wang, Wei, Xinding, and Zhu (2017), inputs move back and forth from two to seven countries on average within GVCs until they are absorbed into the destination market. As tariffs are applied on gross imports rather than on value additions, even small tariffs on intermediate inputs can accumulate and take up a significant portion of the price of a final product. As a result, tariffs between a pair of countries resonate to affect all countries involved in the production network (OECD, 2013). This "magnification effect" could pose a substantial burden to exporting firms. Well-connected nodes in PTA networks are more likely to cover important suppliers of intermediate inputs; hence, countries with well-connected nodes in PTA networks face a lower level of tariff accumulation in production networks than countries that have neighbors with poor or no connections.

The second channel is investment. Many studies have shown that "deep" PTAs covering a range of non-tariff policy areas such as investment protection, dispute settlement mechanisms, technical standards, and labor and environmental regulations, among others, have larger effects on participating countries' economies (Antràs & Staiger, 2012; Baier, Yotov, & Zylkin, 2019; Baldwin, 2016; Chase, 2009; Kim, Milner, et al., 2019; Kim, Lee, & Tay, 2019; Orefice & Rocha, 2014; Osgood, 2018). The main route through which deep PTAs exert greater effects is the connection of firms across multiple production sites. A country with well-connected and deep-PTA seeking neighbors has a lower level of policy uncertainty and provides better protection for investments than a country without well-connected and deep-PTA seeking neighbors.

Our argument for the importance of neighbor networks provides an important refinement of existing theories of trade agreements. Büthe and Milner (2008) and Mansfield and Milner (2012) emphasize that trade agreements provide credible signals of policy consistency to domestic and international audiences by tying the hands of policy-makers. We refine this argument from a network perspective and argue that the value of a PTA as a commitment device depends on how important their PTA partners and partners of their partners are. Forming "deep" trade agreements with well-connected and deep-agreement seeking countries in PTA networks makes a country's commitment to policy consistency and investment protection more credible than forming shallow PTAs with peripheral and shallow-agreement seeking countries.

It is one thing to clarify the concept of a hub in PTA networks. But to empirically investigate whether changes in a hub status actually affect the competitive advantage of a country in international trade is quite another. There are two empirical challenges to this task. First, changes in bilateral trade flow between a pair of countries do not always capture changes in competitive advantage between them. As Baldwin (2016) points out, international trade in the 21st century is characterized by widely dispersed production stages (or tasks) across borders. What are more commonly known as global value chains (GVCs) more accurately describe this new facet of international trade. In GVCs, the division of labor across industries and countries is emphasized more than the total volume of cross-country exchange (bilateral trade flows). PTAs can introduce changes to the global division of labor (through industry-specific tariffs, trade diversion, etc.) without altering aggregate bilateral trade flows. Therefore, "competitive advantage" should be able to reflect on countries' unique contributions to GVCs, which aggregate bilateral flows cannot properly capture (e.g.Amador & Cabral, 2016; Baldwin, 2013, 2016; Elms & Low, 2013; UNIDO, 2018). Second, even when we have an adequate measure of a country's competitive advantage, it may still be challenging to isolate its effect from other endogenous trade-related factors that affect both competitive advantage and the formation of PTAs.

To tackle these empirical challenges, we test the importance of neighbor networks in PTAs on trade performance within GVCs using a dataset of value-added contributions at the country, year, and industry level. Scholars of international trade note that fragmentation of production stages "mandates a new approach to trade data collection" (Grossman & Rossi-Hansberg, 2008, 1996). As such, more and more scholars of international political economy turn to GVCs to test their theoretical arguments (Jensen, Quinn, & Weymouth, 2015; Kim, Milner, et al., 2019). Following this trend, we use a new measure of value-added exports in our empirical test. The input data were obtained from the World Input-Output Dataset (WIOD) (Timmer, Dietzenbacher, Los, Stehrer, & Vries, 2015; Timmer, Los, Stehrer, & Vries, 2016), covering 43 countries and 56 industries from 2000 to 2014. We decompose the multicountry and multisector input–output table into value-added exports at the country–industry–year level using the method proposed by Wang, Wei, and Zhu (2018) (WWZ decomposition hereafter).

One important empirical concern in our design is the homophilous nature of PTAs. That is, countries with similar backgrounds tend to flock together in PTA networks and trade heavily with each other. To address this issue, we need to include a comprehensive list of control variables and fixed effects at the country and year level. One problem with this standard panel treatment is that misspecification of any of these variables (e.g. omitting higher degree interactions) may cause a bias in the estimation of our causal variable. To minimize this bias, we use the machine-learning based panel two-stage regression approach, known as the sample-splitting and cross-fitting panel double machine-learning (DML) method (Belloni, Chernozhukov, & Hansen, 2014; Chernozhukov et al., 2017; Semenova, Goldman, Taddy, & Chernozhukov, 2018).

The results of our analysis show strong evidence for the positive PTA hub effect on value-added export growth. That is, countries with strong PTA hub status (i.e. countries with well-connected and deep-agreement seeking neighbors) have higher domestic and foreign value-added export growth than those with weak PTA hub status. The effects are pronounced among countries in the middle of production chains such as Singapore, Japan, and South Korea. We also find that PTA hub effects have strong distributional implications at the industry level. Manufacturing and service sectors especially those with fragmented production processes using advances in information and communications technology grow faster as the PTA hub status of the country improves.

2 | POSITIONAL ADVANTAGE IN INTERNATIONAL TRADE

Scholars have long pointed out the importance of a country's position as a source of competitive advantage in international trade, and the concept of a hub has played a central role in this discussion. This is largely due to the popularity of the hub-and-spoke structure as a simple conceptual device to theorize complex trade relations. The hub-and-spoke structure in international trade first appeared in Wonnacott (1975), who proposed a hub-seeking strategy for his country, Canada, to survive between two dominant trading blocs, the United States and Europe.

> *Canada should now simultaneously approach the U.S. for an industrial free trade agreement,* and *simultaneously (or soon thereafter) approach the EEC for an industrial free trade agreement … ,* and *approach the remaining Efta (sic) countries (in particular, Sweden and Switzerland) for a similar agreement with them. This solution is not a simple one; but it may be the best means of satisfying both our [Canada's] economic and political objectives (Wonnacott, 1975, 120, emphasis original).*

Interestingly, it was Israel that put Wonnacott's proposal into reality. Israel formed a trade agreement with the European Union in 1975 and with the United States in 1985, which made Israel a classic example of a hub connecting two large trading blocs. Deltas et al. (2012) estimated that "trade between Israel and the EU increased by an additional 29% after the introduction of the U.S.-Israel FTA in 1985" (Deltas et al., 2012, 942).

The hub-and-spoke structure has been popular in theories of international trade, also. For example, Krugman (1993a) found that "[i]f one of the three regions has better access to the other two regions than they have to each other, this superior access can lead to concentration of production in the increasing returns sector" (Krugman, 1993a, 34). In the new-new trade theory, Melitz and Ottaviano (2008) showed that firms in a hub of the hub-and-spoke structure can gain a better access to the other markets and, as a result, their average costs, prices, and mark-ups will go down more significantly than firms in the other two countries (spokes) (Melitz & Ottaviano, 2008, 310–2).

The proliferation of PTAs in the end of the 20th-century reignited interest in network position as a source of competitive advantage in international relations. It did not take long before policy-makers in industrialized countries caught onto this idea; it was competitive advantage gains from an important position in PTA networks that convinced South Korea's left-leaning President Roh Moo-Hyun to decide to make "*dongsidabal*" (concurrent) PTAs with advanced economies his foreign economic policy objective.

> *Accelerated by the Korea-US FTA, FTAs with the EU, Canada, ASEAN, Japan, China, and India will enable Korea to achieve* the Northeast Asian economic hub*, which serves as a link between the world's major economic powers. We have concluded an FTA with the United States in Northeast Asia for the first time, thus laying the groundwork for* becoming a hub of the global market*, …, further solidifying our* position *in Northeast Asia" (Presidential Advisory Policy Committee, 2008, 37, emphasis added).*

Similarly, the Advisory Council on Economic Growth of Canada urged the Canadian government to pursue "new, preferential trade arrangements with large and fast-growing nations, especially in Asia, and more specifically with China, Japan and India" in order to "become a global trading hub and a nexus for global supply chains" (Advisory Council on Economic Growth, 2017, 2).

Despite the popularity of becoming a hub in policy dialogues and academic discussions as a source of competitive advantage in international trade, the concept remains highly elusive. First, what is a hub? In policy dialogues, it sometimes means just a country with many PTA partners or the center of a regional/global trade network. Academic discussions of hubs in trade relations are not much clearer than policy dialogues. The hub-and-spoke structure is such an unrealistic model that it cannot be directly applied to today's dense PTA networks. As of 2019, all WTO members have at least one PTA partner. 91% of WTO members successfully avoid being a "spoke" by holding more than two PTA partners, and the average number of PTA for WTO members is as large as 13.[1]

Second, the narrow definition of a hub in the hub-and-spoke system is not proper to discuss the competitive advantage of a hub, if any, due to its short-lived nature. The cost of forming a PTA is not so prohibitively large that spoke countries can easily connect themselves with unconnected countries to overcome competitive disadvantage. This microlevel incentive generates a network phenomenon called triadic closure, which was reported to have played some role in the formation of the PTA network (Manger, Pickup, & Snijders, 2012).

As such, we need a clear definition of positional advantage or "hub" status in PTA networks beyond THE hub-and-spoke structure.

3 | HUB IN PTA NETWORKS

3.1 | Node Importance in PTA Networks

Identifying a central actor is key to understanding the structure of social relations. In the network literature, there are three different major approaches to identifying important actors: (a) ego-centric (local level), (b) distance-based (global level), and (c) neighbor-based (mesolevel) (Wasserman & Faust, 1994, 169–221).

An ego-centric approach evaluates the relative importance of actors by the number of ties they have. In the context of PTA networks, a country that has more PTA partners than others will be considered more important. Although simplistic and succinct, the ego-centric ignores higher-level information at the group or global level. For example, the ego-centric approach fails to distinguish a

[1]The numbers are computed using the WTO RTA dataset (https://www.wto.org/english/tratop_e/region_e/region_e.htm, accessed on August 8, 2019).

country within a trilateral PTA (all countries have degree 2 including the ego) and a hub country in the hub-and-spoke structure (the hub has degree 2 and spoke countries have degree 1).

In a global-level approach, node importance is measured by the actor's contribution to global network properties such as the average distance in the entire network.[2] The distance-based centrality measures (i.e. betweenness centrality) capture node importance well when edges are transferable. For example, when social ties reflect the flow of information such as news, gossip, and innovative technology, the distance-based centrality measures show who plays an important role in the dissemination of information (Burt, 2001); Granovetter, 1978). However, PTAs have exclusive rules of origin (ROOs) that do not apply beyond signatories. Recently, Conconi, García-Santana, Puccio, and Venturini (2018) showed that PTA's exclusive rules of origin have significant trade-diverting effects. Thus, the assumption of edge transferability embedded in a global-level node importance approach is problematic in the analysis of PTA networks.

In contrast to the above two approaches, a mesolevel (or group-level) approach focuses not only on the importance on the ego, but also on *the importance of the ego's directly connected neighbors*. Thus, unlike the ego or global-level approach, a mesolevel approach to node importance has several important features that capture the distinct nature of PTA networks. First, a mesolevel approach captures the short-ranged edge transferability in PTA networks better than a global-level approach. Countries in the same continent form regional PTAs to share the benefits of exclusive ROOs, or proximate countries form a series of bilateral PTAs to exploit regional production networks. Second, a mesolevel approach effectively shows the power and influence of social actors in social relations. The idea that important nodes in a network can be identified by the importance of its partners is well established in network literature (Bonacich, 1987; Burt, 2010; Katz, 1953). Recently, this idea became highly popularized by web ranking algorithms such as PageRank (Brin & Page, 1998) and Hyperlink-Induced Topic Search (HITS) algorithm (Kleinberg, 1998). Third, a mesolevel approach can be connected with the *strategic* aspect of PTA formation. Ballester, Calvo-Armengol, and Zenou (2006) show that a network game with individual, global, and network effects has a unique Nash equilibrium that is proportional to the eigenvector centrality. As we will explain below in detail, the eigenvector centrality is a core measure of node importance at the mesolevel.[3]

[2]The distance between a pair of actors in a network is represented as a path. A path ψ between actor i and actor j is $\psi_{ij} = \{i, k, h, j\}$ where k and h together are a set of actors needed to travel from i to j. The shortest path between two actors then is a path that contains the smallest number of actors. Centrality scores of an actor based on distance in a network take into account all shortest paths where the given actor is included.

[3]Suppose that country *i's* utility depends on a PTA tie of its own (x_i) and of others ($\mathbf{x}_{-i}$) in the following linear-quadratic form:

$$u_i(x_1, \ldots, x_n) = \alpha_i x_i + \frac{1}{2}\sigma_{ii}x_i^2 + \sum_{j \neq i} \sigma_{ij} x_i x_j \tag{1}$$

where $\sigma ii < 0$ indicating the diminishing marginal utility of PTAs and σij is a cross-effect of *i's* PTA with *j's* PTA on *i's* utility. Then, a $N \times N$ matrix of cross-effects Σ can be decomposed into a combination of an idiosyncratic effect, a global interaction:

$$\mathbf{\Sigma} = -\beta \mathbf{I} - \gamma \mathbf{U} + \lambda \mathbf{G} \tag{2}$$

which gives.

$$u_i(x_1, \ldots, x_n) = \overbrace{\alpha_i x_i - \frac{1}{2}(\beta - \gamma)x_i^2}^{\text{individual effect}} - \overbrace{\gamma \sum_j x_i x_j}^{\text{global interaction effect}} + \overbrace{\lambda \sum_j g_{ij} x_i x_j}^{\text{meso}-\text{level interaction effect}} \tag{3}$$

(Ballester, Calvó-Armengol and Zenou, 2006, 1405–6). If each country maximizes this utility given others' actions in the same way, the aggregate equilibrium outcome is consistent with the Bonacich centrality (Bonacich, 1972), which is a variant of the eigenvector centrality. When we assume that node influence does not travel beyond direct links (i.e. the decay parameter approaches to 0), as PTAs often do, the Bonacich centrality reduces to the eigenvector centrality.

3.2 | How PTA networks affect GVCs?

In GVCs, the price of final goods could entail a process of combining multiple inputs that traverse different countries. Since tariffs are applied to gross imports, each step at which an input crosses border adds an extra cost to the price of final goods. While fragmenting production stages allow firms to benefit from locally abundant factors, those gains can be offset by the incremental nature of tariff accumulation in GVCs (the magnification effect). Thus, firms have a strong interest in locating their production networks where magnification effects can be minimized. Since production networks generally include more than two countries, (according to Wang et al. (2017)'s estimate, two to seven countries are typically involved in a production network), PTAs covering a large number of countries are preferred. More precisely, it would be important for offshoring firms to find a subset of countries interconnected by PTAs. From the perspective of a country, this suggests that having well-connected neighbors in a PTA network will increase the chance that firms will include the given country in their production networks. This leads to our first implication:

Implication 1 *Countries with well-connected neighbors in PTA networks are less exposed to magnification effect and thus more likely to be involved in firms' production networks than countries without well-connected neighbors.*

However, PTAs are not just about reducing tariffs. PTAs have become increasingly heterogeneous in terms of issue coverage. PTAs now cover a range of behind-the-border issues such as foreign investment, intellectual property rights, service sector liberalization, standards, competition policy, and public procurement (Baldwin, 2013, 2016; Orefice & Rocha, 2014; Osnago, Rocha, & Ruta, 2015). Policy issues "that were previously dealt with under dedicated bilateral instruments, such as bilateral investment treaties, customs cooperation agreements, and cooperation on competition policy, are now increasingly incorporated into PTAs" (Chauffour & Maur, 2011, 29).

Scholars of international political economy have noted that PTA heterogeneity plays an important role in firms' investment decisions (Antràs & Staiger, 2012; Baldwin, 2016; Chase, 2009; Kim, Milner, et al., 2019; Kim, Lee, et al., 2019; Orefice & Rocha, 2014; Osgood, 2018). Large firms with sufficient export capabilities have a vested interest in offshoring, allowing them to exploit advantages such as lower factor prices and more favorable locations. One critical issue these firms face is the time-inconsistency problem (or the hold-up problem): A country's commitment to foreign investment may not be credible after the investment is executed. The possibility of unilateral expropriation by a host country calls for "deep" PTAs that encompass non-traditional trade issues including intellectual property rights, investment protection, and dispute settlement mechanisms (Antràs & Staiger, 2012; Orefice & Rocha, 2014). Kim, Milner, et al. (2019) showed that protection from the expropriation of investment assets by host countries was one of the most critical elements of a trade agreement from a firm's perspective. Büthe and Milner (2008), Kim, Lee, et al. (2019) and Kim, Milner, et al. (2019) also found that PTAs incorporating investment clauses and dispute settlement mechanisms provide credibility to host countries' commitments. Other policy areas in deep PTAs such as labor and environmental regulations and harmonization of production standards reduce coordination costs and provide investment-seeking firms a better policy space in which to operate. Policy changes triggered by deep PTAs are less likely to be reversed, motivating firms to make investments in a country where such policy coordination is guaranteed. Thus, deeper economic integration and stronger investment protection along production networks indicate that a country with PTA partners with a strong preference for deep agreements, which we call "deep-PTA neighbors," is likely to accumulate larger benefits than a country without deep-PTA neighbors.

Implication 2 *Countries with deep-PTA neighbors encourage more investment by foreign firms than countries without deep-PTA neighbors.*

Furthermore, scholars of international political economy have pointed out that countries form trade agreements to tie their hands or to send a credible signal of policy consistency to domestic and international audiences (Büthe & Milner, 2008; Mansfield & Milner, 2012; Whalley, 1998). It was also maintained that countries opt for trade agreements to buy insurance against possible trade wars, thereby reducing policy uncertainty and institutionalizing the dispute settlement process (Handley & Limão, 2017). The main problem with these arguments from our perspective is that they are monadic predictions, ignoring the network aspect of trade agreements. First, if we consider PTAs as a dyadic process, we should expect that the value of PTA as a commitment or signaling device varies depending on who the partner is. Second, PTAs are more than a dyadic process. Numerous regional or mega bloc PTAs have been proposed and bilateral and multilateral PTAs have significant externalities to non-participating countries. Thus, we also need to consider who the partners of their partners are. This network perspective provides an important refinement to the existing theories of PTA as a commitment or signaling device.

Implication 3 *Forming "deep" trade agreements with well-connected, deep-PTA neighbors makes a country's commitment to policy consistency and investment protection more credible than forming shallow PTAs with peripheral and shallow-agreement seeking PTA neighbors.*

Unfortunately, these three theoretical implications are not directly testable because the relevant data—cross-border cumulative tariffs, firms' investment decisions, and the credibility of a country's commitment—are either unobserved or hard to measure. Instead, we derive two empirically testable hypotheses from the above theoretical implications. First, we can test our argument by comparing changes in a country's PTA hub status and changes in its value-added export.

Hypothesis 1 *Countries with well-connected, deep-PTA neighbors grow faster within GVCs than countries without well-connected, deep-PTA neighbors.*

As will be clear shortly, value-added exports in GVCs can be further disaggregated at the industry level. Industry-level analysis allows us to investigate the distributional effects of a country's network position across industries. As Stolper and Samuelson (1941) and Rogowski (1989) clearly showed, all factors that affect the price of goods have distributional effects. Given low interindustry factor mobility in industrialized countries (Hiscox, 2002), we expect a positive change in a country's network position to lead to the reallocation of resources in favor of industries that deeply engaged in global production networks (high use of intermediate goods), at the cost of industries that are not embedded in global production networks (little use of intermediate goods).

Hypothesis 2 *Industries that deeply engage in global production networks will grow faster if they are located within a country with well-connected, deep-PTA neighbors than industries that are not embedded in the global production networks.*

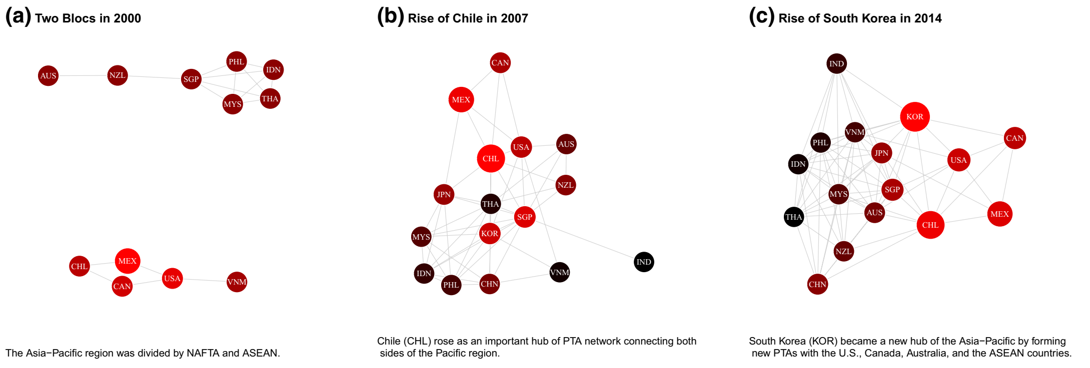

FIGURE 1 PTA hub status changes in the Asia–Pacific Region: The size of nodes is adjusted by PTA hub scores. Bright red colors indicate high PTA hub scores, and dark colors indicate low PTA hub scores [Colour figure can be viewed at wileyonlinelibrary.com]

3.3 | An Illustration: PTA networks in the Asia–pacific region

Before we move to the discussion of our empirical tests, it is helpful to illustrate how mesolevel node importance works in reality. Figure 1 visualizes the evolution of PTA networks in the Asia–Pacific region from 2000 to 2014. We chose the Asia–Pacific region because countries in this region recently experienced dramatic changes in their PTA ties. After two regional trade agreements (RTAs) were formed in 1992, the North American Free Trade Agreement (NAFTA) and the ASEAN Free Trade Area (AFTA), countries in this region competitively signed a series of bilateral PTAs. One observer called the proliferation of PTAs in this region a "spaghetti bowl" (Baldwin, 2006).

For easy interpretation, we drop countries without PTA ties with other countries in the region. Countries are nodes and edges are drawn if there is a signed PTA between a pair of countries. The size of nodes is proportional to our measure of node importance, which we call a PTA hub score.[4] A bright red color indicates a high PTA hub score and a dark color indicates a low PTA hub score. To save space, we show three snapshots of the evolution: 2000, 2007, and 2014. A brief network characteristic is annotated at the bottom of each panel.

The left panel of Figure 1 shows the PTA network in 2000. The network was divided by the two regional PTAs: the NAFTA and the AFTA. In the language of Burt (2009), a "structural hole" (separation between nonredundant contacts) existed in this region's PTA network in 2000. There existed room for gains (brokerage benefits) by connecting disconnected RTAs. The central panel shows that "connecting disconnected RTAs" is exactly what countries in this region have done since 2000. Seven years later, the two RTA blocs were merged into one bloc by PTAs between several countries. Among those countries bridging two blocs, Chile (CHL) stands out as the most important node in 2007. Mexico (MEX), South Korea (KOR), and Singapore (SGP) closely follow Chile in importance.

The right panel shows the Asia–Pacific PTA network as of 2014. One of the most surprising results is the rise of South Korea, which now competes with Chile as a regional PTA hub. South Korea's rise as a PTA hub was largely driven by the successive deep PTAs South Korea formed with important players in global PTA networks such as the AFTA, Canada, Chile, EU, and the United States. Note that most of South Korea's PTA partners are well-connected countries with a strong preference for

[4]PTA hub scores are computed using the entire countries in WTO RTA dataset (https://www.wto.org/english/tratop_e/region_e/region_e.htm). The measurement method will be explained in the next section.

deep PTAs. By forming a series of deep PTAs with these deep-PTA neighbors, South Korea was able to rise as a prominent PTA hub in this region.

If our theory is correct, we should observe stronger trade performance in the countries with high PTA hub status (e.g. Chile, South Korea, the United States, Mexico, Canada, and Singapore), holding other factors constant. In particular, the trade performance of rising PTA hub countries such as South Korea should improve significantly compared to countries without large improvements in their PTA hub status.

4 | DATA AND METHOD

In this section, we explain our empirical strategy for estimating PTA hub effects. We first discuss the construction of the dependent variable using the input–output tables of bilateral trade flows. Next, we discuss the measurement of PTA hub scores using PTA data. Finally, we explain our statistical method for estimating PTA hub effects on value-added exports in GVCs.

4.1 | Dependent variable: Value-added exports

To measure countries' value-added contributions within GVCs, we use the method developed by Wang et al. (2018). As an input dataset for WWZ decomposition, we use World Input-output Dataset (WIOD) collected by Timmer et al. (2015) and updated later by Timmer et al. (2016). The WIOD encompass the sector-level input–output trade data of 43 major economies from 2000 to 2014. It covers 3 categories (primary, manufacturing, service) of 56 industrial sectors, including fishing, mining, manufacturing of machines, manufacturing of textiles and financial service activities.[5]

The WWZ decomposition dissects trade flows into four different dimensions: *Domestic Value Added* (DVA), *Returned Domestic Value* (RDV), *Foreign Value Added* (FVA), and *Pure Double Count* (PDC). Among the four dimensions, we use DVA and FTA as our dependent variables because they show each country's value-added contribution in GVCs than RDV and PDC.[6] DVA and FVA capture two different aspects of value-added contributions. DVA includes all value additions in the exports of final and intermediate goods originated by domestic industries that are absorbed abroad. FVA measures the contribution by domestic industries to the value-added chain initiated by a foreign industry that are absorbed in either domestic or foreign country. For example, a memory chip in an iPhone is manufactured by TSMC in Taiwan and SK Hynix in Korea, which are then imported by China as intermediate goods, assembled into iPhones, and exported as a final good. In the case of iPhones, FVA captures the amount of value addition of foreign origin in China's exports.

[5] The dimension of the data matrix WIOD is 2,408 × 2,408 × 15. The first two dimensions represent the number of country–industry pairs (43 × 54) and the third the time (years 2000 to 2014). Wang, Wei and Zhu (2018) decompose the input–output matrix into a country-level dataset with four categories. While the discussion of the decomposition is important, it contains many technical issues that are not directly related with the main goal of this paper. For more information, refer to Wang, Wei and Zhu (2018), Quast and (Kummritz2015) and Timmer et al. (2016).

[6] *Returned Domestic Value* measures the flows of value-added that originated from home country but eventually return to home country as final goods imports. *Pure Double Count* measures value-added flows that are counted more than once because the flow comes in and out of home country repeatedly. We exclude them from our analysis for consistency and better interpretability. RDV measures value-addition embedded within final goods imports which is a small segment compared to what DVA and FVA measures and may not as easily be categorized as "export strength." PDC is by definition a residual category rather than a measure of trade capability.

Then, we calculate weighted out-strength degrees of value-added exports (Barrat, Barthelemy, & Vespignani, 2007). The out-strength degree of country *i* is defined as.

$$s_i = \sum_{j=1}^{N_v} b_{ij} w_{ij}$$

where *bij* is the binary indicator of trade flow between countries *i* and *j*, and *wij* denotes the volume of value-added flow from country *i* to country *j*. Out-strength degree *si* measures both intensive and extensive margins in value-added exports. That is, an increase in *si* indicates either that country *i* increases its value-added exports to existing partners, or that country *i's* value-added exports have a new destination (a new trade partner).

4.2 | Explanatory variable: PTA hub score

Let $A = (V, E)$ be a PTA network with a country set $V = \{v1, v2, \ldots, vn\}$ and an edge set $E \subseteq V \times V$, where *aij* is an *i*th row and *j*th column element of *A*, which is $d > 0$ if country *i* and country *j* have a PTA with *d*-level depth and 0 if they do not any PTA. Then, we can define an importance of an actor *i* (*vi*) as a recursively additive function of all the directly connected nodes and their PTA depth as follows:

$$v_i = \frac{1}{\lambda}\left(\overbrace{a_{i1}v_1 + a_{i2}v_2 + \ldots}^{\text{neighbor importance}} + \overbrace{a_{ii}v_i}^{\text{ego importance}} + \overbrace{a_{i,i+1}v_{i+1} + \ldots + a_{in}v_n}^{\text{neighbor importance}}\right) \tag{4}$$

That is, node importance of an actor at the mesolevel is a scaled average of its own and its neighbors' importance. Suppose two countries with the same number of PTA partners. We can rewrite Equation (4) using an adjacency matrix *A* and a vector of centrality scores **c**:

$$\lambda \mathbf{c} = A\mathbf{c} \tag{5}$$

Then, **c** is an eigenvector of *A* corresponding to eigenvalue λ. Since *A* is non-negative, the Perron–Frobenius theorem guarantees that λ is the largest eigenvalue and **c** is its unique corresponding eigenvector, containing eigenvector centrality scores for each node.[7]

To account for PTA heterogeneity, we use the Design of Trade Agreements measure (DESTA) (Dür et al., 2014), which counts the number of behind-the-border measures a PTA covers. The key provisions of behind-the-border measures are unconditional tariff reductions in goods, service sector liberalization, investment protection, standards, public procurement, competition, and intellectual property rights. The depth of the PTA is measured according to a scale of how many of these provisions are contained within the PTA. For example, a PTA of depth 5 contains five of the above seven key provisions and a PTA of depth 0 contains none of the seven key provisions.

[7]The Perron–Frobenius theorem states that for a non-negative symmetric matrix, there is an eigenvector with positive real coordinates corresponding to the largest eigenvalue and the eigenvector is unique up to constant multiplication. See Easley and Kleinberg (2010, 376) and Newman (2016, 5).

4.3 | Control variables

We include a comprehensive list of control variables to control for omitted variable bias. For this, we collect 21 input variables that may affect a country's value-added exports independent of a country's PTA hub status. Our goal is to isolate the effect of a country's PTA hub status, holding ego or global-level node importance constant. Thus, we need to control for factors related with the ego-level and the global-level node importance.

First, we include a list of measures reflecting ego-level network effects. A country's value-added exports might be affected simply by the sheer number of PTA partners it has (ego centrality), which contradicts our theory based on the importance of neighbors and PTA depth. Another possible confounder is the number of PTAs at each depth level (ego centrality0, …, ego centrality7). For example, a country's trade performance can be affected by the number of deepest PTAs (depth 7) independent of its neighbor network. If we omit the depth-specific PTA numbers a country has and any of these variables has a positive effect on value-added exports, the estimated PTA hub would be overstated.

Second, we control for network effects at the global level using betweenness centrality scores (Freeman, 1977, 1978), closeness centrality, and participation coefficient (Guimera & Amaral, 2005). The first two centrality measures are well-known distance-based centrality scores. The participation coefficient is less well known and it might be important because it measures node importance at the global level whiling taking into account bloc structures. A high participation coefficient indicates that node i is connecting multiple blocs, whereas a low participation coefficient indicates that node i is exclusively participating in its own bloc. Thus, if the economy of a country connecting multiple blocs of PTAs grows fast, participation will have a positive sign.

Third, we control for the growing size of PTA networks over time by including the total number of PTAs (PTA Number).

Fourth, we include several political and economic variables that might affect a country's value-added exports: the size of economy (log-transformed population, land, and log trans- formed gross domestic product (GDP), the level of economic development (log-transformed gross domestic product per capita GDP per capita), the (log-transformed) net inflow of FDI, polity scores (Polity), the degree of capital account openness (the Chinn-Ito index, MarketOpen) (Chinn & Ito, 2006), a dummy variable for EU members, and a linear time trend.

Last, we include *all the pairwise interactions* between the above input variables, which leads to $\frac{N(N-1)}{2} = 210$ interaction terms.

4.4 | Statistical method

In studying the effect of a PTA on trade, scholars have long warned of the issue of selection bias (Baier & Bergstrand, 2007; Baier et al., 2019; Egger, Egger, & Greenaway, 2008). That is, countries self-select into a PTA when they expect trade gains from it; otherwise, they do not bother to negotiate a PTA. This non-random formation process poses an important challenge in estimating PTA effects on trade. To overcome selection bias, Baier and Bergstrand (2007) use a panel approach to resolve selection bias and Egger et al. (2008) and Baier and Bergstrand (2009) use a matching method to reduce imbalance in the sample and apply a panel method to estimate the PTA effect on trade flows.

However, our empirical goal is different from previous studies in several ways. First, the goal of previous studies was to estimate the average effect of a PTA on bilateral trade flows. Hence, the unit of analysis is a dyad. In contrast, the unit of analysis in our empirical design is a country. Our goal is to estimate the effect of a country’s PTA hub status on a country’s value-added exports. Selection bias

TABLE 1 Fixed-effect analysis of PTA hub effects on value-added exports: The dependent variables are value-added exports measured by DVA and FVA, respectively

	One-way FE		Two-way FE		Between		First-differenced	
	DVA	FVA	DVA	FVA	DVA	FVA	DVA	FVA
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PTA hub	0.19***	0.23***	0.18***	0.21***	1.76*	3.48**	0.11***	0.14**
	(0.04)	(0.06)	(0.03)	(0.05)	(0.96)	(1.29)	(0.04)	(0.06)
Betweenness	0.02	0.05**	0.02**	0.06***	−0.08	−0.05	0.01	0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.08)	(0.11)	(0.01)	(0.02)
Participation	−0.03*	−0.01	−0.03***	−0.003	−0.05	0.09	−0.02***	−0.05***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.20)	(0.27)	(0.01)	(0.01)
Closeness	−0.01	−0.03*	0.03**	0.03	0.31	0.50	−0.004	−0.004
	(0.01)	(0.02)	(0.01)	(0.02)	(0.29)	(0.39)	(0.004)	(0.01)
Ego centrality	−0.08	−0.18*	−0.12**	−0.24***	−1.41	−2.82**	−0.02	−0.03
	(0.06)	(0.10)	(0.05)	(0.07)	(0.83)	(1.12)	(0.04)	(0.07)
Ego centrality$_7$	−0.02**	−0.004	−0.002	0.01	−1.17	−1.38	−0.003	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.72)	(0.96)	(0.01)	(0.01)
Ego centrality$_6$	−0.03***	−0.03***	−0.02***	−0.01*	0.15	0.32	−0.01**	−0.01
	(0.01)	(0.01)	(0.005)	(0.01)	(0.21)	(0.28)	(0.01)	(0.01)
Ego centrality$_5$	−0.04	−0.04	−0.07***	−0.12***	−0.09	−0.31	−0.04*	−0.03
	(0.03)	(0.05)	(0.03)	(0.04)	(0.17)	(0.23)	(0.02)	(0.04)
Ego centrality$_4$	−0.005	−0.02	0.06***	0.09***	0.37	−0.01	−0.05***	−0.13***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.40)	(0.54)	(0.01)	(0.02)
Ego centrality$_3$	0.16*	0.10	0.11	0.09	−0.51*	−0.90**	−0.04	−0.29**
	(0.09)	(0.14)	(0.08)	(0.11)	(0.29)	(0.39)	(0.08)	(0.13)
Ego centrality$_2$	0.01	0.06	0.11***	0.22***	0.10	0.07	0.07**	0.14***
	(0.03)	(0.05)	(0.03)	(0.04)	(0.08)	(0.11)	(0.03)	(0.05)

(Continues)

TABLE 1 (Continued)

	One-way FE		Two-way FE		Between		First-differenced	
	DVA	FVA	DVA	FVA	DVA	FVA	DVA	FVA
Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Ego centrality$_1$	0.01	0.02	−0.03	−0.03	0.29	0.78	−0.02	−0.04
	(0.03)	(0.04)	(0.02)	(0.03)	(0.41)	(0.54)	(0.02)	(0.03)
Ego centrality$_0$	−0.55***	−0.14	−0.36***	0.13	0.17	0.36	−0.14	−0.13
	(0.15)	(0.23)	(0.12)	(0.18)	(0.27)	(0.36)	(0.15)	(0.24)
GDP	−12.79***	−18.00***	−10.93***	−15.16***	1.51	3.72	−1.66	0.42
	(3.19)	(5.00)	(2.58)	(3.76)	(2.48)	(3.33)	(2.96)	(4.82)
Land	−0.33***	−0.43***	−0.25***	−0.29***	0.01	−0.11	0.01	−0.02
	(0.07)	(0.11)	(0.06)	(0.08)	(0.09)	(0.12)	(0.05)	(0.09)
Population	11.93***	16.94***	10.50***	14.65***	−0.37	−2.76	0.39	−2.26
	(3.41)	(5.35)	(2.76)	(4.03)	(2.68)	(3.60)	(3.21)	(5.23)
GDP per capita	8.38***	11.48***	7.09***	9.46***	−0.24	−1.70	1.67	0.40
	(1.96)	(3.07)	(1.58)	(2.31)	(1.52)	(2.04)	(1.82)	(2.96)
FDI	0.02***	0.03***	0.01	0.01	0.12	0.27**	0.01**	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.08)	(0.11)	(0.003)	(0.01)
Polity	0.07**	0.12**	0.02	0.04	−0.11	−0.18*	−0.01	0.02
	(0.03)	(0.05)	(0.03)	(0.04)	(0.07)	(0.10)	(0.02)	(0.03)
MarketOpen	0.07***	0.06***	0.05***	0.04***	0.02	0.09	0.02	0.03
	(0.01)	(0.02)	(0.01)	(0.01)	(0.12)	(0.16)	(0.01)	(0.02)
Trend	0.03***	0.05***			0.03	0.04	0.01	0.06***
	(0.004)	(0.01)			(0.19)	(0.26)	(0.01)	(0.02)
Observations	567	567	567	567	40	40	527	527
R^2	0.92	0.87	0.69	0.45	0.97	0.94	0.65	0.51

(Continues)

TABLE 1 (Continued)

	One-way FE		Two-way FE		Between		First-differenced	
	DVA	FVA	DVA	FVA	DVA	FVA	DVA	FVA
Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Adjusted R^2	0.91	0.86	0.65	0.37	0.93	0.87	0.64	0.49

*$p < .1$.

**$p < .05$.

***$p < .01$.

in our design takes a different form; countries expecting trade gains from PTAs are more likely to form PTAs than others. We need to control for country-specific confounders that affect trade gains from PTAs and the formation of PTAs at the same time. If we consider those country-specific confounders to be time-constant, conventional panel methods such as the fixed-effects method can be used to minimize the bias. For time-varying confounders, we have to use observed covariates to account for their effects on the dependent variable. Second, our dependent variable is different from the ones used by previous studies. Decomposed value-added export data is a more valid measure of a country's trade performance than bilateral trade data, in which a country's value-added contributions are conflated with value-added contributions by other countries producing intermediate goods. Third, a country's PTA hub status is more exogenous to a country's decision to form a PTA than the binary measure of a PTA between a pair of countries. A simple reason is that a country's PTA hub status is a scaled average of its own and its neighbors' importance in PTA networks. A country can choose popular PTA partners, but it is difficult to control partners' future connections. Thus, if we control for the degree centrality of the country in the model, we can separate the effects of neighbor network from the effects of the country's own connections.

A more important empirical concern than selection bias in our design is omitted variable bias coming from the homophilous nature of PTAs. Countries with similar characteristics are likely to form dense blocks in PTA networks and also engage deeply in GVCs with each other. If we omit background variables that influence them to flock together in PTA networks and trade heavily, we may overestimate the effects of PTA hub status. In order to address the endogeneity coming from the homophilous nature of PTAs, we use the machine-learning based panel two-stage regression approach, known as the sample-splitting and cross-fitting panel DML method (Belloni et al., 2014; Chernozhukov et al., 2017; Semenova et al., 2018). We discuss our implementation of the DML method in the Appendix 1.

Another empirical concern in our design is reverse causality. That is, a country's trade performance within GVCs may affect the popularity of its own and its neighbor network, not vice versa. PTA networks are recorded when they are finally signed, however, to avoid the reverse causality, we lag all the PTA-related covariates by two years. This is because according to Moser and Rose (2012), on average, it takes two years for a signed PTA to actually enter into force. Therefore, we need to match the response variable at t with PTA-related covariates at $t - 2$ to estimate PTA effects.[8]

5 | RESULTS

5.1 | Results of the fixed-effect models

Table 1 summarizes the results of the fixed-effect analysis. In order to check the robustness of our results, we employ four different panel treatments to deal with various sources of endogeneity. The first two models employ a one-way fixed-effect model at the country level, which produces within estimates of PTA hub status. That is, the first two models show how the within-country variation of PTA hub status affects each country's value-added exports over time, controlling for all the average differences between the dependent variable and independent variables. The within estimates clearly show that PTA hub has a positive and statistically significant effects on value-added exports in DVA and FVA, which is consistent with hypothesis 1.

[8]Although the timing of PTA effects is beyond the scope of our paper, we note that the effects of PTAs may precede the date of signature because there may be some preemptive responses from consumers and producers in advance to the formation of a PTA. Or, some PTAs have lagged effects due to the uncertainties around ratification and implementation stages in a participating country.

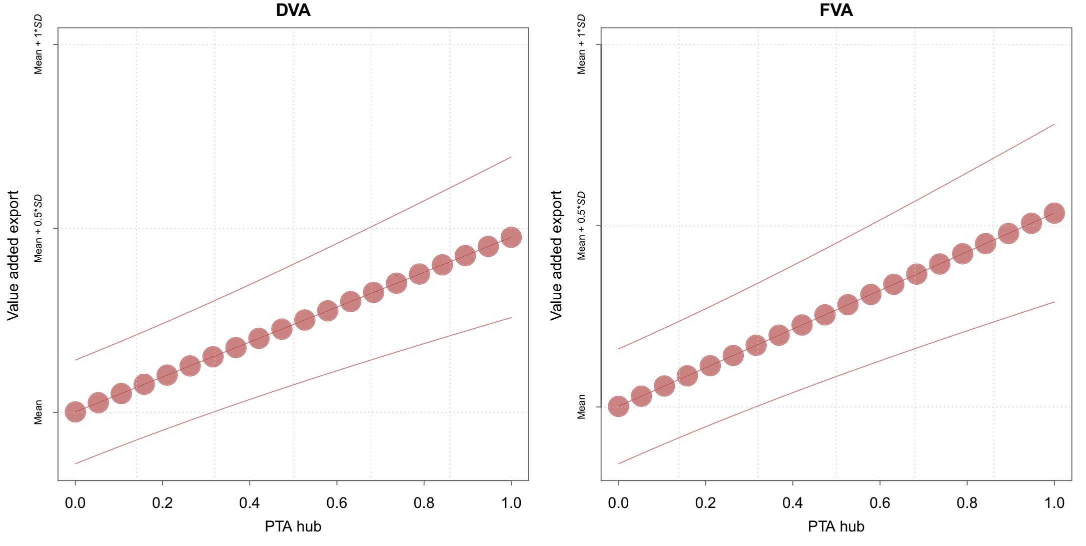

FIGURE 2 Predicted Effects of PTA Hub Score on Value-added Exports [Colour figure can be viewed at wileyonlinelibrary.com]

The next two models ((3)-(4)) show estimates from the two-way fixed effects at the country and year levels. Now, we further control for year-specific effects that may confound our analysis. For example, the global financial crisis and trade disputes between major exporters may affect countries' value-added exports independently of their PTA hub status. Also, the signing of mega bloc PTAs may increase hub status of related countries (members and their neighbors) and decrease that of non-related countries. Controlling for these year-specific factors do not substantively affect the findings; coefficients of PTA hub remain positive and statistically significant.

Aside from within-country variations, hypothesis 1 also implies that PTA hub status must have a positive effect *across countries*. The first four models cannot properly address cross-country variations between PTA hub status and the dependent variables, because of the within transformation to remove unobserved time-constant country-level factors. To test hypothesis 1 across countries, we compute the between estimator of PTA hub status, which is reported in column (5) and (6). Surprisingly, the effect size increases dramatically, implying that country-level differences in PTA hub status explain a lot of the variation in value-added exports, controlling for major covariates of export strength.

Last, we need to consider possible bias coming from serial correlation in the error of our models. As our data have long time series for each country, we fit a first-differenced model to see whether annual changes in PTA hub status affects annual changes in value-added exports, controlling for major covariates of export strength. However, it should be stressed that estimates from the first-difference models are sensitive to measurement error, which could be a not so trivial concern in our case because our causal variable (PTA hub score) is not directly observed but a construction from observed data. With that in mind, columns (7) and (8) show that marginal changes in our causal variable are positively and significantly associated with marginal changes in value-added exports, which is consistent with hypothesis 1.

Statistical significance does not necessarily imply substantively significance. To gauge the substantive importance of our findings, we compute the predicted effects of PTA hub scores on value-added exports. We use a country fixed-effect model reported in columns (1) and (2) in Table 1. After setting all control variables at their means, we vary the size of the causal variable from minimum to maximum. The predicted means and intervals are displayed in Figure 2.

TABLE 2 Estimates of PTA Hub Effects: The dependent variables are DVA and FVA out-strengths. Naive DML indicates a naive DML estimation method without sample-splitting and cross-fitting. Cross-fitting DML indicates the sample-splitting and cross-fitting panel DML estimation (Semenova et al., 2018). Clustered standard errors are reported in SE

		Estimates			
Fixed effects	**Method**	**DVA**	**SE**	**FVA**	**SE**
Country (Detrended)	(1) OLS (one-step estimation)	0.04	0.14	0.17	0.22
	(2) Naive DML (orthogonal estimation)	0.24	0.07	0.43	0.11
	(3) Cross-fitting DML (sample splitting and orthogonal estimation)	0.13	0.06	0.21	0.12

The left panel of Figure 2 shows that a change in the PTA hub score from minimum to maximum produces a half standard deviation increase in DVA. The right panel shows a similar level of change in FVA. In other words, holding all the other covariates constant, by changing a country's PTA hub status from minimum to maximum, its value-added exports can increase by a half standard deviation of the average of value-added exports. In the case of a small open economy with a mid-level PTA hub status, and having a quarter of the global average value-added export, our prediction results tell us that if the country improves its PTA hub status to the highest level its value-added exports in DVA and FVA can be doubled.

5.2 | Results of the sample-splitting and cross-fitting DML method

The above findings from the fixed-effects models are highly consistent with our theoretical hypothesis. However, one important assumption that we could not check in the previous analysis is whether our statistical control using a few observed covariates provides a sufficient condition for *ceteris paribus*. Although we implemented a suite of different model specifications, some of which are reported in the Appendix S1, there is a room for bias coming from model selection mistakes, model misspecifications, and omission of higher order interactions.

One thing we can do to improve our inference is to estimate a consistent coefficient of our causal variable that is orthogonal or immune to possible model selection mistakes or misspecifications in "nuisance" parts, which is why we employ the sample-splitting and cross-fitting panel DML method (Belloni et al., 2014, 34). For variable selection and parameter regularization within the DML method, we use the adaptive lasso method (Zou, 2006), which shows a better performance than the lasso method (Tibshirani, 1996). We also include 210 pairwise interaction terms of the observed control variables, which leads to 232 predictors in total, to account for higher order interactions between control variables.

Table 2 summarizes the results of the sample-splitting and cross-fitting DML analysis at the country level. We report three estimates of PTA hub effects: the one-step OLS estimate, the two-step orthogonal estimate, and the sample-splitting and cross-fitting DML estimate. Naive DML results show regularized coefficients after dividing covariates into the causal variable and nuisance variables, without sample-splitting and cross-fitting. Naive DML produces much larger estimates of PTA hub effects than the fixed-effects estimates. Semenova et al. (2018) discuss that Naive DML estimates can be biased due to correlations within group residuals. To remove this bias, Chernozhukov et al. (2017) and Semenova et al. (2018) suggest the sample-splitting and cross-fitting method, which is reported

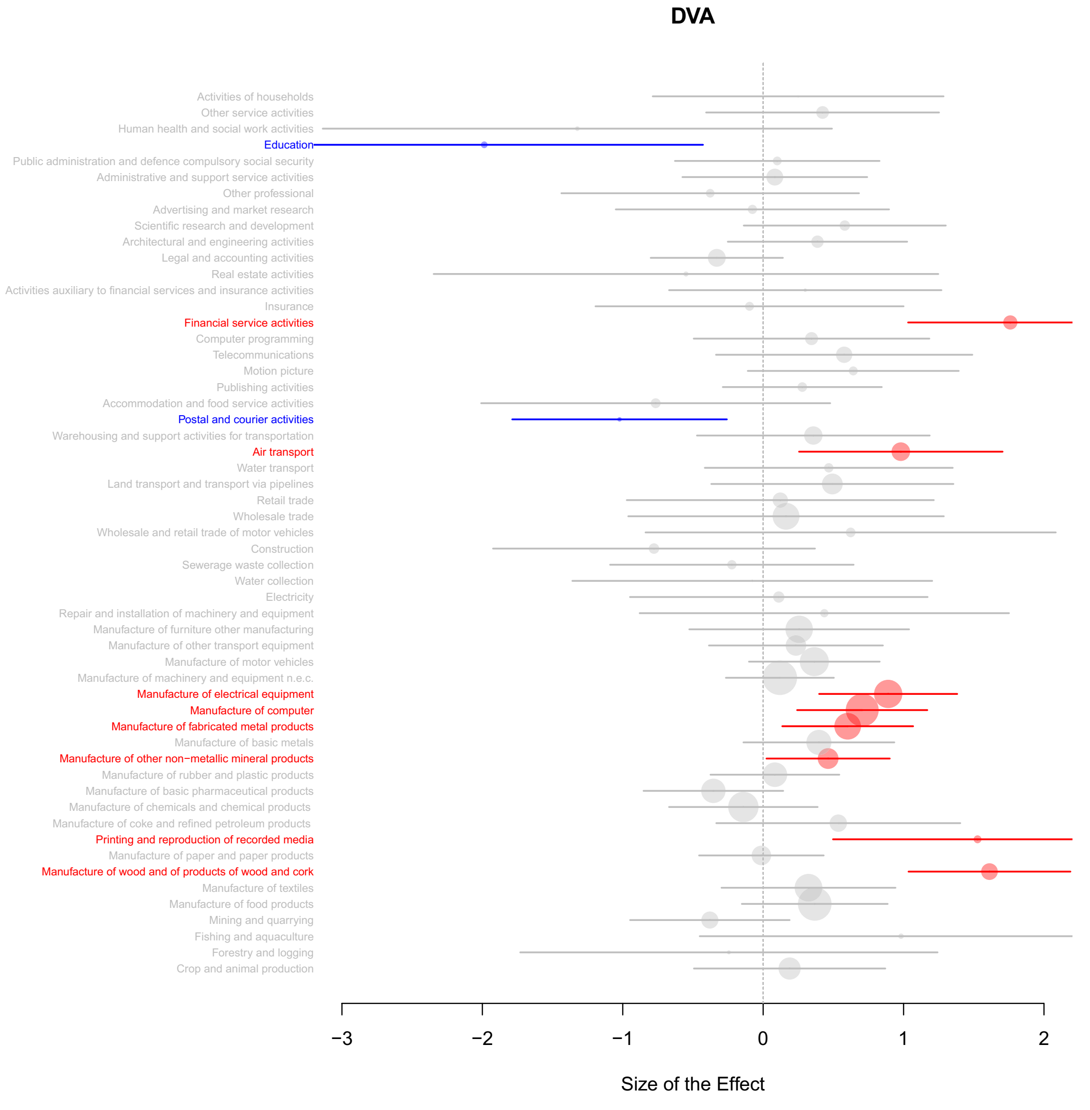

FIGURE 3 Industry-level cross-fitting DML Analysis for DVA: The size of dots is adjusted to be proportional to the export share of each industry. Red colors indicate positive effects and blue colors indicate negative effects. Gray colors indicate vague effects including 0 at the conventional significance level [Colour figure can be viewed at wileyonlinelibrary.com]

in row (3) in Table 2. The sample-splitting and cross-fitting DML method produces estimates similar to those of the fixed-effect methods. The coefficient of the PTA hub score is positive and significant, which is consistent with previous findings and Hypothesis 1: An increase in a country's PTA hub score is associated with an increase in the country's value-added exports in DVA and FVA.

5.3 | Industry-level test

The country-level results are largely consistent with hypothesis 1 that an improvement in a country's PTA hub status leads to an increase in a country's value-added exports. Now we check our second

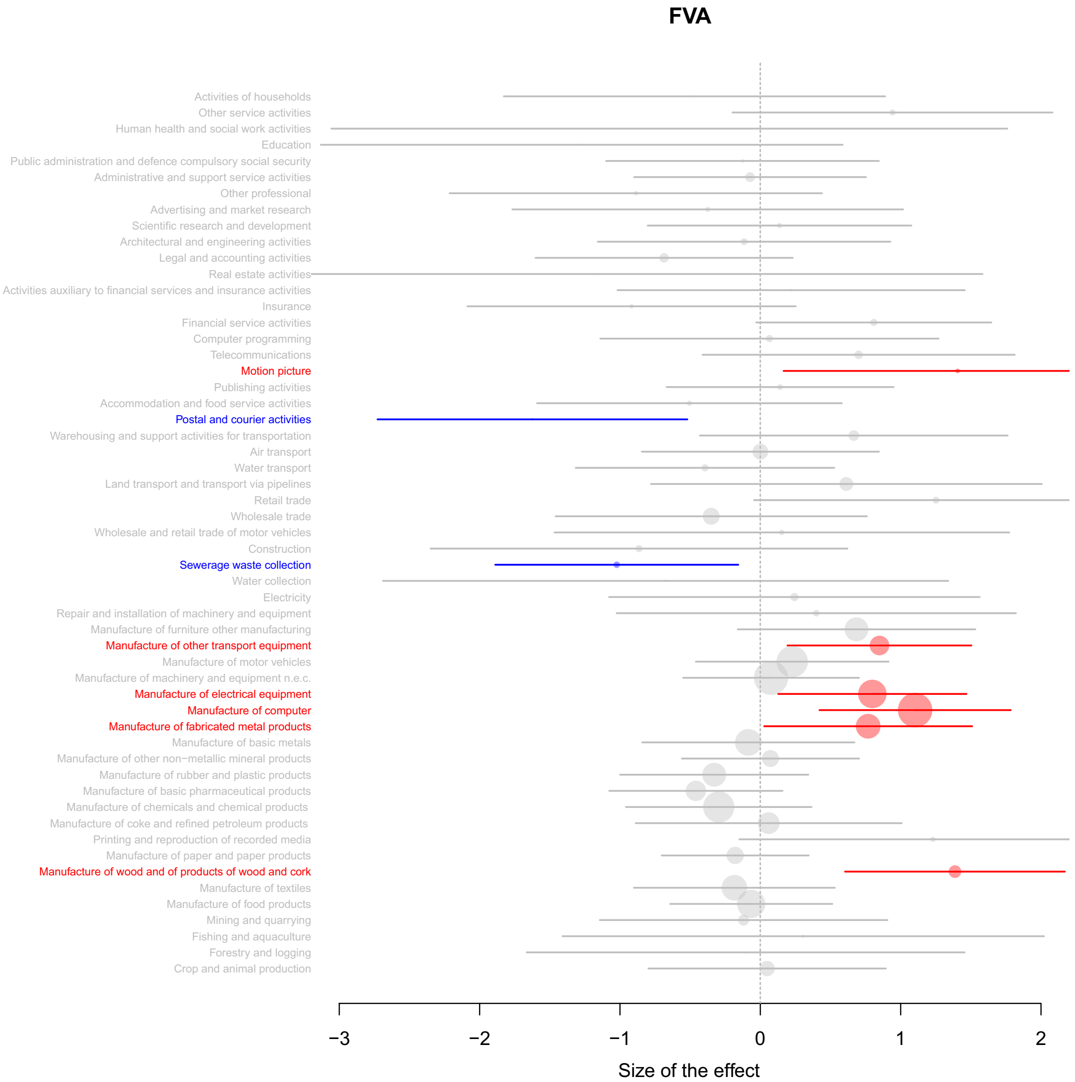

FIGURE 4 Industry-level Cross-fitting DML Analysis for FVA: The size of dots is adjusted to be proportional to the export share of each industry. Red colors indicate positive effects and blue colors indicate negative effects. Gray colors indicate vague effects including 0 at the conventional significance level [Colour figure can be viewed at wileyonlinelibrary.com]

hypothesis: *Industries using many intermediate goods will grow faster if they are located within a country with well-connected, deep-PTA neighbors than industries using fewer intermediate goods.*

We apply the most reliable method (the sample-splitting and cross-fitting DML method with the adaptive lasso regularization method) from our country-level tests to industry-level data. The total number of industries is 55, and hence, we repeat the same analysis 55 times by changing the industry-level dependent variables while the right hand-side variables are held constant. Industry-specific fixed effects are included to account for idiosyncratic factors in each industry.

We visualize industry-specific PTA hub effects as dot plots in Figures 3 and 4. The size of dot is adjusted to be proportional to the export share of each industry. Thus, larger dots indicate industries with larger export shares in GVCs. The color of dots indicates the direction of the effects: Red

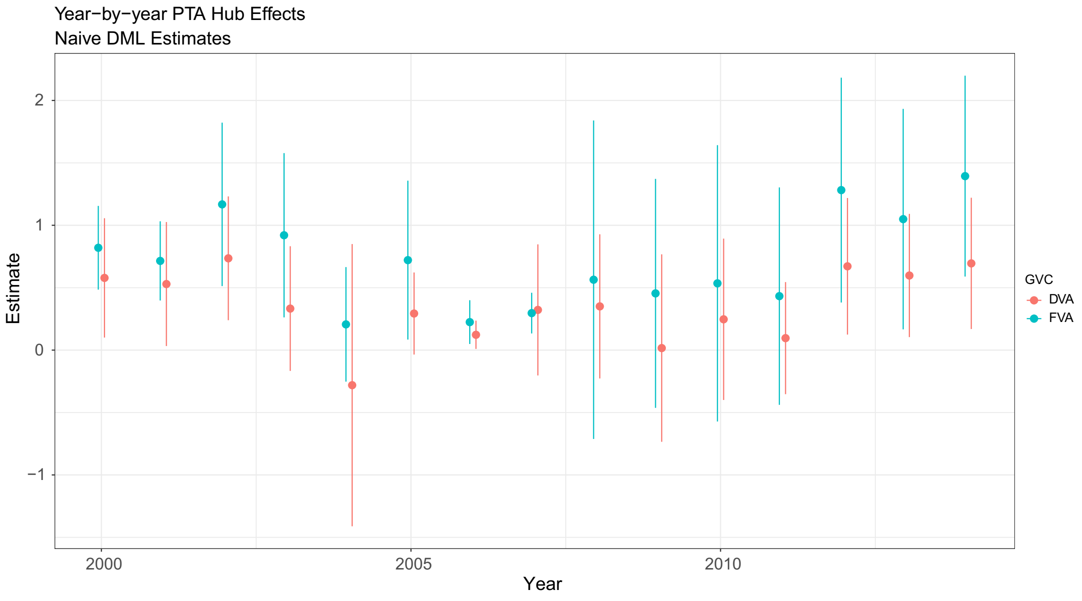

FIGURE 5 Naive DML Estimates of Year-by-year PTA Hub Effects: The estimation method is the naive DML using the adaptive lasso method. The number of observations is 36, with 209 predictors (19 main predictors and 190 interaction terms) [Colour figure can be viewed at wileyonlinelibrary.com]

indicates a positive effect and blue indicates a negative effect. Effects that are not different from zero at the conventional level are displayed as gray dots.

Figures 3 and 4 show that an enhancement in PTA hub status mostly benefits manufacturing sectors. One of the most important beneficiaries is the manufacture of computers. Note that computer manufacturers have the largest industry share in GVCs. Manufacture of electrical equipment, manufacture of fabricated metal products, and manufacture of wood and of products made of wood and cork closely follow the manufacture of computer. Roughly speaking, these four manufacturing sectors drive the positive PTA hub effects. These results are consistent with hypothesis 2. The cross-border diffusion of production stages is driven by manufacturing sectors that are heavily involved in intraindustry trade and information technology (Baldwin, 2013; Elms & Low, 2013; Koopman, Wang, & Wei, 2014). These four manufacturing sectors are key examples of advanced and highly fragmented manufacturing sectors.

Among service sectors, financial service activities, motion pictures, and air transport gain from an enhancement in PTA hub status, while other service sectors such as education, postal and courier activities, and sewerage waste collection suffer from changes brought by stronger PTA hub status. Again, these findings are consistent with hypothesis 2. Financial service activities, motion pictures, and air transport are examples of dynamic or knowledge-intensive service sectors that have a capacity to take advantage of better foreign market access, fast changes in people's tastes, and increased product variety in competition (Wren, Fodor, & Theodoropoulou, 2013). In contrast, traditional and public service sectors do not have a similar capacity to fully take advantage of economic opportunities provided by PTA hub position. As a result, PTA hub position accelerates the reallocation of economic resources from traditional and public service sectors to knowledge-intensive service sectors.

Overall, we found that PTA hub position facilitates reallocation of economic resources into the manufacturing and service sectors, which can reap major benefits from economic opportunities provided by PTA hub position of their home countries. In contrast, PTA hub position hurts static

TABLE 3 Estimates of PTA Hub Effects without Other PTA-related Controls: Other PTA-related predictors except the PTA hub score are dropped. The dependent variables are DVA and FVA out-strengths. Naive DML indicates a naive DML estimation method without sample-splitting and cross-fitting. Cross-fitting DML indicates the sample-splitting and cross-fitting panel DML estimation (Semenova et al., 2018). Clustered standard errors are reported in SE

		Estimates			
Fixed effects	**Method**	**DVA**	**SE**	**FVA**	**SE**
Country (Detrended)	(4) OLS (one-step estimation)	0.08	0.02	0.14	0.03
	(5) Naive DML (orthogonal estimation)	0.09	0.02	0.15	0.03
	(6) Cross-fitting DML (sample splitting and orthogonal estimation)	0.08	0.02	0.13	0.03

economic sectors that are unable to take full advantage of better foreign market access, faster changes in people's tastes, and more product variety.

6 | ROBUSTNESS CHECKS

It is important to check over-time variations because PTA hub effects may be short-term or transient phenomena that exist only when the size of PTA network was relatively small, and decrease systematically as the PTA network expands. If so, PTA hub effects may only be a matter of the past.[9] In order to estimate year-by-year PTA hub effects, we cannot use the sample-splitting and cross-fitting method because the year index was used to split the sample. Instead, we use the DML method without sample-splitting and cross-fitting (naive DML) using the adaptive lasso method for parameter regularization. We also drop a linear trend variable and year-fixed effects, and hence, coefficients are not directly comparable with the previous estimates.

Figure 5 shows yearly (naive DML) estimates of PTA hub effects. While yearly estimates vary quite a lot over time, the point estimates of PTA hub effects remain positive except for a single case (namely, the case of DVA in 2004). One interesting pattern in the yearly estimates is the greater variance in the PTA hub effect during the period between 2008 and 2011, which is associated with the collapse of global trade due to the financial crisis. According to the European Central Bank, "[b]etween the third quarter of 2008 and the second quarter of 2009 global trade volumes declined by approximately 15% and, thus, much more steeply than world GDP, which fell by around 2% over the same period" (European Central Bank, 2010, 16). Since 2012, as global trade started to slowly recover from the financial crisis, the PTA hub effect has increased. There is no sign of diminishing PTA hub effects over time; that is, the competitive advantages of strong PTA hub status remain solid before and after the financial crisis.

Next, we check whether our findings substantively change if we drop other PTA-related predictors from the analysis. The intuition behind this check is that PTA hub effects might be correlated with other PTA-related predictors in unknown ways, and that the estimated PTA hub effects could be sensitive to the inclusion and exclusion of other PTA-related predictors. After dropping all the other

[9]Note that we detrended our original model using a linear trend variable to avoid a spurious time-series regression problem (Granger and Newbold, 1974).

TABLE 4 Effects of alternative measures of PTA centrality: Two-way fixed effects at the country and year level are used for the analysis. Cross-fitting DML indicates the sample-splitting and cross-fitting panel DML estimation (Semenova et al., 2018). Clustered standard errors are reported in SE

		Estimates			
Alternative measures	**Method**	**DVA**	**SE**	**FVA**	**SE**
Degree	(13) Cross-fitting DML (sample splitting and orthogonal estimation)	0.17	0.15	−0.18	0.24
Betweenness	(14) Cross-fitting DML (sample splitting and orthogonal estimation)	−0.00	0.01	0.01	0.02
Participation	(15) Cross-fitting DML (sample splitting and orthogonal estimation)	−0.02	0.01	−0.03	0.02

TABLE 5 Lagged variable sensitivity test

	One-way FE		Two-way FE		Between		First-differenced	
	DVA	FVA	DVA	FVA	DVA	FVA	DVA	FVA
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PTA hub_{t-2}	0.19***	0.19**	0.16***	0.14**	1.47	−1.89	0.10**	0.08
	(0.06)	(0.09)	(0.05)	(0.07)	(3.36)	(4.66)	(0.04)	(0.07)
PTA hub_{t-1}	−0.07	−0.08	−0.09**	−0.10	−8.43	−0.83	0.01	0.06*
	(0.05)	(0.08)	(0.04)	(0.06)	(7.58)	(10.53)	(0.02)	(0.04)
PTA hub_{t}	0.07**	0.14***	0.09***	0.14***	7.70	5.15	−0.02	−0.03
	(0.03)	(0.05)	(0.03)	(0.04)	(4.65)	(6.46)	(0.02)	(0.03)

*$p < .1$.
**$p < .05$.
***$p < .01$.

PTA-related predictors, the reduced model has 35 predictors in total. Table 3 shows the results of the reduced model analysis. Although the magnitudes of effects shrink in comparison with the original model, PTA hub effects are still positive and non-zero in all cases. Note that standard errors in Table 3 are much smaller than standard errors in Table 2, indicating that the lack of statistical control of other PTA-related predictors produces overly confident estimates.

As a placebo test, we check the sensitivity of the sample-splitting and cross-fitting DML estimation method by replacing PTA hub with other measures of node importance (degree, betweenness, and closeness). The intuition behind this placebo check is to see whether other measures of node importance might have similar signs when they are treated as a proper measure of node importance in PTA networks. The estimation method is identical to the one used in Table 2. Table 4 reports the results of the placebo test. Strikingly, none of the alternative measures of node importance show a consistent and statistically meaningful sign. Model (13) tells us that forming an additional PTA that does not improve its hub status does not affect value-added exports significantly. Improving distance-based node importance, measured by betweenness centrality in Model (14), does not increase a country's value-added exports, either. Finally, connecting blocs of PTA networks, measured by participation coefficient in Model (15), has no meaningful effect on a country's value-added exports.

Last, we checked the robustness of our findings to the lag specification using different fixed-effects models. Table 5 reports only the coefficients of our causal variables with different lag specifications to save space. The substantive results do not change much: the two-year lagged PTA hub score has positive and significant signs except the between estimation, which should be taken with caution due to the small sample size ($N = 40$, $K = 23$), and FVA in the first-differenced model. Table 5 also shows that PTA hub status has contemporaneous effects within countries although the effect sizes are smaller than those of the two-year lagged effects.

7 | DISCUSSIONS

In her inaugural address in 2016, Taiwanese President Tsai Ing-wen declared that strengthening Taiwan's *connections* in a PTA network was one of the most important foci of her administration:

> *The first step of reform is to strengthen the vitality and autonomy of our economy, reinforce Taiwan's global and regional* connections*, and actively participate in multilateral and bilateral economic cooperation as well as free trade negotiations including the TPP and RCEP.*[10]

The newly inaugurated president's urgent emphasis on the PTA connections was triggered by Taiwan's isolation in a PTA network; as of 2015 Taiwan only had two PTAs with major economies (Singapore and New Zealand). In fact, Taiwan's isolation had been largely a result of the pressure from China on Taiwan's prospective PTA partners. One source reported that "China urged the European Union to refrain from official contact with Taiwan after the European Commission said it will consider starting talks on investment with the island."[11] Taiwan's isolation in PTA networks has been viewed as a major source of Taiwan's economic decline.[12] One of the most significant blows to Taiwan was the Korea–US FTA that entered into force in 2012. According to one report, "Taiwan's exports during the March 2014-February 2015 period fell 1.13 percent from the period of March 2011-February 2012…However, South Korea's exports to the U.S. market gained 23.44 percent during the three year period."[13]

The tale of Taiwan is just one example out of many cases illustrating the importance of PTA connections in international trade in the 21st century. However, to the best of our knowledge, there has been no study that explains the logic of the importance of network position in a PTA network and empirically examines their effects on trade flows. In this paper, we opened the black box of the positional importance in PTA networks that policy-makers and scholars of international trade have long assumed to exist. We provided a theory of the positional importance in PTA networks, focusing on mesolevel node importance. We explained that a country's value-added exports within GVCs typically stretch over multiple countries and hence are affected not just by the connections they themselves make, but also by connections their PTA partners ("neighbors") make with others.

[10]"President Tsai's Inaugural Address" (http://www.roc-taiwan.org/om_en/post/171.html), emphasis added.

[11]"China's Isolation Strategy Squeezes Taiwan's Exporter Sector" *Bloomberg* November 12, 2015 (https://www.bloomberg.com/news/articles/2015-11-12/china-s-isolation-strategy-squeezes-taiwan-s-exporter-sector).

[12]"Taiwan's Economic Isolation: Desperately Seeking Space" *The Economist*, July 13, 2013.

[13]"U.S.-South Korea FTA affects Taiwan's exports: research report" *Focus Taiwan*, 2016/01/05, http://focustaiwan.tw/news/aeco/201601050032.aspx.

We measured the positional importance by weighted eigenvector centrality scores, taking PTA depth levels as edge weights. Using the decomposed value-added export data, we predicted that an improvement in a country's PTA hub status would lead to an increase in its value-added exports. We also predicted that an improvement in a country's PTA hub status would benefit industries that use many intermediate goods.

The findings of our country-level analysis were consistent with our expectation. Value-added exports grows faster in countries with strong PTA hub status than in those with weak PTA hub status. Our industry-level analysis showed that PTA hub status has significant distributional effects. Manufacturing sectors and service sectors that take advantage of fragmented production processes within GVCs gain most from an increase in PTA hub status.

A change in PTA hub status is brought by governments, while systematic changes in value-added exports are driven by firms in a country. Thus, there are important questions about a firm's decision-making mechanism in response to or in anticipation of changes in its country's PTA hub status. Unfortunately, however, we were unable to directly address this question, due to the unavailability of proper data. Nonetheless, we provide channels through which a country's PTA hub status affects firms' decisions.

First, existing firms would expand their production facilities at home and abroad and diversify their product lines more aggressively when they expect their countries to be better connected with important countries in PTA networks. For example, the Korea–US FTA removed the 5% tariff on flat-screen TVs. At the same time, the Korea–EU FTA that entered into force in 2011 abolished 14% tariffs on flat-screen TVs. Japanese flat-screen TV makers, major competitors of Korean firms, were hit hard by these moves and Japanese trade officials were deeply concerned with the prospects of losing market shares in both Europe and North America.[14] Emboldened by their country's successive move to the center of PTA networks, South Korean flat-screen TV makers made more aggressive investment in next-generation technology such as OLED (organic light-emitting diode) displays.

Second, foreign firms expect that they can take advantage of the fragmented production processes by locating those hub countries that provide more secure protection for foreign investments and a higher credibility of commitments to trade liberalization and the harmonization of domestic rules to global standards (Kim, Lee, et al., 2019).

Third, changes in PTA hub status can widen extensive margins of trade. Domestic firms that have not previously engaged in international trade can take new opportunities in international trade as their country's PTA connections improve over time. As we saw in the industry-level analysis, changes in PTA hub status increase FVA of manufacturing sectors that can take full advantage of fragmented production processes in GVC. That is, changes in PTA hub status can lead to a rapid increase in the number and range of domestic producers involved in the export and import of intermediate goods.

According to our theory and empirical findings, the hub-seeking strategy in PTA networks can be successful if a country can be connected with many important neighbors through deep agreements. Although demands for hub status are almost universal across countries, several domestic and international factors such as domestic backlashes against deep PTAs, the highly selective nature of bilateral PTAs, and the high cost of mega bloc PTAs will affect the distribution of hub status.

[14]Mulgan and Honma (2015), *p.* 13; "Mindful of South Korea, Japan Considers Seeking U.S. Trade Agreement," *The Wall Street Journal*, July 9, 2007; "The Japan syndrome: Japan worries about missing Asia's banquet of free-trade deals," *The Economist*, May 10, 2007.

DATA AVAILABILITY STATEMENT

Data used in the analysis will be available in the corresponding author's dataverse.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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APPENDIX 1

The Sample-splitting and Cross-fitting DML Estimation

We model the amount of value-added exports of country *i* at year *t* (*yit*) as

$$y_{it} = \overbrace{d_{it}\delta}^{\text{hub effect}} + \overbrace{\sum_{k=1}^{K} f(x_{ikt},\beta_k^{(1)})}^{\text{main control}} + \overbrace{\sum_{k=1}^{K}\sum_{h\neq k} g(x_{ikt}\times x_{iht},\gamma_{k,h}^{(1)})}^{\text{interaction control}} + \overbrace{\alpha_i^{(1)} + \nu_t^{(1)}}^{\text{panel control}} + \varepsilon_{it}^{(1)} \tag{6}$$

$$d_{it} = \sum_{k=1}^{K} p(x_{ikt},\beta_k^{(2)}) + \sum_{k=1}^{K}\sum_{h\neq k} q(x_{ikt}\times x_{iht}),\gamma_{k,h}^{(2)}) + \alpha_i^{(2)} + \nu_t^{(2)} + \varepsilon_{it}^{(2)} \tag{7}$$

dit is our key explanatory variable (PTA hub score), **x***it* is a vector of control variables, and *αi* and *νt* are individual effects at the country and year level, respectively. δ is the parameter of our interest and we expect $\delta > 0$.

After controlling for *αi* and *νt* through the method of fixed-effects, it is still challenging to estimate δ in Equation (6) because of unknown forms of nuisance parameters ($f(\cdot)$, $g(\cdot)$, $p(\cdot)$, $q(\cdot)$). If we mis-specify these functional forms, our estimate of δ will be biased and its confidence interval will be invalid. The regularization of Equation (6) will produce the regularization bias in δ by forcing all parameters toward zero (Naive DML in our results). The DML method allows us to learn the functional form of many nuisance parameters ($f(\cdot)$, $g(\cdot)$, $p(\cdot)$, $q(\cdot)$) from data via regularization. Then, we can obtain a root N consistent estimate of dit by Neyman orthogonalization (Chernozhukov et al., 2017). For panel data, Semenova et al. (2018) recently proposed a sample splitting and cross-fitting DML that further ensures the orthogonalization of fitted values between equations.

For the sample-splitting and cross-fitting DML estimation, we rewrite the model by dropping our target variable in the first equation:

$$y_{it} = \sum_{k=1}^{K} f(x_{ikt}, \beta_k^{(1)}) + \sum_{k=1}^{K} \sum_{h \neq k} g(x_{ikt} \times x_{iht}, \gamma_{k,h}^{(1)}) + \alpha_i^{(1)} + \nu_t^{(1)} + \varepsilon_{it}^{(1)} \tag{8}$$

$$d_{it} = \sum_{k=1}^{K} p(x_{ikt}, \beta_k^{(2)}) + \sum_{k=1}^{K} \sum_{h \neq k} q(x_{ikt} \times x_{iht}, \gamma_{k,h}^{(2)}) + \alpha_i^{(2)} + \nu_t^{(2)} + \varepsilon_{it}^{(2)} \tag{9}$$

We group demeaned data into 2-fold partition (c and $-c$) by the year index and estimate coefficients for partition c using $-c$ and vice versa using a regularization method. The regularization method is chosen among the ordinary least squares (OLS), Lasso (Tibshirani, 1996), adaptive Lasso (Zou, 2006) by comparing the residual sum of squares in each stage.

Then, we compute the residuals for partition c using the cross-fit estimates from partition −c and data from partition c. The residuals for partition −c are computed in the same way. We pool the residuals from all partitions and estimate δ by regressing $\tilde{y}it$ (pooled residuals of Equation (8)) on $\tilde{d}$ (pooled residuals of Equation (9)).